Title
Structural Models of the Effects of the Commute Trip on Travel and Activity Participation

Authors
Golob, Thomas F.
Pendyala, Ram M.

Publication Date
1991-11-01

UCI-ITS-AS-WP-91-1

Structural Models of the Effects of the Commute Trip on Travel and Activity Participation

UCI-ITS-AS-WP-91-1

Thomas F. Golob [1]
Ram M. Pendyala [2]

[1] Institute of Transportation Studies
University of California, Irvine, tgolob@uci.edu

[2] Department of Civil Engineering and
Institute of Transportation Studies, University of California, Davis
Davis, CA 95616. U.S.A.

November 1991

Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu

Paper prepared for presentation at the North American Meeting of the Regional Science Association, New Orleans, November 7-10, 1991.

Structural Models of the Effects of the Commute Trip on Travel and Activity Participation

Thomas F. Golob
and
Ram M. Pendyala

Abstract

Travel demand is viewed as being derived from the demand for out-of-home activities. The journey to work can have a significant impact on the travel and activity patterns of workers and other household members. The objective of this research is to model the relationships between travel and activity participation and examine how these relationships are influenced by the time a worker spends commuting between home and his or her worksite. Causal hypotheses are tested using data from approximately 140 workers who responded to two waves of a panel survey collected as part of the State of California Telecommuting Pilot Project. These data contain detailed descriptions of all travel by the survey respondents over three working days in each of two years, 1988 and 1989. A structural equations model is specified in which the durations of four exhaustive categories of out-of-home activities - work, personal business, shopping and social/recreation - generate needs for time spent traveling, and the activity durations and travel times are interrelated in a complex causal structure. The effects of the reduction in travel times for work by telecommuters in the second wave of the panel are captured in terms of additional structural parameters. Results indicate that telecommuting leads directly to increases in shopping activities and decreases in travel for social/recreational activities, and leads indirectly to changes in travel for all purposes. A general modeling framework in which activities and travel relationships can be studied is also discussed.

1. Introduction

The principle underlying the activity-based approach to travel demand analysis is that household travel is a manifestation of the need to perform activities. These activities may be characterized by their frequency, location, timing, duration, and degree of flexibility. The characteristics of some activities may be dependent on those of other activities. Understanding the interdependencies among activities could provide valuable insights into household travel behavior. It is proposed that structural equations models, in which the relationships among several activities and their associated travel characteristics are specified in one comprehensive system of equations, is a useful starting point for testing causal hypotheses involving activities and travel.

Some activities are inherently less flexible than others. For example, the work activity is usually pursued at a fixed work location at a fixed time for a certain duration (say from 8:00 am to 5:00 pm). Work is usually mandatory and does not provide flexibility with respect to location, duration, and timing. On the other hand, a visit to a local park may be done at one's discretion at several possible locations, times and for varying durations. However, a discretionary activity is limited in its flexibility by the constraints imposed by a mandatory activity. In the above example, visiting the park during the working hours of the day is not possible. It must be done either before or after work. In this way, discretionary activities are dependent on and influenced by the nature of mandatory activities. Goulias and Kitamura [1989] have found that the frequencies of discretionary trip types (e.g., social recreation and shopping) are dependent on frequencies of mandatory trip purposes (e.g., work and school).

Work and the associated commute trip play an important role in determining how a person plans other activities and trips. The activity and travel plans of one person may in turn influence the activity engagement patterns of other household members. At the aggregate level, the relatively inflexible timing of the commute trip largely contributes to traffic congestion during the morning and evening rush hours.

The importance of the commute trip in individual and household travel behavior and its effect on aggregate traffic conditions have lead planners to devise travel demand management strategies that aim at reducing the rigidity of the work trip. For example, flexible work hours, four day work weeks, and telecommuting (working outside the conventional office so as to reduce or eliminate the usual commute trip) are all concerned with altering the work trip so as to reduce peak period traffic congestion. However, whether or not these strategies yield overall traffic, energy, and air quality benefits depends on how individuals and households use the increased flexibility and/or discretionary time made available to them. An evaluation of the potential effectiveness of these strategies as transportation control measures hinges upon our understanding of the relationships among work and other activities and travel of households.

The modeling framework used here attempts to identify the effects of the commute trip on the participation in other activities and the travel supporting these activities. Specifically, relationships between the work trip and other activities and trips are hypothesized and tested in a simultaneous equation framework using the method of structural equations. The data set is drawn from the State of California Telecommuting Pilot Project which was conducted to determine the impacts of telecommuting on household travel. When a person telecommutes, the usual commute trip is eliminated. The two-wave panel data set which consists of an experimental telecommuter group and a control group allows a before-and-after impact analysis of telecommuting. The data set provides a unique opportunity to study and isolate the effects of the commute trip on household travel and activity engagement. Moreover, the longitudinal nature of the study provides the potential benefits associated with panel analysis [Kitamura, 1990]. The results of the analysis show that the elimination of the commute trip has a positive effect on the pursuit of shopping and social recreational activities and travel.

This paper is organized as follows. In the next section, various hypotheses of travel behavior relating work and other activities and associated trips will be presented. The third section presents an overview of the data, its advantages, limitations and sample composition. The fourth section provides a preliminary descriptive analysis of demographic and activity/travel characteristics of the study sample. The fifth section is an overview of the formulation of the structural equations modeling methodology. Empirical analysis and model results are the subject of Section 6. Finally, directions for further research are presented in Section 7 while concluding remarks and discussions are presented in Section 8.

2. Hypotheses of Household Activity-Travel Behavior

In this study, the effects of the work trip on household travel behavior is examined by observing households before and after the introduction of telecommuting for one member of the household. In this case, the work trip has been eliminated after the introduction of telecommuting. Many hypotheses can be formulated about the possible effects of the elimination of the commute trip on household travel; for related discussions, see van Wissen, et al. [1989] and Pendyala, et al. [1991]. Some of these effects may be observed in the short-term while others may be observable only in the long-term.

The most direct short-term hypothesis is that the elimination of the twice-daily commute trip will reduce the total number of trips made by that person. Moreover, as work trips are primarily made during the peak period, a reduction in peak-period trips will probably follow as a direct consequence.

When a person does not commute to and from work, additional discretionary time and monetary savings become available. One may then hypothesize that these changes prompt new discretionary out-of-home trips such as social-recreational and shopping trips. Indeed, if it is assumed that a person maximized his or her utility from out-of-home activities subject to budgets on time and money available for travel, then the eliminated commute trips may be replaced by new trips, or the destinations and timing of existing non-work activities could be altered so as to pursue them at more desirable locations and at more convenient times, using up some or all of the time and money originally expended on the eliminated trips [Golob, et al. 1981].

The absence of a commute trip, by itself, may lead to changes in destination choice and timing of out-of-home activities. For example, grocery shopping which used to be done on the way home from work at a location along the commute route, may now be performed at a suburban residential neighborhood grocery store during the late morning or early afternoon (outside the peak period). One may surmise that the spatial distribution of trip ends may be more concentrated around the home location when the commute trip is eliminated. Moreover, the temporal distribution of trips may be more evenly spread during the day. This redistribution of trips may have significant effects on suburban congestion and air quality.

An important consequence of the elimination of the commute trips is the removal of work-related constraints. For example, when a person works conventionally, work begins at 8:00 am, a lunch break must be taken from 12 noon to 1:00 pm, and work ends at 5:00 pm. Relaxation of these constraints is likely to reduce the need to link trips into multi-stop trip chains (home-to-home journey). In fact, Goulias, et al., [1990] found that people increase their linking of trips under tighter constraints. Then, with the removal of constraints, there may be an increase in the number of single-stop trip chains, leading to less efficient travel patterns and more cold starts (having serious air quality implications).

At the household level, the presence of a telecommuter at home with a flexible work schedule may result in a reallocation of tasks among household members. This may streamline the travel patterns of the entire household and increase efficiency in trip making. On the other hand, household members now have more discretionary time (as the person who did not commute has taken up some tasks) and an additional available car. This can possibly lead to increased car trips.

Several long-term hypotheses are also conceivable. The reduced need to commute may prompt a household to reduce car ownership. Also, elimination of the time-bound regular commute reduces the need to live close to work. Households may choose to change residential location further away from work in search of affordable and more pleasant neighborhoods. Testing such long-term hypotheses is however beyond the scope of the reported research.

This section reflects the many changes that are possible as a result of changes in the commute patterns of one household member. Some of the changes may be beneficial while others may not. It is absolutely necessary to see how people use the additional discretionary time and flexibility that results from the elimination of the commute trip.

Such an analysis will provide valuable information about the potential benefit or disbenefit of travel demand management strategies that promote flexibility of the commute trip for the purpose of peak period traffic congestion relief. be tested.

3. The State of California Telecommuting Pilot Project Panel Data

As this research is concerned with the effects of the commute trip on travel behavior, it was necessary to identify a data set in which variations in commute patterns are present. The State of California Telecommuting Pilot Project offers such a unique data set.

The project was intended to determine the impacts of telecommuting on household travel behavior. Telecommuting is the partial or total substitution of the commute to work through the use of telecommunications. Volunteer employees from state agencies were selected to participate in this project. The employees were divided into two groups--the telecommuter group and the control group. The project involved conducting a two-wave longitudinal (panel) survey before and after the introduction of telecommuting. In the first wave (conducted in 1988), all the employees were commuting conventionally to work. In the second wave (conducted in 1989), the telecommuter group had commenced telecommuting while the control group continued to commute conventionally. The presence of the control group allows the isolation of the effects of telecommuting on travel behavior.

Three day travel diaries were filled out by the state employees and driving age members of their households in both waves. In the second wave, telecommuters were requested to fill out the travel diary on three successive days such that at least one day was a telecommuting day (working at home). These travel diaries contained information on all trips made by the individual over the three day period. This information included trip beginning and ending times, origin, destination, length, freeway use, mode, and vehicle occupancy. In addition, selected demographic information was also collected. This included household car ownership, household size, and employment status, age, and gender of each individual respondent.

The travel survey involved households of State employees from 14 agencies. The participants live and work mostly in the Sacramento and Bay Areas. The first wave sample consisted of a total of 430 respondents. 252 respondents were state employees, and 178 were driving-age members of the employees' households. Of the 252 state employees, 137 (54.3%) were scheduled to telecommute in the second wave, while the remaining were assigned to the control group.

In the second wave, attrition was evident. Of the 430 persons who responded in the first wave, only 219 persons responded in the second wave. The others left the survey for various reasons [Kitamura, et al., 1990] which may have included retirement, promotion, family issues, lack of interest, and changing jobs. The additional 38 persons in the second wave survey constituted refreshments. The sample of 219 persons who responded in both waves shall be referred to as "stayers" in this paper. As travel patterns for various commute patterns are available before and after telecommuting for these households, this sample is used in the model estimation. The composition of the sample in each wave and the stayers is presented in Table 1.

Multi-day travel diary information from these 219 persons was used to construct trip-activity profiles which organize all trips and activities (with associated characteristics) in chronological order. These profiles were used to construct a data set with combined travel and activity characteristics. These characteristics are based on 2706 first wave trips and 2235 second wave trips. Details on the construction of the combined activity and travel data set can be found in Pendyala, et al. [1991].

The data set is potentially well suited for structural modeling. The longitudinal nature of the data set helps avoid problems associated with cross-sectional data sets [Kitamura, 1990]. It allows an observation of how changes in commute patterns lead to changes in travel behavior for the same household over time. As such the identification of causal and dynamic relationships becomes more amiable while controlling for unobserved individual effects that do not change over time. Also, the presence of the control group allows us to isolate the effects of the elimination of the commute trip on household travel behavior.

However, there are severe limitations associated with the data. First the sample is made up of volunteers selected to participate in the project; and the employees are all drawn from public agencies. The sample is therefore not representative of the general population. As the project was of a pilot nature, the sample size is small. This was further aggravated by the high rate of attrition, which also contributes to possible biases. Also, the use of a multi-day travel diary may have seen diary fatigue where reporting accuracy diminishes as the survey days progress. Therefore, the model estimation results must be interpreted with care.

4. Preliminary Descriptive Analysis of the Study Sample

In this section, descriptive characteristics of the stayer sample used in this study are presented. Table 2 presents the average values for various demographic characteristics for the two employee groups by wave, while Figures 1 through 6 show comparisons of average travel and activity characteristics across the groups. Indications in Table 2 are that the telecommuter and control groups do not differ substantially. In fact, none of the statistics were found to be significantly different between the two groups at the .05 level. However, it is noteworthy that the control group exhibits consistently smaller numbers in all statistics. The control group employees show a slightly lower average age, smaller numbers of adults, teenagers, and children, and lower car ownership. However, while the control group employees showed a slight increase in their car ownership across the two waves, the telecommuter group did not.

In Figures 1 and 2, the average trip frequencies by purpose are compared for each group across the two waves. For the telecommuter employees, the second wave characteristics are further divided into telecommuting day and commuting day characteristics. The telecommuter employees show relative stability in their trip frequencies between the first wave and the commuting days of the second wave. On telecommuting days, as expected, they make no commute trips and make fewer home trips. However, on average, they pursue a marginally larger number of personal business and shopping trips while reducing their recreational trips. This is rather interesting and unexpected as one would hypothesize that telecommuting might induce additional recreational trips. The control group employees show stability across the two waves for all trip purposes except home trips. There is a reduction in their home trips; the reason for this is unclear and would need further investigation.

Figures 3 and 4 compare total average daily travel durations for different trip types. The telecommuters show decreases in home and work travel durations between the first wave and second wave commuting days. This is quite an unexpected result. The control group employees show a similar decrease in their work travel duration, but no such decrease in their home travel duration. As the control group employees also showed the reduction in work travel duration, it is possible that an external stimulus (such as an improvement in the transportation supply characteristics) contributed to this reduction. Travel times for other activities are similar across the two waves for both groups. Obviously, telecommuters exhibit reduced home-to-work travel durations on telecommuting days. While the frequency of personal business trips on second-wave commuting days showed no increase, travel times for this trip purpose shows an increase.

Figures 5 and 6 show total average activity durations per day for different purposes. These figures represent activity engagement in hours per day. Telecommuters' activity engagement is as expected. On telecommuting days, they spend an additional eight hours at home when compared with commuting days of the first or second waves. This probably corresponds to the eight hours of work. As expected, out-of-home work activity does not exist on telecommuting days. The personal business, shopping, and social recreation show no increases on telecommuting days suggesting that increases in discretionary activities do not take place. Slight increases in personal business and shopping activity durations are observed on second wave commuting days. The control group employees show no change in their activity durations.

In summary, the elimination of the commute trip on telecommuting days does not contribute to increases in the pursuit of non-work activities, at least in the short term. As such, when we model work activity versus non-work activity engagement, we would not expect to see differences in model indications across the two waves. This hypothesis will be tested in the modeling effort that follows.

5. Modeling Methodology

The method used to model activity and travel relationships is structural equations modeling with limited-dependent variables. The estimation method is due to Muthén [1979, 1983, 1984], who extended the classical linear structural equations model with unlimited continuous variables [Jöreskog, 1973] to situations with ordered categorical, censored and truncated dependent variables.

This method has been chosen for various reasons. They are:

> The model must accommodate multiple endogenous variables that are interacting with one another. This will allow the simultaneous depiction of several activity and travel times and relationships among them can be determined.
>
> The methodology must allow the depiction of recursive as well as non-recursive relationships. This is necessary in order to be able to test alternative causal hypotheses regarding relationships among different activities and travel times.
>
> The model should be able to handle limited-dependent variables as activity and travel times are censored from below at zero.
>
> The modeling method should facilitate a comparison of behavior across different sample groups.

The method of multiple-group longitudinal structural equations with limited-dependent variables satisfies the above requirements and more over, is easy to implement via readily available software such as LISCOMP [Muthén, 1987], EQS [Bentler, 1985], and a combination of PRELIS and LISREL7 [Jöreskog and Sörbom, 1987]. Structural equations models have seen increasing use in various fields of behavioral research. In transportation, researchers have used this method to study various aspects of travel behavior such as mode choice [Lyon,1984; Golob, 1988], travel times and car ownership [Golob, 1989], car ownership and utilization [Golob and van Wissen, 1989], and fuel type choice [van Wissen and Golob, 1991].

The structural equation system can be formulated in two components. The first component is the latent variable model while the second component links the latent variables with their observed counterparts.

The latent variable component with p continuous and limited-dependent variables and m exogenous variables may be written as

$$\mathbf{y}^* = \mathbf{B}\mathbf{y}^* + \mathbf{\Gamma}\mathbf{x} + \zeta \tag{1}$$

where

$\mathbf{y}^*$ = (px1) vector of latent endogenous variables
$\mathbf{B}$ = (pxp) matrix of structural effects among the latent variables
$\mathbf{x}$ = (mx1) vector of exogenous variables
$\mathbf{\Gamma}$ = (pxm) matrix of structural effects of $\mathbf{x}$ on $\mathbf{y}^*$
ζ = (px1) vector of disturbance terms with variance-covariance matrix $\Psi = E\{\zeta\zeta'\}$

The second component links the latent endogenous variables with their observed indicators. This is done to transform the observed non-normal variables into normal latent variables so that asymptotically distribution free (ADF) methods can be used to estimate parameters [Browne, 1984]. This transformation component of the model system is referred to as the measurement model. It is discussed in further detail below.

For a continuous variable, the measurement model linking the observed indicator, y, with the latent variable, y*, is simply given by

$$y = y^* \tag{2}$$

However, for the present application, it is more appropriate to treat non-work activity and travel times as variables censored from below at zero. For each activity or travel time, y, it is presumed that there is a latent variable y^* which measures the true propensity of a person to expend time on a certain trip or at a certain activity. If this latent variable is greater than zero, the actual time expended is observed; if it is less than or equal to zero, no time is observed. Then, the measurement model can be written as,

$$y = y^* \qquad \text{if } y^* > 0$$

$$y = 0 \qquad \text{otherwise} \tag{3}$$

The latent variable is assumed to be normally distributed with mean μ and standard deviation σ. For values below the threshold value, in this case zero, the mean of the normal score of the latent variable in this interval is assumed, given by:

$$z = \mu - \sigma \frac{\phi(-\mu/\sigma)}{\Phi(-\mu/\sigma)} \tag{4}$$

where the mean value is conditional upon the exogenous **x** variables in the structural equation system. A solution for the unknown distributional parameters in (4) was originally proposed by Tobin(1958), and this censoring model is now called a tobit (Tobin's probit). The present estimation uses the maximum likelihood solution described in Maddala [1983], pp. 151-159. A similar use of tobit variables in a travel-demand structural equation model is found in van Wissen and Golob [1990].

The complete set of latent variables are thus assumed to be multivariate normally distributed. A simple way of computing the variance-covariance matrix of the transformed variables is to use the normal scores from the marginal distributions of the variables. However, this is not an optimal solution. By using bivariate information of all pairs of variables, polyserial correlations can be computed; these are consistent estimates of the underlying population statistics [Muthén, 1984].

Having defined the model system composed of equations (1) through (4), the structural parameters in **B** and **Γ** and the elements of **y** can be estimated using the Generalized Weighted Least Squares Method developed by Browne [1984]. The covariance matrix of exogenous and latent endogenous variables **S** is the object of analysis. The hypothesized model structure implies a covariance matrix $\boldsymbol{\Sigma}(\mathbf{B},\mathbf{G},\boldsymbol{\zeta})$ for each group. The parameters are estimated such that $\boldsymbol{\Sigma}(\mathbf{B},\mathbf{G},\boldsymbol{\zeta})$ is as close to $\mathbf{S}$ as possible. Parameter estimates with all desirable asymptotic properties are generated by minimizing a fit function which is:

$$F = [s - \boldsymbol{\sigma}(\mathbf{B},\boldsymbol{\Gamma},\boldsymbol{\zeta})]'\mathbf{W}^{-1}[s - \boldsymbol{\sigma}(\mathbf{B},\boldsymbol{\Gamma},\boldsymbol{\zeta})] \tag{5}$$

where

$\mathbf{s}$ = vector of ½(p+m)(p+m+1) elements obtained by placing the non-duplicated elements of $\mathbf{S}$ in a vector

$\boldsymbol{\sigma}$ = vector of ½(p+m)(p+m+1) elements obtained by placing the non-duplicated elements of $\boldsymbol{\Sigma}$ in a vector

$\mathbf{W}$ = ½(p+m)(p+m+1) x ½(p+m)(p+m+1) positive definite weight matrix

The matrix $\mathbf{S}$ consists of all sample variances and covariances among exogenous and latent endogenous variables for each group. Consistent estimators of these underlying population statistics are obtained by using bivariate information of all pairs of information to generate polychoric and polyserial correlation matrices. These correlation matrices provide correlations among underlying multivariate normal latent variables rather than the ordinal or censored observed indicators. Olssen, et al. [1982] describe maximum likelihood estimation procedures of polychoric and polyserial correlations. Estimation of parameters using polyserial correlations provides consistent estimators of structural parameters [Bollen, 1989].

An important result of Browne [1984] is that if the weight matrix, $\mathbf{W}$, is chosen to be a consistent estimator of the asymptotic covariance matrix of $\mathbf{s}$ with $\mathbf{s}$, then the estimates of $\mathbf{B}$, $\boldsymbol{\Gamma}$ and $\boldsymbol{\Psi}$ are asymptotically efficient. Each of the elements of $\mathbf{W}$ is a sample estimator of the fourth-order moment of the observed variables distribution. An estimator of $\mathbf{W}$ is provided by Muthén [1984].

The value of the objective function F, multiplied by the sample size N, is an overall measure of goodness of fit. It is distributed asymptotically as χ^2 with degrees of freedom (p+m)(p+m+1) - r where r is the number of free parameters to be estimated in the model system [Bollen, 1989]. The difference in χ^2 statistics for two nested models (where two models are exactly identical except for one or more constrained parameters) is distributed as a new χ^2 statistic with degrees of freedom equal to the difference in degrees of freedom between the two models. This provides a convenient method for testing the significance of hypotheses.

An important distinction in simultaneous equation systems is that between direct, indirect and total effects. Direct effects are given in the **B** and **Γ** matrices. Indirect effects may exist if a variable a is related to b, which in turn is related to c. Then, there is an indirect effect from a to c through the causal path involving b. Total effects are simply the sum of direct and indirect effects. The formulas for calculating these effects are:

	<u>y* to y*</u>	<u>x to y*</u>
Direct Effects	$\mathbf{B}$	$\mathbf{\Gamma}$
Indirect Effects	$(\mathbf{I}-\mathbf{B})^{-1} - \mathbf{B} - \mathbf{I}$	$(\mathbf{I}-\mathbf{B})^{-1}\mathbf{\Gamma} - \mathbf{\Gamma}$
Total Effects	$(\mathbf{I}-\mathbf{B})^{-1} - \mathbf{I}$	$(\mathbf{I}-\mathbf{B})^{-1}\mathbf{\Gamma}$

6. Model Results

A structural equation system with censored endogenous variables was specified and estimated on a pooled sample of telecommuters and control group workers from both waves of the panel. The wave pooling was necessary in order to increase the sample size. A dummy exogenous variable was used to indicate whether or not the person was a telecommuter in the second wave was included. Formally, it is defined as,

$$D = \begin{cases} 1 & \text{if telecommuter in second wave} \\ 0 & \text{otherwise.} \end{cases}$$

The model relates work, personal business, shopping and social recreational activities and the travel time durations for these activities along with the dummy variable defined above. There were a total of 274 observations (one telecommuter was eliminated from both waves due to missing information). The model variables, eight endogenous and one exogenous, are described in Table 3.

There are 20 free parameters in the estimated model, representing twelve causal links between endogenous variables (non-zero β elements of the **B** matrix in equation (1)), three regression links from the exogenous telecommuting variable (non-zero γ elements), and eight disturbance term variances (ψ elements in the variance-covariance matrix of ζ). The model χ^2 value, computed from objective function (5), is 30.122. For 20 parameters, the χ^2 statistic has 24 degrees-of-freedom, yielding a p value of .1807: The model cannot be rejected at the $p = .05$ level.

The coefficient estimates and associated z-statistics are listed in Tables 4 and 5. All of the structural coefficients in Table 4 are significant at the $p = .05$ level for one-tail tests, and all but one coefficient are significant at the $p = .01$ as well.

As an aid in interpreting the causal structure implied by the coefficient estimates of Table 3, a flow diagram of the model is provided in Figure 7. Each non-zero element in either the **B** or **Γ** matrix of equation (1) is represented by an arrow in such a flow diagram, the arrow showing the direct effect of one variable upon another. In Figure 7, such direct effects are shown in bold with corresponding z-values shown in parentheses. Total effects (discussed at the end of Section 5) are shown in italics in Figure 7; the corresponding indirect effects implied by the model are depicted in Figure 8.

The pursuit of activities leads to travel and therefore the arrows between activity and travel variables in Figure 7 are from activities to travel. While the out-of-home work activity variable has a direct effect only on work travel, work travel in turn has negative direct effects on personal business travel and social/recreational travel and a positive direct effect on shopping travel. Consequently, work activity affects all other travel, and work activity duration affects all other travel through work travel.

This model is also indicative of the following relationships not involving the exogenous telecommuting variable:

All links from activities to travel are strongly positive, which indicates that demand for travel is indeed the manifestation of the demand for activities.

One hour of work activity generates about 0.045 hours of commute. In other words, for an eight hour work day, this sample commutes approximately 20 minutes.

Similarly, 10 minutes of personal business generate travel of 4 minutes duration, 10 minutes of shopping generate a shopping travel of 3 minutes, and 10 minutes of social recreation generate 2 minutes of travel. Note that these observations pertain only to working days. As such, we would not expect employees to make long trips to pursue non-work activities.

Shopping and recreational activities are positively associated with each other. This might result from a tendency to link shopping and recreational activities.

People with longer work travel tend to pursue shorter personal business trip durations.

However, work travel and shopping travel are linked by a positive coefficient and so are personal business and shopping. This suggests that people with longer commutes are making longer shopping trips. Similarly, people who pursue personal business are likely to associate it with a shopping trip too.

Finally, work travel negatively influences travel for social/recreational purposes.

Telecommuting reduces out-of-home work activity (by definition), but the link between work activity and work travel captures the effect of telecommuting on work travel. This indicates that, for this sample, telecommuters and non-telecommuters have similar relationships between work activity and work travel. Telecommuting has pervasive influences on most other activities and travel:

Telecommuting has a positive influence on shopping activity. The increase in shopping activity is related to the decrease in work activity on approximately an eight to one basis. This increase in shopping activities leads to an increase in social/recreational activities through the link from shopping to social/recreational activities.

Telecommuting influences travel for social/recreational purposes through its strong link to work activity and an additional negative direct effect to social/recreational travel. The net influence on recreational travel is slightly positive, due to the indirect effects through work activity. The negative direct effect from telecommuting to social/recreational travel serves to compensate for the positive effect that reducing work out-of-home activity has on social/recreational travel.

The effect of telecommuting on personal business was found to be insignificant.

The estimates of the disturbance term variances, the diagonal elements of the Ψ matrix of equation set (1), are listed in Table 5, together with the sample variances for the $\mathbf{y}^*$ variables and the implied R^2 values. The R^2 value for personal business activity duration is zero because there are no causal links to this variable in the model; the deviation between the sample variance and the estimated variance is due to the very good, but imperfect, fit of the model. Two of the other endogenous activity durations, for work and shopping, exhibit low R^2 values because they are explained in part only by the telecommuting dummy variable; additional exogenous variables, not available in the data set, are needed to explain work and shopping activity duration. However, a significant proportion (approximately 12 percent) of the remaining social/recreational activity duration variable is explained by shopping activity duration.

With respect to explanation of the travel time variables, travel time for work is poorly explained by work activity duration. In contrast, approximately 60 percent of the variance in personal business travel time is explained (directly by personal business activity and work travel and indirectly by telecommuting and work activity).

Moreover, the model structure explains 80 percent of the variance in shopping travel time and 75 percent of the variance in social/recreational travel time. This indicates that activity analysis can be an effective approach to demand forecasting of non-work travel: if activity durations can be explained, so can travel times.

7. Further Research

The model specification has been restricted by limitations of sample size, the lack of socio-demographic variables in both waves, and the observation of trips only on working days. The small sample sizes of 73 telecommuters and 65 control group employees does not provide a large enough data source to estimate dynamic model structures linking the activity and travel participation durations across the waves. As trips were observed only on working days, the occurrence of discretionary activities and trips is rare and discerning a pattern of linkages among activities in a dynamic context becomes an arduous task. Despite these limitations, the models presented in the previous section show significant links among activities and travel and the effect of telecommuting on travel when the observations across the two waves and two groups are pooled.

In this section, we present a general framework in which activity and travel characteristics could have been assessed in the structural equations framework had the data not been a limiting factor. This is based on the concept of multiple-group longitudinal structural equation modeling. Muthén [1989] extended the structural equations method to allow comparisons across multiple-groups. The multiple-group structural equation system follows the formulation presented in Section 5 and consists of two components. The first component is the latent variable model while the second component links the latent variables with their observed counterparts.

The latent variable component with p continuous and limited-dependent variables, m exogenous variables, and G sample groups, may be written as

$$y^{*(g)} = B^{(g)}y^{*(g)} + \Gamma^{(g)}x^{(g)} + \zeta^{(g)} \tag{6}$$

where

$y^{*(g)}$ = (px1) vector of latent endogenous variables

$B^{(g)}$ = (pxp) matrix of structural effects among the latent variables

$x^{(g)}$ = (mx1) vector of exogenous variables

$\Gamma^{(g)}$ = (pxm) matrix of structural effects of **x** on **y***

$\zeta^{(g)}$ = (px1) vector of disturbance terms with variance-covariance matrix $\Psi^{(g)} = E\{\zeta^{(g)}\zeta'^{(g)}\}$ and

g = sample group

The second component links the latent endogenous variables with their observed indicators and is exactly similar to equations (2) and (3).

Having defined the model system composed of equations (5), (2), and (3), the structural parameters in $B^{(g)}$ and $\Gamma^{(g)}$ and the elements of $\Psi^{(g)}$ can be estimated using the Generalized Weighted Least Squared Method developed by Browne [1984]. The covariance matrix of exogenous and latent endogenous variables $S^{(g)}$ is the object of analysis. The hypothesized model structure implies a covariance matrix $\Sigma^{(g)}(B^{(g)},\Gamma^{(g)},\Psi^{(g)})$ for each group. The parameters are estimated such that $\Sigma^{(g)}(B^{(g)},G^{(g)},\Psi^{(g)})$ is as close to $S^{(g)}$ as possible. Parameter estimates with all desirable asymptotic properties are generated by minimizing a fit function which is a weighted combination of the fit for all groups.

The estimation procedure is the same as described in Section 5. The sample size N multiplied by the function F is distributed asymptotically as a χ^2 statistic with degrees of freedom ½(G)(p+m)(p+m+1) - r, where r is the number of free parameters to be estimated in the $B^{(g)}$, $\Gamma^{(g)}$, and $\Psi^{(g)}$ matrices. As before, the difference in χ^2 between two nested models can be used to test hypotheses of parameter equality (restrictions) across groups and/or across waves.

Also, ideally the first and second wave observations in a panel survey should not be treated as independent observations. In fact, activity and travel characteristics from the first wave represent lagged dependent variables with the characteristics of the second wave being dependent upon those of the first wave. Similarly, hypotheses that relationships among activities and travel characteristics are stable can be tested by performing nested χ^2 tests using parameter equality restrictions across waves.

A longitudinal multi-group structural equations model could be used to capture the effects of telecommuting. The approach is to specify the cross-sectional model such as the one described in Section 6, minus the telecommuting exogenous variable, at two points in time. This doubles the number of endogenous variables in the model. The two cross-sectional models are linked with state-dependence structural links and error-term autocorrelations [Golob, 1989]. Importantly, such a dynamic structure allows the specification of individual-specific (random effects) terms, as accomplished by Golob et al. [1991] and van Wissen and Golob [1991]. Such a model can then be estimated as a two-group structure (equation set (6)), with the groups being telecommuters and the control group. Structural parameters for the two groups can be set equal at the first point in time (pre-telecommuting), and tested for equality at the second point in time (post-telecommuting). This is a particularly flexible specification, because it is possible to detect whether or not the relationships among the various activity and travel times changes when telecommuting is introduced.

The Telecommuting Pilot Panel Data did not support such a longitudinal two-group specification due to the relatively small sample size. There are simply too many free parameters in a dynamic two-group model for the number of observations in the data set. This remains a topic for further research.

8. Conclusions

It has been shown that various activities and the travel they generate can be interrelated in a structural equations framework. The specific model estimated here is used to examine the effect of the commute trip and out-of-home work activity on other activities and travel. Estimates are generated using data from the State of California Telecommuting Pilot Project. In this Pilot Project, a group of state employees had begun working from home for a part of the week. Their travel characteristics were observed along with that of a control group at two time points (before and after the introduction of telecommuting).

Results showed that the elimination of out-of home work (telecommuting) reduced work travel, but increased shopping and social recreational activities. These indications were not clear from the descriptive statistics, which did not show significant differences. It is therefore important to study the relationships using a structural model, such as the one presented in this paper, because descriptive statistics and reduced-form models might not reveal causal relationships.

The positive influence of reduced commuting on shopping and recreational activities and their associated travel suggests that people use a part of their discretionary time to pursue non-work activities. This partially mitigates the congestion relief, air pollution reduction, and energy savings advantages attributed to telecommuting. However, further research is suggested before policy implications are drawn from this study. It is possible that telecommuters have taken over the tasks of other household members. If that is the case, the net amount of travel generated by the household would not increase. Moreover, telecommuters are likely to make such trips at non-peak periods [Pendyala, et al. 1991]. It would be fruitful to identify trade-offs in activity participation among household members which would provide insights into such a possibility.

Acknowledgements

This research was sponsored by the University of California Transportation Center, with funding from the U.S. Department of Transportation and the California State Department of Transportation (Caltrans). Preparation costs for data from the State of California Telecommuting Pilot Project were also born by Caltrans. While many useful comments were provided by Ryuichi Kitamura, University of California, Davis, Will Recker, University of California, Irvine, and Jackie Golob of Jacqueline Golob Associates, the authors are solely responsible for any remaining errors.

References

Bentler, P.M. (1985). *Theory and Implementation of EQS, a Structural Equations Program, Version 2*. Los Angeles: BMDP Statistical Software.

Bollen, K.A. (1989). *Structural Equations with Latent Variables.* New York: John Wiley & Sons.

Browne, M.W. (1984). Asymptotically Distribution Free Methods for the Analysis of Covariance Structures. *British Journal of Mathematical and Statistical Psychology*, **37**. 62-83.

Golob, T.F. (1988). Structural Equation Modeling of the Dynamics of Travel Choice Behavior. In the *Proceedings of the Oxford Conference on Travel and Transportation.* July 13-15, Oxford, England.

Golob, T.F. (1989). The Dynamics of Household Travel Time Expenditures and Car Ownership Decisions. In the Proceedings of the International Conference on Dynamic Travel Behavior Analysis. July 18-19. Kyoto, Japan.

Golob, T.F., M.J. Beckmann and Y. Zahavi (1981). A Utility Theory Travel Demand Model Incorporating Travel Budgets. *Transportation Research*, **15B**: 375-398.

Golob, T.F., R. Kitamura and J. Supernak (1991). Effects of the San Diego I-15 Reversible HOV Lanes on Ride-Share Choice, Travel Times, and Attitudes: a Dynamic Simultaneous Equations Model with Individual-Specific Effects. Presented at the 70th Annual Meeting of the Transportation Research Board, January 13-17, Washington.

Golob, T.F. and van Wissen, L.J.G. (1989). A Joint Household Travel Distance Generation and Car Ownership Model. *Transportation Research*, **23B**: : 471-491.

Goulias, K.G. and R. Kitamura (1989). Recursive Model System for Trip Generation and Trip Chaining. *Transportation Research Record* **1236**, National Research Council, Washington D.C.

Jöreskog, K.G. (1973). A General Method for Estimating a Linear Structural Equation System. In A.S. Goldberger and O.D. Duncan (eds.) *Structural Equation Models in the Social Sciences*. 85-112. New York: Seminar Press.

Jöreskog, K. and D. Sörbom (1987). New Developments in LISREL. *Data Analyst*, **4**. 1-22.

Kitamura, R. (1990). Panel Analysis in Transportation Planning: An Overview. *Transportation Research A*, **24A**, 401-415.

Kitamura, R., K.G. Goulias, and R.M. Pendyala (1990). *Telecommuting and Travel Demand: An Impact Assessment for State of California Pilot Project Participants.* Research Report No. UCD-TRG-RR-90-8. Final Report prepared for the California State

Department of Transportation. Institute of Transportation Studies, University of California, Davis, CA 95616.

Lyon, P.K. (1984). Time Dependent Structural Equations Modeling: A Methodology for Analyzing the Dynamic Attitude-Behavior Relationship. *Transportation Science*, **18(4)**. 395-414.

Maddala, G.S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics.* Cambridge: Cambridge University Press.

Muthén, B. (1979). A Structural Probit Model with Latent Variables. *Journal of the American Statistical Association*, **74**. 807-811.

Muthén, B. (1983). Latent Variable Structural Equation Modeling with Categorical Data. *Journal of Econometrics*, **22**. 43-65.

Muthén, B. (1984). A General Structural Equation Model with Dichotomous, Ordered Categorical, and Continuous Latent Variable Indicators. *Psychometrika*, **49**. 115-132.

Muthén, B. (1987). *LISCOMP: Analysis of Linear Structural Equations with a Comprehensive Measurement Model.* Mooresville, IN: Scientific Software, Inc.

Muthén, B. (1989) Multiple-Group Structural Modelling with Non-Normal Continuous Variables. *British Journal of Mathematical and Statistical Psychology*, **42**. 55-62.

Olssen, U., F. Drasgow, and N.J. Dorans (1982). The Polyserial Correlation Coefficient. *Psychometrika*, **47**. 337-347.

Pendyala, R.M., K.G. Goulias, and R. Kitamura (1991). Impact of Telecommuting on Spatial and Temporal Patterns of Household Travel: An Assessment for the State of California Pilot Project Participants. *Transportation* **18(4)**, 383-409.

Tobin, J. (1958). Estimation of Relationships for Limited Dependent Variables. *Econometrica,* 26: 24-36.

van Wissen, L.J.G. and T.F. Golob (1991). A Dynamic Model of Car Fuel Type Choice and Mobility. Paper presented at the 70th Annual Meeting of the Transportation Research Board, January 13-17, Washington D.C. *Transportation Research*, forthcoming

van Wissen, L.J.G., H.J. Meurs, and T.F. Golob (1989). A Simultaneous Dynamic Travel and Activities Time Allocation Model. Working Paper No. UCI-ITS-WP-89-2. Institute of Transportation Studies, University of California, Irvine, CA 92717.

Figure 1
Trip Frequencies for Telecommuter Employees (N=73)

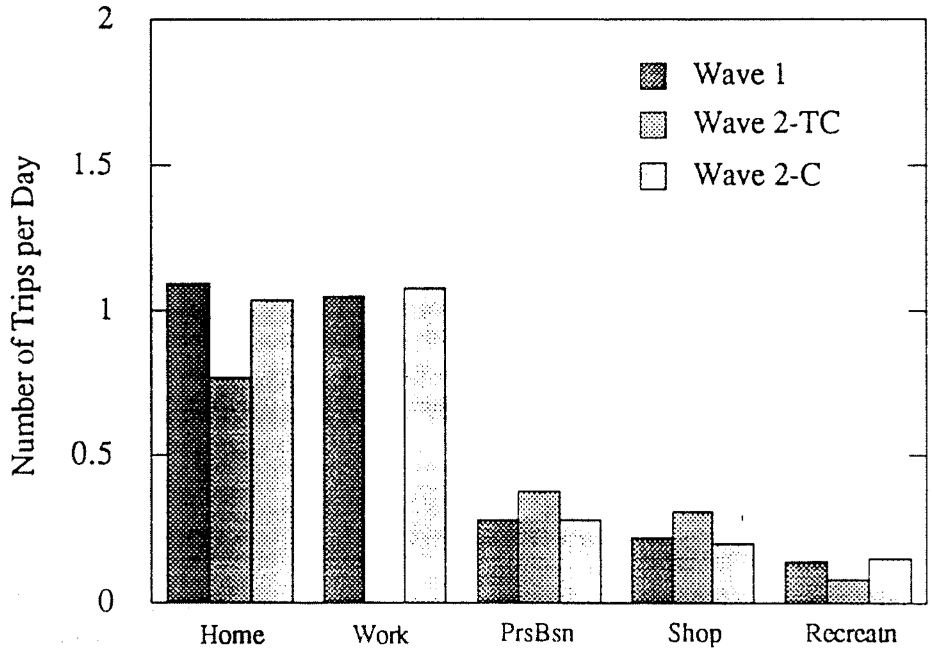


Figure 2
Trip Frequencies for Control Group Employees (N=65)

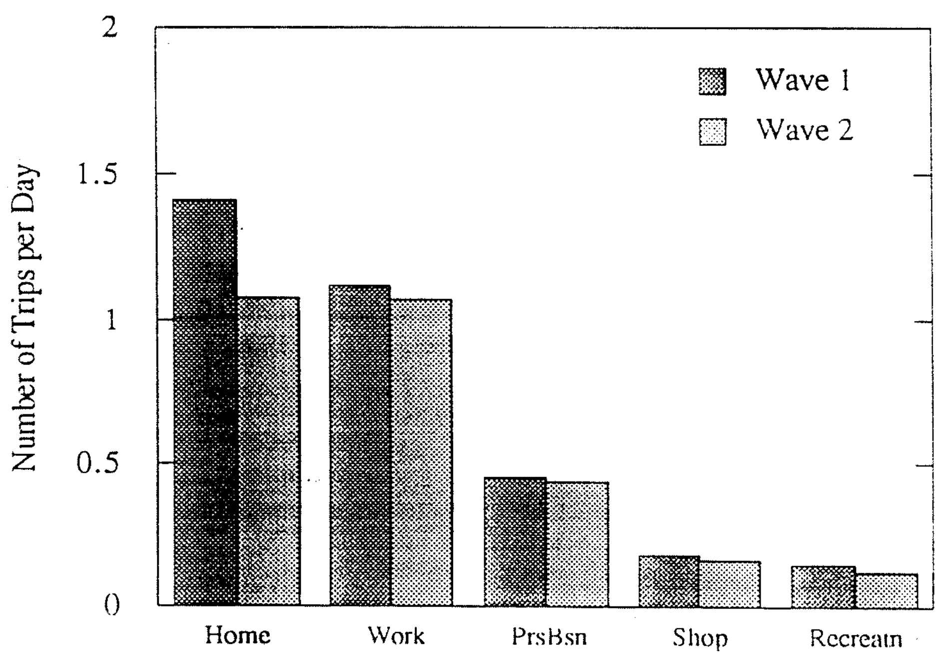


Figure 3
Travel Durations for Telecommuter Employees (N=73)

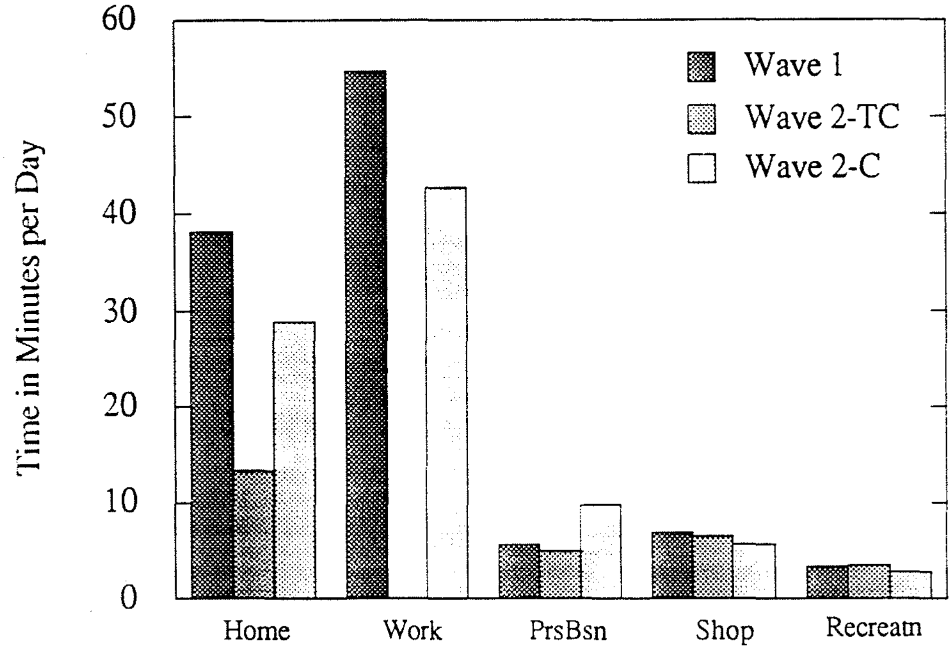


Figure 4
Travel Durations for Control Group Employees (N=65)

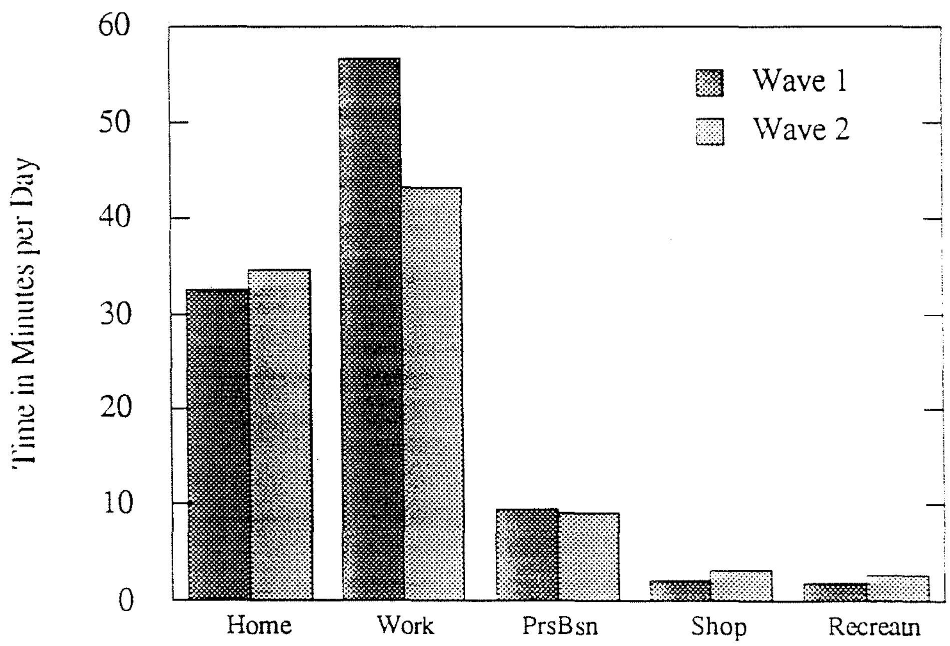


Figure 5

Activity Engagement for Telecommuter Employees (N=73)

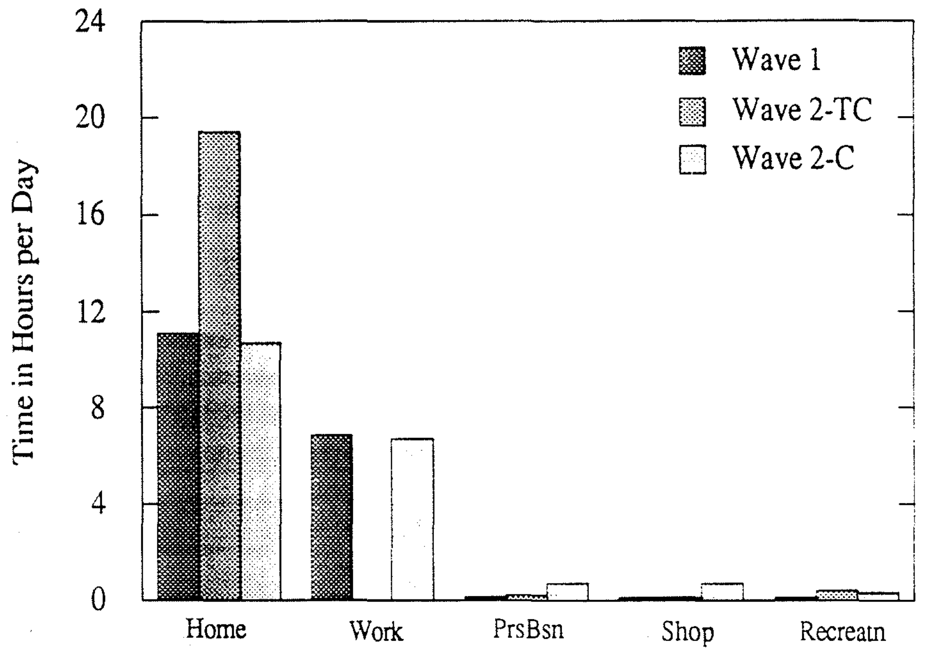


Figure 6

Activity Engagement for Control Group Employees (N=65)

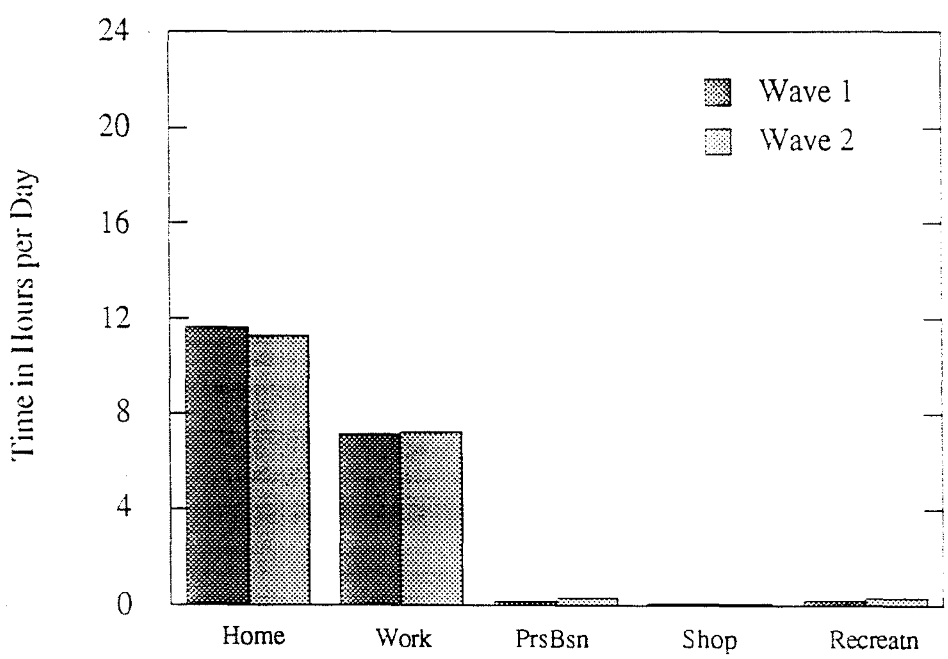
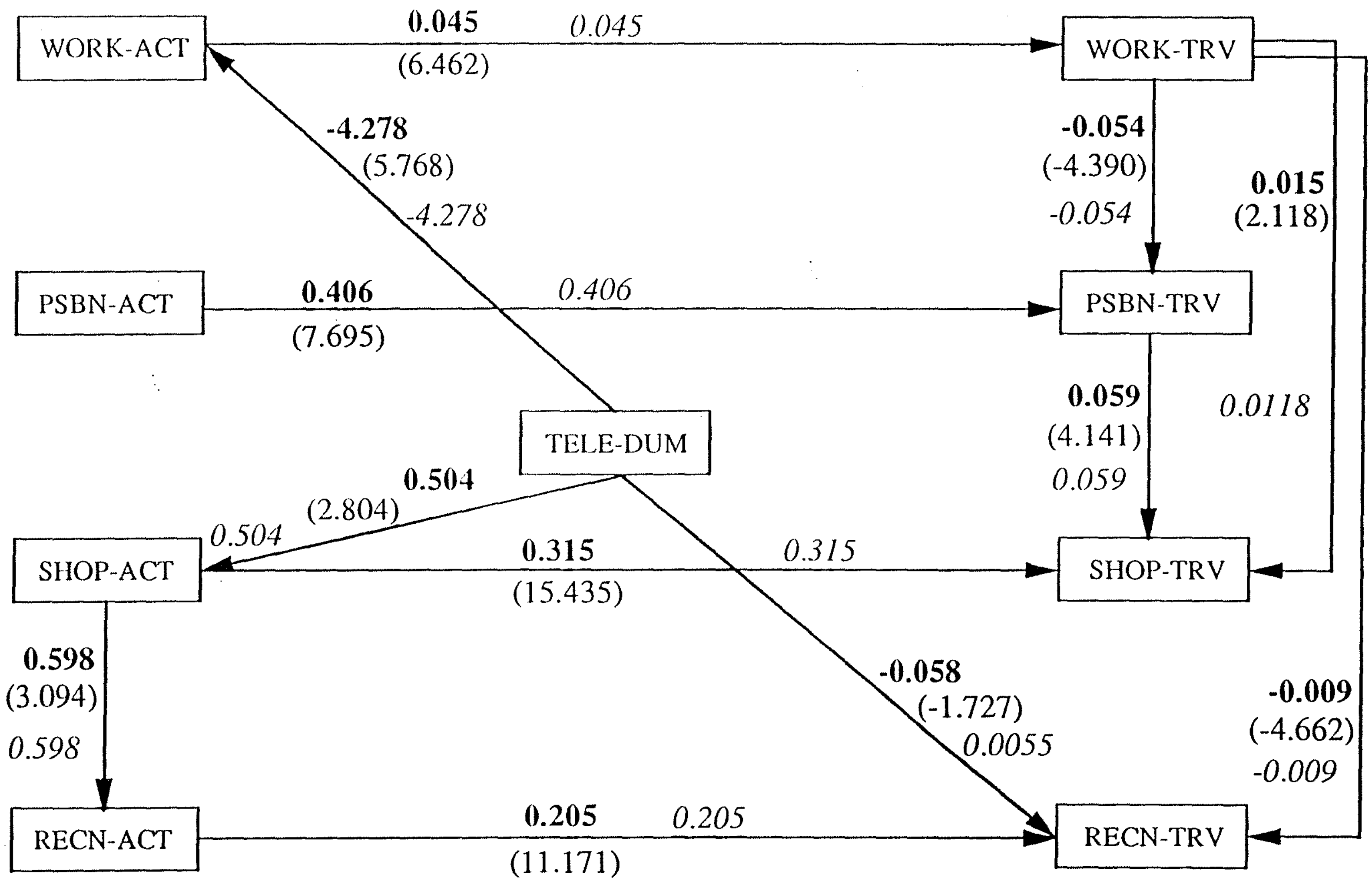
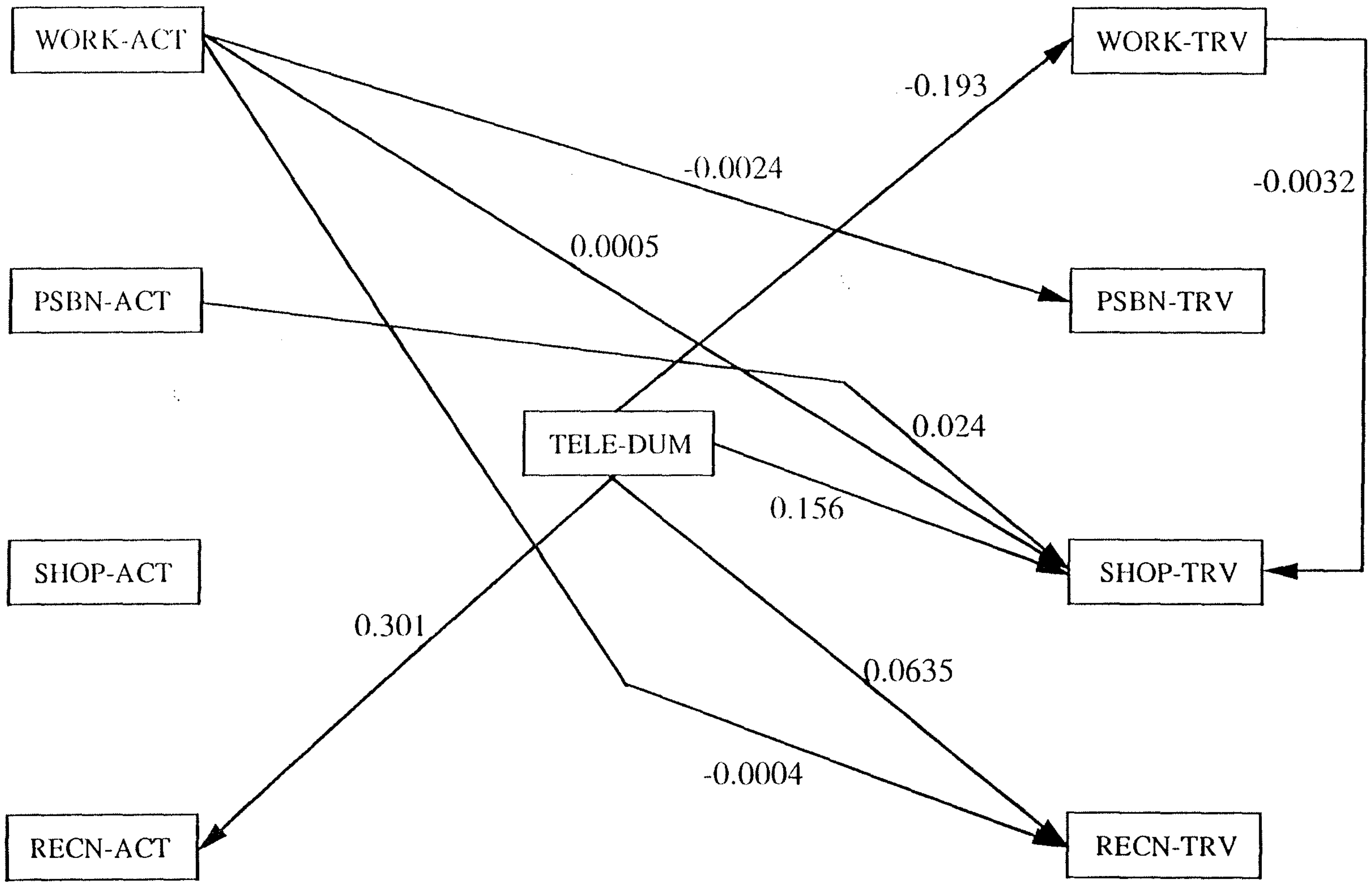


Figure 7. Model Structure (N=274)



Notes:
ACT - Activity Duration; TRV - Travel Duration; WORK - Working outside home; PSBN - Personal Business; SHOP - Shopping; RECN - Recreation
TELE-DUM=1 for telecommuters in second wave.
Direct effects are in bold. Structural parameter estimates to standard error ratios (pseudo t-values) are in parentheses. Total effects are in italics.
Chi-square = 30.122; df = 24; p = 0.1807. Model cannot be rejected at the 0.05 level of significance.

Figure 8. Indirect Effects in Model (N=274)



Notes:
ACT - Activity Duration; TRV - Travel Duration; WORK - Working outside home; PSBN - Personal Business; SHOP - Shopping; RECN - Recreation
TELE-DUM=1 for telecommuters in second wave.

Table 1. Composition of the Sample

Group	Wave 1	Wave 2	Stayers
Telecommuter Employees	137	79	73
Control Group Employees	115	75	65
Telecommuter Household Members	93	56	45
Control Group Household Members	85	47	36
Totals	430	257	219

Table 2. Descriptive Statistics for the Stayer Employee Samples

Characteristic	Telecommuters (N=73)		Control Group (N=65)	
	Wave 1	Wave 2	Wave 1	Wave 2
Age	44.1	n/a	41.2	n/a
No. of Adults in Household	1.83	n/a	1.75	n/a
No. of Teenagers in Household	0.21	n/a	0.15	n/a
No. of Children in Household	0.48	n/a	0.37	n/a
Household Car Ownership	1.83	1.83	1.66	1.69

Table 3. Variable Definitions

Variable	Abbreviation in Flow Diagrams	Treatment
Endogenous variables		
Activity duration - work	WORK-ACT	Continuous
Activity duration - pers. bus.	PSBN-ACT	Censored at 0.
Activity duration - shopping	SHOP-ACT	Censored at 0.
Activity duration - soc./rec.	RECN-ACT	Censored at 0.
Travel Time - work	WORK-TRV	Continuous
Travel Time - pers. bus.	PSBN-TRV	Censored at 0.
Travel Time - shopping	SHOP-TRV	Censored at 0.
Travel Time - soc./rec.	RECN-TRV	Censored at 0.
Exogenous variable		
Telecommuting dummy	TELE-DUM	

Table 4. Structural Parameter Estimates

From	To	Coefficient	Z-statistic
Links between endogenous variables (B matrix elements)			
Activity duration - work	Travel time - work	.045	6.46
Activity duration - pers. bus.	Travel time - pers. bus.	.406	7.70
Activity duration - shopping	Activity duration - soc./rec.	.598	3.09
Activity duration - shopping	Travel time - shopping	.315	15.43
Activity duration - soc./rec.	Travel time - soc./rec.	.205	11.71
Travel time - work	Travel time - pers. bus.	-.054	-4.39
Travel time - work	Travel time - shopping	.015	2.12
Travel time - work	Travel time - soc./rec.	-.009	-4.66
Travel time - pers. bus.	Travel time - shopping	.059	4.14
Links from exogenous to endogenous variables (Γ matrix elements)			
Telecommuter dummy	Activity duration - work	-4.278	-5.77
Telecommuter dummy	Activity duration - shopping	.504	2.80
Telecommuter dummy	Travel time - soc./rec.	-.058	-1.73

Table 5. Disturbance-term Parameter Estimates, Sample Statistics, and R^2 Values

Endogenous variable	Estimated error variance *(ψ param.)*	Sample variance	R^2
Activity duration - work	30.690	31.552	.027
Activity duration - pers. bus.	3.512	3.456	.000
Activity duration - shopping	1.525	1.584	.037
Activity duration - soc./rec.	8.176	9.284	.119
Travel Time - work	2.295	2.323	.012
Travel Time - pers. bus.	.317	.784	.596
Travel Time - shopping	.041	.210	.805
Travel Time - soc./rec.	.108	.431	.749