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1. OBJECTIVES AND SCOPE

In The Netherlands, households have the opportunity to operate cars on an alternative fuel, liquified petroleum gas (L.P.G.). This fuel is priced much lower than benzine (gasoline) and is available at service stations throughout the country. Essentially any spark-ignition engine car can be converted to L.P.G. use, adding fixed car ownership costs either in the form of a retrofit or a premium for L.P.G. cars in the used-car market. L.P.G., is composed primarily of propane and butane, which are the heavier compounds in natural gas. It can thus be produced as a byproduct of Dutch North Sea natural gas. It is stored under low pressure in liquid form and is burned in the engine as a gas with approximately 80 percent the energy density of gasoline (Sperling, 1988). The other alternative fuel to benzine (gasoline) in the Netherlands is diesel fuel (petroleum distillate). The fixed versus operating costs of diesel cars are more similar to benzine than L.P.G. cars, but the lower fuel costs and slightly higher fixed costs of diesel cars relative to gasoline cars places diesel in between gasoline and L.P.G.. According to the Dutch National Mobility Panel, the data source used in the present study, approximately 12 percent of the cars in general use in the Netherlands in 1984-88 were L.P.G., 8 percent were diesel, and the remaining 80 percent gasoline. For single-car households (about 60 percent of all Dutch households), the approximate fuel type breakdown is 11 percent L.P.G., 7 percent diesel, and 82 percent gasoline.

The first question addressed in this research is: how is fuel type choice related to car mobility measured, where mobility is measured in terms of overall usage (kilometers per year) and commuting distance? Causality can be anticipated in both directions: a high travel demand might explain the purchase of a car with lower fuel costs, but the ownership of such a car might result in more travel. The second question is: what are the influences of commuting subsidies, public transport season tickets, income and other background sociodemographic variables on fuel type choice and car mobility?

A joint continuous/discrete choice demand model is specified in terms of a set of dynamic simultaneous equations. The endogenous (dependent) variables are car fuel type, car usage, and commuting distance, each measured at two points in time. Car fuel type is treated as a three category discrete variable ordered in terms of fuel cost; usage is a continuous variable; and commuting distance is a censored continuous variable (having the censoring value zero for households with no workers outside the home location). The model is restricted to single-car households, and is estimated on a pooled sample of the Dutch National Mobility Panel for the years 1984-1988. Elasticities are calculated for each endogenous variable as a function of the other endogenous variables and certain exogenous variables.

2. METHODOLOGY

2.1 Non-Normal Endogenous Variables

Classical theory of simultaneous linear equations assumes that the set of endogenous variables is multivariate normal distributed. This is clearly not the case in the fuel type choice and mobility model: Fuel type is a categorical variable, with an ordering in the categories according to the price of the fuel. Yearly kilometrage is a regular continuous variable (in principle it is censored at zero, but the censoring does not take effect since all single-car households reported some car kilometers each year). Commuting distance is censored at zero; if there are no workers in the household this variable is zero. Hence, the endogenous variables consist of an ordered three category probit (fuel type), a continuous variable (yearly kilometrage) and a tobit variable (commuting distance). In these types of cases, techniques can be applied to transform the observed non-normal variables into normal latent variables, which is possible under certain assumptions. The simultaneous equation system of the transformed normal variables can then be estimated using appropriate distribution-free methods. The model results can be interpreted in terms of the latent variables, but this has limitations, because they cannot be observed. An elasticity calculated for unobserved latent variables is not very meaningful in itself. However, it is possible to evaluate the model results in terms of their observed non-normal counterparts.

The transformation of non-normal to normal variables is performed in the so-called measurement model (sometimes called the "outer" measurement model, to distinguish it from factorial models). The measurement model is discussed for each of the three types of variables used in the model, starting with the simplest case.

For a *continuous* variable the measurement model linking the observed Y and the latent variable Y^* is simply the identity:

$$Y = Y^*$$

For an *ordered probit* it is assumed that there is a latent continuous variable Y^* which is normally distributed with mean zero and unit variance. The latent variable itself is not observed, but there is an ordinal indicator Y that is related to Y^* in the following way:

$$\begin{array}{lll} Y = 1 & \text{if} & \alpha_0 < Y^* < \alpha_1 \\ Y = 2 & \text{if} & \alpha_1 < Y^* < \alpha_2 \\ \vdots & & \vdots \\ Y = K & \text{if} & \alpha_{K-1} < Y^* < \alpha_K \end{array}$$

where

$$\alpha_0 = -\infty\,, \quad \alpha_1 < \alpha_2 < \alpha_3 < \ldots < \alpha_K\,, \quad \alpha_K = +\infty$$

are the threshold values of the cumulative normal distribution corresponding to the marginal distribution of the population over the categories. A variable with K categories has K-1 unknown thresholds. These are estimated as:

$$\hat{\alpha}_k = \Phi^{-1}\left(\sum_{j=1}^{k} n_j / N\right)$$

for k=1, 2, .., K-1, where Φ denotes the standard cumulative normal distribution function. Here, n_j is the subsample size falling in category j of the ordinal variable and N is the effective sample size. In the transformation from ordinal to normal variables the ordinal score Y=k is replaced by the normal score z_k, which is the mean of Y^* in the interval $\alpha_{k-1} < Y^* < \alpha_k$, which is:

$$z_k = \frac{\phi(\alpha_{k-1}) - \phi(\alpha_k)}{\Phi(\alpha_k) - \Phi(\alpha_{k-1})}$$

where ϕ denotes the standard normal density function.

In a similar fashion, a *censored variable* can be transformed to a normal variable. If Y is a censored variable that is observed only if it is positive, then it is assumed that Y is generated by a latent normal variable Y^* that is uncensored. Thus:

$$\begin{aligned} Y &= Y^* \qquad \text{if } Y^* > 0 \\ Y &= 0 \qquad \text{if } Y^* \leq 0 \end{aligned}$$

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

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

These latent variables are 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, polychoric and polyserial correlations can be computed; these are consistent estimates of the underlying population statistics.

2.2 The Structural Model

Having defined the measurement model we now turn to the structural equation system itself. The general form of the equation system is given by:

$$\underline{Y^*} = \mathrm{B}\underline{Y^*} + \Gamma X + \underline{\delta}$$

where $\underline{Y}^*$ is a column vector of p endogenous variables, X is a column vector of q exogenous variables, and $\underline{\delta}$ is a column vector of p disturbance terms. The B matrix, of order (p x p), contains the structural effects among the endogenous variables, and the Γ matrix, of order (q x p), is the matrix of regression coefficients of all exogenous variables on the endogenous variables. The disturbance (or residual) terms are multivariate normally distributed with mean zero and variance-covariance matrix Ψ. The structural model is defined in terms of the latent variables, i.e. after the transformations performed in the measurement model.

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 is in turn related to c. Thus, 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 among the endogenous variables are:

	Y to Y	X to Y
Direct effects:	B	Γ
Indirects effects:	$(I-B)^{-1} - B - I$	$(I-B)^{-1}\,\Gamma - \Gamma$
Total effects:	$(I-B)^{-1} - I$	$(I-B)^{-1}\,\Gamma$

Estimation of the parameters in the model is performed using the Generalized Weighted Least Squares method developed by Browne (1974; 1982; 1984). This method is described in more detail in Golob and van Wissen (1989), and van Wissen and Golob (1990). Asymptotically distribution fee estimates are generated by minimizing the function:

$$F = (\underline{s}-\hat{\underline{\theta}})' W^{-1} (\underline{s}-\hat{\underline{\theta}})$$

where $\underline{s}$ is the vectorized set of all sample variances and covariances (the sample statistics generated in the measurement part of the model), $\hat{\underline{\theta}}$ the vectorized set of estimated variances and covariances, and W the asymptotic variance-covariance matrix of the sample statistics.

The value of F times the sample size N is an overall measure of goodness-of-fit. It is distributed asymptotically as χ^2 with degrees of freedom determined as follows: For p endogenous variables and q exogenous variables, there are $\frac{1}{2}(p^2 + p)$ moments among the endogenous variables and pq regression slopes from exogenous to endogenous variables; thus, the number of degrees of freedom is $\frac{1}{2}(p^2 + p) + pq - r$, where r is the number of free parameters in the model. However, with large sample sizes the χ^2-test will almost always result in a non-fitting model, according to this statistic (Bentler and Bonett, 1980). This does not necessarily imply a bad fitting model. Alternative tests have been proposed for sample sizes larger than 200. One is the statistic N*F / df. If this statistic is less than 3, this indicates a good fit (Carmines and McIver, 1981). Another test is to take the observed N*F value, and calculate the hypothetical sample size, given this statistic, that would be needed to make it a good fitting model. If this sample size is larger than 200, this indicates a good fitting model (Hoelter, 1983).

3. DATA

The model is estimated on a pooled sample of the Dutch National Mobility Panel, 1984-1989. This data set, described in J. Golob et al. (1985) and van Wissen and Meurs (1989), consists of annual (sometimes biannual) observations on approximately 1,800 households originally clustered in twenty communities throughout the Netherlands. These observations involve one-week travel diaries and personal and household questionnaires. For present study, annual measurements conducted in the spring of each of the five years 1984 through 1988 were used to construct a pooled year triplet sample. The sample was restricted to households that had a single car in each of the three years representing approximately 63 percent of all panel households.

The composition of the pooled year triplet sample is shown in Table 1. Each subsample represents the observation of households for three consecutive years. In the model structure, these years are denoted by t_0 (the initial conditions) for year one, t_1 for year two, and t_2 for year three. There were 494 single-car households in the panel for the three years 1984, 1985, and 1986. Similarly, there were 606 single-car households for 1985, 1986, and 1987; and 693 single-car households for 1986, 1987, and 1988. A random selection of 494 households was made for each of the larger two subsamples, resulting in a pooled sample size of 1482 observations of households over three adjacent years.

Triplet	Year 1	Year 2	Year 3	Total Households	Randomly Selected
1	1984	1985	1986	494	494
2	1985	1986	1987	606	494
3	1986	1987	1988	693	494
TOTAL OBSERVATIONS				1793	1482

Table 1 Pooled Year Triplet Sample

Pooled panel sampling is discussed in van der Eijk (1987) and Golob (1989). One major advantage is that two types of effects can be separated and estimated with such a sample: (1) panel conditioning effects due to temporal biases in response, and (2) period effects due to conditions that influence all respondents uniformly at a given point in time. The second advantage is that attrition bias is less in a pooled sample than in a "stayers" sample of only those households that participated in all waves of the panel (in this case 1984 through 1988). This is because households added as panel refreshment (in 1985 and 1986) are included, as are households that dropped out of the panel after three or four years. The disadvantage is that there is sample redundancy, but we feel this disadvantage is outweighed by the advantages of including period effects and reducing sample attrition bias. In particular, the ability to estimate period effects, potentially due to fuel prices, other costs of living, and trends in taste, is central to this study. It is not possible to identify period effects in a cross-sectional model.

The model variables are listed in Tables 2A (the endogenous variables) and 2B (the exogenous variable. The six endogenous variables (Table 2A) represent measurements of the same three travel behavior variables at two points in time, one year apart. Through use of the measurement model (Section 2.1), the endogenous variables (Fuel Type) at t_1 and t_2 are treated as ordered probits. The car usage (Year KM) variables at t_1 and t_2 are treated as continuous variables. And the commuting distance (Comm. Dis.) variables at t_1 and t_2 are treated as tobits.

VARIABLE	ABBREVIATION	DESCRIPTION
Fuel Type T=1	FT_1	3-category fuel type (benzine, diesel, L.P.G.) in year t_1
Year KM T=1	YK_1	Car usage in km/year in year t_1
Comm. Dis. T=1	CD_1	Average commuting distance of primary worker in year t_1
Fuel Type T=2	FT_2	3-category fuel type (benzine, diesel, L.P.G.) in year t_2
Year KM T=2	YK_2	Car usage in km/year in year t_2
Comm. Dis. T=2	CD_2	Average commuting distance of primary worker in year t_2

Table 2A The Endogenous Variables

The sixteen exogenous variables (Table 2B) are subdivided into three groups: (1) initial conditions, (2) time invariant background variables, and (3) dynamic background variables. The three exogenous variables in the initial conditions group are simply the three endogenous behavioral variables measured one year prior to year $t=1$. These variables are taken as given because there is no way to explain these variables in terms of state dependence from a previous year, nor is there any way of specifying autocorrelated disturbance terms. These are the initial conditions in the dynamic process being modeled.

The time invariant group of exogenous variables is divided into three subgroups: The first subgroup (2.1) is comprised of four household economic and sociodemographic variable that remain constant for the vast majority of households over the three-year time horizon. The lack of temporal variation in these variables means that they must be treated the same as variables in a cross-sectional model. These include household size, one life-cycle dummy variable, and two income class dummy variables. Dummy variables for the remaining life-cycle and categories (J. Golob et al., 1984) were tested, but were found to add no explanatory power to the model; they were either not related to the endogenous variable or were redundant with other variables in the model. In addition, the distinction in residential location (between Major urban centers, Regional centers, Suburban cities and Other municipalities) turned out to be unimportant.

The second subgroup (2.2) consists only of the single variable, the natural logarithm of years-to-date in the panel. The use of this variable in reducing panel conditioning and attrition biases is discussed in Golob (1989). The logarithm form is consistent with the biases detected as a function of panel longevity by Meurs et al. (1989).

Finally, subgroup (2.3) is comprised of two dummy variables capturing period effects, one for each of the first and last of the three year-triplet subsamples listed in Table 1. With three pooled panel subsamples it is possible to have two such variables. The variables measure uniform trends over the population that are not explained by the remaining variables (Golob, 1989), with the base period being 1985-1987: links from the PERIOD '84-'86 variable to endogenous variables at t_1 measure period effects for 1985 relative to 1986; links from this same variable to endogenous variables at t_2 variables measure period effects for 1987 relative to 1986, and those from PERIOD '86-'88 to t_2 variables measure period effects for 1988 relative to 1987.

The final group (3) of dynamic exogenous variables consists of three variables measured at each of the two years t_1 and t_2. These three variables are: the number of household workers receiving car commuting subsidies from their employers, the number of adult rail season tickets (including a general rail pass, a public transport pass, or a pass for a specific rail travel corridor), and the number of household workers with non-fixed work locations. The first two of these variables are important for policy evaluation purposes. The third variable was found to be important in explaining the endogenous variables.

VARIABLE TYPE	VARIABLE	DESCRIPTION
Initial conditions	Fuel Type T=0	3-category fuel type in year prior to year t_1
Initial conditions	Year KM T=0	Car usage in year prior to year t_1
Initial conditions	Comm. Dis. T=0	Average commuting distance in year prior to year t_1
Time invariant	H H size	Household size
Time invariant	H D > 35 0 K D	Life cycle dummy: head of household >35, no children
Time invariant	INC 24 -38 K	Income dummy: 24-38,000 fl/year
Time invariant	INC > 38 K	Income dummy: > 38,000 fl/year
Time invariant	Ln (YRS PANEL)	Natural log of years in panel
Time invariant	PERIOD '84-'86	Dummy: year t_0 = 1984 (t_1 = 1985, t_2 = 1986)
Time invariant	PERIOD '86-'88	Dummy: year t_0 = 1986 (t_1 = 1987, t_2 = 1988)
Dynamic	TRAVEL SUBS. T=1	No. of workers with car commuting subsidized by the t_1 employee
Dynamic	RAIL CARD T=1	No. of rail (NS or OV) season tickets in year t_1
Dynamic	NON-FIX W.L.T=1	No. of workers with non-fixed work locations in year t_1
Dynamic	TRAVEL SUBS.T=2	No. of workers with car commuting subsidized by employer in t_2
Dynamic	RAIL CARD T=2	No. of rail (NS or OV) season tickets in year t_2
Dynamic	NON-FIX W.L.T=2	No. of workers with non-fixed work locations in year t_2

Table 2B The Exogenous Variables

4. MODEL SPECIFICATION

4.1 Structural Equations

Our goal is to develop and estimate a *dynamic* model of fuel type choice and car mobility. In a dynamic context it is likely that fuel type and total mobility will show a more complicated pattern of causality than can be specified in a single equation model of fuel type as a function of total mobility. Moreover, commuting distance plays an important role in determining total mobility and fuel type, especially when travel reimbursements and subsidies are taken into account. Therefore, the following variables were defined to be endogenous: (1) fuel type (2) yearly kilometrage, and (3) commuting distance. This implies a simultaneous model system with three endogenous variables per time period. The number of time periods chosen depends on the length of the relevant time lags in the process on the one hand and the constraints of the sample on the other hand. As explained in the data description section we have used a pooled household data file where each observation covers three time periods, each one year apart. Further, in order to estimate a dynamic model we have to control for a number of effects that might otherwise bias our results. These effects are the initial conditions, panel effects and period effects. We have used the first time point as initial conditions: fuel type, yearly kilometrage and commuting distance for year t_0 are treated as exogenous variables, leaving time periods t1 and t_2 to be determined in the model. Thus, the model can estimate time lags of at most one year. The second factor that has to be controlled for is the panel conditioning effect. In previous research (Meurs et al, 1989) it has been shown that the number of years a respondent has participated in the panel is an important conditioning factor for mobility reporting. Consequently, this variable, in log transform, was included as an exogenous variable. Finally, due to the pooling of our sample, we can distinguish pure time effects from period (i.e., pooling subsample) effects. As explained in the data section, there are three pooling subsamples.

The longitudinal character of the data allows inclusion of individual-specific time invariant effects (see Meurs, 1989, or Hensher, 1988, for a detailed exposition of these effects). These effects are included in terms of decompositions of the residual terms in the model. Suppose we have a model of the form:

$$Y_{it} = \sum_j \beta_j X_{it} + \varepsilon_{it}$$

This model could be thought of as predicting yearly kilometrage for household i in year t. Of course the set of predictors X will not be complete. Each household and time point has its own characteristics that determine its mobility level and which are not known to the modeller. Some of these omitted variables are time invariant, e.g. specific habits and tastes that characterize the household's behavior at any point in time. Therefore, the residual error term can be decomposed in a household specific, time invariant part and a "truly random" part:

$$\varepsilon_{it} = \alpha_i + \delta_{it}$$

By decomposing the error term in this way, we control for possible spurious serial correlation or spurious state dependence effects that might obscure the "true" causal pattern underlying the data.

Summarizing, the fuel type and mobility model is defined as follows:

1. It is multivariate, i.e., it treats fuel type, yearly kilometrage and commuting distance as joint endogenous variables.
2. It is dynamic. This involves a number of model features. First, by introducing multiple time periods it is possible to estimate lagged effects among the key variables. Further, the longitudinal character of the data allow estimation of individual, time invariant effects.
3. Initial conditions are controlled for by using data from the first time period as exogenous, rather than endogenous, variables.

4. Panel effects and period effects can be separated using a number of exogenous variables, i.e., the (log of the) number of years participated in the panel, and pooling subsample dummies.
5. The model incorporates the possible conditioning effects of a number of exogenous variables, i.e., travel cost subsidy, income, life cycle, employment variables and other household characteristics.

We can specify the fuel type and mobility model within this general framework. It has the following form:

$$\begin{bmatrix}\underline{V_1}\\ \underline{V_2}\\ \underline{\alpha}\end{bmatrix} = \begin{bmatrix}B_{1,1} & B_{1,2} & B_{1,\alpha}\\ B_{2,1} & B_{2,2} & B_{2,\alpha}\\ \varnothing & \varnothing & \varnothing\end{bmatrix} \cdot \begin{bmatrix}\underline{V_1}\\ \underline{V_2}\\ \underline{\alpha}\end{bmatrix} + \begin{bmatrix}\Gamma_{1,0} & \Gamma_{1,1} & \varnothing & \varnothing & \Gamma_{1,4}\\ \varnothing & \varnothing & \Gamma_{2,2} & \varnothing & \Gamma_{2,4}\\ \varnothing & \varnothing & \varnothing & \Gamma_{3,3} & \varnothing\end{bmatrix} \cdot \begin{bmatrix}\underline{V_0}\\ \underline{X_1}\\ \underline{X_2}\\ \underline{U}\\ \underline{B}\end{bmatrix} + \begin{bmatrix}\underline{\delta_1}\\ \underline{\delta_2}\\ \underline{\delta_\alpha}\end{bmatrix}$$

where the following symbols have been used (see Table 2A for endogenous variable abbreviations):

$$\begin{aligned}\underline{V_t} &= [FT^*, YK^*, CD^*]^T \qquad t=0,1,2\\ \underline{\alpha} &= [\alpha_{FT}, \alpha_{YK}, \alpha_{CD}]^T\\ E(\underline{\delta_t}) &= E(\underline{\delta_\alpha}) = \underline{0}\\ E(\underline{\delta_t}, \underline{\delta_t'}) &= \Psi_t \qquad t=1,2\\ E(\underline{\delta_1}, \underline{\delta_2'}) &= \varnothing\\ E(\underline{\delta_t}, \underline{\delta_\alpha'}) &= \varnothing\\ E(\underline{\delta_\alpha}, \underline{\delta_\alpha'}) &= \Psi_\alpha\end{aligned}$$

There are six endogenous variables in total, three for each time period. The B matrix, broken down into nine submatrices, three of which are null submatrices, contains the causal effects of the endogenous variables upon each other. In $B_{1,1}$ and $B_{2,2}$ the contemporaneous, or instantaneous effects are contained, while in $B_{2,1}$ the lagged effects of period 1 to period 2 are given. The submatrix $B_{1,2}$ is relevant only if anticipatory effects are present. Furthermore, the B matrix contains the individual specific effects α, one for each endogenous variable. The $B_{t,\alpha}$ matrices are diagonal matrices. For pure individual-specific effects these matrices should be identity matrices. However, as will be explained in Section 5, it was necessary to release one diagonal element of $B_{2,\alpha}$.

The Γ matrix contains the regression, or conditioning effects of exogenous variables upon fuel type, yearly kilometrage and commuting distance. Several submatrices can be discerned. First, we have the conditioning effects of period t_0, which correspond to $\underline{V}_0$ in the vector of regressors. Next, there are dynamic variables that have instantaneous effects on the endogenous variables. These coefficients are given in $\Gamma_{1,1}$ and $\Gamma_{2,2}$ and the corresponding regressors are given in X_1 and X_2. A fourth set of regressors is time invariant. They have an influence through the individual specific effects. One could say that they 'explain' part of the time invariant individual specific dispersion in the data. These time invariant regressors are denoted by $\underline{U}$. Finally, we have a set of time dummy variables, $\underline{R}$, as explained previously, that influence the endogenous variables at year t_1 and time year t_2 through the coefficient submatrices $\Gamma_{1,4}$ and $\Gamma_{2,4}$.

4.2 Elasticity Formulas

In this section we will translate the model specifications into elasticities, concentrating on the elasticities among the endogenous variables, i.e., fuel type, year kilometrage and commuting distance. The notion of elasticity is in principle straightforward, but here we deal with both normal and non-normal variables which make the calculation and interpretation of elasticities more complicated. Therefore, some attention will be given to the calculation and interpretation of elasticities in a simultaneous model of non-normal variables.

Elasticity is defined as the percentage change in the dependent variable due to a unit percent change in the independent variable. For probit and tobit variables (that can occur both as dependent and independent variables) some difficulties arise in applying the concept of elasticity. Therefore, each of the relevant causal links among the endogenous variables in the model will be discussed. The structural model defines relationships among the multivariate normal latent variables. These latent variables are equal to the observed variables only with continuous variables. For tobit and probit variables there is a non-linear measurement relation between observed and latent variable, as described in Section 2.1. The model structure is among the *latent* variables. However, elasticities need to be defined in terms of *observed* variables.

In developing observed-variable elasticities, it is convenient to introduce the following notation. We deal with three endogenous variables of different measurement type: yearly kilometers YK; fuel type FT and commuting distance CD. We denote the expected value of the latent underlying variables by $\eta^{(YK)}$ for yearly kilometers; $\eta^{(FT)}$ for fuel type; and $\eta^{(CD)}$ for commuting distance. The expected values of the latent variables for our structural model system can be calculated using the reduced form of the structural equation system:

$$\hat{\eta} = (I-\hat{B})^{-1}\hat{\Gamma}X$$

Due to the non-linearities it will be necessary to calculate the elasticities for each observation. Evaluation of the elasticity functions at sample mean points is not correct. Instead we will calculate mean elasticities by evaluating the elasticity formulas for each observation in the sample. Thus, if ϵ_i is the elasticity evaluated for observation i we calculate the total elasticity as

$$\bar{\epsilon} = \frac{\sum_{i=1}^{N} \epsilon_i}{N}$$

Disregarding the lagged effects of all variables upon themselves, the following causal relations are important:

1. The elasticity of year kilometrage on fuel type: This is an effect from a regular linear variable to an ordered probit. The elasticity of this link is defined as: *the percentage change in the probability of having a particular fuel type due to a percent change in year kilometrage.* Thus, for the three category fuel type variable there are three elasticities, one for each fuel type. Normally we would expect to find opposite signs of elasticities among the cells, since the respective cell probabilities cannot all increase simultaneously. More kilometers traveled will increase the probability of having a cheaper fuel type but decrease the probability of having regular benzine. The elasticity formula is given by:

$$\epsilon_{ik} = \frac{X_{ik}\ \beta_k\{\phi(\alpha_{k-1}-\eta_i^{(FT)})-\phi(\alpha_k-\eta_i^{(FT)})\}}{\Phi(\alpha_k-\eta_i^{(FT)})-\Phi(\alpha_{k-1}-\eta_i^{(FT)})}$$

or more compactly:

$$\epsilon_{ik} = \frac{X_{ik}\ \beta_k\{\phi_{i,k-1}-\phi_{i,k}\}}{\Phi_{i,k}-\Phi_{i,k-1}}$$

where the following notational simplifications have been made:

$$\phi_{i,k} = \phi(\alpha_k-\eta_i^{(FT)})$$
$$\Phi_{i,k} = \Phi(\alpha_k-\eta_i^{(FT)})$$

The index k denotes fuel type category.

2. The elasticity of commuting distance on year kilometrage. Here, we deal with the effects of an independent probit variable (commuting distance) on a continuous variable (year kilometrage). Since the tobit variable is censored at zero, the elasticity of households without commuting distance will be zero. Therefore we have chosen to use the conditional elasticity: *the percentage change in year kilometrage due to a one percent change in commuting distance, given the information of non-zero commuting distance.* The corresponding conditional elasticity is given by:

$$\epsilon_i = \frac{\beta\{\eta_i^{(CD)} + \sigma\frac{\phi(\nu_i)}{\Phi(\nu_i)}\}}{\eta_i^{(YK)}\{1-\nu_i\frac{\phi(\nu_i)}{\Phi(\nu_i)} - \left(\frac{\phi(\nu_i)}{\Phi(\nu_i)}\right)^2\}}$$

where the term between brackets in the numerator is the conditional expectation of commuting distance, given that it is non-zero. Further, ν is the standardized latent variable of the tobit:

$$\nu_i = \frac{\eta_i^{(CD)}}{\sigma}$$

where σ is the standard deviation of the latent variable.

3. The elasticity of commuting distance to fuel type. This is an indirect link in the model, since there is no direct causal relation from commuting distance to fuel type (Section 5). Again, if the household has no commuting distance, the elasticity will be zero. Therefore we use the conditional elasticity which is defined as: *the percentage change in the probability of having a particular fuel type due to a one percent change in commuting distance, given the information of a non-zero commuting distance.* Thus, there are three elasticities, one for each fuel type category. The formula is given by:

$$\epsilon_{i,k} = \frac{\beta\{\phi_{i,k-1} - \phi_{i,k}\}\cdot\{\eta_i^{(CD)} + \sigma\left(\frac{\phi(\nu_i)}{\Phi(\nu_i)}\right)\}}{\{\Phi_{i,k} - \Phi_{i,k-1}\}\cdot\{1 - \nu_i\frac{\phi(\nu_i)}{\Phi(\nu_i)} - \left(\frac{\phi(\nu_i)}{\Phi(\nu_i)}\right)^2\}}$$

where k is the index of the fuel type category.

4. The elasticity of fuel type at t_1 to year kilometrage at t_2. The elasticity of this dynamic link is a good indicator of the travel generating effect of cheaper fuel types and

is defined as: *the percentage change in year kilometrage due to a percent change of the probability of having a particular fuel type.* Since there are three fuel types, we have three elasticities. These are given by:

$$\epsilon_{i,l} = \frac{\beta\{\Phi_{i,l} - \Phi_{i,l-1}\}}{\eta_i^{(YK)}\{\phi_{i,l-1} - \phi_{i,l}\}}$$

with l the index of the fuel type category.

5. The elasticity of fuel type at t_1 to commuting distance at t_2. This is also a dynamic travel generating effect of fuel type. For zero commuting distance, this elasticity is not defined. Therefore we define the conditional elasticity as follows: *the percentage change in commuting distance, due to a one percent change in the probability of having a particular fuel type, given the information of non-zero commuting distance.* The formula for this elasticity is:

$$\epsilon_{i,l} = \frac{\beta\{\Phi_{i,l} - \Phi_{i,l-1}\}\cdot\{1 - \nu_i\frac{\phi(\nu_i)}{\Phi(\nu_i)} - \left(\frac{\phi(\nu_i)}{\Phi(\nu_i)}\right)^2\}}{\{\phi_{i,l-1} - \phi_{i,l}\}\cdot\{\eta_i^{(CD)} + \sigma\left(\frac{\phi(\nu_i)}{\Phi(\nu_i)}\right)\}}$$

5. RESULTS

The model X^2 value was 212.78 with 76 degrees-of-freedom (df) and a sample size of 1482. The X^2/df ratio is 2.8, indicating an acceptable goodness of fit (Carmines and McIver, 1981). The critical sample size for non-rejection of this model at the $p=.05$ level is 583. According to Hoelter (1983) this also indicates an acceptable model because the critical sample size is greater than 200. The R^2 values were 0.35 for Year Km at period t_1, 0.35 for Comm. Dis. at t_1, 0.60 for Year Km at t_2 and 0.37 for Comm. Dis. at t_2. For the fuel type probit variables, the variances are not identified, and thus no R^2 statistic is available. With few exceptions, all parameter estimates are significant at the $p=.05$ level.

5.1 Parameter Estimates

The final model form is depicted in the flow diagrams of Figures 1 through 4, and coefficient estimates are listed in Tables 3 and 4. In this section we will focus on the qualitative results of the model, i.e., the sign and significance of the causal links between variable pairs. The scale of the coefficients is only interpretable when discussing continuous variables. In the next section we have attempted to give a more substantive interpretation to the model coefficients by calculating elasticities.

Income, although retained in the final model, turned out to be a difficult variable. Initially it was specified as a linear variable, by taking class-midpoints. This resulted in non-interpretable results. Finally, income dummies were used as time invariant conditioning effects.

First we turn to the causal structural relations among fuel type, yearly kilometrage and commuting distance (Figure 1 and Table 3). The interpretation of the instantaneous links is clear: the type of fuel used is a direct function of yearly kilometrage, which, in turn is determined to a high degree by commuting distance. So, commuting distance does not have a direct effect upon fuel type. It is yearly kilometrage, the sum of all travel, that has a direct influence on the fuel type. The coefficients have the correct sign: more travel leads to a higher probability of owning a car with a cheaper fuel type. The co-

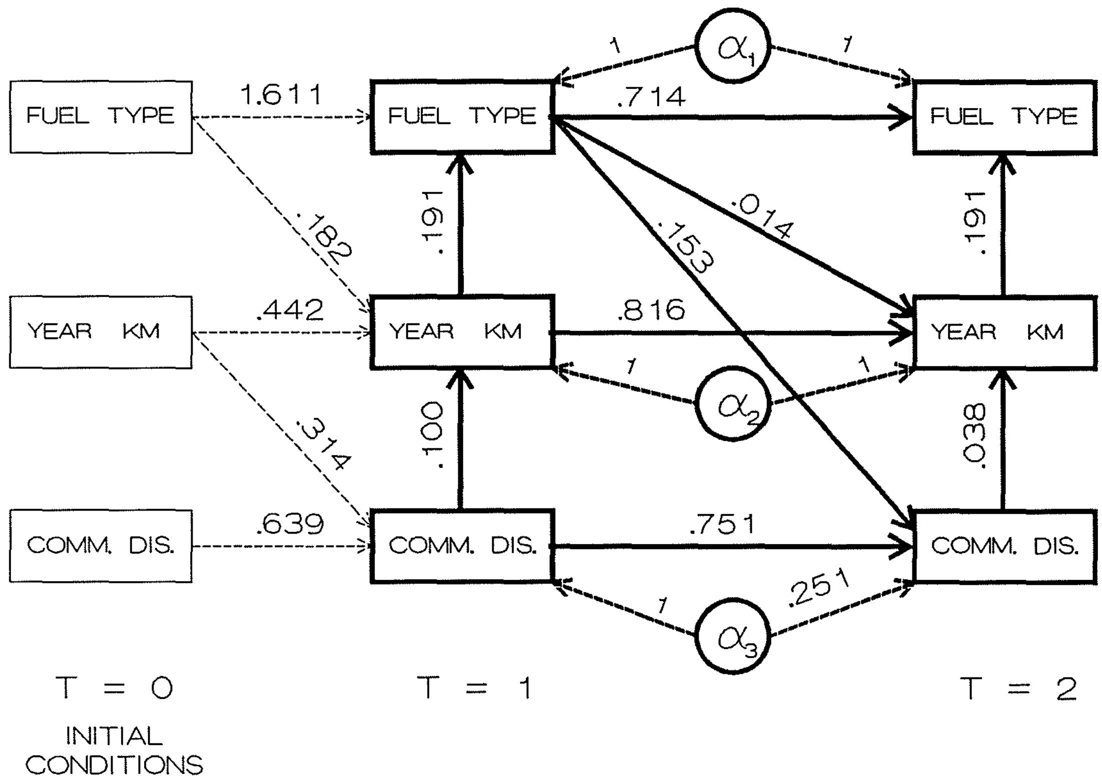

Figure 1 **Dynamic Structure of Fuel Type Model**

efficient of commuting distance to yearly kilometrage varies over time (0.100 in period t_1, versus 0.038 in period $t_{2)}$.

There is an important lagged influence of fuel type on commuting distance in the next period. Cheaper fuels encourage people to start making longer commuting trips, according to this model. There is also an effect of fuel type on total yearly kilometrage, but this effect is much weaker and has a t-value of 1.136, which is questionable. The results seem to imply that commuting distance, and to a lesser extent non-work mobility, is increased as a consequence of cheaper fuel types. (The estimated consequences in

Submatrix:	From:	To:	Estimate:	T-value:
$B_{1,1}$	Year KM	Fuel Type	0.191	8.428
	Comm. Dis.	Year KM	0.100	12.385
$B_{2,2}$	Year KM	Fuel Type	0.191	8.428
	Comm. Dis.	Year KM	0.038	12.385
$B_{2,1}$	Fuel Type	Fuel Type	0.714	26.476
	Fuel Type	Year KM	0.014	1.136
	Fuel Type	Comm. Dis.	0.153	5.048
	Year KM	Year KM	0.816	36.254
	Comm. Dis.	Comm. Dis.	0.751	30.340
$B_{1,\alpha}$	alpha_{FT}	Fuel Type	1.000	-
	alpha_{YK}	Year KM	1.000	-
	alpha_{CD}	Comm. Dis.	1.000	-
$B_{2,\alpha}$	alpha_{FT}	Fuel Type	1.000	-
	alphaYK	Year KM	1.000	-
	alpha_{CD}	Comm. Dis.	0.251	5.146

Table 3 Parameter Estimates and T-values of B Matrix

terms of elasticities are presented in Section 5.2.) Another important feature of the dynamic character of the model is state dependence, expressed through the autolags present in the B-matrix. Fuel type, yearly kilometrage and commuting distance all exhibit a genuine state-dependency, because we have controlled for heterogeneity in the model by means of the individual specific effects.

The time invariant factors, the α's, control for everything that does not change over time for each household. Figure 2 depicts the structure. The estimated coefficients of the time invariant exogenous variables on the α's is given in Table 4. Figure 2 shows the conditioning effects of exogenous variables and a covariance between α_{YK} and α_{CD}, the time invariant components of yearly kilometrage and commuting distance. Strictly speaking, we do not have a time invariant structure on commuting distance, since the link from α_{CD} to commuting distance at time t_2 is different from that at time t_1. Instead, we have a factor structure on these error terms.

The time invariant component of fuel type is influenced by four variables. Household size (HHSIZE) is positively related to cheaper fuel types. Larger households tend to have a cheaper fuel type. Households with heads older than 35, without children at home, on the other hand are more related to more expensive fuel types (a negative sign), as well as total length of participation in the panel (the variable controlling for panel effects). Finally, household income in the range 24-38K (average to slightly below average incomes) implies usage of more expensive fuels. This is a somewhat puzzling result. In prior model runs various alternative specifications with income were tried,

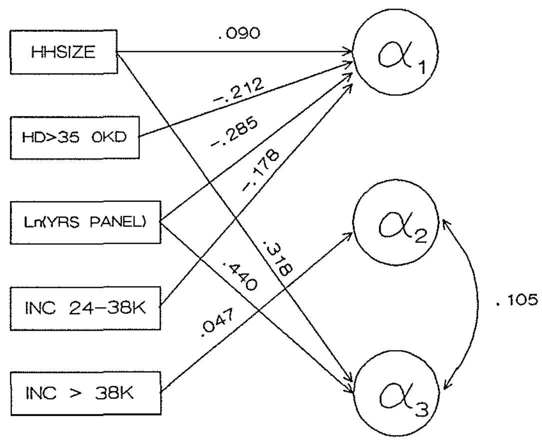

Figure 2 Structure of Individual Specific Effects

specifically with continuous income (class midpoints), or income as an endogenous variable. However, this did not lead to meaningful results. The results with income as a set of four dummy variables (0-17K, 17-24K, 24-38K and 38+K) does not lead to very satisfactory results with respect to fuel type either. It appears that the relation between income and fuel type is a rather complex one. The highest income category (38+K) has a positive effect on yearly kilometrage, which is a more plausible relationship than that on fuel type. Finally, the α for commuting distance is influenced by household size (larger households have longer commuting trips) and the total years of participation in the panel (the weights of these variables for time t_2 have to be multiplied by .251 due to the factor structure).

Decomposition of the variances of each endogenous variable are shown in Table 5 in terms of total variance, time invariant component and residual variance. The time invariant factors account for a large share of the total variance of each variable. For the four continuous variables with known sample variance, the estimated variance of the time-invariant individual-specific effects (α factors) accounts for between 16% and 37% of the total variance. The sample variances of the categorical fuel type is not identified in a probit model, but the residual (unexplained) variances of these two variables was fixed at the conventional standardization value of 1.0. Comparing the estimated variance of the α factor to this fixed residual variance, the variance of the α factor is slightly more than half of the variances of the residuals. This is similar to the result for the four continuous endogenous variables; for these four variables, the estimated variance of the α factors ranges between 38% and 58% of the estimated residual (unexplained) variance of each variable.

Submatrix:	From:	To:	Estimate:	T-value:
$\Gamma_{1,0}$	Fuel Type	Fuel Type	1.611	27.973
(initial	Fuel Type	Year KM	0.182	8.689
conditions)	Year KM	Year KM	0.442	36.895
	Year KM	Comm. Dis.	0.314	10.410
	Comm. Dis.	Comm. Dis.	0.639	39.748
$\Gamma_{1,1}$, $\Gamma_{2,2}$	Travel Subs.	Year KM	0.137	5.709
(instantaneous	Travel Subs.	Comm. Dis.	0.682	10.256
effects)	Rail Card	Fuel Type	-0.154	-2.260
	Rail Card	Year KM	-0.032	-1.146
	Non-Fix W.Loc.	Comm. Dis.	0.573	6.356
$\Gamma_{3,3}$				
(time invariant	HH. Size	α_{FT}	0.090	4.110
effects)	HH. Size	α_{CD}	0.318	7.922
	Head <35 0K.	α_{FT}	-0.212	-2.692
	Log(Y.in Panel)	α_{FT}	-0.285	-1.791
	Log(Y.in Panel)	α_{CD}	0.440	1.737
	Income 24-38K	α_{FT}	-0.178	-2.952
	Income 38+K	α_{YK}	0.047	1.434
$\Gamma_{1,4}$				
(period effects	Period '84-'86	Year KM	-0.273	-6.158
on t=1 vars)	Period '86-'88	Year KM	-0.096	-2.277
$\Gamma_{2,4}$				
(period effects	Period '84-'86	Fuel Type	0.218	2.753
on t=2 vars)	Period '84-'86	Year KM	0.195	5.053
	Period '84-'86	Comm. Dis.	0.350	3.102

Table 4 Parameter Estimates and T-Values of Γ-Matrix

Next we turn to the effects of the time varying exogenous variables on the three endogenous variables (Figure 3 and Table 4). There are three exogenous variables specified for two time periods. No lagged effects are present and the structure was equated for the two time periods t_1 and t_2. An important exogenous variable is whether there is a subsidy provided by the employer. This variable has no direct effect on the type of fuel used but does have a positive effect both on commuting distance and car

Variable	Total Sample Variance	Estimated Residual Variance	Variance of Time-Invariant (Individual-Specific) Effects Estimate	T-value	R^2
Fuel Type	-	1.000	0.519	-	-
Year KM	0.492	0.322	0.124	49.467	0.346
Comm. Dis.	3.982	2.571	1.501	33.943	0.354
Fuel Type	-	1.000	0.519	-	-
Year KM	0.763	0.307	0.124	31.628	0.598
Comm. Dis.	4.134	2.591	1.501	33.900	0.373

Table 5 Variance Decomposition of Endogenous Variables

usage. Taking into account the different scales of yearly kilometers (in thousands of kilometers per year) and commuting distance (in one way distance from home to work) it can be seen that the effect of travel subsidy on commuting distance is almost twice that on yearly kilometerage. Nevertheless, travel subsidies, provided by the employer to cover commuting and business travel costs, have a significant effect on non-work travel. Next, the number of persons in the household having some form of season-ticket or long term discount ticket for the train (identifying the regular train users) is associated with more expensive fuel types (i.e. a negative correlation), and also negatively with the total car usage. This result is intuitively clear: regular train users have a lower usage level of cars and therefore do not shift to lower variable cost, but higher fixed cost cars. There is a clear relation between public transport usage and the level of car operating costs.

The third time varying exogenous variable is the number of workers with a non-fixed work location in the household. As expected, this variable has a high positive influence on commuting distance.

Another set of exogenous variables is the period effect (Figure 4 and Table 4). These are mainly to control for differences among the pooling subsamples. These results indicate that, for car usage, there was an unexplained increase from 1985 to 1986, a flattening of growth from 1986 to 1987, and an accelerated increase from 1987 to 1988.

For fuel type, there was an unexplained increase in the probability of owning L.P.G. and diesel cars over the 1985-1986 interval. Finally, there was a similar unexplained increase in commuting distance over the 1985-1986 interval.

The total effects among the endogenous variables are given in Table 6. All variables at time point t_1 have an effect on variables at time t_2. Moreover, commuting distance has an effect on fuel type through the intermediary variable total yearly kilometrage. These total effects are important in the calculation of elasticities.

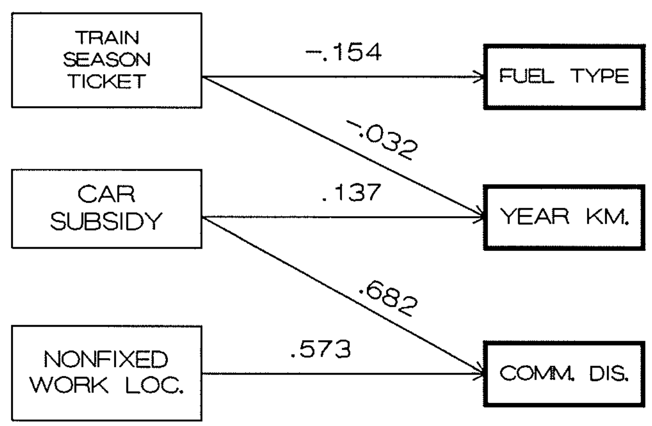

Figure 3 **Exogenous Variables in Fuel Type Model**

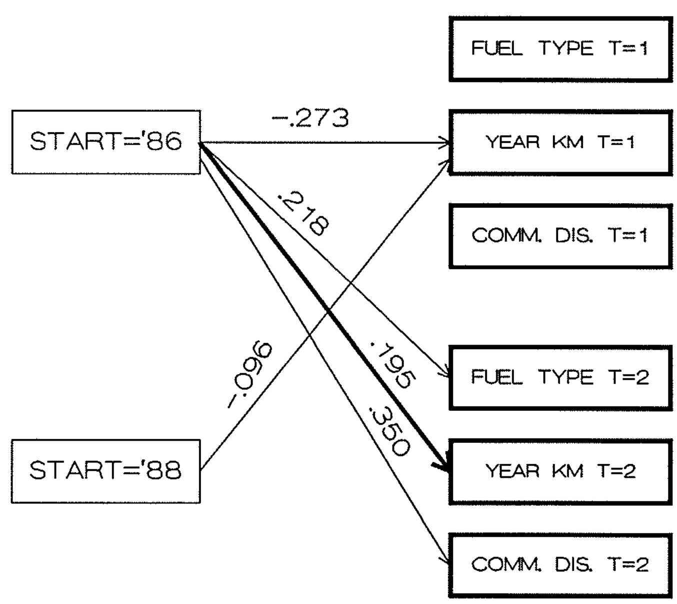

Figure 4 **Time and Period Effects in Fuel Type Model**

Submatrix:	From:	To:	Estimate:
$E_{1,1}$	Year KM	Fuel Type	0.191
	Comm. Dis.	Year KM	0.100
	Comm. Dis.	Fuel Type	0.100
$E_{2,2}$	Year KM	Fuel Type	0.191
	Comm. Dis.	Year KM	0.038
	Comm. Dis.	Fuel Type	0.100
$E_{2,1}$	Fuel Type	Fuel Type	0.714
	Fuel Type	Year KM	0.014
	Fuel Type	Comm. Dis.	0.153
	Year KM	Fuel Type	0.816
	Year KM	Year KM	0.816
	Year KM	Comm. Dis.	0.816
	Comm. Dis.	Fuel Type	0.751
	Comm. Dis.	Year KM	0.751
	Comm. Dis.	Comm. Dis.	0.751

Table 6 Total Effects Matrix E Among the Endogenous Variables

5.2 Elasticities

In this section we will apply the elasticity formulas of Section 4.2 to the set of endogenous variables, to calculate the mean elasticities for the entire sample. It is necessary to distinguish between direct elasticities, calculated from the direct effects (matrix B) and total elasticities, calculated from the total effects (matrix E). The latter elasticities are more relevant for policy evaluation. In addition, we will use the dynamic exogenous variables, which are relevant for transportation policy, to parameterize the mean elasticities over the population: these variables are car commuting subsidies, rail season tickets, and nonfixed work locations (Table 2B).

The mean direct and total elasticities for each pair of endogenous variables is listed in Table 7. Each relevant elasticity will be discussed separately.

Car Usage to Fuel Type Periods t_1 and t_2. As discussed in Section 5.1, the model results indicate that increasing car usage increases the probability of owning a car with lower operating cost (cheaper fuel type). The three elasticities from car usage in the $B_{1,1}$ submatrix in Table 7 show the quantitative strength of this relationship. Both diesel and L.P.G. have positive elasticities (0.16 and 0.45 respectively), but L.P.G. is much more sensitive to usage changes than is diesel. A one percent increase in kilometers per year decreases the probability of owning a benzine (gasoline) engine car by 0.21 percent. Total elasticities are equal to the direct elasticities, and the computed elasticities at time t_2 are somewhat lower than those at t_1.

Next we clarify the sample according to the dynamic exogenous variables. Car usage elasticities for households with and without travel costs subsidy are graphed in Figure 5. Travel subsidy leads to a stronger negative elasticity for benzine and much lower positive elasticity for diesel. There is also a slightly higher positive elasticity for L.P.G.. Thus, travel cost reimbursements give rise to a stronger negative effect of yearly kilometrage on benzine but a much less positive effect on diesel fuel. The effect of a non-fixed work location on elasticities is graphed in Figure 6. Households with a variable work location react much more strongly to changes in yearly kilometrage with respect to ownership of benzine cars. There is also a negative effect on the probability of using diesel, whereas in households with fixed work locations this elasticity is positive. For workers with non-fixed work locations, a desirable alternative is L.P.G. when usage justifies.

Finally, Figure 7 gives the mean elasticities for households with and without rail season tickets. Season ticket holding indicates regular train usage, and in the previous section it was found that this has a profound effect on fuel type choice. Households with a rail season ticket react more strongly to changes in car usage levels with respect to diesel and L.P.G., but less strongly with respect to benzine. Thus, they are more likely to buy diesel or L.P.G. with more kilometers driven, but less likely to change from benzine

Sub-matrix:	From:	To:	Direct Elasticity		Total Elasticity	
			Value	Standard Deviation	Value	Standard Deviation
$B_{1,1}$	Year KM	Fuel Type: benzine	-.21	.40	-.21	.40
	"	Fuel Type: diesel	.16	.46	.16	.46
	"	Fuel Type: L.P.G.	.45	.18	.45	.18
	Comm. Dis.	Fuel Type: benzine	-	-	-.12	.16
	"	Fuel Type: diesel	-	-	.11	.23
	"	Fuel Type: L.P.G.	-	-	.28	.14
	Comm. Dis.	Year KM	.61	.18	.61	.18
$B_{2,2}$	Year KM	Fuel Type: benzine	-.18	.34	-.18	.34
	"	Fuel Type: diesel	.12	.35	.12	.35
	"	Fuel Type: L.P.G.	.34	.14	.34	.14
	Comm. Dis.	Fuel Type: benzine	-	-	-.05	.06
	"	Fuel Type: diesel	-	-	.02	.08
	"	Fuel Type: L.P.G.	-	-	.09	.05
	Comm. Dis.	Year KM	.24	.07	.24	.07
$B_{2,1}$	Fuel Type: benzine	Year KM	-.08	.08	-.11	.12
	Fuel Type: diesel	"	.01	.02	.01	.03
	Fuel Type: L.P.G.	"	.12	1.91	.17	2.71
	Fuel Type: benzine	Comm.Dis.	-.05	.05	-.05	.05
	Fuel Type: diesel	"	.01	.04	.01	.04
	Fuel Type: L.P.G.	"	.32	2.63	.32	2.63
	Year KM	Fuel Type: benzine	-	-	-.30	.55
	"	Fuel Type: diesel	-	-	.23	.60
	"	Fuel Type: L.P.G.	-	-	.63	.25
	Year KM	Comm. Dis.	-	-	.01	.00
	Comm. Dis.	Fuel Type: benzine	-	-	-.21	.23
	"	Fuel Type: diesel	-	-	.18	.34
	"	Fuel Type: L.P.G.	-	-	.46	.21
	Comm. Dis.	Year KM	-	-	.78	.26

Table 7 Direct and Total Elasticities of Fuel Type Model

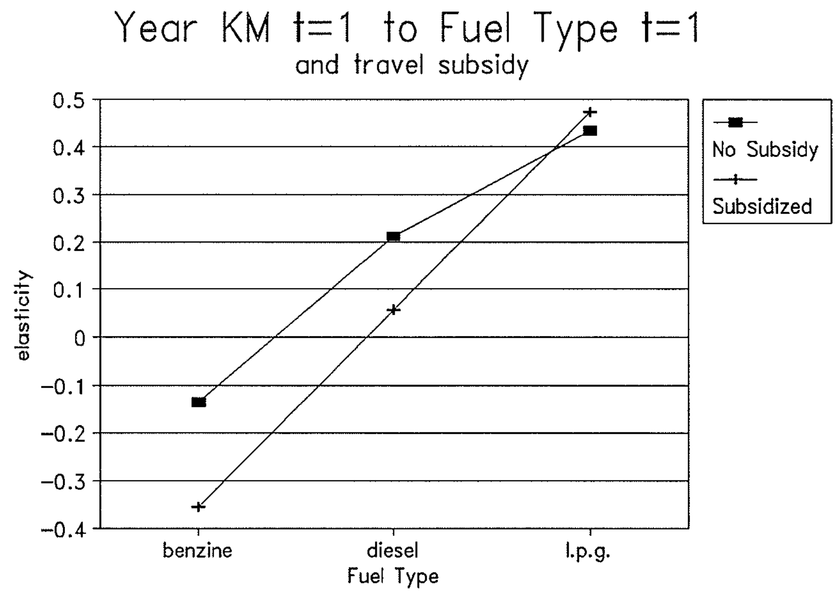

Figure 5 **Total Elasticities of Car Usage at t=1 to Fuel Types at t=1 with and without Travel Subsidies**

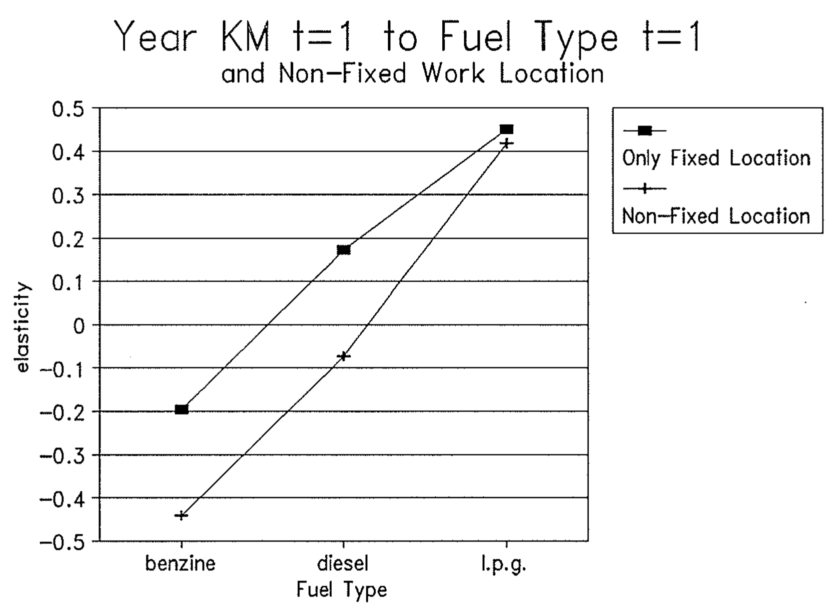

Figure 6 **Total Elasticities of Car Usage at t=1 to Fuel Types at t=1 for Fixed and Non-Fixed Work Locations**

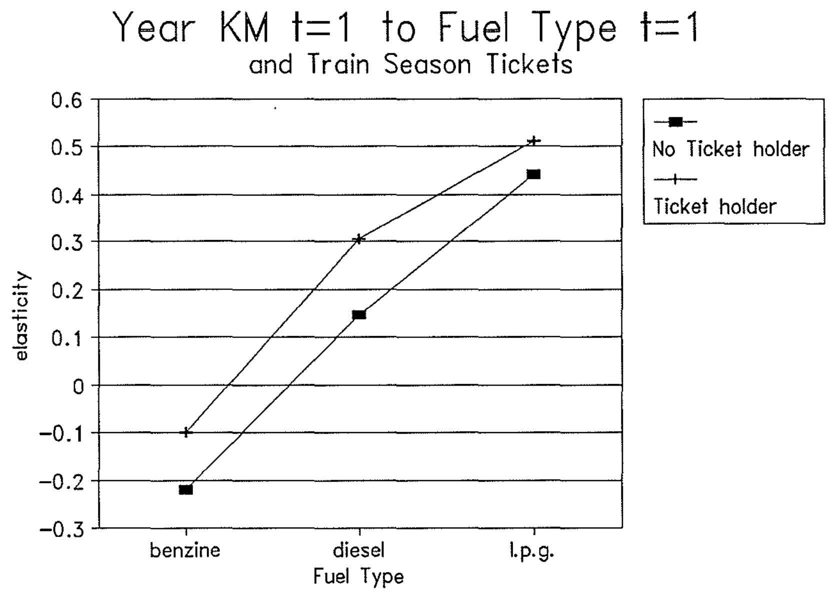

Figure 7 **Total Elasticities of Car Usage at t=1 to Fuel Types at t=1 with and without Train Season Ticket**

to another fuel type.

Commuting Distance to Fuel Type Periods t_1 and t_2. There are no direct elasticities involved in this link, but there is an indirect linkage through yearly car usage. These elasticities are therefore roughly equal to the product of the direct elasticity of Commuting Distance to Yearly Kilometrage (0.61) and the direct elasticity of Yearly Kilometrage to Fuel Type in time t_1. In time t_2 the direct elasticity of Commuting Distance to Yearly Kilometrage is only 0.24 and therefore the elasticities of Commuting Distance to the three fuel types is much lower than at time t_1. Thus, the model indicates an elasticity of commuting distance to benzine in the range of -0.05 to -0.12; to diesel in the range 0.02 to 0.11; and to L.P.G. in the range 0.09 to 0.28. The calculated ranges with respect to the elasticities of Yearly Kilometrage are much smaller.

Commuting Distance to Car Usage Periods t_1 and t_2. At time t_1 this elasticity is 0.61 but at time t_2 the value is only 0.24, due to the non-stationarity of the β coefficient. This result is somewhat unsatisfactory and an elasticity of 0.24 appears to be too low.

Fuel Type at t_1 to Car Usage at t_2. This dynamic effect represents the travel generating effect of cheaper fuels. The coefficient of fuel type to annual car usage is not as strong as that to Commuting Distance. There is a slight negative elasticity from benzine (-0.08) which means that a one percent increase in the probability of using benzine at time t_1 has a negative direct effect of 0.08 percent on yearly kilometrage at t_2. The total elasticity is larger in magnitude (-0.11), because there is an indirect linkage through commuting distance. The direct elasticity reflects the effect on non-work related travel, which is higher than on commuting distance. The effects of diesel fuel type on mobility is almost zero but there is a positive elasticity of L.P.G. on car usage of 0.12 (direct) and 0.17 (total). Some caution is necessary in interpreting this elasticity. The standard deviation is very high, indicating that this value may be the result of some large outlyers. This high variance may be the result of the relatively low number of L.P.G. users in the sample.

The effects of travel subsidy and rail season tickets on the travel generating effects of cheaper fuels are graphed in Figures 8 and 9. First, in Figure 8 it can be noted that the effect of an increase in the propensity to use benzine is less negative for subsidized households (-0.05) than for non-subsidized households. The effects of diesel are almost zero, irrespective of subsidization or not, but there is a clear difference in the logged effects of L.P.G. on car usage. For subsidized households the positive effect on Yearly Kilometrage is much stronger (0.33) than for the non-subsidized households (0.05). Thus, travel cost reimbursements mitigate the travel reducing effects of more expensive fuel and reinforce the positive effects of cheaper fuel. For rail season tickets, it is reversed (Figure 9). Rail tickets reinforce the negative effects on travel mobility of more expensive fuels (an elasticity of -0.24 for train users versus -0.10 for the rest of the sample), mitigating the positive effects of cheaper fuel.

Fuel Type at t_1 to Commuting Distance at t_2. Here we find a similar pattern as with car usage but there are some differences in the level. The elasticity of benzine usage on Yearly Kilometrage (-0.08) is higher than that on Commuting Distance (-0.05). This is evidence of the sensitivity of non-work related travel to fuel costs. Commuting distance is relatively more insensitive to the probability of using benzine than non-work related travel. However, L.P.G. has a much higher elasticity on commuting distance than on annual car usage. Again, some caution must be taken in interpreting this result since the standard deviation of this elasticity is very high.

Car Usage at t_1 to Fuel Type at t_2. These "dynamic" or lagged elasticities are much higher than their contemporaneous equivalents. For instance, the dynamic total elasticity of yearly kilometrage on the probability of using benzine in the next period is -0.30, whereas it is only in the range from -0.18 to -0.21 for contemporaneous linkages. Since a change of fuel type generally implies a change of car (as opposed to retrofit), it is likely that lagged effects of mobility play an important role. These elasticities are generated

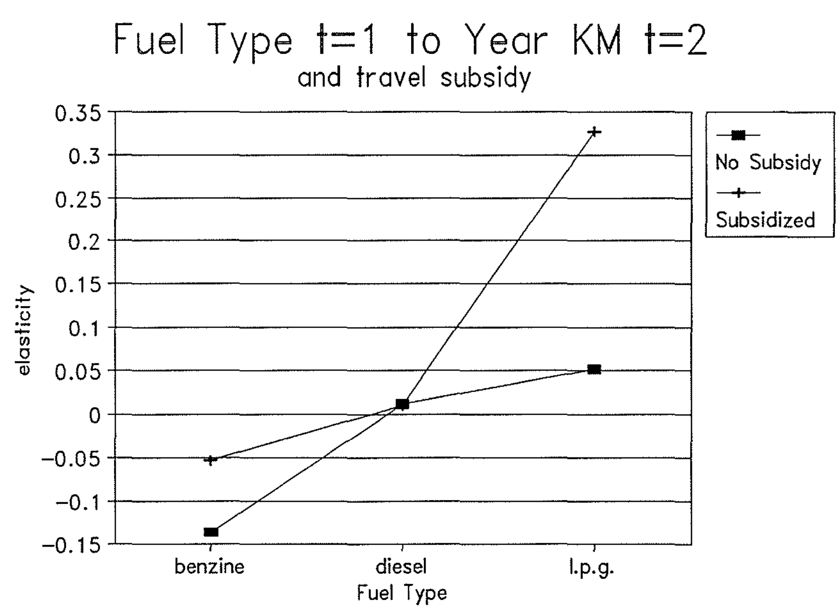

Figure 8 **Total Elasticities of Fuel Types at t=1 to Car Usage at t=2 with and without Travel Subsidy**

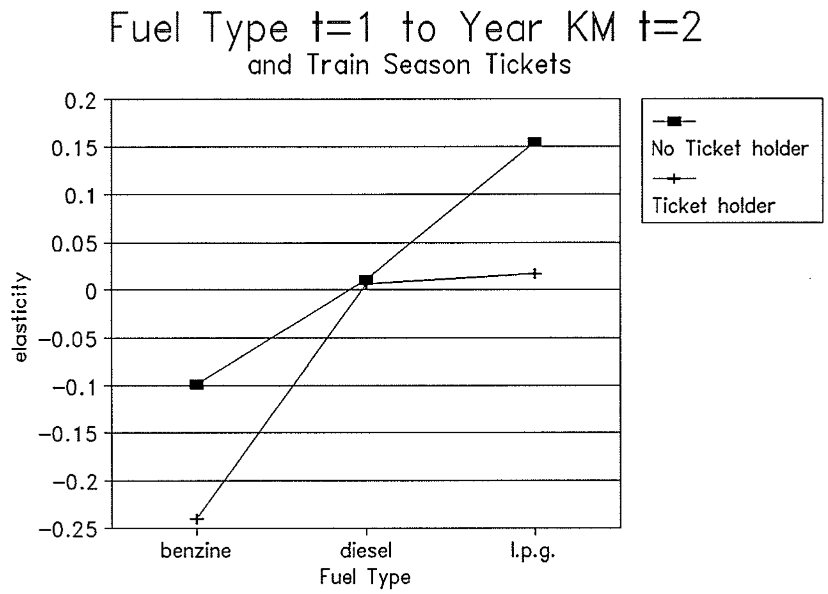

Figure 9 **Total Elasticities of Fuel Types at t=1 to Car Usage at t=2 with and without Train Season Ticket**

solely by direct effects: from car usage at t_1 through Fuel Type at t_1 through car usage at t_2 and Commuting Distance at t_2 to fuel type t_2. According to the model, a high usage at t_1 has a negative impact on owning a benzine car at t_1, which in turn has a diminishing effect on travel at time t_2, which in turn negatively affects the probability of having benzine at time t_2. The total result is a relatively large negative elasticity at time t_2. For diesel and L.P.G. a similar structure leads to a high probability of having these fuel types as a result of high lagged yearly kilometrage. For L.P.G. this lagged elasticity is particularly high (0.63).

Commuting Distance at t_1 to Fuel Type t=2. This is again an indirect effect and the story is similar to the previous lagged elasticity. However, the elasticities of Commuting Distance are somewhat lower than the effects of car usage. L.P.G. is again the most sensitive to changes in mobility: a total elasticity of 0.46.

6. CONCLUSIONS

The model successfully captures the dynamic relationships among car fuel type choice and car mobility, subject to the conditioning effects of commuting subsidies, fixed and variable work locations, rail season tickets, and certain household sociodemographic and income variables. Car mobility is defined in terms of overall usage and commuting distance. The model is a joint continuous/discrete multivariate demand model with lagged effects, individual-specific terms, period effects, and compensation for panel attrition bias. The non-normal endogenous variables are treated as ordered probit and tobit variables. The elasticity estimates calculated for the observed non-normal variables could be useful in policy evaluation and forecasting.

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