Analysis of Long-Distance Vacation Travel Demand in the United States: A Multiple Discrete-Continuous Choice Framework

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ABSTRACT

This study analyzes the annual vacation destination choices and related time allocation patterns of American households. More specifically, an annual vacation destination choice and time allocation model is formulated to simultaneously predict the different vacation destinations that a household visits in a year, and the time (no. of days) it allocates to each of the visited destinations. The model takes the form of a Multiple Discrete-Continuous Extreme Value (MDCEV) structure. Further, a variant of the MDCEV model is proposed to reduce the prediction of unrealistically small amounts of vacation time allocation to the chosen destinations. To do so, the continuously non-linear utility functional form in the MDCEV framework is replaced with a combination of a linear and non-linear form. The empirical analysis was performed using the 1995 American Travel Survey Data, with the United States divided into 210 alternative destinations. The model estimation results provide several insights into the determinants of households' vacation destination choice and time allocation patterns. Results suggest that travel times and travel costs to the destinations, and lodging costs, leisure activity opportunities (measured by employment in the leisure industry), length of coastline, and weather conditions at the destinations influence households' destination choices for vacations. The annual vacation destination choice model developed in this study can be incorporated into a larger national travel modeling framework for predicting the national-level, origin-destination flows for vacation travel.

Keywords: *long-distance travel, leisure travel demand, national travel demand model, destination choice, Kuhn-Tucker demand model systems, multiple discreteness*

INTRODUCTION AND MOTIVATION

In several countries, a significant portion of passenger travel comes from long distance travel, especially for leisure purposes (or vacation). In the United States, for example, in less than 20 years, between 1977 and 1995, the amount of long distance travel increased by more than double to about 1 billion person trips and 827 billion miles (BTS, 1998). While this increase may be attributed to an increase in travel for all purposes, leisure travel is of particular importance due to several reasons. First, leisure travel is an integral part of Americans' lifestyle, constituting a significant share (27%) of long distance travel (BTS, 1997) as well as a significant share of the increase in long-distance travel (BTS 1998). Second, leisure travel has a significant impact on the economy as it is highly consumption-oriented. A recent consumer expenditure report estimates that in the year 2008, U.S. households spent, on average, $1,415 per annum on activities such as dining, lodging, shopping, entertainment and recreation while on vacation (BLS, 2010). It is no surprise that the economy of several destinations thrives on the tourism/leisure travel industry. Thus, vacation travel behavior is one of the most studied topics in the tourism literature and is steadily gaining importance in the transportation literature. Several dimensions of leisure travel behavior have been studied to date, including whether to travel or not, travel purpose, length of stay and time/money allocation, travel frequency, destination, and mode. Notable among these dimensions is the destination choice from both the tourism and transportation planning standpoints. From a tourism standpoint, a better understanding of where people travel for vacation can aid in taking measures to enhance the attractiveness of the destinations for increasing the tourism demand and revenue. Further, understanding the destination preferences of different types of travelers can help in devising targeted promotional campaigns to specific traveler segments. From a transportation planning perspective, understanding the vacation travel flow patterns helps in assessing national and local infrastructure needs and implementing appropriate policies.

1.1 Literature on Long-distance Leisure (of Vacation) Destination Choice Analysis

Leisure destination choice has been extensively studied in the tourism and leisure research literature (Rugg 1973; Seddighi and Theocharous, 2002; Eugenio-Martin, 2003). A popular approach to analyze destination choices is the discrete choice analysis method using multinomial logit or nested logit models. A variety of other methods, such as cognitive mapping and qualitative analysis (Woodside and Lysonski, 1986) have also been used to analyze various behavior aspects of destination choice. Further, most tourism literature can be categorized into: (1) efforts analyzing the outbound tourism demand from one origin to multiple destinations (Haliciolgu, 2008), and (2) studies analyzing the inbound tourism from multiple origins to a single destination (Greenridge, 2001). Only a few studies analyze destination choices between multiple origins and multiple destinations toward estimating nationwide leisure travel flows (LaMondia et al., 2009; Simma et al., 2001).

In the transport planning/modeling literature, though some work exists on short-distance leisure travel behavior within metropolitan areas, very little exists explicitly on long-distance leisure travel. A review of the literature suggests that long-distance travel analysis is a regular exercise in three different forms: (1) Inter-city travel demand analysis between pairs of cities (Koppelman and Sethi, 2005; Yao and Morikawa, 2003), (2) statewide travel models in the US (Horowitz 2006; Outwater et al., 2010), and (3) national-level travel model systems in Europe. Examples of national-level travel model systems include those in Denmark (Fosgerau, 2001), Sweden (Beser and Algers, 2001), Holland (HCG 1990), Germany (Vortsih and Wabmuth, 2007), UK, Switzerland, and the TRANS-TOOLS model to analyze travel between European Union countries (Rich et al., 2009). Moeckel and Donnelly (2010), Ashaibor et al. (2007), Baik et al. (2008) and Epstein et al. (2008) represent recent efforts toward a national travel model in the US (see Lundqvist and Mattson, 2002 and Zhang, 2010 for reviews on national travel models). Despite all these advances, it is worth noting that leisure travel has been treated in very limited ways. For example, in statewide models, inter-state trips are all categorized as external or visitor trips and estimated using aggregate trip distribution methods. While some efforts use disaggregate methods to analyze destination choices (e.g., Outwater et al., 2010) and a few models are based on behaviorally oriented activity/tour-based approaches (e.g., the Danish national model), a drawback of most studies is that the analysis is limited to smaller time frames such as a day or a few weeks. However, as indicated in Eugenio-Martin's (2003) theoretical framework for tourism demand analysis and in Morley (1992), longer time frames such as a year may be more appropriate for vacation travel analysis. This is because vacation travel decisions are likely to be made in the settings of longer time frames, as opposed to daily travel decisions for which shorter time frames may suffice. Most long-distance travel data collection efforts also appear to collect information for smaller time frames other than a few exceptions such as the 1995 American Travel Survey (ATS) in the US and the DATELINE survey in Europe that collect respondent's travel information for one year.

To be sure, a few studies do consider longer time frames. These include van Middlekoop et al's (2004) micro-simulation system for annual leisure activity-travel patterns and the long-distance holiday travel module in the recent TRANS-TOOLS model (see Rich et al., 2009). These studies first predict the frequency of vacation trips for a given time frame and then analyze the destination choices (and other decisions) separately for each trip. A recent study by LaMondia et al (2008) is one of the few exceptions that attempt a simultaneous analysis of vacation choices over a year. However, their focus is on annual time-use patterns for different vacation purposes; not on destination choices. Several studies in the recreational demand literature (see Phaneuf and Smith, 2005) perform simultaneous analysis of destination choices over longer time frames; however, for very specific types of recreation such as fishing.

1.2 Current Research

This paper proposes an annual vacation destination choice and time allocation modeling framework to simultaneously analyze the different vacation destinations that a household visits in a year, and the time it allocates to each visited destination. Specifically, we propose the use of a recently emerging multiple discrete-continuous extreme value (MDCEV) model (Bhat, 2008) to analyze the factors influencing households' annual vacation destination choices and time allocation patterns. The model assumes that households allocate the annual vacation time available at their disposal to one or more destinations in a year in such a way as to maximize the utility derived from their choices. As described in LaMondia et al. (2008), the utility maximization framework is consistent with Iso-Ahola's (1983) *optimal arousal* concept of vacation behavior that people "suffer psychologically and physiologically from understimulating and overstimulating environments" and seek an "optimally arousing experience." The model framework accommodates variety-seeking in households' vacation choices in that households can potentially visit a variety of destinations rather than spending all of their annual vacation time visiting a single destination. Households may seek variety in destination choices due to several reasons. First, households might visit multiple destinations due to satiation effects of increasing time allocation to a destination (i.e., they experience boredom and start seeking variety). Such satiation effects in vacation travel behavior have been noted in previous studies both in the context of visiting multiple destinations within a single vacation trip (Lue et al., 1993) as well as budgeting annual leisure time expenditures for different purposes (LaMondia et al., 2008). Second, people might take vacations for pursuing multiple types of activities (adventure, sightseeing, etc.) and during multiple seasons of the year but no single destination may be ideal for all purposes and during all time periods (hence a variety of destination choices over a year). Third, different members of a household may have different preferences, leading to variety in destinations choices. The MDCEV model incorporates variety in destination choices by employing a non-linear utility framework that allows diminishing marginal utilities of increasing time allocation to a destination. At the same time, by incorporating corner solutions that allow zero time allocations, the model recognizes that households may not necessarily visit all available destinations. An annual vacation time budget is also considered to recognize that households may operate under time budget constraints.

The proposed model is couched within a larger vacation travel modeling framework with various modeling steps as described here. In the first step, households are assumed to determine annual time and money budgets for vacation travel. Given these annual budgets, they are assumed to allocate the time and money budgets to visit one or more destinations in the next step. Subsequently, for each destination they choose to visit, they decide the number of trips to make to that destination, and travel choices for each trip, including mode choice, time (i.e., season) of the year, and length of stay. The analyst can apply this framework to all households in the nation and obtain a nationwide Origin-Destination demand table for vacation travel. Of course, other decision elements, such as the travel party composition for each vacation trip, could be included in the framework. Further, the framework could be refined to include another step (between steps 1 and 2) where households allocate the annual vacation time to different purposes (recreation, sightseeing, etc.) and then decide the destinations to visit depending on the purposes they wish pursue. Notwithstanding which modeling sequence represents households' annual vacation decisions better, this paper focuses on applying the MDCEV framework for modeling households' annual vacation destination choice and time allocation decisions. Further, the paper recognizes that mode choice decisions are closely tied to destination choices (Hackney, 2004) and estimates an auxiliary mode choice model that feeds the level of service characteristics into the destination choice model in the form of a log-sum variable. The empirical data used in this study comes from the 1995 American Travel Survey Data, with the U.S. divided into 210 destination choice alternatives.

Finally, on the methodological front, we propose a variant of the MDCEV model that allows for the possibility that once a good is chosen, at least a certain reasonable amount of the good is consumed, as opposed to an unrealistically small amount of it. This is because satiation effects may start kicking in only after a certain amount of the good is consumed rather than right after the first infinitesimal consumption. In the current, long-distance vacation context, it is reasonable to expect that households allocate at least a certain minimum amount of time (say, at least half a day; as opposed to a few minutes or hours) to long-distance destinations. To accommodate such minimum required time allocation, the continuously non-linear utility functional form in the MDCEV framework is replaced with a combination of a linear and non-linear form, as described in the next section.

2 MODEL STRUCTURE

2.1 Utility form of the MDCEV Model (Bhat, 2008)

Let the U.S. be divided into K number of destination alternatives for vacation travel. Let $\boldsymbol{t}$ be the vector of vacation time investments ($t_1, t_2, \ldots, t_K$) by the household to each of the destination alternatives k (k = 1,2,…,K). Whether or not a specific t_k value (k = 1, 2, K) is zero constitutes the discrete choice component, while the magnitude of each non-zero t_k value constitutes the continuous choice component. Note that these time allocations include the full extent of time away from home, including the travel time. Now, consider the following additive, non-linear, functional form to represent the utility accrued by a household from its annual vacation destination choices:

$$U(\boldsymbol{t}) = \sum_{k=1}^{K} u(t_k) = \sum_{k=1}^{K} \gamma_k \psi_k \ln\left(\frac{t_k}{\gamma_k} + 1\right) \quad (1)$$

In the above expression, the total utility $U(\boldsymbol{t})$ derived from the time allocation to the *K* destination choice alternatives is the sum of the sub-utilities $u(t_k)$ derived from the time allocation to each of the destinations *k*. Within the sub-utility function for an alternative k, ψ_k represents the marginal utility of unit vacation time investment for a destination alternative *k* at the point of zero time investment for the destination. Thus, ψ_k, labeled the baseline marginal utility parameter, controls the discrete choice decision of the household for alternative *k*. Specifically, at the point of zero time allocation to all destinations, the destination with the highest baseline marginal utility value is allocated the first unit of vacation time available to the household. Subsequently, with increasing time allocation to that destination, the marginal utility derived from allocating additional time to that destination decreases (this effect is called satiation). At some point, when the marginal utility for another destination becomes greater, the next unit of time gets allocated to that destination. This process of marginal time allocation to the destination with the highest marginal utility continues until the household runs out of its vacation time budget. In summary, given the additive utility form, the household utility maximization problem can be viewed as an incremental time allocation process, with each additional unit of available time allocated to the alternative with the highest marginal utility at that point in the time allocation process.

The satiation effect described above is captured in the model via a non-linear utility form with respect to the t_k terms. In this context, the γ_k terms accommodate differential satiation rates across different destination alternatives. Specifically, the higher the γ_k value for a destination alternative *k*, the slower the satiation effect; and the greater the time allocation for that alternative (if it is chosen). Further, the γ_k terms allow for the possibility that the household may not choose (or invest no time on) certain destinations.

In the utility function (1), socio-demographic and destination-specific attributes are introduced in the ψ_k and γ_k terms as: $\psi_k = \exp(\beta' z_k + \varepsilon_k)$ and $\gamma_k = \exp(\theta' w_k)$. In these expressions, the vectors z_k and w_k include destination characteristics (e.g., leisure/tourism industry employment and weather at the destination), transportation level of service variables (e.g., distance, travel times and costs), and interactions of these variables with household socio-demographic attributes for alternative *k*. β and θ are parameter vectors corresponding to the explanatory variables in z_k and w_k, respectively. Finally, ε_k are random variables representing the unobserved factors influencing the household's preference for the destination alternatives.

2.2 The MDCEV Model with Minimum Required Consumptions

In the above discourse, the vacation time t_k (k = 1,2,…,K) can potentially take a very small value (e.g., a few minutes) that may not necessarily be realistic in a long-distance vacation travel context. To address this issue, the continuously non-linear utility function of the MDCEV model (as in Equation 1) is replaced with a combination of a linear and non-linear utility form, as below:

$$\begin{aligned} U(\boldsymbol{t}) &= \sum_{k=1}^{K} u(t_k) \\ \text{where } u(t_k) &= \psi_k t_k \quad \text{if } t_k \le t_0, \\ &= \psi_k t_0 + \gamma_k \psi_k \ln\left(\frac{t_k - t_0}{\gamma_k} + 1\right) \quad \text{if } t_k \ge t_0. \end{aligned} \tag{2}$$

In the above equation, t_0 is the minimum amount of time allocated to the destinations that the household chooses to visit. As shown in Figure 1, the utility derived from the time allocation to a destination alternative *k* increases linearly without diminishing marginal utility until the minimum required time t_0 is allocated to that destination, after which the functional form takes a non-linear shape with diminishing marginal utility. This assumption ensures that at least t_0 amount of time is spent at any chosen destination, and helps avoid destination choices with unrealistically small amounts of time allocation.

Figure 1 about here

To understand this, recall the incremental time allocation process discussed earlier. At the point of zero time allocation to all destinations, the first unit of time is allocated to the destination with the highest baseline marginal utility (ψ_k) value. Subsequently, additional units of time are allocated to this same destination until the cumulative time allocation for this destination reaches t_0. It is only after a cumulative time allocation of t_0 that the satiation effect *kicks-in* for that destination and other destinations start competing for the vacation time. As the marginal utility of time allocation for the first chosen destination diminishes, at certain point the destination with the next higher baseline utility becomes stronger (in marginal utility) and gets its first unit of time allocation. Again, until this next destination gets the minimum amount of time (t_0) allocated, no other destination competes for vacation time. This process continues until the annual vacation time budget is exhausted. In summary, the sub-utility functional form in Equation (2) with a linear form at the corner, followed by a non-linear form helps reduce the possibility of unrealistically short vacation durations.

A few notes before we move forward. First, at the end of the incremental time allocation process described above, the last chosen destination can potentially be allocated less than required minimum amount of time simply because there is not enough time left. Thus, the model does not completely preclude destination choices with less than required amounts of time allocated. However, it should help significantly reduce such unrealistic time allocations. Second, we do not estimate t_0, but assume it *a priori* as half a day. Limited experiments to estimate t_0 with the current and other cross-sectional datasets indicate that it is unnecessary to estimate it. One could simply constrain t_0 as the minimum time allocated to the chosen alternatives in the data. Further, since t_0 was assumed as half day for all destinations and for all households by design, model estimations with varying values of t_0 showed the best model fit for $t_0 = 0.5$. Third, the concept of minimum required consumption is not new. For example, Pollak and Wales (1992) discus a linear expenditure system (LES): $U(\boldsymbol{Y}) = \sum_k a_k \ln\left(y_k - b_k\right)$, in which the consumption quantities y_k must always be greater than a minimum amount (or a subsistence quantity) b_k. Thus, such a functional form allows subsistence quantities only for goods that are always consumed, not when corner solutions (zero consumptions) are present. On the other hand, our discussion is for a general case that allows the possibility of corner solutions as well as minimum consumptions. Note that the LES utility function is not defined for consumption quantities below b_k. Instead of specifying such undefined utility functions, we provide a basis for why a minimum amount is consumed by employing a combined linear – non-linear utility form.

2.3 Optimal Time Allocations and Probability Expressions

From the analyst's perspective, a household maximizes the overall utility $U(\boldsymbol{t})$ subject to the vacation time budget constraint: $\sum_k \; t_k = T$, where T is the annual vacation time (in number of household-days) available to that household. The optimal time investments t_k^* (*k* = 1,2,...,*K*) can be determined by forming the Lagrangian function corresponding to the households' utility maximization problem and applying the Kuhn-Tucker (KT) conditions, as below:

$$\text{Lagrangian, L} \;= \sum_k u(t_k) - \lambda\left[\sum_{k=1}^{K} t_k - T\right], \tag{3}$$

where λ is the Lagrangian multiplier associated with the time constraint. The KT conditions for the optimal vacation time allocations are given by:

$$u'(t_k^*) - \lambda = 0 \text{, if } t_k^* > 0 \text{, } k = 1, 2,\ldots, K \tag{4}$$

$$u'(t_k^*) - \lambda < 0 \text{, if } t_k^* = 0 \text{, } k = 1, 2,\ldots, K$$

Without loss of generality, designate destination 1 as a vacation destination to which the household allocates some non-zero amount of time and express λ as $u'(t_1^*)$. Using this, the KT conditions in Equation (4) can be rewritten as:

$$\overline{V}_k + \varepsilon_k = \overline{V}_1 + \varepsilon_1 \text{ if } t_k^* > 0 \; (k = 1, 2, \ldots, K)$$

$$\overline{V}_k + \varepsilon_k < \overline{V}_1 + \varepsilon_1 \text{ if } t_k^* = 0 \; (k = 1, 2, \ldots, K), \tag{5}$$

$$\text{where, } \overline{V}_k = \beta' z_k \quad \text{if } t_k^* \le t_0,$$

$$= \beta' z_k - \ln\left(\frac{t_k^* - t_0}{\gamma_k} + 1\right) \quad \text{if } t_k^* \ge t_0.$$

Assuming that the error terms ε_k (k = 1,2,…,K) are independent and identically distributed across alternatives with a type 1 extreme value distribution, the probability that the household allocates vacation time to the first M of the K destinations (for duration t_1^* in the first destination, t_2^* in the second, …, t_M^* in the M^{th} destination) can be derived as:

$$P(t_1^*, t_2^*, t_3^*, \ldots t_M^*, 0,0,0..0) = \left[\prod_{i=1}^{M} \overline{c}_i\right] \left[\sum_{i=1}^{M} \frac{1}{\overline{c}_i}\right] \left[\frac{\prod_{i=1}^{M} e^{\overline{V}_i}}{\left(\sum_{k=1}^{K} e^{\overline{V}_k}\right)^M}\right] (M-1)! \tag{6}$$

The $\overline{c}_k$ terms in the above equation take an expression $\left(\frac{1}{(t_i^* - t_0) + \gamma_i}\right)$ for all k = 1,2,…,M. Note that if t_o is assumed as zero (i.e., no minimum consumption), the above probability expression collapses to the original MDCEV probability expression as in Bhat (2008). Thus the proposed formulation is a minor variation of the original MDCEV model, with no added complexity.

3 DATA

3.1 Primary data: The 1995 ATS

The 1995 American Travel Survey (ATS) is the primary source of data used in this analysis. The 1995 ATS collected information from 62,609 American households on all long-distance trips of 100 miles or more over the course of an entire year (BTS 1995a). Out of all the surveyed households in the 1995 ATS sample, 48,527 reported at least one long-distance trip. As such, a total of 337,520 trips were reported, along with the information on the purpose, mode, and destination of travel and other travel attributes. 3.5% of all leisure trips were made to international destinations, but the data does not contain information on which country the trip was made to. Thus the scope of current analysis is limited to long distance leisure travel within the United States. Therefore, only 28,210 households that made at least one long-distance trip for one of the leisure purposes within the U.S. – relaxation, sightseeing, outdoor recreation, or entertainment – were considered. Next, only households (94% of the data) that used auto and commercial air modes of travel were considered. While it is desirable to include the inter-city bus, rail, and water modes, it was very difficult to gather the transportation network and level of service characteristics for these modes for the year 1995. For this same reason, the analysis is limited to destination choices within the contiguous states of the U.S. After further processing to clean data with missing information on important variables (e.g., income, travel information for a large part of the year), the dataset was still sizeable with 22,215 households that made 57,989 long-distance leisure trips. 6000 of these households were randomly sampled to estimate the destination choice MDCEV model, while another 715 (again randomly sampled) were kept for validation purposes.

3.2 Destination Alternatives

For the current analysis, the 48 contiguous states in the U.S. were divided into 210 alterative destinations. Specifically, each of the Metropolitan Statistical Areas (MSAs) from each state was counted as a destination alternative, resulting in 162 MSA destinations. Then, the remaining non-MSA area in each state was counted as a single destination (one non-MSA area for each state, with the exception of Rhode Island which was entirely included in the Falls River-Warwick MSA). This resulted in 48 non-MSA destinations. All together, the U.S. was divided into 210 destinations (162 MSAs plus 48 non-MSAs).

3.3 Secondary Data Sources

In addition to the 1995 ATS, several secondary data sources were utilized to compile other required information such as: (1) the transportation level of service variables, including the travel times and costs between each origin-destination pair via air and auto modes, (2) accommodation (lodging), dining and entertainment/recreation prices at each of the 210 destinations, (3) the destination size and attraction variables for the year 1995, including land area, number of employees in different sectors (leisure and/or hospitality, retail, etc.), total population, and gross domestic product, and (4) the destination climate variables, including mean monthly temperatures for different months in a year, miles of coastline at the destination, and the annual number of freezing days experienced at the destination. Gathering all the above information from a variety of data sources required a significant and painstaking amount of effort. We briefly mention the data sources below, but do not discuss the procedures used to create the entire data. Interested readers are referred to the first author's master's thesis (Van Nostrand, 2011) for further details.

The lodging costs per night and non-lodging costs (dining and entertainment/recreation) costs) per day at each destination were synthesized using a two stage process for each household. In the first stage, the per-night lodging price for each household was derived using a regression equation relating the costs to the household's socio-demographic characteristics (income, household size, residential Census region). This regression equation was estimated using household-level microdata on annual vacation expenditures (and the annual number of nights away on vacation) from the 1995 Consumer Expenditure Survey (CEX) conducted by the Bureau of Labor Statistics obtained from ICPSR (2011). Similarly, the per-day non-lodging prices were derived using another regression equation estimated with the CEX data on non-lodging vacation expenditures. Both the above mentioned regression equations recognize the variation in per-night costs by household characteristics. Thus, this approach recognizes that not every household incurs the same costs at a destination. Rather, households make the lodging choices and other expenditure choices according to their income and other characteristics. However, the regression equations do not recognize the variation in the lodging and non-lodging prices across the different destinations. To accommodate such price-variation across destinations, in the second stage, the regressed per-night costs for each household were scaled by a factor capturing how pricy (or less expensive) each destination is compared to an average destination (as measured by the median per-day/night costs at different destinations. To implement this second state strategy, the median values of lodging and other costs of vacationing at each of the 210 destinations were obtained from a database made available by VisitUSA.com (2011). Further details on the above-described process are suppressed here to conserve space but available from the authors.

Data on travel distances and travel times between each origin-destination pair (210x210 pars) by the auto mode was obtained from the Microsoft MapPoint software in conjunction with its Mile Charter add-on (Microsoft, 2009; Winwaed Software Technology, 2009). Note a caution here that these travel times (by the auto mode) may not necessarily be the same as those in 1995. Travel costs by the auto mode were derived as a function of travel distance, average fuel efficiency per gallon (Grush, 1998), and gasoline prices for the year 1995 from the Energy Information Administration (EIA, 1995). Travel times and costs by the air mode for the year 1995 were obtained from the Airline Origin and Destination Survey (DB1B) sample provided by the Bureau of Transportation Statistics (BTS, 1995b).

Destination employment and population data was obtained from the Bureau of Labor Statistics (BLS, 1995) and the 2000 Census data (U.S. Census Bureau, 2000). Other destination data including the gross domestic product of the destinations were obtained from the US Bureau of Economic Analysis (Bureau of Economic Analysis, 1995). Destination climate data, including the mean monthly temperatures for both January and June months (i.e., winter and summer months) and the annual number of freezing days were obtained from the Places Rated Almanac (Savageau and Loftus, 1997) for the year 1995. Length of coastline for each destination was obtained from the National Oceanic and Atmospheric Administration's Ocean and Coastal Resource Management (NOAA, 2011).

3.4 Descriptive Analysis of Household Demographics and Leisure Travel Characteristics

We briefly discuss the estimation sample characteristics in comparison with the overall ATS sample (see Table 1). The average age of householders in the estimation sample (i.e., households who made at least one long-distance leisure trip in the year) is about 46 years. The elderly (65 or older) are less represented in the estimation sample when compared to the overall ATS sample suggesting that the elderly are less likely to make long-distance leisure trips. In terms of income, households in the estimation sample are slightly more affluent than those in the overall ATS sample. It appears that long-distance leisure travel may not be affordable for some low income households. Further, the estimation sample has somewhat larger households than the overall 1995 ATS sample. The second set of rows provides an overview of the leisure travel characteristics in the estimation sample. One can observe that more than half of those who made vacation trips made multiple vacation trips (>1 trips) in a year. Further, a significant portion (40%) of the households visited multiple destinations over a year. But a large percentage (78%) of them visited a destination (if they did so) only once. These results indicate that households are likely to visit multiple destinations per year, but are less likely to re-visit a destination. This suggests multiple discreteness (or variety-seeking) in households' annual destination choices. The third set of rows provides a description of the trip-level characteristics in the data. The most interesting point to note is that a considerable 21.3% of the trips are day-trips. For all these day-trips, 0.5 days were assumed as the time spent on vacation. Thus, the model needs to ensure that at least 0.5 days is allocated for any destination visited by a household. For each household, the sum of all the days spent across all the visited destinations was considered as the annual household long-distance vacation time budget, *T*. This annual vacation time budget varied from 0.5 to as much as 332.5 days, with an average value of 9.11 days in the estimation data. Note that *T* is a sum of household-days on vacation, not person-days. For example, if 2 household members are on a 4-day vacation at the same time, the number of vacation days is 4, not 8.

Table 1 about here

4 MODEL ESTIMATION RESULTS AND DISCUSSION

The empirical specification of the vacation destination choice and time allocation model is provided in Table 2 for both the basic MDCEV model as well as the proposed variant of the MDCEV model that incorporates minimum required time allocations.

Table 2 about here

Baseline Marginal Utility Specification

As discussed earlier, the baseline marginal utility function governs the discrete choices, since it represents the marginal utility derived at zero time investment before any satiation effects begin to occur. A destination alternative with a higher baseline marginal utility is more likely to be visited than that with a lower baseline marginal utility.

Between the two models (i.e., the MDCEV and the MDCEV with minimum required time allocations), there are no significant differences in the baseline marginal utility parameter estimates as well as the corresponding interpretations. Thus, we discuss the variable effects for only one model without any comparisons to the other model.

Level of service variables: The log-sum variable is a composite measure of impedance to travel (i.e., travel times and travel costs) by the auto and air modes. Per standard practice, this variable was constructed using an auxiliary mode choice model estimated based on the observed mode choices to the chosen destinations (the results of the mode choice model are not reported here to save space, but are available from the authors). The smaller the log-sum value is (i.e., the higher negative value it takes), greater is the impedance between the origin (household's residential location) and the alternative destination. Thus, a positive and statistically significant coefficient of the log-sum variable, as expected, indicates a lower attractiveness of destinations with higher impedance to travel (i.e., destinations with greater travel times and travel costs). Although not reported in the table, the log-sum variable incorporates demographic heterogeneity in sensitivity to travel impedance via the interactions of travel cost variables with household income groups in the mode choice model. Specifically, lower income households (income <$30K per annum) are more sensitive to greater travel costs (hence less likely to travel to destinations with greater costs) than higher income households.

The next two variables in the level of service characteristics correspond to indicators for the destination to be in the same state (as the household is), and the adjacent state. The coefficients of these variables are positive and significant, indicating a higher propensity of households to visit familiar (and perhaps close by) locations within their state and adjacent states.

Destination Characteristics: The first of the destination characteristics is the per-night cost of lodging and other expenses at the destinations. As expected, the negative coefficient on this variable suggests that with all else being same, destinations with pricy hotels and expensive attractions are less likely to be preferred. With this variable, the model can be used to understand the influence of destination-specific policies that attempt to reduce prices to attract greater tourism demand. To explore demographic heterogeneity in such sensitivity to prices, we explored interactions of the price variable with household characteristics (e.g., income), but no such interactions turned out statistically significant. However, this result shouldn't be interpreted as absence of demographic heterogeneity in response to prices at the destinations. As discussed earlier, households tend to make their accommodation, dining and recreation/entertainment choices (hence the prices they pay) according to their income and other characteristics. For this same reason, any assessment of the response to changes in prices at the destinations should consider the possibility that households can potentially adjust their lodging and other choices prior to changing the destination choice itself.

The next variable is a size measure (logarithm of the area of the destination) used as a control to account for the differences in the areas across the destinations. The coefficient of the size variable is positive and smaller than one. This can be explained based on the spatial aggregation of several elemental destination alternatives in the model. For example, several MSAs defined in the model may include multiple destination cities (e.g., the Tampa–St.Petersburg–Clearwater MSA with three different cities) and most non-MSAs defined in the model are an aggregation of different individual destinations. As explained in Daly (1982), a smaller than one coefficient on the size variable suggests significant non-homogeneity across the elemental destination alternatives within a destination.

The coefficient on the next variable, MSA dummy, suggests that MSA destinations tend to be more attractive than non-MSA destinations for long-distance leisure travel. This is due to the presence of more opportunities for leisure activities (recreation/entertainment, etc) in MSAs.

The next variable "density of employment in the leisure and hospitality industry" includes the employment levels in food services, arts, entertainment, recreation, and accommodation sectors. As such, the variable is a surrogate measure for leisure activity opportunities at the destination. A positive and statistically significant coefficient for this variable indicates, as one would expect, that places that offer higher leisure activity opportunities are more attractive as vacation destinations. Other employment variables, including a total employment variable and a retail employment variable as well as a population density variable were also explored in the model. But only hospitality employment density (with no other employment or population variables) provided an intuitive interpretation without substantial impact on model fit.

The length of coastline was also included as a destination attractor. The coefficient on this variable is positive and statistically significant, indicating, as expected that destinations with longer coastlines are more attractive. This is because destinations with longer coastlines offer a variety of leisure activity opportunities such as swimming, fishing, boating, or sightseeing.

The next set of variables in the baseline utility function is associated with the climate at the destination. First of these is the difference in the number of freezing days per year (i.e., days with less than 32^{o} Fahrenheit temperature) between the destination and the origin. The negative coefficient on this variable suggests that households are less likely to visit destinations with more freezing days per year than what they experience at their residential end. Colder destinations are less attractive for vacations because freezing temperatures limit many of the activities for which a household may want to travel. In addition to the annual freezing days variable, the mean temperatures for the destination during the months of January and June were included to represent winter and summer temperatures (these are daily maximum temperatures averaged over a month). The January temperatures ranged from a maximum of 75 to a minimum of below freezing temperatures. The corresponding variables and coefficients indicate that households prefer to visit destinations that offered the warmest winter temperatures. As the winter temperatures drop below the 65-75 range, the attractiveness of the destinations decreases. Specifically, *ceteris paribus*, destinations with temperatures near or below freezing point are likely to be the least preferred. For summer temperatures, the results indicate that the utility of a destination does not vary monotonously with temperature. Rather, a moderate temperature range might exist that is comfortable for most people (Savageau and Loftus, 1997), and an increase or decrease of temperatures beyond the moderate ranges may reduce the attractiveness of destinations. We explored different temperature ranges and the best fitting model suggested 65-75 degrees Fahrenheit as a comfortable temperature range. Further, destinations with temperatures below the comfort range (65-75) in June have a higher disutility than those destinations with temperatures above the comfort range. Comparison of the coefficients across January and June temperature variables also suggests that the disutility associated with colder (than moderate) climates is higher in magnitude than that of hotter (than moderate) climates.

Satiation (γ_k) Function Specification

The satiation function coefficients in Table 4 refer to the elements of the θ vector, where the satiation parameter γ_k for vacation type *k* is written as $\exp(\theta' w_k)$. A higher value of the γ_k parameter implies lower satiation for the destination alternative *k* (hence, larger amount of time allocated for that destination). There are perceivable differences between the satiation parameter estimates of the two models (i.e., the MDCEV and the MDCEV with minimum required time allocations), suggesting the influence of accounting for the minimum required time allocations. Thus, we discuss the variable effects for only the latter model.

The positive coefficient on travel distance suggests that travelers tend to allocate more time to farther away destinations. That is, travelers will likely not make a very long (and costly) trip for a very short stay. Another possibility is that farther away destinations simply require longer travel times (hence longer time allocated). Travel distance was also interacted with different levels of annual income of the household. The corresponding coefficients indicate that high income households spend smaller portions of time, where as low income households spend larger portions of annual vacation time for farther away destinations. These income differences may be due to the differences in the travel mode choices between different income groups. High income households travel by air which helps reduce their overall time spent on the vacation trip. Low income households, on the other hand, travel by slower modes and hence need more time for their vacation trips. Besides, low income households might want to derive greater value from the money spent on longer trips by staying longer.

Households in the retirement years tend to allocate greater amount of time at vacation destinations compared to non-retired households. Those in the retirement years tend to have the least familial and career oriented time constraints and a higher amount of time at their disposal. Hence this age group is likely to spend longer vacation times at the destinations they visit.

In summary, the MDCEV model estimates are reasonable and provide important insights into the impact of the travel level of service attributes, destination characteristics, and household socio-demographic characteristics on households' annual vacation destination choices. These results demonstrate the usefulness of the MDCEV model framework for modeling annual vacation destination choices and time allocation patterns. The model fit measures are reported in the last set of rows. The log-likelihood values of both the models show significant improvement over a naïve model with no explanatory variables and no minimum consumptions. Further, the proposed variant of MDCEV provides slightly better fit to the data (rho-squared value = 0.299) when compared to the original MDCEV model (rho-squared value = 0.246).

5 MODEL VALIDATION

A validation exercise was performed using a sample of 715 households from the 1995 American Travel Survey that were not a part of estimation sample. For each of the 715 households, we used 50 sets of random draws from independent type-1 extreme value distributions to simulate the unobserved heterogeneity. For each household and each set of random draws, conditional upon the total annual vacation time available to the household, the MDCEV model estimates were used to predict the annual vacation destination choices and the time allocation to each predicted destination. To do so, we used an algorithm that Pinjari and Bhat (2010) presented for applying the MDCEV model for prediction purposes. The prediction exercise was carried out for both the basic MDCEV model and the proposed variant of the MDCEV model. Subsequently, histograms were plotted to obtain the distributions of the predicted choices over all 715 households and all 50 random draws for both the models.

Figure 2 provides the distributions of home-to-destination distances for the destinations observed in the data and the destinations predicted by the models. Both the models provide similar distributions that are reasonably consistent with the observed distribution. However, the models seem to under-predict destinations in the 500-1000 mile range from the household locations and slightly over-predict destinations in the 1000-5000 mile range. One way to improve these results is to jointly estimate the destination choice and mode choice models. A joint model may help incorporate the sensitivities (to the level of service variables) that are based on both mode choices and destination choices and thereby improve the distance-based validations. Figure 3 provides the observed and predicted distributions of the total number of destinations visited by households in the year. Note that the MDCEV framework does not directly model the number of chosen destinations. Nonetheless, both the models provide similar distributions that are consistent with the observed distribution. In summary, these results demonstrate the model's ability to provide reasonable predictions, at the least at the aggregate level. Note, however, that replicating aggregate-level observed choices should not be the sole yardstick for model validation. Additional tests evaluating its forecasting ability are desirable.

Figures 2 and 3 about here

We also compared the observed and predicted distributions of the time (no. of days) allocated to chosen destinations (not shown in figures). By design, no household in the data is observed to have spent less than 0.5 days for any chosen destination. However, about 10% of the predicted destinations from the basic MDCEV model were allocated less than half a day of time. The proposed variant of the MDCEV model reduces such predictions with less than minimum amount of time allocation to only 2%, although it doesn't completely preclude very small time allocations. These results can be connected to the differences in the satiation parameter estimates between the two models. Further, the results show that the proposed variant of the MDCEV model can be useful in situations when it is important to avoid unrealistically small time allocations.

6 SUMMARY AND CONCLUSIONS

This study provides an analysis of households' annual destination choices and time allocation patterns for long-distance leisure travel purposes. More specifically, an annual vacation destination choice and time allocation model is formulated to simultaneously predict the different destinations that a household visits in a year, and the time it allocates to each of the visited destinations. The model takes the form of a Multiple Discrete-Continuous Extreme Value (MDCEV) framework to accommodate variety-seeking in vacation destination choices in that households can potentially visit a variety of destinations rather than spending all of their annual vacation time for visiting a single destination. At the same time, the model accommodates corner solutions to recognize that households may not necessarily visit all available destinations. An annual vacation time budget is also considered to recognize that households operate under time budget constraints.

The empirical data for this analysis comes from the 1995 American Travel Survey (ATS) data, with the U.S. divided into 210 alternative destinations. The empirical analysis provides important insights into the determinants of long-distance leisure destination choice and time allocation patterns. Select findings are summarized here: (a) Destinations with larger impedance to travel (due to higher travel times and/or travel costs) are less attractive in general. (b) Lodging and non-lodging prices at the destinations, leisure and hospitality employment, length of coastline, number of annual freezing days (relative to the origin), and winter and summer temperatures are other determinants of travelers' attractiveness to a destination. Specifically, destinations that offer, at lower costs, greater number of leisure activity opportunities, longer coastline, and moderate temperatures (65-75 degree Fahrenheit) are more attractive than other destinations. (c) Low income households tend to spend a longer time for vacations to farther destinations followed by medium income and high income households, in that order. (d) Households with retired householders tend to spend longer time at a vacation destination compared to other households.

On the methodological front, the paper proposes a variant of the MDCEV model that helps reduce the prediction of unrealistically small amounts of time allocation to the chosen alternatives. To do so, the continuously non-linear utility functional form in the MDCEV framework is replaced with a combination of a linear and non-linear form. The proposed variant of the MDCEV model provides a better model fit than the original MDCEV model, and reduces the likelihood of destination choices with unrealistically small amounts of time allocation.

The annual destination choice and time allocation models estimated in this study were validated using a validation sample of 715 households. The validation results demonstrated the models' prediction ability in terms of producing reasonable aggregate-level distributions of the predicted distances traveled and the number of destinations visited in a year.

An appealing feature of the proposed models is their applicability in a national, long-distance leisure travel demand model system. The knowledge of the annual destination choices and time allocations predicted by this model can be used for subsequent analysis of the number of trips made (in a year) to each destination and the travel choices for each trip, including mode choice, time (i.e., season) of the year, and length of stay. Thus, the models developed in this study can be incorporated into such a larger national travel modeling framework for predicting the national-level, origin-destination (OD) flows for vacation travel. Further, the model can be used toward anticipating the changes in the vacation travel OD flows in response to changes in prices at the destinations, and travel times and travel costs to different destinations.

The study can be extended in many ways. <u>First</u>, enhancing the model specification with better descriptors of the destination characteristics (instead of proxy variable such as leisure employment at destination) can make it more useful for policy analysis purposes. <u>Second</u>, the proposed modeling framework can be enhanced toward a joint estimation of the destination choice and mode choice models while recognizing that vacation visits will incur a minimum time expenditure of at least the time needed to travel to (and from) the destination. Second, the current model considers time budget constraints and allocation, but ignores money budgets both due to the unavailability of the data and the lack of methods to do so. Incorporation of both time and money budgets into the modeling framework is an important avenue for future research. Third, the model does not consider short-distance leisure travel (i.e., leisure travel within the vicinity of residential neighborhood), because the 1995 ATS data does not collect information on short-distance travel. It would be useful to understand the potential substitution patterns between short-distance leisure travel and long-distance leisure travel. Equally important is the potential substitution between travel for visiting purposes and travel for leisure purposes analyzed in this study. Finally, note that the data used in this study is rather dated. Conducting the same analysis with a more recent data is highly desirable. As such, a sustained data collection program is essential for enhancing our understanding of long-distance travel behavior.

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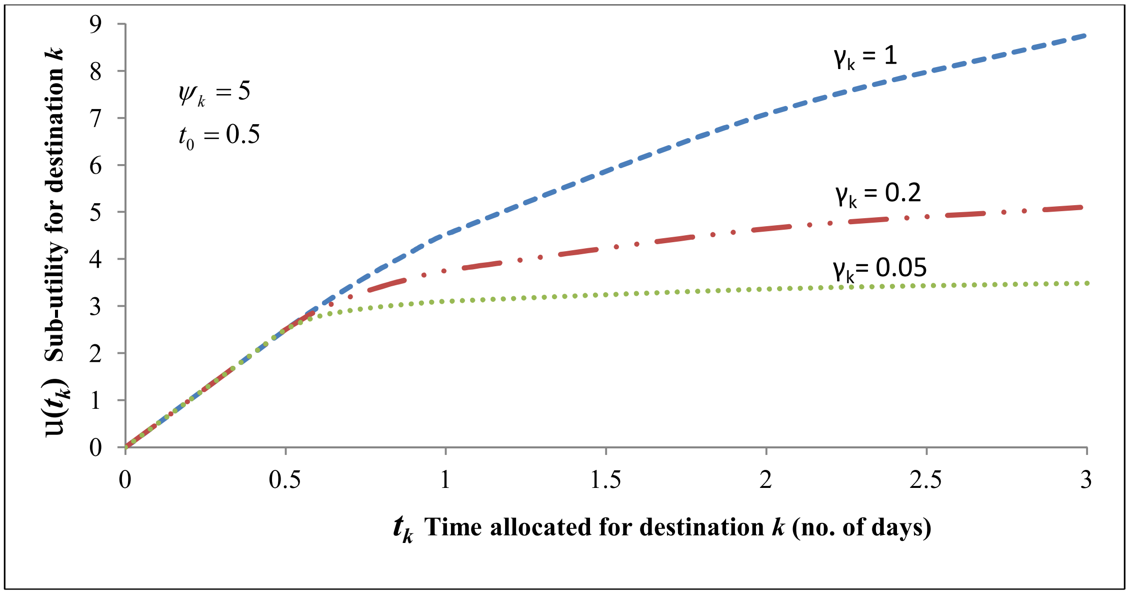

Figure 1: Sub-utility Curves with a Combined Linear and Non-linear Form

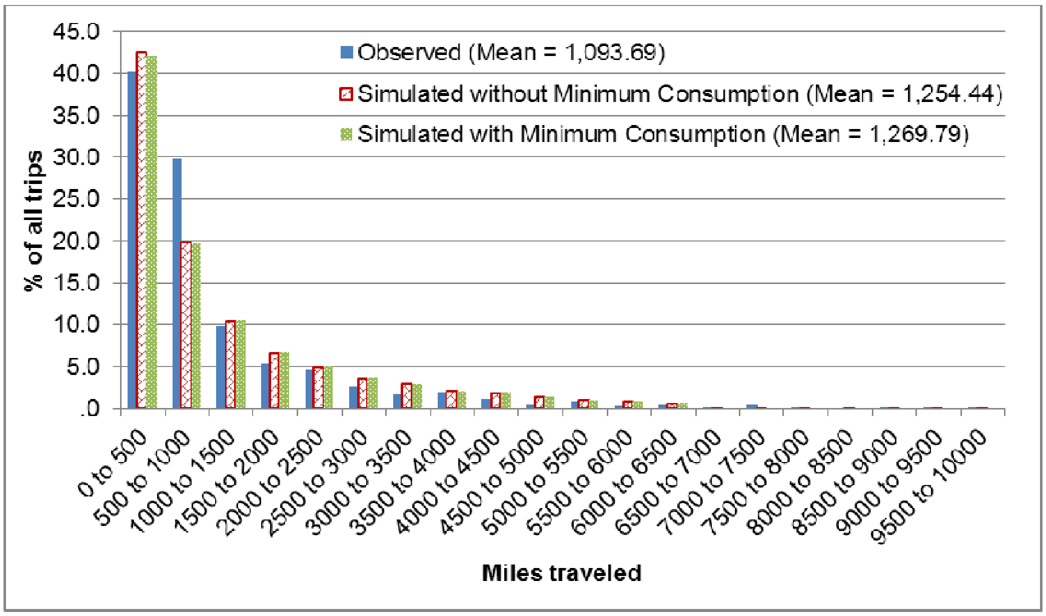

Figure 2: Model Validation Results Based on Distances to Chosen Destinations

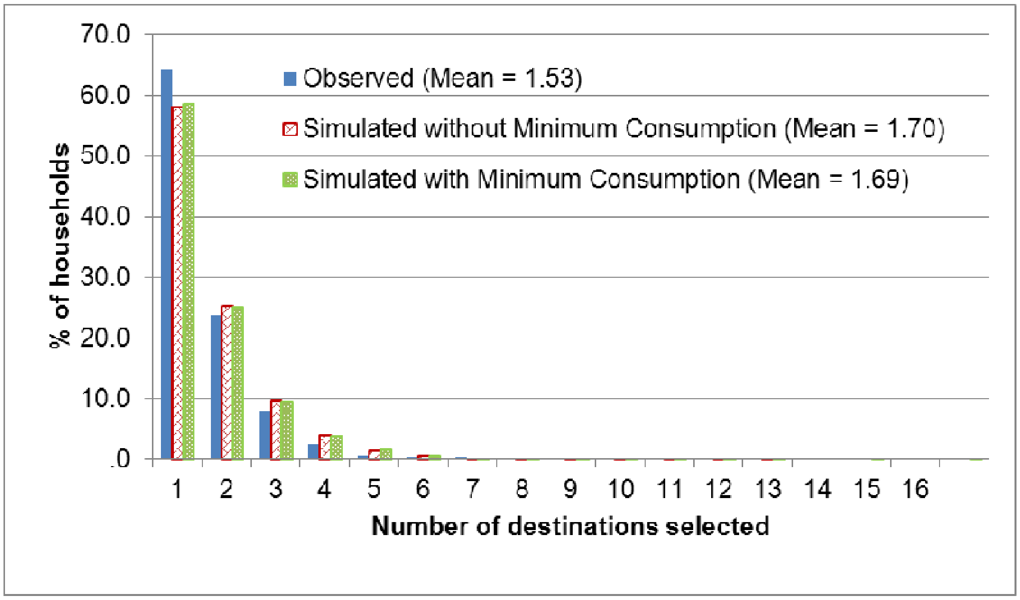

Figure 3: Model Validation Results Based on the Number of Destinations Visited in a Year

Table 1: Household Demographics and Leisure Travel Characteristics in the Sample

Household Sociodemographic Characteristics	1995 ATS	Estimation Sample
Sample size (Households)	**62,609**	**6,000**
Age of householder	50.4 years	46.7 years
25 to 44 years	42.3%	49.4%
45 to 64 years	33.3%	36.0%
65 or older years	24.4%	14.7%
Household yearly income		
Under $30,000 per annum	33.1%	26.1%
$30,000 to $74,999 per annum	57.4%	60.7%
$75,000 or more per annum	9.5%	13.2%
Household size		
1	24.1%	15.7%
2	34.5%	34.7%
3 or more	41.4%	49.6%
Household Leisure Travel Characteristics	**1995 ATS**	**Estimation Sample**
Number of long distance leisure trips	**---**	
1	---	46.9%
2	---	22.0%
3 or more	---	31.1%
Number of destinations visited	**---**	
1	---	60.1%
2	---	25.1%
3	---	9.3%
4 or more	---	5.5%
Number of trips made to a destination*	**---**	
1	---	79.5%
2 or more	---	20.5%
Trip-level Characteristics (for Leisure Trips)	**1995 ATS**	**Estimation Sample**
Sample size (Trips)	---	15,826
Primary mode of transportation	---	**---**
Auto	**---**	89.5%
Air	---	10.5%
Round trip U.S. route distance (miles)	---	**770.86**
100 to 500 miles	---	61.1%
501 to 1,000 miles	---	19.9%
1,001 to 2,000 miles	---	9.6%
Over 2,000 miles	**---**	9.4%
No. of nights away from home on trip**	---	**3.39**
0.5 (day trip)	---	21.3%
1	---	16.1%
2	---	23.2%
3 or more	---	39.4%

*These proportions are of all destinations visited by each household.

** For current analysis, the number of nights variable was used for the number of days (away from home) spent on the trip. For day-trips, it was assumed that half a day (0.5 days) was spent on the trip.

Table 2: Destination Choice Model Specification

	MDCEV		MDCEV w/ minimum required consumption	
Baseline Utility Function (Ψ) Specification	**Coeff**	**t-stat**	**Coeff**	**t-stat**
Distance and level of service characteristics				
Log-sum variable from the mode choice model	0.5298	67.72	0.5278	67.13
Dummy if destination in same state as household residence	1.7720	44.46	1.7517	43.73
Dummy if destination in adjacent state to household residence	1.2807	45.03	1.2782	44.93
Destination Characteristics				
Total lodging and non-lodging price per night (100's of dollars)	-0.1500	-2.71	-0.1400	-2.59
Log(Land area of the destination in sq. miles)	0.5550	37.92	0.5552	37.77
Destination is an MSA (Dummy variable)	1.2412	14.60	1.2515	14.65
Leisure Employment Density in 100's of employees/sq. mile	0.0980	46.26	0.0979	46.00
Length of coastline in 1000's of miles	0.0846	12.48	0.0856	12.58
Difference in number of freezing days (destination minus origin)	0.0097	22.45	0.0097	22.32
Winter (January) temperatures (monthly avg of max daily values)				
55 to 65 degrees Fahrenheit (65-75 degrees as base)	-0.6592	-13.26	-0.6493	-13.02
45 to 55 degrees Fahrenheit (65-75 degrees as base)	-1.2862	-22.62	-1.2940	-22.69
35 to 45 degrees Fahrenheit (65-75 degrees as base)	-1.9574	-28.07	-1.9617	-28.03
Less than 35 degrees Fahrenheit (65-75 degrees as base)	-1.9996	-24.71	-1.9930	-24.555
Summer (June) temperatures (monthly avg of max daily values)				
60 to 65 degrees Fahrenheit (65-75 degrees as base)	-3.4256	-13.11	-3.4367	-13.14
75 to 80 degrees Fahrenheit (65-75 degrees as base)	-0.6378	-16.12	-0.6295	-15.84
80 to 85 degrees Fahrenheit (65-75 degrees as base)	-0.4207	-9.63	-0.4041	-9.22
85 to 90 degrees Fahrenheit (65-75 degrees as base)	-0.7849	-15.86	-0.7911	-15.94
More than 90 degrees Fahrenheit (65-75 degrees as base)	-0.5046	-10.02	-0.4953	-9.81
Satiation Function (γ) Specification				
Highway distance to Destination (100's miles)	0.1927	74.61	0.1651	65.69
Distance*Low income (under $30k) dummy ($30k-$75k is base)	0.0313	5.88	0.0268	5.16
Distance*High income (over $75k) dummy ($30k-$75k is base)	-0.0540	-13.16	-0.0463	-11.42
Householder is retired (Dummy Variable)	0.7449	13.45	0.6888	13.10
Model Fit Measures				
Log-likelihood at convergence: $L(\hat{\beta},\hat{\theta})$	**-48,097.35**		**-44,720.4**	
Log-likelihood without variables and no minimum consumption:L(0)	**-63796.70**		**-63796.70**	
Rho-squared = 1- $\{L(\hat{\beta},\hat{\theta}) / L(0)\}$	**0.246**		**0.299**	

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