UCI-ITS-AS-WP-86-2

A Structural Model of Temporal Change in Multimodal Travel Demand

UCI-ITS-AS-WP-86-2

Thomas F. Golob [1]
Henk Meurs [2]

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

[2] Bureau Goudappel Coffeng BV, P.O. Box 161
7400 Ad Deventer, The Netherlands

August 1986

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

ABSTRACT

A simultaneous equation model is developed to describe temporal trends and shifts in demand among five modes of passenger transportation in the Netherlands. The modes are car driver, car passenger, train, bicycle, and public transit (bus-tram-metro). The time period is one year (1984-1985). The data are from the week-long travel diaries at six-month intervals of a national panel of households in the Nether- lands. The model explains the weekly trip rates for each mode in terms of three types of relationships: links from demand for the same mode at previous points in time (temporal stability or inertia), links to and from demand for other modes at the same point in time (complementarity and competition on a synchronous basis), and links from demand for other modes at previous points in time (substitution effects). A significant model is found with fifteen inertial links, twenty-one synchronous links, and sixteen cross-lag links among the variables. It is proposed in interpretations of the link coefficients and overall effects of one variable on another that relationships among the modes are evolving over time. In particular, the model captures the effect of a public transit fare increase that occurred during the time frame of the panel data.

INTRODUCTION

This research is aimed at developing a model of changes in demand for passenger transport modes over time. The specific application is to changes in demand for five modes in the Netherlands--car driver, car passenger, train, bicycle (an important mode in that country) and bus-tram-metro (considered as one mode)--at three points in time: Spring 1984, Autumn 1984 and Spring 1985. The model attempts to capture temporal trends and shifts in demand among modes that might be caused by events such as a public transit fare increase. Demand changes in general could be caused either by situational factors, such as changes in income, employment status, residential location or household structure, or by factors external to the individual travelers, such as travel costs or levels of service.

The model attempts to explain the level of demand for each mode of transportation in terms of sets of structural relationships involving three sets of explanatory variables: (1) the demand for the same mode at previous points in time, (2) the demand for other modes at the same point in time, and (3) the demand for other modes at previous points in time. To accomplish this, simultaneous equations are estimated using panel data. In panels, the same individuals are surveyed at multiple points in time. The data used are from a national panel in the Netherlands that had approximately 5,600 respondents for its first three waves. The variables in the model are summarized from the week-long travel diaries completed by the panel respondents.

The measure of modal demand used in the modeling was the total number of trips made by each person over the course of a week at each point in time. This use of multi-day travel data is an important aspect of this reseach. There is considerable variation in the numbers of trips by mode on a weekly basis, and infrequent use of a mode (e.g., car passenger travel on weekends only, or train use once a week) is less subject to measurement error when measured on a weekly rather than daily basis.

METHODOLOGY

In a structural relationships approach (also known as causal analysis, path analysis, or simply simultaneous equations), the phenomenon under study is specified in terms of cause-and-effect relationships. This is done prior to empirical testing of the model and estimation of the coefficients, based on theories and prior empirical results. The relationships are always unidirectional in that they each postulate that one variable influences another, and not conversely. If reciprocal influences appear to be appropriate, then relationship can be specified in both directions, but each relationship in general would have a different coefficient. In this way, many structural equations models incorporate both direct and "feedback" influences. Overviews of structural relationship approaches can be found in Bielby and Hauser (1977), Duncan (1975), and Heise (1975).

The format for the specific structural relationships approach of the present modeling effort can be illustrated by organizing the demand variables in flow diagrams according to a five by three matrix, as shown in Figure 1. The rows of this matrix represent the five modes (cross-sectional information) and the columns represent the three waves, each six months apart (temporal information). (The bus-tram-metro mode is abbreviated as "btm" in all figures.) Three types of unidirectional relationships are then specified to link these variables.

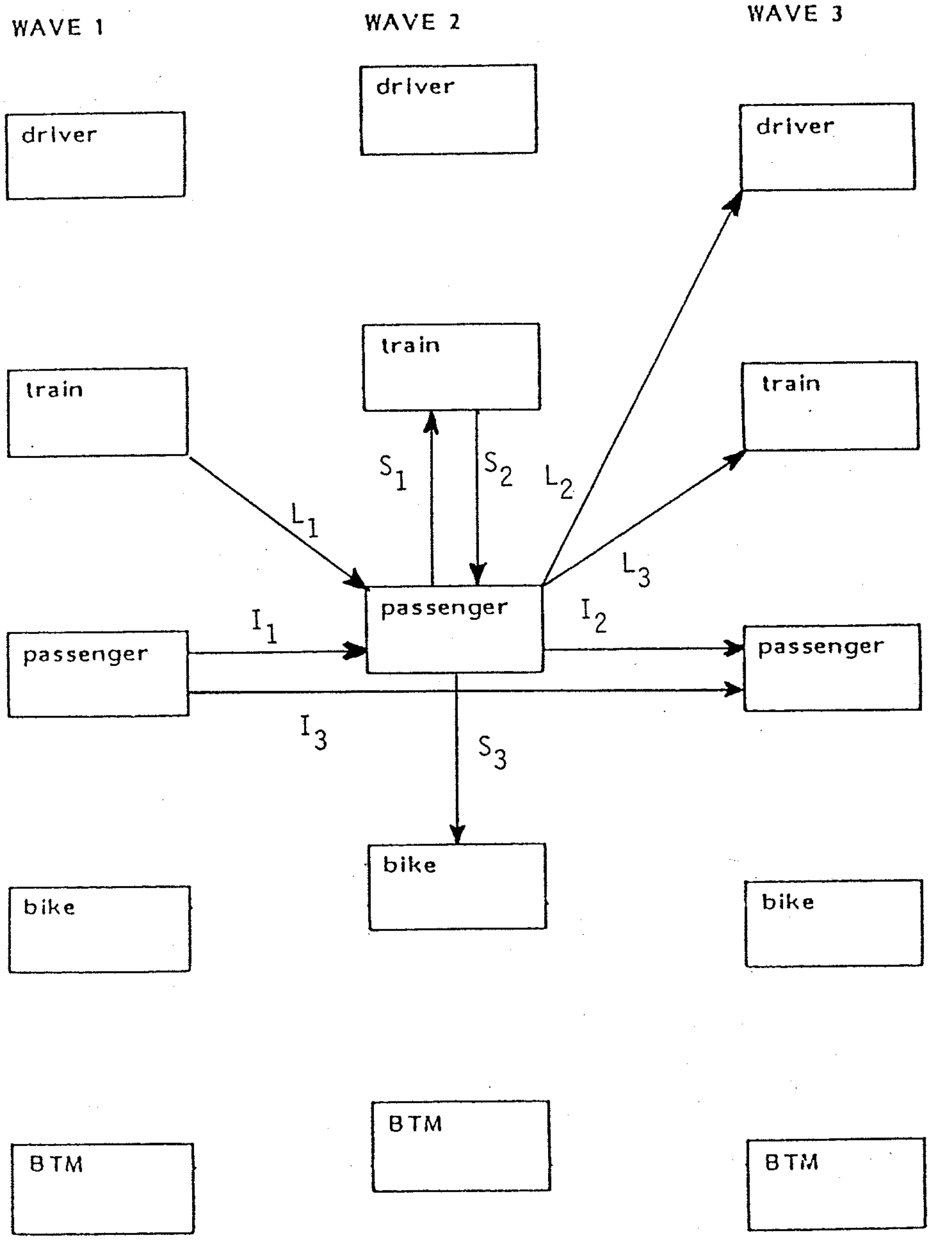

FIGURE 1

ORGANIZATION OF VARIABLES AND HYPOTHETICAL VARIABLE LINKS BY TYPE

First, diachronal relationships between demand levels of the same mode at two points in time capture inertia or stability over time in mode usage. Examples of possible "inertial links" are denoted by the "I" flows in Figure 1. The inertial links between successive panel waves in particular are expected to be strong because of the relatively short period of time between the waves (six months). Also, due to implementation of biannual waves, inertial links between the first and third waves, in the presence of links between successive waves, will capture seasonal demand patterns. Such seasonal patterns have been shown to be present in the Dutch panel data (T. Golob et al., 1986).

Second, synchronous relationships (exemplified by the "S" flows in Figure 1) are used to capture complementarity (positive links) and substitution (negative links) among the modes at any one point in time. These links are postulated on the basis of results from cross-sectional travel demand studies and known facts about the competitiveness of passenger travel modes. For example, strong negative links are expected from the car driver mode to many other modes, and reciprocal positive links are expected between train and bus-tram-metro (the latter mode being typically used as an access and egress mode for the former mode, and both of these public transport modes are often used by non-car owners).

Third, and finally, cross-lagged relationships (the "L" flows in Figure 1) relate the use of one mode at one point in time to another mode at a later point in time. These links can capture systematic adjustments in mode demand (Kenny and Harackiewicz, 1979). The present approach in specifying the model was to test cross-lagged hypotheses after firmly establishing both synchronous and inertial relationships. Significant cross-lagged relationships thus represent dynamics of demand that cannot be explained by combinations of inertial and synchronous changes.

The estimation of model parameters involves simultaneously finding the coefficients for each of the three types of links that reproduce the sample data in some optimal manner. This is accomplished using either least squares (two-stage, three-stage or partial least squares) or maximum likelihood methods. Both two-stage least squares and maximum likelihood methods were used in the present application, the former being employed as initial values for the iterative maximum likelihood solution using the LISREL program (LInear Structural RELationships by the Method of Maximum Likelihood) (Joreskog and Sorbom, 1984) introduced by Joreskog (1973). There were only slight differences between the estimates produced by the two methods. However, the LISREL maximum likelihood method provided extensive diagnostics concerning model goodness-of-fit and possible improvements, and these estimates are documented here.

Unstandardized variables were used in the model because all variables were measured in the same scale: trips per week. Thus, the model estimation involved reproducing the variable variance-covariance matrix, as opposed to the correlation matrix. Denoting:

S (kxk) = sample variance - covariance matrix for the k = 15 variables (5 modes at 3 points in time), and

Σ (kxk) = estimated variance - covariance matrix reproduced by the model,

the objective function for the least-squares initial values is

$$F = \mathrm{tr}\,[(S - \Sigma)^2]/2 \qquad (1)$$

and the objective function for the maximum-likelihood estimates is

$$F = \log|\Sigma| + \mathrm{tr}\,(S\Sigma^{-1}) - \log\,|S| - k \qquad (2)$$

Parameter standard errors are computed from the probability limits of the second-order derivatives of function (2).

Assessing model goodness-of-fit is accomplished first by consulting the chi-square statistic computed from the log-likelihood ratio. This statistic, with degrees of freedom (d), equal to the number of free entries in the variance-covariance matrix minus the number of parameters in the model ($d = (k + 1)k/2 - t$), can be used to test the hypothesis that the model can be rejected and is a general index of goodness-of-fit. Second, an adjusted goodness-of-fit index that measures the relative amount of variances and covariances accounted for by the model is given by

$$AGFI = 1 - [k\,(k + 1)/2d]\,(1 - GFI) \qquad (3)$$

$$GFI = 1 - \mathrm{tr}\,(S - \Sigma)^2/\mathrm{tr}\,(S^2) \qquad (4)$$

and d denotes the degrees-of-freedom of the model. The AGFI is independent of sample size and robust against deviations from normality, but its distribution is unknown for hypothesis testing. Finally, the parameter t-statistics and correlations provide information regarding model specification errors. All hypothesis test were conducted at the $p=.05$, or 95 percent confidence interval.

The estimate of the variance-covariance matrix involves $(k + 1)k/2$ equations, with the number of unknowns equal to t (the number of model parameters). A necessary condition for the model to be identified is thus that $t < (k + 1)k/2$, or in this case, $t < 120$. Further conditions for identification are described in Goldberger

(1964), Geraci (1976) and Joreskog (1977). Identification in the present study was aided by the constraint of having only forward-directed diachronal links.

THE PANEL DATA

The data source is an ongoing panel in the Netherlands begun in 1984 (J. Golob, et al., 1986). The sample of about 1,800 households per wave is continually refreshed to replace drop-outs. It is stratified by life cycle, income and community type and is clustered in twenty communities throughout the Netherlands. The first three panel waves, providing the data for the present study, were conducted in March 1984, September-October 1984, and March 1985. Each of these first three waves involved a household questionnaire and separate questionnaires and travel diaries for all household members over eleven years of age.

Weekly trip rates measuring modal demand were estimated using all 5,614 persons who responded in at least one wave of the panel. Of these persons, 2,274 responded in all of the first three waves, while the remainder dropped out after one or two waves or were added as replacements after the first or second waves. The pair-wise deletion methods was used in the computation of the variance-covariance matrix in order to utilize all information and minimize biases due to selective panel drop-out (Kitamura and Bovy, 1986): the samples employed in computing cross-sectional covariances were all respondents who participated in a specific wave, and the samples for diachronal covariances were all respondents common to the two specific waves. The minimum sample size for any pair of variables was 2273.

Results from an analysis of biases introduced by the under- reporting of trips over time in the seven-day diary (Golob and Meurs, 1986) were used in determining which modes were to be included in the analysis. The reporting of walking trips was found to be substantially biased, and this mode was excluded. The biases in reporting of trips by vehicular modes were similar, mode by mode, and should not affect the results of the present trip-rate analysis. Analyses of changes in mode demands based on dichotomous use/non-use variables by individual mode are reported in T. Golob et al. (1986). The present analysis considers all modes together.

ESTIMATION OF THE COMPLETE MODEL

The flow diagram for the model for five modes at three points in time is shown in Figure 2. The log-likelihood ratio chi-square for this model is 59.1 with 53 degrees-of-freedom. This relatively low value for the degrees-of-freedom represents a good fit as the model cannot be rejected on the basis of this statistic. Moreover, the adjusted goodness-of-fit index (the AGFI of equation (3)) is 0.997, indicating an excellent replication of the trip-rate variance-covariance matrix.

The coefficients of determination (R^2 values) for each endogenous variable are listed in Figure 2. All variables with the exception of car driver in wave one were endogenous; that is, they were influenced by at least one other variable. The R^2 values for wave one can be disregarded because there is no prior information on which to base the estimation of these variables. Regarding the wave two and three demand levels, the degrees of explanation for car driver and bike are the highest, with car passenger the lowest, and bus-tram-metro (btm) and train intermediate.

The model has fifteen inertial links, twenty-one synchronous links, and sixteen cross-lagged links, for a total of fifty-two links. With the addition of fifteen free error parameters, one for each observed variable (no error term covariances were found to be significant), the model thus has sixty-seven parameters. All of the links, with one exception, had coefficients that were

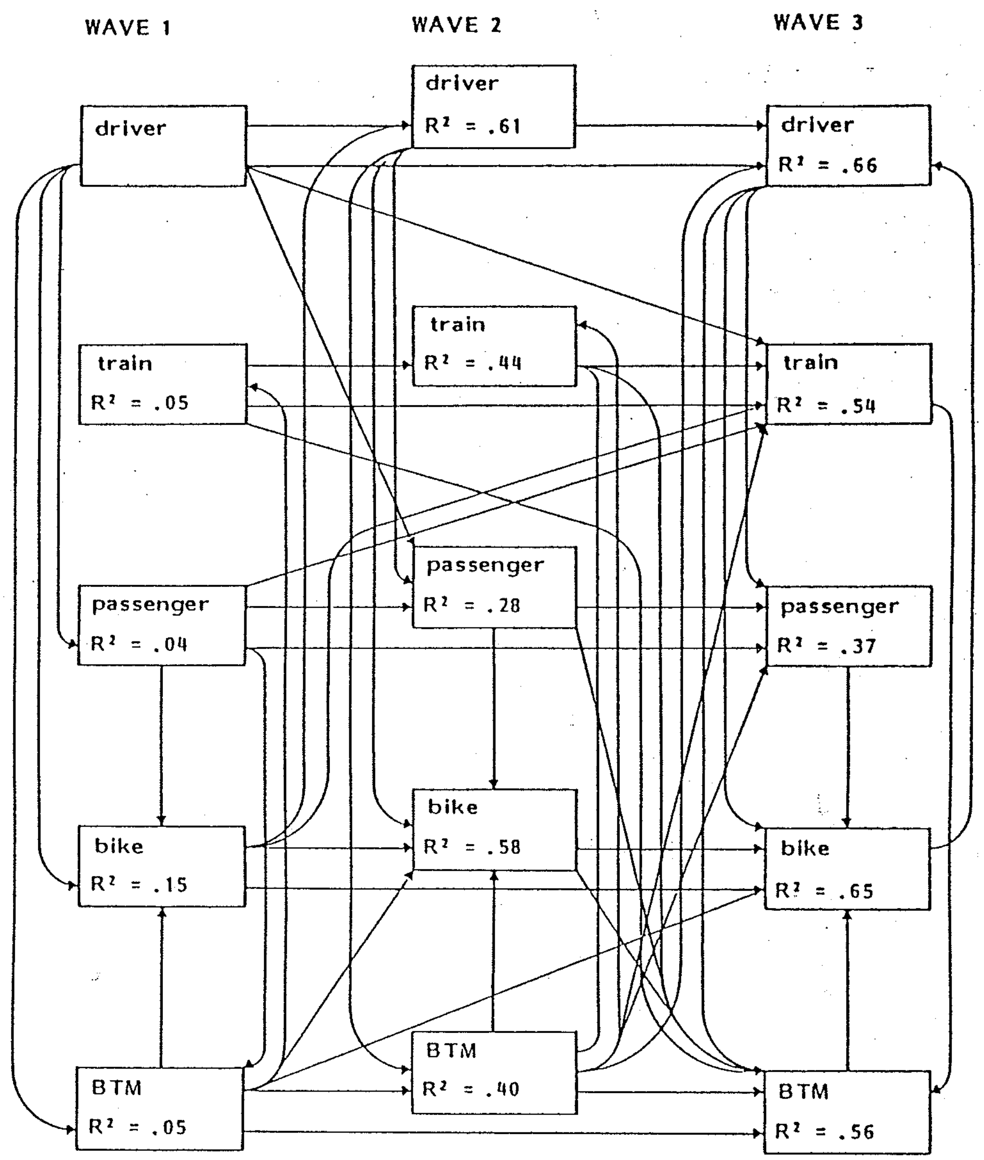

FIGURE 2

FLOW DIAGRAM OF ESTIMATED COMPLETE MODEL WITH 67 PARAMETERS significantly different from zero at the $p = .05$ level. The complete set of coefficients and associated t-statistics are listed in Appendix A. These results are interpreted on a sub-model basis by the three types of links (inertial, synchronous, and cross-lagged) in the next three sections.

THE INERTIAL SUB-MODEL

The coefficients for the inertial links are shown in Figure 3. These coefficients indicate the direct effects on demand level at one point in time from demand levels for the same mode at previous points in time. The coefficients with the highest values as a group are the inertial links from wave one to wave two, and the highest of these are for car driver, bike and train. Of these three modes, train sustains the highest temporal stability in demand from wave two to wave three.

The links from wave one to wave three for each of the five modes can be interpreted as seasonality effects (waves one and three being in the spring of successive years, wave two being in the intervening autumn). All of these links are of modest strength and are highly significant, confirming results reported in Golob, et al. (1986). The lowest seasonality coefficient is that for the car passenger mode.

Overall, car driver, train and bike exhibit the highest degree of temporal stability. Car passenger exhibits the lowest. Bus-tram-metro (btm) shows relatively low inertia between successive waves, but a relatively high seasonality component of stability.

THE SYNCHRONOUS SUB-MODEL

The direct effects associated with the synchronous (or cross-sectional) links are shown in Figure 4. The strongest influence for all three waves is that of bus-tram-metro on bicycle. This indicates that these two modes are competitive,

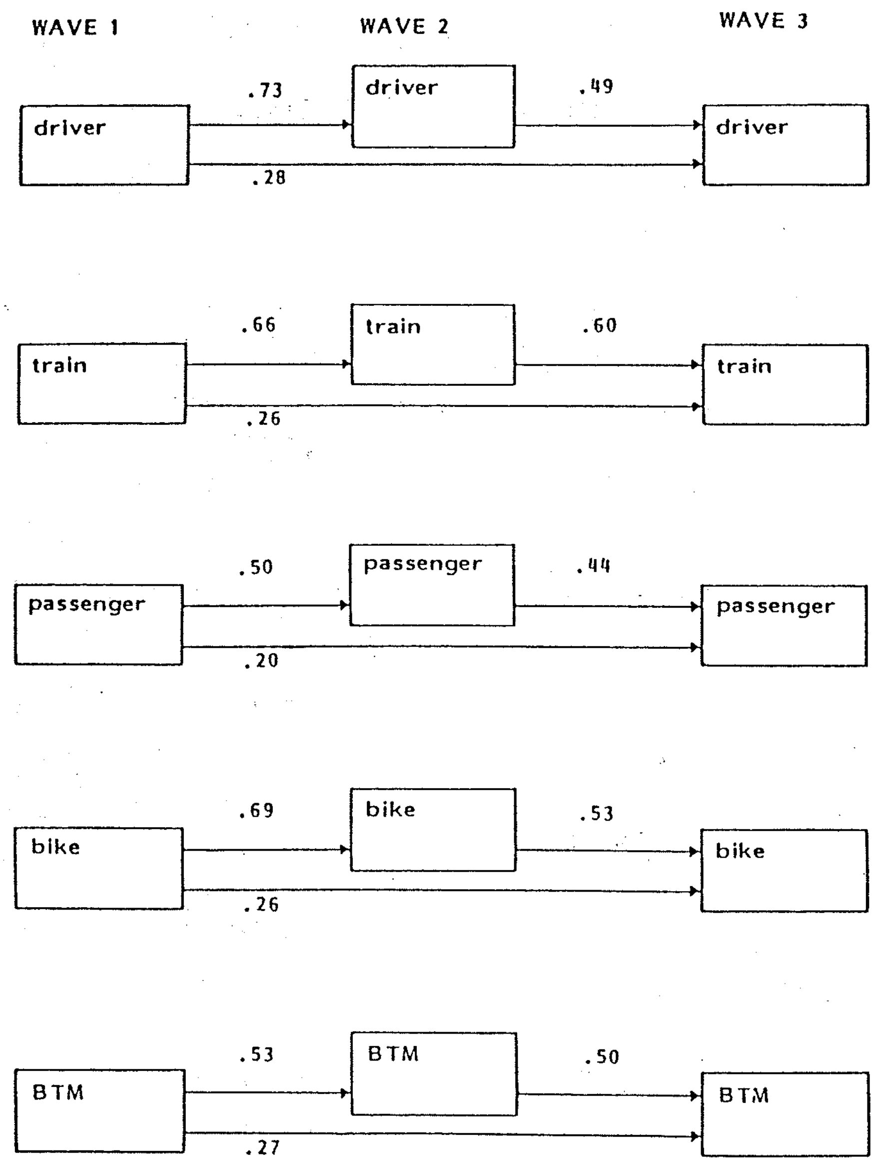

FIGURE 3

LINK COEFFICIENTS FOR INERTIAL SUB-MODEL with bus-tram-metro being the dominant mode: high use of btm causes low use of bike, but not conversely. The similarly negative influences of car diver and car passenger on bike appear to be decreasing over time, and indeed bike begins to exhibit a reciprocal influence on car driver in the third wave.

The complementary relationships between train and bus-tram-metro also appear to be evolving over time. The positive influence from btm to train decreases (from 0.11 in wave one to 0.05 in wave two to insignificance in wave three), while the positive influence from train to btm increases (from insignificance in wave one to 0.15 in wave two to 0.33 in wave three). All efforts to estimate a significant model with consistent synchronous links between these modes at all three waves failed, leading to the conclusion that the synchronous structure is indeed changing over time. A possible interpretation of the evolution in the relationships between this pair of models is that bus-tram-metro is becoming more of an access-egress mode for train over time.

THE CROSS-LAG SUB-MODEL

The cross-lagged effects over successive waves are shown in Figure 5, and those over the year-long period from wave one to wave three are shown in Figure 6. Consistently strong positive links were found from bus-tram-metro demand in wave one to bike demand in wave two (Figure 5) and wave three (Figure 6). These indicate that there was a shift from bus-tram-metro demand in March 1984 to bike demand on both a short-term (autumn 1984) and seasonally adjusted (March 1985) basis. This result is consistent with a public transport fare increase on April 1, 1984 that particularly affected the fare level for school-aged children; bike and bus-tram-metro are known to be competitive modes for this population segment.

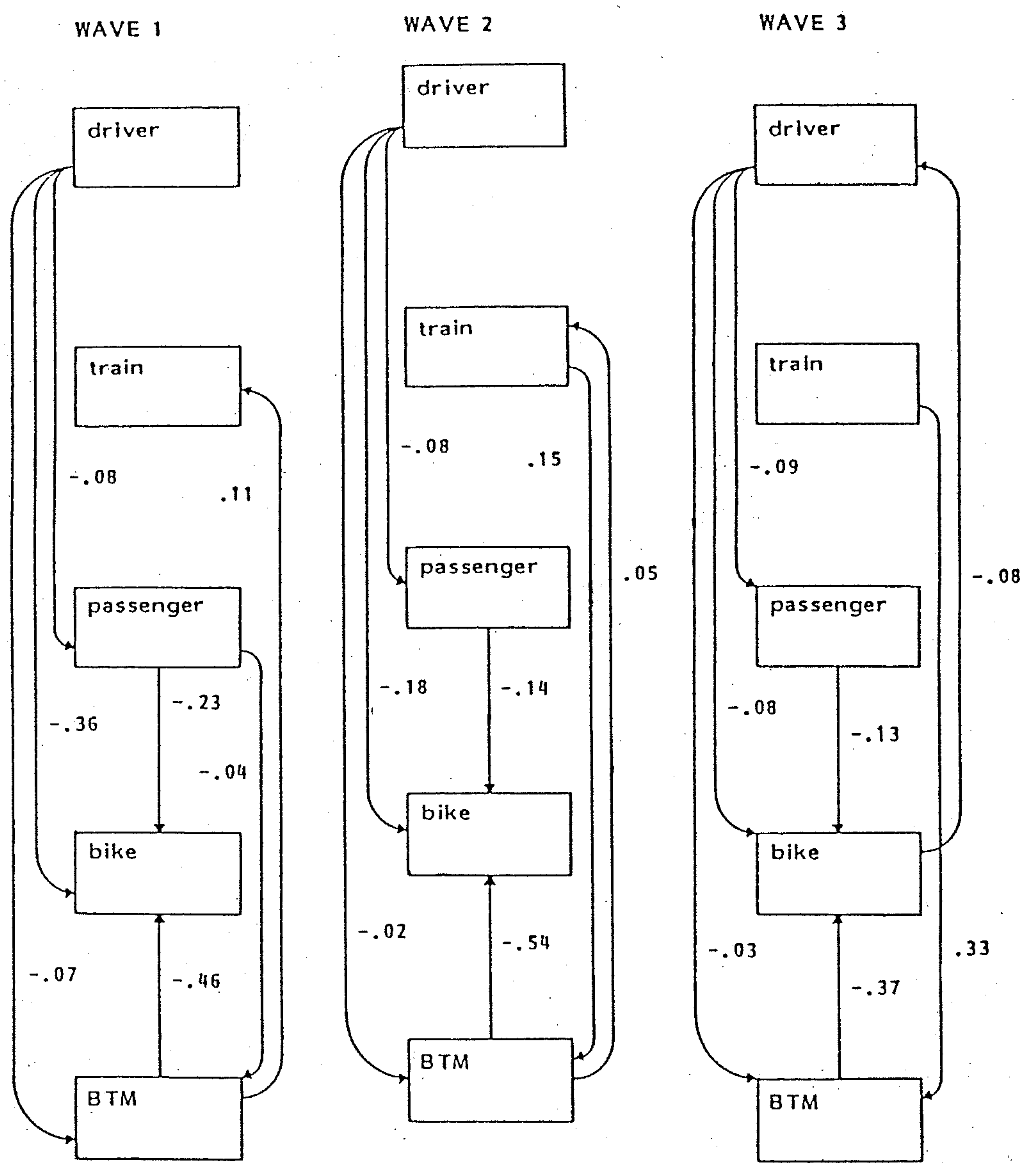

FIGURE 4

LINK COEFFICIENTS FOR SYNCHRONOUS SUB-MODEL

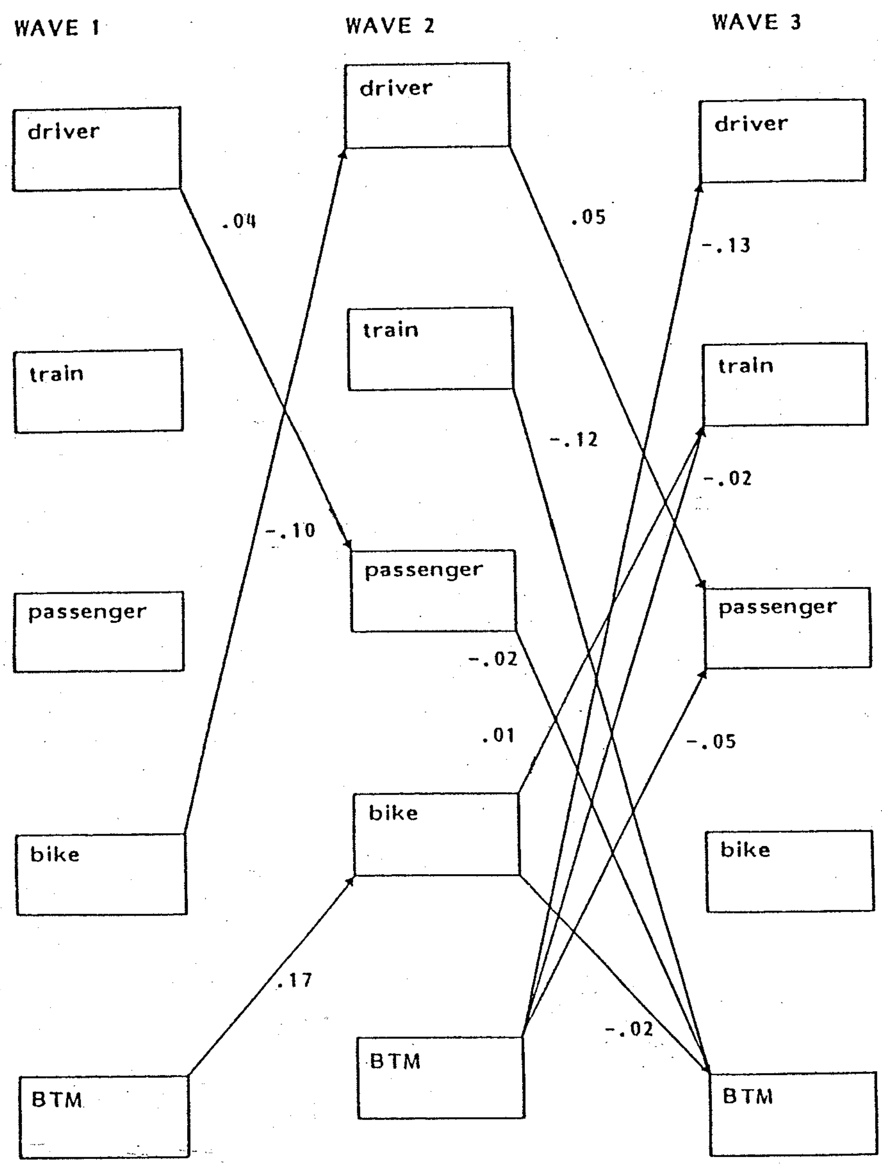

FIGURE 5

LINK COEFFICIENTS FOR CROSS-LAG SUB-MODEL FOR SUCCESSIVE WAVES

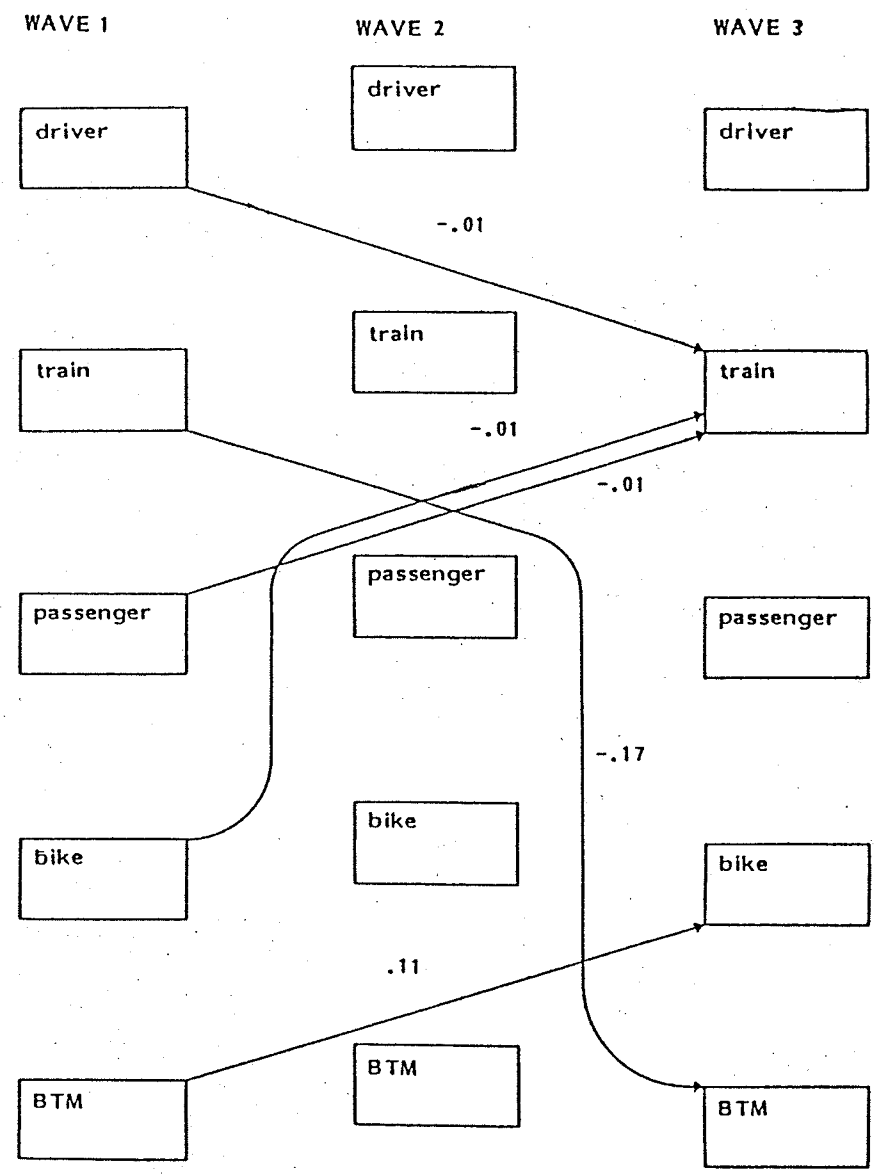

FIGURE 6

LINK COEFFICIENTS FOR CROSS-LAG SUB-MODEL FOR FIRST TO THIRD WAVES

There are also negative links from train in waves one and two to btm in wave three (-0.17 and -0.12 respectively). This could indicate that there was a modest shift during 1984 from train to modes that are generally competitive with bus-tram-metro. This is potentially consistent with heavy annual turn-overs in train season tickets for commuters. Several other cross-lagged links are relatively weak but significant. It appears that the model has captured some shifts in passenger transport demand in the Netherlands over the March 1984 to March 1985 period.

CALCULATED TOTAL EFFECTS

The total effect of one variable on another in such a structural relationships model as that diagrammed in Figure 2 is generally not simply the direct effect expressed in terms of the link coefficients described in the previous section. The total effect of one variable on another includes both direct effects and indirect effects manifested by paths through intermediate variables (Land, 1969; Blalock, 1971). In some cases the direct and indirect effects are of the same sign and reinforce each other, while in the other cases the different effects partially cancel each other.

The total effects implied by the five-mode model of Figure 2 are listed in matrix form in Table 1. Each entry in this matrix represents the total effect from the row modal demand level to the column modal demand level. For small changes, it is possible to interpret the total effects as the change in the column variable that would result from a unit (one trip) increase in the row variable.

TABLE 1

TOTAL EFFECTS FOR THE FIVE-MODE MODEL

	To														
	Wave 1					Wave 2					Wave 3				
From	car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm
car driver		-.01	-.08	-.31	-.06	0.76	-.01	-.06	-.33	-.05	0.68	-.01	-.06	-.29	-.06
train							0.67		-.05	0.10	-.01	0.66	-.01	-.03	0.01
car pass.		-.01		-.21	-.04	0.02	-.01	0.49	-.21	-.02	0.03	-.02	0.41	-.22	-.04
bike						-.10		0.01	0.71	0.01	-.10	-.01	0.01	0.65	-.01
btm		0.11		-.46		0.04	0.10	-.01	-.45	0.54	-.01	0.08	-.03	-.44	0.54
car driver							-.01	-.08	-.16	-.02	0.50	-.01	-.03	-.11	-.02
train							0.01		-.08	0.15	-.01	0.60	-.01	-.10	0.15
car pass.									-.14		0.01	-.01	0.44	-.12	-.02
bike										-.05	0.01	0.01	0.04	-.01	
btm							0.05		-.54	0.01	-.09	0.01	-.04	-.46	0.51
car driver											0.01		-.08	-.06	-.03
train											0.01		-.01	-.12	0.33
car pass.											0.01		-.01	-.13	
bike											-.08		0.01	0.01	0.01
btm											0.03		-.01	-.37	-.01

The total effects in Table 1 with absolute value greater than 0.04 are reproduced in Table 2 to facilitate interpretation. (The value of 0.04 is arbitrary in its present case but is approximately the critical value for correlation coefficients with the given sample sizes.) The total effects to the demand levels in the third wave, given by the entries in the last five columns in Table 2, are of most interest because they reflect influences of both six months and one year durations.

The total effect on demand for the car driver mode in wave three is greatest from car driver demand in waves one and two (the inertial effects). There are also substantial negative effects on car demand from bike demand in all time periods; this shows that bike is competitive with the car driver mode in the Netherlands. Finally, there is a negative total effect from bus-tram-metro in wave two to car driver in wave three, indicating that persons who used btm after the April 1, 1984 fare increase tended to use the car driver mode less in the following spring. These persons represent the basic public transit market.

Train demand is the least influenced by demand for other modes. The train demand level in wave three is influenced only by a person's train demand in the previous time periods and by bus-tram-metro demand in wave one (one year prior). There is no substantial effect on wave three train demand from wave two btm demand because positive and negative effects along different paths between the two variables cancel.

Car passenger demand was previously shown to have the weakest inertial direct effects and these are exhibited in the levels of direct effects from prior demand for the same mode (0.41 and 0.44); these are the lowest among the five modes. Substantial non-inertial effects on car passenger demand are found only from car driver demand one year prior and during the same period. The competitive

TABLE 2

TOTAL EFFECTS FOR THE FIVE-MODE MODEL WITH ABSOLUTE VALUE GREATER THAN 0.04

	To														
	Wave 1					Wave 2					Wave 3				
From	car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm
car driver			-.08	-.31	-.06	0.76		-.06	-.33	-.05	0.68		-.06	-.29	-.06
train							0.67		-.05	0.10		0.66			
car pass.				-.21				0.49	-.21				0.41	-.22	
bike						-.10			0.71		-.10			0.65	
btm		0.11		-.46			0.10		-.45	0.54		0.08		-.44	
car driver								-.08	-.16		0.50			-.11	
train									-.08	0.15		0.60		-.10	0.15
car pass.									-.14				0.44	-.12	
bike											-.05			0.54	
btm							0.05		-.54		-.09			-.46	0.51
car driver													-.08	-.06	
train														-.12	0.33
car pass.														-.13	
bike											-.08				
btm														-.37	

relationship from the dominant car driver to car passenger demand appears to be stronger on a seasonally adjusted basis.

There are substantial direct effects from almost every other variable to bicycle demand in wave three. All of these direct effects, with the exception of the inertial links representing temporal stability in bike use, are negative. Thus, bike demand is higher for those persons who do not use the other four modes. But, the converse is not generally true; there are no substantial effects from bike to other modes with the exception of car driver. Bike users tend to make little use of the car driver mode but their use of other modes is not systematically lower.

Finally, bus-tram-metro demand in wave three is affected by three other demand levels in addition to inertial effects. This demand level is negatively affected by car driver demand one year prior and is positively affected by train demand at the same point in time and train demand six months prior. Thus, the complementary influence of train on btm diminishes with the length of the time lag. Again, this could reflect the relatively high turn-over in train season tickets. By comparing the total effects from train at waves two and three to btm at wave three with similar effects from train at waves one and two to btm at wave two, it appears that the complementary influence of train or btm is also diminishing over time for the spring 1984 to spring 1985 time period.

DIRECTIONS FOR FURTHER RESEARCH

It can concluded that interrelationships among the levels of demand for alternative passenger travel modes at multiple points in time can be effectively represented by structural relationships that take the form of linear simultaneous equations. However, while a good model fit was demonstrated for demand levels for the five modes at the second and third points in time, the model structure was not intended to explain cross-sectional variation in demand at the initial point in time. Such an explanation would typically involve level of service variables, as well as personal and household characteristics. The resulting extended model would represent an integration of conventional modal split modeling, possibly involving discrete choice models, and the dynamic modeling of the present research. Unfortunately, level of service variables were unavailable for the Dutch panel sample at the time of the present research, but it appears that efforts are underway to compute such variables for at least a subsample of the panel households.

Another fruitful extension of the present modeling involves segmenting the population on the basis of either personal and household characteristics or level of service attributes. The model structures for the segments could then be compared statistically; it is possible to analyze data for several segments simultaneously by constraining any number of LISREL model parameters to be equal over segments and by testing the equality of unconstrained parameters (Joreskog and Sorbom, 1984, Chapter V). Segmentations based on personal and household characteristics could be used to test hypotheses relating variables such as income, life cycle, and age to levels of inertia and volatility in mode usage. For instance, do higher income adults exhibit more inertia in car usage than their lower income counterparts? Segmentations based on level of service attributes could lead to refined interpretations of substitution effects and might provide useful information concerning market demand for specific modes. The sample sizes in the Dutch panel are generally appropriate for such segmentations, and the sample is spatially distributed in twenty communities with varying bus-tram-metro and rail levels of service. Further efforts are required.

Acknowledgements

This research was supported, in part, by Grant CEE-84-00830 from the National Science Foundation. It was also sponsored by the Projectbureau for Integrated Traffic and Transport Studies and the Office of the Director General of Transport of the Ministry of Transport and Public Works of the Netherlands. The authors wish to thank the staff of these organizations for their encouragement and support. Errors, of course, remain the sole responsibility of the authors.

REFERENCES

Bielby, W.T. and R.M. Hauser (1977). Structural equation models. Annual Review of Sociology, 3: 137-161.

Blalock, H.M., ed. (1971). Causal Models in the Social Sciences. Chicago: Aldine.

Duncan, O.D. (1975). Introduction to Structural Equation Models. New York: Academic Press.

Geraci, V.J. (1976). Identification of simultaneous equation models with measurement error. Journal of Econometrics, 4: 263-283.

Goldberger, A.S. (1964). Econometric Theory. New York: Wiley.

Golob, J.M, L.J.M. Schreurs and J.G. Smit (1986). The design and policy applications of a panel for studying changes in mobility over time. In Behavioral Research for Transport Policy. Utrecht: VNU Press.

Golob, T.F. and H. Meurs (1986). Biases in response over time in a seven-day travel diary. Transportation, 13: 163-182.

Golob, T.F., L. van Wissen and H. Meurs (1986). A dynamic analysis of travel demand. Transportation Research A, 20A: 401-414.

Heise, D.R. (1975). Causal Analysis. New York: Wiley.

Joreskog, 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.

Joreskog, K.G. (1977). Structural equations models in the social sciences: specification, estimation and testing. In P.R. Krishnaiah, ed. Applications of Statistics. Amsterdam: North Holland.

Joreskog, K.G. and D. Sorbom (1977). Statistical models and methods for analysis of longitudinal data. In D.V. Aigner and A.S. Goldberger, eds., Latent Variables in Socio-economic Models: 285-325. Amsterdam: North-Holland.

Joreskog, K.G. and D. Sorbom (1984). LISREL VI User's Guide. Mooresville, IN: Scientific Software.

Kenny, D.A. and J.M. Harackiewicz (1979). Cross-lagged panel correlation: practice and promise. Journal of Applied Psychology, 64: 372-379.

Kitamura, R. and P.H.L. Bovy (1985). Attrition and trip reporting in the first two waves of Dutch mobility panel data. Presented at Annual Meeting of Transportation Research Board, Washington.

Land, K.C. (1969). Principles in path analysis. In E.F. Borgatta, ed., Sociological Methodology, 1969. San Francisco: Jossey-Bass.

APPENDIX TABLE 1

COEFFICIENTS AND T-VALUES FOR THE COMPLETE TRIP RATE MODEL

		Link					
	Coefficient	From		To			
Type	Number	Wave	Mode	Wave	Mode	Coefficient	T-Value
	1	1	car driver	2	car driver	0.73	54.5
	2	2	car driver	3	car driver	0.49	26.5
	3	1	car driver	3	car driver	0.28	15.5
I	4	1	train	2	train	0.67	40.3
N	5	2	train	3	train	0.60	30.7
E	6	1	train	3	train	0.26	12.6
R	7	1	car passenger	2	car passenger	0.50	28.4
T	8	2	car passenger	3	car passenger	0.44	23.6
I	9	1	car passenger	3	car passenger	0.20	10.9
A	10	1	bike	2	bike	0.69	46.5
L	11	2	bike	3	bike	0.53	30.3
	12	1	bike	3	bike	0.26	14.7
	13	1	bus-tram-metro	2	bus-tram-metro	0.53	35.1
	14	2	bus-tram-metro	3	bus-tram-metro	0.50	28.4
	15	1	bus-tram-metro	3	bus-tram-metro	0.27	16.9
	16	1	car driver	1	car passenger	-.08	-9.91
	17	1	car driver	1	bike	-.36	-20.4
	18	1	car driver	1	bus-tram-metro	-.07	-11.3
	19	1	car passenger	1	bike	-.23	-5.50
	20	1	bus-tram-metro	1	bike	-.46	-7.60
S	21	1	car passenger	1	bus-tram-metro	-.04	3.01
Y	22	1	bus-tram-metro	1	train	0.11	11.4
N	23	2	car driver	2	car passenger	-.08	-6.61
C	24	2	car driver	2	bike	-.18	-13.1
H	25	2	car driver	2	bus-tram-metro	-.02	-5.73
R	26	2	car passenger	2	bike	-.14	-4.57
O	27	2	bus-tram-metro	2	bike	-.54	-8.85
N	28	2	train	2	bus-tram-metro	0.15	4.07
O	29	2	bus-tram-metro	2	train	0.05	3.94
U	30	3	car driver	3	car passenger	-.08	-7.68
S	31	3	car driver	3	bike	-.08	-5.42
	32	3	car driver	3	bus-tram-metro	-.03	-5.91
	33	3	car passenger	3	bike	-.13	-4.48
	34	3	bus-tram-metro	3	bike	-.37	-6.86
	35	3	train	3	bus-tram-metro	0.33	10.0
	36	3	bike	3	car driver	-.08	-5.52

APPENDIX TABLE 1 (continued)

Type	Coefficient Number	Link From Wave	Link From Mode	Link To Wave	Link To Mode	Coefficient	T-Value
	37	1	car driver	2	car passenger	0.04	3.17
	38	1	bike	2	car driver	-.10	-6.35
C	39	1	bus-tram-metro	2	bike	0.17	3.07
R	40	2	car driver	3	car passenger	0.05	4.63
O	41	2	train	3	bus-tram-metro	-.12	-3.30
S	42	2	car passenger	3	bus-tram-metro	-.02	-2.48
S	43	2	bike	3	train	0.01	3.20
	44	2	bike	3	bus-tram-metro	-.02	-3.51
L	45	2	bus-tram-metro	3	car driver	-.13	-2.89
A	46	2	bus-tram-metro	3	train	-.02	-1.70
G	47	2	bus-tram-metro	3	car passenger	-.05	-2.05
G	48	1	car driver	3	train	-.01	-2.66
E	49	1	train	3	bus-tram-metro	-.17	-5.05
D	50	1	car passenger	3	train	-.01	-2.35
	51	1	bike	3	train	-.01	-3.01
	52	1	bus-tram-metro	3	bike	0.11	2.35