INTEGRATED TRANSPORTATION PRICING STRATEGY FOR NEWPORT

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16. Abstract

Like many tourist destinations, Newport, Rhode Island relies upon high season tourist volumes for its economic health. Most visitors arrive by car, concentrated during certain hours on summer weekends, severely congesting the town's major arteries and forcing many visitors to spend considerable time in their car. A transportation planning strategy which reduced congestion would enhance the quality of the visiting experience, increase the time visitors are able to spend in shops and at attractions, and draw additional visitors. However, identifying effective solutions requires understanding factors which affect tourists' transit choices. We develop a conceptual model of Newport visitors' parking and transit choices, expanding traditional transit choice models to include features such as scenery we expect to influence tourists. Using a stated preference survey of visitors, we find scenery, transit model options and congestion are the major drivers of tourists' parking choices. We also develop welfare estimates to enable analysis of proposed transportation plans.

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I. INTRODUCTION

On warm summer weekends, tourists flock to small oceanside, bayside, riverside and lakeside communities throughout the country. This concentration of travelers often badly congests roads in and around the targeted communities, leaving visitors to sit in traffic for long periods of time before reaching their final destination. Even on local streets, traffic can be so heavy that considerable time is necessary for tourists to move among attractions, and residents have difficulty completing their daily business.

Transportation strategies that relieve this congestion can offer several benefits for seasonal tourist communities. First, reducing the time visitors must spend in the car to reach their destination increases the amount of time they can spend at that destination, or the number of attractions that can be visited. Increasing the time at attractions increases opportunities for tourists to spend money in the community. Second, visitors will have a higher-quality vacationing experience, making it more likely they will repeat visit. Third, reducing congestion may attract additional visitors who were discouraged from coming by traffic. These visitors may either have elected to stay home, or to visit another community. These additional visitors may partially or fully offset the reduction in congestion from the initial transit plan, but the reduction effort nevertheless benefits the community because it is hosting more visitors, with their associated spending activity, at a constant level of congestion. Finally, actual traffic reductions improve environmental quality, as fewer idling cars means a quieter, safer and less polluted community.

While tourist communities stand to benefit by reducing congestion, tourist congestion is probably not best solved by expanding infrastructure: constructing large roads may destroy the small-town character that often draws tourists escaping cities crossed with superhighways, and the capital expense may not be justified on welfare grounds because it would only be used to capacity a few days each year. Instead, tourist-targeted transportation strategies must provide parking and public transit options that allow access to attractions and enhance the visiting experience (1). Proposed solutions frequently involve a combination of strategically priced parking lots, with public transportation provided among remote lots and top attractions (2). Identifying whether such solutions are likely to be effective requires an understanding of the factors that motivate tourist transit choices, and tailoring solutions to those preferences.

Incorporating traveler preferences into transportation planning is not a new idea. Revealed and stated preference methods have been used to identify demand for specific transit projects around the world. For example, McFadden (3) used survey and revealed preference data to assess the effect of the Bay Area Rapid Transit light rail system on commuting patterns in San Francisco; Gillen (4) and Westin and Gillen (5) use trip choice data to understand parking and mode selection among Toronto commuters, and whether parking taxed could be an effective substitute for road pricing; Fan, Miller and Badoe (6) also use Toronto commuters to understand preferences over car-rail combinations; Peng, Dueker and Strathman (7) use observed trip data to measure the effect of parking prices on mode use among suburban and urban commuters in Portland, Oregon. In most such applications, researchers have used real or hypothetical choice data to understand travelers' preferences over transit alternatives, with the intention of using preference information to evaluate new transit plans and policies.

However, all of these studies have been directed at understanding and developing policies to influence the transit choices of commuters (8). Tourists differ from commuters in several ways which suggest different transit strategies may be necessary. First, while each commuter must get to her particular place of work, tourists may choose to visit another city or to stay home if traffic or parking problems decrease their enjoyment of the trip (9). This option not to visit a region underscores the importance of tourist transit planning, because inadequate services reduce economic activity.

Second, commuters are usually interested in finding the fastest way to work, but visitors may prefer longer scenic routes (over land or water), so any congestion reduction strategy must address the aesthetic value of the journey. Thus, while a commuter may view a bus ride as slow and inconvenient, tourists may appreciate the pace and circuitous routes often associated with public transportation.

Third, most of the commuter literature has focused on reducing the number of vehicles by encouraging carpooling. Carpooling is probably not a viable option for visitors who come as families in full cars, who are not coming from the same region, who do not know each other, and who are not going to the same attractions. Thus, reducing the number of vehicles on the road requires encouraging people to park their cars and use public transit.

Fourth, the problem of congestion created by commuters is present year-round, whereas tourist destinations are congested only a relatively few days each year, during the high tourist season. Efficient transportation strategies will then be flexible in scale, able to increase capacity during periods of peak demand so as not to be badly overcapitalized in the off season.

Fifth, because commuters must return to the same place of work each day, commuter congestion tends to occur consistently in the same location. Many tourist destinations feature special events at a variety of locations throughout the community, leading to pockets of congestion at different locations from hour-to-hour or week-to-week. Therefore, tourist-oriented transit strategies must be flexible in location as well as scale, to account for spatially shifting demand.

A final economically important difference between commuters and tourists is that tourists lack local knowledge and must search for the convenient and affordable parking and transportation, whereas commuters who develop local knowledge from their daily trip do not search for the lowest price each day. This search activity is a significant contributor to congestion, so transit strategies must provide options that are appealing enough to be selected immediately, without first searching for better options, or sufficient information that best options are identified quickly.

With these important differences between commuters and tourists in mind, we develop a conceptual model of tourist parking and transit choices that can predict tourist response to, and measure the welfare changes associated with, alternative transit strategies in seasonal tourist destinations. We calibrate the model using a stated preference survey of tourists visiting Newport, Rhode Island on several busy weekends. Based on the survey, we find that factors such as scenery, which are not traditionally considered in commuter-based studies, significantly influence tourist transit decisions, and therefore need to be considered in developing intermodal transportation strategies for tourists. Below we introduce the case study city of Newport, Rhode

Island, the destination which motivated our study. The following section introduces the conceptual model and the stated preference survey which implements it. Section IV explains the random effects and random coefficients logit models used to analyze the survey data. Section V presents the survey results, which are robust to a wide range of statistical model specifications. Section VI presents an example application of the model results to a simple alternative proposal. Section VII concludes with a discussion of our results' policy applications.

Newport, Rhode Island

Newport, Rhode Island attracts more than three million visitors each year, primarily in the Summer and early Fall, representing the largest municipal contributor to the state's 3.5 billion dollar leisure travel industry. Figure 1 shows the geographical distribution of major tourist attractions in the city. Newport sits on an island on the east shore of Narragansett Bay. The major shopping and restaurant district, and the Gateway Visitors' Center, sits on the wharfs along the waterfront facing the bay. The International Tennis Hall of Fame and the mansions (Gilded Age Summer cottages of Vanderbilts, Astors and other wealthy families) are arrayed along the east edge of the island, with the Cliff Walk between them and the shoreline. The scenic Ocean Drive, Fort Adams State Park and the Newport Yachting Museum draw visitors through downtown to the south shore of the island. Newport Grand Casino and Jai Alai attract visitors to the northern part of the city.

Visitors arrive either from the west across the bay via the Newport Bridge, or from the north along Route 114. Parking is arrayed in public and private lots along America's Cup Avenue, which runs along the waterfront, and on metered and unmetered street parking throughout the town center. On peak days, parking charges range from $20 or more per day in private lots in the town center, to hourly-charge city lots in the town center and at the Gateway Visitors' Center, to free in lots at certain attractions such as the mansions and in two-hour on-street parking (at the time of the study, one could also park illegally on residential streets and risk a $20 fine). Table 1 shows an inventory of parking options in Newport, their capacity and parking rates. The parking meter locations and their capacities are depicted in Table 2. In Summer 2003, parking fines were $10 for exceeding posted time limits on the street and $15 for exceeding time limits on meters.

TABLE 1. Newport Parking Pricing Data

Parking Lot Name	Parsons #	Capacity	Ownership	Parking rate (11 am - noon 7/10/2002)
City Meters			City	0.25/15 minutes - 3 hour limit
Gateway Visitor Center	12	450	City	$1 first 1/2hr + 0.75 each added 1/2hr. Max per day $12.25. 1/2 hr free if validated
Long Wharf Mall North	7	120	Private	$2.0 first 1/2 hr + $1.5 each added 1/2 hr. Up to 2 hrs free for store stamps
Long Wharf Mall South	8	77	Private	$2.25 first 1/2 hr + $1.75 each added 1/2hr. Up to 2 hrs free for store stamps

Sea Fare Restaurant	9	57	Private	$2.25 first 1/2 hr + $1.75 each added 1/2hr. Up to 2 hrs free for store stamps
Mary Street Lot	17	120	City	$2.00 first 1/2hr + $1.00 each added 1/2hr. Up to $15.25 all day.
Citizen's Bank	10	65	Private	Bank customers only
Bank of Newport	22	26	Private	Bank customers only
Newport Harbor Hotel	6	120	Private	$10 flat rate
Bowen's Wharf	20	22	Private	$2.0 first 1/2 hr + $1.5 each added 1/2hr
Moorings Restaurant	26	125	Private	8 AM to 3:30 pm $2.0 first 1/2hr + $1/75 each added 1/2 hr. 3:30 pm to 2 am flat rate
Newport Yachting Center	27	205	Private	$8
Blue's Café	Not –21 b	35	Private	$5
People's Credit Union	21	25	Private	Bank customers only
Perry Mill Wharf	Not –19 B	?	Private	$8 flat rate
Christies Restaurant	19	70	Private	Christie's customers only
J.T. Ship Chandlery	23	52	Private	$8 flat rate - note: full at 12:30
Brewerr Street	Not 23 B	27	Private	$7 flat rate
Lee Wharf	24	100	Private	$7 flat rate
Lee Wharf	16	20	Private	Customers only
Thames Restaurant	18	6	Private	Customers only

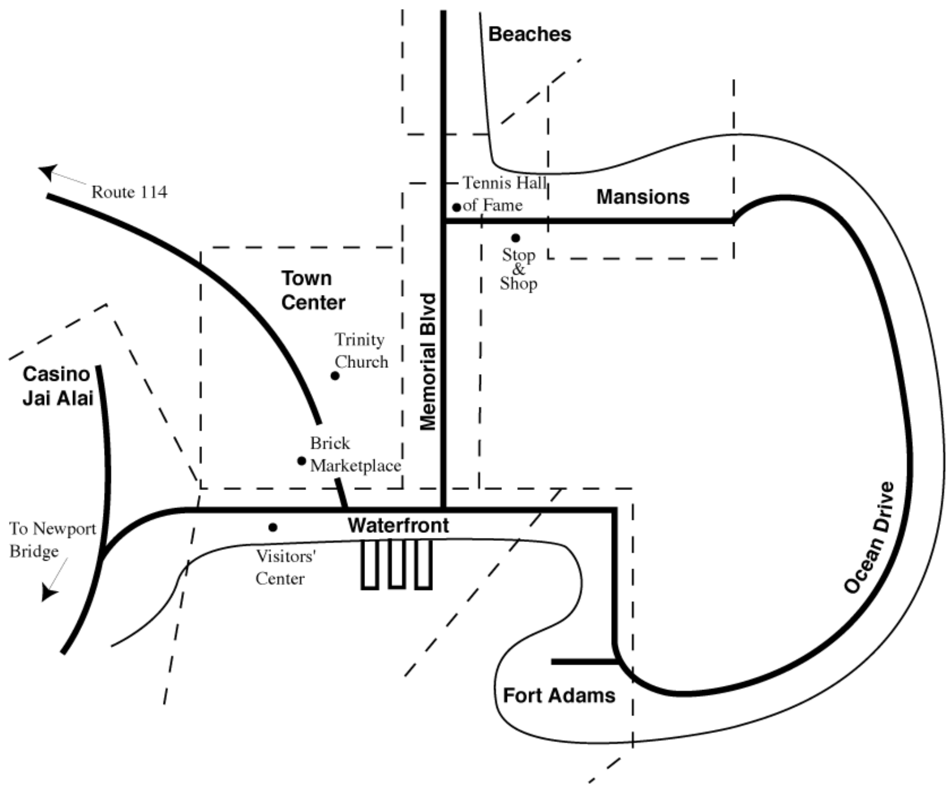
TABLE 2. Parking Meter Location And Capacity

Area	Street/Location	Number of meters
1.	Washington Square, Touro street	40 6
2.	Meeting street, Charles street, Duke street	7 9 9
3.	Touro court	31
4.	Long wharf	33
5.	Thames street	82
6.	Franklin street Post Office	10 18
7.	Lower Thames street	22
8.	Market Square	26
10.	Memorial Boluevard	57
11.	Eastons Beach	27
Total		377

These parking locations are scattered in and around the waterfront and town center, within easy walking distance of most attractions. Except for casino visitors, tourists seeking all major destinations or parking locations must drive along America's Cup Avenue, a four-lane street dividing the wharfs from downtown shopping and restaurants. Tourists seeking parking and moving among attractions badly congest this thoroughfare, up Memorial Boulevard, past the mansions, and often back to the city's major supply arteries. This geography constrains the number of cars that may move into and through the city, and therefore the quantity of visitors and extent of economic activity.

Once they park, visitors may navigate the city on foot (all town center and waterfront attractions are within easy walking distance) or move among city attractions on state-sponsored trolleys. State-sponsored water shuttles, between the wharfs and Fort Adams, have also been proposed. Given a destination, each parking alternative implies a best modal alternative for travel between the parking lot and the destination. This study focuses on the joint choice of parking location and within-city transit mode, hypothesizing that factors other than those commonly considered in commuter studies significantly influence tourists' intermodal transit choices.

FIGURE 1. Map of Major Regions of Newport, RI



Not to scale. North is to the left.

II. THE ECONOMICS OF TRAVEL CHOICE BEHAVIOR

Understanding the transit choices of any traveler requires understanding how features of different transportation alternatives affect her utility. The relevant features are likely to depend heavily on the purpose of the trip, and in turn will drive her choice of mode and parking location. Thus, transit choices are not a final objective in themselves; but rather a concomitant of activities possible at the destination (3). For commuters and local residents running errands, modal, route and parking location choices are often driven primarily by the desire to reach the destination, and thus are modeled primarily based on travel time and parking and travel cost (8). For tourists, however, recreational characteristics of the journey itself may complement activities at the destination. Therefore, accurately modeling tourist transit behavior requires incorporating into the transit choice model features of the journey which may influence tourists' choices.

Tourists seek a variety of scenic, cultural, historical and recreational characteristics that are intrinsic to their destination. This group of characteristics is important to the pre-travel choice of a geographic region to be visited (e.g., Newport) as well as to the specific attractions visited once there and to the in-travel modal and route choices. Tyrrell and Devitt (10) find that tourists are willing to spend more time and money in transit to utilize scenic roadways and routes that offer attractions, in addition to trying to reduce travel time and cost. In addition to considering additional factors, tourists may also consider differently characteristics of a trip which are considered by other travelers. For example, tourists may be more likely to use a tourist trolley than a city bus, though both fulfill the same function. Tourists may also feel differently about congestion, accepting it as part of the communal experience of getting out of the city and appreciating the slower pace of traffic along scenic roadways, or dislike it more as slow traffic makes a car full of irritable children worse than sitting alone in an urban traffic jam.

To better understand the differences between tourists and other travelers, we model tourist transit choices as a function of several categories of trip characteristics: trip cost, in terms of parking lot and transit fees and driving and public transit time; route features, including scenery and level of congestion; modal options from the chosen parking lot to the destination attraction, including walking, public trolley and water shuttle; and demographic factors, the travelers' ages, income levels, and whether there are children in the party. When faced with multiple transit alternatives, tourists will evaluate the utility they receive from each alternative, and select the option yielding the greatest utility. By understanding the weight each of these trip characteristics receives in a representative utility function, we can evaluate a new transit alternative based on the level of each trip characteristic it provides, estimate the utility a representative traveler would receive from it, and predict whether or not travelers will prefer it to existing alternatives.

III. STATED PREFERENCE SURVEY DESIGN

To test the hypothesis that tourist choices are influenced by trip characteristics not commonly thought to influence commuters, and to quantify their effect for design of effective tourist-centered transit policy, we designed a stated preference survey to be administered to a sample of Newport visitors. The survey presents respondents with a set of independent questions posing a hypothetical choice between two parking lots, and the associated public transit, which would allow them to reach an unspecified target destination. Previous studies of commuters suggest a strong relationship between parking lot and modal choice, recommending the two choices be considered jointly (5, 11, 12). In our survey, the lots are described in terms of the trip characteristics discussed in the previous section. Respondents are asked to indicate which of the two described lots they prefer. Given sufficient data we can recover an underlying representative utility function using statistical techniques.

Such stated preference methods have been widely used in modeling demand for new transit alternatives in a variety of applications around the world (13, 14). For example, Brown (15) used stated preference data to assess the extent to which changes in parking pricing would affect transit demand; Kuppam and Pendyala (16) use hypothetical survey data to understand how parking pricing can be used to curb vehicular demand in Washington, D.C.; and Hensher and King (17) use hypothetical survey data to model the effect of parking time restrictions on modal use around the central business district of Sydney, Australia.

The hypothetical methodology provides several advantages. It allows us to identify tourists' true preferences: actual parking lot choices on a given day may be influenced by factors such as lack of information about alternatives (which may particularly affect tourists' choices), or by people parking in less preferred lots because their most preferred lots are full. By posing hypothetical questions, choices are not affected by these constraints and people's true preferences can be identified, and policies tailored to meet them. Although the questions pose hypothetical choices, it can be considered a dominant strategy for respondents to answer binary questions truthfully as long they believe there is some chance for their answers to affect policy (18, 19).

Our stated preference survey consists of two sections. The first section collects demographic information about the respondent and her traveling party, including, household income (greater or less than $100,000) and age of the respondent (younger or older than 50), place of residence, distance traveled on the survey day, transit mode for arriving in Newport, intended attractions, and the number of children in the party. Collection of this data allows us to consider how parking preferences vary with these factors.

The second section of the survey includes seven stated choice questions of the format shown in Figure 2. Each question asks the respondent to consider the choice between two parking lots with different costs, travel characteristics and options for getting from the parking lot to the destination attraction. Respondents are asked to imagine they are at the entrance to Parking Lot A. The visitor may park in Lot A for the stated price ($20) and get to her destination by a described mode, in this example walking 20 minutes, enjoying the moderate quality scenery along the way. Or, she may continue driving to Lot B, which in this example also costs $20, but from which she could take a 5 minute water shuttle ride to her destination. On the five-minute drive to Lot B, she would encounter poor scenery and no traffic congestion. Considering these factors, respondents were asked to indicate whether they preferred to park in Lot A or Lot B by checking the appropriate box.

The graphical format of the survey shown in Figure 2 was the result of focus group testing of alternative question presentations (20, 21, 22, 14). The chosen format was compared to a tabular presentation of the parking alternatives and a graphical formulation without icons. The focus group found the graphics aided them in quickly understanding the structure of the question and the alternatives before them. However, there is no empirical evidence that graphical presentations improve the validity of stated preference responses (23).

The possible values of each lot attribute are shown in Table 3. The statistical design included five versions of the survey with seven questions each, for a total of 35 questions. The attribute levels of each lot presented in the choice between lots A and B were chosen using the modified Federov method to search over a large number of randomly generated feasible designs to select the one which minimized the maximum variance of the estimates of coefficients of the main factors in a linear model. To ensure questions did not require respondents to consider differences on too many attributes, which Mazzota and Opaluch (24) find reduces response reliability, we restricted the design to questions in which lots differed on no more than three attributes.

The survey was conducted in person at different locations in Newport on several peak travel weekends in the late summer and early Fall of 2002. The survey locations were attractions which draw large numbers of visitors, and which are visited by almost everyone who visits Newport. On several weekends, the survey was administered at The Breakers, the most frequently visited mansion, and the Gateway Visitor's Center, run by the Newport Convention and Visitors' Bureau, because it is the largest downtown parking lot, the public bus stop and starting point of several package tours and also close to the sites of several special weekend events on the waterfront. Other locations were at special one-weekend events around the city, including a wharf at the Newport International Boat Show, and the Taste of Rhode Island.

Graduate and undergraduate students, as well as faculty and Newport Preservation Society employees, interviewed a sample of 298 groups of visitors to Newport about their actual and hypothetical behavior with regard to transportation and parking in Newport. The respondents were talked though an example choice question. For most respondents this example was sufficient instruction; for a few, additional assistance interpreting survey questions was necessary. Out of 298 surveys, only 23 choice responses were missing, giving a total of 2063 choice responses for analysis.

FIGURE 2. Sample Stated Preference Question

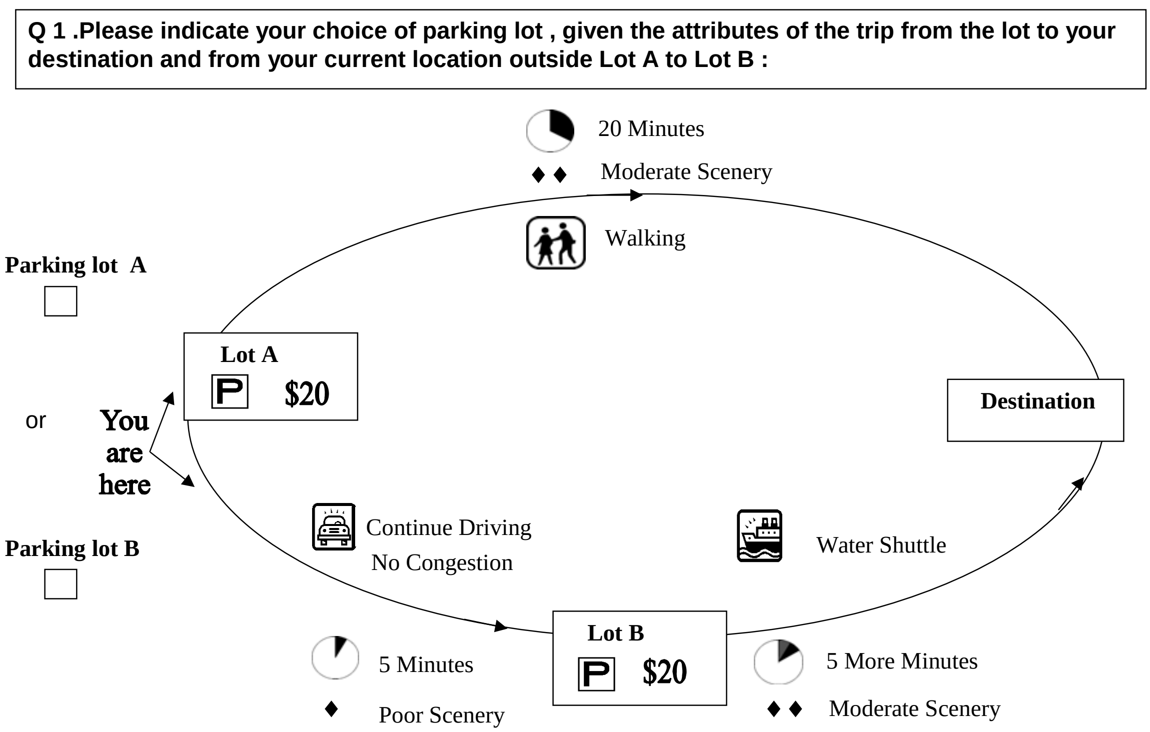


TABLE 3. Parking Lot Characteristics

Characteristics	Level Descriptions
Parking Price	$0 (free) $5 $10 $20
Scenery Quality from the parking lot to the destination	Poor – Very Little or None Moderate – Moderate, medium quality Excellent – Considerable, high quality
(Best) Mode of transit from parking lot to destination	Trolley Walk Water Shuttle
Time to reach destination from parking lot	2 Minutes 5 Minutes 10 Minutes 20 Minutes
Driving Time from Lot A to Lot B	5 Minutes 10 minutes 20 minutes
Scenery quality on drive from Lot A to Lot B	Poor – Very Little or None Moderate – Moderate, medium quality Excellent – Considerable, high quality
Congestion encountered on drive from Lot A to Lot B	No – Very Little or None Moderate – Moderate, medium quality Heavy – Considerable, high quality.

IV. THE BINARY CONTINGENT CHOICE MODEL

The purpose of the survey is to understand the preferences of tourists, and how they are affected by changes in the levels of described attributes. To do this, a framework to map choices into preferences is necessary. Random utility models (25, 26, 3) provide such a framework, while acknowledging that surveys do not include all factors that affect respondents' decisions. In a random utility model, the utility that person i receives from choosing alternative j is represented by $U_{ij}=V_{ij} + \varepsilon_{ij}$, where V_{ij} is a known (to the investigator) component of utility based on the described attributes, and ε_{ij} is an unknown component, treated as random to the investigator, based on both the measured attributes and other factors. When evaluating a choice between alternatives A and B, the respondent compares the utility from each alternative and selects the one yielding higher utility. From the perspective of the investigator, who does not know ε, the probability A is chosen is given by

$$\Pr(Y_i=A) = \Pr(U_{iA}>U_{iB}) = \Pr(V_{iA}-V_{iB}>\varepsilon_{iB}-\varepsilon_{iA}).$$

When ε_{iB} and ε_{iA} are assumed to have a Type I extreme value distribution, this probability is given by

$$\Pr(Y_i=A) = \exp(V_{iA}-V_{iB})/(1+ \exp(V_{iA}-V_{iB})).$$

This probabilistic choice statement can be leveraged to recover the weights placed on the attributes in the known component of utility by specifying a functional form $V_{ij}=X_{ij}\beta$, where X_{ij} is a vector describing the attributes of alternative j and β is a vector of weights on those attributes. If $X_i =(X_{iA} - X_{iB})$, then the β vector, which represents preferences, can be estimated by maximizing the log-likelihood of a large number N of observed choices using the function

$$\ln L(Y|\beta)=\textstyle\sum_{i=1}^{N} \{Y_i=A\} \ln(\psi(X_i\beta)) + (1-\{Y_i=A\}) \ln(1- \psi (X_i\beta)),$$

where $\psi(X_i\beta)$ is the cumulative density function of a logistic distribution and the expression in curry brackets is a indicator function that takes on a value of 1 when $Y_i=A$ and 0, otherwise. This is the likelihood function of a standard binary logit model (3, 27, 14). However, it must be modified for our survey because we ask each respondent to answer more than one question. Because each person's choices are based on attitudes toward tourism and transit, the unobserved utility components, ε_{ij}, may be correlated across the responses of the same individual (28, 29). To account for this correlation, we assume the random utility model represents the difference between A and B as $(U_{itA} - U_{itB})=(V_{itA} - V_{itB}) + \eta_i + (\varepsilon_{itA} - \varepsilon_{itB})$, where η_i is an individual-specific component of the unknown utility which linearly affects all i's T_i observations. If $X_i =(X_{itA} - X_{itB})$ and the η_is are assumed to be normally distributed in the population, the investigator can estimate β from a random effects logit model using the likelihood function

$$\ln L(Y|\beta,\sigma_\eta)=\textstyle\sum_{i=1}^{I} \int \left[\sum_{t=1}^{T_i} \{Y_{it}=A\} \ln(\psi(X_{it}\beta+\eta)) + (1-\{Y_{it}=A\}) \ln(1- \psi (X_{it}\beta+\eta))\right]\phi(\eta)d\eta$$

where the data consist of T_i observations on each of I individuals and $\phi(\eta)$ is a normal distribution with mean 0 and estimated standard deviation σ_η. Using a random effects model guards against overconfidence in statistical estimates arising from assuming correlated observations are independent. Therefore, we use this random effects model as our primary tool of analysis.

Random Coefficients Analysis

While the random effects logit represents population heterogeneity and correlation among each individual's responses as entering the model linearly, recent research has focused on the intuitively appealing proposition that tastes vary within the population, and by explicitly including this variation the investigator can achieve a more accurate representation of preferences (30, 31, 32, 33). Hensher (34) reports random coefficient models lead to higher valuations than multinomial logit in stated preference data on travel time savings. Taste heterogeneity assumes that the known component of the random utility model is $V_{itj}=X_{itj}\beta_i$, where each individual has her own vector of attribute weights which determines her utility and therefore her choices. To represent this heterogeneity, the β_i are assumed to be drawn from some multivariate distribution $\Lambda(\theta)$, where θ is a vector of moments of Λ to be estimated to maximize the likelihood function

$$\ln L(Y|\theta)=\sum_{i=1}^{I}\int\left[\sum_{t=1}^{T_i}\{Y_{it}=A\}\ln(\psi(X_{it}\beta_i))+(1-\{Y_{it}=A\})\ln(1-\psi(X_{it}\beta_i))\right]\Lambda(\beta_i|\theta)d\beta_i.$$

In this model, coefficients are not estimated directly, but indirectly through moments of population distributions of coefficients. In practice, the expectation over $\Lambda(\theta)$ can be computationally complex, since it could specify a marginal distribution in the coefficient on each element in X and a covariance among those distributions, so some restrictions are imposed on θ (35). To reduce the complexity of this problem, distributions of coefficients are typically assumed to be independent across attributes and the integration is carried out numerically (30). We use a random coefficients model, where all marginal coefficient distributions are assumed to be normally distributed, to confirm that the conclusions about tourist parking preferences drawn based on the random effects model are robust to explicit consideration of preference heterogeneity.

V. ESTIMATION AND RESULTS

Table 4 presents a summary of the descriptive statistics of our sample. Most were traveling in groups of two people, and only 12.8% had children in the party. 37.9% of respondents were over 50, and 38.3% came from households earning over $100,000 a year. This is consistent with previous city reports which have shown visitors to Newport to be a little older and wealthier than a typical American. About six in ten respondents had previously visited Newport.

TABLE 4. Summary Statistics of Survey Sample

Average traveling group size	2.28
Percent older than 50	37.9%
Percent earning over $100,000	38.3%
Percent traveling with children	12.8%
Percent previously visited Newport	60.9%

Table 5 presents the results of random effects logit estimation of four models, and one random coefficients logit model. The multiple models are presented to demonstrate the robustness of the model conclusions to the inclusion of alternative variables in the model, and to alternative specifications of population heterogeneity. Overall, the results are extremely strong, and align well with expectations. In Table 5, a positive coefficient implies a higher level of that attribute leads to higher utility, and therefore to increased likelihood of choosing the parking lot with more of that attribute. A positive coefficient for the D-variables, describing the drive from Lot A to Lot B, implies an increased likelihood of choosing Lot B.

The first column of Table 5 presents the baseline model, which includes variables for the main attribute effects along with a basic set of demographic variables, age, income and whether or not children are traveling with the party. Consistent with previous parking and modal choice studies on commuters, and with economic theory, monetary cost has a significantly negative coefficient of –0.108 ($p<10^{-16}$), suggesting that, *ceteris paribus*, tourists prefer less expensive parking alternatives. It is a nice validity check that the two time variables, *Time* (to destination), with a coefficient of –0.048 ($p<10^{-8}$) and *DTime* (to Lot B), with a coefficient of –0.047 (p=0.015), are nearly identical, indicating time spent in the two activities affects utility in the same way, and that *ceteris paribus*, tourists want to get to their destination faster. However, this is an interesting contrast to commuter studies, which suggest in-car time is about 2.5 times less valuable than lot-to-destination time (8).

The trade off between cost and other attributes can be summarized by the ratio of *Cost*, which represents the marginal utility of income, and the attribute coefficient, which represents the marginal utility of that attribute (36, 37). This gives a willingness to pay, or an amount of money that the average respondent would be willing to give up to get another unit of the attribute. Thus, according to the baseline model, an average tourist is willing to pay $0.44(-0.048/-0.108) per minute closer to her destination she can park. Though payment is frequently expressed in money terms for policy purposes, similar ratios with other numeraires, such as time, could be used to value changes in transportation alternatives.

While tourists value time and money like commuters, the size and significance of the *Scenery* coefficient, 0.584 ($p<10^{-16}$) and *DScenery* coefficient, 0.315 (p=0.016) indicate that tourists' preferences are in fact different than those typically ascribed to commuters. Therefore, tourists are more likely to continue searching for parking if the driving is scenic, and willing to pay $5.41 more for parking if the journey from the lot to their destination is scenic. However, slow travel offsets any scenery value, as indicated by the –0.548 coefficient on *DCongestion*, which is highly significant ($p<10^{-14}$) and negative, implying that tourists are willing to pay almost $5.07 to avoid a one code-level increase in congestion. We are not aware of any other studies that have separated the effect of congestion from the travel time it implies, and therefore cannot compare tourist and commuter preferences for congestion, but it is clear that congestion is a dominant factor in determining tourists' parking preferences, and significantly affects enjoyment of the trip.

TABLE 5. Estimated Attribute Coefficients

	Random Effects Logit Models				Random Coefficients Logit	
Variable Name	**Baseline Model**	**Income Interaction**	**Transit Difficulty**	**Grand Model**	**Mean (μ)**	**Stds (σ)**
Cost	-0.108	-0.132	-0.108	-0.131	-0.143	
	(-8.48)	(-7.84)	(-8.50)	(-7.81)	(-7.78)	
Scenery	0.584	0.591	0.566	0.573	0.650	0.537
	(8.04)	(8.09)	(7.65)	(7.72)	(7.17)	(3.24)
Trolley	0.384	0.382	0.398	0.397	0.484	0.003
	(2.60)	(2.57)	(2.68)	(2.66)	(2.98)	(0.005)
Walk	0.060	0.039	0.189	0.178	0.185	0.093
	(0.48)	(0.31)	(1.16)	(1.08)	(1.07)	(0.12)
Time	-0.048	-0.046	-0.046	-0.044	-0.049	0.010
	(-5.30)	(-3.98)	(-4.93)	(-3.81)	(-4.00)	(0.41)
DTime	-0.047	-0.059	-0.048	-0.059	-0.064	0.016
	(-2.43)	(-2.78)	(-2.46)	(-2.78)	(-2.73)	(0.47)
DScenery	0.315	0.323	0.322	0.330	0.325	0.208
	(2.40)	(2.45)	(2.44)	(2.49)	(2.16)	(1.78)
DCongestion	-0.548	-0.564	-0.569	-0.582	-0.597	0.548
	(-7.55)	(-7.69)	(-7.68)	(-7.80)	(-6.76)	(8.33)
Income	0.021	-0.228	0.012	-0.212	-0.425	
	(0.12)	(-0.83)	(0.07)	(-0.77)	(-1.42)	
Children	-0.039	-0.056	-0.264	-0.237	-0.011	
	(-0.15)	(-0.21)	(-0.89)	(-0.80)	(-0.03)	
Age	-0.045	-0.045	-0.022	-0.023	-0.013	
	(-0.26)	(-0.26)	(-0.13)	(-0.13)	(-0.07)	
Time× Income		-0.008		-0.007	-0.011	
		(-0.44)		(-0.37)	(-0.56)	
DTime×Income		0.030		0.028	0.041	
		(1.36)		(1.27)	(1.69)	
Cost×Income		0.055		0.053	0.060	
		(2.24)		(2.16)	(2.31)	
Children×Walk			0.451	0.362	0.286	
			(1.28)	(1.02)	(0.71)	
Children×Time			-0.033	-0.026	-0.001	
			(-1.51)	(-1.22)	(-0.05)	
Walk×Scenery			-0.215	-0.210	-0.190	
			(-1.15)	(-1.12)	(-0.83)	
Walk×Age			-0.367	-0.363	-0.358	
			(-1.61)	(-1.58)	(-1.47)	
Constant	0.469	0.579	0.507	0.601	0.575	
	(1.95)	(2.23)	(2.09)	(2.30)	(2.16)	
LnL	-1147.729	-1141.140	-1143.575	-1137.776	-1107.058	

N= 1867. Student's *t*-statistics are reported in parentheses.

The lot-to-destination modal choice preferences are represented by coefficients on the *Trolley* and *Walk* mode indicator variables. Tourists prefer the trolley, with a coefficient of 0.384, over the omitted category of water shuttle (p=0.009), and are indifferent between walking, with coefficient 0.060, and taking a water shuttle (p=0.632). This translates to a willingness to pay \$3.56 more for a trolley ride to the destination than a water shuttle ride. Willingness to pay for walking rather than taking a water shuttle is \$0.56, but since walking is usually free, this is more sensibly interpreted as a lot offering a water shuttle as its best transit option must be \$0.56 better on some other attribute, such as being faster or cheaper.

The demographic variables in the baseline model are not significant, suggesting demographic factors do not affect tourists' propensity to choose Lot B, which would reflect a preference to stay in or get out of the car once they are near their destination.

While the results of the baseline model align well with expectations, it is important to verify that they are robust. The second column of Table 5 presents the results of the income interaction model, which evaluates the extent to which people with higher incomes (greater than \$100,000) value time and money differently than people with lower incomes. Interacting a high income indicator variable with the *Time* and *Cost* variables reveals that higher income people have a much lower marginal utility of income, as the *Cost*×*Income* interaction has a significantly positive coefficient of 0.055 (p=0.025); the coefficient on *Cost* falls to –0.132, from –0.108 in the baseline, once the wealthier respondents are considered separately. Overall, this suggests a *Cost* coefficient of –0.077 for high income people, and one of –0.132 for people with incomes under \$100,000 a year. This reflects an unsurprising difference in willingness to pay, as higher income people are willing to spend \$0.70 to park each additional minute closer to the destination and \$4.96 for a trolley ride, compared to \$0.35 and \$2.89 for lower income people. However, even wealthy people are time constrained when touring, and they want to avoid travel time as much as lower-income people, even if their cars are more comfortable. As a result, the interactions of high income with *DTime* and *Time* yield insignificant differences from other visitors (p=0.173 and p=0.657, respectively).

The third column of Table 5 reports the results of a different specification, designed to test robustness of the baseline model conclusions to factors which make traveling more difficult. Many Newport visitors have children, or have reduced mobility associated with age. The transit difficulty model interacts the *Walk* mode with *Age* (over 50) and the presence of children, *Time* with presence of potentially impatient children, and the *Walk* mode with *Scenery*, which could distract impatient children or reward the slower pace age might imply. Except for *Children*×*Walk* all transit difficulty variables have negative signs, suggesting age and children do make travel more difficult. However, only *Walk*×*Age* and C*hildren*×*Time* are even borderline significant, with coefficients of –0.367 (p=0.108) and –0.033 (p=0.131), respectively. The *Walk*×*Age* interaction implies a *Walk* effect of –0.178 for people over 50, as compared with 0.189 for people under 50. This reflects that younger people are far more likely to prefer walking and willing to pay \$1.75 for walking mode, whereas non-walking modal alternatives must be provided for older visitors if they are to park other than very near their destination. The *Children*×*Time* interaction indicates a *Time* effect of –0.079 for people with children and of –0.046 for people without children, implying visitors with children in the group are willing to pay \$0.30 more per minute closer to their destination they can park.

The fourth column of Table 5 reports the results of the grand model, which incorporates all the variables in the baseline, income and transit difficulty models. It shows that the main results of the random effects analysis are robust to the inclusion of additional sensible covariates. Like commuters, tourists dislike high costs, long travel times and congestion. Tourists are willing to use public transportation, with especially older visitors preferring public trolleys to walking. However, the study also reveals that scenery is one of the most important attributes to tourists, an effect not usually directly considered in transportation plans oriented toward commuters.

The fifth and sixth columns report the estimated means and standard deviations of main attribute coefficients from a random parameters specification of the grand model.[1] In this model, attribute coefficients are assumed to be normally distributed in the population, and respondents' coefficients are independently distributed across attributes. Interaction and demographic variables are assumed to shift means, and not to have distributions themselves. To avoid identification problems, the constant term is assumed not to have a distribution (35, note 8). To avoid having to compute the ratio of two distributions to develop welfare measures, the *Cost* coefficient is also assumed not to vary among respondents. Although Train (38) computes willingness to pay as the ratio of a normal and log-normal distribution, most investigators using random coefficients logit on stated preference data have chosen to estimate a fixed cost parameter, (39, 35, 40, 41, 42).

The results obtained from the random coefficient logit model are consistent with those of the random effects analysis, but some additional insight into population heterogeneity is provided. The mean coefficients on the *Cost*, *Time* and *DTime* attributes remain significantly negative, and have the same magnitudes as in the random effects models. Modal preferences correspond with those revealed by the random effects models, with trolley being a favorite mode, followed by walk and water shuttle (though the latter difference is not highly significant). Older visitors continue to prefer a trolley to walking. Finally, the effect of scenery, both on the trip from the parking lot to the destination attraction and between parking lots, continues to be both significant and large relative to other measured effects.

These major results are robust not only to respecification, but also to consideration of diverse preferences in the population. *Time*, *DTime*, and the modal preferences all vary little in the population, with none having estimated standard deviations that are a significant fraction of the respective mean (and therefore suggesting a different effect for a meaningful portion of the population), and none have standard deviations which are statistically different from zero. However, the *Scenery* effect appears to vary significantly in the population, with a significantly positive mean of 0.650 ($p<10^{-13}$), but a standard deviation of 0.537 ($p=0.001$). Under the assumed normal distribution, this means that 89% of the population appreciates scenery, some a good deal, but it is not important, or even bad, for the remaining 11% who have negative coefficients on scenery. Additionally, the coefficient on *DCongestion* varies widely around its mean of –0.597 ($p<10^{-12}$), with a significant standard deviation of 0.548 ($p<10^{-16}$). This means that 86% of the population dislikes congestion, and many very strongly. Thus, while the representative agent random effects models capture an average effect of choice attributes on tourists' transit decisions, there is some uncaptured population heterogeneity.

[1] We used GAUSS to estimate the mixed logit model and STATA to estimate the other fixed-effect models. We estimated the mixed logit with 125 Halton draws and we also recognized the panel aspect of the data.

Table 6 provides a summary of the willingness to pay calculations for key lot choice attributes for the grand random effects model and the random coefficients model. The attributes are ordered by the absolute value of the coefficients to give a sense of ordered importance, though the differing scales of the categorical scenery, congestion and modal variables is not comparable to the closer-to-continuous time variables. Comparing the willingness to pay from the representative agent random effects model to the mean willingness to pay in the random coefficients model, there is remarkable agreement in the value and importance ranking of the attributes. Both models rank *Scenery* and *DCongestion* as the two attributes most affecting parking lot choice, and assign similar values for *Trolley* and *Dscenery*.

While the mean values given by the random coefficients model are similar to those of the random effects model, it provides additional information about the attributes over which there is variation in preferences in the population. The random coefficient model indicates wide variation in the willingness to pay for scenery: although the mean is $4.55 and, the standard deviation $3.76 indicating that while about 7.3% of people are willing to pay more than $10 for a code-level improvement in scenery, 11% people do not have positive willingness to pay, and are either indifferent to scenery or seek out less scenic routes. There are similarly wide-ranging opinions of driving congestion, with a mean of $4.17 and standard deviation of $3.83 for *DCongestion*. In developing policies, it is important to remember the heterogeneity associated with these attributes, because not everyone will respond to new policies in the same way.

TABLE 6. Willingness to Pay for Attributes (by low income people under 50)

Attributes	Random Coefficients		Random Effects (Grand Model)
	Mean	Std. Dev.	
Scenery	4.55	3.76	4.37(0.77)
DCongestion	-4.17	3.83	-4.44(0.83)
Trolley	3.38	0.02	3.03(1.30)
DScenery	2.27	1.45	2.52(1.07)
Walk	1.29	0.65	1.36(1.32)
DTime	-0.45	0.11	-0.45(0.16)
Time	-0.34	0.07	-0.34(0.07)

Note: A positive sign means WTP to have more of that attribute and negative sign implies the WTP to have less of that attribute. Bootstrapped standard errors are shown in the parentheses.

VI. A SIMPLE APPLICATION OF THE MODEL

The purpose of the survey and estimation exercise was to develop a model of tourist preferences that could be used in developing systems of strategic parking prices and public transit to affect tourist transit use and improve traffic patterns and visit quality. This section demonstrates an application of the preferences model to a stylized transportation plan evaluation.

In actual cities, planners and tourists are typically faced with many more than the two parking lot and mode choices presented in each survey question. An extension of the above binary analysis to a multinomial choice situation is required to help policy makers predict behavior in these more complex environments. Extension is possible because the survey was not designed to understand respondents' preferences between two specific alternative plans, but rather to assess their underlying preferences over the domain of alternatives often available in seasonal waterside tourist destinations. Because the survey was designed with random utility model estimation in mind, the estimates can be applied within a random utility framework to understand how tourists might respond to far more complex decision problems. As in the estimation process, a utility index can be constructed for each alternative *j* from its attributes X_j and the utility function parameters estimated from the survey responses, β. The utility *i* will receive from alternative *j* is the sum of this known utility index and an unknown term, ε_{ij}, $V_{ij} = X_j\beta + \varepsilon_{ij}$. If the ε_{ij} are assumed to be distributed Type I extreme value, the probability *i* chooses alternative *j* is given by

$$\Pr(Y_i = j) = \exp[X_j\beta] \,/\, \Sigma_{k=1}^{J} \exp[X_k\beta]$$

For a policymaker trying to understand the decision behavior of a large number of people, this probability can be interpreted as the proportion of people faced with the choice among the *J* alternatives who would choose alternative *j*. This would allow a planner to understand the effect of changes in attributes on demand within a transportation system.[2]

To illustrate, consider a tourist destination with a transportation system of three lots characterized as shown in Table 7. The transportation planner wishes to know whether the moderate congestion on a residential street leading to lot Z could be relieved by the addition of trolley service from lot Y, a satellite lot. For this illustration, assume all visitors are less than 50 years old, are not traveling with children and have incomes less than $100,000. Using the baseline model estimates shown in Table 7 and the equation above, we compute the predicted proportion of tourists using each lot. The plurality of visitors, 41%, choose lot X, preferring the lower price than lot Z and the availability of public transportation, a water shuttle. Lot Y attracts 31% of users, and lot Z the remaining 28%.

Now suppose a trolley service is introduced from lot Y to the same final destination, and that the trolley takes only 5 minutes to reach the destination. All other characteristics of the system remain unchanged. As a result of the trolley 9% of the visitors' will switch their choice from lot X to Y and 6% of the visitors switch their choice from lot Z to lot Y. This is because visitors prefer trolley rides to water shuttles and walking. Therefore, the planner can divert a proportion of the traffic from lot Z to lot Y by adding a trolley, and relieve congestion on the residential street to lot Z. However, she will also have to anticipate a considerable switch from lot X, and plan trolley and lot capacities accordingly.

TABLE 7. A Simple System of Parking Lots

Attributes of Parking Lots	Parking Lot X	Parking Lot Y	Parking Lot Z
Scenery to destination	Moderate	Moderate	Moderate
Time to destination	15 Minutes	12 minutes	2 minutes
Transport to destination	Water shuttle	Walk	Walk
Price of parking	$10 per day	$5 per day	$15 per day
Driving scenery		Moderate	High
Driving time		12 Minutes	8 Minutes
Congestion		Moderate	Moderate

VII. DISCUSSION

Heavy traffic congestion is a perennial problem at seasonal tourist destinations throughout the country and the world. Communities which depend on tourism stand to gain from reducing this congestion because time tourists save fighting traffic can be spent visiting local

[2] This multinomial logit formulation has the possibly undesirable independence of irrelevant alternatives property, which may lead to improperly predicting change probabilities when preferences for alternatives are correlated. Mixed logit models do not have this property, though we are not aware of any results that establish that mixed logit sensibly captures correlation among added alternatives that were not part of the estimated choice set. It is straightforward to adapt this framework using mixed logit estimates.

shops, restaurants and attractions; visit quality will increase, attracting repeat and additional visitors; and traffic-related environmental problems will be reduced. Actually reducing congestion without discouraging visitors requires a tourist-targeted parking pricing and public transit system designed to encourage visitors to park their cars upon arrival and walk or take public transportation. This analysis contributes to that effort by characterizing the transit preferences of tourists in Newport, Rhode Island, a popular summer weekend tourist destination typical of such destinations nationwide.

Tourists share many preferences with commuters, on whom most of our knowledge of traveler behavior is based. Like commuters, tourists prefer cheaper transit alternatives, and they dislike spending time in transit. However, they appear to about equally value time in-car and out-of-car transit time, in contrast to commuters who prefer to stay in their cars. That out-of-car time would be more enjoyable when touring is not surprising, because out-of-car time allows the visitor to experience the destination town, if not the destination attraction. Further, tourists dislike sitting in congestion, even beyond the travel time it implies. Tourists are also responsive to scenery quality, a preference which is not often considered in designing transit systems used by commuters. These conclusions are very robust to including various demographic variables in the econometric model, and to a random coefficients representation of respondent preference heterogeneity.

With this model of tourist preferences, the effect of alternative transit plans on parking lot demand and traffic patterns can be estimated. In principle, the demand for an entire parking and transit system within a town could be modeled following the example of section VI. For example, the major roads, parking areas and attractions could be identified on Figure 1, and the scenery, congestion levels and travel times could be rated and recorded, giving a description of all parking and transit options for each destination in terms of the attributes for which preferences have been measured. Given data about the mixture of source arteries and intended attractions, the number of people demanding each parking lot and subsequent transit link to their respective destinations could be predicted under the extant transit plan. Proposals for new developments could then be evaluated on the basis of how demand shifts among lots when new alternatives are introduced. For communities which attract demographically similar visitors to similar attractions as Newport, the preferences expressed in the estimates of Table 5 probably provide a good quantitative starting point for such analysis; for communities with different attractions, they may merely be indicative of the types of attributes which must be considered in designing transportation plans targeted at tourists (cf. 43).

As populations increase and more people gravitate toward coastal cities, seasonal tourist communities will continue to see increased demand for their recreation services. Often, hours sitting in traffic is part of the experience of a weekend away, and increased demand only promises to make getting to and around top tourist destinations more difficult. Communities which better plan their transportation services and infrastructures to address current and future peak demand levels will reward tourists with more enjoyable visits, and themselves with higher levels of tourism spending.

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