ESTIMATING THE NONMARKET VALUE OF BEACH RECREATION IN SOUTHERN CALIFORNIA ACROSS RACE AND ETHNICITY: AN ONSITE TRAVEL COST MODEL

by

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(Under the Direction of Craig Landry)

ABSTRACT

Southern California's beaches are some of the most well-known and widely used recreation sites in the world. For stakeholders who must balance competing interests in such a culturally diverse context it is important to understand if people from different racial backgrounds have distinct preferences for beach recreation. An onsite travel cost model is used to determine the consumer surplus of beach recreation in the Los Angeles. Racial variables are interacted with travel cost to determine if demand varies across racial groups. A Negative Binomial Model, corrected for truncation and endogenous stratification due to onsite sampling, is employed. The results indicate that Black and Asian visitors take fewer trips and Hispanic beachgoers have a distinct demand for recreation characterized by fewer, higher value trips. Additionally, different specifications of travel cost do effect consumer surplus estimates and impact the significance of the Hispanic*Travel Cost interaction term.

INDEX WORDS: Travel cost, recreation demand, beach, non-market valuation, race, ethnicity, onsite sample, negative binomial, consumer surplus, Los Angeles, California

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CHAPTER 1

INTRODUCTION

Beaches are some of the most popular outdoor recreation sites and are extremely significant for coastal communities. Beaches offer a wide variety of water-based recreation activities including swimming, fishing, and surfing as well as various forms of sand and shore-based recreation. They provide recreation opportunities for costal residents and attract tourists and outside investment to coastal communities. Beach recreation is a vital part of California's culture and its costal economy. The California Coastal Act protects access to public beaches in the state which are an important source of open recreation space, especially along the urbanized coastline. Southern California's 350 km of shoreline has more than 75 recreational beaches which are visited more than 129 million times every year. (Dwight et al., 2007)[1]. A 2002 survey by the California Department of Boating and Waterways estimates that 63.4 percent of Californians visited a California beach at least once per year, 2.5 times the national average, and the Public Policy Institute of California (2003) found that 72 percent of Californians made at least one beach trip. California's beaches are also important economic assets. Tourism and beach recreation accounts for over 59 percent of California's $42.9 Billion ocean economy and supports an estimated 504,000 jobs in the state. (Judith Kildow & Colgan, 2005). Southern California beaches generate much of this economic activity as they account for 85% of the beach visits in the state (J Kildow & Shivendu, 2001). Dwight et al. (2012) find that Southern

[1] King, P. and A. McGregor (2012) question the accuracy the agency beach attendance reports used by of Dwight, Brinks et. al (2007) to construct the estimate of beach total attendance. They find that reported beach attendance rarely corresponds to actual beach attendance and that there is a tendency for agencies to overestimate, in some cases by a factor of over 500%.

California Beaches generate over $3.5 billion in beach related expenditures every year with $2.5 billion of that spent directly at beaches. The huge number of visitors to these Southern California alongside the population centers of Los Angeles and San Diego place heavy burdens on both ecological and man-made recreational assets. Beach goers, property owners, and business all desire different mixtures of housing, retail, parking, and undeveloped land along the cost. Conflict over the development of remaining open space has fueled controversy between developers, environmentalists and local governments (Wolch & Zhang, 2004). The decisions of local governments regarding storm runoff and infrastructure investment directly impact water quality and beach attendance (Atiyah et al., 2013). Managers must appropriate resources to a variety of amenities including lifeguards, boardwalks, restrooms, trash pickup, and firepits. They also formulate and enforce regulations regarding parking fees, dogs, alcohol, and other issues.

Study Rationale

With such a large array of management challenges, and such high economic stakes, understanding the value of beach recreation under different conditions is extremely important. Knowing the economic value of beach recreation helps managers, the government, and businesses efficiently allocate resources across competing private, public, and ecological interests. Beach recreation generates economic impact through market transactions such as parking and entry fees, and housing and equipment rentals. These market transactions represent economic inputs for the local economy when money is spent by outside visitors and represent transfers from alternative activities when visitors are local residents (Pendleton et al., 2006). However, the full economic value of beaches is not fully captured in commercial markets. Beach trips generate a consumer surplus when visitors value beach trips more than the costs they paid to visit the beach. Beach access in California is generally free, except for parking fees. The low price of recreation increases its consumer surplus. Given high potential consumer surplus, management challenges, and economic and cultural importance of beach recreation it is not surprising that many researchers have attempted to determine the non- market value of Southern California Beaches (Leeworthy & Wiley, 1993; Leggett et al., 2018; Pendleton et al., 2006). This study draws upon those previous studies and expands upon them in several important ways.

Study Objectives

The primary objective of this study is to estimate the consumer surplus generated by beach trips to Southern California Beaches. The objectives are met by applying a pooled site travel cost model. Poisson and Negative-binomial model specifications are employed and compared.

The specific objectives are as follows:

1. To generate summary statistics corrected for avidity bias due to onsite sampling
2. To generate consumer surplus estimates for Southern California beach trips using recent data and econometric techniques
3. To understand how demand consumer surplus change with the race[2] of the visitor
4. To explore how different specifications of travel cost effect both baseline consumer surplus and differences observed across races

Organization of Study

This study has been organized into five chapters. Chapter one provides background information on Southern California Beach Recreation and defines the purpose and research objectives of this study. Chapter two reviews previous literature on recreation demand and non-market valuation, travel cost model theory and econometric challenges, California beach valuation, and the inclusion of race in recreation demand models. Chapter three provides the research methods

[2] In the context of this study "race" includes categories of ethnicity, specifically hispanic.

including survey design and implementation, study area description, data cleaning and construction of variables, and model specification. Chapter four presents and discusses empirical results from descriptive statistics, avidity corrected summary statistics, and travel cost models. Lastly, chapter five presents conclusions and study limitations.

CHAPTER 2:

LITERATURE REVIEW

This chapter reviews empirical studies that establish research methods and framework necessary to estimate the consumer surplus provided by Southern California Beach visits. The chapter begins with a discussion of non-market valuation and recreation demand. Travel cost models are further discussed with a review of the method and challenges inherent to the method including the specification of travel cost. Next this chapter reviews literature applying the travel cost model to beach recreation and previous studies valuing Southern California beaches. After beach valuation literature the chapter reviews the inclusion of race as determinant of demand in recreation valuation literature.

Nonmarket Valuation and Recreation Demand

Measuring the economic value of recreation sites and amenities is important to inform regulatory policy and management decisions. It also serves an important legal function in assessing damages from disasters such as oil spills, which are particularly relevant for beach recreation sites. Public recreation sites often provide goods and services which are not directly sold in the market. Without easily measurable prices determining the demand for and value of non-market goods such as recreation sites is a challenge which economists have been addressing for over 60 years (Hotelling, 1949). Economists have developed many non-market valuation methods, which aim to estimate consumer demand and surplus for non-market goods in monetary terms. These methods are based on the theory of welfare economics and utilize stated preference data, revealed preference data, or both to explore the quantity of a non-market good or service demanded at different price points.

Stated preference methods ask consumers to report their anticipated activity under hypothetical circumstances, or directly report how much they would be willing to pay or willing to accept for a hypothetical change in circumstance. These methods are flexible and can value any scenario researchers choose to ask about. However, they are subject to the hypothetical bias wherein respondents stated hypothetical behaviors would not necessarily match their actual behavior if the scenario was realized. Revealed preference methods rely only on previous behavior to uncover a demand schedule. While these methods avoid the hypothetical bias, they are limited to measuring pre-existing circumstances and behaviors. They can effectively value current conditions but are of limited use when valuing significant or unprecedented changes. Additionally, because the prices of non-market goods do not reflect their economic value some form of price must be constructed to derive welfare and value estimates. The welfare estimates of revealed preference methods are very sensitive to changes in the construction of this variable (Gonzalez et al., 2008). Revealed preference methods are also limited to quantifying the use-value of recreation sites. They do not measure non-use values such as the value people place one a site’s existence regardless of their intended use of the site, known as existence value, the ability to change the nature of the site in the future, known as option value, and the value of leaving a site to future generations, known as bequest value. Stated preference methods can incorporate non-use values, but if respondents only report future visitation behavior non-use values are not captured (Harris, 2006).

Travel Cost Models

The most common revealed preference method in the recreation valuation literature is the travel cost method. The travel cost method utilizes the cost of reaching recreation site as a shadow price that individuals must pay to access the site. The assumption is that individuals who live closer to a site will visit more often because traveling to the site requires less time and money. Thus individuals reveal their willingness to pay for recreation sites based on the sites they choose to visit and the number of visits the chose to make (Parsons, 2017).

The earliest travel cost models used zonal data, geographic zones surrounding a site were defined such that distance to the site varied across zones. Concentric rings are one very simple way to accomplish this. The number of visits per person is calculated for each zone. Regressing visitation rates on travel cost, based on the distance of each zone from the site, allows researchers to infer an aggregate demand function. Hotelling (1949) proposed the zonal method in a study valuing national parks. As computation power increased in the 1970s most travel cost modeling moved to individual based data rather than aggregate zonal data (Brown & Nawas, 1973). This ties the travel cost model more closely to consumer theory. The 1980's saw the adoption of random utility maximization models, which incorporate site choice across many alternative sites, as part of an effort to better value changes based on recreation quality (Bockstael et al., 1987; McFadden, 2001). During the 1990's travel cost literature expanded to a many different recreation types including fishing, swimming, beach use, boating, hiking, hunting, and skiing among others (Parsons, 2017). Econometric methods also advanced as limited dependent variable and count data models became the norm for single site methods (Haab & McConnell, 1996; Hellerstein & Mendelsohn, 1993; Shaw, 1988). These models are better reflections of the integer nature of trip data and the tendency of trip data to be skewed towards fewer trips. More recently advances in travel cost models have been concentrated in the characterization of heterogeneity of trip demand using latent class models, mixed logit, and finite mixture logit models (Hilger & Hanemann, 2008; Hynes & Greene, 2016; Train, 1998). Single site models have also been extended by incorporating stated preference data alongside revealed behavior, which can also be incorporated into multi-site modes. This allows researchers to estimate the value of policy relevant changes to the site (Cunha-e-Sá et al., 2004; Gonzalez et al., 2008; Landry & Liu, 2009).

Travel cost models can be subdivided into single-site models and multi-site models. Single site models analyze the demand for a single site or an aggregated group of sites where trip cost is a treated as the price of the good and the number of trips taken is the quantity demanded. Multi-site models focus on which recreation site an individual will choose to visit from among a group of possible sites. The site chosen is assumed to be a function of site attributes and travel cost. This framework allows researchers to value many different sites and determine the values of additional amenities or quality changes which are applicable to the entire set of analyzed sites. Multi-site models, unlike single site models also directly incorporate substitution between compatible sites. The biggest disadvantage of multi-site models is that they require much more information about many different sites and information characterizing the relevant choice sets of all respondents (Parsons, 2017). Random utility maximization models and Kuhn Tucker Models are multi-site methods commonly used in recreation valuation. Simpler forms of multi-site models focus exclusively on modeling site choice. Site participation is assumed to be equal to the reported number of trips. Other random utility models can be extended to incorporate a no-trip alternative. These models estimate both participation, as a function of individual characteristics believed to influence the probability of an individual taking a trip, and site choice contingent on participation. (Parsons, 2017). Kuhn-Tucker approaches rely on a single structural framework to simultaneously model participation decisions and site selection (Kuriyama et al., 2010).

In this study we estimate a pooled single site travel cost model. Travel cost methods are most easily applied to sites that are discrete and removed from population centers. This allows the visiting population to be easily identified and the distance between the site and visitors' residences to be easily observed (Ward & Beal, 2000). In contrast beaches are often continuous features of shorelines, not easily divisible into separate sites and are sometimes adjacent to population centers. This is certainly the case in Southern California. These circumstances mean that it is difficult to effectively identify visitor groups and access costs for a specific beach site, and to address heterogeneity in visitation patterns including visitors who cross into multiple sites in a single trip due to the continuous nature of beaches (Dwight et al., 2012). One way to address these challenges is to aggregate individual "beaches" into one site representing a section of coastline. Rolfe and Gregg (2012) estimate recreation values for 1,400 km of coastline in Northeastern Australia to using a survey of residents within 50 km of the shore. In this study we use onsite survey data from 11 sites in Ventura County, LA County, and Orange County California to construct a model intended to reflect the demand for beach recreation across Southern California. The survey and dataset are further discussed in Chapter 3.

Another important consideration in single site travel cost models is the inclusion of the cost of substitute sites. Substitute prices are commonly included and if relevant substitutes are excluded can bias welfare estimates (Gentner, 2007). However, in some cases it is appropriate to omit substitute sites. The more discrete and disaggregated the travel destination(s) in question is the more obvious it is that substitute costs should be included. For a single discrete site, other destinations are direct substitutes and are likely considered by individuals when deciding whether and how often to visit the site. In contrast if the study site(s) constitutes a whole coastline the selection of one location on that cost line as opposed to any other is incorporated into the travel cost (Blaine et al., 2015). Site attribute variables can be included to account for differences between sites in a pooled site model (Huang et al., 2011). In this study we omit the cost of substitute sites and include site binary variables to account for variation between sites because there are no close substitutes for the entire coastline of Southern California.

It is not particularly surprising that the most important independent variable in a "Travel Cost" model is the travel cost variable. What is more surprising is there is no consensus on the correct way to construct the travel cost variable despite extensive research devoted to the subject (Feather & Shaw, 1999; Hynes et al., 2009; McKean et al., 2012). Alarmingly welfare estimates are not robust against alternative constructions of the travel cost variable. They differ significantly across methods (Englin & Shonkwiler, 1995; Hynes et al., 2009). Travel costs can be broken down into two components direct travel costs, also known as transportation costs, and the value of travel time.

Direct travel cost consists of all monetary costs incurred by travelers to visit the site. This includes parking and entry fees, required equipment[3], and the costs of vehicle operation, or driving costs[4]. When fees and requires equipment costs are observed by the researcher they are simply added into the travel cost. By far the most common method of constructing the cost of vehicle operation is multiplying the round-trip distance traveled by a per mile vehicle operation cost from an organization such as the American Automobile Association (Parsons, 2017). This common method has been called into question. Hagerty and Moeltner (2005) compare three

[3] Equipment costs are only included if they are incurred on a per trip basis and are required to participate in the recreation activity. Hunting and fishing licenses are treated in the same way. If equipment or licenses can be used for multiple trips they are not included in the per trip travel cost (Parsons, 2017)

[4] While this component of cost could include the cost of plane or bus fares most studies assume car transportation or restrict their analysis to visitors who traveled by car transportation.

alternative specifications of driving costs: the standard flat per mile rate, a refined per mile rate accounting for vehicle type, passenger load, and vehicle cargo load, and an estimate of perceived cost per based on individual's estimates of the costs they incur. They find that these three measures of driving costs differ substantially but did not lead to a significant difference in welfare measures. They find that refined prescribed driving cost estimate is larger than the baseline per mile rate and that the perceived per mile driving costs were the smallest of the three measures. Ovaskainen et al. (2012) also asked participants to estimate their driving costs and asked if those costs effected their decision. Only 10 percent of their respondents stated that prior to the survey they had an estimate of their driving costs which influenced their recreation decisions in any way. Despite this they found that a model in which only self-estimated individual driving cost was used in constructing the travel cost variable performed well in terms of significance and fit and that the travel cost variable was highly significant. This suggest that even if visitors don't consciously consider driving costs when making recreation decisions or even if they report unrealistically low driving costs, as seen in Hagerty and Moeltner (2005), they still incorporate driving costs into the decision making process on a heuristic or unconscious level. They argue, based on Randall (1994) that using perceived costs is more theoretically consistent because travelers make decisions based on their own perceptions and that it did not raise problems such as non-response.

The second component to travel cost is the value of travel time. Traditionally, the value of an hour travel time in travel has been set equal to the hourly wage of participants[5] [6] or a fraction of their wage (McKean et al., 2012). Setting the value of travel time equal to the wage

[5] Often surveys determine yearly income and wage is computed by dividing yearly income by the number of working hours in a year such as 2000.
[6] In many surveys including the survey used in this study household income is solicited rather than individual income. This is explored further in Chapter 3, construction of variables.

rate is rooted in Becker's neoclassical model which assumes an equilibrating labor market, wherein the marginal value of leisure is assumed to equal the wage rate (Becker, 1965). Cesario and Knetsch (1976) are considered the first to suggest using a fraction of an individual's wage rate to approximate travel time in a recreational demand setting. One third of hourly wage has become the standard approximation of the value of travel time. This precedent stems from early transportation literature (Feather & Shaw, 1999). There are two main justifications for using a fraction of hourly wage. The first is that most people cannot freely substitute labor for leisure time. This violates the assumptions of the neoclassical model and opens the possibility that respondents could be underemployed, in which case they would value leisure time at a lower level than their wage rate (Feather & Shaw, 1999). The second justification is that value of travel time will differ from the marginal value of leisure time if driving provides utility beyond simply moving visitors from their residences to recreation sites (*Victoria Transport Policy Institute* 2012). Researchers have built upon both justifications to further refine the value of travel time.

Feather and Shaw (1999) compute a "shadow wage" by asking respondents if they have flexible work hours and if they consider themselves underemployed or overemployed. They estimate a separate likelihood function for each group. They regress the natural log of wage on variables presumed to influence the desire to work but not the market wage obtainable: family size, nonlabor income, gender, and number of hours worked[7]. This yields a value of leisure time which is higher than the wage rate if overemployed and lower than the wage rate if underemployed. When compared with models estimated using fractions of observed wage the welfare estimates from the shadow wage model fall between models using a time value equal to 100 percent and 33 percent of the wage rate. Hynes et al. (2009) compare models using fractions

[7] They assume that as the number of hours worked increases the marginal value of leisure time increases

of reported income with those using an estimated wage from a secondary data source. They find that estimated wages were approximately half of reported wage and led to signifiagantly lower welfare estimates. They attribute this to the auxiliary wage regression estimating net wage (post tax, pension, etc.) rather than gross wage. They claim this is more accurate because individuals consider opportunity cost based on what they can afford to pay (net wage). Their auxiliary wage regression and any hedonic wage regression has the advantage of providing a usable wage value for individuals who do not respond to the income question, the unemployed, students, and retirees. Presumably these people still consider their time valuable and a wage regression helps include that vale. This comes at the cost of potentially discarding information regarding their role in the labor market (Feather & Shaw, 1999). McKean et al. (2012) compare a traditional model, based on a fraction of the wage rate, with a two-step model which separates the long-term labor decision from the short-term allocation of leisure time[8]. They find the welfare measure from the two-step decision model to be around half as large as the model using one third of the reported wage. They conclude that the two-step decision model is superior to the neoclassical models.

Rather than focusing on the labor market Earnhart (2004) uses a stated preference method, contingent valuation, to adjust the valuation of time costs and driving costs. They base the contingent valuation on the tradeoff between access fees, assumed to be valued at their full dollar amount, time costs[9], and driving costs. They jointly estimate the revealed and stated preference data then revise the value of travel time and driving cost based on the results. One benefit of this method is that only a subset of the sample needs to be given the contingent valuation portion of the survey. Their results yield an adjusted travel time value of 18 percent of

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[8] They also estimate a McConnell Strand Model (McConnell and Strand 1981) which attempts to internally estimate the appropriate fraction of the wage rate with which to value leisure time. However, this model was rejected because the internal estimation failed.

[9] They acknowledge that respondents may be especially sensitive to hypothetical increases in access fees. This would bias the revised driving cost and value of travel time downward.

the wage rate for respondents with inflexible income and nine percent of respondents with flexible income. They conclude that the results strongly indicate the adjusted valuation is proper because it greatly improves consistency between the revealed and stated preference data.

Ovaskainen et al. (2012) use respondent reported driving costs and derive their value of travel time from a contingent valuation, valuing willingness to pay to cut travel time in half. Their travel time results are similar to their driving cost results. Only 6 present stated that they viewed travel time as a cost. However, including the contingent valuation data produced a value of travel time which significantly increased the consumer surplus despite approximately 65 percent of respondents indicating no willingness to pay[10]. They find that using the contingent valuation data to construct willingness to pay significantly increased their consumer surplus estimates. They conclude that their method has advantages over methods utilizing prescribed values of travel time, but their higher consumer surplus could also be due to hypothetical bias.

Fezzi et al. (2014) is possibly the only study to construct a value of travel time from revealed preference data in the context of recreation demand. They collected data on which routes visitors took on their way to the beach and used the tradeoff between faster toll roads and slower open access roads to construct a value of travel time. They compare this value to wage-based valuations of travel time and find it very closely comparable to three quarters of the wage rate[11]. This simple, compelling, and surprisingly high result is complicated by the fact that most respondents used GPS to navigate, choosing either a route with no tolls or the fastest route including all toll roads rather than optimizing across a more complete choice set.

[10] In their preferred model they use a predicted willingness to pay, regressed on individual characteristics, rather than individual willingness to pay. This reduces welfare estimates by reducing the influence of outliers.

[11] Interestingly three quarters of the average wage rate is a slightly closer match.

Looking across the spectrum of research addressing this issue many compelling methods have been proposed, but the literate does not seem to be converging towards a set of best practices or new rule of thumb to replace one third of hourly wage. This frustrating state of affairs may be due to a phenomenon which is well known in transportation literature. The cost of travel time is not a simple function of time and a per hour value. For example, studies have found that personal trips of around thirty minutes or less tend are perceived as either very low cost or as enjoyable. In contrast above ninety minutes cost rises steeply (Mokhtarian & Salomon, 2001). Generally, in transportation literature recreation travel time, especially trips under one hour, would be assigned a value of zero. Specific travel conditions are also important when valuing travel time. Driving through congestion and meeting unexpected traffic delays both cause a significant spike in the value of travel time under those conditions (*Victoria Transport Policy Institute* 2012). Another important finding is that values vary widely across individuals and that a minority of motorists can drive much of the willingness to pay to avoid travel (Burris et al., 2016). Ovaskainen et al. (2012) found this result in their recreation demand model.

California Beach Nonmarket Valuation

The non-market value of a beach day depends on many characteristics of the beach in question including its geographic location, associated facilitates and amenities, quality of the beach, water quality, and weather or water temperature (Pendleton et al., 2006). The consumer surplus value of a beach day also varies based on the characteristics of the beach-goer. Age, income, race, household composition, and beach activity preferences all impact demand for beach recreation and thus impact the consumer surplus associated with a day at the beach (Pendleton et al., 2006; Wolch & Zhang, 2004).

Many studies have used travel cost models to estimate non-market values for beach use in California. Prior to 2000 several technical reports were produced which include consumer surplus estimates for California beaches using travel cost models. Dornbusch et al. (1987) estimates the loss in consumer surplus associated with a 10,000-gallon oil spill off the coast of Orange and Humboldt counties, California, on behalf of the Department of the Interior Minerals Management Service. Leeworthy and Wiley (1993) study the recreational use value for three Southern California beaches in Santa Monica County on behalf of the National Oceanic and Atmospheric Administration, Office of Ocean Resources and Conservation. Hanemann (1997) estimates recreational damages resulting from the American Trader Oil Spill in a report to the California Attorney General's Office. Hanemann's estimate, discounted by 10 percent was used as the legal basis for a jury reward for lost beach recreation (Pendleton et al., 2006). The consumer surplus estimates and available details are summarized in table 1. Unfortunately, the full text of these reports was not available for the composition of this study and therefore the context of their estimates is limited.

After 2000 California beach valuation saw increasing academic interest. P. G. King (2001) in a report commissioned by the City of San Clemente, studied beach spending, the fiscal impact of beaches on the city, and visitation patterns. P. G. King (2001) conducted a single site travel cost model with a log-log functional form. It utilized household income in constructing the value of travel time and the resulting consumer surplus was divided by the size of the household. He estimated the value of a beach day consumer surplus during the high season, $41.81[12], and the low season of October to early May, $4.10. He also estimated annual average consumer surplus across for the four included beaches.

[12] All values adjusted to 2016 dollars via CPI for All Urban Consumers: All items in West. If study does not specify a base year, year of publication is presumed, rather than year of data collection.

Possibly the first academic study travel cost study of California beach values to be published is Lew and Larson (2005). They employ a mixed logit Random Utility Maximization model of recreational site choice and jointly estimate individuals' value of leisure time based on results from Larson and Shaikh (2001). They apply this model to a phone survey of San Diego County residents from 2000 to 2001. Lew and Larson (2005) derive implicit prices for policy relevant beach attributes including lifeguards, parking, and cobblestone surfaces and they find that water quality did not play a significant role in site selection despite users indicating that it was important. The find that the average consumer surplus of a beach day across the sample is $35.77 and the median value is $38.33.

Hilger and Hanemann (2008) utilize an extensive dataset of trip diaries from 595 beach recreators in Southern California representing 4,642 beach trips to study the heterogeneity in preferences for water quality at Southern California beaches. They employ a finite mixture logit model which sorts each choice into one of four segments based on season of trip, if they entered the water, number of children in the household, education, and employment. Unlike Lew and Larson (2005) they find a significant average willingness to pay for improved water quality, this varies greatly across segments. Of note is their finding that among visitors who enter the water groups with children have a lower willingness to pay for improved water quality, possibly due to cognitive dissonance whereby parents are justifying their own behavior. Consumer surplus of beach days is not the focus of the study, but they do estimate a decrease in consumer surplus of $12.70 per visitor per year if 13 popular beaches are closed.

Lew and Larson (2008) expand on Lew and Larson (2005). They utilize the same travel diary dataset as Hilger and Hanemann (2008) rather than the phone survey dataset which only contained data on the single most recent trip. They utilize a repeated nested multinomial logit model to describe the two-stage decision making process in which individuals first choose if they will visit the beach (participation) and if so which beach they will visit (site choice). They use labor market information, including sociodemographic variables, and recreational choice decisions to jointly estimate stochastic shadow value of leisure time functions. They specify 60 site participation choice occasions to which is consistent with observations of daily beach visits during the two-month period. They estimate a full sites model and an aggregate sites model which combines contiguous sites decreasing the number of possible sites from 31 to 16. The aggregate site model, which has the higher likelihood ratio index, yields a mean expected per choice compensating variation of $24.90 per day.

Pendleton et al. (2012) investigate the economic impacts of beach erosion and beach nourishment using data from a yearlong telephone survey in the los Angeles area. They construct a three stage a nested multinomial logit model, which estimates participation, activity choice and site choice. Participation choice is modeled using seasonal and demographic variables. Activity choice, contingent on participation sorts visitors into water, sand and pavement-based activities is estimated using demographics and time of year. Site choice, conditional on activity choice is estimated using site attributes. The model yields detailed values of beach widths for the three activity segments. Generally, these are characterized by diminishing returns to width. Water-based recreators have the highest marginal willingness to pay for additional width, turning negative at 60m. Surprisingly sand-based recreators have lower willingness to pay also turning negative after 60m. Pavement recreators are characterized by lower initial willingness to pay, but constant marginal returns, probably reflecting indifference and a lack of significant coefficients. Pendleton et al. (2012) simulate several counterfactual beach width scenarios. While they result in different numbers of lost or gained trips the welfare change per trip remains consistent at

$141.70 per trip. Pendleton et al. (2012) posit this high value may result from accounting for more substitution possibilities.

Leggett et al. (2018) use a random utility maximization nested site choice model to assess the benefits of reduction in marine debris at Southern California beaches. They use data from a 2013 mail survey of Orange County residents in which respondents provided data on beach trips over the summer beach season. Their combined model incorporates participation decisions and site choice. Participation is modeled across 184 choice occasions, two for each day of the summer months and is estimated using demographic variables. Site choice is modeled using site characteristics and travel costs including observed concentration of marine debris. They find that a decrease in marine debris by 25% is equivalent to a 4% increase in aggregate consumer surplus. That magnitude indicates that a variety of debris cleanup programs are likely cost effective. Leggett et al. (2018) calculate the per trip consumer surplus as the estimated loss associated with the closure of all beach sites divided by the number of trips. This yields a consumer surplus of $29.49 per trip[13].

Consumer surplus values for day trips to California beaches have been thoroughly studied. However, this study expands the literature in several ways. Firstly, it utilizes data from a 2016 survey, 3 years more recent than Leggett et al. (2018). Secondly, the data was collected onsite. Random utility maximization models and general population surveys have many benefits especially when accounting for substitution patterns, but they miss everyone who isn't included in the localized surveys used to construct the model. This study can capture visitors from father away including overnight vacationers who have been largely ignored in the literature summarized above. Lastly, we investigate the roll of race in California beach demand. Other

[13] Not per beach day because in their model a day has two choice occasions.

recent studies have included race as a determinant of site and activity choice (Pendleton et al., 2012) or in the participation decision (Leggett et al., 2018). This study follows the example of Bowker and Leeworthy (1998) by interacting race and ethnicity indicators with travel cost to determine if different races have different elasticities of demand or consumer surplus. The Los Angeles area is extremely racially diverse which makes this dataset highly suitable for this analysis.

Table 1. Travel cost model consumer surplus estimates for Southern California beaches.

Study	Consumer Surplus	CS Measure	Data Source	Primary Objective of Study	Method, Functional Form	Nature of Income Used	Travel Time Value
Dornbusch, Systems et al. (1987)[14]	\$32.17 - \$34.25[15]	Consumer Surplus per trip[16]	1987, Orange and Humboldt counties	Estimate loss in consumer surplus associated with hypothetical 12-mile oil spill.	Traditional Single Site Travel Cost Method	Unknown	Unknown
Leeworthy and Wiley (1993)14	\$15.38 - \$97.88[17]	Consumer Surplus per beach day	1989, Cabrillo-Long Beach, Leo Carrillo State Beach, and Santa Monica	Determine recreational use value for the three beaches	Traditional Single Site Travel Cost Method	Unknown	Unknown
Hanemann (1997)14	\$23.02	Consumer Surplus per beach day	1997, Huntington Beach	Quantify lost consumer surplus from the American Trader Oil Spill	Traditional Travel Cost Method	Unknown	Unknown
King (2001)	\$41.81[18]	Consumer Surplus per beach day	2001, San Clemente Beaches	Analysis of recreational benefits and fiscal impacts of beach recreation	Traditional Travel Cost Method, Log-Log	Household income[19]	1/3rd of hourly income
Lew and Larson (2005)	\$35.77	Consumer Surplus per beach day	2000 - 2001 San Diego County Telephone Survey, Single Most Recent Trip	Generate values for beach days, beach closures and beach amenities.	RUM Mixed Logit Model, including simultaneous estimation of SVLT	Unknown, likely household based on mean of over \$65,000	SVLT function jointly estimated with recreational choice model
Hilger and Hanemann (2008)	\$12.70	CS lost per person-year if 13 popular beaches are closed	2000 - 2001 Southern California Survey and Trip Dairy	Investigate the heterogeneity of preferences for water quality at Southern California Beaches	Finite mixture logit, model indicates 4 preference groups	Unknown	1/2 of hourly income
Lew and Larson (2008)	\$24.90	Expected per-choice occasion (day) compensating variation	2000 - 2001 Southern California Survey and Trip Dairy	Valuing a beach day while explaining site participation and choice and estimating SVLT	RUM Nested Logit Model, of site participation and choice, including estimation of SVLT	Individual wage income is distinguished from nonwage income in estimating SVLT	SVLT function jointly estimated with recreational choice model
Pendleton, Mohn et al. (2012)	\$141.70	Consumer surplus per beach day	2000, Los Angeles area phone survey, conducted over 12 months	Valuing beach width in the context of beach erosion and nourishment	Nested Multinomial Logit of participation, activity choice, and site choice	Unknown	1/2 of hourly income
Leggett, Scherer et al. (2018)	\$29.49	Per trip[20] value associated with closure of all beaches	2013, Mail Survey of Orange County residents focused on summer beach season	Valuing reductions in marine debris	RUM Nested Logit Model, of site participation and choice	Household income	1/3rd of hourly income

[14] Full text not accessed.
[15] All values adjusted to 2016 dollars via CPI for All Urban Consumers: All items in West. If study does not specify a base year, year of publication is presumed, rather than year of data collection.
[16] In most studies, only single day trips are considered. In those cases, beach trip value and beach day value are equivalent.
[17] \$15.38 is the value for Cabrillo-Long Beach, \$97.88 is the value for Leo Carrillo State Beach..
[18] \$41.81 is the value during "high season" as opposed to "low season" (October to early May) value of \$3.00.
[19] Annual household surplus is calculated and divided by the number of individuals per household.
[20] They incorporate 184 choice occasions, 2 per day for the summer months. Thus, surplus is per trip rather than per "beach day".

Race and Ethnicity in Recreation Demand

Race has been established as an important factor in demand for outdoor recreation in the United States. Generally, minority (non-white) individuals have been found to exhibit a lower demand for outdoor recreation (Bowker et al., 2006). The two major competing theories explaining this phenomenon are Ethnicity theory and Marginality theory (Washburne, 1978). Ethnicity theory maintains that the lower demand for outdoor recreation is explained by distinct subcultural values about leisure. In economic terms preferences for outdoor recreation differ across races. Marginality theory attributes lower demand for recreation among minorities to social and structural barriers such as economic factors, which should be controlled for in any economic study, clustering of minorities in urban areas farther from recreation sites, which is controlled for in a travel cost model, historical discrimination such as segregated parks and swimming pools, and ongoing fear of harassment, violence, or social consequences when engaging in outdoor recreation. The two theories are not entirely disconnected. The social and economic discrimination, and class differences which are key to Marginality theory inform the differences in preference for outdoor recreation which are key to Ethnicity theory (Johnson et al., 1997). Wolch and Zhang (2004) are the first to apply this framework specifically to beach recreation. They use data from a telephone survey of residents in Los Angeles, California. They construct a multivariable tobit model testing the extent to which demographics (including race), attitudes and knowledge of relevant information, past activities, and ease of access influence beach recreation. They find that African Americans and Latinos have lower beach use rates. Age, income, immigrant status, distance to the beach, fishing, tidepool collecting, and biocentric attitudes are also found to be significant predictors of demand. Both Ethnicity and Marginality perspectives were supported by their findings.

Bowker and Leeworthy (1998) examine race and trip taking behavior associated with natural resource-based recreation in the Florida Keys. They include a varying parameter to test the congruency of demand and economic value between Hispanic and White user groups which is an interaction of a binary Hispanic variable and travel cost. They find that Hispanic recreationists take more trips to the Keys than Non-Hispanic recreationists. The significance of the travel cost interaction term implies that Hispanics are more sensitive to price increases including increases in travel cost and therefore they derive lower consumer surplus from visiting the Keys. They raise equity concerns that the Hispanic population could be priced out of the market. In this study we binary variables and travel cost interactions for Hispanic, Black, and Asian recreationists[21].

[21] Native American or Pacific Islander was included as an option in the survey but is not included in this analysis. Fourteen respondents identified themselves as Native American or Pacific islander. Of those fourteen three indicated exclusively Native American or Pacific Islander.

CHAPTER 3:

RESEARCH METHODS

This chapter presents: information on the study area, the survey origin, design, and implementation information, data cleaning and the assumptions made in that process, the construction of variables used and analyzed, procedures for obtaining corrected summary statistics, model specifications including corrections for truncation and endogenous stratification, and the derivation of marginal effects, price elasticity and consumer surplus.

Study Area

This study examines demand for beach recreation in Southern California around the city of Los Angeles. Los Angeles is the second largest city in the United States. It is a hub for immigrants to the United States and has one of the fastest growing and most diverse populations in the country (Wolch, 2004). The area's costal coastline is one of it's the most economically and culturally value assets. Due to high population, proximity to the urban center and favorable climate conditions there is a huge demand for beach recreation. Consequently, there are huge pressures beaches with managers, local officials, developers, environmentalists, and beachgoers all advocating for different priorities.

The eleven sites sampled in this study are outlined in figure one. They span Ventura County, Orange County, and Los Angeles County. Ventura Pier is the northernmost beach sampled and Doheney is the southernmost beach. They were chosen in consultation with experts and advisers to represent the diversity of sites and recreationists in the region which is curtail if the results of this study are to be generalized to the Los Angeles area or Southern California as a whole.

Table 2. Sites Surveyed

Site	County	Observations Used
Ventura Pier	Ventura	50
Marina Park	Ventura	61
Port Hueneme	Ventura	58
Silver Strand	Ventura	58
Zuma	Los Angeles	96
Santa Monica	Los Angeles	120
Dockweiler	Los Angeles	65
Redondo	Los Angeles	79
Huntington	Orange	124
Strands	Orange	91
Doheney	Orange	84

Figure 1. Sites Surveyed

Survey Design and Implementation

The survey was conducted in the summer of 2016 under the leadership of Jon Christensen of the Institute of the Environment and Sustainability, UCLA and Dr. Philip King of the San Francisco State University School of Business. The overarching goal of the project is to explore the fact that it's getting harder people with lower incomes to live near the coast and therefore harder to get to the beach. For example, the California Coastal Commission and California Coastal Conservancy have advocated for less expensive hotels and more camp sites. The project is particularly concerned with access for minorities and other low-income households. This is especially relevant in Los Angeles due to high racial diversity and a history of racial tension. To meet these goals, they designed the survey to determine who goes to California beaches, why they visit the beach, if they experience obstacles which keep them from going to the beach, how the value of the beach differs between coastal and inland Californians, and how willingness to pay for lodging varies across income. They included demographic questions including detailed racial and ethnic classifications. They inquired about on the beach trip including time onsite, number of nights stayed, activities engaged in, willingness to pay for lodging and walk from parking, and transportation method. They ascertained demand for beach recreation by asking for the total number of trips to this beach and other beaches in California. They had participants indicate the importance of beach amenities, access features such as free parking, and visitor characteristics. Participants also indicated the severity of difficulties or obstacles they faced when visiting the beach. The full survey is included in Appendix A.

When selecting sites, they consulted with an experts and advisers to ensure that the locations chosen represent the diversity of visitors in the area. Research assistances were recruited with a priority being given to having at least one Spanish speaker per group so that the survey could be given in Spanish. They were given human subject research training at UCLA Phil King to conduct the survey with cultural competency. They conducted intercept surveys as visitors left the beach. They randomly selected participants and had a high response rate of 80 to 90%. They collected 1074 responses 889 of which are used in this study. This study addresses the goals of the project by exploring how race impacts consumer surplus and price response of beach recreation.

Data Cleaning and Assumptions

Data cleaning required making some assumptions. Some data was imputed due to non-response and observations were dropped in some cases. Many of these acts are reported here, some are reserved for the next section on variable construction. One general principle which was always followed is that when the survey contained a range of values it is represented by its mean.

When reporting on multiday, overnight, trips some respondents gave contradictory answers. If they gave a lodging type and number of nights stayed but indicated that it was not an overnight trip overnight was set to a positive value. If they reported that both lodging, and number of nights was not applicable, but still indicted that it was an overnight trip the overnight value was set to a negative value. If they indicated lodging as “primary residence” or “my home” overnight was set to a negative value. Otherwise if they did not indicate that a trip was overnight it was assumed to be a day trip.

Some respondents on overnight trips indicated that they traveled by foot but lived too far away to walk. It is assumed that they traveled by car and they misunderstood the question which intended to ask how they traveled from their primary residence.

Questions about race, number of visits, and activities participated in included option open ended responses. When given these were coded when it was reasonably clear what was intended.

For example, visiting “three times a week during the summer” was coded as 39 trips, while “a lot” was coded as a missing value. Additionally, if a question such as employment status had a “other” option without an open-ended response “other” was coded as a missing value because it does not represent a cohesive category.

If hours onsite or household size were missing they were replace by their mean. If transportation method was not indicated car was assumed because most respondents traveled by car. If gender was not indicated female was assumed because most respondents were female. Income was imputed using the mean of income of respondents in the same education category. If education was omitted a secondary education, more than high school and less than a four-year degree, was assumed because this most closely matched the income level of these responses. If race was not indicated, the respondent was assumed to not be Black, Hispanic, or Asian.

Multi-purpose trips were not explicitly identified in the survey but were inferred in some cases including: open ended primary activity responses such as “soccer trip in the area,” and if lodging was indicated as family or friend, in which case visiting that person is likely a secondary purpose.

Observations where choice of residence and beach recreation were likely to be endogenous were dropped because spending on housing is effectively replacing travel cost. This included indicating lodging as their vacation home, and respondents who indicated they visited the beach every other day or more, over 182 times per year. Dropping these observations removes the most intensive users, but if their travel cost does not reflect the true cost of a beach trip information gained from these observations can only mislead.

Observations missing zip code, and therefore missing distance to beach, were dropped, observations missing both income and education data were dropped, and observations where distance was greater than 600 were dropped because air travel and hotel costs are not considered and at 50 mph 600 miles represents a 12-hour drive. Beyond that point the odds of omitted air travel and hotel costs sharply increase.

Variable Construction

The dependent variable of the study is number of trips to the beach at which the visitor was intercepted[22] in the past year. This is derived by simply adding one to the response to the question “Not including this trip, how many trips have you made to this beach in the past 12 months?”

The most crucial independent variable is travel cost. This has two components: the driving/transportation costs, and value of travel time. The transportation costs differ between different transportation types. For car travel transportation cost is represented by:

$$Transportation\ Costs\ for\ Drivers = TrC_d = Roundtrip\ Distance * 0.1697^{23} \quad (1)$$

For bus travel within 25 miles of the beach twice the standard bus fare of $1.75 is used (CBS Los Angeles, CBS Los Angeles Radio, 2014). For bus travel beyond 25 miles half the transportation cost for drivers is used. Bikers and walkers are assigned no transportation cost.

There are three specifications of time cost used in this model. They also differ based on transportation type. The first specification for cars is:

$$Time\ Costs\ for\ Drivers = TmC_d = \ Duration\ of\ travel * \frac{household^{24}\ income^{25}}{2000} * \frac{1}{3} \quad (2)$$

[22] Data on number of trips to other California beaches and if this trip is “typical” of other trips exists in the dataset but is not used in this study’s models.
[23] Operating cost per mile for a medium sedan (AAA, 2017)
[24] The nature of the income variable is discussed later in this section.
[25] Giving implied household hourly wage.

This is the traditional specification of time cost as 1/3rd of income. For bus riders the trip is assumed to take 1.5 times as long as drivers. Bikers are assumed to travel at 10 mph and walkers at 3 mph.

The second specification is designed to be consistent with transportation literature. All trips under 30 minutes are assigned a time cost of zero (*Victoria Transport Policy Institute* 2012). Trips longer than thirty minutes are given a cost of 1/6th of hourly income because in transportation literature 1/3rd of income is more commonly cited as a work commute value not a recreation travel time value.

The third specification gives an upper bound for travel cost. 100 percent of hourly income is not used because the pre-tax nature of the income variable and the inability of most people to freely trade income for leisure time makes this specification difficult to defend. Following the findings of Fezzi et al. (2014) 3/4ths of hourly income is used as the final specification.

A binary "college" variable is constructed of everyone who earned a four-year degree or higher and is included in the model. Two binary water activity variables are constructed the first includes every respondent whose primary purpose for visiting the beach was an activity performed in the water such as "swim or wade." The second includes all respondents who indicated that they participated in any activity performed in the water. These are not included in the model because beach activity may be endogenous with the number of trips taken but they are summarized.

Because the survey solicits household income and includes no data on the number of adults who shared transportation costs the initial model estimates household income per trip. To estimate individual consumer surplus, the household consumer surplus must be divided by the number of household members at the beach. This variable is estimated using the "household" and "party[26]" (number of people in beach group) variables. Two variations are estimated. The first estimates the number of household members at the beach, including children. It is equal to the household size if party size exceeds household size and is equal to the household size and otherwise is equal to party size. The second variation attempts to estimate the number of adults in the household present. It is derived by simply truncating the values of the first specification such that the maximum number of household members is two[27].

Onsite Sampling and Correction of Summary Statistics

Onsite surveys are a simple and cost-effective method of gathering data on recreation demand, including beach visits. However, onsite sampling introduces problems not found in surveys of the general population. Onsite samples only capture people who visit or use the site, providing no information on the rest of the population. This truncates the distribution of observed visits at one. Truncation prevents researchers from analyzing the extensive margin of recreation demand, such as non-users who would visit a site if more amenities were provided or cost was decreased. Additionally, unless the total number visitors to the site is known, onsite sampling can't determine the percentage of the population who visit the site. The second problem caused by onsite sampling is endogenous stratification, in which the likelihood of a visit being included in the sample varies due to other variables. People who visit the beach more often are more likely to be sampled, which is a manifestation of avidity bias.

More broadly anything that violates the second OLS assumption and leads to non-random sampling based on another variable introduces endogenous stratification. In our sample site

[26] The survey specifies that "party" should only include household members. This seems to have been completely ignored as around 1/3rd of party sizes exceed household sizes.
[27] This under estimates if there are more than 2 adults in a household and over estimates if one adult brings multiple children to the beach.

choice would introduce bias if the eleven chosen sites do not accurately represent Southern California beaches. If the precise locations, times, and frequency of the surveys do not effectively capture a reprehensive sample of the visitor population then any analysis that fails to correct for this would be biased.

Avidity bias effects sample means and variances as well as regression results. Thomson (1991) derives mean and variance estimators which correct for avidity bias in onsite samples. Let N denote the total number of visitors to a site in a given year. When sampling from a population of beachgoers the probability of selecting any given individual will be:

$$Prob(intercepting\ visitor\ i) = t_i/T \qquad (3)$$

Where	t_i = Number of trips taken annually by visitor i T = Total Number of trip-days taken annually by the population, usually unknown = $\sum_{j=1}^{N} T_j$

Equation (1) illustrates that onsite samples will be endogenously stratified by trip frequency with higher intensity users having a greater probability of being sampled. Also if d_i = 0 the probability of intercepting visitors is also 0; non- users are truncated.

Thomson (1991) shows when P_i is the probability of selecting individual i the number of individuals in the population (N) and the population total for the variable of interest (Z) can be estimated by:

$$\widehat{N} = \frac{1}{m}\sum_{i=l}^{m}\frac{1}{P_i} \qquad (4)$$

$$\hat{Z} = \frac{1}{m}\sum_{i=l}^{m}\frac{Z_i}{P_i} \tag{5}$$

Where m is the sample size.[28] Substituting in the selection probability P_i from equation (1) into equations (4) and (5) gives:

$$\hat{N} = \frac{T}{m}\sum_{i=l}^{m}\frac{1}{t_i} \tag{6}$$

$$\hat{Z} = \frac{T}{m}\sum_{i=l}^{m}\frac{Z_i}{t_i} \tag{7}$$

Using equations (4) and (5) the population mean $\bar{z}$ can be estimated by[4]:

$$\hat{\bar{Z}} = \hat{Z}/_{\hat{N}} = \frac{\sum^{m}(Z_i/t_i)}{\sum^{m}(1/t_i)} \tag{8}$$

Equation 8 estimates the population mean, while requiring only information on the onsite sample29. Because the summations in the population mean estimator are weighted by the inverse of trips we expect the raw sample mean for variables which are negatively correlated with trips to be downward biased. Because onsite expenditures and travel distance are expected to be negatively correlated with avidity, estimates of economic impacts which don't correct for avidity likely underestimate the impact of the recreation site in question.

Thomson (1991), also derives the variance of the population mean:

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[28] Thompson (1991) specifies m' samples of size m'=1 because when sampling probabilities are not uniform the derivation of statistics for non-replacement sampling is much more complicated than for replacement samples.

[29] Note that this does not account for the fact that multi-night visitors who visit the beach multiple times are more likely to be sampled. This is a case of length of stay bias. Surveys were conducted using exit interviews and multi-night visitors can exit the beach multiple times in one trip.

$$var(\hat{Z}, \widehat{N}) = \frac{(N-1)}{Nm}\,\bar{Z}^2 \left[\frac{S_{Z/T}^2}{\bar{Z}^2} + \frac{S_{1/T}^2}{1} + \frac{S_{(Z/T)(1/T)}^2}{\bar{Z}}\right] \tag{9}$$

$$S_{Z/T}^2 = var\left(\frac{Z}{T}\right) = \frac{T^2}{N(N-1)} \sum_{i=1}^{N} \frac{t_i}{T} \left(\frac{Z_i}{t_i} - \frac{Z}{T}\right)^2$$

$$S_{1/T}^2 = var\left(\frac{1}{T}\right) = \frac{T^2}{N(N-1)} \sum_{i=1}^{N} \frac{t_i}{T} \left(\frac{1_i}{T_i} - \frac{N}{T}\right)^2$$

$$S_{(Z/T)(1/T)}^2 = cov\left(\frac{Z}{T}, \frac{1}{T}\right) = \frac{T^2}{N(N-1)} \sum_{i=1}^{N} \frac{T_i}{T} \left(\frac{Z_i}{T_i} - \frac{Z}{T}\right)\left(\frac{1_i}{T_i} - \frac{N}{T}\right)$$

Equation (9) can be estimated from the sample using:

$$\widehat{var}(\hat{Z}, \widehat{N}) = \hat{\bar{Z}}^2 \, \frac{1}{m} \left[\frac{S_{Z/T}^2}{\hat{\bar{Z}}^2} + \frac{S_{1/T}^2}{1} + \frac{2S_{(Z/T)(1/T)}}{\hat{\bar{Z}}}\right] \tag{10}$$

$$S_{Z/T}^2 = var\left(\frac{Z}{T}\right) = \frac{\bar{T}^2}{(m-1)} \left[\sum_{i=1}^{m} \left(\frac{Z_i}{t_i}\right)^2 - \frac{1}{m}\left(\sum_{i=1}^{m} \frac{Z_i}{t_i}\right)^2\right]$$

$$S_{1/T}^2 = var\left(\frac{1}{T}\right) = \frac{\bar{T}^2}{(m-1)} \left[\sum_{i=1}^{m} \left(\frac{1}{t_i}\right)^2 - \frac{1}{m}\left(\sum_{i=1}^{m} \frac{1}{t_i}\right)^2\right]$$

$$S_{(Z/D)(1/D)} = cov\left(\frac{Z}{T}, \frac{1}{T}\right) = \frac{\bar{T}^2}{(m-1)} \left[\sum_{i=1}^{m} \left(\frac{Z_i}{t_i} * \frac{1}{t_i}\right) - \frac{1}{m} \sum_{i=1}^{m} \frac{Z_i}{t_i} \sum_{i=1}^{m} \frac{1}{t_i}\right]$$

Where $\bar{T}$ is the average number of trip days, computed as: $T/\widehat{N} = \frac{m}{\Sigma(1/t_{i)}}$, via equation (6).

<u>Correcting Avidity Bias in Travel Cost Models</u>

Endogenous stratification and truncation must also be addressed in the travel cost model itself.

Shaw (1988) presents a correction for avidity bias using the Poisson Model. When taking an onsite sample an individual's number of desired trips (t_i*) can only be observed by the analyst, t_i = t_i*, if they visit at least once, t_i* > 0. All individuals for whom t_i* = 0 are unobserved. The population conditional density of demand, f(t_i*|x), must be inferred from the truncated conditional density of demand:

$$g(t_i|x) = \frac{f(t_i^*|x)}{Pr(t_i^* > 0)} \tag{11}$$

Where x is a vector of explanatory variables. When the sample population is generated by random draws from the truncated density (11), the probability of intercepting an individual i, conditional on covariate vector x, is given by:

$$Prob(intercepting\ visitor\ i \mid x) = \frac{t_i}{Tx} \tag{12}$$

Where	T_x is the total number of trips taken by visitors with characteristics x = $\sum_{j=1}^{N_x} t_j$
	N_x is the total number of visitors with characteristics x, N = $\sum_x N_x$

Equation (12) implies that users who take more trips are more likely to be sampled and that non-users are truncated.

Shaw (1988) derives the probability of observing a specific number of trips, t, in the onsite sample (conditional on covariates x) as the sum across all individuals in the sample (m) of truncated onsite densities (equation 11), weighted by the probability of intercepting an individual (equation 12):

$$\Pr(t = t_i|x) = \sum_{i=1}^{m} [\Pr(intercept\ i|x) * g(t_i|x)] = \sum_{i=1}^{m} \left[\frac{t_i}{T_x} * \frac{f(t_i^*|x)}{Pr(t_i^* > 0)}\right] \tag{13}$$

In the probability limit m terms can be factored out of the equation:

$$\Pr(t = t_i|x) = \frac{m}{Tx} * t_i * \frac{f(t_i^*|x)}{Pr(t_i^* > 0)}$$

Where m/T_x is equal to the inverse of the expected value of trips from the truncated density (11):

$$\Pr(t = t_i|x) = \frac{1}{\sum_{t=1}^{\infty} t * g(t|x)} * t_i * \frac{f(t_i^*|x)}{Pr(t_i^* > 0)} = \frac{t_i}{\sum_{t=1}^{\infty} t * \frac{f(t|x)}{Pr(t > 0)}} * \frac{f(t_i^*|x)}{Pr(t_i^* > 0)}$$

Assuming many observations the onsite density function for an observation, v_i, given x, will be:

$$\mathrm{h}(t_i|x_i) = \frac{t_i}{\sum_{t=1}^{\infty} t * f(t|x_i)} * f(t_i|x_i) = \frac{t_i}{E(t_i|x_i)} * f(t_i|x_i) \quad (14)$$

Where $\frac{t_i}{E(t_i|x_i)}$ is a weight which corrects for the truncation and endogenous stratification which results from avidity bias in the onsite distribution. If $f(t_i|x_i)$ follows a Poisson distribution where Shaw (1988) shows that:

$$\mathrm{h}(t_i|x_i) = \frac{t_i}{\lambda_i} * \frac{\exp(-\lambda_i)\,\lambda_i^{\,t_i}}{t_i!} = \frac{\exp(-\lambda_i)\,\lambda_i^{\,(t_i-1)}}{(t_i-1)!} \quad (15)$$

Where $\lambda_i = \exp(x_i\beta) = E(t_i|x_i)$, in the standard poisson model, and β is a vector of unknown parameters to be estimated. Thus substituting $u_i = (t_i - 1)$ as the dependent variable in the poisson model in place of t_i corrects for trucation and engogenous stratification. The expected value and variance of equation (13) are:

$$E(t_i|x_i) = \lambda_i + 1, \quad var(t_i|x_i) = \lambda_i$$

If data support the assumption that $var(t_i|x_i) = \lambda_i$ equation (13) offers a convinent way produce unbiased estimators from onsite data. However, often data does not support this assumption. Travel cost models are often overdispersed with variances significantly greater than the mean. The negative binomial model (NB2) introduces overdispersion by adding an unobserved error term to the conditional mean function. $E(t_i|x_i) = \exp(x_i\beta + \varepsilon_i)$ where ε_i follows a one parameter gamma distribution $G(\alpha^{-1}, \alpha^{-1})$. Englin and Shonkwiler (1995) apply the correction in equation (14) to the NB2 model

$$f(t_i|x_i) = \frac{\Gamma(t_i + \alpha^{-1})}{t_i!\ \Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda_i}\right)^{\alpha^{-1}} \left(\frac{\lambda_i}{\alpha^{-1} + \lambda_i}\right)^{t_i} \tag{16}$$

$$f(t_i|x_i) = \frac{\Gamma(t_i + \alpha^{-1})\alpha^{t_i}\lambda_i^{t_i}(1 + \alpha\lambda_i)^{-(t_i+1/\alpha)}}{\Gamma(t_i + 1)\ \Gamma(\alpha^{-1})}$$

$$\mathrm{h}(t_i|x_i) = \frac{t_i}{\lambda_i}\frac{\Gamma(t_i + \alpha^{-1})\alpha^{t_i}\lambda_i^{t_i}(1 + \alpha\lambda_i)^{-\left(t_i+\frac{1}{\alpha}\right)}}{\Gamma(t_i + 1)\ \Gamma(\alpha^{-1})} \tag{17}$$

$$\mathrm{h}(t_i|x_i) = \frac{t_i\Gamma(t_i + \alpha^{-1})\alpha^{t_i}\lambda_i^{t_i-1}(1 + \alpha\lambda_i)^{-(t_i+1/\alpha)}}{\Gamma(t_i + 1)\ \Gamma(\alpha^{-1})}$$

Where λ_i is the mean, α is the dispersion parameter to be estimated.

$$E(t_i|x_i) = \lambda_i + 1 + \alpha\lambda_i \qquad var(t_i|x_i) = \lambda_i(1 + \alpha + \alpha\lambda_i + \alpha^2\lambda_i)$$

As α approaches 0 the variance and conditional expected value of equation (17) converges to those of equation (15), the Shaw Poisson Estimator. This suggests that if the dispersion parameter is not significantly different from zero the Poisson Estimator is appropriate.

Model Specification

The theory underlying travel cost models is that the value of recreation derives from consumers maximizing utility of recreational experiences subject to the budget and time constraints (Stoll, 1983). The travel cost method assumes that as travel cost increases participants will visit recreation sites less frequently. Because of this the number of trips individuals take reflects their budget of time and money and the utility they derive from the site. By regressing the number of trips taken, on travel cost and other variables, travel cost models construct a demand curve for recreation which can be used to derive welfare measures such as consumer surplus. In this study the utility of a beach trip is assumed to be:

$$Utility(trips) = f(Cost, Trip\ Characteristics, Demographics,\ Site\ Attributes)$$

Where response to cost can vary across demographics and trip characteristics. In more detail:

$$Trips = f(TC,\ TC * Overnight, TC *\ Race^{30}, Overnight, Demographics, Site\ Bianaries^{31})$$

The variables are presented in table 3.

The coefficient on travel cost is expected to be negative because as the cost of a good rises the quantity demanded decreases. The coefficients for overnight trips is expected to be negative because individuals who take longer trips are expected to take fewer due to time constraints. There is no expectation for the coefficient on income. The quantity demanded of any normal good should increase with income, but when valuing public recreation sites, the coefficient on income is often negative. It is possible that beaches are inferior goods due to their low cost of entry (Blaine et al., 2015). It is also possible that because travel cost models (including this model) often exclude trips from outside driving range that high value luxury visitors are being systematically excluded. The coefficient on college is expected to be positive because education has been found to increase demand for beach recreation (Leggett et al., 2018). Male and age are often insignificant in travel cost models so there is no prior expectation for

[30] A model including a "Spanish" variable, indicating which respondents took the survey in Spanish, and a Spanish*Travel Cost interaction term was tested. Neither variable was significant, in the negative binomial model, and they did not improve the fit of the model.

[31] A model including interaction terms between the 11 site binary terms and travel cost was also estimated. Only one of the interaction terms was found to be significant, at p=.10, in the negative binomial model. This is no more than would be expected by chance and including the interaction terms did not improve the fir of the models.

their coefficients. Wolch and Zhang (2004) found Black and Hispanic had lower recreation demand, so their coefficients are expected to be negative.

Table 3. Definition of Variables

Variable	Definition	Expectation
Trips	Number of trips taken annually to site	
TravelCost[32]	Transportation Cost + Value of Travel Time[33]	-
Overnight	Indicator: 1 if trip was overnight	-
Income	Household annual income, in thousands	None
Age	Age of respondent	None
College	Indicator: 1 4-year degree or more	+
Employed	Indicator: 1 if respondent is employed	-
Male	Indicator: 1 if respondent is male	None
Asian	Indicator: 1 if respondent is Asian	None
Black	Indicator: 1 if respondent is Black	-
Hispanic	Indicator: 1 if respondent is Hispanic	-
Site Constants	Site specific constants	

[32] Three variations of travel cost are specified with different values of travel time.
[33] Travel cost is interacted with the three race variables, and overnight

Marginal Effects

Marginal effects measure the expected change in the dependent variable if an independent variable changes by one unit. Because the models are logarithmic functions the marginal effects of are calculated using:

$$\frac{dE(Y)}{dX} = \beta Y \qquad (18)$$

In isolation the coefficient β gives a percentage change in the dependent variable due to a unit change in the independent variable. When multiplied by the average of the dependent variable (beach trips) the coefficients yield a marginal effect.

Price Elasticity of Demand

The price elasticity of demand (η) is a unitless measure of the response of demand for a good to small changes in the price for that good. It is obtained by dividing the percentage change in quantity demanded by the percentage change in price. In the case of travel cost models travel cost is the price of recreation trips.

$$\eta = \frac{dTrips}{Trips} \Big/ \frac{dTravel\ Cost}{Travel\ Cost} = \frac{Travel\ Cost}{Trips} * \frac{dTrips}{dTravel\ Cost} = Average\ Travel\ Cost * \beta_{Travel\ Cost} \ (19)$$

Because price and quantity demanded are inversely related price elasticity has a negative value.

Demand is more "elastic" (responsive to changes in price) when elasticity is more negative. Demand is termed unit elastic when the elasticity is equal to negative one, elastic when it is larger (in absolute terms) and inelastic when it is smaller (in absolute terms). Elasticity is strongly affected by the presence of substitutes. If close substitutes are available consumers can easily switch goods if price rises. Because the model does not include substitutes it may underestimate elasticity (Rosenberger & Stanley, 2007).

Consumer Surplus

Welfare associated with recreation is often measured in consumer surplus. Consumer surplus is the difference between an individual's willingness to pay for a good and the price they must pay to obtain the good. Consumer surplus can be obtained by integrating the demand function between the price of a good and the choke price at which a consumer is indifferent to purchasing the good. Because beach recreation has few if any required monetary costs it often exhibits high consumer surplus. When count data models are used the average consumer surplus can be calculated as the negative inverse of the travel cost coefficient (Creel & Loomis, 1990).

$$CS = \frac{-1}{\beta_{TC}} \qquad (20)$$

CHAPTER 4:

RESULTS

This chapter reports and discusses corrected summary statistics, compares the poisson and negative binomial models. The preferred model is estimated using the three specifications and the results are reported and discussed. Welfare measures are compared across the specifications.

Avidity Corrected Summary Statistics

Following (Thomson, 1991) we correct summary statistics for endogenous stratification. The corrected statistics for the variables included in the models are included[34] in table 4.

Table 4. Avidity Corrected Summary statistics for variables included in the model.

	Mean	SD	Corrected Mean	Corrected SD
Trips	9.123	(14.858)	3.398	(0.108)
Travelcost, low	22.615	(40.480)	33.897	(2.688)
Travelcost, 1/3rd income	31.174	(52.881)	44.861	(3.538)
Travelcost, high	49.737	(86.191)	70.292	(5.775)
Overnight	0.103	(0.304)	0.175	(0.020)
Income	87.739	(52.583)	80.933	(2.326)
Age	38.519	(13.706)	37.458	(0.582)
College	0.435	(0.496)	0.417	(0.023)
Employed	0.772	(0.420)	0.770	(0.019)
Male	0.372	(0.484)	0.377	(0.022)
Asian[35]	0.106	(0.308)	0.112	(0.015)
Black	0.056	(0.231)	0.060	(0.011)
Hispanic	0.410	(0.492)	0.451	(0.023)

As expected the avidity correction drastically lowers the mean of trips. The corrected mean of 3.398 is less than half of the mean drawn directly from the sample population. Variables whose

[34] We exclude site binary variables because they provide no additional information about the sample participants
[35] Note that race variables are not inclusive. Many participants identified themselves as multiracial.

means decrease when corrected are positively correlated with avidity. Income decreases slightly from an average of $88 thousand to an average of $81 thousand. As expected, all the travel cost variables' means increase because they are negatively correlated with the number of trips. They increase by around $10 to $20. Overnight also increases as expected. The proportion of overnight trips increases from 10% to 18%. The proportion of Hispanic beachgoers increased by approximately 4% from 41% to 45%. Most of the other variables show little response to the correction for avidity bias. However, the differences may still be significant because the standard deviation of all variables decreased drastically. For example, the standard deviation of trips decreases to 0.108, less than one tenth of its original value. This suggests that the data may not be overdispersed. While it is possible that this result was reached in error, correcting standard deviations for avidity can result in a substantial gain in precision (Landry et al., 2016; Thomson, 1991). .

Table 5. Corrected Transportation Summary Statistics

	Mean	SD	Corrected Mean	Corrected SD
Car	93.5%	(0.247)	95.3%	(0.009)
Foot	2.8%	(0.166)	1.2%	(0.003)
Bus	2.6%	(0.159)	2.5%	(0.006)
Bike	1.1%	(0.106)	1.0%	(0.005)

Table 6. Corrected Employment Summary Statistics

	Mean	SD	Corrected Mean	Corrected SD
Employed	77.2%	(0.420)	77.0%	(0.019)
Retired	5.4%	(0.226)	4.8%	(0.009)
Student	7.3%	(0.261)	7.3%	(0.012)
Unemployed	10.0%	(0.301)	10.9%	(0.015)

Neither transportation or employment was affected very strongly, although both also show drastically decreased standard errors. The transportation summary illustrates that cars are the dominant form of transportation in Los Angeles. The proportion of people who traveled by foot decreased by over half from 2.8% to 1.2%. While small in magnitude this large relative decrease illustrates that people, who can walk to the beach, and therefore live close by, are more likely to be frequent visitors. The biggest relative change in employment was the decrease in the corrected proportion of retired visitors from 5.4% to 4.8%. The retired are not included as a separate category in the model.

Table 7. Additional Corrected Variables of Interest

	Mean	SD	Corrected Mean	Corrected SD
Hours Onsite	4.145	(1.923)	4.315	(0.10)
Party Size	3.562	(2.10)	3.742	(0.105)
Household	3.498	(1.668)	3.543	(0.083)
Include Water	0.716	(0.451)	0.654	(0.023)
Prime Water	0.177	(0.382)	0.142	(0.015)

All variables continue to exhibit drastically decreased corrected standard errors. Of interest in table 7. is the high proportion of respondents who participated in water activities. When corrected for avidity the proportion decreases from 72% to 65%. The corrected value is still much higher than others have found for Southern California beaches (Hilger & Hanemann, 2008). This is likely partially due to the sample being taken in the summer, but it may also be due to improved data collection. In contrast a corrected proportion of only 15% of respondents stated that their primary activity was water based. This illustrates that if researchers only solicit a primary activity they will underestimate the number of people effected by water quality issues.

Model Comparison

We estimate corrected and uncorrected poisson and negative binomial models using the 1/3rd of income travel cost specification to determine which functional form provides the best fit. Tables 8 and 9 contain results of the regressions.

Table 8. Poisson Model Comparison

	Uncorrected Model		Corrected Model	
	Coefficient	SE	Coefficient	SE
Travelcost	-0.0174***	[0.001]	-0.0208***	[0.001]
TC_Asian	-0.00560**	[0.002]	-0.00884***	[0.003]
TC_Black	0.000255	[0.002]	-0.00084	[0.003]
TC_Hispanic	0.00333***	[0.001]	0.00400***	[0.001]
TC_Overnight	0.0120***	[0.001]	0.0139***	[0.001]
Male	0.243***	[0.023]	0.272***	[0.024]
Age	0.00284***	[0.001]	0.00315***	[0.001]
Income	0.00368***	[0.000]	0.00415***	[0.000]
College	-0.0781***	[0.025]	-0.0930***	[0.026]
Employed	0.256***	[0.030]	0.292***	[0.032]
Asian	-0.134**	[0.056]	-0.109*	[0.063]
Black	-0.369***	[0.073]	-0.410***	[0.083]
Hispanic	-0.429***	[0.033]	-0.488***	[0.036]
Overnight	-0.831***	[0.081]	-0.956***	[0.092]
Doheney[36]	0.474***	[0.066]	0.555***	[0.073]
Huntington	0.417***	[0.072]	0.498***	[0.078]
Hueneme	0.502***	[0.064]	0.592***	[0.070]
Marina Park	0.0266	[0.076]	0.0428	[0.084]
Redondo	0.595***	[0.065]	0.680***	[0.071]
Santa Monica	0.181***	[0.066]	0.213***	[0.073]
Silver Strand	0.112	[0.073]	0.148*	[0.080]
Strands	0.682***	[0.064]	0.763***	[0.069]
Ventura Pier	0.903***	[0.071]	1.050***	[0.077]
Zuma	0.157**	[0.068]	0.212***	[0.075]
Constant	1.618***	[0.074]	1.409***	[0.080]
Log Likelihood	-5479.25		-5735.533	
AIC	-11008.49		11521.07	
BIC	-11128.16		11640.73	
N	886		886	

[36] In this and all following models Dockweiler beach is used as the base case

Table 9. Negative Binomial Model Comparison

	Uncorrected Model		Corrected Model	
	Coefficient	SE	Coefficient	SE
Travelcost	-0.0115***	[0.002]	-0.0139***	[0.002]
TC_Asian	-0.00104	[0.003]	-0.000966	[0.003]
TC_Black	-0.000556	[0.003]	-0.00179	[0.004]
TC_Hispanic	0.00250*	[0.001]	0.0029	[0.002]
TC_Overnight	0.00662***	[0.002]	0.00767***	[0.002]
Male	0.186***	[0.064]	0.212***	[0.078]
Age	0.00175	[0.002]	0.00193	[0.003]
Income	0.00371***	[0.001]	0.00437***	[0.001]
College	-0.00555	[0.067]	0.00746	[0.081]
Employed	0.140*	[0.076]	0.142	[0.092]
Asian	-0.217*	[0.125]	-0.256*	[0.151]
Black	-0.320**	[0.163]	-0.345*	[0.196]
Hispanic	-0.443***	[0.082]	-0.509***	[0.099]
Overnight	-0.674***	[0.162]	-0.788***	[0.194]
Doheney	0.353**	[0.161]	0.396**	[0.194]
Huntington	0.319*	[0.169]	0.370*	[0.203]
Hueneme	0.367**	[0.151]	0.425**	[0.182]
Marina Park	-0.0132	[0.168]	-0.00337	[0.202]
Redondo	0.493***	[0.157]	0.555***	[0.189]
Santa Monica	0.133	[0.148]	0.144	[0.178]
Silver Strand	-0.00804	[0.170]	-0.0241	[0.205]
Strands	0.543***	[0.160]	0.580***	[0.193]
Ventura Pier	0.770***	[0.176]	0.892***	[0.212]
Zuma	0.0667	[0.153]	0.0915	[0.184]
Const	1.743***	[0.178]	-1.966	[1.778]
alpha	0.656***	(0.034)	32.826	(59.754)
Log Likelyhood	-2732.49		-2627.51	
AIC	5516.98		5307.01	
BIC	5641.44		5431.46	
N	886		886	

In all four models the coefficient on travel cost is negative and significant at the 1% level. The poisson models are characterized by high levels of significance for many different variables, everything but the interaction of Travelcost with Black and two site binary variables. This is not necessarily an indication of superior fit. The two negative binomial models have many fewer significant coefficients. However, the log likelihoods of the negative binomial models are roughly half as large as the poisson models and their information criteria are both approximately half as large as the poisson models. This indicates superior fit. Additionally, in the uncorrected model the dispersion parameter alpha is strongly significant. Unfortunately, in the corrected model the dispersion parameter is no longer significant[37]. This indicates that the model may not be correctly specified. However, given that the diagnostic criteria so strongly favor the negative binomial models and that the uncorrected model is known to fall prey to very significant avidity bias. The corrected negative binomial model is the best fit for the data.

Corrected Negative Binomial Travel Cost Specification Comparison

The corrected negative binomial model is estimated using the threes specifications of travel cost: the traditional specification using 1/3rd the implied household hourly income as the value of travel time, a upper bound model using 3/4 of implied household hourly income as the value of travel time, and a conservative model specifying a time value of 0 for all trips under 30 minutes and a time value of 1/6th of income for longer trips. The result of the three specifications is recorded in table 10.

Across the three models the coefficient on travel cost is negative and significant at least the 1% level. As travel cost increases the coefficient on travel cost becomes smaller (less negative) which translates to increased consumer surplus as travel cost increases. This is intuitive given that we are adjusting the shadow price of beach recreation without changing the behavior

[37] The natural log of the dispersion parameter is significant at the 10% level.

of beachgoers. If price decreases, but behavior remains constant a lower consumer surplus is implied, and the opposite is true for price increases.

Table 10.

	Low Travel Cost		Medium Travel Cost		High Travel Cost	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Travelcost[38]	-0.0209***	[0.002]	-0.0139***	[0.002]	-0.00753***	[0.001]
TC_Asian	-0.00143	[0.004]	-0.000966	[0.003]	-0.000304	[0.002]
TC_Black	-0.00129	[0.005]	-0.00179	[0.004]	0.00181	[0.003]
TC_Hispanic	0.00556**	[0.002]	0.00290[39]	[0.002]	0.00123	[0.001]
TC_Overnight	0.0124***	[0.003]	0.00767***	[0.002]	0.00389***	[0.001]
Male	0.219***	[0.077]	0.212***	[0.078]	0.212***	[0.078]
Age	0.00187	[0.003]	0.00193	[0.003]	0.00198	[0.003]
Income	0.00367***	[0.001]	0.00437***	[0.001]	0.00476***	[0.001]
College	-0.0108	[0.080]	0.00746	[0.081]	0.0135	[0.081]
Employed	0.134	[0.091]	0.142	[0.092]	0.146	[0.092]
Asian	-0.260*	[0.143]	-0.256*	[0.151]	-0.267*	[0.153]
Black	-0.329*	[0.192]	-0.345*	[0.196]	-0.334*	[0.197]
Hispanic	-0.491***	[0.097]	-0.509***	[0.099]	-0.508***	[0.098]
Overnight	-0.804***	[0.195]	-0.788***	[0.194]	-0.778***	[0.188]
Doheney	0.425**	[0.193]	0.396**	[0.194]	0.387**	[0.195]
Huntington	0.269	[0.201]	0.370*	[0.203]	0.413**	[0.204]
Hueneme	0.448**	[0.180]	0.425**	[0.182]	0.419**	[0.183]
Marina Park	-0.0659	[0.200]	-0.00337	[0.202]	0.0165	[0.204]
Redondo	0.570***	[0.188]	0.555***	[0.189]	0.561***	[0.190]
Santa Monica	0.149	[0.177]	0.144	[0.178]	0.141	[0.179]
Silver Strand	-0.0267	[0.202]	-0.0241	[0.205]	-0.00806	[0.206]
Strands	0.604***	[0.191]	0.580***	[0.193]	0.579***	[0.194]
Ventura Pier	0.931***	[0.210]	0.892***	[0.212]	0.879***	[0.212]
Zuma	0.135	[0.183]	0.0915	[0.184]	0.085	[0.185]
Const	-1.27	[0.927]	-1.97	[1.778]	-2.84	[4.044]
alpha	16.636	(15.947)	32.826	(59.754)	75.207	(307.822)
Log Likelihood	-2617.79		-2627.51		-2633.67	
AIC	5287.59		5307.01		5319.33	
BIC	5412.04		5431.46		5443.79	

[38] The travel cost variable and subsequent interaction terms vary across the three models (low, medium, and high). They are presented alongside each other for ease of comparison.
[39] The TC*Hispanic variable for the medium travel cost model is significant at p=.107, just missing the .10 cutoff.

The significance of coefficients is mostly stable across the three models. With two exceptions all variables maintain the same significance variables across all three models. Crucially for this analysis the interaction of Hispanic*Travelcost decreases in magnitude and significance as travel costs increase. The interaction term is significant at p= 0.021 for the low travel cost model, p= 0.107 for the medium travel cost model (just missing conventional significance) and at p=.251 for the high travel cost model. This indicates that the consumer surplus of Hispanic beach goers is increasing less quickly than others as travel costs increase and that this difference is not robust across different specifications of the travel cost variable. The interaction variable between travel cost and overnight trips behaves similarly to the Hispanic interaction term, indicating a slower increase in consumer surplus. However, that interaction term maintains significance.

The coefficient on income increases with travel cost implying that a high income increases trips more if travel costs are higher, a reasonable result. The coefficients on Hispanic Black, Asian, Male, and Overnight trips remain nearly constant as travel cost changes.

Consumer Surplus Across Travel Cost Specifications

Consumer surplus is calculated from the model results by taking the negative of the reciprocal of the travel cost coefficient. To determine how consumer surplus changes across groups we add interaction terms to the travel cost coefficient before taking the negative reciprocal. Because the interaction terms travelcost*overnight and travelcost*hispanic are significant in the low travel cost model and nearly significant (p=0.107) in the medium travel cost model we include them in this analysis. Additionally, overnight consumer surplus is evaluated on both a per trip and per night basis by dividing the consumer surplus by the average number of nights spent by overnight visitors (4.871)[40]. The base consumer surplus from this model is household consumer surplus because household income is used to calculate the value of travel time and the cost of transportation is also shared by the whole household. Table 11 displays estimated household consumer surplus values.

Table 11. Household consumer surplus.

	Low TC	Med TC	High TC
Base CS	$47.85	$71.94	$132.80
Hispanic	$65.19	$90.91	$158.73[41]
Overnight Total[42]	$117.65	$160.51	$274.73
Overnight Per Night	$24.15	$32.95	$56.40

These consumer surplus estimates are high compared to previous literature, but they represent total household values. Consumer surplus value per individual can be inferred by dividing the household consumer surplus by the avidity corrected average number household members at the beach (2.771). Consumer surplus per adult can be inferred by dividing the household consumer surplus by the avidity corrected average number of adults per household group (1.762).[43] Tables 12 and 13 contain these values.

Within household consumer surplus the overnight values are especially interesting. While the values initially appear high, the model does not account for other required overnight costs such as food and lodging or spending on complementary goods. As a result, the model likely overstates the consumer surplus of overnight visitors. Dividing the consumer surplus across the number of nights stayed yields an even smaller consumer surplus. In this context it is likely that overnight visitors experience a lower consumer surplus than day trippers.

[40] This differs from table 4 because it only includes overnight visitors, leaving out many visitors who are day trippers and stay for 0 nights per trip.
[41] In the high consumer surplus model, the coefficient on Hispanic is not significant
[42] These values represent overnight visitors who are not hispanic.
[43] Estimates for the number of adults per group and the number of household members per party are derived in Chapter 3 construction of variables.

Hispanic visitors appear to have larger consumer surplus values than other visitors. This may be due to differing preferences between user groups, and part of the consumer surplus could be due to differences in household size. Everything else equal larger household size leads to larger household surplus values.

Table 12. Per adult consumer surplus.

	Low TC	Med TC	High TC
Base CS	$27.15	$40.83	$75.37
Hispanic	$37.00	$51.59	$90.09
Overnight Total	$66.77	$91.10	$155.92
Overnight Per Night	$13.71	$18.70	$32.01

Table 13. Per individual consumer surplus.

	Low TC	Med TC	High TC
Base CS	$17.27	$25.96	$47.93
Hispanic	$23.53	$32.81	$57.28
Overnight Total	$42.46	$57.93	$99.14
Overnight Per Night	$8.72	$11.89	$20.35

Per adult and per individual consumer surplus are simple fractions of household surplus and thus provide minimal additional information. Overall consumer surplus values for Los Angeles beaches are found to be very substantial. Even the lowest estimate of $17.27 per individual (including children) is in line with historic estimate of consumer surplus for Southern California beaches. Pendleton et al. (2012) who also analyzed beach recreation in the Los Angeles area also found very high consumer surplus, with a large confidence interval.

Aggregate Consumer Surplus

To generate an estimate of aggregate consumer surplus the population of visitors must be specified in both space and time. Due to the locations of the sites sampled this study values beaches in the Southern California counties of Los Angeles, Ventura County, and Orange

Counties, excluding San Diego County. The survey was taken in the Summer. Because multiple studies have found demand for beaches in the area varies across seasons we restrict the valuation to summer recreation in the three counties with are represented (Hilger & Hanemann, 2008; P. G. King, 2001). Dwight et al. (2007) estimates 129 million beach visits occur yearly in Southern California using data from 2000-2004[44]. This estimate does not include Ventura County and includes San Diego County, which accounts for around 30% the estimated visits. To roughly account for this the 129 million is revised downwards by 20% due to the exclusion of San Diego County and the inclusion of Ventura Country. Dwight et al. (2007) also finds that 53% of the visits take place during the summer months. This suggests around 54.7 million visits to the relevant area per summer. Our corrected statistics suggest that around 17.5%, or 9.6 million of these are overnight visits and 45.1 million are day trips. Using base per adult consumer surplus[45] of $27.15, $40.83, or $75.37 gives a total consumer surplus of $1.23, $1.84, or $3.40 billion for Summer day trips to Los Angeles, Orange, and Ventura counties depending on the travel cost specification used[46]. Per adult consumer surplus for overnight trips this yields $0.64, $0.87, or $1.50 billion in consumer surplus to the area in the Summer from overnight trips, not accounting for onsite costs. Combined the consumer surplus comes to $1.87, $2.71, or $4.9 billion across the three consumer surplus specifications for Los Angeles, Orange, and Ventura Counties during the Summer months. Dwight et al. (2012) find that $3.5 billion is spent annually on total beach expenditures in Southern California, which includes the Winter months and San Diego County.

[44] This may understate current visitation because the population of California has increased, it is also much smaller than the (*California Beach Restoration Study*, 2002) estimate of over 378 million day trips (to the entire state). It may also overstate current visitation. P. King and McGregor (2012) criticize this estimate for relying on inflated agency estimates.

[45] Minors are often not surveyed and therefore not accounted for in consumer surplus statistics.

[46] The highest travel cost specification likely overestimates the value of travel time. The middle travel cost specification is most directly comparable to prior research.

This suggests large consumer surplus relative to expenditures, which is reasonable given the open access nature of the resource.

Marginal Effects

The Hispanic, Asian, and Black variables all produce significant marginal effects. The Hispanic variable is the largest and most significant ($p<0.01$). Hispanic visitors take around 51% fewer trips. Because the average number of trips is 3.398 this suggests a reduction of 1.67 trips. Given the higher consumer surplus experienced by Hispanic visitors, at least in the lowest travel cost scenario, they seem to take fewer beach trips. However, those they do take are more valuable and they do not decrease as rapidly as travel cost increases. The coefficient on the Asian and Black indicators are significant at $p<0.10$. Black visitors take 35% fewer visits, suggesting an average of 2.21 visits per year. Black visitors take around 25% fewer visits, suggesting an average of 2.55 visits per year. This lower attendance among minority visitors is consistent with prior recreation research. Previous analysis in the Los Angeles area found lower beach attendance by Black and Hispanic visitors, but not Asian visitors (Wolch & Zhang, 2004).

Overnight trips and income also have a significant marginal effect on trips taken ($p< 0.01$) in all three models. An overnight trip is associated with an approximately 79% reduction in trips taken in all three models. This suggests a decrease of almost three trips down to an expected .71 trips. This could be problematic considering the data is truncated at zero and everyone took at least one trip. However, that assumes an income and age of 0 which is not a realistic scenario. An increase of $10,000 in income results in an approximately 4.4% increase in trips. An increase of around $66,000 in income results in an expected 1 additional beach trip per year. This magnitude is reasonable and consistent with the context of Los Angeles where beach access is becoming less affordable as opposed to more rural recreation sites that don't experience the same population pressures.

Price Elasticity

Price elasticities measures the responsiveness of demand to changes in price. They are calculated by multiplying the coefficient of travel cost by the average travel cost[47]. Price elasticities across user groups and travel cost specifications are reported in table 14.

Table 14. Price elasticity of demand.

	Low TC	Med TC	High TC
Base	-0.708	-0.624	-0.529
Hispanic	-0.520	-0.493	-0.443
Overnight	-0.288	-0.279	-0.256

Demand for beach trips in the Los Angeles area is inelastic across all user groups. In the base case for the medium travel cost scenario a 1% increase in travel cost results in around 0.62% decrease in trips taken. Elasticity is lower for Hispanic visitors and under half as large for overnight visitors which is expected from their higher consumer surplus values. Demand appears less elastic as the magnitude of travel cost increases.

[47] Avidity corrected average travel costs are reported in table 4.

CHAPTER 5

CONCLUSIONS:

Travel cost models are a powerful tool, which enable researchers to illuminate the value of outdoor recreation sites which would otherwise go under appreciated. In this study we add to a wealth of literature exploring the value of beaches in Southern California. Recent studies have begun including race as an explanatory factor in demand for beach trips (Leggett et al., 2018; Pendleton et al., 2012). Following the example of Bowker and Leeworthy (1998) we include interaction terms between travel cost and three different race variables: Hispanic, Black, and Asian. Our results indicate that Hispanic beachgoers have a different demand structure than non-hispanic beach goers. Like Wolch and Zhang (2004) we find that Hispanic people demand fewer beach trips. However, we also find that Hispanic beach goers have a lower response to travel cost and therefore derive greater consumer surplus from each trip. This differs from the finding of Bowker and Leeworthy (1998) in the Florida Keys where Hispanic recreationists were found to have lower consumer surplus and higher price elasticity. The higher consumer surplus for Hispanic visitors, especially in the models with lower travel cost specifications[48], diverge from the typical narrative that minorities have a lower demand for and value of outdoor recreation. Around 45% of the population of Los Angeles is Hispanic. If this user group has a distinct pattern of beach recreation understanding that pattern could be very important. The size of the Hispanic population

[48]While the Hispanic*TC variable does not approach significance in the highest travel cost model this model is the least realistic specification.

of Los Angeles may also explain why a significant difference in repose to travel cost was found. Over three times as many respondents identified as Hispanic than identified as Asian and over five times as many respondents identified as Hispanic as identified as Black. Black and Asian visitors were also found to have a lower demand for beach recreation, around 35% and 25% lower respectively. Their consumer surplus did not differ significantly from other visitors. This is consistent with prior research into recreation demand which suggests that minorities in the United States have a lower demand for outdoor recreation. Wolch and Zhang (2004) found that Black and Hispanic resident of Los Angeles had lower recreation demand, but unlike this study did not find that Asian recreators have a significantly lower demand[49].

The specification of the travel cost variable, especially the value of travel time is an ongoing controversy in travel cost literature. This study tests three specifications of travel cost which shift both the magnitude of travel cost and its distribution by including a specification which sets the travel cost of all trips of thirty minutes or less. As expected and well documented in the literature this has a significant impact on consumer surplus estimates. Critically travel cost specifications did have a meaningful impact on the Hispanic*Travelcost interaction term. Relative consumer surplus across the models remained reasonably stable. However, as the specified travel cost increased the coefficient of travel cost and the interaction term decreased in magnitude. This caused the interaction term to decrease in significance from $p= 0.021$ to $p= 0.107$ to $p=.251$. Our findings suggest that different specifications of travel cost can substantially impact measures of difference in consumer surplus between racial and ethnic groups.

[49] Survey results indicate that, even only within the sphere of racial and ethnic identity, there is immense diversity within the groups characterized as “Hispanic” “Black” and “Asian.” Sample size and collinearity limit the practicality of incorporating this diversity into an economic model.

The travel cost model generates consumer surplus estimates which are consistent with most historical estimates including more recent studies in the Los Angeles area (Pendleton et al., 2012). Because data was collected onsite we can include more visitors from farther away than studies which survey local population. Including overnight visits takes advantage of this fact. The consumer surplus estimates for overnight visits are high, but do not account for costs of food and lodging necessary to make the trip. One these are accounted for it is very possible that overnight visitors have lower consumer surplus per trip in addition to taking fewer trips.

Base per adult consumer surplus implies an aggregate consumer surplus of $1.23 to $1.84 billion for Summer day trips to Los Angeles, Orange, and Ventura counties for the two lower travel cost specifications and between $0.64 and $0.87 billion from overnight trips, not accounting for onsite costs. Compared to an estimated $3.5 billion in total annual expenditures (including San Diego County and non-Summer trips) consumer surplus from beach visitation is substantial.

Because the data contains household income and lacks detailed information on the number of adults per trip this study estimates household consumer surplus and extrapolates reasonable values for individual consumer surplus. Far too many studies do not specify what measure of income is solicited from respondents (Hilger & Hanemann, 2008; Lew & Larson, 2008; Pendleton et al., 2012). This study demonstrates what a huge difference this distinction makes. Disagreements over how income should be included in the value of travel time are meaningless without specifying the nature of the income variable.

This study has several shortcomings. Foremost among them is that the dispersion parameter on the corrected negative binomial model is not significant, even though the negative binomial model explains the data much better than the poisson model. Additionally, the magnitude of the marginal effect of overnight trips is very large and suggests an expected number of trips of less than one. This calls into question the model's ability to explain overnight visitor's demand for beach recreation.

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APPENDIX A

Southern California Coastal User Survey

We are conducting a survey as part of a larger project through UCLA. Our goal is to learn about the activities you will participate in at the beach and what difficulties/obstacles you encounter in getting to the beach. We would appreciate your help by taking a few minutes to complete this questionnaire.

Please note that your responses are anonymous and you are not identified in any way with this information.

1. **Including yourself, how many people from your family/household came with you to the beach today?**

   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ If 8 or more how many ________

2. **How did you get to the beach today?**

   ☐ By Car ☐ By foot ☐ By Bicycle ☐ By Bus ☐ Other __________

3. **Home (primary residence) zip code:** _________

   a. If not living in the United States, where do you live: ________________________

4. **How long do you plan to be at the beach today?**

   ☐ Less than an hour ☐1 to 2 hrs ☐2 to 4 hrs ☐4 to 6 hrs ☐6 to 8 hrs ☐8 to 10 hrs ☐10 hrs or more

5. **Is this current beach trip typical for you (in terms of location, # people, time onsite)?** ☐ Yes ☐ No

6. **Is this an overnight trip away from your primary residence?** ☐ Yes ☐ No → **If 'NO', skip to Question 7**

   6a. How many nights will you stay overnight in the area on this trip?

   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ If 8 or more how many ________

   6b. What type of lodging will you be using?

   ☐ Hotel ☐ Short term rental ☐ Family or friend ☐ Camping ☐ 2nd Residence ☐Other__________

7. **Not including this trip, how many trips have you made to this beach in the past 12 months?**

   ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ If 8 or more how many _______

8. **How many trips have you made to other beaches in California over the past 12 months?**

   ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ If 8 or more how many _______

9. **What is the main reason for your trip to the beach today (choose one)?**

   ☐ Children can play ☐ Walk ☐ Sand recreation (e.g., volleyball) ☐ Enjoy scenery or relax

   ☐ Swim/wade ☐ Surf ☐ Water recreation (e.g., kayak) ☐ BBQ or picnic

   ☐ View marine life ☐ Fish ☐ Snorkel or dive ☐ Celebration/Party ☐ Other __________

10. What other activities will your party engage in today (choose as many as apply)?

☐ Children can play ☐ Walk ☐ Sand recreation (e.g., volleyball) ☐ Enjoy scenery or relax

☐ Swim/wade ☐ Surf ☐ Water recreation (e.g., kayak) ☐ BBQ or picnic

☐ View marine life ☐ Fish ☐ Snorkel or dive ☐ Celebration/Party ☐ Other ___________

11. If there were overnight accommodations near this beach, what would be the most you would be willing to pay per night for your household to stay? Either circle a number, or put an "x" if you are willing to pay in between two numbers.

$0----$25----$50----$75----$100----$125----$150----$175----$200----$225----$250 >$250 how much ______

12. What is the farthest you are willing to travel from a parking spot or a public transportation stop to visit this beach (choose one)?

☐ Less than a block ☐ 1 to 3 blocks ☐ one-quarter mile ☐ one-half mile ☐ more than a one-half mile

13. In general, how important are the following factors to your beach experience? Circle one number for each category/row.

Beach Amenities	**Level of Importance** 1 = Not at all important 5 = Extremely important
Lifeguards on duty	1 2 3 4 5
Signs about beach access and amenities	1 2 3 4 5
Boardwalk or bike/running path	1 2 3 4 5
Pier	1 2 3 4 5
Restrooms	1 2 3 4 5
Showers	1 2 3 4 5
Food and drink concessions	1 2 3 4 5
Beach rental equipment	1 2 3 4 5
Picnic Areas/Tables/Shaded Structure	1 2 3 4 5
Nearby sports fields (basketball, soccer etc)	1 2 3 4 5
Bonfire pits	1 2 3 4 5
Trash cans	1 2 3 4 5

Beach Access	**Level of Importance** 1 = Not at all important 5 = Extremely important
Parking lot nearby	1 2 3 4 5
Street parking nearby	1 2 3 4 5
Inexpensive or free parking	1 2 3 4 5
Public transportation nearby	1 2 3 4 5
Hotels and motels nearby	1 2 3 4 5
Camping nearby	1 2 3 4 5

13. Continued from previous page. **In general how important are the following to your beach experience?**
Circle one number for each category/row.

Beach Visitors/Characteristics	**Level of Importance** 1 = Not at all important 5 = Extremely important
Beach is busy, good social experience	1 2 3 4 5
Beach is not crowded, plenty of open space	1 2 3 4 5
People of my own racial/ethnic background	1 2 3 4 5
People from my neighborhood/community	1 2 3 4 5
People similar in age	1 2 3 4 5
Good water quality	1 2 3 4 5
Good sand quality, no litter or junk	1 2 3 4 5
Size of the beach/ enough space	1 2 3 4 5
Presence of marine life and shorebirds	1 2 3 4 5
Ability to bring your dog	1 2 3 4 5

14. What are the main difficulties/obstacles for you in going to the beach: Circle one number for each category/row.

Beach Going	**THIS Beach**	**OTHER Beaches you might like to go to**
	Level of Difficulty 1 = Not an Obstacle at all	5 = A Serious Obstacle
Getting time off of work	1 2 3 4 5	1 2 3 4 5
Amount of time to travel to the beach	1 2 3 4 5	1 2 3 4 5
Cost to visit the beach	1 2 3 4 5	1 2 3 4 5
Parking options	1 2 3 4 5	1 2 3 4 5
Public transportation options	1 2 3 4 5	1 2 3 4 5

15. What have been your experiences, if any, with law enforcement during trips you take to the beach?

☐ Very positive ☐ Positive ☐ Neither positive or negative ☐ Negative ☐ Very negative ☐ N/A

16. Is there anything that could be done to make your trip to the beach more enjoyable? If so, please tell us your ideas in the box below.

Demographic Information: The following questions are designed to give us a better idea of the characteristics of visitors. *Please note that your responses are anonymous and you are not identified in any way with this information.*

17. What is your age:

☐ 18 to 24 years ☐ 25 to 34 years ☐ 35 to 44 years ☐ 45 to 54 years

☐ 55 to 64 years ☐ 65 to 74 years ☐ 75 years and over

18. Are you: ☐ Male ☐ Female

19. Race/Ethnicity (choose all that apply):

☐ White ☐ Hispanic or Latino ☐ Black or African American ☐ American Indian or Alaskan Native

☐ Pacific Islander ☐ Indian/South Asian ☐ Chinese ☐ Filipino

☐ Japanese ☐ Korean ☐ Vietnamese ☐ Other Asian ☐ Other _______________

20. If you are Hispanic or Latino, please mark the answer(s) below that best reflect your background.

☐ Mexican ☐ Puerto Rican ☐ Central American ☐ Latin American ☐ South American

☐ Afro-Latino ☐ Other Spanish/Latino Origin ___________________

21. What is your highest level of education completed (choose only one):

☐ No formal education ☐ Elementary/Junior High ☐ High School or Diploma

☐ Vocational School ☐ Some College ☐ Associates Degree

☐ Four-year College ☐ Graduate School

22. Employment status (choose only one):

☐ Employed ☐ Not employed ☐ Retired ☐ Student ☐ Other

23. Including yourself, how many people are in your current household (i.e., people you live and share financial resources with)?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6-7 ☐ 8-9 ☐ 10 or more

24. Total annual household income for last year before taxes (from all sources):

☐ Less than $10,000 ☐ $10,000 to $14,999 ☐ $15,000 to $24,999 ☐ $25,000 to $34,999

☐ $35,000 to $49,999 ☐ $50,000 to $74,999 ☐ $75,000 to $99,999 ☐ $100,000 to $149,999

☐ $150,000 or more

To be filled out by surveyor:		
Name ___________	Beach________________	Beach Subarea__________________
Date_____________	Time_________________	