Constrained Allocation of Time and Money between Activities and Travel: A Review of Modeling Methodologies and a New Utility Maximization Model

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by

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Abstract

This paper first reviews several different methodologies that have been applied to model the amount of time individuals spend traveling, or the allocation of time between activities and travel: single linear equations, structural equations, duration analysis, and utility maximization. However, people are not always able to freely allocate their time between activities and travel. For example, going to work for 8 hours may require a minimum of 30 minutes’ travel. Or, going to dine at a restaurant might require a minimum of 20 minutes of travel. None of the empirical studies we reviewed addresses this issue. In addition, then, we propose a utility maximization framework that explicitly deals with the linkage between activities and the time required to access them. Through the use of the Almost Ideal Demand System (AIDS) approach, closed-form demand functions can be derived for variables of interest (activity durations and travel times) in the share form. The constraints specified in the model include not only a time budget but also a monetary budget. The demand functions are derived from a flexible cost function and are first-order approximations to any demand functions derived from a utility maximization framework. The demand functions can also be viewed as being derived independently of the utility maximization principle. Restrictions that make the model consistent with utility maximization can be checked in the empirical studies. With this model, activity durations and travel time can be estimated simultaneously. The structural equations modeling approach is recommended for estimation.
1. Introduction

Time expenditures, whether for activities or travel, have long been an interesting subject to researchers of different disciplines. With respect to travel time expenditures in particular, a long-standing issue in the transportation profession has been the existence (or not) of a “travel time budget”, that is an average expenditure that is relatively stable across time and geographic regions. A companion paper to this one (Mokhtarian and Chen, 2002) reviews and analyzes the empirical literature on travel time budgets.

Even the earliest and most ardent proponents of the travel time budget concept, however, recognized that at least at the disaggregate level (and actually even at the aggregate level as well), travel time expenditures are not constant (e.g., Zahavi and Talvitie, 1980). But those expenditures do appear to be related to demographic, land use, and activity engagement variables, and as such are capable of being to some extent modeled and explained as functions of those types of variables.

The relationship between time expenditures on activities and on travel is also intriguing, since there are possible tradeoffs between activity duration and travel. Numerous studies have addressed this issue. A common consensus is that activity duration and travel time are positively related (Hamed and Mannering, 1993; Kitamura et al., 1997). In other words, ceteris paribus, people are willing to spend more time on travel if the planned time expenditure at the destination is longer. Some researchers (e.g., Ma and Goulias, 1998) have also examined the relationship for different kinds of activities. They found that the interaction between the two was only pronounced for subsistence activities.

One purpose of the present paper, then, is to review the methodologies that have been used to model the expenditure of time on travel, and/or the allocation of time between activities and travel. All the reviewed empirical studies implicitly assume free allocation of time between activities and travel. This is not exactly the case in reality. Because of the spatial distribution of various activities, some activities are associated with a minimum travel requirement. In other words, in order to perform those activities, a minimum amount of travel must be done. The examples are common in our daily lives. Most of us must travel to work; we must travel to dine at a restaurant; and we must travel to watch a newly released movie. This special relationship between activities and travel is first recognized by Evans (1972). He commented (p.10) that “the amount of time [an individual] decides to spend traveling [should not be] assumed to be completely independent of the amount of time he [or she] chooses to spend in any other activity” because sometimes an individual may not want to travel (that much) but must travel a minimum amount in order to perform another activity.

Thus, a second purpose of this paper is to propose a model framework that explicitly addresses the special relationship between activity duration and travel. Based on their two-way causal relationship, we construct a behaviorally sound model that addresses activity duration and travel time at the same time. The model incorporates three categories of activities: mandatory (e.g. paid work), maintenance (e.g., grocery shopping, medical appointments) and discretionary (e.g., social, recreational) activities. These three categories in general encompass all daily activities. Section 2 of this paper discusses four different approaches to disaggregate modeling of time and
money allocations to travel and activities: three statistical estimation techniques, and a utility maximization framework within which each of the three statistical techniques may be applied. In Section 2.1, we present the single linear equation approach, which assumes a single endogenous variable. Where there is more than one endogenous variable, seemingly unrelated regression (SUR) equations or structural equations modeling, described in Section 2.2, are more appropriate. Duration analysis, discussed in Section 2.3, may also be used to model individuals’ time allocation behavior. In Section 2.4, we review studies that are constructed under the utility maximization framework. We propose our new model in Section 3 of this paper. We discuss estimation issues in Section 4, and data needs in Section 5. Section 6 offers some concluding remarks.

2. Review of Travel/Activity Time (and Money) Modeling Methodologies

2.1. Single Linear Equation

The simplest way to model individuals’ expenditures on travel is via the use of a single linear equation. As a special type of linear regression, a few studies have used analysis of variance to identify significant factors associated with travel time expenditures. For example, using data from a 1976 three-weekday trip diary in Munich, Germany, Zahavi and Talvitie (1980) show that household size, car ownership and the interaction between the two have statistically significant effects on travel time expenditures.

Kitamura et al. (1992) separately estimated a number of log-linear models in which time expenditure on the \( j \)-th activity is a function of total time available and other explanatory variables. The main purpose of the model estimation was to examine whether the ratio of time expenditures allocated to two activities is invariant to the total amount of time available. They found that the results rejected the hypothesis of proportional time allocation to activities.

Levinson (1999) estimated single linear equations on daily travel duration associated with an activity. The independent variables included daily frequency and daily duration of activities. The model was estimated for different types of activities including home, work and related, shopping, personal business, school and church, doctor visits, visits to friends and relatives, social/recreation and other activities. The results showed that the activity frequency had a significant and positive effect on travel time allocation to all types of activities. Except for work and related activities, activity duration had a significant effect on travel time expenditure for the corresponding activity type. Travel time expenditure decreased as the amount of time spent on home activities increased; increased as the amount of time spent on all other activities (except for work and related activities) increased. The insignificant relationship between work duration and travel time to work is probably due to the generally fixed nature of work durations. In other words, work duration is relatively constant (eight hours a day for most full-time workers) no matter how long one has to travel to work. However, empirical results are mixed on this point, as seen immediately below.

One dilemma with the single linear equation approach is whether to include activity duration in the function for modeling travel expenditures. If included, activity duration is more likely to be endogenous than exogenous and consequently the Ordinary Least Squares (OLS) estimates will
be inconsistent. If excluded, the estimates will be biased, unless omitted variables are independent of included variables, which in practice is more the exception than the rule (Greene, 1997). In the case where some regressors are endogenous, the 2-Stage Least Squares (2SLS) method may be used. In an effort to model how individuals allocate their time throughout a day, Ma and Goulias (1998) developed models for travel time expenditures on different types of activities. 2SLS was used to estimate the model due to the expected endogeneity of activity duration. In contrast to Levinson, Ma and Goulias (1998, p. 11) found that “activity duration is endogenous to travel time only when a person travels to participate in a subsistence activity”. In the model of travel time to subsistence (i.e., mandatory) activities (the only estimation model that was presented), both work-related characteristics and person and household-related socio-economic characteristics had significant effects on travel time. Full-time workers and those who lived farther away from work traveled longer than others. However, Ma and Goulias also found that working outside of home decreased the travel time to subsistence activities, a result that appeared to contradict the outcome just mentioned. Travel time to subsistence activities was found to be negatively related to home departure time, amount of time spent on past activity participation and travel on the same day, and number of activities conducted earlier on the same day. Additionally, travel time to subsistence activities was also positively related to the travel time to a previous subsistence activity on the same day and negatively related to the travel time to a previous leisure activity on the same day.

Another problem that might arise with single linear equations is that, if a large number of observations in the data set have zero travel time, the OLS estimates will be inconsistent. One ad hoc solution is to add a small positive quantity to all observations, as Kitamura et al. (1992) did. A more rigorous approach is to estimate a tobit model, which is appropriate for cases in which the dependent variable is censored from below and/or above. Flood (1985) used a tobit model approach to account for the problem of a large number of zero observations in modeling the time expenditures on market work, home production and leisure by males and females. He found that the non-labor income decreased the amount of time allocated to market work for both males and females; it however increased males’ time allocated to leisure activities. The wage rate had an insignificant effect on males’ time allocation, but significantly increased females’ time allocated to market work. A high level of education significantly increased females’ time allocated to market work, but reduced their time allocated to leisure activities. Like the wage rate, age had an insignificant effect on males’ time allocation, but significantly increased females’ participation in market work. Being a homeowner did not seem to make a difference in males’ time allocation, but significantly reduced females’ participation in market work. Larger households placed a burden on both female and male adults; it significantly reduced females’ time allocation to market work, increased their home production time, and reduced males’ time allocated to leisure activities. The availability of household technology, surprisingly, increased females’ time allocation to home production. The presence of children less than 5 years old significantly reduced females’ participation in market work and increased their time on home production.

2.2. Systems of Equations

Within our context, if we were to use the single linear equation approach for both time and money expenditures, and including the three activity types (mandatory, maintenance, and discretionary) as well as travel, we would be modeling eight equations separately. These eight
single linear equations may well share some explanatory variables, both observed and unobserved. We may gain some efficiency by modeling them jointly. This is especially the case when the ε’s (random disturbance terms) are correlated with each other and/or correlated with explanatory variables. Even if all explanatory variables on the right hand side of the equation are exogenous, the ε’s could be correlated with each other. This is because the random disturbance terms may not only include factors that are specific to a particular equation, but also factors that are common to more than one equation. When endogenous variables are also present on the right hand side, the ε’s are not only correlated with each other across equations but also correlated with explanatory variables within the equation.

In the case where all explanatory variables are exogenous but the ε’s are correlated across equations, the set of equations is called a Seemingly Unrelated Regression (SUR) Equation System, which can be estimated using the Generalized Least Squares (GLS) method. In the case where endogenous variables are present on the right hand side, the set of equations is called a Structural Equations System (SES). In structural equations systems, endogenous variables are not only directly influenced by the right-hand variables (both endogenous and exogenous) in its own equation, but also indirectly influenced by variables in other equations (through the influence of those variables on the endogenous variables of those equations). The presence of endogenous variables on the right hand side means that the endogenous variables are correlated with the disturbance terms, in violation of the assumption of OLS. Using OLS to estimate a SES will result in inconsistent estimates. Thus, SESs are estimated using the 3-Stage Least Squares (3SLS) method or Full Information Maximum Likelihood (FIML) method.

A number of researchers have used structural equation systems to estimate models of time expenditure on activities and travel. Flood (1985) developed four structural equation systems to examine time expenditures on various activities by male and female adults in the household. The first system, for home-related activities, consisted of eight single equations, corresponding to home production, leisure, household work, and TV-watching activities by males and females respectively. Estimation of such a system was performed by the 2SLS method. The second system modeled time expenditures on market work. Due to a large number of zero observations for market work for females, a latent variable was added to the system, defined by Flood as the latent preference for time allocation to market work (which could take on negative as well as positive values). The third and fourth systems also had latent variables to deal with zero observations for time spent on child care and home repair activities, respectively. Estimation of the second, third, and fourth systems was similar to the 2SLS method.

Flood found that there was no substantial gain in treating the allocation of time in the household as a system. The results estimated from structural equations systems were essentially the same as those from separate estimation of single linear equations. In general, females’ time allocation had no significant effect on males’ time allocation behavior. Males’ time allocation had a significant effect only on females’ leisure and home repair activities.

Golob (1990) examined how travel times by different modes interacted with each other and with car ownership over time, using a longitudinal structural equation system with limited and categorical dependent variables. The exogenous variables Golob examined included dynamic variables that were measured both at the same point in time and the previous year, and static
variables that were measured only at the same point in time. Dynamic variables included two measures related to income, number of persons 18 or older in household, number of persons 12-17 in household, household composed of 2 adults, presence of children less than 12 years old, number of household drivers, presence of 3 or more drivers, and number of household workers. Static variables included four measures related to residential location.

He found that there were significant associations among travel times by different modes and with car ownership. For example, among the direct effects, travel time by car increased with contemporaneous car ownership and transit travel time; travel time by non-motorized modes decreased with car ownership and with travel time by car. Golob also found significant impacts of exogenous variables on travel times by different modes and car ownership both at the same point in time and in the previous year.

Fujii et al. (1997, cited by Kitamura et al., 1997) developed a structural equation system analyzing trade-offs between time expenditures on activities and travel. They found that a 10-minute reduction of commute time would increase average total out-of-home activity duration by 1.88 minutes, average total in-home activity duration by 7.11 minutes, and average total travel time by 0.36 minutes. The number of home-based trip chains after returning home from work would increase about 30%, from 0.03 to 0.04.

Golob and McNally (1997) estimated a structural equation model system examining the trade-off in time expenditure on different activities (work, maintenance, and discretionary) and corresponding travel to each type of activity, separately by females and males residing in the same household. Similar to the study by Golob (1990), they not only found significant associations among dependent variables, but also significant impacts of exogenous variables on dependent variables. For example, among the direct effects, about 22.6 minutes of travel were involved for every eight hours of out-of-home work activity, and about 7.8 minutes of travel were involved for every hour of out-of-home maintenance activity. With respect to total (direct plus indirect) effects, it was interesting that males’ travel times for work and maintenance were not significantly influenced by women’s travel and activity durations (similar to the results of Flood, 1985), whereas women’s travel for these purposes was significantly influenced by their male partners’ behavior as well as by their own. However, discretionary travel time for both males and females was significantly influenced by the behavior of themselves and their partners.

Lu and Pas (1999) examined the interaction between individuals’ activity participation and travel behavior. They found that daily travel time increased with the amount of time spent on maintenance and out-of-home activities, but decreased with the amount of time spent on in-home activities. As for socio-demographics, total daily travel time was positively related to age, income, and number of workers, and negatively related to number of vehicles and number of children. The likely explanation for the relationship to number of vehicles is that households with fewer vehicles must rely more on slower transit and walk modes, resulting in longer travel times.
2.3. Duration Analysis

Expenditures of time on activities and travel may also be modeled via duration analysis. A key element in duration analysis is the specification of the hazard rate function, which represents the rate at which a duration ends after time \( t \), given that it has lasted \( t \) units so far. The hazard rate function \( \lambda(t) \) can take many forms. Commonly assumed distributions include exponential, Weibull, and log-logistic. For the exponential distribution, the hazard rate \( \lambda(t) = \gamma \) where \( \gamma \) is a constant. In other words, the hazard function is memoryless; the rate at which the spell is completed does not depend on the duration of the spell. For the Weibull distribution, the hazard rate \( \lambda(t) = \gamma \alpha t^{\alpha-1} \), where \( \gamma > 0 \) and \( \alpha > 0 \). Depending on the values of \( \gamma \) and \( \alpha \), the hazard rate function can be either monotonically increasing or decreasing, with the exponential distribution resulting as the special case when \( \alpha = 1 \). For the log-logistic distribution, the hazard rate \( \lambda(t) = \gamma \alpha t^{\alpha-1} / (1 + t^{\alpha \gamma}) \), where \( \gamma > 0 \) and \( \alpha > 0 \). For \( \alpha > 1 \), the hazard function first increases with duration \( t \) and then decreases. For \( 0 < \alpha < 1 \), the hazard function first decreases with duration and then increases. For \( \alpha = 1 \), the hazard function monotonically decreases with \( t \).

The estimation of the hazard rate function can be done either parametrically or non-parametrically. In the parametric method, the duration density function is assumed to be \( f(t, \theta) \), where \( t \) is the duration and \( \theta \) refers to parameters to be estimated. The likelihood function may be expressed as \( L = \prod_{i=1}^{n} f(t_i, \theta) \) for a sample of \( n \) completed spells. Given an assumed functional form of \( \lambda \), consistent parameter estimates can be obtained via the usual maximum likelihood procedure.

Sometimes, not only the duration \( t \), but also other explanatory variables, affect the hazard function. For example, the hazard rate may be affected by the socio-economic characteristics of the individual. Kiefer (1988) summarized a number of specifications in which explanatory variables can be included. Common ones include the proportional hazard model and the accelerated lifetime model. Proportional hazard model specifications allow fairly general transformations of the duration variable but restrict the error distribution to only the type I extreme value distribution, whereas the accelerated lifetime hazard model specifications allow fairly general specifications of the error distribution but restrict the transformation of the duration variable (Kiefer, 1988).

Neither proportional hazard model specifications nor accelerated model specifications allow for interaction between the explanatory variables and the duration \( t \), which sometimes may be too restrictive. Within our context, one may hypothesize, for example, that the effect of age on duration of travel time may become stronger with the length of the spell. To remedy this problem, the hazard rate function may include explanatory variables that interact with time.

There have been several applications of duration models to travel behavior analysis. Hamed and Mannering (1993) used a hazard rate function with a Weibull distribution to model travelers’ postwork home-stay duration. They found that the home-stay duration was positively related to number of workers in the household, and negatively related to the number of children in the household. If the individual arrived home between 9:00 am and 4:00 pm, the chance of
participating in activities outside of home was greater than if the individual arrived at home at other times. If the individual arrived home between 6:00 pm and 8:00 pm, the chance of participating in activities outside of home was less than if the individual arrived home at other times. The estimated duration parameter $\alpha$ (in the hazard rate function $\lambda(t) = \gamma \alpha t^{\alpha-1}$) was less than one, suggesting that the longer an individual stays at home, the less likely that he will participate in an activity outside of home.

In modeling the duration of shopping during the return home trip from work, Bhat (1996a) compared proportional hazard models with a Weibull baseline specification and with a non-parametric baseline specification. Within each specification, he also compared among models without heterogeneity, with gamma heterogeneity, and with non-parametric heterogeneity. He found that the parametric baseline specification provided biased estimates. Control of heterogeneity did not alleviate the problem of biased estimates, though ignoring heterogeneity did not underestimate the duration dependence. In conclusion, Bhat recommended using a non-parametric baseline model specification and testing for various distributions to control for heterogeneity, in preference to arbitrarily choosing a particular parametric baseline model specification.

The above discussion of duration analysis only concerns spells with a single exit. This may be undesirable in some situations under which spells can end in a number of ways. For example, the spell of a particular activity such as paid work could end at the start of a recreational activity or a shopping activity. The hazard rate for the transition from paid work to recreational activity may well be very different from that for the transition from paid work to shopping activity. Competing risk models have been developed to deal with spells with more than one exit.

Competing risk models have also been applied in travel behavior modeling. Ettema et al. (1995) used competing risk models to model the activity duration and the type of activity for the new engagement. They compared both a generic model specification (a model that was generic to all types of activity) and an activity type-specific model specification. They found that the performance of the generic model was not as good as the activity type-specific model specification in terms of the goodness of fit ratios.

Bhat (1996b) estimated a joint model of outcome and outcome-specific hazards to predict the duration of shopping and social/recreation activities of workers during the evening commute home. In the sample, the individual may choose to go directly home, to participate in shopping activities before returning home, or to participate in social/recreational activities before returning home. Bhat estimated two versions of the model: one assuming independence between activity type choice and activity duration and the other accommodating the potential correlation between activity type choice and activity duration. The parameter estimates for the activity type choice model were almost identical for both versions of the model. Older age increased the probability of choosing shopping activities, but decreased the probability of choosing recreational activities. Compared to females, males were more likely to participate in recreational activities than in shopping activities. The presence of children under eleven years old decreased the probabilities of choosing both shopping and recreational activities. Higher household income increased the probability of choosing recreational activities, but had no impact on shopping activities. Availability of an automobile and being able to depart from work before 4:00 pm increased the
probability of choosing recreational activities. Long work duration increased the probability of going directly home.

For duration models for shopping and recreational activities, the parameter estimates agreed in sign, but differed in magnitude. The duration of recreational activities was positively related to being male, household income, and returning young adult (1 if the individual is an employed adult living with one or both parents) and negatively related to work duration. The duration of shopping activities was positively related to returning young adult and departure from work before 4:00 pm and negatively related to driving alone to work and work duration. Bhat also noted that the model accommodating the potential correlation between activity type choice and duration was better than the model assuming independence between the two because the estimated correlation coefficient was found to be significantly different from zero.

In an effort to model how individuals allocate their time throughout a day, Ma and Goulias (1998) developed a number of competing risk duration models in the form of an accelerated lifetime specification to model activity duration and probabilities associated with various activity types (including subsistence, maintenance, and leisure activities). Ma and Goulias (1998) argued that the traditional competing risk model has the assumption of independence between activity type and the time that the activity will terminate, which is not realistic. For estimation, they adopted the two-step approach of Cardell (1997; cited in Ma and Goulias, 1998), in which they first estimated a multinomial logit model for the probabilities of activity types in which to engage, followed by an activity duration model that included a log-sum term from the multinomial logit model.

2.4. Utility Maximization Framework

An approach that is different from those previously discussed is the utility maximization framework, under which individuals are assumed to make choices in order to maximize an underlying utility function. Utility maximization is usually not unrestricted; rather the utility is maximized subject to constraints (e.g., a budget constraint). If the utility function is properly specified, closed-form demand functions for variables of interest can be derived. The unknown parameters of those demand functions can then be estimated using one or more of the three approaches reviewed earlier in this section.

Kitamura (1984) examined how individuals allocate time among various activities under a utility maximization framework. It is assumed that the total utility of an individual’s time allocation pattern can be expressed as the sum of weighted utilities for each activity. Assuming there are two types of activities, mandatory and discretionary, Kitamura formulated a tobit model that accommodated zero time allocated to one of the activities. The estimation results using the 1977 Baltimore Travel Demand Data Set showed that both work-related variables and socio-economic variables were significant. More specifically, having a work location within the city of Baltimore or arriving at work after 9 A.M. reduced the time allocated to discretionary activities. Although not verified by comparing the commute times of those who allocated little time and those who allocated much time to discretionary activities, the significance of these two variables may suggest relatively long commutes by the former group either due to long distances or slow traffic speeds. The use of an automobile for the work trip had a positive impact on the time allocated to
discretionary activities. As expected, work duration had a negative effect on the time allocated to discretionary activities. Time allocated to discretionary activities seemed to vary by day of week, with Friday being the highest among weekdays. In terms of socio-economic characteristics, availability of cars in the household and number of nonworkers increased the amount of time allocated to discretionary activities. Males spent more time on discretionary activities than females. Time allocated to discretionary activities decreased significantly with age and number of children in the household. However, women with children between 5 to 15 years old spent more time on discretionary activities than did others, probably due to participating in activities with their children.

Flood (1985) modeled the amount of time spent on home production, leisure, sleep and personal care, and market work activities by male and female adults in the same household. Following Becker (1965), Flood converted the monetary budget constraint to one in terms of full income. By using the indirect translog utility function (Christensen et al., 1975) and Roy’s identity, Flood was able to derive closed-form demand functions. The explanatory variables included in Flood’s model were mainly socio-economic characteristics related to the individual and the household. He found that the presence of children had a significant impact on females’ time allocation behavior: with the presence of young children in the household, females spent almost two more hours on home production, 25 minutes less on sleeping/personal care, and an hour and 20 minutes less working. The effect on female time allocation of having one additional household member was the same in sign to that of the presence of young children, but of lesser magnitude. The largest effect of having an additional member was on the female’s time allocation to home production, which increased by 42 minutes. Being a homeowner increased time allocation to home production and leisure for both males and females, and females’ time allocation to sleep/personal care. However it reduced time allocated to market work for both males and females, and males’ time for sleep/personal care. Compared to other variables, age and education had a minimal effect on time allocation behavior. Age had a negative effect on males’ market work time but a positive effect on males’ sleep/personal care time. Higher education increased females’ market work time, but decreased females’ leisure time and males’ market work time. The negative relationship between education level and males’ market work time was quite unexpected. At the same education level, females spent more time on market work than did their male counterparts.

Neither Kitamura nor Flood accounted for time allocation to travel in their studies. Kraan (1996), on the other hand, formulated a model whose utility function included five terms: time allocated to out-of-home/non-work activities, total distance traveled, frequency of out-of-home/non-work activities, time allocated to in-home/non-work activities, and total amount of money spent on consumption goods and services. Total travel time entered the model via the time constraints; travel time was expressed as the ratio of total distance traveled and the average speed. Her formulation sets the marginal utility with respect to each of these five arguments as positive and diminishing. This is based on the assumption that *ceteris paribus*, one would prefer to have more of each of these five arguments, but that the marginal impact of an additional unit declines the more one already has.

Through the above formulation, Kraan was able to derive closed-form non-linear demand functions for the five arguments of the utility function. Due to the unavailability of data, the
empirical application of the above model was conducted by forgoing the monetary budget constraint. In estimation, Kraan used the Netherlands Time Budget Survey Data of 1990. She estimated the demand functions for the entire sample and all activities, for the entire sample and only discretionary activities, and for various population groups by all activities and only discretionary activities. In the estimation that involved all activities and all subjects in the sample, she found that time allocations to out-of-home/non-work activities, in-home/non-work activities, and travel increased with the total time budget (measured as 24 hours minus the hours needed for sleep). The increase was the largest for out-of-home/non-work activities. The increases for in-home activities and total travel time were similar in terms of their magnitude. In the estimation that involved only discretionary activities and all subjects in the sample, Kraan found that the largest (and positive) effect of the total time budget was on in-home/non-work activities. Time allocated to out-of-home/non-work activities also increased with the total time budget, but (in contrast to the model including all activities) total travel time decreased with the total time budget.

For the estimation that compared different population groups and for all activities, Kraan divided the sample into six clusters based on employment status, including full-time workers, part-time workers, students, housewives, pensioners, and unemployed. Demand functions were estimated for each of these clusters. Additional demand functions were estimated for students living on their own (a subgroup within the students cluster) and for single workers, which includes single workers from both full-time workers and part-time workers. Kraan found that except for time allocated to in-home/non-work activities for single workers and total travel time for single workers, all estimated slope coefficients were significant at a 95% confidence level. Kraan also estimated the demand functions for only discretionary activities for the same set of clusters. Again, she found that all slope coefficients were significant at a 95% confidence level, meaning a significant impact of the total time budget on all types of time allocation for all types of population groups.

3. Proposed New Utility Maximization Model

Due to the endogenous relationship between activity duration and travel time, we believe it is important to incorporate both terms into the utility function. Neither Kitamura’s nor Flood’s models accounted for time spent on travel. Kraan’s model incorporated both activity duration and travel time into the utility function, but she did not address the linkage between activities and the minimum travel time required to reach them. We take Evans’ (1972, p.10) model as the starting point for our purpose. Evans noted that the problem with the traditional utility theory is assuming that every consumer is free to “allocate his time among activities in any way he/she chooses” (1972, p.10). He noted that there is distinction between the time a consumer must spend at the minimum and the time a consumer wishes to spend. This distinction may be found in most of our daily activities. For example, we may not wish to spend 8 hours a day working, but we must. We may only wish to spend 10 minutes commuting every day, but we must spend half an hour commuting. In Evans’ model, he recognizes this distinction by creating a linear constraint between the time one spends on an activity and the time he or she must travel to that activity.

Evans’ model is formulated as follows:
Max.

\[ U = u(a_w; a_t, a_c; a_i) \]

Subject to:

\[ a_w + a_t + a_c + \sum a_i = T \]
\[ b a_c - a_t \leq 0 \]
\[ r_w a_w + r_t a_t + r_c a_c + \sum r_i a_i = 0 \]

where,

- \( i \) is the \( i \)-th activity,
- \( a_w \) is the time spent on working,
- \( a_t \) is the time spent on traveling to the cinema,
- \( a_c \) is the time spent at the cinema,
- \( a_i \) is the time spent on the \( i \)-th activity,
- \( r_w < 0 \) is the individual’s rate of pay,
- \( b \geq 0 \) is the number of units of travel time (generally fractional) associated with one unit of time spent at the cinema,
- \( T \) is the total time available, and
- \( r_w, r_t, \) and \( r_i > 0 \) are the direct financial costs per hour of the time spent traveling, of the time spent at the cinema, and of the time spent on the \( i \)-th activity respectively.

In the model described above, the individual is assumed to maximize a utility function that includes time spent on work, cinema, other activities, and time spent on traveling to the cinema. The utility function is subject to three constraints. The first constraint is a time constraint. The second constraint states that for every hour the individual spends at the cinema, he must spend at least \( b \) hours traveling. For example, if \( b = \frac{1}{4} \) and \( a_c = 2 \) hours, then \( a_t \geq 30 \) minutes, meaning that for two hours’ time at the cinema, the individual must spend at least 30 minutes traveling. The third constraint is a budget constraint, indicating that all expenses must be exactly equal to the total income available, which is expressed as the product of rate of pay and hours of working.

Evans’ model essentially matches our desired model framework. Instead of accounting for every single activity, we want to account for three categories of activities (mandatory, maintenance, and discretionary) in addition to travel. In our case, the time spent on travel is not the time spent on going to a single activity, but the total travel time spent throughout a certain period. For the budget constraint, we also want to include the cost of other goods and services as well as unearned income. These considerations lead to a modified Evans’ model as follows:

Max.

\[ V(a_w, a_m, a_d, a_t, G) \]

subject to:

\[ a_w + a_m + a_d + a_t = \tau, \quad a_w, a_m, a_d, a_t \geq 0, \]
\[ c_m a_m + c_d a_d + c_t a_t + G = w \cdot a_w + Y, \]
\[ a_t \geq b_w a_w + b_m a_m + b_d a_d, \quad b_w, b_m, b_d \geq 0, \]

where

- \( a_w \) is the time spent on working,
- \( a_m \) is the time spent on maintenance activities,
- \( a_d \) is the time spent on discretionary activities,
$a_t$ is the time spent on travel,
$G \geq 0$ is the cost of other goods and services consumed,
$\tau$ is the total time available,
$c_m$ is the unit cost of maintenance activities,
$c_d$ is the unit cost of discretionary activities,
$c_t$ is the unit cost of travel,
$w$ is the wage rate,
$Y$ is all unearned income including dividends, interest, etc., and
$b_w, b_m, \text{ and } b_d$ are the number of units of travel time (generally fractional) associated with one unit of time spent on work, maintenance, and discretionary activities, respectively.

In the above formulation, the first constraint is the time constraint while the second constraint is the monetary constraint. In the last constraint, we assume a linear inequality relating the time allocated to activities and the travel to engage in those activities. The linear specification is probably quite a simplification of reality, nevertheless it serves as a first step toward modeling the relationship between activity duration and travel time expenditure. This constraint hypothesizes that each unit of time spent on an activity requires at least $b$ units of travel time. If the individual derives only negative utility from travel, he will not spend more than the required minimum on travel. If the individual also derives positive utility from travel (e.g., one may well derive positive utility from driving through Yosemite National Park), he may spend more than the required minimum on travel. In the discussion of this approach, we will set this constraint to an equality. The equality constraint represents the boundary condition, for the case where the individual wants to spend exactly the required minimum amount of time on travel. When the equality constraint is applied even in the case where the individual wants to spend more than the required minimum amount of time on travel, the positive utility derived from travel is reflected in inflated estimates of the $b$'s.

Our next task is to derive demand functions for the arguments of $V$ from the above model framework. We could specify a particular utility function as Kitamura and Kraan did, and then derive the demand functions from it. Alternatively due to duality between utility and cost, we could derive demand functions from a cost function. We decided to derive demand functions from a cost function because then the derived demand functions are “first order approximations to any set of demand functions derived from utility-maximizing behavior” (Deaton and Muellbauer, 1980, p. 315). There are different ways to derive demand functions from a cost function, such as the Almost Ideal Demand System, abbreviated as AIDS (Deaton and Muellbauer, 1980), the Rotterdam model (Theil, 1965, 1976) and the translog model (Christensen, et al., 1975). Due to its overall advantages over other models (Deaton and Muellbauer, 1980), we decided to use the AIDS approach. We describe the derivation of demand functions via AIDS below.

Let us first examine the constraint: $a_w + a_m + a_d + a_t = \tau$, which can be rewritten as: $a_t = \tau - a_w - a_m - a_d$. In other words, we only need to solve the demand functions for $a_w$, $a_m$, and $a_d$. As noted earlier, we will also set the inequality constraint: $a_t \geq b_w a_w + b_m a_m + b_d a_d$, to
an equality constraint: \( a_i = b_w a_w + b_m a_m + b_d a_d \). Substituting \( a_i \) in the constraint: \( c_m a_m + c_d a_d + c_i a_i + G = w_a a_w + Y \), we obtain the following equation:

\[
(-w + c_b) a_w + (c_m + c_i b_m) a_m + (c_d + c_i b_d) a_d + G = Y .
\]

Let

\[
\begin{align*}
p_w &= -w + c_b, \\
p_m &= c_m + c_i b_m, \\
p_d &= c_d + c_i b_d, \text{ and} \\
p_G &= 1.
\end{align*}
\]

We then can re-write the constraint as: \( p_w a_w + p_m a_m + p_d a_d + p_G G = Y \). Following the notation of Becker (1965), we may term \( p_w, p_m, \) and \( p_d \) as full prices of maintenance, discretionary and work activities, that is, the cost of the activity itself plus the cost of the required associated travel time. The full price of the work activity is negative, representing the net income earned by that activity. \( p_G \) is the price of other consumption goods, which is set to be 1. This revised constraint conforms to the usual monetary budget in classical microeconomics problems.

Following the approach of Deaton and Muellbauer (1980), any arbitrary cost function can be approximated by the following function, provided that: \( \sum_i \alpha_i = 1, \sum_j \gamma_{ij} = \sum_i \gamma_{ij}^i = \sum_j \beta_j = 0 \): \[
\log c(u, p) = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_k \sum_j \gamma_{ij}^k \log p_k \log p_j + \mu \prod_k p_k^\beta_k
\]

where

\[
\begin{align*}
\log c(u, p) & \text{ is the logarithm of the cost function,} \\
u & \text{ is the utility level, } 0 \leq u \leq 1, \\
p & \text{ is a vector of prices for various goods and services, and} \\
\alpha_0, \alpha_k, \gamma_{ij}^k, \mu, \beta_0, \beta_k & \text{ are parameters.}
\end{align*}
\]

Any cost function has a fundamental property: \( \partial c(u, p) / \partial p_i = q_i \), where \( q_i \) is the quantity of the \( i \)-th good or service or the duration of performing the \( i \)-th activity (the \( \alpha_s \) in our notation). \( \partial c(u, p) / \partial p_i = q_i \) can be re-written as: \[
\frac{\partial \log c(u, p)}{\partial \log p_i} = \frac{p_i q_i}{c(u, p)} = w_i ,
\]

where \( w_i \) is the budget share of good \( i \). From this property, Deaton and Muellbauer (1980) derived demand functions for the budget share of good \( i \), called the Almost Ideal Demand System (AIDS). As our formulation of the model has conformed to the classical microeconomic problem, we can now apply the AIDS system in our context. The demand functions for \( a_w, a_m, a_d \) and \( G \) in the share form can be derived as follows:

\[
\begin{align*}
\frac{p_w a_w}{Y} &= \alpha_w + \gamma_{ww} \log p_w + \gamma_{wm} \log p_m + \gamma_{wd} \log p_d + \beta_w \log(Y / P), \\
\frac{p_m a_m}{Y} &= \alpha_m + \gamma_{mw} \log p_w + \gamma_{mm} \log p_m + \gamma_{md} \log p_d + \beta_m \log(Y / P),
\end{align*}
\]
\[
\frac{p_d a_d}{Y} = \alpha_d + \gamma_{dw} \log p_w + \gamma_{dm} \log p_m + \gamma_{dd} \log p_d + \beta_d \log(Y / P),
\]
\[
G \quad \frac{Y}{Y} = \alpha_G + \gamma_{Gw} \log p_w + \gamma_{Gm} \log p_m + \gamma_{Gd} \log p_d + \beta_G \log(Y / P),
\]
where

\[
\log P = \alpha_0 + \alpha_w \log p_w + \alpha_m \log p_m + \alpha_d \log p_d + \frac{1}{2} \gamma_{ww} (\log p_w)^2 + \frac{1}{2} \gamma_{wm} \log p_m \log p_w + \frac{1}{2} \gamma_{wd} \log p_d \log p_w + \frac{1}{2} \gamma_{md} \log p_m \log p_d + \frac{1}{2} \gamma_{dd} (\log p_d)^2,
\]

and

\[
\gamma_{ij} = \frac{1}{2} (\gamma_{ij}^* + \gamma_{ji}^*).
\]

Setting \( \gamma_{mw} = \gamma_{wm} \), \( \gamma_{dw} = \gamma_{wd} \), and \( \gamma_{dm} = \gamma_{md} \), \( \log P \) can be written as follows:

\[
\log P = \alpha_0 + \alpha_w \log p_w + \alpha_m \log p_m + \alpha_d \log p_d + \frac{1}{2} \gamma_{ww} (\log p_w)^2 + \gamma_{mw} \log p_m \log p_w + \gamma_{dw} \log p_d \log p_w + \frac{1}{2} \gamma_{mm} (\log p_m)^2 + \gamma_{dm} \log p_d \log p_m + \frac{1}{2} \gamma_{dd} (\log p_d)^2.
\]

In the above system of demand functions, parameters to be estimated include \( \alpha_0, \alpha_w, \alpha_d, \alpha_m, \alpha_G, \beta_w, \beta_d, \beta_m, \beta_G, \gamma_{ww}, \gamma_{mw}, \gamma_{wm}, \gamma_{mm}, \gamma_{dd}, \gamma_{dm}, \gamma_{md}, \gamma_{Gw}, \gamma_{Gm}, \gamma_{Gd}, \) and \( \gamma_{Gd} \). Variables whose values are known include \( a_w, a_d, a_m, a_t, \) and \( G \) as well as \( Y \). For \( p's \), the \( c's \) are known and the \( b's \) can be calculated for each individual in the data set. Once the \( b's \) are calculated, other parameters of interest can be estimated. It is worth noting that the \( b's \) are not exogenous but endogenous, as the time allocation between in-home and out-of-home activities and within out-of-home activities may change according to various circumstances. Instead of each individual having his or her own \( b's \), there may be a pattern that people with particular socio-economic characteristics have similar \( b's \). Certainly more research is called for into this area.

One advantage of the AIDS system is that the demand functions do not require the assumption of utility maximization. If utility maximizing behavior is not assumed, the budget shares can be viewed as “unknown functions of \( \log p \) and \( \log \{Y\} \)” (Deaton and Muellbauer, 1980, p. 315). In this case, we relax the restrictions imposed earlier: \( \sum_i \alpha_i = 1, \sum_j \gamma_{ij} = \sum_k \gamma_{ij} = \sum_j \beta_j = 0 \).

These restrictions (adding up, homogeneity and symmetry) are imposed to make the model consistent with utility maximization. In an actual estimation, these restrictions (except adding up) may be checked to see if the demand functions reflect behavior under the utility maximization framework. This represents a significant advantage over models directly derived from a utility maximization framework (e.g., Kitamura’s and Kraan’s models) because we are not restricted to demand functions based on utility maximization and yet we have the freedom to check restrictions that make the model consistent with the utility maximization model.

In the actual estimation of the model, specification of the monetary constraint can be quite a problem. The wage rate is easy to determine but the unit costs of maintenance and discretionary
activities and travel are difficult to determine due to the tremendous variation in costs from individual to individual. The difficulty is also aggravated by the lack of data on the costs of different activities and travel. Most time use studies only collect information on subjects’ time use, not their monetary expenditures. Therefore, in the actual estimation of the model, one may have to forgo the monetary constraint entirely (as Kraan did), in which case, the model formulation is expressed as follows:

Max.

\[ V(a_w, a_m, a_d, a_t) \]
subject to:
\[ a_w + a_m + a_d + a_t = \tau, \text{ and } a_t = b_w a_w + b_m a_m + b_d a_d. \]

The two constraints can be consolidated into one by substituting the second constraint into the first time constraint. The consolidated constraint can be expressed as follows:

\[ (1 + b_w) a_w + (1 + b_m) a_m + (1 + b_d) a_d = \tau. \]

The consolidated constraint again conforms to the classical microeconomic problem, by setting \( p'_w = 1 + b_w, \ p'_m = 1 + b_m, \) and \( p'_d = 1 + b_d \). Similarly, the demand functions for \( a_w, a_m, \) and \( a_d \) in the share form can be derived as follows:

\[ \frac{p'_w a_w}{\tau} = \alpha_w + \gamma_{ww} \log p'_w + \gamma_{wm} \log p'_m + \gamma_{wd} \log p'_d + \beta_w \log(\tau / P'), \]
\[ \frac{p'_m a_m}{\tau} = \alpha_m + \gamma_{mw} \log p'_w + \gamma_{mm} \log p'_m + \gamma_{md} \log p'_d + \beta_m \log(\tau / P'), \]
\[ \frac{p'_d a_d}{\tau} = \alpha_d + \gamma_{dw} \log p'_w + \gamma_{dm} \log p'_m + \gamma_{dd} \log p'_d + \beta_d \log(\tau / P'), \]

where
\[ \log P' = \alpha_0 + \alpha_w \log p'_w + \alpha_m \log p'_m + \alpha_d \log p'_d + \frac{1}{2} \gamma_{ww} (\log p'_w)^2 + \frac{1}{2} \gamma_{mm} (\log p'_m)^2 + \frac{1}{2} \gamma_{dd} (\log p'_d)^2. \]

Similarly, by setting \( \gamma_{mw} = \gamma_{wm}, \ \gamma_{dw} = \gamma_{wd}, \) and \( \gamma_{dm} = \gamma_{md}, \) we obtain the following function.
\[ \log P' = \alpha_0 + \alpha_w \log p'_w + \alpha_m \log p'_m + \alpha_d \log p'_d + \frac{1}{2} \gamma_{ww} (\log p'_w)^2 + \gamma_{mm} (\log p'_m)^2 + \gamma_{dd} (\log p'_d)^2. \]

Calculation of the \( b \)'s and the estimation of parameters of interest are the same as stated above.
4. Estimation Issues

In this paper, we have discussed how a single linear equation, structural equations modeling, and duration analysis can be (and have been) applied to model travel time and money expenditures. The advantage of the single linear equation approach is its simplicity to estimate and interpret. The disadvantage is its inability to handle the potential association between activity duration and travel time expenditure correctly. Although the demand functions in our model do not explicitly include activity duration and travel time, the $b$’s are calculated by using activity duration and travel time and thus we consider that the demand functions implicitly include activity duration and travel time. Given this, if OLS estimation were used, it would result in inconsistent and biased estimates. Due to the endogeneity with activity duration, one may use 2SLS in which one first regresses activity duration against a number of exogenous variables and obtains the predicted values of activity duration, and then regresses travel time expenditure using the predicted values of activity duration.

In view of the potential association between travel time expenditure and activity duration, it may be more insightful to examine both ends of the relationship. One may hypothesize that not only does activity duration affect travel time expenditure, but also vice versa. The single linear equation is incapable of examining this two-way relationship, even with 2SLS. Additionally, because 2SLS still estimates two single linear equations separately, the information contained in both equations is not fully utilized. To remedy this problem, one may regress equations for activity duration and equations for travel time expenditure simultaneously and this is where seemingly unrelated regression equations and structural equations modeling come into the picture. A seemingly unrelated equations system assumes exogeneity of the explanatory variables but allows correlation of error terms across equations. The structural equations system goes one step further, allowing endogeneity of explanatory variables.

None of the above models account for the dependence of the choice of whether to terminate travel on the duration of the endogenous variables themselves. This sometimes becomes undesirable because one may hypothesize that the longer a person has traveled, the more likely he is to terminate that travel. In this case, the likelihood that a trip will be terminated (and hence affect total travel time expenditure) depends upon how long the trip has lasted. Duration models are designed to account for such a dependence.

Despite their promising aspects, duration models are not without problems. In application, it is often assumed that not only the duration of the dependent variable itself, but also other explanatory variables affect the likelihood that the spell (dependent variable) will terminate. In order to obtain consistent estimates, the set of explanatory variables entered must be exogenous. This can hardly be the case if duration models were applied in our context to model travel time expenditure, due to the endogeneity of activity duration. Like the single equation approach, duration models are incapable of examining the two-way relationship between activity time expenditure and travel time expenditure, as can be done with a structural equations system. Another issue that arises if duration models were applied in our context is that the estimated travel time expenditure is the total duration of multiple spells of travel during the study period (e.g., a week). In other words, the travel time expenditure of interest is not continuous. This may well complicate the shape of the hazard rate curve.
The above considerations lead us to recommend the Structural Equations System as a theoretically superior way to estimate the derived demand functions. In practice, the differences in results obtained from different estimation methods may vary from study to study. Flood (1985) used single linear equations, structural equations modeling, and utility maximization to analyze data on household allocation. He concluded that results (in terms of signs of coefficients) were similar for these approaches. It would be desirable to conduct additional comparative studies of this nature, but Flood’s results suggest a certain amount of robustness with respect to the modeling approach taken.

5. Data Needs

Although differing in the way that models are estimated, for each of the approaches we have described, we would expect travel time and activity duration and expenditure to be a function of the same set of variables. Specifically, for application of any of these methodologies, ideally the following set of variables is needed:

- duration of travel over a study period,
- duration of activities over a study period,
- money allocation to travel,
- money allocation to activities,
- expenditures on other goods and services,
- personal and household characteristics,
- transportation network-related characteristics, and
- other variables including personality, lifestyle, and attitudinal variables.

A measure of the duration of travel over a study period is obviously unavoidable if one is interested in travel time allocation. Similarly, if one is also interested in monetary expenditure on travel, the cost of the observed travel needs to be measured. Collection of information on activities is mainly due to the belief in the existence of a linkage between activities and travel. In fact, a number of empirical studies have verified the existence of such a linkage. From the resource perspective, the linkage between activities and travel exists because every one of us faces finite budgets in terms of time and money. From the conceptual perspective, the linkage exists because engaging in certain activities comes with a travel “overhead”. Empirical evidence has also shown that variables identifying personal and household characteristics as well as transportation network-related characteristics are important in individuals’ travel time and money allocation behavior. Other variables such as attitudes may also play an important role in travel time and money allocation and warrant further investigation.

In a typical activity diary, duration of activities is usually measured and duration of travel can be derived. Similarly, in a typical trip diary, duration of travel is usually measured and duration of activities can be derived. Generally, a trip diary also collects out-of-pocket travel-related expenditures, such as parking fees, transit fares, and tolls. The operating cost of a personal vehicle may be calculated based on the mileage. As for activity-related costs, neither activity nor trip diaries usually collect this information. The same applies to expenditures on other goods and services. In other words, to examine a complete picture of travel time and money allocation, a
new data collection effort may be needed to collect information on activity-related costs and expenditures on other goods and services. Information on personal and household characteristics is usually collected along with either an activity or trip diary. Information on transportation network-related characteristics can be obtained from land use and travel surveys. If the researchers are interested in testing the significance of other variables (e.g., attitudinal variables), data collection on these variables may need to be initiated as they are not generally measured in travel or activity diary studies.

We consider the ideal study period to be relatively long – for example, a week or a month or even a year. This would allow the capture of activities and travel that people do not conduct on a daily basis. Examples include long distance business travel and vacation travel. In addition, by using a long study period, we avoid the situation where the amount of time allocated to a particular type of activity is zero (in the utility maximization framework, for mathematical tractability it is often assumed that the amount of time allocated to each type of activity is greater than zero). In reality, of course, obtaining data for longer than a few days is problematic due to the burden it imposes on the participant. However, recent advances in the use of devices involving Global Positioning Satellite technology to automatically collect real-time data on geographical location may make long-term data collection more practical.

Although having access to all of the variables listed above would be ideal, the lack of some of them would not necessarily invalidate a modeling effort. For example, even though data on money allocation may not be available, it is still productive to analyze travel time allocation. Many interesting research questions on travel time allocation exist and these research inquiries well deserve a modeling effort. For example, one might want to investigate the applicability of duration models in our context. Or, one might want to simply apply our utility maximization framework with real-world data sets and test the theoretical framework.

Tables 1 and 2 list four selected available data sets in the US. The Nationwide Personal Transportation Survey (NPTS) collected information on individuals throughout the US while the other three are regional household surveys. All of these would permit (with varying levels of accuracy) the estimation of time expenditures on travel and activities. All but the NPTS have data on travel costs; none have data on activity costs. All contain some data on personal and household characteristics. Transportation network characteristics could be inferred for the three regional data sets. The NPTS and the Puget Sound data sets also contain a limited amount of attitudinal data.

(Tables 1 and 2 go about here)

The Puget Sound Transportation Survey is a panel survey that started in 1989. In a panel survey, information on sample households and individuals is collected at multiple times throughout a study period that usually lasts multiple years. As time progresses, the households and individuals who drop out are replaced by newly-recruited households and individuals with similar characteristics. Use of panel surveys has many advantages in travel behavior analysis and these advantages are readily applicable in our context.
By examining multiple measurements for the same observation unit, many unobserved factors can be controlled and thus more precise measurement of behavioral changes can be obtained (Kitamura, 1990). For example, typical cross-sectional studies might attribute the differences in travel behavior to age differences while in fact the difference should be attributed to a generation effect. Or if there were a period effect (e.g., the effect of oil embargo years on travel behavior), a typical cross-section survey cannot detect it.

Panel survey analysis can also be very useful in forecasting. The validity of applying results from a cross-sectional data set to forecast the future must be based on the following conditions (Kitamura, 1990, p. 402). First, “behavioral changes are instantaneous.” Second, “behavioral changes are symmetric, or reversible.” And last, the “behavioral relation is stationary (invariant over time).” Evidence from recent literature and our own observations of daily lives casts serious doubts on these conditions. Behavioral change over time is a gradual, dynamic adaptation to the stimuli and this process may involve time lags and asymmetry. Panel data sets can be used to model these dynamic behavioral changes more precisely than cross-sectional data sets.

The many advantages of panel data sets do not come without drawbacks. When using panel data sets in modeling, researchers must also handle problems such as attrition (households/individuals who drop out in later waves) and panel conditioning (the responses in later waves are influenced by responses in early waves). And these problems usually imply that more complicated modeling procedures ought to be used. Therefore, the decision on whether to use a panel data set must be weighed carefully in the modeling effort.

6. Conclusions

In this paper, we review several methodologies that have been used to model travel/activity time allocation. Further, we use a utility maximization framework to propose a new model of travel time and money expenditures. The utility maximization framework allows us to construct individuals’ time allocation behavior in a meaningful way. We derive the demand functions through a flexible form cost function and the derived demand functions are first order approximations to any set of demand functions, whether based on the utility maximization principle or not. We are also able to build the special relationship between activity duration and travel time into the constraint set. If data are available, a monetary constraint can also be added. This theoretical development marks an improved way to model travel time and money expenditures.

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<table>
<thead>
<tr>
<th>Data Sets</th>
<th>Location</th>
<th>Survey Year</th>
<th>Administration</th>
<th>Sample Size</th>
<th>Diary Period</th>
<th>Cost</th>
<th>Contact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nationwide Personal Transportation Survey</td>
<td>USA</td>
<td>May, 1995 to July, 1996</td>
<td>Telephone interview</td>
<td>42,000 households (all hhld. members who are 5 years or older)</td>
<td>1 day</td>
<td>Free</td>
<td><a href="http://www-cta.ornl.gov/npts/1995/download_table.shtml">http://www-cta.ornl.gov/npts/1995/download_table.shtml</a></td>
</tr>
<tr>
<td>Oregon and Southwest Washington</td>
<td>Portland, Oregon</td>
<td>Spring, 1994 to Winter 1995</td>
<td>Telephone and mail-back surveys</td>
<td>4,451 hhlds for RP data; 3,244 hhlds for SP data</td>
<td>2 days</td>
<td>Free to research organizations</td>
<td>Kyung-Hwa Kim at <a href="mailto:kimk@metro.dst.or.us">kimk@metro.dst.or.us</a></td>
</tr>
<tr>
<td>Bay Area Household Survey</td>
<td>9 counties including San Francisco, San Mateo, Santa Clara, Alameda, Contra Costa, Solano, Napa, Sonoma, and Marin</td>
<td>2000</td>
<td>Random Digit Dialing (RDD) recruitment, telephone reminder calls, mail-back surveys, and CATI data retrieval</td>
<td>15,000 households</td>
<td>2 days</td>
<td>Free to research organizations</td>
<td>For additional information, contact MTC planning staff at 510-464-7700. Also see <a href="http://www.mtc.dst.ca.us/datamart/index.htm">www.mtc.dst.ca.us/datamart/index.htm</a></td>
</tr>
<tr>
<td>Puget Sound Transportation Panel Survey 1989-2000</td>
<td>4 counties including King, Kitsap, Pierce, and Snohomish</td>
<td>1989-2000</td>
<td>Random Digit Dialing (RDD), and mail-back surveys</td>
<td>About 1700 households</td>
<td>2 days</td>
<td>Free to research organizations</td>
<td>For additional information, contact PSRC planning staff at 206-464-7964</td>
</tr>
</tbody>
</table>
Table 2: Components of Selected US Data Sets

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Types of Data Collected</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nationwide Personal Transportation Survey (NPTS)</td>
<td>Stated Preference</td>
<td>Household: Household size, number of household vehicles, income, location</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Person: Age, gender, education, relationship within the household, driver status, annual miles driven if a worker</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Attitudes: Rating of potential problems in traveling, such as mobility, congestion, safety, traffic conditions, and pavement conditions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vehicle: Annual miles driven (based on odometer readings recorded typically two months apart), make, model, model year</td>
</tr>
<tr>
<td></td>
<td>Revealed Preference</td>
<td>Trip level: Trip purpose, mode, length (in miles and minutes), time of day, vehicle characteristics (if a household vehicle was used), number of occupants, driver characteristics (for private vehicle trips only and if a household member was driving)</td>
</tr>
<tr>
<td>Oregon and Southwest Washington Household Activity and Travel Surveys</td>
<td>Stated Preference</td>
<td>Pricing effects (roads, congestion and parking)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Residential location choice</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Automobile acquisition</td>
</tr>
<tr>
<td></td>
<td>Revealed Preference</td>
<td>Household: Address, size, survey dates, structure, income, number of phone lines, number of cell or car phones, presence/absence of visitors on the survey date, tenure at the current address, zip code of previous address, own or rent, number of vehicles, shared phone lines, and transportation disability</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Person: Gender, race, English proficiency, employment status, age, household language, drivers’ license, student status, employee-related information, and student-related information</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Activity: Type, location, starting and ending times, duration, accompanying young people</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Trip: Mode, starting and ending times, cost</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vehicle: Year, make, model, type, year purchased, fuel type, ownership, purchased as a replacement or add-on, odometer reading at beginning of the 1st survey day and at the end of the 2nd survey day</td>
</tr>
</tbody>
</table>
Table 2: Components of Selected US Data Sets (Continued)

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Types of Data Collected</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bay Area Household Survey</strong></td>
<td>Stated Preference</td>
<td>Pricing effects on cost and travel time</td>
</tr>
<tr>
<td></td>
<td>Revealed Preference</td>
<td>Household size, income, type of dwelling, address</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Person Gender, age, driver’s license, employment status, number of jobs, industry, occupation, length of employment, student status, student level, race, income</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Activity Type, location, starting and ending times</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Trip Mode, destination, starting and ending times, vehicle used, number of people accompanying, parking cost, parking location, transit route, fare, type of payment, whether across the Bay or not, etc.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vehicle Number of vehicles, make, model, year, fuel efficiency, number of bicycles</td>
</tr>
<tr>
<td><strong>Puget Sound Transportation Panel Survey 1989-1996</strong></td>
<td>Stated Preference</td>
<td>None</td>
</tr>
<tr>
<td></td>
<td>Revealed Preference</td>
<td>Household Household income, lifecycle stage, household size, number of adults, number of children in different age groups, number of household vehicles, change of residence, zip code, census tract, traffic analysis zone etc.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Person Age, gender, employment status, occupation, city code for work location, travel mode to/from work, number of work days per week, frequency that children are picked up, travel mode to/from school, frequency using bus per week, have transit pass or not, driver’s license, parking costs, panel participation, occupation change code, workplace change code, work zip code, work census tract, work traffic analysis zone etc.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Attitudes Importance ratings of travel attributes (e.g., safety, on time), performance ratings of alternative travel modes (SOV, bus, carpool), agreement and disagreement statements related to features of alternative modes, importance ratings of alternative improvements in land use, transportation, and environment.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Trip Mode, starting and ending times, cost, vehicles used, trip origin census tract, trip origin traffic analysis zone, trip destination census tract, trip destination traffic analysis zone, travel distance, etc.</td>
</tr>
</tbody>
</table>