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ABSTRACT

Levels of demand over time are analyzed for five modes of passenger transportation. The data are for the modes car driver, car passenger, train, bicycle, and public transit are compiled from week-long travel diaries collected at six-month intervals from a nationwide panel in the Netherlands. Three types of empirical relationships are present in these panel data: (1) autocorrelative relationships, capturing temporal stability in demand for the same mode at different points in time, (2) contemporaneous relationships capturing complementarity and competition among different modes at the same point in time, and (3) cross-lagged effects, potentially capturing systematic shifts in demand. Simultaneous equation systems are used to test the temporal stability of demand for each mode and the stationarity of the contemporaneous relationships among the modes. The dynamic structure of both trip rates and travel times are modeled successfully according to several goodness-of-fit indices. The equation systems capture nonstationarity in the contemporaneous relationships, as well as important cross-lagged effects. These results quantify changes in the structure of demand over time in the Netherlands and are shown to be directly related to the event of a public transit fare increase.

1. OBJECTIVES AND SCOPE

The objective of the reported research is to model the dynamic structure of demand for passenger transportation modes. The models are intended to provide information useful in addressing questions such as:

(1) Is demand stable over time for a given mode? Are there seasonal effects?

(2) Can demand for a given mode be forecasted from information about prior levels of demand for that mode only, or is information also required concerning levels of demand for other modes?

(3) Are pairs of modes changing over time in terms of their roles as substitutes or complements?

(4) Has there been a shift over a specific time interval from demand for one mode to demand for another mode or other modes?

(5) Can changes in demand structure be related to an intervention effect (such as a fare increase)?

The detection of structural relationships among variables through the analysis of pooled time-series and cross-sectional data has attracted considerable interest in economics (e.g., Granger, 1969; and Pierce, 1977), psychology (e.g., Kenny and Harackiewicz, 1979; and Rogosa, 1980) and sociology (e.g., Heise, 1970, 1975). The definitions of structural relationships vary across the disciplines, but a definition of causality based on predictability is pervasive: one time series displays a causal effect on another time series if present values of the latter (affected) series can be predicted better using the past values of both series than by using past values of the latter series alone (Pierce and Haugh, 1977; and Rogoza, 1980). The present application involves the assessment of structural relationships among demand levels for five modes (car driver, car passenger, train, bus-tram-metro, and bicycle) over a one-year period (1984-1985) in the Netherlands. The pooled time-series and cross-sectional data are provided by a nationwide panel survey.

The present research is limited in that it does not attempt to explain mobility directly in terms of either situational factors (such as changes in income, employment status, residential location or household structure) or in terms of factors external to the individual travelers (such as travel costs or levels of service). However, the present model does provide information concerning the stability of demand for each mode and the equilibrium of the interrelationships among demands for different modes. Kitamura (1986) and van der Hoorn and Kitamura (1987) explored the stationarity of cross-sectional trip generation equations using panel data, reaching the conclusion that forecasting with cross-sectional models is suspect due to lack of stationarity in the behavioral relationship. The present study attempts to provide information relevant in assessing cross-sectional mode choice models by investigating the stationarity of the relationships among demands for different modes.

The approach is to model relationships among individuals' demands over time for the different modes. This is accomplished in terms of a simultaneous equation system. Each equation in the system represents the direct effect of the demand for mode i at time t on the demand for mode j at time u. For the same mode ($i = j$), such effects measure stability or inertia in mode use. For different modes at the same time period ($t = u$), contemporaneous or synchronous effects are measured. For the final combination of different modes at different time periods, lagged effects can measure potential structural changes in demand. This approach is simply the structural equations method applied to pooled cross-sectional and time series data provided by a panel survey. (Structural equations, a generalization of path analysis, is described in, for example, Duncan, 1975; Heise, 1975; or Bielby and Hauser, 1977.)

A sequence of hierarchical, or nested, models is explored. The variables in all the models are the same, but each successive model represents a more complicated exploration of the variance structure of the data. Each model has more equations than the previous model, and the explanatory power of the additional equations (direct effects between variable pairs) is tested. (Adding equations in a simultaneous equation system is not the same as adding variables in a stepwise multiple regression.) Each equation corresponds to a prior postulate based on previous research and common beliefs about travel behavior. Reduced form coefficients can be calculated for an estimated simultaneous equation system, and these coefficients measure the total effects on each endogenous variable from every other variable (Golob and Meurs, 1987).

The hierarchical models represent the following hypotheses:

1. The covariance structure can be explained in terms of history-dependent processes for each mode independently with single-period time lags (i.e., simple dynamic stability, or inertia) plus random effects.

2. If the first hypothesis is rejected, the data can be explained in terms of more complicated mode-independent history-dependent processes with multiple-period lags.

3. If the second hypothesis is rejected, interdependence among the modes is introduced in terms of contemporaneous, or synchronous, relationships at each point in time.

4. Finally, if the third hierarchical model fails to explain the variance structure, cross-lagged effects are introduced. Each significant cross-lagged effect implies a shift in demand: use of one mode at one point in time implies a change in the use of a different mode at a later point in time. Due to the hierarchical approach, cross-lags are thus introduced only if inertial and contemporaneous effects fail to fully explain the covariance structure.

2. METHODOLOGY

Structural equation models are estimated using either a variance-covariance or correlation matrix (the latter approach yielding standardized parameter estimates). The models here were estimated using the sample variance-covariance matrix rather than the correlation matrix because the units of measurement are common for all variables, and these units have real meaning in terms of demand (trips or minutes of travel time).

A variance-covariance matrix of panel data captures three basic types of empirical relationships (Kenny and Harackiewicz, 1979). First, synchronous covariances in this case reflect the relationships between the use of two transport modes in the same time period. The modes can be substitutes--the frequent use of one transport mode implying only limited use of another mode--or complements--one mode being used as access to another, or both being low-cost modes, for instance. Second, there are diachronal auto-covariances in which use of a particular mode of transport at one time period is related to use of the same mode in another time period. Auto-covariances between demand levels for adjacent time periods are a measure of stability. Finally, there are diachronal cross-lagged covariances in which demand for a particular mode at one time period is related to demand for another mode in another time period. In the determination of stationarity in travel demand, these cross-lagged covariances are of primary importance. Originally explored by Campbell (1963) and elaborated by Rozelle and Campbell (1969), Heise (1970), Kenny (1973), Yee and Gage (1968), and Kenny and Harackiewicz (1979), cross-lagged covariances can be evidence to the presence of dynamic shifts in demand when analyzed in the presence of synchronous and autocorrelative relationships.

The structural equations models can be specified as follows:

$$Y = B\mathbf{Y} + \zeta \tag{1}$$

where $\mathbf{Y}$ is the vector of fifteen y_i demand variables (five modes at three points in time), B is a (15 x 15) matrix of b_{ij} coefficients with zeros in the diagonal, and ζ is a random vector of residuals. (This notation system is consistent with that of the LISREL (Linear Structural Relationships) model estimation procedure; Jöreskog and Sörbom, 1984.) The parameters to be estimated are the non-zero elements b_{ij} of B and the non-zero elements of ψ, the triangular (15 x 15) variance-covariance matrix of ζ. Each b_{ij} measures the direct effect of variable y_j on variable y_i.

For purposes of interpretation, the B matrix can be partitioned into nine (5 x 5) submatrices:

$$\mathbf{B} = \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{21} & B_{22} & B_{23} \\ B_{31} & B_{32} & B_{33} \end{bmatrix} \tag{2}$$

corresponding to the partition of Y into three five-element time periods. Here parameters in submatrices B_{11}, B_{22}, and B_{33} represent contemporaneous relationships at the three time periods. Parameters in B_{21} capture effects from wave one demand levels to wave two demand levels; likewise, B_{32} parameters capture wave two to wave three effects, and B_{31} parameters wave one to wave three effects. Subject to model identifications restrictions, parameters in submatrices B_{11}, B_{22}, B_{33}, B_{21}, B_{23}, and B_{31} can be estimated as tests of specific hypotheses concerning the dynamic structure of demand. However, the B_{12}, B_{23}, and B_{13} submatrices are always logically null matrices (a demand level cannot affect any demand level at a previous point in time). Under the assumption that I - B is non-singular, the estimate of the sample variance-covariance matrix generated by an identified model is

$$\Sigma = (I - B)^{-1} \psi (I - B')^{-1} \qquad (3)$$

Structural equations models can be estimated using least squares (two-stage, three-stage, or partial least-squares) or maximum likelihood methods. The latter approach was adopted in the present research using the computer package LISREL VI (Jöreskog and Sörbom, 1984). The use of maximum likelihood was motivated by two considerations. First, the models can be expanded to include measurement sub-models in which observed variables such as trip rates, travel distance, and travel times by mode are combined into latent variables that are interrelated through the structural equations (Goldberger, 1972; Jöreskog, 1973); this expansion is not reported here but represents a potentially important direction for further research. Second, the LISREL VI program provides unique model diagnostics useful in determining the effects of changes in model structure on goodness-of-fit and hypothesis testing results. However, for the types of models specified in the present study, there was very little difference between the maximum likelihood estimates and those of two-state least squares used in the program as initial estimates. The maximum-likelihood method is scale free (Anderson and Rubin, 1956), and this is a useful property in the present application.

Maximum likelihood estimates for the model parameters are determined in the LISREL program by minimizing the function

$$F = \ln |\Sigma| + \mathrm{tr}\,(S \ \Sigma^{-1}) - \ln \ |S| - k \qquad (4)$$

where Σ is given in equation (3), S is the sample variance covariance matrix, and k is the number of variables (here, 15). The objective function represents maximum likelihood for a multivariate normal distribution. Under this assumption, the estimates are optimal for a large sample (Jöreskog, 1967). Maximum likelihood estimates are asymptotically equivalent to generalized least squares estimates (Lee, 1977), and the maximum likelihood objective function (4) becomes equivalent to the generalized least squares objective function as Σ approaches S (Browne, 1974).

Boomsma (1982a) has investigated the performance of the LISREL estimator in situations of skewed and categorized distributions and has found them to be robust in terms of precision. The optimization procedure uses a modified Fletcher-Powell algorithm. The parameter standard errors are obtainable from the inverse of the information matrix based on the second derivatives of F (the information matrix being almost certainly positive definite for identified models). In general, such estimates of standard errors are suspect when distributions are not multivariate normal, but the estimates of standard errors in the LISREL method have been demonstrated to be robust (Boomsma, 1982a).

The number of direct effects between demand variables that can be estimated is limited by the number of free entries in the variance-covariance matrix, which for fifteen variables (five modes at three points in time) is 120. Further conditions necessary for the identification of the structural equation model are discussed in Goldberger (1964), Geraci (1976) and Jöreskog (1977). In the present application, identified structures were found for all tested hypotheses partly because of the logical constraint of having only forward-directed longitudinal links.

Indications of model goodness of fit were obtained by consulting five sets of test statistics: the first is the log-likelihood statistic given by the objective function (4) multiplied by the sample size minus one. This statistic is chi-square distributed under the assumption of a multivariate normal distribution with a large sample size; the degrees of freedom being given by the number of free entries in the covariance matrix minus the number of free parameters in the model (Browne, 1974; Lee, 1977). The statistic provides a test of the proposed model against the alternative that the variables are correlated by chance (Bentler and Bonett, 1980). It has been shown to be biased in the presence of deviations from normality (Boomsma, 1982a), and, as with all chi-square statistics, the probability of rejecting any model increases with sample size. Consequently, this statistic is used only as a crude approximation, and because of the relatively large sample size in the present application, it is likely that the maximum likelihood chi-square statistic will be biased in the direction of rejecting a true model.

An important use of the chi-square statistic is in comparing nested or hierarchical models (Bentler and Bonett, 1980). In such cases the difference in the maximum likelihood chi-square statistics of two models is chi-square distributed with degrees of freedom equal to the difference in degrees of freedom of the two models, which is the difference in the number of free parameters in the models. In the present application, the nested models progress from simple to complex. The simplest model is a logical starting point in that it attempts to explain the covariance structure as an autocorrelative process with history dependence of only a single period. Successive models represent logical increases in complexity, the contributions of which can be tested against the null hypothesis of random correlation using chi-square difference tests.

The second set of statistics consists of the squared multiple correlations for the reduced-form structural equations associated with each endogenous variable. These are relevant only for demand levels in the second and third waves because there are no diachronous explanatory variables for first-wave demand levels.

Third is an adjusted goodness-of-fit index calculated as:

$$AGFI = 1 - [\mathbf{k}\ (\mathbf{k} + 1)/2\mathbf{d}]\ (1 - GFI) \tag{5}$$

where

$$GFI = 1 - \mathbf{tr}\ (\ \Sigma^{-1}\ S - I)^2/\mathbf{tr}\ (\ \Sigma^{-1}\ S)^2 \tag{6}$$

Here **d** represents the degrees of freedom of the model, and k, Σ, and S are defined with equation (4). The AGFI is useful as an index of fit because it is independent of sample size and robust against deviations from normality. However, its distribution is unknown (Jöreskog and Sörbom, 1984).

The fourth goodness-of-fit index is the root mean square residual (RMSR), given by:

$$RMSR = [2 \sum_{i=1}^{k} \sum_{j=1}^{i} (s_{ij} - \sigma_{ij})^2 / k\ (k + 1)\ ]^{1/2} \tag{7}$$

where the s_{ij} are the elements of the sample variance-covariance matrix, and σ_{ij} are the elements of the estimated variance-covariance matrix reproduced by the model.

Finally, the fifth set of statistical criteria for model development and testing consists of the coefficients, their standard errors, and correlations. The signs and relative strengths of the coefficients should correspond with expectations, wherever possible, and all coefficients in the model should be significantly different from zero. High correlations between any pair of estimated coefficients in the present application would indicate specification errors.

The p = .05, or 95 percent confidence, interval was used in all hypothesis testing. This probability level is in fact a stricter test of model fit than the p = .01 level concerning the chi-square maximum likelihood ratio test statistic, because the test involves whether or not the model can be rejected.

3. DATA AND SOURCES OF POTENTIAL BIASES

The variables analyzed represent the weekly numbers of trips by five modes for three time periods six months apart. The data are from an ongoing national panel of Dutch households that was instituted in 1984 with the goal of supporting studies of changes in the mobility of the Dutch population over time. The development of the panel is documented in Baanders and Slootman (1982), and its structure and the general use of its data are discussed in J. Golob, et al. (1986). Specific applications of the data are documented in T. Golob, et al. (1985, 1986), Meurs and Klok (1985), Van Wissen and Zondag (1985), and Golob and Meurs (1986).

The panel sample is stratified by life cycle group, income and community type and is clustered in twenty communities spread throughout the Netherlands. The present analysis is based on the first three waves of data collection: March 1984, September-October 1985 and March 1985. Each wave has involved a household questionnaire and separate questionnaires and seven-day travel diaries for all household members over eleven years of age. The total number of trips by mode recorded for each person over each seven-day period and the total travel time for each mode over the seven-day period comprise the data used in the present study.

The week-long duration of the travel diaries in the Dutch panel is an important aspect in the modeling. The usual problem of day-to-day variation that affects the reliability of one-day travel diaries is translated into a problem of week-to-week variation; and infrequent use of a mode, especially regular use on a weekly basis, is likely to be registered. Moreover, there is considerably more variation in the numbers of trips and travel times over the course of a week.

Panel data are susceptible to bias due to selective drop out (panel attrition or mortality). Of the 5,614 persons who responded to at least one of the first three waves of the Dutch panel, 2,274 (from 1,031 households) responded in all three waves, while one-half of the remainder dropped out after one or two waves, and an approximately equal number of respondents were added as replacements. Kitamura and Bovy (1987) studied the effect on estimates of trip generation attributable to panel attrition between the first to second waves of the Dutch panel, concluding that there were detectable but relatively minor effects. This is consistent with results from sociological studies that have investigated the effects of sample attrition on relationships among variables measured on different panel waves and found no significant effects (Suchman, 1962; Tauberman and Wales, 1974; Sewell and Hauser, 1975).

In order to test for panel attrition bias in the present analysis, the complete structural equation model for trip rates was estimated on two different variance-covariance matrices. The first variance-covariance matrix was computed using the data from all 5,614 persons who responded in any one or more than one of the first three panel waves. This matrix was computed using the pairwise-present method. That is, the covariance between any two variables was computed using a sample of all persons for whom complete information is available on both variables: cross-sectional comparisons utilize the sample available at each particular wave, and cross-wave comparisons utilize the sample of persons who responded to both waves in question. The pairwise-present approach yields consistent estimates of variable relationships when data are missing at random (Glasser, 1964). The objective of the comparison pursued in the present study is to uncover evidence of the extent to which data in the Dutch panel are not missing at random.

The second trip-rate variance-covariance matrix was computed using only the 2,274 persons who responded to all three waves of the panel. The model estimated on this matrix was then compared to that estimated on the variance-covariance matrix computed using the pairwise-present method and all 5,614 persons who were in any of the three panel waves. There were only minor differences in the parameter estimates and goodness of fit for the two models. This demonstrates that the additional information obtained from the portion of the sub-sample that dropped out or was added as refreshment to the panel was not substantially different from the information available for the sub-sample that persisted in all three panel waves. While certainly not proving the absence of panel mortality bias, this test does provide empirical evidence that such bias might lead to only minor differences in the results.

The choice was to use variance-covariance matrices estimated using the pairwise-present method in the analyses reported here. This method uses the maximum information available for all comparisons, and Rubin (1974) and Marini, et al. (1980), have demonstrated that maximum-likehood estimates of variable relationships can be generated for panel data with missing data due to panel drop-out using the pairwise-present method of estimating correlations. The minimum sample size for any pair of variables was 2,273 persons, and this was used as conservative estimate of the sample size for hypothesis testing purposes. Because of this relatively large sample size, biases associated with the robustness of the methodology against small sample size are not a problem here (Boomsma, 1982b).

4. A MODEL OF TRIP DEMAND

4.1 Dynamic Stability of Demand

The first model specifies that the demand level for each of the five modes is a function only of the demand level for the same mode at the previous point in time. This model represents the simplest possible inertial process, history dependence of a single time period. It is important to test whether the covariance structure can be replicated by this simple process with random disturbances. For this model, the only free b_{ij} elements of the parameter matrix B of equation (2) are the diagonal elements of the submatrices B_{21} and B_{32} . Each b_{ij} direct effect in this model is a pure measure of inertia, or stability for a specific mode over a specific time interval. These direct effects are listed on the path diagram of Figure 1; as expected, all of the coefficients were significantly different from zero at the $p = .05$ level. The coefficients of determination (R^2 values) associated with each endogenous variable indicate that car driver and bicycle demand are best explained in terms of demand stability, while car passenger demand is least well explained.

The chi-square maximum likelihood ratio statistic was 2,616.5 with 95 degrees of freedom, which indicates that the model can be rejected as a full description of the demand structure. The adjusted goodness-of-fit index (AGFI) given in equation (2) is 0.85, and the root mean square residual (RMSR)

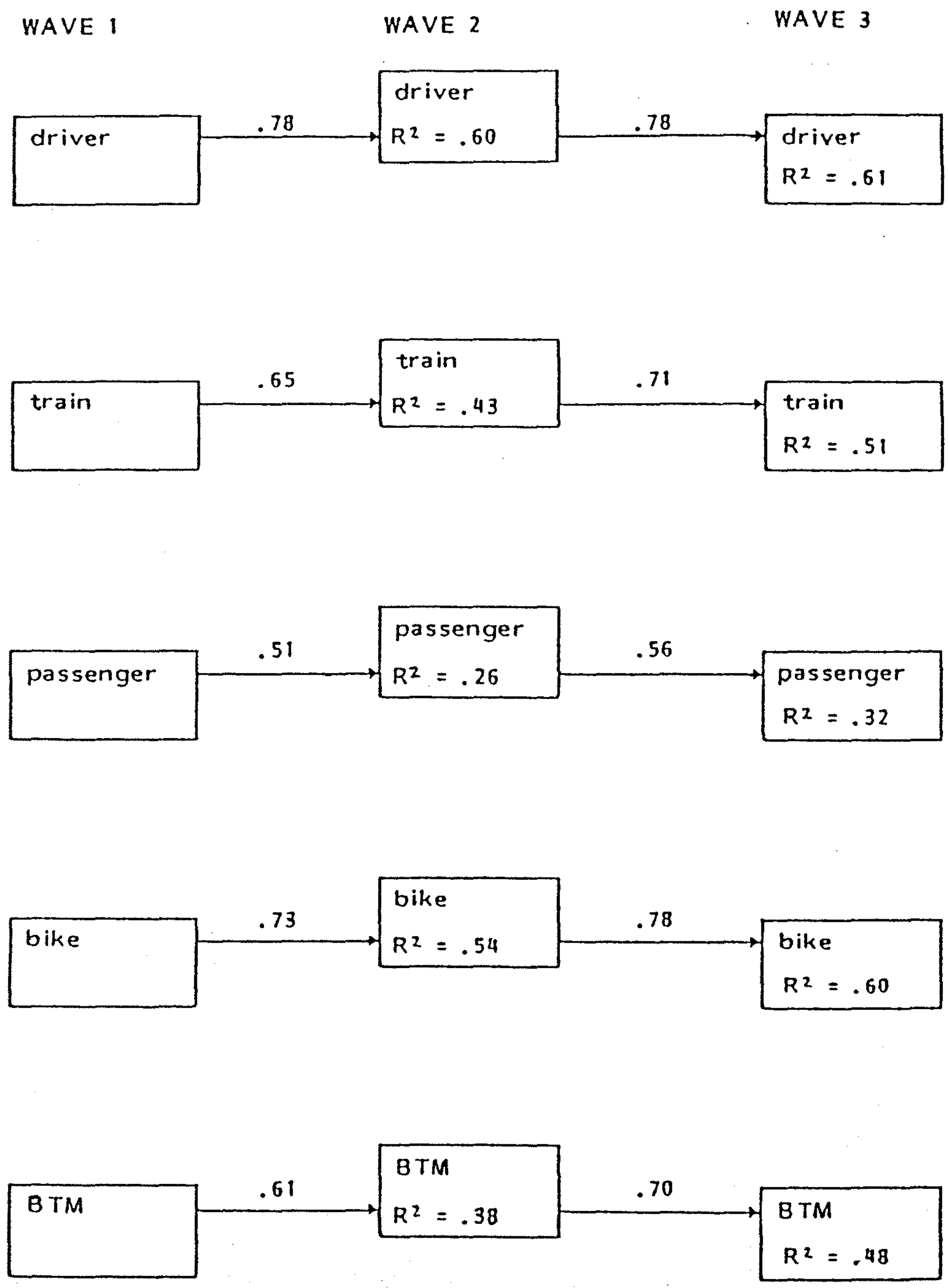

FIGURE 1

A SIMPLE TEMPORAL STABILITY MODEL

of equation (3) is 8.15. These indices provide a basis of comparison for more complex models.

A more sophisticated stability model is specified by adding seasonality effects from the first wave to the third wave for each mode, because data for the first and third panel waves were collected in the spring of successive years, while the second wave data were collected in the intervening autumn period. In such a model, depicted in the path diagram of Figure 2, there are fifteen direct effects with the diagonal elements of submatrix B_{31} in equation (2) being freely estimated together with the diagonal elements of submatrices B_{21} and B_{32} . All coefficients measuring the direct effects are highly significant, and the R^2 values improve for all third-wave variables when compared to the model of Figure 1. In particular, the bus-tram-metro demand is demonstrated to have a substantial seasonal component.

The chi-square maximum likelihood statistic for this stability model with seasonal effects is 1,604 with 90 degrees of freedom. This represents a reduction in chi-square from the first model of about 1,000 for decrease of five degrees of freedom, which is a highly significant difference for the nested or hierarchical models. The AGFI for the seasonal model is 0.90, a 10 percent improvement over the first mode, but the RMSR dropped only to 8.05 from an original value of 8.15. The chi-square value of 1,604 with 90 degrees of freedom still leads to a rejection of the model as a good representation of the complete demand structure.

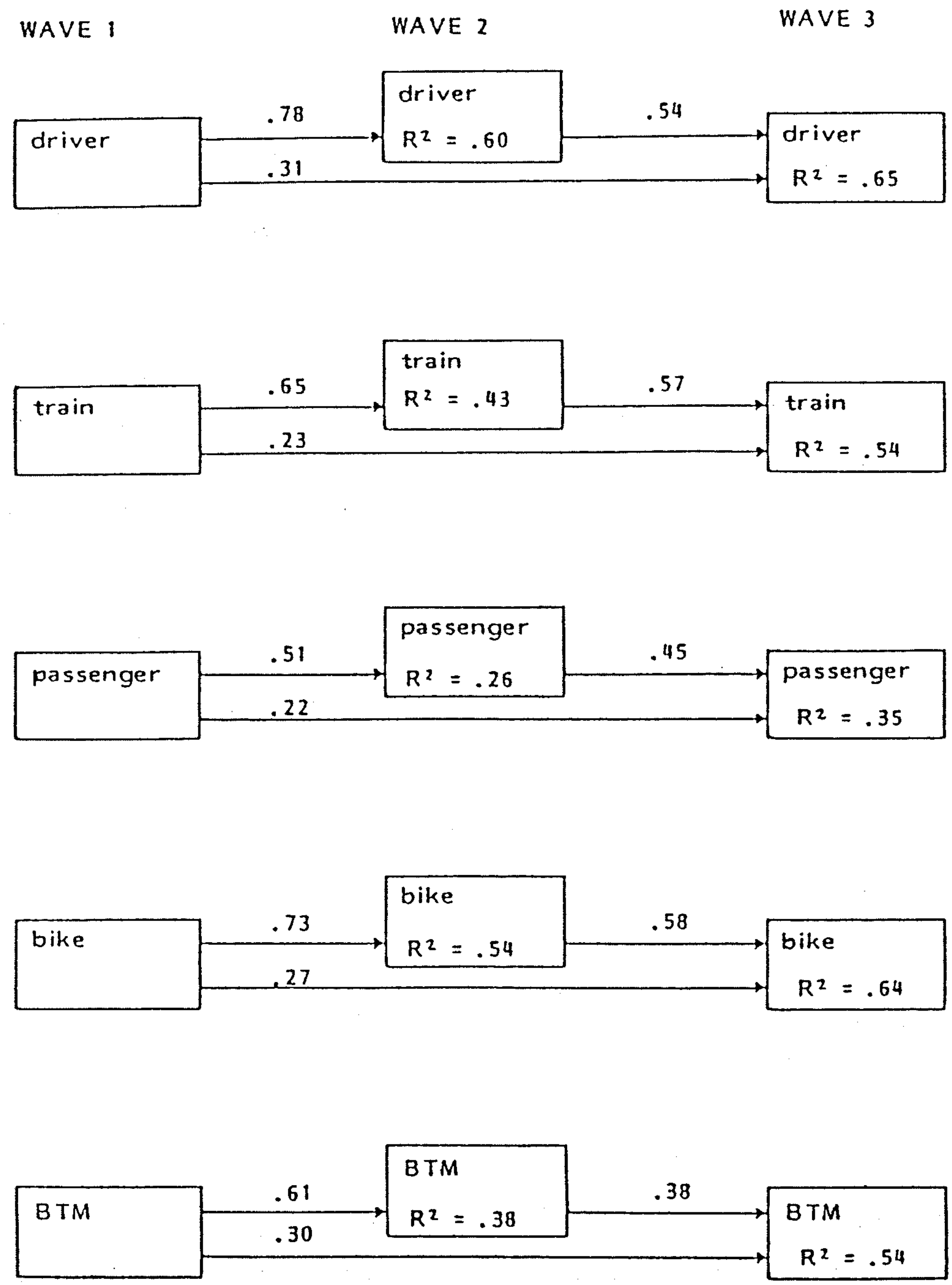

FIGURE 2

A TEMPORAL STABILITY MODEL WITH SEASONAL EFFECTS

4.2 Contemporaneous Relationships

Contemporaneous (synchronous or cross-sectional) relationships capture substitution and complementarity among modes at a given point in time. These relationships are captured by the parameters of the B_{11} , B_{22} , and B_{33} submatrices in a simultaneous equation system of equations (1) and (2). The approach here is to postulate a stable (time-invariant) structure of direct effects patterns for the three submatrices and to subject each direct effect to hypothesis testing. Effects with coefficients insignificantly different from zero were then removed from the structure (i.e., the equations were removed from the simultaneous equation system) and the model was re-estimated. Modification indices were then calculated for each effect not hypothesized a priori. (These modification indices represent the minimum improvement in maximum-likelihood chi-square resulting from inclusion of the equation representing the missing direct effect in the simultaneous equation system.) Effects representing significant improvements were then added in the order of magnitude of improvement in maximum likelihood, and the process was reiterated until no statistically significant improvement was possible. An attempt was made to vary as little as possible from a stationary contemporaneous structure, and all non-stationary structures were tested relative to the optimal stationary structure. These tests (described in Section 4.4), involved comparing numerous combinations of equations, and it was found that the chosen model was unique in providing the best explanation of the covariance structure.

The postulated stationary contemporaneous structure involved seven direct effects among the modes:

(1) car driver to train,

(2) car driver to car passenger,

(3) car driver to bicycle,

(4) car driver to bus-tram-metro

(5) train to bus-tram-metro,

(6) bus-tram-metro to train, and

(7) bus-tram-metro to bicycle.

The first four effects represent a postulated dominance of the car driver mode: driving a car implies less demand for all other modes. The fifth and sixth postulated effects represent reciprocal relationships between train and bus-tram-metro: train use frequently implies the use of bus-tram-metro as access and egress modes; bus-tram-metro use often indicates lower car accessibility and subsequent use of train for inter-city travel; also, certain types of public transit season tickets cover both train and bus-tram-metro use. Finally, the seventh effect postulates that bus-tram-metro users often do not choose to use (and in some cases physically cannot use) bicycles, which are considered a feasible alternative to motorized modes in the Netherlands.

Sixteen of the postulated twenty-one stationary contemporaneous relationships (seven direct effects at three points in time) were found to be significant. Five direct effects not postulated a priori were found to be significant and were required to achieve the best complete model. The resultant model with simultaneous stability and synchronous direct effects is depicted in the path diagram of Figure 3. Because the synchronous effects were determined from theoretical considerations rather than a search for optimal correlations, the model might understate the ability of any combined synchronous and inertial process to explain the covariance structure.

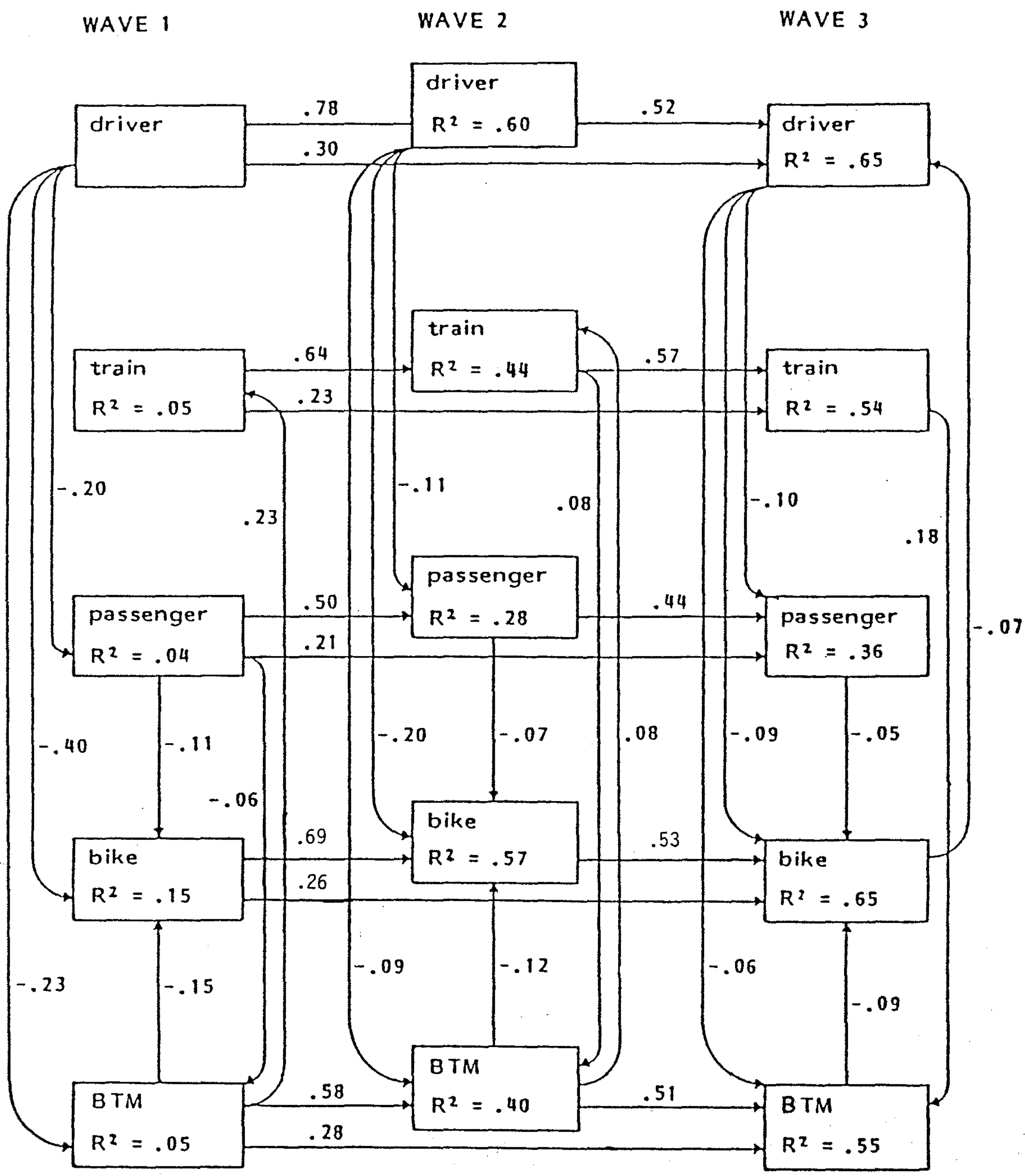

FIGURE 3

A TRIP-RATE MODEL WITH ONLY STABILITY AND CONTEMPORANEOUS EFFECTS

However, the emphasis here is on hypothesis testing rather than exploratory data analysis.

The model reveals an evolutionary cross-sectional structure of modal demand in the Netherlands. As postulated, the linkages from the car driver mode to car passenger, bicycle, and bus-tram-metro are consistent at all points in time: demand for the car driver mode implies less demand for bicycle, bus-tram-metro, and car passenger. However, the postulated link from car driver to train is rejected at all three points in time. Apparently, the choice of train use is not conditional upon non-use of the car driver mode. The links to the bicycle mode from bus-tram-metro are similarly consistent: demand for bus-tram-metro implies less demand for bicycle travel.

Focusing on the unanticipated contemporaneous relationships, there is a persistent direct effect from car passenger to bicycle at all three points in time. This implies that car passenger demand, as well as car driver and bus-tram-metro demand, partially determines bicycle demand. Regarding non-stationary effects, there is a negative direct effect from car passenger to bus-tram-metro that is only present in the first wave. Moreover, the interrelationships between train and bus-tram-metro evolve over time from a positive link from bus-tram-metro to train (wave one) to the postulated mutual positive links (wave two) to a positive link from train to both (wave three).

The conclusion is that the contemporaneous component of the structure among the modal demand levels is <u>not stationary</u>. Further tests of this result were conducted within the context of the complete trip rate model (Section 4.4).

All direct effects have coefficients that are significantly different from zero at the $p= .05$ level. The chi-square statistic for the model is 258.0 with 69 degrees of freedom. This represents an improvement in the maximum likelihood chi-square statistic of approximately 1,346 associated with the addition of 21 synchronous direct effects (or the loss of 21 degrees of freedom), which is a highly significant improvement in the test of nested models. However, the model shown in Figure 4 can still be rejected at the $p = .05$ level (the critical chi-square value for non-rejection being approximately 90 with 69 degrees-of-freedom). Compared to the stability model, the AGFI improves to 0.95 (from 0.90) for the model shown in the path diagram of Figure 3, and the RMSR improves dramatically to 0.99 (from 8.05). The improvements in the R^2 values are mostly confined to the first two waves. All variables with the exception of wave one car passenger are endogenous in the model of Figure 3.

4.3 The Complete Trip Rate Model

It was postulated that all cross-lagged direct effects were negligible. That is, all off-diagonal elements of the B_{21}, B_{32}, and B_{31} submatrices of equation (2) were set to zero. Each possible cross-lagged effect was then investigated in terms of the potential of the additional equation significantly improving the goodness-of-fit of the simultaneous equation system. Parsimony was respected in including only cross-lagged effects that were required for a model which could not be rejected as an adequate representation of the dynamic variance-covariance structure of demand. Nevertheless, an unexpectedly large number of sixteen cross-lagged direct effects were required.

The equations of the complete model are depicted in the path diagram of Figure 4. Nine of the sixteen cross-lagged equations involved the bus-tram-metro mode as either an explanatory or dependent variable. The consistently strong positive links found from bus-tram-metro demand in wave

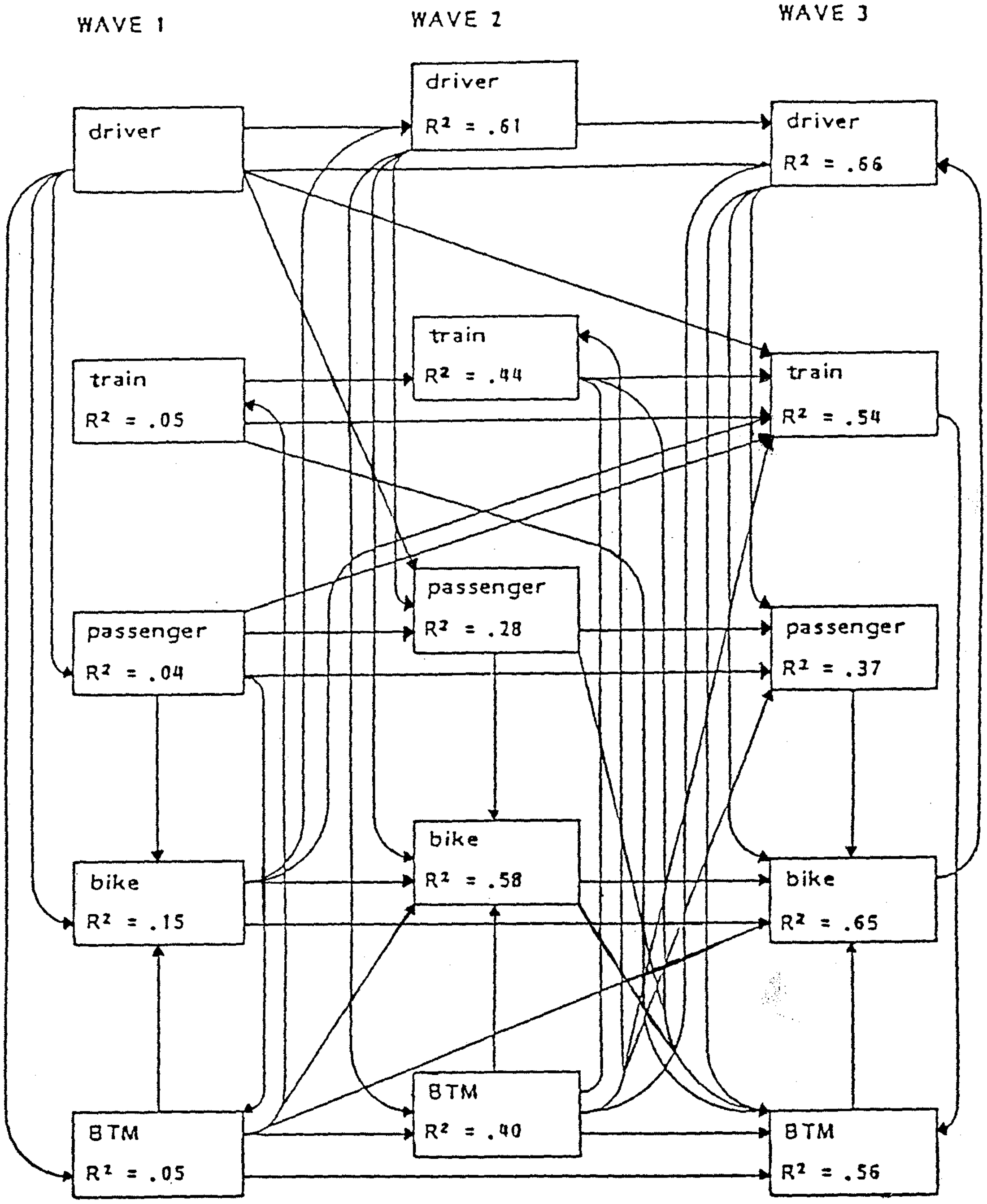

FIGURE 4

THE FULL TRIP RATE MODEL WITH INERTIAL, SYNCHRONOUS, AND CROSS-LAGGED EFFECTS one to bike demand in wave two and wave three indicate that there was a shift from bus-tram-metro demand to bike demand on both a short-term and seasonally adjusted basis. This result is consistent with a public transport fare increase affected the fare level for school-aged children; bike and bus-tram-metro are known to be competitive modes for this population segment. Negative direct effects are also present from train in waves one and two to bus-tram-metro in wave three. This indicates a shift from train to modes that are generally competitive with bus-tram-metro, a phenomenon consistent with the fare increase.

The log-likehood ratio statistic for the complete model is 59.1 with 53 degrees of freedom. This represents a highly significant improvement in chi-square over the stability and contemporaneous model of approximately 199 for 16 degrees of freedom. Importantly, the model of Figure 4 <u>cannot</u> be rejected at the $p = .05$ level as the chi-square value of 59.1 is substantially below the critical value of about 71 with 53 degrees of freedom. The AGFI rose to 0.997, and the RMSR fell to a very low 0.30 (compared to the value of 8.15 for the model shown in Figure 2). The interpretation is that the model is a good representation of the dynamic structure of modal demand. A comparison of all of the models estimated in the construction of the complete model is summarized in Table 1.

The coefficients of the direct-effect equations and their associated t-values are listed in Table 2. With one exception, all coefficients are signficantly different from zero at the $p = .05$ level. The coefficients in Table 2 are group according to whether or not they are diachronal, synchronous, or cross-lagged.

Regarding temporal stability, the strongest inertial coefficients as a group are those that capture the direct effects of wave one trip rates on wave

TABLE 1

SUMMARY STATISTICS FOR TRIP RATE MODELS

Model	Number of Links			Adjusted Goodness-of-Fit Index	Root Mean Square Residual	Maximum Likelihood Statistic	
	Diachronal	Synchronous	Cross-Lagged			Chi-Square	Degrees-of-Freedom
Simple Stability Model (Figure 1)	10	0	0	0.849	8.15	2,617	95
Stability Model with Seasonality Effects (Figure 2)	15	0	0	0.904	8.05	1,604	90
Stability and Synchronous Effects Model (Figure 3)	15	21	0	0.976	0.99	258	69
Complete Structural Model	15	21	16	0.997	0.30	59.1*	53

* Model cannot be rejected at p = .05 level.

TABLE 2

COEFFICIENTS AND T-VALUES FOR THE COMPLETE TRIP RATE MODEL

Type	Coefficient Number	Link From Wave	Link From Mode	Link To Wave	Link To 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
	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

two trip rates. The strongest of these, indicating the highest degree of stability or inertia in trip making, are for car driver (coefficient 1), bike (coefficient 10) and train (coefficient 4). The train mode also has the highest stability coefficient for the wave two to wave three period (comparing coefficients 2, 5, 8, 11, and 14). In general, the weakest stability effects are for car passenger, followed by bus-tram-metro. The seasonality effects (coefficients 3, 6, 9, 12 and 15), are approximately the same for all modes with the exception of car passenger, which exhibits the weakest effect.

With respect to the synchronous links among the modes, the consistently strongest direct effects over all three modes are those from bus-tram-metro to bike (coefficients 20, 27, and 34). The similarly negative influence from car driver to bike decreases over time (coefficients 17, 24, and 31); and the positive influence from train to bus-tram-metro increases over time (zero, or no link for wave one to the 0.15 value for coefficient 28, to the 0.33 value for coefficients 35).

Finally, regarding the cross-lagged effects, the strongest effects are from bus-tram-metro tripmaking in wave one to bike trip making in wave two (the positive coefficient 39) and from train in wave one to bus-tram-metro tripmaking in wave three (the negative coefficient 49). The former link indicates that there was a shift in the Netherlands from bus-tram-metro to bike over the wave one to wave two period (spring 1984 to autumn 1984). This is corroborated by a slightly weaker link from bus-tram-metro in wave one to bike in wave three (coefficient 52) and is consistent with a public transport fare increase during this period that was directed particularly to the fare level for school-aged children; bike and bus-tram-metro are competitive modes for this population segment. The latter link (train/wave one to bus-tram-metro/wave three, corroborated by a similar link from train/wave two to bus-tram-metro/wave three) indicates there is a shift from train use during 1984 to modes that are competitive with bus-tram-metro in 1985. This is consistent with heavy turn-overs in train use by persons with train season tickets. The model appears to capture some fundamental adjustments in travel behavior.

4.4 Tests of Stationarity

Two sets of tests of structural stationarity were conducted. The first set of tests was applied to the model of stability and contemporaneous relationships depicted in the path diagram of Figure 3. These tests assessed the need for cross-lagged relationships, the results from which led to the estimation of the complete model of Figure 4. The second set of tests was applied to the complete model itself and was aimed at assessing whether or not a consistent contemporaneous structure was possible at all three time periods.

It is often possible to detect specification errors in a simultaneous equation system by investigating the covariances among the error terms. The model depicted in the path diagram of Figure 3 incorporates all possible stability effects (autocorrelative relationships) and all contemporaneous effects that have equations with statistically significant coefficients. It is likely that specification errors in this model are due to the absence of significant cross-lagged effects. Shown in Table 3 are the minimum possible significant improvements in the likelihood ratio statistic attainable through the incorporation of specific error covariance terms in the simultaneous equation system. (A non-zero effect is possible for all covariance terms of the errors of any two demand levels not linked in a direct effect equation.) The presense of 26 error covariances with significant likelihood ratio reduction effects indicates misspecification, and most of the error

TABLE 3

IMPROVEMENTS IN THE -2 LOG-LIKELIHOOD RATIO STATISTIC
ATTAINABLE THROUGH INCLUSIONS OF ERROR TERM COVARIANCES*--
STABILITY AND CONTEMPORANEOUS EFFECTS MODEL**

		Wave 1					Wave 2					Wave 3				
		car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm
W	car driver															
A	train	4.4														
V	car pass.															
E	bike															
1	btm		5.4													
W	car driver				43.4											
A	train															
V	car pass.	10.1		10.1			10.1									
E	bike		4.5		4.8	10.5										
2	btm				5.2					9.0						
W	car driver										7.6					
A	train	5.5		5.2						10.6	5.5					
V	car pass.	9.5		9.5			5.1		22.4		5.3	23.1				
E	bike					4.8										
3	btm		44.2								21.5		48.0			

* Only statistically significant improvements shown.
** Path Diagram of Figure 3.

covariances highlighted in Table 3 are associated with cross-lagged relationships.

Regarding the complete structural model depicted in the path diagram of Figure 4, two tests of stationarity were conducted. First, a strict test of stationarity of the contemporaneous effects involved restricting the parameters of the contemporaneous equations to be equal at all three points in time. A comparison of the free and restricted models is given in Table 4. Included in this comparison are misspecification indices based on counts of the number of error term covariances (of the type shown in Table 3) and illogical effects (backward in time) that could significantly improve the models. The restricted model fails on all comparison criteria. The best new complete model built up from the restricted model by removing insignificant cross-lagged effects and adding new cross-lagged effects was still inferior to the base model of Figure 4 and could be rejected.

Finally, a less restrictive model was developed in which the contemporaneous effects were consistent across points in time in terms of the specification of equations, but estimates of the parameters of all equations were unrestricted and the optimal cross-lagged effects were found. This model was still mis-specified, as indicated by the error term covariance effects listed in Table 5. Thus, it is not possible to confirm that a stationary demand structure underlies the data. This lack of stationarity might in fact be due to limitations of the data: only three time periods are available over one year. It is possible that time lags of a longer duration are present, and the relatively short duration makes the problem of initial conditions especially acute. Confirmation or rejection of the present results can be accomplished by extending the model to further waves of the panel.

TABLE 4

COMPARISON OF TWO TRIP RATE MODELS

Model	Adjusted Goodness-of-Fit Index	Root Mean Square Residual	Maximum Likelihood Statistic: Chi-Square	Maximum Likelihood Statistic: Degrees-of-Freedom	Misspecification: Significant Chi-Square Improvements Attainable: Error Covariances	Misspecification: Significant Chi-Square Improvements Attainable: Illogical Effects
Complete Structural Model	0.997	0.30	59.1*	53	0	0
Complete Model with Identical Contemporaneous Effects	0.968	2.30	410.9	82	40	37

* Model cannot be rejected at p = .05 level.

TABLE 5

IMPROVEMENTS IN THE -2 LOG-LIKELIHOOD RATIO STATISTIC
ATTAINABLE THROUGH INCLUSIONS OF ERROR TERM COVARIANCES*--
STABILITY AND CONTEMPORANEOUS EFFECTS MODEL WITH CONSISTENT CONTEMPORANEOUS SPECIFICATION

		Wave 1					Wave 2					Wave 3				
		car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm	car driver	train	car pass.	bike	btm
W	car driver															
A	train															
V	car pass.															
E	bike															
1	btm			10.0												
W	car driver				5.0	4.2										
A	train															
V	car pass.				4.0											
E	bike	6.7					6.7									
2	btm															
W	car driver															
A	train															
V	car pass.															
E	bike															
3	btm															

* Only statistically significant improvements shown.

5. A MODEL OF DEMAND FOR TRAVEL TIMES

An attempt was made to replicate the trip rate model using travel times. That is, the variance-covariance matrix of travel times was substituted for the variance-covariance matrix of trip rates for the same five modes over three time periods and a simultaneous equation system as structured in the path diagram of Figure 4 was estimated. This model can be rejected as a representation of dynamic interrelationships among modal travel times.

A model that does fit the travel time data is depicted in the path diagram of Figure 5. This model is compared with the complete trip rate model in Table 6. The travel time structure is simpler than the trip rate structure, with only 46 significant links among the variables. According to the AGFI, the two model fits are approximately the same.

The coefficients of determination shown in the path diagram of Figure 5 for the endogenous variables, when compared to similar values in the path diagram of Figure 4, reveal that variations in travel times are more difficult to explain than variations in trip rates. The coefficients and associated t-values for the travel time model are listed in Table 7. As in the case of trip rates, these coefficients are divided into three groups--inertial links, synchronous links, and cross-lagged links--and all coefficients can be interpreted as the direct effects of one variable upon another.

The strengths of the stability relationships reveal that the inertial and seasonal effects for travel times are generally weaker than similar effects for trip rates. However, car driver and bicycle travel times are the most stable among the five modes. It is probable that this stability is due to the considerable use of these two modes for non-discretionary trips in the Netherlands, such as work, school, and certain types of shopping and personal business trips.

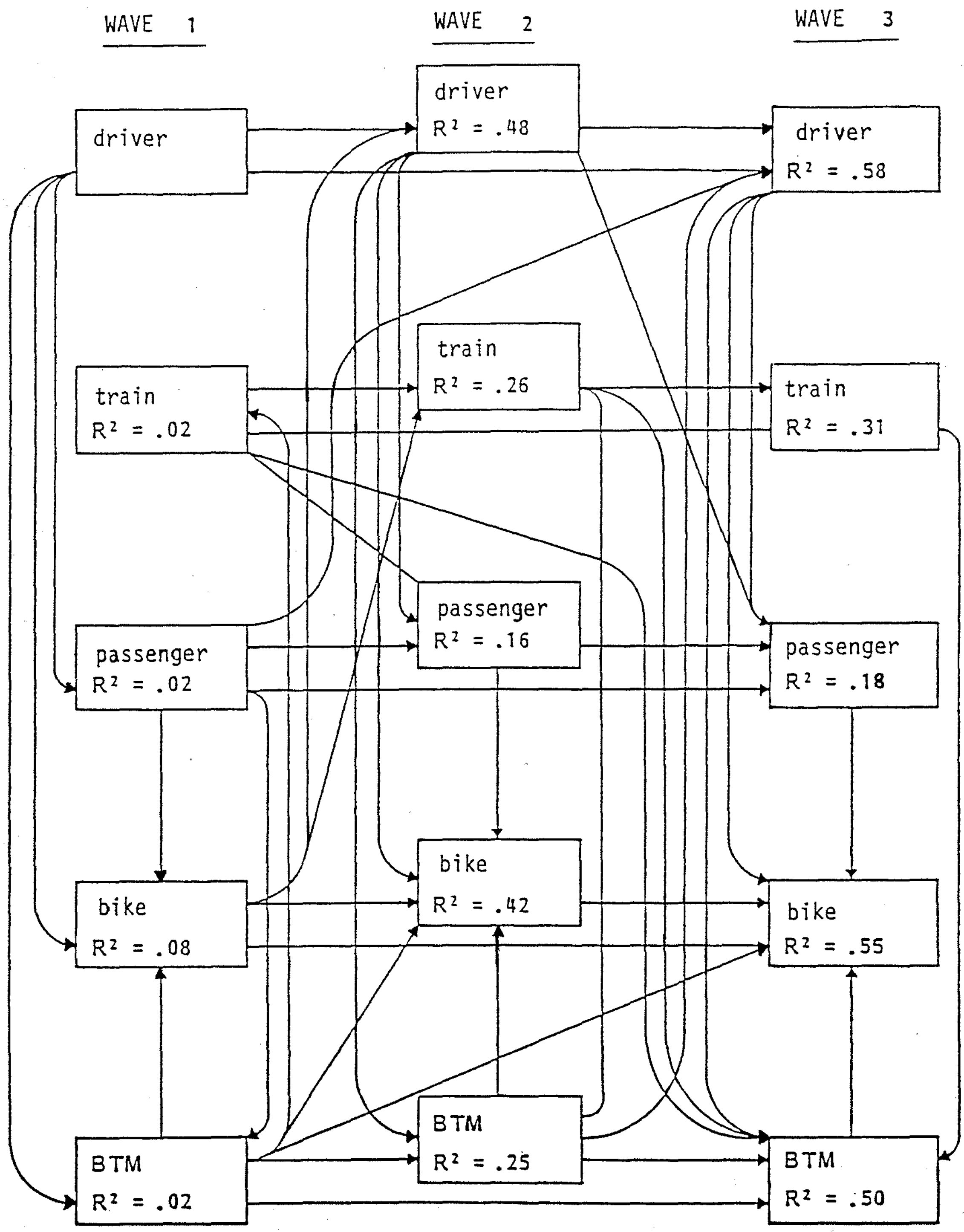

FIGURE 5

THE TRAVEL TIME MODEL

TABLE 6

COMPARISON OF TRIP RATE AND TRAVEL TIME MODELS

Model	Number of Links	Adjusted Goodness-of-Fit Index	Maximum Likelihood Statistic		
			Chi-Square	Degrees-of-Freedom	Can Model Be Rejected?
Trips	52	0.997	59.1	53	No
Travel Times	46	0.992	67.5	59	No

There are two significant synchronous links in the trip rate model (Table 2) that are not present in the travel time model (Table 7). First, the positive direct effect from bus-tram-metro to train disappears at the second and third waves in terms of travel time, whereas this link disappears at only the third wave in terms of trip rate. But the trend is similar: the complementarity shifts over time from the direction "bus-tram-metro to train" to the direction "train to bus-tram-metro." The model structures are consistent in this regard. Second, the negative link from bike to car driver at the third wave is present in trip rates but not in travel times. Instead, there is a negative link from travel time by car driver to travel time by train; the link is weak but significant.

There are considerably fewer significant cross-lagged relationships in the travel time model, indicating that relationships among modal travel time are more consistent over time than are relationships among trip rates. The positive cross-lags from bus-tram-metro in wave one to bicycle in waves two and three (coefficients 39 and 46 in Table 7) are present in terms of travel

TABLE 7

COEFFICIENTS AND T-VALUES FOR THE TRAVEL TIME MODEL

Type	Coefficient Number	Link From Wave	Link From Mode	Link To Wave	Link To Mode	Coefficient	T-Value
	1	1	car driver	2	car driver	0.74	44.68
	2	2	car driver	3	car driver	0.39	25.58
d	3	1	car driver	3	car driver	0.28	16.95
i	4	1	train	2	train	0.56	28.99
a	5	2	train	3	train	0.41	21.29
c	6	1	train	3	train	0.22	10.26
h	7	1	car passenger	2	car passenger	0.38	19.64
r	8	2	car passenger	3	car passenger	0.28	15.33
o	9	1	car passenger	3	car passenger	0.15	8.07
n	10	1	bike	2	bike	0.63	36.94
o	11	2	bike	3	bike	0.50	29.29
u	12	1	bike	3	bike	0.26	14.21
s	13	1	bus-tram-metro	2	bus-tram-metro	0.53	26.80
	14	2	bus-tram-metro	3	bus-tram-metro	0.38	26.87
	15	1	bus-tram-metro	3	bus-tram-metro	0.32	20.81
	16	1	car driver	1	car passenger	-.06	-6.38
	17	1	car driver	1	bike	-.15	-14.32
	18	1	car driver	1	bus-tram-metro	-.06	-7.59
	19	1	car passenger	1	bike	-.11	-4.97
s	20	1	bus-tram-metro	1	bike	-.11	-4.33
y	21	1	car passenger	1	bus-tram-metro	-.04	-2.02
n	22	1	bus-tram-metro	1	train	0.08	5.98
c	23	2	car driver	2	car passenger	-.05	-6.12
h	24	2	car driver	2	bike	-.08	-9.56
r	25	2	car driver	2	bus-tram-metro	-.02	-2.99
o	26	2	car passenger	2	bike	-.06	-3.28
n	27	2	bus-tram-metro	2	bike	-.13	-6.03
o	28	2	train	2	bus-tram-metro	0.09	3.43
u	29	3	car driver	3	car passenger	-.06	-4.30
s	30	3	car driver	3	bike	-.05	-5.89
	31	3	car driver	3	bus-tram-metro	-.02	-3.87
	32	3	car passenger	3	bike	-.06	-3.72
	33	3	bus-tram-metro	3	bike	-.16	-6.97
	34	3	train	3	bus-tram-metro	0.17	7.48
	35	3	car driver	3	train	-.01	-2.46
c							
r	36	1	train	2	car passenger	-.06	-2.04
o	37	1	bike	2	car driver	-.12	-3.58
s	38	1	bike	2	train	0.02	2.08
s	39	1	bus-tram-metro	2	bike	0.09	3.61
	40	2	car driver	3	car passenger	0.02	2.13
l	41	2	train	3	bus-tram-metro	-.05	-2.05
a	42	2	bike	3	car driver	-.12	-5.32
g	43	2	bus-tram-metro	3	car driver	-.08	-3.13
g	44	1	train	3	bus-tram-metro	-.06	-2.32
e	45	1	car passenger	3	car driver	-.08	-3.19
d	46	1	bus-tram-metro	3	bike	0.06	2.99

times as they were in terms of trip rates. This reinforces the conclusion that factors during the wave one to wave two period (spring to autumn 1984) caused diversion from bus-tram-metro to bicycle.

Disregarding the very weak cross-lags in the trip rate model, which might simply be too weak to detect in terms of travel times, all major links in the trip rate model are also present in the travel time model: consistently specified are the negative link from bike in wave one to car driver in wave two (coefficient 37 in Table 7), the negative links from train in waves ones and two to bus-tram-metro in wave three (coefficients 41 and 44), and the negative link from bus-tram-metro in wave two to car driver in wave three (coefficient 43). However, again disregarding very weak but significant links, there are several cross-lags in the travel time model that are not present in the trip rate model. The strongest of these is the link from bike in wave two to car driver in wave three (coefficient 42). Also directed to car driver in wave three is a link from car passenger in wave one (coefficient 45). Car driver travel times in the spring of 1985 thus appear to be relatively lower for persons who are users of these two alternative modes in the autumn and spring of 1984. Finally, there is a negative cross-lag from train in wave one to car passenger in wave two (coefficient 36), indicating that car passenger was not generally a substitute mode for switchers from train during the spring to autumn 1984 time period.

6. CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

Regarding demand measured in terms of trip rates, the following answers were found for the five questions listed under Objectives and Scope:

(1) The results of Section 4.1 indicate that there are potential instabilities in demand for each of the five modes, but particularly for the car passenger and bus-tram-metro modes. The significant improvement of the second nested model (Figure 2) over the first (Figure 1) reveals that there are multi-period time lags in the data that are potentially seasonal effects.

(2) The significant improvement of the third model (Figure 3) over the second reveals that there are significant contemporaneous relationships among the demands for the different modes. The car driver mode is a substitute for each of the other modes with the exception of train, and car passenger and bus-tram-metro are substitutes for the bicycle mode; bus-tram-metro and train are complementary modes.

(3) It was found that there were changes over time in the contemporaneous relationships among the modes, according to the results of Sections 4.2 and 4.4. In particular, the mutually complementary relationships between bus-tram-metro and train evolved over the course of the three panel measurements.

(4) The significant improvement in explanatory power from the third (Figure 3) to fourth nested model (Figure 4) revealed that cross-lagged effects were needed to successfully explain the covariance structure. These cross lags indicated shifts in demand among the modes.

(5) Specifically, some of the identified shifts in demand are consistant with the intervention of a public transport fare increase between the first and second points in time. For instance, the strongest cross-lagged effects are a positive link from bus-tram-metro at the first point in time to bicycle at the second point, and for a negative link from train at the first point in time to bus-tram-metro at the third point in time. The former link indicates a shift from bus-tram-metro to a competitive mode after the fare increase, while the latter link indicates a seasonally-adjusted discontinuation of bus-tram-metro as an access mode for train; the latter link is also consistent with high rates of turnover in season tickets for train and bus-tram-metro use.

Models using trip rates as measures of demand were similar in overall structure, but different in some specific details, to models using travel times as measures of demand.

An attempt was made to estimate a structural latent-variable model in which modal demand was measured jointly by trip rates and total travel times. The attempt failed in establishing an adequate model. It is possible that such a general model can be fitted successfully after further refinements in the latent-variable measurement models and estimates using data for specific population segmentations.

A potentially productive further step would be to include socio-demographic and economic variables as segmentation variables. Structural modeling techniques such as LISREL provide mechanisms for testing equivalences of parameter values among subsamples. Such a model would attempt to explain demand changes in terms of the changing situations of travelers and their households by identifying relationships that are unique to different segments.

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