Estimating Peak Demand for Beach Parking Spaces Under Capacity Constraints

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Abstract: Increasing coastal development and recent hurricane activity have heightened interest in beach protection activities. The United States Army Corps of Engineers requires that beach communities provide public parking to satisfy peak demand in order to qualify for Federal cost share funds for beach sand renourishment projects. Estimating potential peak demand is complicated by existing parking capacity constraints in most beach communities. A Tobit regression model is developed to estimate the number of parking spaces needed to meet potential, unconstrained parking demand. In an empirical example, the model is applied to beach communities in southeastern North Carolina.

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1. Introduction

Many beaches in the United States experience both chronic beach sand erosion due to gradual beach migration and catastrophic erosion due to storm events (NRC 1990). In order to maintain the recreational and beachfront property protection values of the beach, many beach communities engage in periodic beach sand "renourishment" (NRC 1995). Renourishment is the replacement of beach sand that has been lost to erosion. Beach sand renourishment is both expensive and controversial (Pilkey and Dixon 1996). Nevertheless, many beach communities have been successful in securing Federal cost-share funding (65 percent Federal, 35 percent local) for renourishment projects. The Federal cost share is usually justified by appealing to the argument that the beaches are public goods visited by many non-local recreationists.

The United States Army Corps of Engineers (USACE) typically manages beach renourishment projects that receive Federal cost share dollars. USACE Economic and Environmental Planning and Guidance (USACE 2004) stipulates that in order to qualify for Federal cost sharing of Hurricane and Storm Damage Reduction renourishment projects, the local beach community must, at a minimum, provide public access to the beach every one half mile and parking with a one quarter mile radius of those access points. Parking must satisfy the peak hour demand for the peak day of the peak season for that beach community. The definition of "satisfy" in the preceding sentence is ambiguous and has been the source of controversy. Because the opportunity cost of using coastal land for parking lots is high, coastal communities often wish to minimize the amount of land used for public parking lots. However, the argument for Federal cost sharing depends on the ability of non-resident recreationists to access the beach. Some non-local recreationists stay in beachfront hotels or cottages with private parking; public access parking is not intended to accommodate these visitors. Other non-local recreationists drive to the beach for day trips or drive to the beach from non-beachfront hotels and cottages; it is these day trip visitors that the public access parking is intended to accommodate. An objective methodology is needed for estimating peak beach parking demand that could be used in Federal cost share renourishment project analysis.

Although economists and transportation analysts have investigated the relationship between parking fees, parking and road congestion (Anderson and de Palma 2004; Arnott 1999; Glazer and Niskanen 1992), the relationship between parking capacity and public transit ridership (Merriman 1998), the efficiency of commercial zoning regulations that require parking lots (Shoup 1999), and the impact of employer-paid parking on parking demand (Willson 1992), it appears that little is known about parking demand at public beaches.

The purpose of this study is to develop a method for estimating peak day trip demand for beach parking spaces. The problem is complicated by the fact that existing parking is often inadequate to meet peak demand at many beaches, resulting in parking data that is capacity-constrained at the existing parking lot capacities. The goal of the study is to estimate the peak number of parking spaces demanded were parking capacity unconstrained. A Tobit regression model is developed to estimate the number of parking spaces that would be necessary to meet unconstrained demand on a given percentage of peak demand days. For example, the model can be used to estimate the number of parking spaces that would be adequate to meet peak demand on 90% of peak parking days. The model is applied to 2003 data from ten North Carolina beaches.

2. Data

The Wilmington District of the USACE sponsored an on-site survey of beach recreationists and beach parking spaces at ten North Carolina beaches during the summer of 2003 (Herstine et al. 2005). A subsequent telephone survey of eastern North Carolina residents conducted in 2004 collected data on trips made to seventeen North Carolina beaches in 2003, including the ten beaches covered in the 2003 on-site survey. The on-site survey respondents' home zip codes were used to estimate the geographic sample frame for the telephone survey. The telephone survey data are used to estimate an index of beach trip demand across beaches that will serve as one of the explanatory variables in the beach parking model. Although beach trip demand and beach parking are simultaneously determined theoretically, existing variation in the number of parking spaces across beaches was found not to be a significant determinant of beach demand when other determinants of beach demand were controlled (see Appendix 1), whereas the index of beach demand was found to have a significant impact on filled parking spaces. As a result, we consider a two-stage model in which an index of beach demand is determined in the first stage, followed by estimation of filled parking spaces as a function of the beach demand index.

2.1 Telephone Survey Data

A telephone survey of study area beach recreationists was conducted during May 2004, with a target population based upon the results of the on-site field survey conducted during the summer of 2003 (Herstine et al., 2005). The field survey found that the vast majority (approximately 73%) of day users, the primary users of public beach parking, traveled 120 miles or less to get to the beach. As a result, the population sampled by the telephone survey included all residents living in North Carolina counties within 120 miles of any of the 17 study beaches. Survey Sampling, Inc. provided a stratified random sample of target population telephone numbers, and the Survey Research Laboratory (SRL) at the University of North Carolina Wilmington administered the survey. The telephone survey response rate was 52 percent. Of the 1876 household responses, 1,187 (63%), reported taking at least one trip to one or more study area beaches in 2003. Approximately 80 percent of the respondents stated that 2003 was a typical year in terms of their oceanfront beach trips to the southeastern North Carolina coast. Of those who reported that 2003 was not a typical year, 75 percent normally would have taken more trips. Of all respondents who took at least one trip to the southeastern North Carolina coast, 96 percent planned to take at least one oceanfront beach trip to the area in 2004.

Additional telephone survey questions collected information on each household's number of trips to each study area beach in 2003. Of the 1,187 households taking at least one beach trip to the study area, 1,067 provided answers to further survey questions on the number of trips each beach. These 1,067 households reported taking a total of 9,002 trips to study area beaches in 2003 (Table 1).

2.2 On-Site Parking Lot Data

As part of the on-site field survey effort in 2003, ancillary data were collected on the number of parking lots, parking spaces (SPACES), and filled parking spaces (FILLEDSP) at each beach, for several times each day, during peak (weekend) days of July and August, 2003. Two holidays (dummy HOLIDAY) were included in the survey effort: the Fourth of July weekend, and the Labor Day weekend. These holidays represent the “peak of the peak” days in terms of beach parking demand. Preliminary tests of significance of time of day dummy variables in the parking model described below indicated that hours could be pooled into three time periods, morning (dummy DMORN), midday (dummy DMID) and afternoon (dummy DAFTN). The on-site survey of beach recreationists provided an estimate of the average number of hours spent on the beach by each party of recreationists for each beach (STAYTIME). The STAYTIME variable provides an index of parking space turnover time. Descriptive statistics for SPACES, FILLEDSP, HOLIDAY, STAYTIME, TRIPINDX (described in the preceding section), and time of day dummy variables (DMORN, DAFTN) are presented in Table 3. (Descriptive statistics by beach are available upon request from the authors.)

3. Tobit Parking Model

A censored regression model, or “Tobit” model, is used to estimate parking space demand for each beach (McDonald and Moffitt (1980); Greene (2003), pages 762-766, especially example 22.3 for an analogous situation). The dependent variable, $FILLEDSP_{idt}$ is the number of parking spaces that are filled at beach i, on day d, at hour t. When parking lots are full, the dependent variable is "censored," in the sense that some visitors may not be able to find parking spaces, and hence their visits will not be reflected in the value of the dependent variable. In effect, the parking needs of these visitors are "censored" from the dependent variable values.

The Tobit regression model estimates the unconditional probability distributions of FILLEDSP, i.e., the number of FILLEDSP that would occur if the number of parking spaces were unconstrained. The resulting probability distributions can be used to estimate parking demand (and potential parking requirements) beyond current parking space capacity.

The independent variables used in the Tobit regression model are: $TRIPINDX_i$, an index of household demand for trips to beach i, $STAYTIME_{id}$, the average length of time in hours that a visitor remained at beach i on day d, DB_i, beach-specific dummy variables that shift the regression intercept, where i indicates beach 00-09 (the dummy for beach 10 is omitted to avoid the dummy variable trap; note that beach 08 is omitted from the entire analysis due to lack of sufficient survey data for beach 08), DMORN and DAFTN, dummy variables capturing time of day effects (if t = 9am-11am, DMORN = 1, DMORN = 0 otherwise; if t = 3pm-5pm, DAFTN = 1, DAFTN = 0 otherwise; note that potential dummy variable DMID = 1 when t = 12noon-2pm is omitted to avoid the dummy variable trap), and $HOLIDAY_d$, a dummy variable equal to 1 if the day is July 4 or 5, or

August 30 or 31, days corresponding to the Fourth of July and Labor Day holidays. Note that under this specification, with all dummy variables set to zero, the Tobit regression predicts uncensored FILLEDSP at midday on a non-holiday weekend day on beach 10 (Atlantic Beach, NC). Setting appropriate dummy variables to the value "1" adjusts the regression predictions for alternative time of day or beach destination.

The TRIPINDX variable can be any measure of relative recreation demand across beaches. For this study, TRIPINDX values were developed via a separate Poisson regression (see Haab and McConnell, 2002, pp164-174; LIMDEP Chapter E20) using telephone survey data. Trips taken in 2003 by telephone survey household j to each of seventeen southeastern North Carolina beaches i ($TRIPS_{ij}$) are regressed on a list of explanatory variables measuring characteristics of the households and characteristics of the beaches (see Appendix 1). $TRIPINDX_i$, (Table 2) is formed by summing predicted values of $TRIPS_{ij}$ over the 1,067 households in the sample. The expected number of day trips to beach i per household per year, denoted $ETRIPS_i$ (Table 2), is estimated by dividing $TRIPINDX_i$ by 1,067. Although not the primary goal of this study, the Poisson trip model results can be used to find mean household Willingness to Pay per trip to beach i, WTP_i (Haab and McConnell 2002). Willingness to pay estimates for each beach are presented in Table 2.

Variable $SPACES_{i,}$, which gives the existing number of parking spaces at beach i, is used as a censoring variable by the Tobit regression procedure. Each beach i is allowed a separate censoring limit, as specified by the $SPACES_i$ variable.

The Tobit regression model (with upper and lower tail censoring) is specified in equation (1):

$$\ln(\mathrm{FILLEDSP}_{idt}) = \beta_0 + \beta_1\ \mathrm{DMORN} + \beta_2\ \mathrm{DAFTN} + \beta_3\ \mathrm{DB}_{00} + \ldots + \beta_{11}\ \mathrm{DB}_{09} + \beta_{12}\ \mathrm{STAYTIME}_{id} + \beta_{13}\ \mathrm{HOLIDAY}_d + \beta_{14}\ \mathrm{TRIPINDX}_i + e_{idt}, \tag{1}$$

$$\text{if } \ln(\mathrm{FILLEDSP}_{idt}) \leq 0, \text{ then } \ln(\mathrm{FILLEDSP}_{idt}) = 0,$$

$$\text{if } \ln(\mathrm{FILLEDSP}_{idt}) \geq \ln(\mathrm{SPACES}_i), \text{ then } \ln(\mathrm{FILLEDSP}_{idt}) = \ln(\mathrm{SPACES}_i),$$

where FILLEDSP, SPACES, DMORN, DAFTN, DB_{00} . . . DB_{09}, STAYTIME, HOLIDAY and TRIPINDX are variables as defined above, β_0-β_{14} are parameters to be estimated, and e_{idt} is a heteroskedastic error term. The error term is specified as $e_{it} \sim N(0, \sigma^2 \cdot \exp(\alpha \cdot \mathrm{TRIPINDX}_i))$, where σ (the standard deviation of the uncensored dependent variable in the absence of heteroskedasticity) and α are parameters to be estimated. Parameter α allows testing for heteroskedasticity as a function of the beach demand index $\mathrm{TRIPINDX}_i$; if H_0: $\alpha = 0$ is rejected, the null hypothesis of homoskedasticity is rejected in favor of heteroskedasticity as a function of the beach demand index $\mathrm{TRIPINDX}_i$.

4. Tobit Parking Model Results

Tobit regression results are presented in Table 4. The Tobit regression is estimated using LIMDEP (2002, see Chapter E21). A likelihood ratio test indicates that the overall regression is significant at the $p < 0.01$ level. The negative coefficients on DMORN and DAFTN indicate that the number of filled spaces is lower in the morning and afternoon, but the effect is not statistically significant for this sample (recall that we are examining a sample that includes only summer season, weekend days). Beach specific, fixed effect dummy variables $DB_{00} \ldots DB_{09}$ vary in sign, reflecting differences in the estimated value of ln(FILLEDSP) at midday across beaches. However, after controlling for other variables in the regression, only beach dummy DB_{09} is statistically significant. STAYTIME has a positive but insignificant effect on ln(FILLEDSP). HOLIDAY has a positive and strongly significant effect on filled spaces. TRIPINDX, a beach-specific index of recreation demand, is positive and strongly significant. The heteroskedasticity parameter α is positive and strongly significant, indicating that larger values of TRIPINDX increase the variance of ln(FILLEDSP).

With the estimated Tobit model, it is possible to calculate the number of spaces that would be necessary to accommodate all peak (weekend holiday) day beach visitors 60% of the time, 95% of the time, etc. For each beach, ln(FILLEDSP) follows a normal distribution, with a beach-specific, unconditional mean values $\overline{\mu}_i$ given by the Tobit regression equation (2) (with mean values inserted for the variables):

$$\bar{\mu}_i = \beta_0 + \beta_1 \text{ DMORN} + \beta_2 \text{ DAFTN} + \beta_3 \text{ DB}_{00} + \ldots + \beta_{11} \text{ DB}_{09} \qquad (2)$$

$$+ \beta_{12} \text{ STAYTIME}_{id} + \beta_{13} \text{ HOLIDAY}_d + \beta_{14} \text{ TRIPINDX}_i, \qquad i = 00 \ldots 09,$$

and beach-specific standard deviations SD_i given by equation (3):

$$SD_i = \sigma^2 \cdot \exp[\alpha \cdot \text{TRIPINDX}_i])^{0.5}. \qquad (3)$$

The unconditional 90 percentile, for example, of FILLEDSP_i is then given by (4):

$$\text{FILLEDSP}_{i,\ 90\ \text{percentile}} = \text{EXP}(\text{NORMINV}(0.90,\ \bar{\mu}_i\ , \text{SD}_i)), \qquad (4)$$

where NORMINV is the inverse normal cumulative distribution function.

5. Discussion and Conclusion

Using the estimated Tobit model results, it is possible to calculate the number of beach parking spaces that would be necessary to accommodate all peak, weekend day beach visitors 90% of the time, 95% of the time, etc. For each beach, the cumulative frequency of filled parking spaces can be graphed against the number of filled spaces, and the frequency with which peak parking space demand can be accommodated by alternative numbers of parking spaces can be determined. For example, Figure 1 shows the estimated cumulative frequency of (latent, uncensored) filled parking spaces at Topsail Beach, North Carolina, on peak, summer weekend holidays in base year 2004. The current number of parking spaces at Topsail Beach is 374, indicated by the dashed, vertical indicator line. Sixty-three percent of the cumulative frequency distribution of FILLEDSP occurs to the left of 374 spaces, indicating that the 374 existing spaces fully accommodate all Topsail Beach visitors on sixty-three percent of peak (summer holiday weekend) days. However, thirty-seven percent of the cumulative frequency of FILLEDSP lies to the right of 374 spaces, indicating that the existing spaces do not accommodate all Topsail Beach visitors on thirty-seven percent of peak days. Providing additional parking spaces would accommodate additional visitors. For each value of "Filled Parking Spaces" along the horizontal axis, the associated cumulative frequency indicates the percentage of peak days on which all Topsail Beach visitors would be accommodated (i.e., have access to a parking space). Conversely, for a given "accommodation policy target," say, "accommodate all visitors on 90 percent of peak days," finding the corresponding percentage value on the vertical cumulative frequency axis and then reading the associated value for Filled Parking Spaces indicates the number of parking spaces required to accommodate all visitors 90 percent of peak days. In Figure 1, the number of parking spaces required to achieve 90 percent accommodation is approximately 620.

Changes in beach conditions may shift the cumulative frequency distribution of FILLEDSP and the associated number of parking spaces needed to meet a given accommodation policy target. For example, Figure 1 shows the cumulative frequency of FILLEDSP at Topsail Beach with a 50 ft increase in beach width. The increase in beach width attracts additional beach visitation (i.e., an increase in the BWIDTH variable in the

TRIPS regression equation presented in Appendix 1 increases the value of TRIPINDX), which shifts the cumulative frequency distribution to the right (as per the Tobit regression equation). As the distribution shifts to the right, the current number of parking spaces accommodates all visitors less frequently. In the Topsail Beach example, the 374 existing spaces accommodate all Topsail Beach visitors on only fifty-three percent of peak days after a 50 ft increase in beach width. Additional spaces would be needed to meet a given accommodation policy target with an increase in beach width.

As state population increases, the number of visitors to Topsail Beach is expected to increase, assuming that the number of trips per household remains roughly constant. Table 5 shows the predicted frequency of FILLEDSP at Topsail Beach under + 50 ft beach width conditions from the year 2004 through 2024, based on State of North Carolina population projections for the telephone survey region. Under the assumption that an increase in projected population in the telephone survey region results in a proportional increase in the $TRIPINDX_i$ value for Topsail Beach, the cumulative frequency distribution of FILLEDSP for Topsail Beach shifts to the right. As the curve shifts to the right, the current number of parking spaces accommodates all Topsail Beach visitors less frequently. By 2008, it is estimated that 763 parking spaces would be necessary to accommodate peak demand on ninety percent of peak days.

Results vary across beaches. Results for some beaches in the sample (not shown here) indicate that current parking capacity can accommodate demand on ninety percent of peak days. Existing parking capacity at other beaches accommodates all peak day visitors much less often. Similarly, the impacts of changes in beach characteristics (such as beach width) vary across beaches due to the nonlinear structure and beach-specific parameters of the TRIPINDX sub-model (see Appendix 1).

In conclusion, the Tobit model provides a promising framework for estimating peak demand for beach parking spaces. The framework is especially useful for those beaches where current parking capacity constrains parking on peak days. Under such conditions, the Tobit model provides a method for estimating the parking demand of visitors who do not find parking spaces (as well as the demand of visitors who do find parking), in contrast to traditional demand estimation techniques that may neglect the demand of such "potential" or 'latent" visitors. The Tobit model provides a reasonable method for developing parking space requirement policy. While estimating latent parking demand may increase the current parking space requirements of beach communities seeking federal cost share dollars for beach renourishment, such estimates may ease the minds of local officials by reducing uncertainty regarding future parking requirements and the parking requirement planning process.

Appendix 1.

An index of relative (across beaches) beach trip demand is desired for use as an explanatory variable in the Tobit beach parking model described in section 3. This appendix describes how data from the telephone survey are used to develop such an index of beach trip demand, TRIPINDX.

TRIPINDX is derived from the results of a regression of telephone survey household beach trips on a list of explanatory variables measuring characteristics of the households and characteristics of the beaches. Dependent variable, TRIPS, is an integer variable. A Poisson/Negative Binomial regression modeling framework is typically used for such "count data" (see Haab and McConnell, 2002, pp164-174; LIMDEP Chapter E20). The Poisson regression form of the model is appropriate unless the data are over-dispersed (the data are over-dispersed when the variance in trips per year is greater than mean trips per year). If the data are over-dispersed, the Negative Binomial form is appropriate.

The Poisson/Negative Binomial regression equation for trips to beach i made by household j is specified in equation (A1):

(A1)

$$TRIPS_{i,j} = EXP[\beta_0 + (\beta_1 + \beta_i\ DDD_i)\ ACCPRI_{i,j} + \beta_{18}\ BWIDTH_i + \beta_{19}\ BLENGTH_i + \beta_{20}\ BSPACES_i + \beta_{21}\ BACCESS_i + \beta_{22}\ INCOME_j + \beta_{23}\ FEMALE_j + \beta_{24}\ MARRIED_j + \beta_{25}\ NUMKIDS_j + \beta_{26}\ MINORITY_j + \beta_{27}\ AGE_j + \beta_{28}\ AGESQ_j + e_{i,j}],$$

where "EXP" is the exponentiation operator, β_0-β_{28} are coefficients estimated by the regression, and $e_{i,j}$ is a normally-distributed error term. Dependent variable $TRIPS_{i,j}$ is the number of trips taken in 2003 by household j to beach i. Independent variables are the travel cost/access price for household j to beach i ($ACCPRI_{i,j}$), beach width ($BWIDTH_i$), beach length ($BLENGTH_i$), beach parking spaces ($BSPACES_i$), beach access points ($BACCESS_i$), household's household jncome in \$1,000's ($INCOME_j$), the respondent's age (AGE_j) and age squared ($AGESQ_j$), the number of children in the respondent's household ($NUMKIDS_j$), and dummy variables indicating whether the respondent was $FEMALE_j$, $MARRIED_j$, or a member of a racial $MINORITY_j$. A system of dummy variables DDD_i, i = 01 . . .06, 08, . . . 17, was created to allow each of the seventeen beaches to have a separate slope coefficient for variable $ACCPRI_{i,j}$; this allows the effect of access price on trips to vary by beach. (Dummy variable DDD_{00} is omitted to avoid the dummy variable trap. Dummy variable DDD_{07} is omitted because the few observations for beach 07 were merged with those for geographically-adjacent beach 08.)

For each survey household j and each beach i, the travel cost/access price, $ACCPRI_{i,j}$, is the sum of automobile travel cost and the opportunity cost of the household's time, as given by equation (A2):

(A2)

$$ACCPRI_{i,j} =(0.37*2*DIST_{i,j}) + (((1/3)*(INCOME_j/2000))*(2*DIST_{i,j}/SPED_{i,j})),$$

where one-way travel distances $DIST_{i,j}$ and average travel speeds $SPED_{i,j}$ were calculated using PCMiler Software (PCMiler 2005) based on the survey respondents' home zip codes and beach zip codes. Automobile travel cost per travel mile was $0.37, the national average automobile driving cost for 2003 as reported by American Automobile Association (AAA) (AAA Personal communication 2005). Assuming approximately 2,000 work hours per year, one-third of the household hourly wage rate [$(1/3*INCOME_j/(2000hrs/yr)$] was used to value the opportunity cost of time.

The data for each of the 1,067 telephone survey households were expanded into 17 rows, one row for each beach. (The data set used for the Poisson regression therefore has 1,067*17 = 18,139 observations, with 17 observations for each survey respondent.) For a given survey respondent, the numbers of trips reported to the various study area beaches may be correlated. For example, a survey respondent who reports a large number of trips to one beach may be more likely to report larger numbers of trips to other beaches, relative to other survey respondents, perhaps due to higher household income or closer proximity to the coast. A cluster estimator (LIMDEP 2002, p. E20-15) form of the Poisson/Negative Binomial regression model is developed to allow for correlation among the reported numbers of trips for each household. This specification of the model adjusts the variance-covariance matrix to allow for correlation among the seventeen responses for each survey respondent. A random effects panel data version of the Poisson/Negative Binomial model was also attempted, but it did not converge during estimation.

Descriptive statistics for the variables used in the Poisson/Negative Binomial cluster regression model are presented in Table A1.

LIMDEP econometrics software (LIMDEP 2002) was used to conduct the Poisson/Negative Binomial cluster regression. Regression results are presented in Table A2. Results from two tests of over-dispersion (LIMDEP 2002, p. E20-12) for the Poisson regression model indicate that the data are *not* over-dispersed. Therefore, results for the Poisson version of the model are retained, and the Negative Binomial version of the model is not pursued. A likelihood ratio test indicates that the overall Poisson regression model is significant with $p < 0.01$. In general, the estimated coefficients in the Poisson regression results are of the anticipated signs and are statistically significant. Higher access prices ACCPRI reduce the number of expected beach TRIPS, while higher INCOME increases expected TRIPS. Increases in beach width BWIDTH, beach length BLENGTH, the number of parking spaces BSPACES, or the number of beach accesses BACCESS increase expected TRIPS, while being MARRIED, having a larger number of children (NUMKIDS), being a member of a MINORITY group, or being older (AGE), decrease the number of expected TRIPS.

The Poisson trip model results can be used to find mean household Willingness to Pay per trip to beach i, WTP_i, as given by equation (A3) (Haab and McConnell 2002):

$$WTP_i = -1/(\beta_1 + \beta_i) \qquad \text{(A3)}$$

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Table 1.
Beach trips made by 1,067 telephone survey respondents to Southeastern North Carolina beaches in 2003.

Beach Number	Beach Name	2003 Beach Trips In Sample
00	Caswell Beach	163
01	Oak Island Beach	163
02	Holden Beach	183
03	North Topsail Beach	719
04	Surf City Beach	279
05	Topsail Beach	245
06	Pine Knoll Shores Beach	143
08	Salter Path and Indian Beaches	135
09	Emerald Isle Beach	1083
10	Atlantic Beach	919
11	Fort Macon Beach	251
12	Carolina Beach	1502
13	Kure Beach	360
14	Fort Fisher Beach	404
15	Ocean Isle Beach	353
16	Sunset Beach	153
17	Wrightsville Beach	1947
	Total Trips	9002

Table 2.
TRIPINDX, ETRIPS, and WTP by beach.

Beach Number	Beach Name	TRIPINDX	ETRIPS	WTP Per Trip
0	Caswell	146	0.14	$39.17
1	Oak Island	254	0.24	$23.61
2	Holden	333	0.31	$39.03
3	North Topsail	589	0.55	$32.59
4	Surf City	489	0.46	$36.51
5	Topsail	403	0.38	$31.41
6	Pine Knoll Shores	181	0.17	$40.48
8	Salter Path and Indian Beaches	148	0.14	$42.55
9	Emerald Isle	924	0.87	$42.82
10	Atlantic	816	0.77	$73.39
11	Fort Macon	193	0.18	$41.95
12	Carolina	986	0.92	$61.02
13	Kure	384	0.36	$39.12
14	Fort Fisher	522	0.49	$38.77
15	Ocean Isle	337	0.32	$49.33
16	Sunset	136	0.13	$28.96
17	Wrightsville	2160	2.02	$49.65

Table 3.
Descriptive statistics for variables used in Tobit regression.
(Mean values across all beaches. n = 668)

Variable	Mean	Std.Dev.	Minimum	Maximum
SPACES	436.47	294.30	75	929
FILLEDSP	282.86	221.49	2	909
DMORN	0.38	0.49	0.00	1.00
DAFTN	0.21	0.41	0.00	1.00
STAYTIME	4.34	1.32	0.19	9.50
HOLIDAY	0.53	0.50	0.00	1.00
TRIPINDX	428.96	255.16	146.00	924.00

Table 4.
Tobit regression model results.

Variable	Coefficient	Std. Error	t-stat	p-value	Mean values of variables across all beaches
Constant	β_0 = 4.556553	0.506238	9.001	0	1
DMORN	β_1 = -0.6657	0.488227	-1.364	0.1727	0.377246
DAFTN	β_2 = -0.30681	0.489813	-0.626	0.5311	0.211078
DB00	β_3 = -0.51883	0.56687	-0.915	0.3601	3.29E-02
DB01	β_4 = 0.699366	0.512413	1.365	0.1723	4.49E-02
DB02	β_5 = -0.3789	0.52703	-0.719	0.4722	4.04E-02
DB03	β_6 = 0.166154	0.595628	0.279	0.7803	4.49E-02
DB04	β_7 = -0.70571	0.563638	-1.252	0.2105	4.04E-02
DB05	β_8 = -0.10134	0.543425	-0.186	0.8521	4.04E-02
DB06	β_9 = -0.26222	0.55776	-0.47	0.6383	3.89E-02
DB07	β_{10} = -0.94633	0.537796	-1.76	0.0785	4.04E-02
DB09	β_{11} = -1.27148	0.554439	-2.293	0.0218	4.34E-02
STAYTIME	β_{12} = 7.45E-03	2.06E-02	0.362	0.7175	4.339445
HOLIDAY	β_{13} = 0.363506	5.36E-02	6.78	0	0.532934
TRIPINDX	β_{14} = 2.26E-03	1.80E-04	12.6	0	428.9566
Sigma	σ = 0.450791	1.61E-02	28.023	0	-----
Alpha	α = 7.52E-04	6.84E-05	10.992	0	-----

Table 5.
Projected Topsail Beach parking space requirements, 2004-2024.
(+50 ft beach width conditions)

Year	Telephone Survey Region Population Index (2004 Base Year)	TRIPINDX	Mean FILLEDSP	60%tile FILLEDSP	70%tile FILLEDSP	80%tile FILLEDSP	90%tile FILLEDSP	95%tile FILLEDSP
2004	1.000	454.0	357.6	409.4	473.3	560.8	709.5	861.6
2005	1.015	460.9	363.2	416.1	481.1	570.3	722.0	877.2
2006	1.031	468.1	369.1	423.0	489.3	580.3	735.0	893.5
2007	1.047	475.4	375.3	430.2	497.9	590.8	748.8	910.8
2008	1.064	482.9	381.7	437.7	506.8	601.6	763.1	928.7
2009	1.080	490.5	388.4	445.5	516.0	612.9	777.9	947.2
2010	1.097	498.0	395.0	453.3	525.3	624.1	792.8	965.9
2011	1.112	504.9	401.2	460.6	533.9	634.7	806.6	983.2
2012	1.127	511.8	407.5	468.0	542.7	645.4	820.8	1001.0
2013	1.143	518.9	414.1	475.7	551.9	656.7	835.6	1019.6
2014	1.159	526.2	421.0	483.8	561.5	668.4	851.2	1039.2
2015	1.175	533.6	428.1	492.3	571.5	680.7	867.4	1059.5
2016	1.192	541.1	435.4	500.9	581.8	693.2	883.9	1080.4
2017	1.209	548.7	443.0	509.7	592.3	706.1	901.0	1101.9
2018	1.226	556.4	450.8	518.9	603.3	719.6	918.8	1124.4
2019	1.243	564.5	459.0	528.7	614.9	733.8	937.7	1148.1
2020	1.261	572.3	467.3	538.4	626.5	748.0	956.5	1171.9
2021	1.276	579.2	474.7	547.1	636.8	760.7	973.4	1193.2
2022	1.291	586.2	482.2	556.0	647.4	773.8	990.7	1215.1
2023	1.307	593.3	490.0	565.2	658.5	787.3	1008.8	1237.9
2024	1.323	600.7	498.3	575.0	670.1	801.6	1027.8	1262.0

Table A1.
Descriptive statistics for variables used in Poisson/Negative Binomial cluster regression model (n = 1,067).

Variable	Mean	Std.Dev.	Minimum	Maximum
TRIPS	0.50	5.88	0	200
ACCPRI	160.42	135.89	0	1169.75
BWIDTH	129.53	73.25	80	400
BLENGTH	4.55	2.90	1.1	11.5
BSPACES	448.18	353.90	56	1479
BACCESS	27.47	19.93	2	69
INCOME	58.83	28.51	15	110
FEMALE	0.63	0.48	0	1
MARRIED	0.72	0.45	0	1
NUMKIDS	0.94	1.14	0	8
MINORITY	0.19	0.39	0	1
AGE	42.43	14.91	18	104
AGESQ	2022.38	1403.12	324	10816

Table A2.
Poisson/Negative binomial cluster regression model results.

Variable	Coefficient	Std.Err.	t-ratio	p-value	Variable Means
Constant	-1.09355	0.968624	-1.129	0.2589	1
ACCPRI	-0.02553	0.006365	-4.011	0.0001	160.4209
DDD01	-0.01683	0.011313	-1.488	0.1368	10.45277
DDD02	-.902962 E-04	0.007629	-0.012	0.9906	9.215456
DDD03	-0.00515	0.009826	-0.524	0.6003	8.580884
DDD04	-0.00186	0.00739	-0.252	0.8008	8.292163
DDD05	-0.00631	0.009542	-0.661	0.5083	8.292163
DDD06	0.000829	0.006838	0.121	0.9035	9.93717
DDD08	0.002027	0.006035	0.336	0.737	9.910301
DDD09	0.002177	0.0105	0.207	0.8357	9.656682
DDD10	0.011904	0.005727	2.079	0.0377	9.93717
DDD11	0.001691	0.006004	0.282	0.7782	9.93717
DDD12	0.009143	0.006296	1.452	0.1465	8.714047
DDD13	-.297979 E-04	0.005936	-0.005	0.996	8.961451
DDD14	-0.00026	0.009382	-0.028	0.9777	8.961451
DDD15	0.005259	0.005899	0.892	0.3726	10.5665
DDD16	-0.009	0.010376	-0.868	0.3856	10.48006
DDD17	0.005387	0.006758	0.797	0.4253	8.072745
BWIDTH	0.002394	0.002572	0.931	0.352	129.5294
BLENGTH	0.025076	0.119415	0.21	0.8337	4.547059
BSPACES	0.000493	0.000452	1.091	0.2754	448.1765
BACCESS	0.017385	0.019619	0.886	0.3755	27.47059
INCOME	0.019647	0.005355	3.669	0.0002	58.83318
FEMALE	-0.25952	0.240868	-1.077	0.2813	0.633552
MARRIED	-0.36621	0.218787	-1.674	0.0942	0.715089
NUMKIDS	0.091765	0.100994	0.909	0.3635	0.940019
MINORITY	-0.65093	0.287471	-2.264	0.0236	0.192127
AGE	0.038489	0.030273	1.271	0.2036	42.42737
AGESQ	-0.00046	0.000314	-1.462	0.1437	2022.382

Table Captions

Table 1. [none]

Table 2.

Observations for beach 07 are pooled with those for geographically-adjacent beach 08 due to an insufficient number of observations for independent analysis of beach 07. Results for beach 08 reflect combined results for beaches 07 and 08.

Table 3. [none]

Table 4.

Dependent Variable: ln(FILLEDSP)

Number of observations = 668

Log-likelihood, unrestricted = -623.6610

Log-likelihood, restricted (all coeffs=0) = -897.0134

Likelihood ratio = -2[(-897.0134)-(-623.6610)] = 546.7048

Table 5. [none]

Table A1. [none]

TableA2.

Dependent Variable: TRIPS

Number of observations = 18,139 (17 obs on each of 1067 individuals in panel)

Log-likelihood, unrestricted = -27202.17

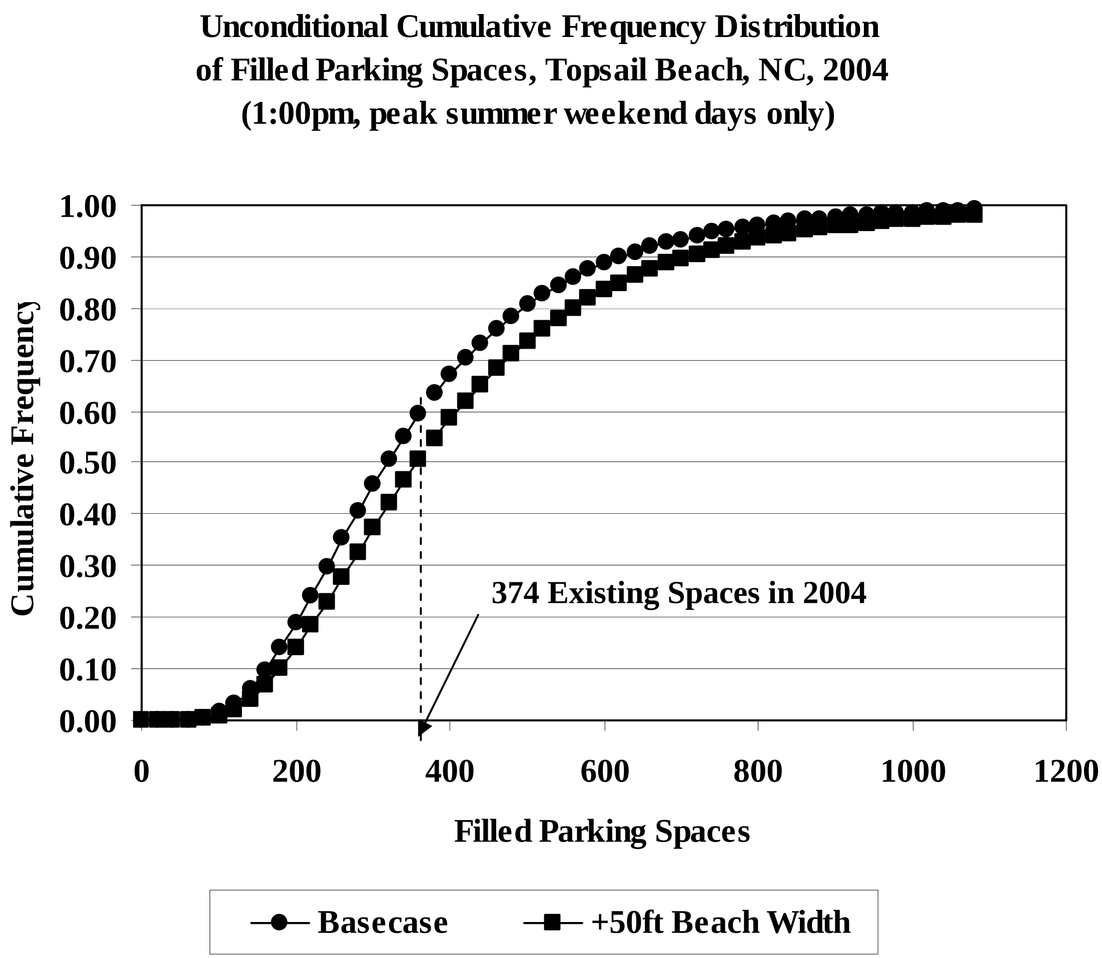
Log-likelihood, restricted (all coeffs=0) = -38389.06

Likelihood ratio = -2[(-38389.06)-(- 27202.17)] = 22373

Chi-square with 28 d.f. at α = 0.99 level of significance is 48.3

22373 > 48.3 → Ho: "all coeffs = 0" rejected at $p < 0.01$.

Figure 1.


Unconditional Cumulative Frequency Distribution
of Filled Parking Spaces, Topsail Beach, NC, 2004
(1:00pm, peak summer weekend days only)
Cumulative Frequency
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
200
400
600
800
1000
1200
Filled Parking Spaces
374 Existing Spaces in 2004
Basecase
+50ft Beach Width