FEASIBLE ACTIVITY AND TRAVEL TIME ALLOCATIONS WITH A DISCRETE CHOICE MODEL: AN EXPLORATORY STUDY

An exploratory study using a discrete choice framework for time-use allocations is described. Instead of treating time use as continuous and dependent, it is treated as discrete and independent. By doing this, the restriction that the consumption bundle must lie on the boundary of the budget set can be enforced. Using responses collected from the 1996 travel survey for the San Francisco Bay Area, estimation of the model results is a good fit in terms of adjusted R^2. This suggests that a discrete choice framework of time allocation to activities and travel is a worthwhile effort that certainly needs further investigation.

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INTRODUCTION

Travel behavior research investigates how people make travel-related choices. Over the last half century, the role of travel behavior research in demand forecasting and modeling has become increasingly significant. Travel-demand models were first developed during the 1950s and 1960s. During that time, America was in a state where (RDC, 1995):

- "urban population was rapidly growing,
- motorization was progressing, and
- suburban sprawling was starting."

Given this, the main transportation-planning issue at hand was the development of infrastructure. Consequently, issues such as where to build highways and how many lanes are needed were among the highest priorities. The logic behind transportation planning was to increase or maintain people's mobility by building more highways. The four-step travel-demand models were developed to meet such a need. The four-step travel-demand model consists of the following steps: trip generation that determines frequency of daily travel, trip distribution that determines origin-destination choice, mode split that determines mode choice, and trip assignment that determines route choice within mode. The four-step models are hardly behaviorally sound but they were sufficient for the need at the time when highway development was a major issue in planning. There are a number of recognized problems with the four-step travel-demand models. For example, the travel time and costs used in trip distribution and mode choice are different from those derived from trip assignment. For a more complete list of problems, see RDC, Inc. (1995, p.2).

The development of random utility models, formalized by Manski (1977), marked a significant breakthrough in travel-demand forecasting models, especially discrete choice models. The random utility theory assumes that each alternative is associated with a utility value, measuring the amount of satisfaction that individuals obtain from selecting the alternative and individuals will always choose the alternative with the highest utility. The utility is treated as a random variable. The randomness does not come from the rationality of the decision maker (as the decision maker always wants to maximize the utility), but comes from the lack of information associated with characteristics of the alternatives and the decision maker on the part of the analyst. For example, unobserved attributes, unobserved taste variations, measurement errors, imperfect information and instrumental or proxy variables all contribute to the randomness (Manski, 1977). Choice probabilities associated with each alternative may be derived by assuming a joint probability distribution for the random part of the utilities. Based on this random utility theory, a large number of models have been developed including logit models, probit models, nested logit models, cross-nested logit models, paired combinatorial logit models, and most recently, mixed logit models (Bhat, 2001).

Initially after the development of random utility models, a large number of trip-based disaggregate mode choice or destination choice models were developed, followed by a surge in the activity-based analysis in the late 1980s and early 1990s. Activity-based analysis was motivated by the long-recognized concept of travel as a derived demand and the recognition of historical and future interdependence between activities and travel. Although the research objectives remain to forecast travel behavior and make transportation policy recommendations, the study focus has largely shifted from travel to activity. Activity-based researchers are placing a greater emphasis on the behavioral aspects of observed patterns, particularly why, where, when, and how long people engage in activities distributed in space. It is believed that understanding how people make activity-related choices will improve our understanding of travel-related choices and thus improve travel-demand forecasting models in general.

As an important area within activity-based research, time-use research concerns people's time allocation behavior to various types of activities and travel. Time-use researchers reason that to understand how people make travel-related choices and how they spend time on traveling, one must first understand people's activity needs. Two reasons contribute to this logic. First, the widely recognized notion of travel as a derived demand suggests that people, in general, do not travel for the purpose of traveling, but for the purpose of conducting activities that are distributed in space. Second, every one of us, rich or poor, is equally bounded by 24 hours a day. Therefore, more time allocated to one activity/travel will result in less time allocated to another activity/travel. How much time one can allocate to a particular activity or travel is affected by the physical distribution of the activities and how fast one can travel (Hagerstrand, 1970). For a prolonged period, the concept of "a constant travel time budget" has been claimed by a number of researchers (Zahavi, 1979; Zahavi and Talvitie, 1980; and Metz, 2004). Constant travel budget suggests that people tend to spend a fixed amount of time on travel per day. Although the constancy of daily travel time has been indeed observed at the aggregate level in a number of geographical locations at various time points, recent research (Mokhtarian and Chen, 2004) suggested that "a constant travel time budget" at the aggregate level should not be taken as a universal rule to be applied in any geographical area and at any time point. Furthermore, a constant travel time budget does not exist at the disaggregate level. The travel time expenditure at the disaggregate level is highly variable and has been found to be a function of a number of variables including socio-demographics, built environment, and time allocation to activities. In addition to tradeoffs between time allocation to activities and travel, there are also tradeoffs between time allocation to different types of activities and tradeoffs between time allocation to in-home and out-of-home activities. All these are important subjects within the time-use literature.

In the past, a substantial number of researchers have conducted analyses investigating the association between time-use behavior and individuals' socio-economic and demographic characteristics (Principio and Pas, 1997), association between time use and built environment (Kitamura et al., 1997; Wigan and Morris, 1981; and Levinson, 1999), and time-use behavior over time (Robinson and Nicosia, 1991). A variety of mathematical models have also been developed to explain and predict time-use behavior, including simple linear equations (Zahavi and Talvitie, 1980; Levinson, 1999; Flood, 1985; Kitamura et al., 1992; and Chen, 2004), systems of equations (Flood, 1985; Golob, 1990; Lu and Pas, 1999; and Ma and Goulias, 1998), and survival models (Hamed and Mannering, 1993). All these studies treat time allocation to activities and travel as a continuous and dependent variable, which is the traditional way of modeling time-use behavior.

One limitation of treating time allocation to activities and travel as a continuous and dependent variable is that in prediction, the constraint that daily time allocation to different activities and travel must be bounded by 24 hours a day can not be enforced. The resulting predicted time allocation to various activities and travel can be over 24 hours or a negative number, both of which are impossible. As an alternative to treating time-use as a continuous and dependent variable, one may use a discrete choice framework. Though not used in the context of time-use behavior, this framework has been used in the context of labor supplies (van Soest, 1995; and Keane and Moffit, 1998). The biggest advantage of this approach is to ensure that the consumption bundle (time allocation to activities and travel) will be on the budget line. Furthermore, by using a flexible utility function designed to provide second-order approximation to any utility functions (the direct translog utility function as used in this study), one can add as many details as one might desire into the utility function. The main disadvantage that comes with the use of the discrete choice framework is the introduction of classification error, which arises when the continuous time-use variable is being converted into a discrete variable.

In this paper, an exploratory study using a discrete choice framework to model time allocation to activities and travel is presented. Three types of activities plus traveling are considered. The three activities include mandatory, maintenance and discretionary activities. Mandatory activities refer to work and school-related activities, which usually have to be performed at a particular location and for a certain time. Maintenance activities refer to those activities that help maintain one's normal functions as a human being. Activities such as sleeping, eating, grocery shopping, and personal business activities belong to this category. Discretionary activities refer to those activities that will provide us with positive utility[1] during the activity-performance process. Activities such as sports, social recreation and visiting belong to discretionary activities. The justification underlying the classification of these three types of activities lies in the level of priority and the spatial and temporal fixities[2] associated with the activities (Hagerstrand, 1970). Mandatory activities often have to be performed at a fixed location and for a fixed duration; they often have higher priority than other activities. Maintenance activities, on the other hand, typically have lower levels of priorities and levels of spatial and temporal fixities. For example, although shopping can only be done at a store and during its hours of operation, people can choose where to shop and for how long. Compared to mandatory and maintenance activities, discretionary activities typically have the lowest levels of fixities and priority. Recent research suggested that people decide the time allocation to mandatory activities first, followed by maintenance activities and discretionary activities respectively (Chen, 2004).

The paper is organized as follows. The proposed model framework is described in Section 2. Following this, the dataset is described in Section 3. Estimation results are presented in Section 4, followed by a description of the generation of the choice set in Section 5. The conclusions are provided in Section 6.

MODEL FRAMEWORK

Given a total budget of 24 hours a day, there are K number of patterns[3] available for one to choose from. Suppose that the individual selects the k^{th} pattern, through which his or her utility is maximized. Mathematically, the following may be written:

$$(1)\quad \max.\quad U_{ik} = f(p_{ik}, X_i, \beta)$$

$$(2)\quad p_{ik} = [t_{1k}, t_{2k}, \ldots, t_{jk}, \ldots, t_{Jk}],\ \forall\, j \in (1,2,\ldots,J)$$

where,

p_{ik} is the k^{th} pattern consisting of the time allocation to J number of activities and travel,

t_j is the time allocation to j^{th} type of activities or travel,

U_{ik} is the maximized utility obtained by individual i by choosing k^{th} pattern,

X_i is the vector of the individual's socio-demographic characteristics, and β is the parameter vector that needs to be estimated.

Equation 1 indicates that the total amount of utility one obtains by choosing the k^{th} pattern of time allocation is a function of the amount of time allocated to the activities and travel and the individual-related socio-demographic characteristics.

Given that there are K number of activity and travel patterns available, the random-utility theory suggests that *if* $U_{ik} \geq U_{im}$ (k and m are indices for k^{th} and m^{th} alternative in the choice set for individual i), then the k^{th} alternative is chosen. Furthermore, suppose the utility function can be divided into two components: the systematic part (V_i) and the random part (ε_i). The systematic utility contains variables associated with the alternative and the individual and can be measured by the analyst, while the random utility part contains those variables that can neither be measured nor observed by the analyst. The probability of choosing an alternative can be further written as:

$$P(k) = P(U_{ik} \geq U_{im}) = P(V_{ik} + \varepsilon_{ik} \geq V_{im} + \varepsilon_{im})$$
$$= P(\varepsilon_{im} - \varepsilon_{ik} \leq V_{ik} - V_{im}).$$

Assuming that ε_{im}-ε_{ik} has an extreme value type I distribution[4], the probability function has a close form solution, which is the standard logit model and is expressed as $P(k) = \frac{\exp(V_{ik})}{\sum \exp(V_{im})}$.

The utility function for the kth pattern can take a variety of forms. Given that J = 4 in this paper (maintenance, discretionary and mandatory activities plus travel), the direct translog utility function can be applied, which in theory will provide second-order approximation to any utility function (Christensen et al., 1975). The direct translog utility function can be expressed as follows:

$$\beta_d = \sum_{h=1}^{H} \beta_{dh} x_h + \varepsilon_d \tag{6}$$

$$\beta_m = \sum_{h=1}^{H} \beta_{mh} x_h + \varepsilon_m \tag{7}$$

In equations 4 – 7, x_h is the individual's hth socio-demographic characteristic, such as age, gender, and household size. The ε_w, ε_m, ε_d, and ε_t are unobserved preferences in the time allocation to mandatory, maintenance, discretionary activities and traveling. The β_{wh}, β_{mh}, β_{dh}, and β_{th} are hth related parameters associated with mandatory activities, maintenance activities, discretionary activities, and traveling.

Based on the notion of travel as derived demand, which essentially states that people obtain positive utilities from performing activities and negative utilities from traveling, are generally expected. Taking the first derivatives of the utility function (equation 3) will result in the following functions (equations 8-11).

$$\begin{aligned} U(t_w, t_m, t_d, t_t) = {} & \beta_w \log(t_w) + \beta_m \log(t_m) + \beta_d \log(t_d) + \beta_t \log(t_t) + \\ & \beta_{ww}(\log(t_w))^2 + \beta_{mm}(\log(t_m))^2 + \beta_{dd}(\log(t_d))^2 + \beta_{tt}(\log(t_t))^2 + \\ & 2\beta_{wm}\log(t_w)\log(t_m) + 2\beta_{wd}\log(t_w)\log(t_d) + 2\beta_{wt}\log(t_w)\log(t_t) + \\ & 2\beta_{md}\log(t_m)\log(t_d) + 2\beta_{mt}\log(t_m)\log(t_t) + 2\beta_{dt}\log(t_d)\log(t_t) + \varepsilon \end{aligned} \tag{3}$$

In equation 3, t_m, t_w, t_d, and t_t are time allocations to maintenance activities, mandatory activities, discretionary activities and traveling. β is the vector of corresponding parameters that need to be estimated and ε is the random disturbance term. As individuals with different socio-demographic characteristics may display preferences for time allocation to different types of activities, the following equations are further specified:

$$\beta_w = \sum_{h=1}^{H} \beta_{wh} x_h + \varepsilon_w \tag{4}$$

$$\beta_t = \sum_{h=1}^{H} \beta_{th} x_h + \varepsilon_t \tag{5}$$

Depending on whether the time allocated to a particular activity or traveling is greater than 1.0[5] and the values of β_m, β_d, β_w, and β_t, there can be many possibilities for the values and the signs of β_{mm}, β_{dd}, β_{ww}, and β_{tt}, as well as β_{mw}, β_{md}, β_{mt}, β_{dw}, β_{dt}, and β_{wt}. For this reason, Table 1 only identifies the expected signs for socio-demographic related independent variables.

Table 1 identifies the expected signs of the socio-demographic related independent variables in the model. The employed are expected to spend more time on mandatory activities, which also means that they will probably spend less time on maintenance and discretionary activities, given the fixed total daily time budget. They are also expected to travel more, simply because of the added commuting time that must be added to their

(8) $$\frac{\partial U}{\partial t_w} = 2\beta_{ww}\log(t_w)\frac{1}{t_w} + 2\beta_{wm}\log(t_m)\frac{1}{t_w} + 2\beta_{wd}\log(t_d)\frac{1}{t_w} + 2\beta_{wt}\log(t_t)\frac{1}{t_w} + \frac{\beta_w}{t_w}$$

(9) $$\frac{\partial U}{\partial t_d} = 2\beta_{dd}\log(t_d)\frac{1}{t_d} + 2\beta_{dm}\log(t_m)\frac{1}{t_d} + 2\beta_{dw}\log(t_w)\frac{1}{t_d} + 2\beta_{dt}\log(t_t)\frac{1}{t_d} + \frac{\beta_d}{t_d}$$

(10) $$\frac{\partial U}{\partial t_m} = 2\beta_{mm}\log(t_m)\frac{1}{t_m} + 2\beta_{mw}\log(t_m)\frac{1}{t_m} + 2\beta_{md}\log(t_d)\frac{1}{t_m} + 2\beta_{mt}\log(t_t)\frac{1}{t_m} + \frac{\beta_m}{t_m}$$

(11) $$\frac{\partial U}{\partial t_t} = 2\beta_{tt}\log(t_t)\frac{1}{t_t} + 2\beta_{tm}\log(t_m)\frac{1}{t_t} + 2\beta_{td}\log(t_d)\frac{1}{t_t} + 2\beta_{tw}\log(t_t)\frac{1}{t_t} + \frac{\beta_t}{t_t}$$

daily travel. Females have been found to spend less time on mandatory activities (Flood, 1985; Bell and Hart, 1998; McGrattan and Rogerson, 2004) and more time on maintenance activities than males (Flood, 1985; Kuppam and Pendyala, 2001), probably because of females' traditional roles of being a caregiver in the household.[6] The relationship between females and time allocation to discretionary activities is unknown. This is because while males tend to spend more time on sports-related activities, females may spend more time visiting and socializing. In addition, whether females travel more or less depends on their commuting time (if they are employed), their family responsibilities, and their preferences to conduct discretionary activities out-of-home. People with driver licenses and people who own multiple vehicles are expected to spend more time on discretionary activities, especially out-of-home discretionary activities. This is the case because having a drivers license or having access to a vehicle is essential to conduct many types of out-of-home activities. People who own multiple vehicles and people with driver licenses are also expected to travel more because of the easy access to transportation. Allocating more time to discretionary activities and travel would likely result in less time allocated to other types of activities, such as mandatory activities. Therefore, a negative relationship between people with driver licenses and time allocated to mandatory activities is expected. A similar logic may also apply to the relationship between people who own multiple vehicles and the amount of time spent on mandatory activities. Older people are expected to spend more time on discretionary activities because they have fewer mandatory activities.

Table 1: Expectations of the Impacts of Socio-Demographic Related Independent Variables on the Dependent Variables

Independent Variables	Exp. Signs	Explanation
Mandatory activities		
Employed	+	Employed people spend more time working
Female		Females spend less time working
License		People with driver licenses spend less time working
Number of vehicles		People who own multiple vehicles spend less time working
Maintenance activities		
Female	+	Females spend more time doing maintenance activities
Employed		The employed spend less time doing maintenance activities
Discretionary activities		
Age	+	Older people spend more time doing discretionary activities
Female	+/-	Males tend to spend more time on sports-related activities while females may spend more time visiting and socializing
Employed		The employed spend less time doing discretionary activities
Licensed	+	People with driver licenses spend more time doing discretionary activities
Number of vehicles	+	People who own multiple vehicles spend more time doing discretionary activities
Travel		
Female	+/-	Females may or may not spend more time traveling
Number of vehicles	+	People who own multiple vehicles travel more
Licensed	+	People with driver licenses travel more
Employed	+	The employed travel more

DATASET DESCRIPTION

The database used in this study comprises responses to the 1996 San Francisco Bay Area Household Travel Survey (MTC, 1996). The survey consisted of a two-day activity and travel diary. It contained information on household and personal characteristics, vehicle characteristics, and activity and travel-related information obtained from the two-day activity and travel diary. The original sample of the 1996 survey comprises responses from 3,618 households and 7,990 people.

The activities that are included under mandatory, maintenance and discretionary categories are listed in Table 2. Observations having activities that were coded as “out of area” or “do not know/ refused” or “other” were excluded and observations with these unknown activity types were also dropped from the sample. For some observations, the total duration of their activities and trips during the two-day survey period does not add up to 48 hours (due to missing departure and/or arrival time or due to obviously mis-entered information). Those observations were dropped from the sample.

Table 2: List of Activities Classified as Mandatory, Maintenance and Discretionary

Mandatory Activities	Maintenance Activities	Discretionary Activities
Working/related	Shopping	Recreation/rest
Schooling/related	Meals/preparation	Recreation/play
	Sleep	Amusement at home
	Day care/after school care	Visiting
	Personal service	Entertainment
	Medical service	Religion/civic services
	Professional business	Civic/volunteer services
	Household/personal service	Amusement outside home
	Household/maintenance chores	Hobbies
	Household/obligation and family care	Exercise/athletics
	Sick/ill	Computer
	Waiting	Get ready[1]
	Morning routine	
	Evening routine	
	Get ready[1]	
	Hygiene	
	Diary	

[1] Depending on the type of activity that follows this "get ready" activity, this activity may be classified as a mandatory, maintenance or discretionary activity.

The resulting sample comprises responses from 3,624 people.

Table 3 shows sample statistics of the 3,624 people used for model estimation. The average household size is 2.93. About 65% of households own their current residence; 32% rent and less than 1% belong to the other category (staying with relatives and/or friends). Only 3.8% of the households do not have a vehicle; 89% have between one and three vehicles and 7.5% have more than three vehicles. The gender divide is relatively balanced between males and females. Close to 90% of the people have driver licenses. About 72% of the people are employed, and a majority of them (94%) have one job. The income distribution is relatively balanced among the poor, the middle class, and the rich.

CHOICE SET GENERATION

Based on the minimums and maximums of the sample[7], the following constraints set was created in generating all possible combinations of time allocated to mandatory, maintenance, and discretionary activities as well as traveling:

(12) $0 \leq t_w \leq 40$ *hours*

(13) $0 \leq t_m \leq 40$ *hours*

(14) $0 \leq t_d \leq 40$ *hours*

(15) $0 \leq t_t \leq 40$ *hours*

(16) $t_w + t_m + t_d + t_t = 48$ *hours*

Assuming an increment of one hour (i.e., only activity patterns that differ from each other by more than one hour in any type of activities and travel are distinguished from each other), the above set of constraints results in a total of 17,985 possible combinations of time allocations to the three types of activities and traveling. Although decreasing the increment to less than one hour will inevitably increase the total number of possible combinations of time allocations to activities and travel, it should not significantly affect the model results. Ben-Akiva and Lerman (1985) noted that a random sample of the alternatives will still result in consistent estimates for discrete choice models. Also

Table 3: Sample Statistics of the Dataset Used for Estimation Purposes

Variables	Sample Statistics
Sample size	N=3,624
Household size	
Mean	2.93
Home ownership	
Own	65.3%
Rent	31.9%
Other	0.23%
# of vehicles	
0	3.8%
1-3	88.6%
>3	7.5%
Gender	
Males	50.1%
Females	49.8%
License	
Have a license	89.9%
Not have a license	9.9%
Employment	
Employed	71.5%
Unemployed	28.1%
# of jobs	
1	93.8%
>1	5.88
Income level	
< 15k[1]	6.1%
[15k, 30k)	11.7%
[30k, 45k)	11.2%
[45k, 60k)	15.5%
[60k, 75k)	11.2%
[75k, 100k)	14.9%
≥ 100k	12.2%

[1] k: thousands of dollars.

because of this property, cluster analysis[8] is then applied to further classify these possible combinations into 20 clusters. Given that the observed pattern of time allocation belongs to one of the identified clusters, one pattern is randomly generated from the rest of the 19 clusters. This creates 20 alternatives (including the chosen one) for each person in the sample.

MODEL RESULTS

The model is a standard multinomial logit model and is estimated with the Maximum Likelihood Estimation (MLE) method. The MLE method is designed to identify parameters such that the likelihood of the sample is maximized. The log-likelihood (which is equivalent to the likelihood from the estimation perspective) function of the sample can be written as:

$$\sum_{i=1}^{N}\sum_{j=1}^{20} y_{ij} \ln p_{ij},$$

where y_{ij} = 1.0 if individual i chooses alternative j ($\forall$j=1,2,…,20) and y_{ij} = 0 for otherwise. The probability of individual i's choosing alternative m and is equal to: $\frac{\exp(V_m)}{\sum_{j=1}^{20}\exp(V_j)}$, where both m and j belong to the choice set and V_j is the systematic utility portion of the random utility form described in equation 3 previously. The Limdep software is applied to estimate the model.

Overall, the model has a good fit, with the adjusted R-squared value of 0.80 with respect to the case when all $\hat{\beta}$ equal to zero and of 0.66 with respect to the constant-only case.

Table 4 shows estimation results of the model. The first set of coefficients are coefficients of the squares of the time allocated to mandatory, maintenance, discretionary and traveling in the log form $(\log(t_w))^2$, $(\log(t_m))^2$, $((\log(t_d))^2$, and $(\log(t_t))^2)$. They are positive for all three types of activities and negative for traveling. This suggests that more time spent on maintenance, mandatory, and discretionary activities results in higher utility for the person who performs it; more time spent on traveling results in less utility. This result is consistent with the widely recognized notion of travel as a derived-demand concept.

As shown in equations 8 to 11, the signs of the coefficients for $((\log(t_w))^2$, $(\log(t_m))^2$, $\log(t_d))^2$, and $(\log(t_t))^2$ should also be interpreted together with other variables in the utility function (equation 3). The second set of coefficients contains coefficients of interactions of the time allocated to discretionary, mandatory, maintenance and traveling in the log form. Combined together, they show that if one increases the time allocated to discretionary and maintenance activities, the utility obtained will be increased. The same applies to the pair of mandatory and maintenance activities, though the relationship is not statistically significant. An increase in the time allocated to discretionary and mandatory activities, however, will result in positive effects derived from the square of the time allocated to discretionary and mandatory activities as well as negative effects derived from the interaction between the two.

The effect on other activities and traveling is more complicated. If one increases the time spent on discretionary activities and traveling, there are not only positive effects derived from the square of the time allocated to the discretionary activities, but also a negative effect from the square of the time allocated to traveling and the interaction between traveling and discretionary activities. The same applies to the pair of maintenance activities and traveling. If one increases the time allocated to mandatory activities and traveling, there are positive effects derived from the squares of the time allocated to mandatory activities and the interaction between the two, as well as negative effects derived from the squares of the time allocated to traveling.

The third set of coefficients show individuals' preferences toward performing different types of activities and travel, given their socio-demographic characteristics. The signs of all coefficients are within expectation. Older people, people with a driver license, and people with multiple vehicles tend to allocate more time to discretionary activities. Females also allocate more time to discretionary activities than males, verifying the earlier hypothesis that females are probably spending more time on activities such as visiting and socializing. The employed tend to allocate less time to discretionary activities and more time to mandatory activities compared to the unemployed. Females tend to allocate more time to maintenance activities compared to males. They also allocate less time to mandatory activities compared to males. People with multiple vehicles and people with driver licenses also allocate less time to mandatory activities. People with driver licenses, people with multiple vehicles, and the employed also tend to spend more time traveling than others.[9]

Table 4: Estimation Results

Variables	Estimates	Std. error	t-ratios
First set			
$(\log(t_w))^2$	1.23	0.061	20.17
$(\log(t_m))^2$	1.45	0.074	19.56
$(\log(t_d))^2$	0.36	0.033	10.67
$(\log(t_t))^2$	-0.43	0.065	-6.62
Second set			
$(\log(t_d))(\log(t_w))$	-0.83	0.046	-17.99
$(\log(t_d))(\log(t_m))$	0.35	0.049	7.16
$(\log(t_d))(\log(t_t))$	-0.49	0.059	-8.31
$(\log(t_w))(\log(t_m))$	0.8E-2	0.052	0.15
$(\log(t_w))(\log(t_t))$	1.24	0.063	19.70
$(\log(t_m))(\log(t_t))$	-1.42	0.083	-17.05
Third set			
age*$\log(t_d)$	0.04	0.025	14.93
female*$\log(t_d)$	0.29	0.077	3.77
employed*$\log(t_d)$	-0.40	0.101	-3.96
licensed*$\log(t_d)$	0.64	0.134	4.77
number of vehicles*$\log(t_d)$	0.13	0.031	4.18
female*$\log(t_m)$	0.91	0.163	5.58
female*$\log(t_w)$	-0.56	0.101	-5.45
license*$\log(t_w)$	-1.54	0.150	-10.30
employed*$\log(t_w)$	1.01	0.100	10.09
number of vehicles*$\log(t_w)$	-0.14	0.036	-3.85
number of vehicles*$\log(t_t)$	0.04	0.043	0.99
licensed*$\log(t_t)$	0.32	0.154	2.06
female*$\log(t_t)$	0.008	0.104	0.076
employed*$\log(t_t)$	0.57	0.142	4.01
n = 3,624			
L(0) = -10856.53	L(C) = -6289.90	$L(\hat{\beta}) = -2145.08$	
Adj. R^2 with zero coefficients: 0.80	Adj. R^2 with constants: 0.65		

CONCLUSIONS

Because our daily time budget of 24 hours must be spent in one form or the other, the maximization of the utility function subject to constraints must result in a solution that lies on the boundary of the budget line. In other words, the optimal solution of the consumption bundle must be the case that all time is spent. The traditional way of modeling time-use behavior is to treat time use as a continuous and dependent variable. The problem with this method is the restriction that the consumption bundle must lie on the boundary of the budget set can not be enforced. When used for forecasting purposes, these models can result in consumption bundles (time allocation to activities and travel) that are less (sometimes even in negative numbers) or greater than the available budget.

In this paper, an exploratory study using a discrete choice framework for time-use allocations is described. Instead of treating time-use as a continuous and dependent variable as in the traditional way, time-use behavior is treated as a discrete and independent variable. By doing this, the restriction that the consumption bundle must lie on the boundary of the budget set can be easily enforced. Furthermore, by using the direct translog utility function, one can easily enter as many details into the utility function as desired.

Using the responses collected from the 1996 household travel survey for the San Francisco Bay Area, the proposed model has a good fit in terms of adjusted R^2. The associated effects between individuals and households' socio-demographic variables and time-use behavior are all within expectations.

There are a number of limitations associated with the model and deserve future investigation. The first is the existence of the classification error that is completely ignored by the present study. Classification errors arise when the continuous time-use variables are aggregated into discrete categories. This represents the biggest challenge when applying the discrete choice approach for time-use behavior. MaCurdy et al. (1990) proposes a non-linear function linking the actual hours and the reported hours, which can be built into the log-likelihood function. The empirical validity of this function is worth investigating in future research. A related issue is the correlation of alternatives within the choice set. Because every alternative represents a particular pattern of time allocations to activities and travel, it is likely that some of these alternatives are correlated with each other. This problem can probably be solved with the use of the Mixed Logit models (Bhat, 2001; and Train, 2003).

Endnotes

1. The word "utility" can be viewed as amount of satisfaction one obtains.

2. The concepts of spatial and temporal fixities were originally derived from Hagerstrand (1970). Spatial fixity of an activity refers to how fixed an activity is in space while the temporal fixity of an activity refers to how fixed an activity is in time. Mandatory activities (for example, work-related activities) are typically fixed in space and time, because people usually must start working at a particular time, at a particular location, and for a particular time duration. On the other hand, maintenance and discretionary activities (for example, shopping) are less fixed in time and space than mandatory activities, because people typically have a choice in terms of when to go, where to go and for how long.

3. Theoretically, there may be an infinite number of possible combinations as the amount of time spent on activities and travel is continuous. However, many of these combinations are similar to each other. For example, a difference of less than one hour in the same type of activities and travel may mean that the two patterns are similar to each other. Therefore, if we only count possible combinations that are significantly different from each other, there are K combinations.

4. The extreme value distribution deals with outlying observations that do not belong to a normal parent distribution. There can be only three types of extreme value distribution: type I, type II, and type III. The extreme value type I distribution is the most referenced distribution in the literature (Johnson et al., 1995).

5. Because of the log form, a value less than 1.0 will result in a negative number and a value greater than 1.0 will result in a positive number.

6. Although females' working hours have significantly increased over time, they are still less than males' working hours. Females have also been found to spend more time on household related activities.

7. A descriptive analysis of the sample for this study shows that the minimums and the maximums of the time allocation to mandatory, maintenance, and discretionary activities as well as traveling fall in the ranges of (0,40), (0,40), (0,40), and (0,40) respectively.

8. Cluster analysis was designed to group similar observations together into a cluster. Cluster analysis can be performed with any statistical software available on the market. SAS was used for this study.

9. Females were also found to spend more time traveling, but the effect was not statistically significant.

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