Modeling the Commute Activity-Travel Pattern of Workers: Formulation and Empirical Analysis

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Abstract

This paper proposes a methodological framework to analyze the activity and travel pattern of workers during the evening commute. The framework uses a discrete-continuous econometric system to jointly model the decision to participate in an activity during the evening commute and the following attributes of the participation: activity type, activity duration, and travel time deviation to the activity location relative to the direct travel time from work to home. The model parameters are estimated using a sample of workers from the 1991 Boston Household Activity Survey. The paper also presents the mathematical expressions to evaluate the effect of changes in socio-demographic variables and policy-relevant exogenous variables on the temporal pattern of trips and cold starts due to commute stops. The application of the model indicates that failure to accommodate the joint nature of the activity decisions during the evening commute can lead to misdirected policy actions for traffic congestion alleviation and for mobile-source emissions reduction.

Introduction

The analysis of commute trip patterns has always been of considerable interest in the travel demand literature since the commute pattern has a decisive impact on peak period traffic congestion on roadways. Several studies have examined commute patterns from metropolitan areas in the United States in the past decade. A consistent finding of these studies has been that the commute pattern is becoming more complex due to an increasing tendency to make nonwork stops during the commute, especially in the evening. For example, Lockwood and Demetsky (1994) noted that almost 44% of workers in the Washington D.C. metropolitan area make stops during the morning or evening commutes, and that individuals are almost twice as likely to make stops in the evening as in the morning. Bhat (1997a) found in another study using the 1991 Boston Household Travel Survey that about 38% of individuals made stops during the commute and that evening commute stop-making was about twice as prevalent as morning commute stop-making. Davidson (1991) found similar results from her analysis of commute behavior in a suburban setting. Other studies (such as Gordon *et al*., 1988 and Purvis, 1994) also provide empirical evidence of increased stop-making during the commute periods.

The discussion above highlights the importance of studying stop-making behavior during the work commute, especially during the evening commute. The focus of this paper is on examining evening commute stop-making behavior. The broad objective is to model the entire activity-travel pattern of the worker between the time s/he leaves work (the departure time from work is assumed to be exogenously determined based on the work schedule of the worker) to the time s/he returns home at the end of the evening commute. The attributes characterizing the evening commute activity-travel pattern include: a) number of stops (including zero stops, which implies that the worker heads home directly), b) sequence of stops (if the number of stops is more than one) c) activity type of each stop, d) activity duration of each stop, e) travel time deviation to each stop from previous stop (or from work if the stop is the first one) relative to the direct travel time from previous stop to home (we will refer to this simply as the travel time deviation from previous stop), and e) location of each stop (the travel mode used to the stop is almost always the same as the one used for the journey to work and so this dimension of the nonwork stop is not identified).

The dimensions of evening commute behavior listed above determine the spatial and temporal distribution of vehicular demand on roadways. In addition, the activity duration dimension determines the type of engine start for the trip subsequent to the stop. This information constitutes an important input to estimating mobile source emissions (an engine start is classified as a "cold" start if the engine is "off" for more than 60 minutes; a "cold" start leads to substantially higher mobile source emissions than a "hot" start).

The author has been involved in the development of a broader framework to model the entire daily activity-travel pattern of workers based on an empirical investigation of travel behavior from several metropolitan areas in the US (see Bhat and Singh, 1999). The investigation indicates that there is little interaction in after-work dimensions of activity-travel choices with activity behavior at earlier times of the day. This is because of the nature of activities pursued after work and at other times of the day. Most activities after work tend to be social-recreational or shopping-oriented, while activities at earlier times serve more basic functions (for example, serve-child activities during the before-work period and eating during the mid-day), or are personal business activities (banking, post office trips, *etc.*) which are unavailable for participation after work because of restricted open times of facilities. Based on these and other observations, Bhat and Singh have developed a comprehensive daily activity-travel pattern framework that includes a sub-model for the after-work activity pattern of workers. The current research contributes toward estimating such a sub-model within the scope of a larger daily activity pattern model.

The daily activity pattern framework of Bhat and Singh (1999) considers all attributes of an entire daily activity-travel pattern and emphasizes temporal detail by considering activity-travel patterns in the context of a continuous time domain. This is in contrast to earlier trip-chain and other activity scheduling models which focus on limited number of dimensions of the activity schedule and/or do not model the temporal dimension adequately. Bhat and Singh's framework is also able to accommodate space-time interactions because joint modeling of stop attributes is undertaken. The framework, at the same time, provides an overarching structure to allow interactions across patterns/tours in the day where such interactions are important. A potential down side to Bhat and Singh's framework is that the mathematical structures of the model components are not commonly used in travel demand modeling and are more sophisticated than traditional discrete choice models. But they are still rather easily estimated.

Work-related choices such as work participation and work schedule times (hours of work, departure time of work, *etc.*) are relatively longer-term decisions and are not modeled in the current paper. The view is that decisions on whether to work, where to work, and times of work are not determined on a day-to-day basis. These dimensions may be modeled prior to the analysis of daily activity-travel patterns, as done by Bhat and Koppelman (1993).

The joint modeling of all the dimensions characterizing the evening commute pattern is quite complex, if not infeasible. However, the modeling framework can be considerably simplified by noting that most individuals either travel home directly after work or make one stop. For example, a descriptive analysis of the 1991 Boston area household travel survey indicated that about 88.5% of individuals either traveled home directly after work or made one stop in the evening commute. The corresponding figure from a 1988 Washington D.C. household travel survey was 94.7%. A reasonable modeling strategy, then, is to focus on the presence/absence of a first stop (along with the various characteristics of this first stop), next model the presence/absence of a second stop (and the attributes of the second stop) conditional on the presence and characteristics of the first stop, and so on. An important point to note is that the number and sequence of stops is modeled implicitly in this proposed framework.

An alternative strategy to modeling evening commute non-work stops might be to model the stop with highest "priority" first (this is in contrast to our proposed approach of stop modeling based on temporal sequence). Unfortunately, the concept of "priority" is difficult to define. Even if a definition is developed, priority assignment can be very subjective and may even change for the same person from one time to another. For example, assume that activity type is used to determine priority. Shopping activity may be of higher priority than social-recreational activity for some individuals, but the reverse may be true for others. For the same person, shopping activity may be of higher priority if it involves the purchase of an essential item (say, milk) and if the corresponding social-recreational activity is a self-imposed appointment to exercise. On the other hand, on a different day, shopping activity may be of lower priority if it involves the purchase of a non-critical item and if the corresponding social-recreational activity involves an appointment with a colleague to play racquetball. A more fundamental problem with the use of activity type to determine priority is that activity type is an endogenous variable. It is part of the activity-travel behavior decisions of individuals which we would like to model. It cannot be used exogenously to inform the modeling process. Similarly, while activity duration and/or travel time deviation may be used to identify activity priority (for example, higher duration activities are assigned higher priority), this procedure would be flawed since activity duration and travel time deviation are endogenous variables of interest. To summarize, the alternative approach of prioritizing activities is difficult to use, is ad hoc, and is theoretically inappropriate. We prefer to use the simple and more straight-forward assumption of temporal sequentiality. Besides, given that most individuals make one commute stop (if a stop is made), the temporal sequencing structure is not likely to lead to substantial errors in forecasting. Adopting this assumption but modeling all the attributes of each stop jointly is, in our opinion, a better approach than purporting to capture interactions amongst stops but really capturing interactions only along a few dimensions, adopting a very restrictive interaction structure, modeling only a limited number of stop dimensions, and ignoring the jointness in choice dimensions for the same stop. Our proposed structure is based on the empirical finding in earlier studies that there are substantial interactions among choice dimensions for a particular stop (see Hamed and Mannering, 1993 and Bhat, 1998) and on the empirical finding that few individuals pursue multiple stops.

At each stop level of the framework, the dimensions to be modeled include the presence/absence of a stop, type of stop, activity duration of stop, travel time deviation from previous stop (or from work for the first stop), and location of stop. We further simplify this structure by focusing initially on the first four dimensions and proposing to model location of the stop subsequently by formulating a travel time-constrained destination choice model. Such an approach accommodates the spatial-temporal interactions in stop-making decisions. Thill and Horowitz (1997a) have recently demonstrated the importance of considering such interactions in determining the consideration set in a destination choice model.

In the rest of this paper, we will confine our attention to the modeling of the presence/absence of a first stop in the evening commute and the following attributes of the first stop: type of stop, activity duration, and travel time deviation to stop relative to the direct travel time from work to home. The location of the first stop may be modeled subsequently using disaggregate spatial destination choice models (the technical details of the formulation for such a destination choice model are available in Bhat, 1999). The same framework may then be applied to analyze additional evening commute stops.

There have been several earlier studies examining different aspects of stop-making behavior during the work commute. However, almost all these studies have focused on a limited number of dimensions characterizing the commute activity-travel pattern. For example, Oster (1979), Adiv (1983), Kondo and Kitamura (1987), Nishii *et al*. (1988), Strathman *et al*. (1994), and Bhat (1997b) focus only on whether individuals make one or more stops during the commute. These studies do not model the attributes characterizing the stops. Damm's (1980) study emphasizes the choice of stop-making (whether to make no stops or at least one stop) and the duration of time spent at the stop(s). Damm does not model activity type of the stop and the travel time involved in participating in the stop. The studies by Bhat (1996a,b) and Niemeier and Morita (1997) are narrowly focused on the duration of activity stops made during the commute. Hamed and Mannering (1993) and Murthy (1997) model all the relevant dimensions of a stop, but use sequential estimation methods (rather than a full-information maximum likelihood technique) to model the various dimensions. Further, both these studies (and another recent study on post-home activity behavior by Bhat, 1998) focus only on model estimation; they do not develop and implement procedures to examine changes in trip-making patterns and cold starts due to changes in policy-relevant or socio-demographic variables.

The distinguishing characteristic of the current study is that it jointly models the dimensions of stop-making choice, activity type, activity duration and travel time deviation, and also develops and applies appropriate techniques to examine the impact of changes in exogenous variables on trip-making patterns and cold-starts.

The next section of the paper presents the econometric structure of the joint model. Section 2 discusses the data source and sample used in the empirical analysis. Section 3 presents empirical results. Section 4 examines the impact of policy actions using the model. The final section summarizes the important findings from the research.

1. Methodology

The decision to make a first stop, activity type choice of the stop, activity duration of the stop and travel time deviation to the stop (relative to the direct work-to-home path) are modeled using a discrete/continuous econometric framework (see Bhat, 1998). The decision to participate in a first stop and the activity type choice together are represented as a discrete choice system, while activity duration and travel time deviation are the continuous decisions.

The joint nature of the decisions regarding whether to make a stop, the type of stop, the duration of the stop, and the travel time deviation to the stop arises because the choices are caused or determined by certain common underlying observed and unobserved factors (see Train, 1986; page 85). For example, a high income may lead to a) more stop-making during the commute, b) a higher propensity to participate in a particular out-of-home activity type (say recreation), c) a longer activity duration, and d) a higher travel time deviation. Thus, there is a jointness among the choices because of a common underlying observed variable. Similarly, an individual's intrinsic (unobserved) preference to be involved in a particular out-of-home activity type may manifest itself in the form of a high likelihood of participating in that activity type as well as a long activity duration of participation in that activity type and a willingness to travel farther to participate in that activity type. The association among the activity decisions in this case arises because of a common underlying unobserved preference measure.

In the following presentation, we will use the index i (i = 1,2,...,I) to represent both the participation choice and activity-type choice (subject to participation) with the notational convention that i = 1 identifies the choice of going directly home from work and higher values of i indicate participation in a stop of a particular type. The index q (q = 1,2,...,Q) is used to represent individuals. The equation system can be written as:

$$
\begin{aligned}
u_{qi}^{*} &= \beta_i' z_{qi} + \epsilon_{qi} \\
a_{qi} &= \theta_i' x_{qi} + \omega_{qi} \text{ for } i = 2,3,\ldots,I \\
t_{qi} &= \gamma_i' y_{qi} + \eta_{qi} \text{ for } i = 2,3,\ldots,I
\end{aligned}
\tag{1}
$$

u_{qi}^{*} is the indirect (latent) utility that the qth individual derives from either going home (i=1) or participating in an out-of-home activity type (i=2,3,...,I). a_{qi} is the logarithm of the activity duration of participation in out-of-home activity type i for the qth individual, and t_{qi} is the logarithm of the travel time deviation associated with participation in out-of-home activity type i for the qth individual. $z_{qi}, x_{qi},$ and y_{qi} are column vectors of exogenous variables and $\beta_i, \theta_i,$ and γ_i are corresponding column vectors of parameters to be estimated. We assume that the $\epsilon_{qi}'s$ are identically distributed across alternatives i and individuals q, and that they are independently distributed across individuals. We also assume that each of them has a location parameter equal to zero and that their joint (cumulative) distribution function, $H(\epsilon_{q1}, \epsilon_{q2}, ..., \epsilon_{qI})$, results in a nested logit structure with correlation among the error terms of the out-of-home activity types:

$$H(\epsilon_{q1}, \epsilon_{q2}, ... \epsilon_{qI}) = \exp\left\{ -\exp(-\epsilon_{q1}) - \left[\sum_{i=2}^{I} \exp\left(-\epsilon_{qi}/\delta \right) \right]^{\delta} \right\} \tag{2}$$

The δ term is a dissimilarity parameter that introduces correlation among the error terms of the out-of-home activity types (i=2,3,...,I). The $\omega_{qi}'s$ and $\eta_{qi}'s$ are assumed to be distributed identically across individuals. We specify a bivariate cumulative normal distribution function $\Phi_2(0,0,\sigma^2_{\omega_i},\sigma^2_{\eta_i},\rho_{\eta_i\omega_i})$ for ω_{qi} and η_{qi} in each out-of-home activity type regime i. $\sigma^2_{\omega_i}$ and $\sigma^2_{\eta_i}$ are the variances of the error terms ω_i and η_i, respectively, and $\rho_{\eta_i\omega_i}$ is the correlation between the two error terms.

We considered two alternative functional forms; linear and logarithmic; for activity duration and travel time deviation in equation (1). These are the two forms commonly used in the literature to model time duration (for example, Steinberg *et al*., 1980 use a linear functional form, while Hamed and Mannering, 1993 use a logarithmic form). We evaluated these functional forms on the basis of statistical fit and distribution of residuals. We found that the logarithmic form provided a superior statistical fit in both the activity duration and travel time deviation equations. We also found that the linear form yielded highly skewed distributions for the residuals in both equations. Therefore, we chose the logarithmic functional form for OH activity duration and home-stay duration. An additional advantage of the logarithmic functional form is that it guarantees the positivity of activity and travel time durations in forecasting.

The continuous variables a_{qi} and t_{qi} in equation (1) are observed if and only if the ith out-of-home activity type (i=2,3,...,I) is chosen. The alternative i (i=1,2,...,I) will be chosen by an individual if the utility of that alternative is the maximum of the I alternatives. Let R_{qi} be a dichotomous variable with values 0 and 1; $R_{qi} = 1$ if the ith alternative is chosen by the qth individual and $R_{qi} = 0$ otherwise. Defining

$$v_{qi} = \left\{ \max_{j=1,2,...I, j \neq i} u_{qj}^{*} \right\} - \epsilon_{qi}, \tag{3}$$

the utility maximizing condition for the choice of the ith alternative may be written as:

$$R_{qi} = 1 \text{ if and only if } \beta_i' z_{qi} > v_{qi} \tag{4}$$

Thus, we now have the situation that a_{qi} and t_{qi} are observed if and only if $v_{qi} < \beta' z_{qi}$ (i = 2,3,...,I). Let $F_i(v_{qi})$ represent the marginal distribution function of v_{qi} implied by the assumed joint distribution function $H(\epsilon_{q1}, \epsilon_{q2}, ..., \epsilon_{qI})$ and the relationship in equation (3). The random variable v_{qi} is non-normal because of the nested logit structure for the errors in the activity participation/type choice model. Following Lee (1983), let us transform this non-normal random variable into a standard normal random variable:

$$v_{qi}^{*} = J_i(v_{qi}) = \Phi^{-1}(F_i(v_{qi})), \tag{5}$$

where $\Phi(.)$ is the standard normal distribution function. Then, equation (4) can be written as

$$\begin{aligned} R_{qi} &= 1 \text{ if and only if } J_i(\beta_i' z_{qi}) > J_i(v_{qi}), \text{ or equivalently,} \\ R_{qi} &= 1 \text{ if and only if } J_i(\beta_i' z_{qi}) > v_{qi}^{*} \ . \end{aligned} \tag{6}$$

We can now write down the likelihood function for our model system based on equation (6) and the fact that a_{qi} and t_{qi} are observed only if $R_{qi} = 1$ (i=2,3,...,I). Let the correlation between v_{qi}^{*} and ω_{qi} be ρ_{ω_i} and that between v_{qi}^{*} and η_{qi} be ρ_{η_i} . Combined with the assumed marginal bi-variate distribution for ω_{qi} and η_{qi} and the standard normal marginal distribution of v_{qi}^{*} , this implies a trivariate normal distribution of $(v_{qi}^{*}, \omega_{qi}, \eta_{qi})$ for each out-of-home activity type i with a mean vector of zero and variance-covariance matrix:

$$\Sigma_i\,(i = 2,3,...I) \;=\; \begin{bmatrix} 1 & \rho_{\omega_i}\sigma_{\omega_i} & \rho_{\eta_i}\sigma_{\eta_i} \\ \rho_{\omega_i}\sigma_{\omega_i} & \sigma^2_{\omega_i} & \rho_{\eta_i\omega_i}\sigma_{\omega_i}\sigma_{\eta_i} \\ \rho_{\eta_i}\sigma_{\eta_i} & \rho_{\eta_i\omega_i}\sigma_{\omega_i}\sigma_{\eta_i} & \sigma^2_{\eta_i} \end{bmatrix}. \tag{7}$$

The parameters to be estimated in the model system are the β_i parameters in the activity participation/type choice model and the following parameters in the activity duration and travel time deviation equations for each out-of-home activity regime (i=2,3,...,I): $\theta_i, \gamma_i, \sigma_{\omega_i}, \sigma_{\eta_i}, \rho_{\omega_i}, \rho_{\eta_i}$, and $\rho_{\eta_i\omega_i}$. The likelihood function for estimating the parameters is quite complicated (though straightforward to derive). Define the following quantities for each out-of-home activity type i (i=2,3,...,I):

$$\begin{aligned}
g_{qi} &= (\sigma_{\eta_i})^{-1}\,(t_{qi} - \gamma_i' y_{qi})\;, \\
l_{qi} &= (\sigma_{\omega_i})^{-1}\,(a_{qi} - \theta_i' x_{qi})\;, \\
d_{qi} &= \left(\sqrt{1-\rho^2_{\eta_i\omega_i}}\right)^{-1}\,(l_{qi} - \rho_{\eta_i\omega_i} g_{qi})\,, \\
k_{qi} &= [(\rho_{\eta_i} - \rho_{\eta_i\omega_i}\rho_{\omega_i})g_{qi} + (\rho_{\omega_i} - \rho_{\eta_i\omega_i}\rho_{\eta_i})l_{qi}] \,/\, 1-\rho^2_{\eta_i\omega_i}\,, \\
\varrho_i &= \sqrt{1 - [(\rho^2_{\eta_i} - 2\rho_{\eta_i}\rho_{\omega_i}\rho_{\eta_i\omega_i} + \rho^2_{\omega_i})/(1-\rho^2_{\eta_i\omega_i})]}\,, \text{ and} \\
b_{qi} &= [\Phi^{-1}\left\{F_i(\beta_i' z_{qi})\right\} - k_{qi}] \,/\, \varrho_i\;.
\end{aligned} \tag{8}$$

The likelihood function to be maximized is:

$$\mathfrak{L} \;=\; \prod_{q=1}^{N} \left\{ [F_1(\beta_1' z_{q1})]^{R_{q1}} \prod_{i=2}^{I} \left[\frac{1}{\sigma_{\eta_i}\sigma_{\omega_i}\sqrt{1-\rho_{\eta_i\omega_i}}} \phi(g_{qi})\,\phi(d_{qi})\,\Phi(b_{qi}) \right]^{R_{qi}} \right\}, \tag{9}$$

where $\phi(.)$ is the standard normal density function, and

$$F_1(\beta_1' z_{q1}) = \frac{\exp(\beta_1' z_{q1})}{\exp(\beta_1' z_{q1}) + [\sum_{j=2}^{I} \exp(\beta_j' z_{qj}/\delta)]^{\delta}} \; ;$$

$$F_i(\beta_i' z_{qi}) = \frac{[\sum_{j=2}^{I} \exp(\beta_j' z_{qj}/\delta)]^{\delta}}{\exp(\beta_1' z_{q1}) + [\sum_{j=2}^{I} \exp(\beta_j' z_{qj}/\delta)]^{\delta}} \cdot \frac{\exp(\beta_i' z_{qi}/\delta)}{\sum_{j=2}^{I} \exp(\beta_j' z_{qj}/\delta)} \, , \; i = 2,3,\ldots,I. \tag{10}$$

It is easy to see that if ρ_{ω_i} and ρ_{η_i} are zero for all out-of-home activity types i (i=2,3,...,I), the likelihood function in equation (9) partitions into a component corresponding to the activity participation/type discrete choice model and another component representing the likelihood function for the seemingly unrelated regression model (see Greene, 1990; page 516) of the two continuous duration choices. The GAUSS matrix programming language is used in estimation. The standard error of parameters is computed from the cross-product matrix of the gradients evaluated at the estimated parameter values.

2. Data Source and Sample

The data source used in the present study is a household activity survey conducted by the Central Transportation Planning Staff (CTPS) in the Boston Metropolitan region. The survey was conducted in April of 1991 and collected data on socio-demographic characteristics of the household and each individual in the household (see Stopher, 1992). The survey also included a one-day (mid-week working day) activity diary to be filled out by all members of the household above five years of age. Each activity pursued by an individual was described by: a) start time, b) stop time, c) location of activity participation, d) travel time from previous activity, e) travel mode to activity location, and f) activity type.

The sample for the current analysis comprises 2285 employed adult individuals who made a work-trip on the diary day and were older than 16 years (complete details of the screening and data cleaning procedures employed in arriving at this sample from the overall activity diary data is provided in Murthy, 1997). Some of the individuals made more than one stop during the evening commute, but we focus in this paper only on the presence/absence of a first stop and the characteristics of the first stop (as discussed earlier). The activity type of the stop was characterized by three categories: shopping, social/recreational (including eating out), and personal business (including banking).

The travel time from work to home (if an individual chooses to proceed directly home after work) is obtained from network level-of-service data provided by the Central Transportation Planning Staff (CTPS). The network level-of-service data includes travel time information by mode for each traffic zonal pair in the Boston metropolitan area. Since the mode used by an individual to work and her/his home traffic zone and work traffic zone are known, we appended the appropriate travel time from the level-of-service data to each individual's record. Similarly, we obtained the travel time from work to activity location and from activity location to home for those individuals who made a commute stop. From the above information, we computed the travel time deviation for individuals making commute stops.

The number of individuals not participating in any activity during the evening commute in the sample is 1610 (70.5%). The number participating in the three out-of-home activity types is as follows: 242 (10.6%) in shopping activity, 185 (8.1%) in social/recreational activity, and 248 (10.9%) in personal business. The average duration of out-of-home activity participation (across all out-of-home activity types) is 47 minutes and the average travel time deviation is 14 minutes. Among the different activity types, participation in social-recreational activity is associated with a larger activity duration (average of 96 minutes) and a larger travel time deviation (18 minutes).

The percentage of individuals making stops during their evening commute is about 30% in the sample. This is a sizeable fraction, especially when viewed from the perspective that about one in three commuters make an evening commute stop. Given the total number of commuters in metropolitan regions, this would imply a sizeable number of evening commute stops. Further, the Boston data set used here was collected in 1991. Descriptive studies (for example, Purvis, 1994 and Lockwood and Demetsky, 1994) suggest an increasing trend to make evening commute stops. Thus, it is important to focus on this aspect of activity-travel behavior of commuters.

3. Empirical Analysis

This section discusses the model specification, overall data fit of the model, and the estimation results.

3.1. Model specification

A number of different variable specifications were attempted in our study for the different components of the joint model system. We considered four sets of explanatory variables in the analysis: individual socio-demographics, household socio-demographics, work-related characteristics, and home/work location attributes. Table 1 provides a listing of these explanatory variables and their associated descriptive statistics in the sample.

In the model specifications, we tested the nested logit structure for the activity participation/type sub-component of the joint model (with correlation among the utilities of the out-of-home activity type alternatives) against a multinomial logit structure. We found that the dissimilarity parameter δ in the nested logit structure (see equation 2) was not significantly different from one in all the alternative variable specifications we attempted. A further test of the hypothesis of the absence of the independence of irrelevant alternatives (IIA) property of the MNL against the alternative hypothesis of its presence using the Small and Hsiao test (see Ben-Akiva and Lerman, 1985; page 185) also did not reject the MNL structure. Thus, we chose to model the activity participation/type choice model using the simple MNL formulation.

We constrained the correlation parameters between the travel time deviation equation and the activity duration equation to be the same across different out-of-home activity type regimes. The correlation between unobserved factors affecting the propensity to participate in an out-of-home activity type and the activity duration in that activity type was not statistically different across the three out-of-home activity type regimes. So these three correlations were constrained to be equal. A similar result was observed for the correlation in unobserved factors between out-of-home activity type choice and the travel time deviation across the three activity type regimes, and so these three correlations were also constrained to be equal.

3.2. Overall empirical results

The log-likelihood at convergence of the joint model system is -3675.79. The likelihood value when only alternative specific constants are included in the activity type/participation model and when only constants (differentiated by activity type) are introduced in the activity duration and travel time deviation models (with different variances allowed across the different activity types in the activity duration and travel time deviation equations, but all correlation parameters set to zero) is -3920.05. A log-likelihood ratio test clearly rejects the hypothesis that all exogenous variable parameters and error correlations are zero. A further test of the joint model with an independent model (where all exogenous variables are included, but the correlation terms are set to zero) rejects the hypothesis that activity participation and type, activity duration, and travel time deviation are independently determined (the log-likelihood value of the independent model is -3695.4; the likelihood ratio test value is 39.22 which is larger than the chi-squared statistic with three degrees of freedom at any reasonable significance level.

The next four sections of the paper present the results of the multinomial activity participation/type choice model, the activity duration model, the travel time deviation model model, and the error correlation parameter estimates, respectively. The exogenous variable parameters in the different sub-models and those of the error correlations are estimated simultaneously. We discuss them separately for ease in presentation (in the remainder of the paper, we will refer to social-recreation activity as recreational activity).

3.3. Activity participation/type choice model

Table 2 presents the results of the activity participation/type choice model. Among the individual socio-demographic variables, age has a positive effect on the choice of shopping and personal business activities, though the marginal positive effect decreases with age as indicated by the negative sign on the square of age (the age effect remains positive till 96 years, after which it turns negative; this result should be interpreted cautiously since the maximum age in the estimation sample is 88 years). The results also indicate that older individuals are less likely to participate in recreational activity compared to participating in other out-of-home activities or going directly home. Women are more likely to participate in shopping and personal business activities compared to men. This is consistent with the finding of many earlier studies (see, for example, Bianco and Lawson, 1996 and Mensah, 1995), possibly reflecting the continuing trend of women to shoulder a major part of household maintenance responsibilities.

Several variables associated with household socio-demographics affect the decision to participate in an activity and the activity type of participation. A higher household income increases the propensity of individuals to make shopping or recreational stops (a result also found by Goulias and Kitamura, 1989 and Strathman *et al*., 1994). Individuals with small children in their household are likely to return directly home after work rather than make an evening commute stop, while the reverse is true for individuals who live alone. These effects may be associated with familial responsibilities (or lack thereof). The final two variables are introduced to represent the effect of the allocation of non-work activities among adults in a household. An interesting result is that this effect appears to be independent of whether the additional adult is employed or not.

The work-related characteristics affecting activity participation and type choice include work schedule characteristics and the travel mode to work. The duration at work determines the time available for post-work activities and, consequently, has a negative effect on evening commute stop-making propensity. The departure time variables from work are introduced with the departure time between 4 pm and 6 pm being the base. The results indicate that individuals who leave work before 4 pm are more likely to make personal business stops than to go home directly or to make stops for other activities. On the other hand, individuals who leave work after 6 pm are unlikely to participate in shopping or recreational activity. As one would expect, individuals who use the car mode to work are less likely to proceed home directly.

Finally, an individual whose home is located in an urban area is more likely to return home directly after work (*i.e.*, is less likely to make a stop during the evening commute).

3.4. Activity duration model

The activity duration model results represent the effect of exogenous variables on the desired duration of participation. The effect of individual socio-demographics (Table 3) indicate that older individuals and women are more likely to need an extended duration of shopping activity participation than younger individuals and men, respectively. Further, with increasing age, individuals are likely to engage in recreational activity for shorter periods of time. Among the household socio-demographics, income has the expected positive effect on duration for all out-of-home activity types, while presence of additional unemployed adults results in shorter activity durations. The effect of duration at work and departure time from work reflect time constraints. The location variables, in combination, suggest a shorter desired duration of participation for individuals residing in urban areas and working in non-urban areas.

An important issue that we would like to point out is that the effects of work duration and departure time were very insignificant (from a statistical standpoint) in the independent model (which ignores the joint nature of the choice of activity participation/type and activity duration).

Additionally, the parameters on the activity participation constants in the duration equation were much higher in magnitude and significance in the independent model compared to the constants in the joint model. These differences are associated with the different structures of the independent and joint models. Let's consider the effect of work duration. The independent model assumes that the activity participation/type choice decision is made prior to the activity duration decision. Since the choice of participating in an activity is generally associated with a lower work duration (Table 2), any negative effect of work duration on activity duration (*i.e.*, a higher activity duration because of a lower work duration) is implicitly captured in the positive activity participation constants in the duration equation. This leads to the (incorrect) exaggerated positive parameters on the activity participation constants and an insignificant parameter on work duration in the activity duration equation. In contrast, the joint model recognizes the endogenous nature of activity participation choice; that is, it recognizes that the decision to participate in an out-of-home activity and the duration of participation constitute a joint "package" choice. Therefore, it correctly captures the negative effect of work duration on activity duration. A similar explanation can be provided for the (incorrect) insignificant effect of an early departure from work on activity duration estimated by the independent model. More generally, if a variable appears in both the activity participation/type model and the duration equation, its effect on duration tends to be underestimated in magnitude by the independent model because the effect is partially or completely absorbed in the activity participation constants.

3.5. Travel time deviation model

Table 3 also presents the results of the travel time deviation model. None of the individual socio-demographic variables have a significant effect on travel time deviation. Three variables associated with household socio-demographics have a marginally significant impact, while departure from work after 6 pm, car mode to work and the home/work location variables have a highly significant effect.

The parameters on variables common to the activity participation/type model and the travel time deviation model are generally underestimated in the travel time deviation equation by the independent model (for the same reasons discussed in the earlier section).

3.6. Standard error and correlation parameters

There are five distinct elements, $\sigma_{\omega_i}, \sigma_{\eta_i}, \rho_{\omega_i}, \rho_{\eta_i}$, and $\rho_{\omega_i \eta_i}$, in the error variance-covariance matrix for each out-of-home activity type regime (see equation 7). As indicated earlier, we maintained the same correlation parameters across the three out-of-home activity regimes. There are two standard error parameters (corresponding to the activity duration and travel time deviation equations) in each regime (for a total of six standard error parameters) and three correlation parameters to be estimated.

The standard errors in the activity duration equation are 0.9288 (12.55), 0.9638 (12.32), and 1.1374 (11.81) for shopping activity, recreational activity and personal business activity, respectively (values in parenthesis are t-statistics). These values suggest a larger dispersion in activity duration (among individuals with "identical" observed exogenous characteristics) for the personal business activity relative to the shopping and recreational activities. This may be a result of lesser homogeneity in the sub-types of activities characterizing personal business compared to the other two activity types or because the variables in the specification are better explaining the variability in shopping/recreational activity than the personal business activity (or a combination of the two). The standard errors in the travel time deviation equation are 0.7907 (13.56), 0.9589 (12.20), and 0.8988 (13.64) for the shopping, recreational, and personal business activity, respectively.

The joint modeling of activity participation/type choice, activity duration, and travel time deviation is necessitated by the potential presence of correlation in unobserved elements affecting the three decisions. We obtained the following correlation parameter estimates (t-statistics): ρ_ω =-0.4121 (-2.66), ρ_η =-0.4778 (-3.79), and $\rho_{\omega\eta}$ =0.3315 (4.716). ρ_ω is the correlation between v^*_{qi} and ω_{qi}, ρ_η is the correlation between v^*_{qi} and η_{qi}, and $\rho_{\omega\eta}$ is the correlation between ω_{qi} and η_{qi} (see equation 7). The correlation estimates are statistically significant, emphasizing the need to model the activity participation/type, activity duration, and travel time deviation choices jointly. To interpret the correlation terms, we write equation (6) as a binary probit model:

$$
\begin{aligned}
R_{qi}^{*} &= J_i(\beta' z_{qi}) - v_{qi}^{*} \\
R_{qi} &= 1 \quad \text{if } R_{qi}^{*} > 0 \\
R_{qi} &= 0 \quad \text{if } R_{qi}^{*} \leq 0
\end{aligned}
\tag{11}
$$

where R_{qi}^{*} is the latent unobserved propensity of individual *q* to participate in activity *i*. The error term v_{qi}^{*} enters with a negative sign in the propensity equation. Therefore, our correlation estimates indicate that unobserved factors (say, intrinsic preference for a particular activity type) that increase the propensity of participating in any out-of-home activity type also increase the desired duration of participation in that activity type and the travel time deviation to participate in that activity type. That is, individuals who would like to participate in a particular out-of-home activity type for a long duration, and individuals who are willing to invest time in travel to participate in a particular activity type, are most likely to participate in that activity type (all observed characteristics being equal). The positive sign for $\rho_{\omega\eta}$ suggests that individuals desirous of spending a long duration in an activity are also more willing to accept a larger travel time deviation to that activity.

4. Application of the Model

The model formulated in this paper can be applied in several ways. The model can be applied to obtain the probability distribution of travel time deviation for each individual. This information can be used as an input to estimate a destination choice model for nonwork stops with probabilistic choice set generation based on travel time deviation (see Bhat, 1999). Our proposed procedure is different from that of probabilistic choice set generation approaches in the past in which the parameters of the choice set generation process are estimated jointly with those of the destination choice process (see Thill and Horowitz, 1997b). In the proposed framework, the estimation process is considerably simplified as the distribution of travel time is known *a priori*. In addition, since the travel time deviation is determined jointly with the activity participation/type and activity duration dimensions of choice, the inter-relationship among these choice decisions and destination choice is implicitly captured in the resulting spatial model.

The model can also be used to determine the change in the number and temporal pattern of nonwork trips during the evening commute due to changes in socio-demographic characteristics over time or due to policy actions that alter the work schedule of individuals. In combination with a subsequent destination choice model, the model can determine the changes in temporal and spatial patterns of trip-making. Finally, the model can predict changes in the number of cold engine starts associated with nonwork evening commute stops due to socio-demographic changes or policy actions.

In this paper, we demonstrate the application of the model by focusing on the effect of two work schedule-related policy measures on the temporal pattern of trips and cold starts (it will be understood that we are referring to trips and cold starts associated with evening commute stops). We will analyze the effect of the policy measures on a) the number of auto-trips generated in the evening peak (peak auto trips), b) the number of cold starts in the evening peak (peak cold starts), and c) the total number of cold starts.

The next section presents the mathematical expressions for obtaining the number of peak auto trips, peak cold starts and total cold starts. Section 5.2 compares the effects (of the two work schedule policy measures) estimated by the joint model and an independent model which ignores the jointness in the choices.

4.1. Mathematical expressions

We will assume that 4 to 7 pm represents the peak evening period. To obtain the peak auto trip starts and peak cold starts, we will need to obtain the travel time T_{qi}^{ws} for individual q from the work location to the stop location should s/he participate in out-of-home activity type i. Let T_{qi}^{sh} represent the travel time from the stop location to home should individual q participate in out-of-home activity type i and let T_{q}^{wh} represent the direct travel time from work to home if individual q were to return home directly. In our model, we use the logarithm of the travel time deviation T_{qi} $(= T_{qi}^{ws} + T_{qi}^{sh} - T_{q}^{wh})$ as the dependent variable (such a deviation measure better captures the travel time investment that would be entailed by participation in an out-of-home activity compared to the travel time to the stop; the deviation measure is also more appropriate to capture the interaction of the travel time investment with activity duration and the decision to participate in an activity). Since the travel time from work to home, T_{q}^{wh}, is exogenous (the work location and home location are considered to be pre-determined), the model provides an estimate of the sum of the travel times from work to the stop and from the stop to home (*i.e.*, $T_{qi}^{ws} + T_{qi}^{sh}$) for any individual (should s/he participate in an activity). To obtain T_{qi}^{ws}, we use a simple fractional sub-model that apportions the estimated value of $(T_{qi}^{ws} + T_{qi}^{sh})$ into its components. This sub-model takes the form:

$$\delta_q = (1 + e^{-(\alpha' w_q + \xi_q)}.)^{-1} \tag{12}$$

where δ_q is the fraction of total time apportioned by individual q to travel from work to the stop location (we assume the same relationship across all out-of-home activity types), w_q is a vector of relevant exogenous variables (including a constant), α is a parameter vector, and ξ_q is a random error term assumed to be normally distributed with zero mean and variance ϖ^2. ξ_q and w_q are assumed to be independent. After suitable transformations, we can write equation (12) in the following linear regression form:

$$\ln\left\{\delta_q/(1 - \delta_q)\right\} = \alpha' w_q + \xi_q. \tag{13}$$

Estimating α and the error standard deviation ϖ in the above regression using individuals in the sample who actually make a commute stop may be inappropriate if such individuals are systematically likely to apportion a larger or smaller fraction of the total time, $T_{qi}^{ws} + T_{qi}^{sh}$, to the leg from work to activity location. We tested for the presence of such self-selection bias by including a Heckman correction term (see Heckman, 1976) to the right side of equation (13). The parameter on this correction term was statistically insignificant, suggesting the absence of self-selection bias in apportionment. So α and ϖ may be consistently estimated using the subset of individuals in the sample who actually make a stop. The variables that significantly affect the apportionment include work duration, age, use of auto mode to work, urban work location, and urban residential location. The detailed results of this sub-model are not presented here.

The expected value of δ_q can be obtained for any individual q (should s/he decide to make a stop) from the estimates of α and ϖ :

$$E(\delta_q) = \int_{m=-\infty}^{+\infty} \left(1 + e^{-(\alpha' w_q + m\varpi)}\right)^{-1} \phi(m)\, dm \ . \qquad (14)$$

The above integration can be achieved using numerical gauss-hermite quadrature.

The travel time from the work location to the activity location (should individual q decide to participate in out-of-home activity type i) is $T_{qi}^{ws} = \delta_q (T_q^{wh} + T_{qi})$. The main model of this paper provides the distribution of T_{qi} (since its logarithm is a dependent variable). T_q^{wh} is a fixed (exogenous) variable and we will ignore the stochasticity in the estimate of δ_q (the minimum value of T_{qi}^{ws} is $\delta_q T_q^{wh}$; this occurs when the travel time deviation $T_{qi} \rightarrow 0$.

Let 12:00 midnight be the start of the day and define a time scale which represents the number of minutes past midnight. On this scale, 4 pm would be 960 minutes and 7 pm would be 1140 minutes. Let π_q be the departure time from work for individual q on the above time scale. Define the following:

$$f_q = (960 - \delta_q T_q^{wh} - \pi_q) \text{ and } c_q = (1140 - \delta_q T_q^{wh} - \pi_q) \ . \qquad (15)$$

f_q is defined only if the individual departs from work before $960 - \delta_q T_q^{wh}$ and c_q is defined only if the individual leaves work before $1140 - \delta_q T_q^{wh}$. Let $\phi_3(h,p,s)$ be the trivariate standard normal density function computed as follows:

$$\phi_3(h,p,s) = (1/\rho^*)\,\phi\left\{h/\rho^* - \left[\frac{(\rho_\eta - \rho_{\omega\eta}\rho_\omega)p \;+\; (\rho_\omega - \rho_{\eta\omega}\rho_\eta)s}{1-\rho_{\omega\eta}^2}\right]/\rho^*\right\}\phi(p)\,\phi\;(s^*)\;, \tag{16}$$

$$where \quad \rho^* \;=\; \sqrt{1-[(\rho_\omega^2 - 2\rho_\omega\rho_\eta\rho_{\omega\eta} + \rho_\eta^2)/(1-\rho_{\omega\eta}^2)}\;,\quad s^* = (s-\rho_{\omega\eta}p)/\sqrt{1-\rho_{\omega\eta}^2}$$

4.1.1. Number of peak auto trips

In this section, we will consider only those individuals who use the auto mode to work and depart from work before $1140 - \delta_q T_q^{wh}$. Individuals who depart after $1140 - \delta_q T_q^{wh}$ will not make a peak auto trip start (even if they choose to make an evening stop) because the minimum travel time to the stop would be $\delta_q T_q^{wh}$. Let us classify each individual q into one of two categories: those who depart work before $(960 - \delta_q T_q^{wh})$ and those who depart work after $(960 - \delta_q T_q^{wh})$.

Consider an individual q who departs work before $(960 - \delta_q T_q^{wh})$. If s/he makes a stop of activity type i whose duration A_{qi} is less than f_q , then the conditions that need to be satisfied for the trip start (subsequent to the stop) to begin in the evening peak are: $(A_{qi} + T_{qi}^{ws}) > (f_q + \delta_q T_{qi}^{wh})$ and $(A_{qi} + T_{qi}^{ws}) < (c_q + \delta_q T_q^{wh})$. The first condition ensures that the trip starts after 4 pm. The second condition ensures that the trip starts before 7 pm. Using the relationship $T_{qi}^{ws} = \delta_q(T_q^{wh} + T_{qi})$, the first condition is equivalent to $T_{qi} > (f_q - A_{qi})/\delta_q$ and the second condition is equivalent to $T_{qi} < (c_q - A_{qi})/\delta_q$. The probability that individual q participates in activity type i, $A_{qi} < f_q$, and the two conditions above on travel time deviation are satisfied can be obtained using simple (though cumbersome) transformations and algebraic manipulations. The resulting probability is:

$$G_{qi1} = \int_{h=-\infty}^{h=\zeta} \int_{p=-\infty}^{p=\vartheta} \int_{s=\lambda}^{s=\mu} \phi_3(h,p,s)\, dh\, dp\, ds, \text{ where}$$

$$\zeta = \Phi^{-1} F_i(\beta_i' z_{qi}),\ \vartheta = \frac{\ln f_q - \theta_i' x_{qi}}{\sigma_{\omega_i}},\ \lambda = \frac{\ln\left[(f_q - e^{\{\theta_i' x_{qi} + \sigma_{\omega_i} p\}})/\delta_q\right] - \gamma_i' y_{qi}}{\sigma_{\eta_i}}, \text{ and} \tag{17}$$

$$\mu = \frac{\ln\left[(c_q - e^{\{\theta_i' x_{qi} + \sigma_{\omega_i} p\}})/\delta_q\right] - \gamma_i' y_{qi}}{\sigma_{\eta_i}}.$$

Next, consider an individual q who departs work before $(960 - \delta_q T_q^{wh})$, but whose duration A_{qi} is greater than f_q should s/he makes a stop of activity type i. Since the minimum possible value for T_{qi}^{ws} is $\delta_q T_q^{wh}$, this person's trip-start subsequent to the stop will be beyond 4 pm. If this trip-start is to begin before 7 pm, the condition that needs to be satisfied is $(A_{qi} + T_{qi}^{ws}) < (c_q + \delta_q T_q^{wh})$, *i.e.*, $T_{qi} < (c_q - A_{qi})/\delta_q$. The probability that individual q participates in activity type i, $A > f_q$, and the trip-start begins in the evening peak can be computed as:

$$G_{qi2} = \int_{h=-\infty}^{h=\zeta} \int_{p=\vartheta}^{p=\pi} \int_{s=-\infty}^{s=\mu} \phi_3(h,p,s)\, dh\, dp\, ds \text{ ,where} \tag{18}$$

$$\pi = \frac{\ln c_q - \theta_i' x_{qi}}{\sigma_{\omega_i}},$$ and other limits of integration have been defined as equation 17.

The overall probability that an individual who departs work before $960 - \delta_q T_q^{wh}$ will have a peak trip-start can be computed from equations (17) and (18) as $G_q = \sum_{i=2}^{I} (G_{qi1} + G_{qi2})$, where the sum is taken over all out-of-home activity types.

The probability that an individual q who departs work after $(960 - \delta_q T_q^{wh})$ will make a stop and a peak period trip start can be obtained by a similar analysis as:

$$L_q = \sum_{i=2}^{I} \int_{h=-\infty}^{h=\zeta} \int_{p=-\infty}^{p=\pi} \int_{s=-\infty}^{s=\mu} \phi_3(h,p,s)\, dh\, dp\, ds \tag{19}$$

The expected number of individuals who make peak auto-trip starts can finally be obtained as $\sum_q (G_q + L_q)$. The expressions in equation (17) through (19) need to be computed using numerical integration methods.

4.1.2. Number of peak cold engine starts

An engine start after a nonwork stop is classified as "cold" if the duration of the stop exceeds 60 minutes. In this section, we will consider only those individuals who use the auto mode to work and depart from work before $1080 - \delta_q T_q^{wh}$. Individuals who depart after $1080 - \delta_q T_q^{wh}$ cannot contribute toward peak period cold engine starts (even if they choose to make an evening stop) because the sum of the minimum travel time to the stop and an activity duration of 60 minutes would place the trip start beyond 7 pm. Let us classify each individual *q* into one of two categories: those departing work before $(900 - \delta_q T_q^{wh})$ and those departing work after $(900 - \delta_q T_q^{wh})$.

Consider an individual *q* who departs work before $(900 - \delta_q T_q^{wh})$. If s/he makes a stop of activity type *i* whose duration A_{qi} is less than f_q the conditions that need to be satisfied for the trip start (subsequent to the stop) to begin in the evening peak are: $(A_{qi} + T_{qi}^{ws}) > (f_q + \delta_q T_{qi}^{wh})$ and $(A_{qi} + T_{qi}^{ws}) < (c_q + \delta_q T_q^{wh})$. However, the duration should also be greater than 60 minutes. This probability can be derived to be:

$$Q_{qi1} = \int_{h=-\infty}^{h=\zeta} \int_{p=\psi}^{p=\vartheta} \int_{s=\lambda}^{s=\mu} \phi_3(h,p,s)\, dh\, dp\, ds \ . \tag{20}$$

Next, consider an individual *q* who departs work before $(900 - \delta_q T_q^{wh})$, but whose duration A_{qi} is greater than f_q should s/he makes a stop of activity type *i*. By construction, this person's duration is greater than 60 minutes and the engine start subsequent to the stop is a "cold" one occurring beyond 4 pm. If this cold engine start is to begin before 7 pm, the condition $(A_{qi} + T_{qi}^{ws}) < (c_q + \delta_q T_q^{wh})$ needs to be satisfied. This probability is:

$$Q_{qi2} = \int_{h=-\infty}^{h=\zeta} \int_{p=\vartheta}^{p=\pi} \int_{s=-\infty}^{s=\mu} \phi_3(h,p,s)\, dh\, dp\, ds \tag{21}$$

The overall probability that an individual who departs work before $900 - \delta_q T_q^{wh}$ will make a peak cold engine start is $Q_q = \sum_{i=2}^{I} (Q_{qi1} + Q_{qi2}),$ where the sum is taken over all out-of-home activity types.

The probability that an individual q who departs work after $(900 - \delta_q T_q^{wh})$ will make a peak cold engine start is:

$$S_q = \sum_{i=2}^{I} \int_{h=-\infty}^{h=\zeta} \int_{p=\psi}^{p=\pi} \int_{s=-\infty}^{s=\mu} \phi_3(h,p,s)\, dh\, dp\, ds \tag{22}$$

The expected number of individuals who make peak cold engine starts can finally be obtained as $\sum_q (Q_q + S_q)$.

4.1.3. Total cold engine starts (both peak and non-peak)

The probability that an individual q who uses the auto mode to work will make a cold engine start is given by:

$$B_q = \sum_{i=2}^{I} \left\{ F_i(\beta_i' z_{qi}) - \Phi_2\left[\Phi^{-1} F_i(\beta_i' z_{qi}), \frac{\ln 60 - \theta_i' x_{qi}}{\sigma_{\omega_i}}, \rho_\omega\right] \right\} \tag{23}$$

The expected total number of cold engine starts is obtained by summing the above probability across all individuals who use the auto mode to work.

4.2. Policy analysis

We consider two work schedule-related transportation control measures (TCMs) and examine their impact on peak auto trips, peak cold engine starts, and total cold engine starts (due to nonwork stops in the evening commute). The two TCMs are work staggering and an increase in daily work duration due to a compressed work week policy. In examining the impact of these TCMs, it is critical to assess their effect on peak period trips and cold starts due to nonwork stops. This is the focus of the current section.

The work staggering policy is "implemented" by randomly selecting 20% of individuals in the sample who currently leave work between 4 pm and 6 pm and subtracting 120 minutes from the departure time of these individuals. The result is that the work departure time of all these individuals is staggered to before 4 pm. The original departure time distribution from work in the sample is as follows: 597 (26%) leave before 4 pm, 1365 (60%) leave between 4 and 6 pm, and 323 (14%) leave after 6 pm. After "implementing" the work staggering policy, the departure time distribution is altered: 870 (38%) leave before 4 pm, 1092 (48%) leave work between 4 and 6 pm, and 323 (14%) leave work after 6 pm.

The work week compression policy is realized by increasing the daily work duration of a subset of individuals by 25% (this results in a 4 day work week with the same number of total weekly work duration as the original 5 day work week). The subset (for which the work duration is increased) comprises individuals who depart work between 4 and 5 pm and work less than 8 hours. We assume that the increase in work duration is equally split between an earlier arrival to work in the morning and a later departure from work in the evening. Thus, after the increase in work duration, the latest work departure for individuals in the subset is still before 6 pm.

The impact of the policy actions is evaluated by modifying exogenous variables to reflect a change, computing revised expected aggregate values for number of peak auto trips, peak cold engine starts, and total cold engine starts (using the formulae presented in the previous section), and then obtaining a percentage change from the baseline estimates. Table 4 provides the results estimated by the joint model of this paper and an independent model which ignores the jointness in choices among activity type/participation, activity duration, and travel time deviation (*i.e.*, a model that constrains all unobserved correlations to zero). We discuss the results in the subsequent two sections.

4.2.1. Work staggering policy

Both the independent and joint models indicate a decrease in peak auto trips and an increase in peak and total colds starts due to the work staggering policy. The decrease in peak auto trips is because the distribution of travel time to the stop and activity duration is such that the time difference between leaving work and the trip-start subsequent to a commute stop is rather small. Thus, though the total number of commute stops increases due to the policy (note that departure before 4 pm increases the probability of making personal business stops, see table 2), many individuals who earlier were contributing to a peak trip start (subsequent to a commute stop) now have a trip start before 4 pm. The joint model predicts, however, a smaller reduction in peak auto trip starts than the independent model. This is because of the positive correlation in unobserved factors affecting the activity participation decision in an out-of-home activity and the corresponding duration and travel time deviation associated with such a participation. The joint model predicts a larger activity duration and travel time deviation associated with the additional commute stops than does the independent model. This extends the time difference between departure time from work and the trip start after a commute stop and places more trip starts in the peak period.

The increase in peak cold starts and total cold starts is a result of more stop-making due to work staggering. The joint model predicts substantially more peak and total cold starts than does the independent model because it associates larger activity durations with the increased propensity to make stops.

In summary, the independent model overestimates the percentage reduction in peak auto trips by more than 25% compared to the joint model. It also underestimates the percentage increase in peak cold starts (total cold starts) by 23% (67%). Overall, the independent model projects an overly optimistic view of the impact of a work staggering policy.

It is interesting to note that while a work staggering policy reduces peak trip starts due to commute stops, it also increases cold starts. There is a conflict between reducing peak period traffic congestion and increasing air pollution. The model formulated in this paper allows policy makers to evaluate the positive benefits due to traffic congestion reduction against the detrimental impact on air pollution, and make an informed policy decision.

4.2.2. Work week compression policy

The work week compression policy results in a larger daily work duration. Table 4 shows that both the independent and joint models predict a reduction in peak auto trips, peak cold starts and total cold starts due to the work week compression policy.

The reduction in peak auto trips is a result of two reinforcing effects. First, a longer work duration has a negative effect on commute stop-making (Table 2), reducing total auto trips (the percentage reduction in total auto trips was about 1.27% in both the joint and independent models). Second, the longer work duration results in a later departure from work, leading to a shift in the trip start distribution (subsequent to a commute stop) beyond the peak evening period. Between the joint and independent models, the joint model predicts a lower percentage reduction in peak auto trips. The joint model estimates smaller activity durations and travel time deviations associated with the lower likelihood of participation in an activity (because of unobserved correlation effects). The net result is that there is less of a shift in the trip start distribution beyond the peak period in the joint model relative to the independent model.

The decrease in peak and cold starts in the independent and joint models is due to a reduction in stop-making due to an expanded work duration. The joint model estimates a greater percentage reduction in total cold starts because it associates lower activity durations with a lower likelihood of making a stop. Interestingly, however, the lower activity duration predictions from the joint model also keeps a larger fraction of the cold starts within the peak period, resulting in a lower reduction in peak cold starts.

In summary, the independent model overestimates the percentage reduction in peak auto trips and peak cold starts by 52% and 7%, respectively. It also underestimates the percentage reduction in total cold starts by about 32%.

The work week compression policy leads to a reduction in peak auto trips, peak cold starts, and total cold starts (unlike the work staggering policy). However, it appears to be substantially less effective than a work staggering policy in terms of alleviating peak period traffic congestion.

An important point to note here. A work week compression policy will probably lead to increased stop-making and longer activity durations on the additional day the individual does not work. Thus, some of the traffic congestion and air pollution impacts may be shifted to the additional non-work day. The current model does not account for this, since it focuses only on the work day. A more comprehensive analysis of traffic congestion and air pollution impacts will use an entire week as the unit of analysis, so it can address substitution effects in stop-making among days of the week (including work and non-work days). Of course, doing so makes the modeling framework more complex.

5. Conclusions

This paper develops a methodological framework to analyze the activity-travel pattern of individuals during the evening commute. The framework involves modeling the presence/absence and attributes of the first commute stop, followed by the presence/absence and attributes of the second commute stop conditional on the presence and characteristics of the first stop, and so on. The focus of the current paper is on modeling the presence/absence of a first stop and the following attributes associated with the stop: activity type, activity duration, and travel time deviation to stop relative to the direct travel time from work.

The paper uses a joint discrete/continuous choice system in estimation. The discrete choices include the participation and activity type decisions and the continuous choices include the activity duration and travel time deviation decisions. The joint model system is estimated using a full-information maximum likelihood (FIML) procedure.

The empirical analysis uses a data set from the Boston Metropolitan area. The results indicate the strong effects of individual and household socio-demographics, work schedule characteristics, and residential/workplace location characteristics on the activity participation decision and associated dimensions of the activity participation. The analysis also shows strong correlations in unobserved components among activity participation/type choice, activity duration, and travel time deviation to the stop. Ignoring these correlations leads to inappropriate estimates of the effect of work-schedule characteristics and other variables on activity duration and travel time deviation. The joint model that accommodates the correlation among the activity and travel dimensions outperforms (in terms of data fit) an independent model that ignores the jointness among the choices.

The paper derives the necessary expressions for application of the model to determine the change in number and temporal pattern of trip-making and cold starts due to changes in policy-relevant exogenous variables or socio-demographic variables. Using these expressions, the paper applies the model to evaluate the effect of a work staggering policy and a work week compression policy. The author is not aware of any other study which develops and applies such formulae in the context of a continuous-discrete choice system.

The application of the model indicates that failure to accommodate the joint nature of the activity participation, activity type, activity duration, and travel time deviation decisions leads to incorrect conclusions regarding the effects of the work staggering and work week compression policies. Such mis-informed results can lead to misdirected policy actions for traffic congestion alleviation and for mobile-source emissions reduction.

Acknowledgement

The author would like to thank the Central Transportation Planning Staff in Boston for making the Boston household activity survey data available for this research. Pushkar Murthy provided help in assembling the data. This research was funded, in part, by National Science Foundation grants DMS 9208758 and DMS 9313013 to the National Institute of Statistical Sciences (NISS).

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Table Legend

Table 1: List of Exogenous Variables in the Model

Variable	Definition	Sample Stats.	
		mean	std.dev
Individual socio-demographics			
Age	Age of individual in years ($x10^{-1}$)	4.11	1.22
Female	1 if individual is female	0.46	0.50
Household socio-demographics			
Income	Annual Household income in $0000's of dollars	6.16	2.83
Presence of young children	1 if there are children less than or equal to 11 years in individual's household	0.15	0.36
Single individual household	1 if individual lives alone	0.11	0.31
Number of additional employed adults	Number of additional employed adults in the individual's household	1.02	0.84
Number of additional unemployed adults	Number of additional unemployed adults in the individual's household	0.33	0.58
Work-related characteristics			
Work duration	Work duration (in 100's of minutes)	5.00	1.21
Departure from work before 4 pm	1 if individual departs work in the evening before 4 pm	0.26	0.44
Departure from work after 6 pm	1 if individual departs work in the evening after 6 pm	0.14	0.35
Car mode	1 if individual uses the car mode to work	0.88	0.33
Home/Work location variables			
Urban residence	1 if individual's household is located in an urban area	0.40	0.49
Urban work location	1 if individual's workplace is in an urban area	0.50	0.50

Table 2. Activity-Type Choice Model Estimates

Variable	Coef.	t-stat
Activity Type constants (proceeding directly home is base)		
Shopping	-4.605	-6.50
Recreation	-0.866	-1.69
Personal Business	-4.351	-6.29
Individual socio-demographics		
Age (shopping/personal business)	1.125	3.87
Age (recreation)	-0.213	-3.32
Square of age (shopping/personal business)	-0.118	-3.64
Female (shopping)	0.766	4.93
Female (recreation)	-0.030	-0.18
Female (personal business)	0.507	3.60
Household socio-demographics		
Income (shopping)	0.075	3.05
Income (recreation)	0.108	3.94
Presence of young children (proceeding directly home)	0.674	4.43
Single individual household (proceeding directly home)	-0.341	-1.99
Number of additional employed adults (proceeding directly home)	0.247	3.38
Number of additional unemployed adults (proceeding directly home)	0.282	2.89
Work-related characteristics		
Work duration (shopping/personal business)	-0.177	-3.40
Work duration (recreation)	-0.266	-4.04
Departure from work before 4 pm (personal business)	0.887	6.02
Departure from work after 6 pm (shopping)	-0.618	-2.35
Departure from work after 6 pm (recreation)	-1.074	-3.08
Car mode to work (proceeding directly home)	-0.645	-4.66
Home/Work location variables		
Urban residence (proceeding directly home)	0.259	2.45

Table 3. Activity Duration Model and Travel Time Deviation Model Estimates

Variable	Activity duration model		Travel time deviation model	
	Coefficient	t-stat.	Coefficient	t-stat.
Constants				
Shopping	1.187	2.60	2.049	8.63
Recreation	4.121	10.39	2.138	7.04
Personal Business	2.099	5.36	2.022	7.72
Individual socio-demographics				
Age (shopping)	0.201	3.81	-	-
Age (recreation)	-0.119	-2.21	-	-
Female (shopping)	0.555	4.20	-	-
Household socio-demographics				
Income	0.019	1.35	0.017	1.56
Presence of young children	-	-	-0.159	-1.48
Number of additional unemployed adults	-0.131	-1.82	-0.141	-1.92
Work-related characteristics				
Work duration	-0.064	-1.66	-	-
Departure from work before 4 pm	0.156	1.60	-	-
Departure from work after 6 pm	-	-	-0.482	-3.38
Car mode to work	-	-	-0.647	-6.83
Home/work location variables				
Urban residence	-0.151	-1.62	-0.276	-3.58
Urban work location	0.127	1.44	0.356	4.59

Note: Variable that are not listed as specific to an out-of-home activity type are generic across all out-of-home activity types.

Table 4. Effect of Work Schedule Policy Measures

Policy	Model	Percentage change in		
		Peak trip starts	Peak cold starts	Total cold starts
Work staggering	Independent	-15.77	11.79	1.14
	Joint	-12.57	15.36	3.49
Work week compression	Independent	-5.01	-9.17	-1.39
	Joint	-3.29	-8.60	-2.03