MODELLING THE DEMAND FOR FREIGHT TRANSPORT

A New Approach

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1. INTRODUCTION

The demand for freight transport was the subject of very many studies in the 1970s and early 1980s. Yet during recent years there has been renewed interest by researchers and government agencies in this vitally important topic. It is expected that even more interest on the part of public and private agencies will become apparent with the signing of the 1989 Free Trade Agreement between Canada and the United States. Previous studies varied in their scope of analysis, according to their objectives. For example, studies that were primarily concerned with the investigation of modal competition used different techniques and procedures from those that were concerned with predicting the amount of freight movement at local or national level.

A review of the literature on freight transport demand reveals that most studies have used models in a sequential decision-making framework. The lack of adequate data on goods movement has slowed down the development and application of "simultaneous" demand models of freight transport. In an attempt to bridge the gap, this paper presents a demand model for freight transport that: (1) combines the two decisions on mode choice and shipment size, and (2) uses the same amount and quality of data as would be required to develop a standard disaggregate mode choice model.

The paper is organised as follows. Section 2 presents a review of previous approaches towards modelling demand for freight transport. Section 3 presents the theoretical model. Issues of identification and estimation of the proposed model are discussed in section 4. The application of this model to study the demand for freight transport is discussed in section 5. Finally, section 6 contains the conclusions.

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2. PREVIOUS APPROACHES TO STUDYING DEMAND FOR FREIGHT TRANSPORT

There are many possible ways to classify models of demand for freight transport. Smith (1974) offers a discussion of methods of studying demand for freight transport with a special emphasis on non-econometric models. A critical evaluation and an overview of these methods with a special emphasis on econometric models can be found in Winston (1983). In terms of data employed in the analysis, Winston (1983) classified these methods into aggregate and disaggregate. Two basic aggregate models have been used in studying freight demand: the "aggregate modal split model", and one of the neoclassic economic aggregate models. Examples of the first type include the work of Perle (1964), Kullman (1973), Boyer (1977), and Levin (1978). The second type is explained in the studies by Oum (1977, 1979), Friedlaender and Spady (1977, 1980, 1981), and Lewis and Widup (1982), among others.

Disaggregate freight demand models are classified in the literature as behavioural and inventory (Winston, 1983, page 421). The behavioural models are essentially behavioural mode choice models, the analysis of which is motivated by the proposition of "utility maximisation" by the decision maker. The inventory-based models, on the other hand, attempt to analyse freight demand from the perspective of an inventory manager. The basic difference between behavioural and inventory models is that, while behavioural "mode-choice" models deal with only one decision, inventory models attempt to integrate the mode choice and other production decisions.


3. A SWITCHING SIMULTANEOUS EQUATIONS MODEL

Background

Various specifications of switching simultaneous systems have been reported in the literature. This section discusses the specification of the proposed system of equations which will be used in section 5.
Limited dependent variable models were first discussed by Tobin (1958), whose approach is now known as Tobit analysis. Tobin used a maximum likelihood procedure to estimate a model with a truncated dependent variable. Subsequently, many researchers have extended Tobin’s analysis to study more complicated situations. For example, some researchers noticed that, in many applications, data on the dependent variable are censored. For these situations, Heckman (1974) and Nelson (1975) derived “censored dependent variable models” to estimate labour supply curves. Other extensions of Tobin’s work include studies of disequilibrium market models by Fair and Jaffee (1972), Maddala and Nelson (1974), and Goldfeld and Quandt (1975), among others. Researchers in various branches of sociology have also applied these models in their studies of educational behaviour and criminology (see Mare and Winship (1988) for an example of this type and a list of other studies).

The model
Lee, Maddala and Trost (1980) described the general structure of the model as “two simultaneous equations systems corresponding to two regimes [alternatives] and a selectivity criterion that determines whether the observations correspond to the first or second regime”. In models of this type, the problem is the simulation of two interdependent choices. This problem is further complicated by the fact that one of the choices is discrete (for example, mode choice), while the other is continuous (for example, shipment size). However, this difficulty can be overcome to a large extent by using a system of three, rather than two, equations to describe the entire decision-making process. In simple terms, two equations are used to predict the shipment size by each mode, and a third equation is used to predict the choice of one of the two modes.

The interaction between the two decisions can be made possible by carefully specifying the disturbances of the three equations. Therefore, for any cross-sectional observation, one would observe data on two of the three equations. By including enough observations on the choice of the two modes, one could specify a system of equations which describes the entire decision-making process. A system of simultaneous equations model may be specified as:

\[ I_i^* = Z_i \gamma + \varepsilon_i \]  
\[ Y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i}, \text{ iff } I_i^* > 0 \]  
\[ Y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i}, \text{ iff } I_i^* \leq 0 \]

\( I_i^* \) is an unobserved index which determines the choices, \( Y_{1i} \) and \( Y_{2i} \) are endogenous dependent variables; \( X_{1i} \) and \( X_{2i} \) are vectors of exogenous independent variables; \( \beta_1, \beta_2, \) and \( \gamma \) are vectors of parameters; and \( Z_i \) is a vector consisting of some or all the exogenous variables in \( X_{1i} \) and \( X_{2i} \) and also additional exogenous variables. Equation (1) is the reduced form of the criterion function which determines the choices into the two regimes. The structural form of this equation is discussed in the next section. The residuals \( \varepsilon_{1i}, \varepsilon_{2i}, \) and \( \varepsilon_i \) are serially independent and have a trivariate normal distribution with mean vector \( \mathbf{0} \) and non-singular covariance matrix \( \Sigma \).
The model of equations (1)-(3) is the switching regression model considered by Lee (1976, 1979), Lee and Trost (1978), and Maddala (1983, pages 223-28). It can be interpreted as follows: given exogenous variables \(X_{1i}, X_{2i}, \text{and } Z_i\), the observed sample \(Y_i\) is generated from the first regime if the condition \(I_i^* > 0\) is satisfied; otherwise it is generated from the second regime. Applied to the issue of freight transport, the criterion function is equivalent to a "satisfaction threshold" associated with each mode. If the threshold of a certain mode, as perceived by a shipper, is exceeded when he is making a shipment, the shipper will choose that mode; otherwise the shipper will choose one of the other competing modes. In economic terms, this is the utility maximisation principle used to derive disaggregate mode choice models. A necessary condition for the estimability of the proposed model is that sample separation is available; that is, that the binary outcome can be observed. This sample separation can be denoted by a dichotomous variable \(I_i\), such that \(I_i = 1 \iff I_i^* > 0, I_i = 0\) otherwise. Empirical applications of this class of models are given by Lee, Maddala, and Trost (1980).

4. IDENTIFICATION, ESTIMATION AND STATISTICAL TESTS

Background
Since the introduction of limited dependent variable models in the late 1950s, only maximum likelihood estimation methods have been suggested, in spite of their structural complexity. However, during the 1970s many researchers have noticed that the successful use of these maximum likelihood procedures is critically dependent upon the available computational resources. Therefore, probably the most notable advancement in the application of simultaneous equations models over the past two decades has been the development of estimation methods simpler than maximum likelihood.

These new methods were suggested by Amemiya (1974) and extended by Heckman (1976). In fact, Heckman (1976) proposed the two-stage type of estimator using probit analysis for the criterion function. Lee, Maddala and Trost (1980) considered a general simultaneous equations model with sample separation given by probit-type and tobit-type criterion functions, and derived the covariance matrices for these two estimators. The theoretical analysis included in this paper relies heavily on the work of Heckman (1976), Lee (1976), Lee and Trost (1978) and Maddala and Trost (1980).

The remainder of this section focuses on particular issues concerning the identification and estimation of switching simultaneous models. The consideration of the identification problem comes before the consideration of the estimation problem, because the identification of a model is a necessary condition for its estimation.
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Identification

The following discussion is concerned with the identification of the structural parameters of the proposed model. Since identification of a model is critically dependent upon the specification of that model, it will be discussed in greater detail with the specification of the freight demand model in section 5.

The model presented in equations (1) to (3) consists of two regression equations to measure the outcomes of the two regimes, and a criterion function to determine the selection into the two regimes. In fact, equation (1) represents the “reduced form” of the criterion function, and it can be expanded to show the structural parameters as follows:

\[ I^* = X_{10} \delta + Y_{11} \eta_1 + Y_{22} \eta_2 - v_i \]  

(4)

The model as represented by equations (2) to (4) is a “binary choice model with interrelated continuous endogenous variables”. This form of switching simultaneous systems is discussed by Westin (1975). It is based on the assumption that the outcomes of the two regimes (\( Y_1 \) and \( Y_2 \)) affect the choice of regime. Equation (4) consists of two types of variables: predetermined (\( X_{10} \)) and dependent (\( Y_{11} \) and \( Y_{22} \)). However, the dependent variables are functions of the predetermined variables (\( X_{11} \) and \( X_{22} \)); and in order to estimate equation (4) as a binary choice model, we must transform it into an equation which consists of only predetermined variables. This can be achieved by substituting the values of \( Y_{11} \) and \( Y_{22} \) from equations (2) and (3) into equation (4) to get the reduced form (equation 1):

\[ I^* = X_{10} \delta + X_{11} \beta_1 \eta_1 + X_{22} \beta_2 \eta_2 - \tilde{v}_i = Z_i \gamma - \epsilon_i \]  

(5)

where \( \epsilon_i = (v_i - \eta_1 e_{1i} - \eta_2 e_{2i}) / \sigma^* \), where \( \sigma^* \) is the variance of \( \epsilon_i \); \( \sigma^* = E(\epsilon_i - \eta_1 e_{1i} - \eta_2 e_{2i})^2 \). Without loss of generality, \( \sigma^* \) can be normalised to 1.0. Therefore, the parameters \( \delta, \eta_1, \eta_2 \) are estimable only up to proportionality factor. Lee (1976, 1979) discussed the identification of this model. He showed that a necessary condition for the identification of the parameters \( \delta, \eta_1, \eta_2 \) is that at least two exogenous variables which appear in the \( X_1 \) or \( X_2 \) are excluded from \( X_0 \).

Although no further conditions are required for the identification of the coefficients of the model, it should be noticed that, in practice, the precision with which the coefficients are identified may be considerably improved if some of the predetermined variables do not appear in all equations. Mare and Winship (1988, page 147) observed that such exclusion restrictions “should derive from substantive reasoning rather than ex post inspection of empirical results”. However, it should be noted that knowledge of the structural parameters is not absolutely necessary if prediction or forecasting is the primary purpose of the model, because forecasts can be obtained through reduced-form equations directly.

Two-stage Least Squares (2SLS) Estimation

Note that equations (2) and (3) cannot be estimated by ordinary least squares (OLS) because the conditional expectations of the residuals are non-zeros; that is, \( E(\epsilon_{1i} | I_i) \neq 0 \), and \( E(\epsilon_{2i} | I_i) \neq 0 \). Since sample separation is observed, as assumed earlier, we have the observations \( I_i \), and we can apply the maximum likelihood (ML) procedure to estimate the reduced-form parameters of the probit model:

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\[ I_i^* = Z_i \gamma - \varepsilon_i \]

Since the probit likelihood function is concave, the maximum likelihood estimates \( \gamma \) of \( \gamma \) can be easily obtained. This concludes the estimation of the reduced form parameters of the criterion function. To estimate the regression equations, we make use of the distributional characteristics of truncated normal variables.

It can be shown by simple manipulations of the properties of truncated normal variables (see for example Maddala, 1983) that:

\[
E(\varepsilon_i | I_i = 1) = -\frac{\sigma_{1e} \cdot \phi(Z_i \gamma)}{\Phi(Z_i \gamma)}
\]

\[
E(\varepsilon_i | I_i = 0) = \sigma_{2e} \cdot \frac{\phi(Z_i \gamma)}{1 - \Phi(Z_i \gamma)}
\]

where \( \phi(\cdot) \) and \( \Phi(\cdot) \) are, respectively, the density and cumulative density functions of the standard normal distribution. \( \sigma_{1e} \) and \( \sigma_{2e} \) are the covariances defined in the above matrix, \( \Sigma \). Taking expectations of both sides of equations (2) and (3), and additall disturbact terms, we get two linear regression equations which satisfy the classical assumptions of ordinary least squares (OLS) estimation method:

\[
\text{Truck: } Y_i = X_{i1} \beta_1 - \sigma_{1e} \cdot W_{1i} + \xi_{1i}
\]

\[
\text{Rail: } Y_i = X_{i2} \beta_2 + \sigma_{2e} \cdot W_{2i} + \xi_{2i}
\]

where

\[ W_{1i} = \frac{\phi(Z_i \gamma)}{\Phi(Z_i \gamma)} \text{ and } W_{2i} = \frac{\phi(Z_i \gamma)}{1 - \Phi(Z_i \gamma)} \]

with \( E(\xi_{1i} | I_i = 1) = E(\xi_{2i} | I_i = 0) = 0 \).

The two-stage estimation procedure can now be carried out as follows. With the probit ML estimates \( \hat{\gamma} \) in hand, we calculate \( \hat{W}_{1i} \) and \( \hat{W}_{2i} \), by substituting \( \hat{\gamma} \) for \( \gamma \) in \( Z_i \gamma \). Then the values \( \hat{W}_{1i} \) and \( \hat{W}_{2i} \) are substituted instead of \( W_{1i} \) and \( W_{2i} \) in equations (8) and (9):

\[
\text{Truck: } Y_i = X_{i1} \hat{\beta}_1 - \sigma_{1e} \cdot \hat{W}_{1i} + \hat{\xi}_{1i}
\]

\[
\text{Rail: } Y_i = X_{i2} \hat{\beta}_2 + \sigma_{2e} \cdot \hat{W}_{2i} + \hat{\xi}_{2i}
\]

Equation (10) can now be estimated by OLS from sample observations on truck. Similarly, we can estimate equation (11) from sample observations on rail. The resulting estimates of \( \hat{\beta}_1, \sigma_{1e}, \hat{\beta}_2, \) and \( \sigma_{2e} \) are consistent, but not efficient — the consistency of these estimates is proved in Lee and Trost (1978). Efficient estimates of these parameters may be obtained by using ML procedures.

So far, we have obtained estimates of all the reduced form parameters: \( \gamma \) (by probit ML), and \( \hat{\beta}_1, \hat{\beta}_2, \sigma_{1e}, \) and \( \sigma_{2e} \) (by OLS). We still have to estimate the structural parameters of the probit model \( (\delta, \eta_1, \eta_2 \text{ in equation 4}) \). One way of doing that has been suggested by Lee (1976), who called it two-stage probit. It involves the estimation of the following probit model:

\[
I_i^* = X_0 \delta + (X_{i1} \hat{\beta}_1) \eta_1 + (X_{i2} \hat{\beta}_2) \eta_2 - \varepsilon_i
\]

where \( \varepsilon_i \) is a resultant disturbance which is asymptotically standard normal.
**Maximum likelihood estimation**

The general model and its restricted forms can also be estimated simultaneously in one step by the maximum likelihood (ML) technique. In addition to providing efficient estimates of the parameters, the use of ML for the estimation of this type of model has the advantage of allowing the analyst to impose restrictions on the general model and to use statistics (for example, likelihood ratio) to test the validity of these restrictions. The proper likelihood function for the estimation of the simultaneous equation model of equations (1) to (3) is given by:

\[
L(\beta_1, \beta_2, \gamma, \sigma_1, \sigma_2, \sigma_{12}) = \prod_i \left[ \int_{-\infty}^{z_{i1}} f_i(\varepsilon_i | \varepsilon_{i1}) g_i(\varepsilon_{i2}) d\varepsilon_{i2} \right]^{y_i} \times \left[ \int_{z_{i1}}^{\infty} f_i(\varepsilon_i | \varepsilon_{i1}) g_i(\varepsilon_{i2}) d\varepsilon_{i2} \right]^{1-y_i}
\]

(13)

Note that the parameter \( \sigma_{12} \) does not appear in the likelihood function, and therefore it is unidentifiable. The consistent estimates obtained by the two-stage method can be used as initial estimates for the maximum likelihood procedure. For the above model, Lee and Trost (1978) provided the following formulae for the density functions:

\[
f_i(\varepsilon_i | \varepsilon_{i1}) = \frac{1}{\sqrt{2\pi(1-\rho_{i1}^2)}} \exp \left\{ -\frac{1}{2(1-\rho_{i1}^2)} \left( \frac{\varepsilon_i - \rho_{i1} \varepsilon_{i1}}{\sigma_i} \right)^2 \right\}
\]

(14)

\[
g_i(\varepsilon_{i2}) = \frac{1}{\sqrt{2\pi \sigma_{i2}}} \exp \left\{ -\frac{(\varepsilon_{i2})^2}{2\sigma_{i2}^2} \right\}
\]

(15)

\[
f_i(\varepsilon_i | \varepsilon_{i2}) = \frac{1}{\sqrt{2\pi(1-\rho_{i2}^2)}} \exp \left\{ -\frac{1}{2(1-\rho_{i2}^2)} \left( \frac{\varepsilon_i - \rho_{i2} \varepsilon_{i2}}{\sigma_i} \right)^2 \right\}
\]

(16)

\[
g_i(\varepsilon_{i2}) = \frac{1}{\sqrt{2\pi \sigma_{i2}}} \exp \left\{ -\frac{(\varepsilon_{i2})^2}{2\sigma_{i2}^2} \right\}
\]

(17)

where \( \rho_{i1} \) and \( \rho_{i2} \) are the correlation coefficients of \( (\varepsilon_{i1}, \varepsilon_i) \) and \( (\varepsilon_{i2}, \varepsilon_i) \), respectively. The residuals \( \varepsilon_{i1} \) and \( \varepsilon_{i2} \) are substituted in equations (14) to (17) as: \( \varepsilon_{i1} = Y - X_1 \beta_1 \) and \( \varepsilon_{i2} = Y - X_2 \beta_2 \).

Taking the logarithms of both sides of equation (13) and simplifying:

\[
L^* = \ln L(\beta_1, \beta_2, \gamma, \sigma_1, \sigma_2, \rho_{i1}, \rho_{i2})
\]

(18)

\[
= \sum_{i=1}^{L} \left\{ I_i \left[ \ln g_i(Y - X_1 \beta_1) + \ln \int_{-\infty}^{z_{i1}} \phi(i) d\varepsilon_{i1} \right] + (1 - I_i) \left[ \ln g_i(Y - X_2 \beta_2) + \ln \int_{z_{i1}}^{\infty} \phi(i) d\varepsilon_{i1} \right] \right\}
\]

where \( \phi(*) \) is the standard normal density function, and:

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\[
\mu_1(\beta_1, \gamma, \sigma_1, \rho_{1e}) = \frac{1}{\sqrt{1 - \rho_{1e}^2}} \left[ Z_i Y - \frac{\sigma_{1e}}{\sigma_1} (Y - X_i \beta_1) \right]
\]

\[
\mu_2(\beta_2, \gamma, \sigma_2, \rho_{2e}) = \frac{1}{\sqrt{1 - \rho_{2e}^2}} \left[ Z_i Y - \frac{\sigma_{2e}}{\sigma_2} (Y - X_i \beta_2) \right]
\]

Numerical optimisation algorithms must be used to calculate the ML estimates of the above parameters. Because the likelihood function is highly nonlinear, these computations will be quite complicated. However, since the initial estimates are consistent, Lee and Trost (1978, pages 368-69) suggested a simpler version of the ML technique that needs only one iteration of the Newton-Raphson method to achieve convergence. In addition, with the advancement in computing technology and the introduction of super computers, it has become possible to perform calculations of this scale with less computational resources.

**Statistical tests**

Equations (2) to (4) represent the general form of the model in which a two-way interaction is assumed between the two choices of mode and shipment size. Other structural models can be derived by imposing certain restrictions on the parameters of the general model. Assuming that shippers choose modes based on observed (predetermined) characteristics, and that shipment sizes do not affect their choices of mode, a restricted form of the model can be derived by applying to equation (12) the restriction: \( \eta_1 = \eta_2 = 0 \). The resulting model is similar to the "ascription model" derived by Mare and Winship (1988) in their study of academic tracking and achievement:

\[
I^*_i = X_{0i} \delta - \overline{e}_i
\]  \hspace{1cm} (19)

It should be noted that in equation (19) \( \overline{e}_i = e_i \) which is, under the above condition, uncorrelated with \( e_{1i} \) and \( e_{2i} \). Under these restrictions, the shipment size equations can be estimated using OLS. To test the validity of the model, note that it is nested in the general model, and a standard likelihood ratio test can be used for that purpose.

The specification of the model into two separate regimes and a criterion function allows other statistical tests to be performed on the parameters. It is noticed that the underlying assumptions in the specification of the model are: (a) the existence of "significant" interaction between the choices of mode and shipment size, and (b) the existence of "significant" difference in the choice of shipment size between the two regimes (modes).

The first assumption can be tested in two ways. One way is the likelihood ratio test mentioned above, and another way is the "t-statistic" associated with the estimates of \( \sigma_{1e} \) and \( \sigma_{2e} \). If the \( t \) statistics show that \( \sigma_{1e} \) and \( \sigma_{2e} \) are significantly different from zero, then we reject the hypothesis of "no significant interaction" between the choices of mode and shipment size.

The second assumption can also be tested in two ways, according to the test results of the first assumption. If the first assumption fails — that is, if there is no significant interaction between the choices of mode and shipment size — then a standard Chow test can be applied to the parameters of the two regimes. The Chow test requires the development of a third regression equation, which is estimated from the pooled data
of the two regimes. The Chow test can be designed so that the null hypothesis
assumes that there is no significant difference between the vectors of parameters
obtained from the first and second regression equations; that is, the two structures are
identical. However, if there is a significant interaction (that is, if the null hypothesis
of assumption (a) is rejected), then it remains to test the difference in the way the two
regimes interact with the criterion function. The hypotheses in this case are:

\[ H_0: \sigma_{1e} = \sigma_{2e} = 0 \quad \text{Vs.} \quad H_1: \sigma_{1e} \neq \sigma_{2e} \neq 0 \]

A standard \( t \)-test can be used for this purpose, and if the test fails we reject the
hypothesis of no significant difference between \( \sigma_{1e} \) and \( \sigma_{2e} \). These are examples of
some of the statistical tests that can be applied to the model. Some of these tests (for
example, likelihood ratio test) are validation tests for more restrictive forms of the
model.

5. A MODE-CHOICE/SHIPMENT-SIZE FREIGHT DEMAND MODEL

The Model

This section discusses the specification of the theoretical model presented in section
3 to study the demand for freight transport. The scope of the model includes the
investigation of two important issues related to the determination of demand for
freight transport by rail and truck. These issues are the understanding of modal choice
behaviour, and the estimation of shipment size in a simultaneous decision-making
framework. McFadden, Winston and Boersch-Supan (1985) used a different
approach to estimate a joint mode-choice/shipment-size model. Their model consisted
of a marginal probability equation for the choice of shipment size, and a conditional
probability equation for the choice of mode. The simultaneity between the two
decisions in their model was attained by allowing the residuals of the two equations
to be correlated. The resulting model was estimated using full information maximum
likelihood (FIML) procedures.

In the following formulation of the model, it is assumed that inputs are purchased
FOB factory and outputs are sold on a CIF basis. Therefore, the decision-maker is
the receiver, and the choice of location concerns supplier rather than destination.
However, this decision variable is not included in the model for the following
reasons:

It is believed that the demand for freight transport is determined by a complex
hierarchy of choices. This hierarchy can be structured on the basis of the time
lag involved in changing decisions in response to changes in the transport
system or market situation. A simple representation of this hierarchy is shown
in Figure 1. This shows that a truly comprehensive freight demand model
should, in principle, include all decision variables. However, because of
methodological difficulties, studies of demand for freight transport have been
confined in scope to only a subset of these decisions, usually to those of the
short- and intermediate-run nature. The model proposed in this paper is
essentially a short-run model, as the choice of supplier is assumed to have been
narrowed down by the longer-run decisions, such as location and size of the
plant. In addition, in many cases the receiver (purchaser) will have to enter into a multi-order contract (also known in the shipping industry as ordering routine) with a supplier, thus making the choice of supplier more of an intermediate-run decision than either the decision on mode or that on shipment size.

The inclusion of the choice of supplier requires additional data, which are unavailable in most applications. These data include the price and quality of material in all potential supplying markets.

A principal requirement in the formulation of the choice of supplier at the level of the individual receiver is the identification of all feasible (or potential)
choices. This is particularly difficult (if not impossible) in models dealing with multi-industry, multi-commodity freight movements. For example, if a model is concerned with only one commodity or commodity group, it would be easier to identify, though very roughly and at a very aggregate level, the feasible choices available for receivers. It is by no means easy in the present model, since it deals with the entire manufacturing industry.

There is also a methodological difficulty in the inclusion of the choice of supplier in the proposed system of simultaneous equations with mixed discrete and continuous dependent variables. There are very few studies which explicitly dealt with the choice of supplier. A study by Chiang et al. (1980) employed a multinomial logit model to study the choices of mode and shipment size. Because the problem was so complex, Chiang et al. were forced to make the critical assumption that supplier location for any given input was fixed. Another study by Kim (1984) used the formulation of Chiang et al. in an attempt to model the choices of mode, shipment size and supplier in the US steel industry. After encountering estimation difficulties, Kim was forced to separate the choices of mode and shipment size from the choice of supplier. Even with this simplifying procedure, and in spite of the fact that her model deals with one major commodity, the author had to aggregate the entire US steel market into five geographical regions, thus limiting the number of choices of supplier to a "manageable" size.

It is believed that there is a trade-off between accuracy and complexity in any model designed to study a complicated issue such as the demand for freight transport. It is hoped that the additional insight gained from the simultaneous consideration of two very important freight decisions, such as those on mode and shipment size, will pay off for the loss of generality due to the exclusion of the supplier-choice decision. After all, this framework is intended as an enhancement to an already acceptable and widely used class of models, namely, standard behavioural mode choice models. Such an enhancement is particularly desirable if it does not require the collection of additional data — a factor that is extremely critical in developing any type of model in freight transport.

The specification of the model proposed in this paper uses data that would usually be required for the calibration of disaggregate mode choice models. In particular, data relating to modal attributes (freight charges, mean and reliability of transit times, etc.), and shipment attributes (commodity value and density, shipment size, etc.) are used in the specification of the criterion function (that is, the probit mode choice function). The choice of shipment size for each mode is specified as a function of modal, commodity and market attributes. The specification of this 3-equation model may be presented as:

\[ ST_i = \beta_0 + \beta_1 \cdot CA + \beta_2 \cdot MA + \beta_3 \cdot OA + \epsilon_i \]  \hspace{1cm} (20)
\[ SR_i = \beta'_0 + \beta'_1 \cdot CA + \beta'_2 \cdot MA + \beta'_3 \cdot OA + \epsilon'_i \]  \hspace{1cm} (21)
\[ I_i = \theta_0 + \theta_1 \cdot CA + \theta_2 \cdot MA + \theta_3 \cdot OA + \psi_i \cdot ST_i + \psi_2 \cdot SR_i + \lambda_i \]  \hspace{1cm} (22)

where
\[ ST_i = \text{shipment size of the } i^{th} \text{ truck shipment (lbs or tons)}, \]
\[ SR_i = \text{shipment size of the } i^{th} \text{ rail shipment (lbs or tons)}, \]
\[ I*_{it} = \text{an unobserved index which determines the mode choice (truck vs. rail)}, \]
\[ CA = \text{a vector of commodity attributes (e.g. value, density, state)}, \]
\[ MA = \text{a vector of modal attributes (e.g., freight charges, reliability, and transit time by each mode)}, \]
\[ OA = \text{a vector of other attributes (e.g. regional dummy variables, volume of commodity moved on each link by each mode)}, \]
\[ \beta', \beta', \theta = \text{parameters to be estimated, and} \]
\[ \epsilon_{it}, \epsilon_{it}', \lambda_i = \text{disturbances of the truck shipment size, rail shipment size, and mode choice equations, respectively.} \]

The corresponding reduced form of equation (22) is given by:

\[ I*_{it} = \pi_0 + \pi_1 \cdot CA + \pi_2 \cdot MA + \pi_3 \cdot OA + \epsilon_i \quad (23) \]

Thus equations (20), (21), (22) describe the structural form of the demand model; and equations (20), (21), (23) describe the corresponding reduced form of the model.

The choice of explanatory variables in the above equations is governed by many factors. Some of these factors relate to practical issues, such as availability of data, while others relate to statistical issues, such as the existence of high correlation among some of the explanatory variables (for example, distance and travel time).

Above all, the choice of explanatory variables must be based on some “cause and effect” relationship between the variables and the corresponding dependent variable. The model with the best specification is derived after vigorous examination of several possible combinations of variables subject to various statistical measures. Before we go into the specification of the mode choice/shipment size model, a brief description of the data used in the study is in order.

Data

One of the most comprehensive data bases on intercity commodity flows is prepared by the US Bureau of Census as part of its Commodity Transportation Survey (CTS). The CTS is one of three economic censuses conducted as part of the census of transport twice each decade, in years ending in the figures 2 and 7. The CTS was first conducted in 1963 and subsequently in 1967, 1972, 1977 and 1983. Data collected in 1983 were not published because they were of poor quality. Therefore, the 1977 CTS is considered to give the latest reliable data on intercity goods movement that can be used for the purpose of calibrating the model of this study.

The CTS data base is made available by the Census Bureau in the form of two public use tapes, which are referred to as CTS-OD1 and CTS-OD2. The first tape (CTS-OD1), which was used in this study, contains origin-destination (OD) commodity flows among 49 production/consumption areas. Each area consists of a large Standard Metropolitan Statistical Area (SMSA) or a cluster of SMSA’s that represents essentially a single geographic industrial complex with 900 or more manufacturing establishments (US Bureau of Census, 1977). These data were used in the study because they represent the most disaggregate data available from the Census of Transportation. A detailed description of the data can be found in US Bureau of Census (1981).
MODELLING DEMAND FOR FREIGHT TRANSPORT  
W. Abdelwahab and M. Sargious

The CTS data base is the most extensive source of information in intercity freight flows, but it has several shortcomings, the most serious of which is the lack of data on level of service variables, market attributes or shipper characteristics. Data for these variables were obtained from other sources. Two external sources were used to supplement the CTS data base. These are: (1) the MIT Commodity Attribute Data File (Samuelson and Roberts, 1975), and (2) a collection of theoretical models developed by various researchers to predict freight transport level of service attributes (Roberts and Wang, 1979). By the use of these two sources and the original data base, the following additional variables were derived and added for each shipping record:

- freight charges for truck and rail,
- transit time and reliability of transit time for truck and rail, and
- susceptibility of a shipment to loss and damage when moved by truck and rail.

Empirical Results

The final form of the 3-equation system was derived after experimenting with various specifications and functional forms. The best specification of each equation is given in Table 1. The variables used in Table 1 are:

- $ST = $truck shipment size (tons; 1 ton = 2000 pounds),
- $SR = $rail shipment size (tons; 1 ton = 2000 pounds),
- $I* = choice index = 1 if truck is chosen; 0 otherwise,
- $TON = total tons of a given commodity moved over a given O-D link by a given mode (thousands of tons),
- $DEN = commodity density (pounds per cubic foot),
- $VAL = commodity value (dollars per pound),
- $LIQ = 1 if commodity is a liquid; 0 otherwise,
- $GAS = 1 if commodity is a gas; 0 otherwise,
- $PART = 1 if commodity is a particulate; 0 otherwise,
- $TMP = 1 if commodity requires temperature control; 0 otherwise,
- $SHK = 1 if commodity requires shock protection; 0 otherwise,
- $RD1 = 1 if commodity destination is in the “Official Territory” as defined by the ICC; 0 otherwise,
- $RD2 = 1 if commodity destination is in the “Southern Territory” as defined by the ICC; 0 otherwise,
- $RD4 = 1 if commodity destination is in the “Southwestern Territory” as defined by the ICC; 0 otherwise,
- $TTIME = transit time by truck (days),
- $RTIME = transit time by rail (days),
- $TCOST = truck freight charges (cents per cwt),
- $TLD = loss and damage as a percentage of value on tons shipped by truck,
- $RLD = loss and damage as a percentage of value on tons shipped by rail,
- $TREL = truck transit time reliability, expressed as the number of days above the mean on which 95% of arrival is achieved, and
- $RCOST = rail freight charges (cents per cwt).

Table 2 gives a description of the explanatory variables for rail and truck shipments, as well as for the entire data set. Equations (21), (22) and (23) were
### TABLE 1

**Specification of the 3-Equations System**

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Truck Shipment Size, ST</th>
<th>Rail Shipment Size, SR</th>
<th>Truck/Rail Mode Choice, ( l^*_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>( \alpha_0 )</td>
<td>( \beta_0 )</td>
<td>( \pi_0 )</td>
</tr>
<tr>
<td>TON</td>
<td>( \alpha_1 )</td>
<td>( \beta_1 )</td>
<td>( \pi_1 )</td>
</tr>
<tr>
<td>DEN</td>
<td>( \alpha_2 )</td>
<td>( \beta_2 )</td>
<td>( \pi_2 )</td>
</tr>
<tr>
<td>VAL</td>
<td>( \alpha_3 )</td>
<td>( \beta_3 )</td>
<td>( \pi_3 )</td>
</tr>
<tr>
<td>LIQ</td>
<td></td>
<td>( \beta_4 )</td>
<td>( \pi_4 )</td>
</tr>
<tr>
<td>GAS</td>
<td>( \alpha_5 )</td>
<td>( \beta_5 )</td>
<td>( \pi_5 )</td>
</tr>
<tr>
<td>PART</td>
<td>( \alpha_6 )</td>
<td>( \beta_6 )</td>
<td>( \pi_6 )</td>
</tr>
<tr>
<td>TMP</td>
<td></td>
<td>( \beta_7 )</td>
<td>( \pi_7 )</td>
</tr>
<tr>
<td>SHK</td>
<td>( \alpha_8 )</td>
<td>( \beta_8 )</td>
<td>( \pi_8 )</td>
</tr>
<tr>
<td>RD1</td>
<td></td>
<td>( \beta_9 )</td>
<td>( \pi_9 )</td>
</tr>
<tr>
<td>RD2</td>
<td>( \alpha_{10} )</td>
<td>( \beta_{10} )</td>
<td>( \pi_{10} )</td>
</tr>
<tr>
<td>RDA</td>
<td>( \alpha_{11} )</td>
<td>( \beta_{11} )</td>
<td>( \pi_{11} )</td>
</tr>
<tr>
<td>TTIME</td>
<td></td>
<td>( \beta_{12} )</td>
<td>( \pi_{12} )</td>
</tr>
<tr>
<td>RTEIME</td>
<td>( \alpha_{12} )</td>
<td>( \beta_{13} )</td>
<td>( \pi_{13} )</td>
</tr>
<tr>
<td>TCOST</td>
<td>( \alpha_{13} )</td>
<td>( \beta_{14} )</td>
<td>( \pi_{14} )</td>
</tr>
</tbody>
</table>

estimated simultaneously, using a quasi-maximum likelihood procedure\(^1\) (Avery and Hotz, 1985). To get starting values for the maximum likelihood routine, the three equations were first estimated by the 2SLS method described in section 4. To economise on space, only the maximum likelihood estimates of the model will be reported. It should be mentioned that the 2SLS consistent estimates of the model's coefficients were very similar in magnitude to those obtained by the ML method. However, as explained in the previous section, the standard errors of the estimates are generally incorrect, and, in principle, they need to be corrected. Lee, Maddala and Trost (1980) show that the correct variance-covariance matrix of the 2SLS estimates is very complicated. They also derived an approximation to the correct matrix that can be used to calculate approximate standard errors of estimates.

The reduced form estimates of the probit mode choice model are shown in Table

\(^1\) The estimation was carried out using the HOTZTRAN package. We thank Dr. V. Joseph Hotz for providing us with a copy of the computer program.
3. All the levels of service variables in Table 3 are significant and have the correct sign. Of the commodity attributes, only DEN, VAL and SHK seem to have significant influence on the choice of mode. The negative coefficient of DEN suggests that truck is favoured over rail for transporting lighter commodities. This is further illustrated by the positive sign of VAL, which suggests that truck is favoured over rail for moving commodities of higher values.\(^2\) The effect of the requirement for shock protection (SHK) on the choice of mode is less clear, though the negative sign of SHK in Table 3 suggests that rail is favoured over truck in moving commodities requiring shock protection. This may not be true in the practice of the shipping industry, as in most cases commodities that require shock protection are those of high values and/or low shelf life. In discussing the results of the shipment size equations, it will be shown that the sign of SHK in the probit choice model is, in fact, counter-intuitive.

\(^2\) A negative (but small) correlation coefficient was observed between DEN and VAL.

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TABLE 3

ML Estimates of the Reduced Form Truck/Rail Choice Equation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter</th>
<th>ML Estimate</th>
<th>&quot;t&quot;-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>( \pi_0 )</td>
<td>2.4795</td>
<td>18.4*</td>
</tr>
<tr>
<td>TON</td>
<td>( \pi_1 )</td>
<td>-0.0100</td>
<td>-3.8*</td>
</tr>
<tr>
<td>DEN</td>
<td>( \pi_2 )</td>
<td>-0.0030</td>
<td>-5.0*</td>
</tr>
<tr>
<td>VAL</td>
<td>( \pi_3 )</td>
<td>0.1014</td>
<td>3.0*</td>
</tr>
<tr>
<td>LIQ</td>
<td>( \pi_4 )</td>
<td>0.0462</td>
<td>0.5</td>
</tr>
<tr>
<td>GAS</td>
<td>( \pi_5 )</td>
<td>-0.2916</td>
<td>-1.0</td>
</tr>
<tr>
<td>PART</td>
<td>( \pi_6 )</td>
<td>-0.0584</td>
<td>-0.6</td>
</tr>
<tr>
<td>TMP</td>
<td>( \pi_7 )</td>
<td>-0.2092</td>
<td>-1.2</td>
</tr>
<tr>
<td>SHK</td>
<td>( \pi_8 )</td>
<td>-0.5912</td>
<td>-2.7*</td>
</tr>
<tr>
<td>RD2</td>
<td>( \pi_9 )</td>
<td>0.4905</td>
<td>6.1*</td>
</tr>
<tr>
<td>RD4</td>
<td>( \pi_{10} )</td>
<td>0.2718</td>
<td>2.2*</td>
</tr>
<tr>
<td>TTIME</td>
<td>( \pi_{11} )</td>
<td>-1.6943</td>
<td>-17.0*</td>
</tr>
<tr>
<td>TCOST</td>
<td>( \pi_{12} )</td>
<td>-0.1183</td>
<td>-13.7*</td>
</tr>
<tr>
<td>TLD</td>
<td>( \pi_{13} )</td>
<td>-0.0149</td>
<td>-9.1*</td>
</tr>
<tr>
<td>RCOST</td>
<td>( \pi_{14} )</td>
<td>0.0160</td>
<td>20.4*</td>
</tr>
</tbody>
</table>

\[ \hat{\rho}^2 = 0.4086 \]
\[ L(\hat{\beta}) = -682.7 \]
\% Truck = 0.6324
Mean Prob. = 0.6306
N. Obs. = 1586

* Significant at 5% level.

The statistical performance of the model seems satisfactory, as can be seen from the statistics reported at the end of Table 3. The log-likelihood statistic is \(-682.7\), and the likelihood ratio index is 0.4089. The log-likelihood statistic tests the hypothesis that all the coefficients of the model are collectively not different from zero. This statistic is \( \chi^2 \) distributed with degrees of freedom equal to the number of estimated parameters. At the above values, the hypothesis is strongly rejected. The \( \hat{\rho}^2 \) statistic is similar to the classical regression \( R^2 \) value; a value of greater than 0.30 is considered satisfactory for models of this type.

The estimation results of the second part of the model (the shipment size equations, \( ST \) and \( SR \)) are reported in Tables 4 and 5, respectively. First, it should be kept in mind that \( ST \) and \( SR \) are limited dependent variables. That is, \( ST \) is observed for truck shipments only, and \( SR \) is observed for rail shipments only. This is why an OLS estimation of these equations produces biased results.
## TABLE 4

**ML Estimates of the Truck Shipment Size Equation, ST**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter</th>
<th>ML Estimate</th>
<th>“t”-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>$\alpha_0$</td>
<td>13.9352</td>
<td>45.9*</td>
</tr>
<tr>
<td>TON</td>
<td>$\alpha_1$</td>
<td>0.0336</td>
<td>5.3*</td>
</tr>
<tr>
<td>DEN</td>
<td>$\alpha_2$</td>
<td>0.0084</td>
<td>6.7*</td>
</tr>
<tr>
<td>GAS</td>
<td>$\alpha_3$</td>
<td>2.3496</td>
<td>3.3*</td>
</tr>
<tr>
<td>PART</td>
<td>$\alpha_4$</td>
<td>0.5734</td>
<td>3.4*</td>
</tr>
<tr>
<td>TMP</td>
<td>$\alpha_5$</td>
<td>1.0467</td>
<td>3.6*</td>
</tr>
<tr>
<td>SHK</td>
<td>$\alpha_6$</td>
<td>-1.0597</td>
<td>-2.2*</td>
</tr>
<tr>
<td>RD1</td>
<td>$\alpha_7$</td>
<td>-0.6262</td>
<td>-3.8*</td>
</tr>
<tr>
<td>RD2</td>
<td>$\alpha_8$</td>
<td>-4.4183</td>
<td>-19.7*</td>
</tr>
<tr>
<td>RD4</td>
<td>$\alpha_9$</td>
<td>-4.8770</td>
<td>-14.4*</td>
</tr>
<tr>
<td>TTIME</td>
<td>$\alpha_{10}$</td>
<td>16.6232</td>
<td>76.5*</td>
</tr>
<tr>
<td>TCOST</td>
<td>$\alpha_{11}$</td>
<td>0.0149</td>
<td>6.2*</td>
</tr>
<tr>
<td>TLD</td>
<td>$\alpha_{12}$</td>
<td>0.2630</td>
<td>10.0*</td>
</tr>
<tr>
<td>RCOST</td>
<td>$\alpha_{13}$</td>
<td>-0.0935</td>
<td>-46.8*</td>
</tr>
</tbody>
</table>

$R^2 = 0.8249$

$L(\hat{\beta}) = -2293.7$

$\hat{\delta}_1 = 2.3827$

$\rho_1 = -0.1936 (t = -1.65**)$

N. Obs. = 1003

* Significant at 5% level.
** Significant at 10% level.

A look at Tables 4 and 5 shows that all explanatory variables are significant at the 5 per cent level. This is not surprising, as it is a direct result of a screening procedure carried out before the variables were entered into the ML routine. The screening procedure was done by running the entire set of explanatory variables (a total of 27 variables) into a regression routine that tries all possible combinations of the given set of explanatory variables and outputs the regression with the best overall result.3

The effect of commodity attributes on the choice of truck shipment size (Table 4) can be summarised as follows: (1) denser commodities tend to be moved in larger volumes ($\alpha_2$ is positive); (2) commodities which are of gaseous or particulate nature also tend to be moved in larger sizes, as indicated by their respective coefficients ($\alpha_3$.

3 This procedure is available in the BMDP statistical package under procedure P9R. A variety of selection criteria is available to choose the best regression. In our case, the minimum Mallows’ $C_p$ was used (see BMDP, 1985)
TABLE 5

ML Estimates of the Rail Shipment Size Equation, SR

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter</th>
<th>ML Estimate</th>
<th>&quot;t&quot;-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>$\beta_0$</td>
<td>83.2765</td>
<td>6.1*</td>
</tr>
<tr>
<td>TON</td>
<td>$\beta_1$</td>
<td>0.2594</td>
<td>10.7*</td>
</tr>
<tr>
<td>DEN</td>
<td>$\beta_2$</td>
<td>0.0894</td>
<td>9.8*</td>
</tr>
<tr>
<td>VAL</td>
<td>$\beta_3$</td>
<td>-1.7730</td>
<td>-3.4*</td>
</tr>
<tr>
<td>LIQ</td>
<td>$\beta_4$</td>
<td>4.8161</td>
<td>3.3*</td>
</tr>
<tr>
<td>GAS</td>
<td>$\beta_5$</td>
<td>29.8602</td>
<td>9.0*</td>
</tr>
<tr>
<td>PART</td>
<td>$\beta_6$</td>
<td>5.9057</td>
<td>4.6*</td>
</tr>
<tr>
<td>RD2</td>
<td>$\beta_7$</td>
<td>-11.7037</td>
<td>-11.2*</td>
</tr>
<tr>
<td>RD4</td>
<td>$\beta_8$</td>
<td>-9.4014</td>
<td>-6.9*</td>
</tr>
<tr>
<td>RTIME</td>
<td>$\beta_9$</td>
<td>9.8227</td>
<td>10.7*</td>
</tr>
<tr>
<td>TCOST</td>
<td>$\beta_{10}$</td>
<td>0.1601</td>
<td>10.4*</td>
</tr>
<tr>
<td>TLD</td>
<td>$\beta_{11}$</td>
<td>2.2626</td>
<td>5.6*</td>
</tr>
<tr>
<td>TREL</td>
<td>$\beta_{12}$</td>
<td>-51.7894</td>
<td>-6.7*</td>
</tr>
<tr>
<td>RLD</td>
<td>$\beta_{13}$</td>
<td>-0.4760</td>
<td>-4.6*</td>
</tr>
<tr>
<td>RCOST</td>
<td>$\beta_{14}$</td>
<td>-0.2703</td>
<td>-33.0*</td>
</tr>
</tbody>
</table>

$R^2 = 0.7238$
$L(\hat{\beta}) = -2356.3$
$\hat{\theta}_2 = 13.7720$
$\rho_{2c} = 0.4868 \ (t = 2.66*)$
N. Obs. = 583

* Significant at 5% level.

and $\alpha_4$ are positive); (3) commodities that require temperature control tend to be moved in larger quantities ($\alpha_3$ is positive), while commodities that require shock protection tend to be moved in smaller quantities ($\alpha_6$ is negative). The effect of traffic density ($TON$) on the choice of shipment size by truck seems to be positive ($\alpha_1$ is positive). This is probably because carriers using routes with heavier freight flows are better able to offer volume discounts to shippers than carriers using routes with very light commodity flow. This, in turn, would serve to support the hypothesis of existing economies of route density, which is found by many researchers (for example, LaMond, 1980).

Table 4 also suggests the existence of significant differentials in the choice of shipment size in the Official, Southern, and Southwestern Territories in comparison with the Mountain Pacific Territory as defined by the ICC.

The interpretation of the effect of level of service variables on the shipment size by either mode is less straightforward. This is mainly because of the way in which the shipment size variable is treated in the 3-equations system. That is, the shipment size equations reflect the impact that a change in any explanatory variable may have
on the shipment size, given that a particular mode is chosen. For example, equation (20) can be used to predict the impact that an increase in truck freight charges may have on choosing the size of shipment by truck. The same equation cannot and should not be used to make a direct prediction of the impact of a change in some explanatory variable on a potential modal shift by shippers. The question of modal shift is directly handled by the mode choice equation, and it is the interdependence between this equation and the shipment size equations that constitutes the main feature of this modelling approach. In other words, it is not possible to interpret the results of Tables 4 and 5 without taking the results of Table 3 into consideration at the same time.

To illustrate this joint interpretation of the results, consider the effect of an increase in truck freight charges (TCOST). From Table 3, the negative sign of \( \pi_{13} \) suggests that the probability of choosing truck over rail will decrease. Now, to find out how this effect translates on the choice of shipment size by truck and rail, one must use the results of Tables 4 and 5. To examine the impact of this change on truck shipment size, Table 4 suggests that the truck shipment size will increase (probably to make use of a potential rate discount on larger shipments), and Table 5 suggests that the rail shipment size will also increase. If a shipper is currently using truck, then the overall effect of an increase in truck freight charges will be an increase in that shipper's shipment size, which will eventually translate to favour a shift towards rail (which is supported by the expected reduction in probability of choosing truck).

Another important level of service variable is transit time by each mode. Transit time by truck (TTIME) appears significant and with the correct sign in Table 3. The negative side of TTIME in the mode choice equation indicates that the greater the distance, the less likely is it that truck will be chosen. This is because transit time is used as a proxy for distance. It is noted that transit time by rail (RTIME) is not used in the reduced-form mode choice model because it is highly correlated with TTIME (correlation coefficient = 0.96). However, when RTIME was used instead of TTIME in the mode choice model, it had a negative sign, confirming the fact that transit time is working as a surrogate for distance. It is well known that rail has an advantage over truck in long distances; this suggests that the signs of TTIME (in Table 4) and RTIME (in Table 5) are correct. The question which transit time to use (TTIME or RTIME) will be avoided in the estimation of the structural parameters of the mode choice equation. In that case, the difference between the two transit times will be entered into the model rather than the two values separately; this avoids the problem of collinearity between the two values.

Using the above example, the coefficients of the other parameters can be interpreted in a similar fashion. In general, to be compatible with the notion of simultaneous decision-making behaviour by shippers, a coefficient appearing in Table 4 or Table 5 (the shipment size equations) must have an opposite sign to that appearing in Table 3 (the mode choice equation). Among all explanatory variables appearing in Tables 3, 4 and 5, only LIQ and SHK carry the wrong signs in Table 3.

Finally, to examine the magnitude and significance of the interdependence between mode choice and shipment size decisions illustrated above, one needs to

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4 From the argument of the previous paragraph, it can be seen that the variable SHK should have a positive sign, which better conforms to the observed practice of the industry.
observe the coefficients of correlation between the error terms discussed in section 4. Table 4 shows a fairly large and significant value for the correlation coefficient between the error term of the truck shipment size equation and that of the mode choice equation, $\rho_{1e}$. Although the significance is observed at only the 10 per cent level, it does serve to show the potential of having a negative selection bias between mode and truck shipment sizes. In the case of rail shipments, Table 5 shows an even higher and more significant value for the parameter $\rho_{2e}$. This time it is significant at the 5 per cent level and has a positive sign, indicating the potential of significant positive selection bias when a shipment size equation is estimated as a linear OLS model.

6. CONCLUSIONS
A new approach to studying the demand for freight transport is introduced. The approach is based on the notion of simultaneous decision-making on the choices of mode and shipment size. A switching simultaneous system is used to derive a joint mode choice/shipment size freight demand model. Specifically, the mode choice process is formulated as a binary probit choice model, and two linear regression equations are used to simulate the choices of shipment size by rail and by truck. Two alternative estimation methods are discussed. One method requires the formulation of the maximum likelihood function for the simultaneous equations system. This method has the advantages of estimating the parameters of the models simultaneously in one step; this enables the analyst to impose restrictions on the estimated parameters. A less computationally involved method is the two-stage estimation, whereby an ML probit is applied to estimate the mode choice model in the first step, and OLS is applied to estimate the shipment size equations in the second step. This method, called two stage least squares (2SLS), is simple, consistent, and generally more familiar to analysts with limited knowledge in econometrics and mathematical procedures. The ML method is, however, more efficient than the 2SLS. To reduce estimation cost, estimates obtained by 2SLS are often used as starting values in the maximum likelihood method.

The proposed model is then applied to study the choice of mode (rail versus truck) and the choice of shipment size by each mode. Data from the Census of Transportation were used to demonstrate the application of the proposed method to study the demand for intercity freight transport by truck and rail. Statistically reliable models were estimated by the maximum likelihood method. The resulting coefficient estimates of the mode choice and shipment size equations supported the hypothesis of interdependence between the two decisions on mode and shipment size. Potential bias arises in the case of single equation estimation of mode choice or shipment size; this was highlighted.

Date of receipt of final typescript: April 1991
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