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Foreword

In the paper Approaches to Modal Transferability and Updating: The Combined Transfer Estimator, by Ben-Akiva and Bolduc, model transferability is found to be a practical approach for estimating a model when the size of the available sample is small. The combined transfer estimator, which is based on a mean squares error criterion, extends the Bayesian procedure to explicitly discount for the presence of transfer bias. The combined estimator has better accuracy in a mean square error sense than direct estimation when the transfer bias is small.

In his paper Assessment of Transfer Penalty to Bus Riders in Taipei: A Disaggregate Demand Modeling Approach, Han discusses transfer penalty in monetary and time units and assesses it with a disaggregate demand modeling approach. The modes developed use a binary logit format with two alternative path choices. The first path requires a transfer en route; the other does not. In current practice, transit planners may underestimate the transfer penalty to bus riders.

In Neels' and Mather's paper, Forecasting Intermodal Competition in a Multimodal Environment, mathematical structure of an innovative model to allocate demand across seven primary modes is described. Representation of the intermodal competition this model provides is considered. Its properties are contrasted with those of some commonly used variants of the familiar logit model. The paper also presents the empirical and cross elasticities of demand implied by the model coefficients, broken down by mode, service attribute, and geographic area.

In a second paper, Modeling Mode Choice in New Jersey, Neels and Mather describe a mode choice model for evaluating proposals for increasing capacity and use of the existing Hudson River crossing focusing on the choice of a.m. peak period east-bound commuters. Data sources used in the effort, specifications of the model, procedures used to estimate the model coefficients, statistical results of the model estimation, and the model's forecasting performance are discussed.

In their paper North Carolina Procedure for Synthesizing Travel Movements, Poole and Newman describe procedures developed by the staff of the North Carolina Department of Transportation for synthesizing travel movement in small and medium-sized urban areas. The four methods discussed require comprehensive traffic volume counts and inventories of employment, commercial vehicles, and dwelling units. The procedures reduce time and cost for the modeling phase, increasing time for travel forecasting, plan development, and evaluation.

In the paper Characteristics of Urban Transportation Demand: An Updated and Revised Handbook, Parody et al. survey data on urban travel demand characteristics incorporated into a newly revised and updated handbook. The handbook is a convenient reference for analysts who need particular statistics or who would like to compare forecast of travel demand with critical volume data. The handbook will be progressively updated.

Approaches to Model Transferability and Updating: The Combined Transfer Estimator

MOSHE BEN-AKIVA AND DENIS BOLDUC

The idea of model transferability is to use previously estimated model parameters from a different area for model estimation. The combined transfer estimator is based on the mean squares error criterion and extends the Bayesian procedure to explicitly account for the presence of a transfer bias. The suggested estimator is easy to apply because it is expressed as a linear combination of the direct estimation results and the previously estimated parameters. The combined estimator is shown to have superior accuracy in a mean square error sense to a direct (unbiased nontransfer) estimator whenever the transfer bias is relatively small. Numerical examples of the transfer region—where the combined estimator is superior to the direct estimator—are provided.

Model transferability is a practical approach to the problem of estimating a model for a study in an area for which the size of the available sample is small [for detailed discussions of transferability methods, see Ben-Akiva *(1)* and Koppelman and Wilmot *(2)*]. The model transfer approach is based on the idea that estimated model parameters from a previous study in a different area may provide useful information for estimating the parameters for the same model in a new area, even when the true values of the parameters are not expected to be equal. In the present notation, β_1 and β_2 denote the true $(K \times 1)$ parameter vectors of Areas 1 and 2 (the new area), respectively. The difference $\Delta = \beta_1 - \beta_2$ is called the transfer bias. In model transferability, one attempts to use the estimated parameters from Area 1, denoted by b_1, to improve the accuracy of the estimation of β_2. The difficulty occurs because b_1 is an estimator of β_1 and not of β_2.

If the transfer bias is negligible (as indicated, for example, by a Chow test of the null hypothesis that the vectors, or specific subvectors, of the model parameters for the two areas are equal), the two data sets can be pooled, and identical parametric values can be estimated for the two areas. Alternatively, and particularly if the original data for Area 1 are not available, a Bayesian updating procedure can be used *(3)*. However, these pooled and Bayesian estimators are not appropriate for situations in which coefficients for the transfer bias cannot be assumed to be negligible. The transfer scaling approach previously applied in these situations is described in the following section. It takes the estimator b_1 and attempts a correction of the transfer bias by using the data from Area 2.

In this paper, a new model transfer estimator, the combined transfer estimator, is developed. It is stated as a weighted average of the direct estimators b_1 and b_2. The term direct estimator is used in this paper to mean an unbiased estimation procedure that would be performed if no transfer was attempted. The weights are assigned in such a way that for each value of the transfer bias, the mean square error (MSE) of the combined estimator is minimized. This approach is expected to yield better estimates of β_2 when the transfer bias is small.

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THE TRANSFER SCALING APPROACH

A relationship between the true values of the parameters in the two areas is called a transfer bias model. Consider the following:

$$\beta_2 = \mathrm{diag}(\mu)\beta_1 = \mathrm{diag}(\beta_1)\mu \tag{1}$$

where μ is a $(K \times 1)$ vector of unknown bias scale parameters and $\mathrm{diag}(\mu)$ and $\mathrm{diag}(\beta_1)$ are $(K \times K)$ diagonal matrices in which the *kk*th elements are μ_k and β_{1k}, respectively. For simplicity, the matrix $\mathrm{diag}(\mu)$ will be denoted by M. The relation $\beta_2 = \mathrm{M}\beta_1$ is such that the transfer bias, $(\beta_1 - \beta_2) = (\mathrm{I} - \mathrm{M})\beta_1$, is nonzero unless $\mu_k = 1, \forall k = 1, \ldots, K$. Denote the number of distinct parameters in μ by M. In general, $M \leq K$, and the usefulness of the transfer scaling approach, described in the following, is for cases where $M < K$. Gunn et al. *(4)* thoroughly tested the transfer scaling approach by classifying the independent variables of a travel demand model into groups with similar transfer bias properties.

Equation 1 can also be expressed as

$$\begin{aligned}\beta_2 &= \mathrm{M}\beta_1 = \mathrm{M}b_1 + \mathrm{M}(\beta_1 - b_1)\\ &= \mathrm{diag}(b_1)\mu + M(\beta_1 - b_1)\end{aligned} \tag{2}$$

If b_1 is an unbiased estimator of β_1, the vector $\mathrm{M}(\beta_1 - b_1)$ is a simple transformation of the sampling error in Area 1 estimates and has an expected value of zero. In a transfer scaled model, μ denotes the vector of parameters that are estimated from Area 2 data. If m is called the vector of estimates for μ, the transfer scaling estimator of β_2 is computed as $\mathrm{diag}(b_1)m$. In all previous applications of the transfer scaling approach, the term $\mathrm{M}(\beta_1 - b_1)$ has been ignored. In the estimation with Area 2 data, it represents measurement errors in the independent variables. This term plays a critical role because unless it is negligible, the transfer scaling estimator is inefficient and potentially biased because it is correlated with the independent variables in the model estimated with Area 2 data.

The transfer scaling approach can be implemented at different levels of detail with M (the number of bias scale parameters) ranging from none (i.e., assuming $\beta_1 - \beta_2 = 0$ by imposing $\mu_1 = \mu_2 = \ldots = \mu_K = 1$) to K (i.e., one bias scale parameter per model parameter). For $M = K$, the transfer scale estimator $\mathrm{diag}(b_1)m$ is identical to Area 2 direct estimator b_2.

Thus transfer scaling is a useful approach when the data available for the new area permit estimation of only a small number of new parameters and an accurate estimator, that is, one with small $(b_1 - \beta_1)$, is available from another area. The latter requirement is needed to justify the assumption that the term $\mathrm{M}(\beta_1 - b_1)$ is negligible.

In a related paper, Ben-Akiva and Bolduc *(5)* also develop a second model transferability approach—a mixed estimation procedure that jointly estimates the new area model and a transfer bias model. This mixed estimation may be viewed as an extension of the transfer scaling approach that overcomes the deficiencies due to a nonnegligible $\mathrm{M}(\beta_1 - b_1)$ value.

MINIMUM MSE ESTIMATOR

The objective of model transfer is to improve the estimation of β_2 by combining the sample information from Area 2 with knowledge of b_1. The transfer scaling approach achieves this objective by postulating a specific transfer bias model and estimating the parameters of the transfer bias model from Area 2 data. The Area 2 data are used only to correct the transfer bias, and differences in sampling errors between the two data sets are not explicitly recognized. By using the two direct estimates b_1 and b_2 directly, an estimator is developed that treates the trade-off between sampling errors and transfer biases explicitly.

The Problem

Given the direct estimators b_1 and b_2, find a combined estimator defined by the function

$$\ddot{b}_2 = h(b_2, b_1)$$

that in some sense is a better estimator of β_2 than the direct estimator b_2.

We use the MSE criterion, which implies, for example, that for a variance reduction one is willing to allow a bias. A brief description of optimal MSE estimation with a single parameter follows. A more extended treatment can be found in the work of Judge et al. *(6)*.

The Minimum MSE Approach

Use the MSE criterion to find whether

$$\mathrm{MSE}(\ddot{b}_2) \leq \mathrm{MSE}(b_2)$$

or

$$E(\ddot{b}_2 - \beta_2)^2 \leq E(b_2 - \beta_2)^2 \tag{3}$$

holds. An MSE is equal to the square of the bias plus the variance. Because b_2 is assumed to be unbiased, the criterion is reduced to

$$E(\ddot{b}_2 - \beta_2)^2 \leq \mathrm{Var}\,(b_2) \tag{4}$$

or

$$\mathrm{Var}\,(\ddot{b}_2) + \mathrm{B}^2(\ddot{b}_2) \leq \mathrm{Var}\,(b_2) \tag{5}$$

where the bias of $\ddot{b}_2$ is defined as $\mathrm{B}(\ddot{b}_2) = E(\ddot{b}_2) - \beta_2$ and the variance definition is, for example, $\mathrm{Var}\,[\ddot{b}_2 - E(\ddot{b}_2)]^2$. This inequality, demonstrated in Figure 1, reveals how the advantage gained from variance reduction [i.e., $\mathrm{Var}(\ddot{b}_2) \leq \mathrm{Var}(b_2)$] may be significantly reduced or even totally lost by the presence of a significant transfer bias.

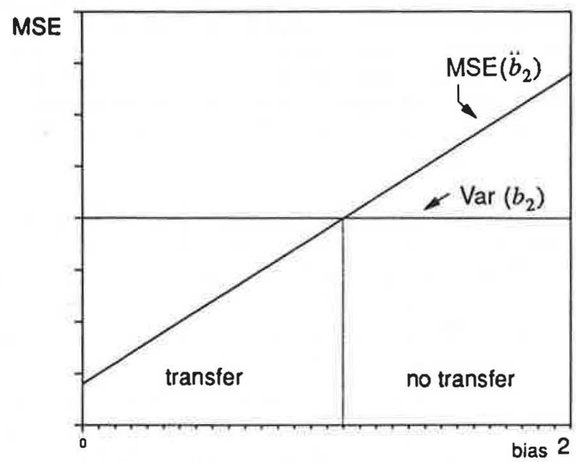

FIGURE 1 When to transfer as a function of the transfer bias.

For a model with K parameters, the combined transfer estimator developed later in this paper is based on a weighted average of the two direct estimators (i.e., h is assumed to be a linear function) and is expressed as follows:

$$\ddot{b}_2 = (\mathrm{I} - \mathrm{A})b_2 + \mathrm{A}b_1$$

or

$$\ddot{b}_2 = b_2 + \mathrm{A}(b_1 - b_2) \tag{6}$$

where A is a $(K \times K)$ matrix of weights. The matrix A is a general matrix for which element a_{ij} of matrix A gives the relative importance of b_{1j} in the estimation of $\ddot{b}_{2i}$.

THE COMBINED TRANSFER ESTIMATOR

The MSE optimal value for the weighting matrix A of the combined estimator can now be obtained. First, the one parameter case is developed in detail and then the derivation is extended to the multiparameter case.

Derivation of the Combined Transfer Estimator

For $K = 1$, the combined transfer estimator is expressed as a linear combination of the direct estimators with fixed weights, as follows:

$$\ddot{b}_2 = (\alpha_1 + \alpha_2)^{-1}\alpha_1 b_1 + (\alpha_1 + \alpha_2)^{-1}\alpha_2 b_2$$
$$= b_2 + \alpha(b_1 - b_2) \quad (7)$$

where $\alpha_1, \alpha_2 \geq 0$ and $\alpha = (\alpha_1 + \alpha_2)^{-1}\alpha_1$. This is a non-Bayesian estimator that combines the information from the two samples. In a Bayesian setting the random vector b_1 would be replaced by the fixed mean of the prior distribution of β_2.

The expected value of $\ddot{b}_2$ is

$$E(\ddot{b}_2) = \beta_2 + \alpha(\beta_1 - \beta_2) \quad (8)$$

The MSE optimal value for α is obtained by minimizing the MSE as a function of α:

$$\underset{\alpha}{\text{Minimize}}\ \text{MSE} = [\text{Var}(\ddot{b}_2) + B^2(\ddot{b}_2)]$$
$$= \alpha^2\sigma_1^2 + (1 - \alpha)^2\sigma_2^2 + \alpha^2(\beta_1 - \beta_2)^2 \quad (9)$$

where

$$\sigma_i^2 = \text{Var}(b_i) \qquad i = 1, 2$$

The first-order condition is

$$\frac{\partial \text{MSE}}{\partial \alpha} = 2\alpha\sigma_1^2 - 2(1 - \alpha)\sigma_2^2 + 2\alpha\Delta^2 = 0$$

which implies

$$\alpha = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2 + \Delta^2} = \frac{\sigma_2^2}{D} \quad (10)$$

where $\Delta = \beta_1 - \beta_2$ and $D = \sigma_1^2 + \sigma_2^2 + \Delta^2$. Because α is a function of Δ (which is an unknown quantity), in an empirical application Δ will have to be replaced by an observed quantity. Use of $d = b_1 - b_2$ is suggested. Another possibility is to apply the transfer scaling approach to estimate the transfer bias. Therefore, α is random in practice. The implications of this fact will be analyzed later on.

At this value of α, the optimal combined estimator is expressed as

$$\ddot{b}_2 = b_2 + \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2 + \Delta^2}(b_1 - b_2)$$

Multiplying α by

$$\frac{(\sigma_1^2 + \Delta^2)^{-1}\sigma_2^{-2}}{(\sigma_1^2 + \Delta^2)^{-1}\sigma_2^{-2}}$$

implies

$$\alpha = \frac{(\sigma_1^2 + \Delta^2)^{-1}}{(\sigma_1^2 + \Delta^2)^{-1} + \sigma_2^{-2}}$$

For $\Delta = 0$, the weights are obtained in the Bayesian updating formula, which is MSE optimal if the transfer bias is zero.

Properties of the Combined Transfer Estimator

The optimal combined estimator $\ddot{b}_2$ just derived can be compared with b_2, the direct estimator. Substitution of α from Equation 10 in the objective function of Equation 9 yields

$$\text{MSE}(\ddot{b}_2) = \alpha\sigma_1^2\frac{\sigma_2^2}{D} + (1 - \alpha)\left[\frac{\sigma_1^2 + \Delta^2}{D}\right]\sigma_2^2 + \alpha\frac{\sigma_2^2}{D}\Delta^2$$
$$= \alpha\left[\frac{\sigma_1^2 + \Delta^2}{D}\right]\sigma_2^2 + (1 - \alpha)\left[\frac{\sigma_1^2 + \Delta^2}{D}\right]\sigma_2^2$$
$$= \left[\frac{\sigma_1^2 + \Delta^2}{D}\right]\sigma_2^2$$
$$= (1 - \alpha)\sigma_2^2 \quad (11)$$

Because $0 \leq \alpha \leq 1$,

$$\text{MSE}(\ddot{b}_2) \leq \text{Var}(b_2) \qquad \forall\Delta^2 \geq 0 \quad (12)$$

Thus the optimal combined estimator always stays in the transfer region. It is always better because as the bias increases α decreases, and for $|\beta_1 - \beta_2| \rightarrow \infty$, $\alpha \rightarrow 0$, and $\ddot{b}_2 \rightarrow b_2$. The pattern of MSE($\ddot{b}_2$) as a function of the transfer bais is investigated next. The first and second derivatives with respect to Δ^2 are as follows:

$$\frac{\partial \text{MSE}(\ddot{b}_2)}{\partial \Delta^2} = \frac{\partial \text{MSE}(\ddot{b}_2)}{\partial \alpha} \cdot \frac{\partial \alpha}{\partial \Delta^2} = \alpha^2 \geq 0$$

$$\frac{\partial^2 \text{MSE}(\ddot{b}_2)}{(\partial \Delta^2)^2} = \frac{\partial \alpha^2}{\partial \Delta^2} = -2\frac{\alpha^2}{D} \leq 0$$

This is because

$$\frac{\partial \alpha}{\partial \Delta^2} = -\frac{\sigma_2^2}{D^2} = -\frac{\alpha}{D}$$

At $\Delta = 0$, MSE($\ddot{b}_2$) $= \sigma_2^2[\sigma_1^2/(\sigma_1^2 + \sigma_2^2)]$. The pattern of MSE($\ddot{b}_2$) as a function of Δ^2 is shown in Figure 2.

The results of the analysis have been obtained under the hypothesis that α is a known fixed constant. When Δ is replaced by an estimate d (i.e., a random variable), it becomes difficult to evaluate E($\ddot{b}_2$) and Var ($\ddot{b}_2$). In what follows, these moments are approximated by a Taylor's series expansion. It will be shown that in the case of an estimated α it is not impossible for the combined estimator to be inferior to the direct estimator. In this analysis, σ_1^2 and σ_2^2 are assumed to be known, and therefore the randomness in α arises only from the substitution of d for Δ.

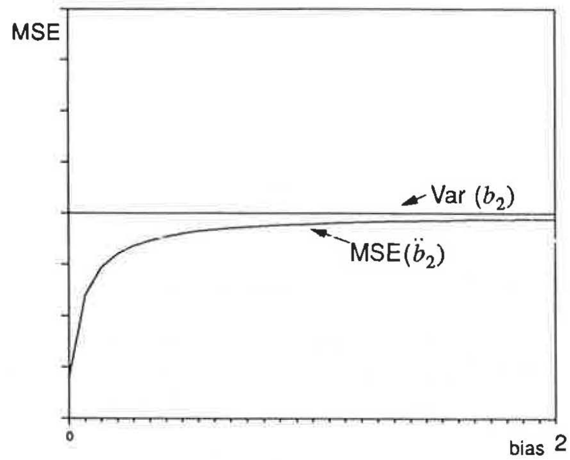

FIGURE 2 The combined estimator is always superior.

Recall the combined estimator in Equation 10, and replace Δ with its estimator d, as follows:

$$\tilde{b}_2 = b_2 + a(b_1 - b_2) \tag{13}$$

with

$$a = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2 + d^2} = \frac{\sigma_2^2}{\hat{D}}$$

where

$$\hat{D} = \sigma_1^2 + \sigma_2^2 + d^2$$

The $\tilde{b}_2$ is a nonlinear function of the random variables b_1, b_2, and d. The moments of $\tilde{b}_2$ are approximated by a Taylor's series expansion around the true values of β_1 and β_2 (as well as $\Delta = \beta_1 - \beta_2$), as follows:

$$E(\tilde{b}_2) = \beta_2 + \alpha\Delta \tag{14}$$

and

$$\mathrm{Var}(\tilde{b}_2) = J'\Sigma J \tag{15}$$

where

$$J' = [\partial\tilde{b}_2/\partial b_1, \partial\tilde{b}_2/\partial b_2]_{\beta_1,\beta_2}$$

and

$$\Sigma = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}$$

The calculations are performed under the assumption

$$d = b_1 - b_2 \tag{16}$$

The partial derivatives of $\tilde{b}_2$ in J are derived by Ben-Akiva and Bolduc *(7)* and lead to

$$J' = [\alpha - 2\Delta^2\alpha/D, 1 - \alpha + 2\Delta^2\alpha/D] \tag{17}$$

Substitution of Equation 17 into Equation 15 yields

$$\mathrm{Var}(\tilde{b}_2) = \sigma_1^2\alpha^2(1 - 2\Delta^2/D)^2 + \sigma_2^2(1 - \alpha)^2[1 + 2\Delta^2\alpha/D(1 - \alpha)]^2$$

The MSE is

$$\mathrm{MSE}(\tilde{b}_2) = \alpha^2\Delta^2 + \mathrm{Var}(\tilde{b}_2)$$

At the two limits $\Delta^2 = 0$ and $\Delta^2 \to \infty$, this MSE expression coincides with the one obtained before for deterministic α. However, depending on the values of the parameters, it is now possible that for a finite value of Δ^2 the MSE of the combined estimator, MSE($\tilde{b}_2$), will exceed the variance of the Area 2 direct estimator, Var(b_2). This is demonstrated in the numerical example in Figure 3 for $\sigma_1^2 = 1$ and $\sigma_2^2 = 4$.

The combined estimator presents an improvement over a direct estimator only within a limited transfer region in which the transfer bias is relatively small. If the transfer bias is greater than some critical value, the combined estimator is, in fact, inferior to the direct estimator. Thus in practical applications the transfer region for the optimal combined estimator is not global. Clearly, any application of the notion of transferability is based on the prior assumption that the transfer bias is relatively small, or in other words, that there are a priori expectations that the model parameters are similar between the two areas.

The sensitivity of the transfer region to the values of σ_1^2 and σ_2^2 is demonstrated in Figures 4 and 5, respectively. In general, it is shown that increasing σ_1^2 or σ_2^2 leads to a larger transfer region. Figure 4 shows that as σ_1^2 gets larger, the gain in accuracy from the transfer estimator is reduced in situations with small transfer bias. In general, as σ_1^2 increases, the value of α decreases, and the combined estimator approaches the direct estimator. Thus for $\sigma_1^2 \to \infty$ (inaccurate information from Sample 1) the MSE($\tilde{b}_2$) curve approaches the horizontal line of σ_2^2. The dramatic effects of σ_2^2 on the transfer region and the accuracy of the combined estimator are demonstrated in Figure 5. The size of the transfer region appears to be more sensitive to σ_2^2 than to σ_1^2, and at the limit for $\sigma_2^2 \to \infty$ the transfer region is obviously global.

Monte Carlo experiments were performed to evaluate the accuracy of the expression for MSE($\tilde{b}_2$) that was developed under the assumption of known σ_1^2 and σ_2^2 and a first-order Taylor's series approximation. The experiments, described by Ben-Akiva and Bolduc *(7)*, compare the true MSE and the MSE curve computed by using the previous approximations. The results clearly show that the approximate MSE curve significantly underestimates the point at which the true MSE curves intersect with σ_2^2. In other words, the approximate MSE curve provides a conservative estimate of the transfer region. The Monte Carlo results show that the critical value may be as

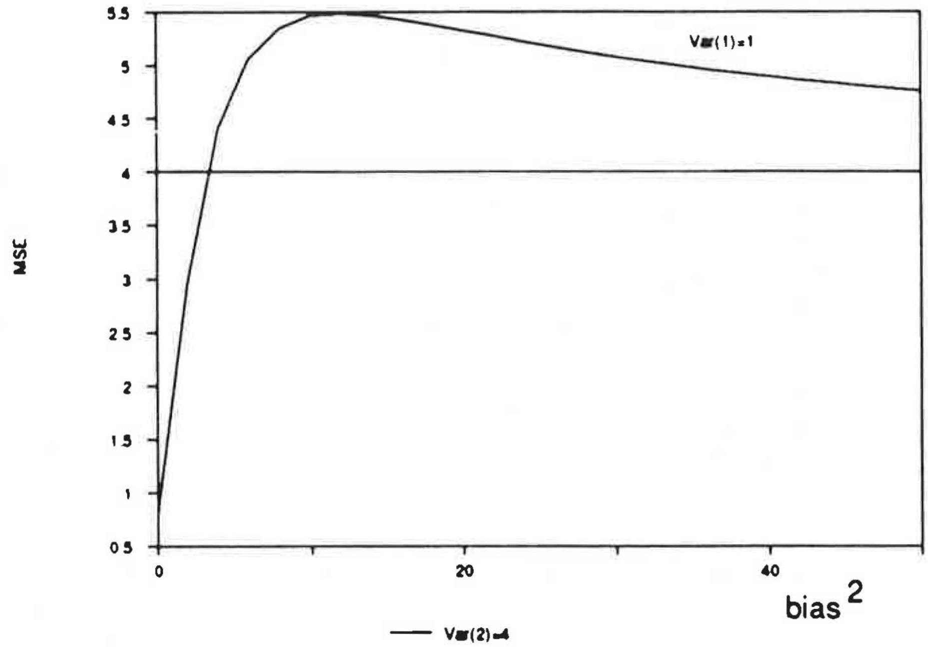

FIGURE 3 The transfer region of the combined estimator.

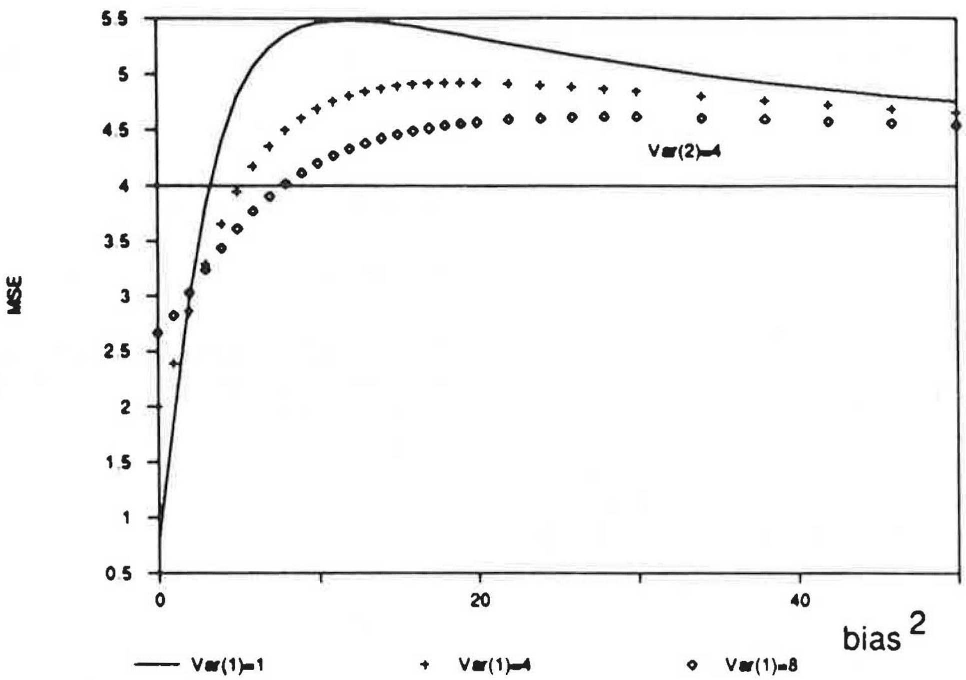

FIGURE 4 The effect on the transfer region of Var *(1)*.

high as 3 or 4 times greater than the one obtained from the approximate analysis. This result should be taken into account in empirical applications.

THE MULTIVARIATE EXTENSION OF THE COMBINED ESTIMATOR

Here, the derivation of the combined transfer estimator is extended to the multivariate case. The combined estimator is defined with nonsingular fixed-weight matrices A_1 and A_2 as follows:

$$\ddot{b}_2 = (A_1 + A_2)^{-1}A_1b_1 + (A_1 + A_2)^{-1}A_2b_2 \qquad (18)$$

Let

$$A = (A_1 + A_2)^{-1}A_1$$

and note that

$$(A_1 + A_2)^{-1}A_2 = I - A$$

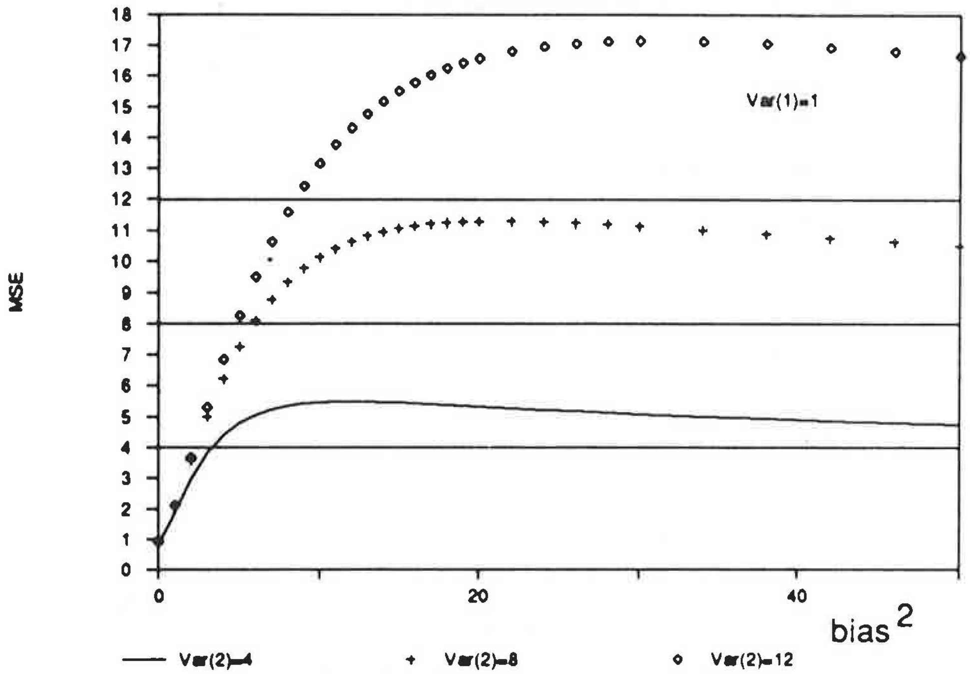

FIGURE 5 The effect on the transfer region of Var *(2)*.

Rewrite the combined estimator (Equation 18) as

$$\ddot{b}_2 = (I - A)b_2 + Ab_1 = b_2 + A(b_1 - b_2)$$

and obtain the following expectation of $\ddot{b}_2$:

$$E(\ddot{b}_2) = \beta_2 + A(\beta_1 - \beta_2) \quad (19)$$

Let $\Delta = \beta_1 - \beta_2$ and express the bias of $\ddot{b}_2$ by

$$B(\ddot{b}_2) = E(\ddot{b}_2) - \beta_2 = A\Delta$$

Denote the covariance matrices of the direct estimators by $\mathrm{Var}(b_i) = \Sigma_i$, $i = 1, 2$. The two samples are independent, and as a consequence, b_1 and b_2 are independently distributed. Under this hypothesis, the covariance matrix of the combined estimator is given by

$$\begin{aligned}\mathrm{Var}(\ddot{b}_2) &= (I - A)\Sigma_2(I - A)' + A\Sigma_1A' \\ &= \Sigma_2 - \Sigma_2A' - A\Sigma_2 + A\Sigma_2A' + A\Sigma_1A'\end{aligned}$$

The latter results in the following MSE expression for $\ddot{b}_2$:

$$\begin{aligned}\mathrm{MSE}(\ddot{b}_2) &= \Sigma_2 - \Sigma_2A' - A\Sigma_2 \\ &\quad + A(\Sigma_1 + \Delta\Delta' + \Sigma_2)A' \quad (20)\end{aligned}$$

Define the optimal weighted average estimator as the matrix A that minimizes the trace of the $\mathrm{MSE}(\ddot{b}_2)$ matrix, as follows:

$$\begin{aligned}\mathrm{tr}\,[\mathrm{MSE}(\ddot{b}_2)] &= \mathrm{tr}\,[\Sigma_2] - 2\,\mathrm{tr}\,[\Sigma_2A'] \\ &\quad + \mathrm{tr}\,[A(\Sigma_1 + \Delta\Delta' + \Sigma_2)A']\end{aligned}$$

The optimal value of matrix A is given by

$$A = \Sigma_2(\Sigma_1 + \Delta\Delta' + \Sigma_2)^{-1} \quad (21)$$

which can also be written as

$$A = [(\Sigma_1 + \Delta\Delta')^{-1} + \Sigma_2^{-1}]^{-1}\,(\Sigma_1 + \Delta\Delta')^{-1}$$

For a detailed derivation, see Ben-Akiva and Bolduc *(7)*. Note that in the scalar case (e.g., $K = 1$), the matrix A reduces to the value of α derived earlier.

Equation 21 implies that the optimal weight matrices can be taken to be

$$A_1 = (\Sigma_1 + \Delta\Delta')^{-1}$$

$$A_2 = \Sigma_2^{-1}$$

Substitution of these matrices in the estimator (Equation 18) yields

$$\begin{aligned}\ddot{b}_2 &= [(\Sigma + \Delta\Delta')^{-1} + \Sigma_2^{-1}]^{-1}\,[(\Sigma_1 \\ &\quad + \Delta\Delta')^{-1}b_1 + \Sigma_2^{-1}b_2] \quad (22)\end{aligned}$$

As in the scalar case for $\Delta = 0$, this estimator reduces to the Bayesian updating formula.

The approach used in the single parameter case is now used to derive an expression for $\mathrm{MSE}(\tilde{b}_2)$ when the matrix A is replaced by an estimate $\hat{A}$. As in the one-parameter case, assume that Σ_1 and Σ_2 are known and that the randomness in $\hat{A}$ arises from the use of d, which is an estimate of Δ. As suggested earlier, the most straightforward estimate of Δ is the difference between the direct estimates: $d = b_1 - b_2$.

Recall matrix A in Equation 21 and replace Δ with its estimate d, as follows:

$$\tilde{b}_2 = b_2 + \hat{A}(b_1 - b_2)$$

with

$$\hat{A} = \Sigma_2(\Sigma_1 + dd' + \Sigma_2)^{-1} = \Sigma_2\hat{D}^{-1}$$

where

$$\hat{D} = \Sigma_1 + dd' + \Sigma_2$$

The Taylor's series approximation yields the following:

$$E(\tilde{b}_2) = \beta_2 + A\Delta$$

$$\mathrm{Var}(\tilde{b}_2) = J'\Sigma J$$

where

$$J' = [\partial\tilde{b}_2/\partial b_1', \partial\tilde{b}_2/\partial b_2']_{\beta_1,\beta_2}$$

$$\Sigma = \begin{pmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{pmatrix}$$

The partial derivatives of $\tilde{b}_2$ are

$$\partial\tilde{b}_2/\partial b_1' = \hat{A} - d'\hat{D}^{-1}d \otimes \hat{A} - d'\hat{D}^{-1} \otimes \hat{A}d$$

and

$$\partial\tilde{b}_2/\partial b_2' = I - \hat{A} + d'\hat{D}^{-1}d \otimes \hat{A} + d'\hat{D}^{-1} \otimes \hat{A}d$$

where $\otimes$ denotes a Kronecker product [for details, see Ben-Akiva and Bolduc *(7)*]. These expressions can be used to derive the multivariate transfer regions that are useful in situations with significant off-diagonal elements in Σ_1 and Σ_2.

CONCLUSION

A new approach to model transferability based on the MSE criterion was developed. The combined transfer estimator was derived, and it was shown that for sufficiently small transfer bias it dominates the direct estimator of the model in a new area. The combined estimator may be viewed as an extension of the Bayesian updating procedure that explicitly accounts for the possible presence of a transfer bias. The computational requirements of the combined transfer estimator are the same as those of the transfer scaling or the Bayesian updating procedures.

A linear approximation was employed to analyze the properties of the combined transfer estimator. However, results of Monte Carlo experiments have shown that the linear approximation underestimates the improvement of the combined estimator over the direct estimation. To overcome this problem, it will be necessary in further research to develop exact distributional results for the combined estimator.

Another approach that overcomes the statistical deficiencies of the transfer scaling approach but is computationally more demanding is to view transferability as a mixed estimation problem. In a related paper, a mixed estimator is proposed that jointly estimates the new area model and the transfer bias model used in the transfer scaling approach *(5)*.

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Assessment of Transfer Penalty to Bus Riders in Taipei: A Disaggregate Demand Modeling Approach

ANTHONY FU-WHA HAN

A transfer penalty to bus riders has long been recognized as an important factor characterizing the service performance of a transit system. Nevertheless, the way the transfer penalty is treated in current transit network design and improvement planning processes is rather subjective. The transfer penalty is usually treated by use of either subjective values assigned by transit planners or time-value proxies inferred from activities irrelevant to transfers in transit travel. In this paper, the transfer penalty is assessed in terms of monetary and time units with a disaggregate demand modeling approach. The models developed take a binary logit format with two alternative path choices, one that requires a transfer en route and another that does not. Data collected from 1,850 randomly sampled transit users in Taipei are used for model calibration. The penalty of one bus-to-bus transfer is approximately equivalent to the cost of 4.5 N.T. dollars (14 U.S. cents), 30 min of in-bus travel, or 10 min of waiting at a bus stop. The assessment results suggest that in current practice transit planners may underestimate the transfer penalty to bus riders. Some characteristics of transit travel in Taipei are also explored and discussed.

Transfer penalty or transfer inconvenience to transit users has long been recognized as one important factor characterizing the service performance of a transit system *(1, 2)*. Nevertheless, in the past, few studies have been concerned with the assessment of transfer penalties to transit users. Recently, some studies *(3, 4)* have attempted to derive subjective values of transfer penalties by using market research methods for scaling attitude measures of user perceptions of transfers into numerical values. Results of these studies can help promote better understanding of the demand of transit travel and predict responses of transit users to service-oriented actions. However, subjective values of transfer penalties have limited use for transit network optimization and evaluation purposes. As a result, the way the factor of transfer penalty is treated in current transit network design or optimization models *(5, 6)* is arbitrary. Specifically, transfer penalty is usually treated through the use of either subjective values assigned by transit planners or proxies inferred from time value analyses that are irrelevant to transfer activities.

In this study, results more useful than subjective values of transfer penalties are derived. A behavior-based choice-modeling approach is applied to determine the values of transfer penalty and other related service attributes such as in-vehicle travel time, wait time, and walk time in transit travel. These values, when assessed in monetary or equivalent time units, can be used for quantifying economic benefits of service-oriented transit projects, enhancing current transit planning to achieve better service performance.

Analysis procedure of this study consists of three steps. First, disaggregate binary logit choice models were specified for describing the behavior of bus riders choosing between two alternative paths, of which one requires a transfer en route and the other does not. Second, the utility functions underlying the choice model were calibrated with data of 327 sampled bus riders in Taipei, Taiwan. Finally, values of transfer penalty and related attributes were assessed from the estimates of coefficients associated with various attributes in the calibrated utility functions.

Before describing the analysis works of this study, a brief introduction of the Taipei transit system is given at the outset of this paper.

TAIPEI TRANSIT SYSTEM

Taipei is the capital city of Taiwan, the Republic of China. The city is hilly in the southeast, mountainous in the northeast, and flat in the west. The central part of the city is surrounded by three natural boundaries—the Tamsui, Hsintein, and Keelung Rivers. The southwest portion, from where the city originated, is now the city's central business district (CBD) area. Currently, the city of Taipei has an area of 272 km^2 within its administrative boundaries, and a population of about 2.5 million *(7)*.

As population and travel activity increased rapidly in the last 20 years, the city expanded and developed along its six radiating transportation corridors from the old city district into its surrounding areas to form a metropolitan area about 20 km in diameter. With a land area of 538 km^2, the Taipei metropolitan area currently has an estimated population of about 4.5 million. Following this growth trend, the population in the metropolitan area is expected to reach about 6.1 million by the year 2001 *(8)*.

At present, all travelers in Taipei depend almost entirely on a road-based transportation system. Bus transit is the most important transportation mode. It carries more than 40 percent of the total daily passenger trips generated in the metropolitan area. The remaining trips rely on paratransit as well as private transportation modes such as taxis, automobiles, motorcycles, and bicycles (Table 1).

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TABLE 1 DAILY PASSENGER TRIP VOLUME IN TAIPEI

MODE	1981		2001 PREDICTION	
	TRIP/DAY (10^3)	MODE SHARE	TRIP/DAY (10^3)	MODE SHARE
PUBLIC TRANSPORTATION	2,508	41.6%	4,479	39%
PRIVATE TRANSPORTATION	2,647	43.9%	5,616	48.9%
TAXI	606	10.5%	978	8.5%
OTHERS	270	4.0%	414	3.6%
TOTAL	6,031	100.0%	11,487	100.0%

Scheduled transit services in the Taipei area are currently provided by 17 bus companies of which 10 major companies have joined to form the Unified Operating System (UOS). In 1985, the UOS operated 205 routes with 3,158 buses, carrying approximately 2.6 million passenger trips per day *(7)*. All UOS companies use the same tickets for providing convenient transfers between UOS routes. Students, policeman, the military, and the elderly are privileged to use discount bus tickets of which the price is half that of the regular tickets. It was estimated in 1985 that approximately 48.9 percent of UOS bus riders were discount ticket users (data provided by UOS).

A significant portion of passenger trips in Taipei transit travel involves transfers. Major bus transfer locations in the Taipei area are shown in Figure 1. On the average about 60 percent of passenger trips originating from bus stops at these locations are transfer trips. It is roughly estimated that in the Taipei area more than 1 million passenger trips per day are made through bus transfers.

CHOICE MODELING ANALYSIS

Binary Choice Set

Disaggregate binary choice models are developed in this study to assess transfer penalties in transit travel. The choice set of each individual is defined by two alternative paths connecting a fixed pair of origin and destination points. As shown in Figure 2, Path 1 is the no-transfer choice alternative; Path 2 is the one-transfer alternative, which requires a bus transfer en route. Because the Taipei area is well covered by more than 200 bus routes, most of the bus riders in the Taipei area can complete their trips with no more than one transfer. Therefore, for simplicity, the path choices involving more than one transfer en route are not considered in this study.

Note that, due to the overlapping route structure of the Taipei transit network, the actual situation in Taipei is slightly different from that depicted in Figure 2. Specifically, in most cases in Taipei, the boarding stops A and A' as well as transfer stops B and B' coincide with each other. When the two alternative paths start with the same boarding bus stop, a bus rider's choice may be influenced by which bus arrives at the stop first. The factor of first-arrival bus is thus considered in the analysis and will be discussed later.

As mentioned earlier, the transit network in Taipei is characterized by its overlapping route structure; almost all bus routes overlap in part with other bus routes. Although many transit systems outside North America are characterized by networks with extensively overlapping routes *(9)*, the competition among the 17 bus companies makes this phenomenon even more significant in Taipei. At major transfer locations in Taipei as shown earlier in Figure 1, there are generally more than 25 bus routes passing the same streets. Therefore, the no-transfer path alternative is actually an abstract presentation of a set of overlapping bus routes connecting A and C (Figure 2). Similarly, the one-transfer alternative represents the combination of two sets of overlapping routes connecting A' and B, and B' and C, respectively. Consequently, the service attributes (travel time, walk time, wait time, fare, etc.) associated with the two choice alternatives are measures of the overall performance of a set of overlapping routes rather than those performance measures of a specific route.

Model Specification

The choice models developed in this study take the format of binary logit models. The two choice alternatives are as defined in the previous section: Alternative 1 is the no transfer alternative, and Alternative 2 the one-transfer alternative. Notation used for specifying the utilities functions of these two alternatives is defined as follows:

V_i = measured utility of Alternative i (i = 1, 2);
WK_i = walk time in minutes of Alternative i (i = 1, 2);
WT_i = wait time in minutes of Alternative i (i = 1, 2);

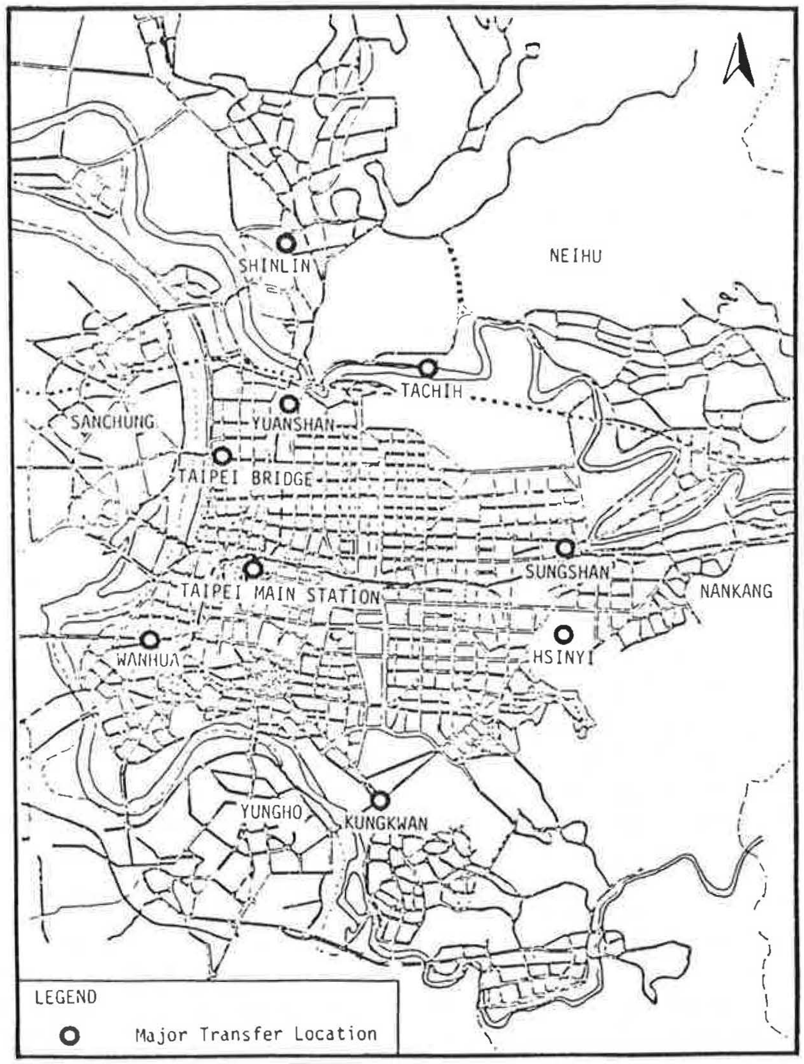

FIGURE 1 Major transfer locations in Taipei metropolitan area.

IV_i = in-vehicle travel time in minutes of Alternative i (i = 1, 2);
FR_i = bus fare in N.T. dollars of Alternative i (i = 1, 2);
OV_i = out-of-vehicle time of Alternative i, $OV_i = WK_i + WT_i$ (i = 1, 2);
δ_i = 1 if the first available bus belongs to Alternative i, 0 otherwise (i = 1, 2); and
β_j = coefficients to be estimated (j = 1, 2, . . .)

Although most of these attributes are well-defined, a few points need to be clarified. The wait time associated with the one-transfer alternative WT_2 includes wait times both for the first and second bus en route. WK_2 includes walk times both from the trip origin to the first boarding stop and from the first alighting stop to the second boarding stop. Similarly, both IV_2 and FR_2 consist of two components each of which is associated with the first and second bus journey, respectively. Therefore, in this study the transfer penalty means the inconvenience of the bus-to-bus transfer activity per se, and does not include that of the additional in- or out-of-vehicle travel times of the second bus journey. The dummy variable δ_i needs to be explained as well. The variable denotes the first available bus instead of the first arrival bus because in Taipei, particularly during peak hours, the buses are usually operated close to or at their capacities. As a result, in Taipei the first arrival bus at a bus stop may not be the first available bus for an individual to get on board. Therefore, for this study the factor of the first available bus is considered more appropriate than that of the first arrival bus.

Three model specifications are given in Table 2. All three of these models have generic service attributes of WK, WT, IV, and FR to form linear utility functions, and use the constant term β_1 to measure the revealed utility (or disutility) of one bus-to-bus transfer to the rider. Yet these models are somewhat different from each other. Model 1 (as defined in Table 2) includes only the aforementioned four service attributes and is the simplest one among the three. Both Models 2 and 3 take the dummy variable δ_i for the first available bus into consideration. Model 3 combines WK and WT into a single attribute OV, and is just a simplified version of Model 2. The model yielding the best results will be applied to determine the values of transfer penalties and other related service attributes.

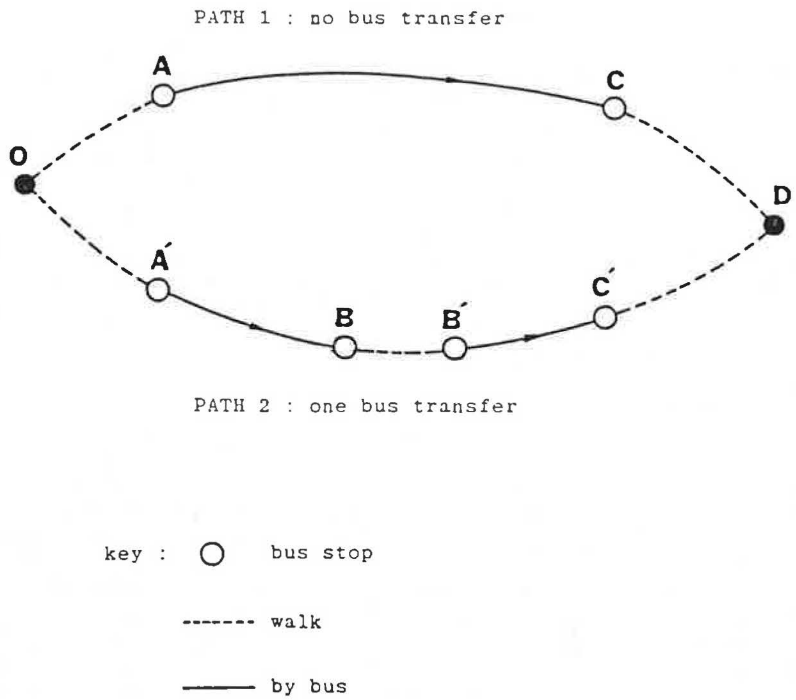

FIGURE 2 Two path choices.

TABLE 2 MODEL SPECIFICATION

Model 1	$V_1 = \beta_1 + \beta_2(WK)_1 + \beta_3(WT)_1 + \beta_4(IV)_1 + \beta_5(FR)_1$ $V_2 = \beta_2(WK)_2 + \beta_3(WT)_2 + \beta_4(IV)_2 + \beta_5(FR)_2$
Model 2	$V_1 = \beta_1 + \beta_2(WK)_1 + \beta_3(WT)_1 + \beta_4(IV)_1 + \beta_5(FR)_1 + \beta_6(\delta_1)$ $V_2 = \beta_2(WK)_2 + \beta_3(WT)_2 + \beta_4(IV)_2 + \beta_5(FR)_2 + \beta_6(\delta_2)$
Model 3	$V_1 = \beta_1 + \beta_2(OV)_1 + \beta_3(IV)_1 + \beta_4(FR)_1 + \beta_5(\delta_1)$ $V_2 = \beta_2(OV)_2 + \beta_3(IV)_2 + \beta_4(FR)_2 + \beta_5(\delta_2)$

Data Sampling

The three models are calibrated with a data set containing disaggregate information associated with 327 bus riders in Taipei. The data collection was done during the period from December 1985 through January 1986. There were 1,850 bus riders randomly selected and interviewed at the major transfer locations in Taipei, as shown in Figure 1. Each interviewee was asked to provide detailed data associated with the interviewee's previous bus trips. The data items included estimates of service attributes (walk time, wait time, bus fare, and in-vehicle travel time) as well as the path choice made during the last bus trip. Among those 1,850 interviewed, 327 riders provided complete information on their experienced path choices, forming the basis of the data set used for model calibration.

Some characteristics of the 327 sampled bus riders are as follows:

1. Age is approximately normally distributed; the majority (63.6 percent) is in the range of 20 to 30 years of age.
2. In occupation 54.4 percent of the sampled riders are students; 20.4 percent work for private business or industries, and 12.9 percent for government agencies; the other 12.3 percent are not employed.
3. Most trips are school trips (53.8 percent) and work trips (34.3 percent); the other 11.9 percent of trips are social and shopping trips.
4. Sampled riders using discount tickets amount to 56.3 percent.

No statistical tests have been conducted to show the lack of bias of the sample of 327 bus riders. Yet the aforementioned characteristics of the sample show a reasonable profile of transit travel in Taipei; the sample is thus deemed appropriate for representing the target population of riders who regularly face the binary path choices defined by our models.

Model Calibration

The TROMP computer package developed by Sparmann and Daganzo *(10)* was applied to calibrate the three binary logit

TABLE 3 CALIBRATION RESULTS

(Sample Size : N = 327)

Attribute	Model 1		Model 2		Model 3	
	$\hat{\beta}$	t*	$\hat{\beta}$	t	$\hat{\beta}$	t
Constant Term, β_1	0.328	1.695	0.600	2.815	0.446	2.168
Walk Time, WK	-0.133	-5.143	-0.121	-4.430	NA**	NA
Wait Time, WT	-0.078	-4.089	-0.059	-2.870	NA	NA
Out-of-Vehicle Time, OV	NA	NA	NA	NA	-0.081	-4.776
In-Vehicle Time, IV	-0.028	-2.194	-0.020	-1.421	-0.023	-1.589
Bus Fare, FR	-0.123	-2.502	-0.134	-2.508	-0.124	-2.387
Dummy Variable, δ	NA	NA	0.875	5.382	0.858	5.474
$LL(\hat{\beta})$	-178.668		-160.307		-162.674	
$LL(0)$	-226.659		-226.659		-226.659	
$\rho^2 = 1 - \frac{LL(\hat{\beta})}{LL(0)}$	0.212		0.293		0.282	

* Asymtotic t value

** Not Applicable

models specified in Table 2. Calibration results of each model included the estimates of coefficients $\hat{\beta}$, the asymptotic *t* values of the estimates, and the value of the likelihood ratio index ρ^2. These results are presented in Table 3.

As shown in Table 3, all three models yield estimates of reasonable signs, explaining logical travel behavior underlying the specified utility functions. Nevertheless, Model 1 does not yield a statistically significant estimate of β_1, which is essential for the assessment of the transfer penalty, and thus cannot be accepted for further analysis. Models 2 and 3 yield similar results; both yield a ρ^2 value greater than 0.28 and statistically significant estimates of all parameters except for that of in-vehicle travel time *IV* (of which the absolute asymptotic *t* value is less than 2). Yet Model 2 explores significantly different values of walk time *WK* and wait time *WT*; thus, calibration results of Model 2 will be used for determining the values of transfer penalties and other related service attributes.

The choice behavior of bus riders using regular tickets is not much different from that of bus riders using discount tickets. As shown in Table 4, Model 2 yields statistically indifferent results when calibrated with two subsamples of regular and discount ticket users. The formal statistical test procedure given in the appendix shows no significantly different taste variations between the two subgroups of transit users in Taipei. Therefore, the assessment of transfer penalties will be made for all transit users in Taipei as a whole; detailed assessment for different subgroups of bus riders seems unnecessary.

ASSESSMENT RESULTS AND DISCUSSION

The values of transfer penalty and other related attributes can now be determined on the basis of the calibration results of Model 2. Specifically, the estimate of a coefficient in the utility functions represents the value in utility units per unit of its corresponding attribute. The negative of the estimated constant β_1 represents the disutility or penalty of one transfer. Time or money equivalents of the values of each attribute can be obtained from the ratios between appropriate pairs of the estimates. The assessment results are given in Table 5.

TABLE 4 RESULTS OF TWO SUBSAMPLES

Attribute	Regular Ticket Users (N=143)		Discount Ticket Users (N=184)	
	$\hat{\beta}$	t	$\hat{\beta}$	t
Constant Term, β_1	0.605	1.748	0.665	2.522
Walk Time, WK	-0.112	-2.844	-0.131	-3.164
Wait Time, WT	-0.068	-2.509	-0.045	-1.546
In-Vehicle Time, IV	-0.019	-0.951	-0.023	-1.385
Bus Fare, FR	-0.140	-2.006	-0.111	-1.334
Dummy Varialbe, δ	0.956	3.641	0.857	4.420
$LL(\hat{\beta})$	-65.233		-94.626	
$LL(0)$	-99.120		-127.539	
$\rho^2 = 1 - \frac{LL(\hat{\beta})}{LL(0)}$	0.342		0.258	

As presented in Table 5, the disutility of one bus transfer perceived by an average transit user in Taipei is approximately equivalent to 4.5 N.T. dollars (about 14 U.S. cents, assuming an

TABLE 5 ASSESSMENT RESULTS

Attribute / Value	In-Vehicle Time (minute)	Wait Time (minute)	Walk Time (minute)	Bus Fare (N.T. Dollar)	Transfer Penalty* (utility unit)
Estimate of Coefficient (utility unit)	-0.020	-0.059	-0.121	-0.134	-0.600
Money Equivalency (N.T. Dollar)	0.15	0.44	0.90	1.00	4.48
In-Bus Travel Time Equivalency (minute)	1.00	2.95	6.05	6.70	30.00
Wait Time Equivalency (minute)	0.34	1.00	2.05	2.27	10.17
Walk Time Equivalency (minute)	0.16	0.49	1.00	1.11	4.96

*The disutility of one bus transfer.

exchange rate of 1 U.S. dollar to 32 N.T. dollars), 5 min of walk time, 10 min of wait time, or 30 min of in-bus travel time. These values suggest that in current practice transit planners may underestimate the transfer penalty to bus riders. Consequently, a truly optimal transit network structure might be more connective than what transit planners originally thought.

The estimated values of walk time, wait time, and in-bus travel time associated with transit travel in Taipei are also given in Table 5. The value of in-bus travel time is approximately 9 N.T. dollars (28 U.S. cents) per hour, which is about 10.5 percent of the hourly wages of an average worker in Taipei. The value of wait time is about 26.4 N.T. dollars (82.5 U.S. cents) per hour, and the value of walk time is about 54 N.T. dollars (1.68 U.S. dollars).

The values of walk time and wait time are six and three times of the value of in-bus travel time, respectively. The apparently overestimated value of walk time implies that pedestrians in Taipei are experiencing significant inconvenience or unpleasantness when they walk on the streets because the design of traffic signs and signals in Taipei tends to ignore the pedestrian traffic. Pedestrians in Taipei also lack adequate walking space. Many sidewalks are blocked with parked motorcycles, and most covered walkways are constantly crowded with stalls of illegal peddlers. All this makes it difficult for pedestrians to move about in Taipei.

The first available bus has a tremendous influence on the transit behavior of bus riders in Taipei. As shown in the calibrated utility function of Model 2 (Table 3), the preference for the first available bus is even greater than that for avoiding a bus transfer: $\beta_6 = 0.875$, which is greater than $\beta_1 = 0.60$. This difference means that a bus rider in Taipei is likely to get on board the first available bus, even if it requires a transfer en route. Specifically, all other factors being equal, a first available bus requiring one transfer en route would be preferred with a probability of 0.56. This preference implies that when the capacity of a transit system is not sufficient to carry its demand, bus riders might be more concerned about getting on a bus than about avoiding bus transfers.

The assessment results and implications reported in this paper may not apply to those transit systems in North America that have relatively low demand volumes as compared to their capacities. To what degree the assessment results of transfer penalty to bus riders in Taipei can be transferred or applied to transit systems in other geographic areas appears to be an interesting question and needs to be further studied.

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APPENDIX: TEST OF TASTE VARIATIONS BETWEEN TWO GROUPS OF TRANSIT USERS IN TAIPEI

The transit users in Taipei can be divided into two groups: one that uses regular tickets; the other, discount tickets. Let two market segments, $g = 1$ and 2, which represent regular and discount ticket user groups, respectively, be defined. To test if there are significant taste variations between these two groups of transit users in Taipei, the following hypothesis testing is performed.

The null hypothesis is that there are no taste variations between the two groups of users or market segments, that is,

$$H_0: \quad \beta^1 = \beta^2$$

where β^g is the vector of coefficients of market segment g (g = 1, 2). The test statistic is given by

$$-2\left[L_N(\hat{\beta}) - \sum_{g=1}^{2} L_{N_g}(\hat{\beta}^g)\right]$$

where

$L_N(\hat{\beta})$ = the maximum log likelihood of the restricted model that is estimated on the pooled data set with N observations, and

$L_{N_g}(\hat{\beta}^g)$ = the maximum log likelihood of the model estimated on the gth subset of the data with N_g observations (g = 1, 2).

From Tables 3 and 4, using the results of Model 2,

$N = 327$,
$N_1 = 143$,
$N_2 = 184$,
$L_N(\hat{\beta}) = -160.307$,
$L_{N_1}(\hat{\beta}^1) = -65.233$, and
$L_{N_2}(\hat{\beta}^2) = -94.626$.

The value of the test statistic is thus 0.448.

The test statistic as just defined is χ^2 distributed with six degrees of freedom. At $\alpha = 0.05$, the critical value is $\chi^2_{0.05,6}$ = 12.592, which is larger than the calculated test statistic, 0.448. Therefore, H_0 cannot be rejected. This result implies that there are no significant taste variations between the two groups of transit users in Taipei.

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Forecasting Intermodal Competition in a Multimodal Environment

KEVIN NEELS AND JOSEPH MATHER

In this paper, the problem of accurately describing patterns of intermodal competition in a situation in which there are a large number of alternative modes available is discussed. This research was motivated by efforts to increase the capacity and usage of the existing Hudson River crossings connecting Manhattan and northern New Jersey. This corridor is characterized by the presence of an unusually large number of distinct transportation options and a high level of transit use. In such a setting, it is important to know not just how many commuters might use a new service, but also from which existing services they would be drawn. The mathematical structure of an innovative model developed for NJ Transit and the Port Authority of New York and New Jersey to allocate demand across seven primary modes is presented. The representation of intermodal competition that this model provides is considered, and its properties are contrasted with those of some commonly used variants of the familiar logit model. Empirical estimates of the own- and cross-elasticities of demand implied by the model coefficients are broken down by mode, service attribute, and geographic area.

In recent years the situation in the corridor connecting northern New Jersey and Manhattan has been described as a crisis. In the early 1980s after a decade of relative stability, the demand for travel across the Hudson River into Manhattan began to grow. As a result of changes in the structure and growth rate of the Manhattan economy, as well as shifts in the pattern of development in northern New Jersey, peak travel demand in the trans-Hudson corridor increased substantially throughout the early years of the decade. Because of the geography of the region and the structure of its transportation network, all of these trips had to funnel through one of a limited number of river crossings. Congestion at these bottlenecks increased dramatically, generating serious needs for extra capacity and improvements in service.

NJ Transit, the agency charged with responsibility for provision of public transportation services in the state of New Jersey, responded to this need by initiating a major program of improvements to the trans-Hudson system. A wide range of proposals was developed to increase the capacity and use of the existing Hudson River crossings. In order to assess the cost-effectiveness of these proposals and design the package of improvements that would relieve the crisis in the most efficient way, NJ Transit needed a planning tool that would permit the agency to predict the responses of trans-Hudson commuters to the proposed improvements. In cooperation with the Port Authority of New York and New Jersey, NJ Transit asked Charles River Associates to develop a modal split model for the northern New Jersey-Manhattan travel market.

It was immediately apparent that in order to address the key policy questions raised by the trans-Hudson crisis and NJ Transit's efforts to resolve it, it was essential that the model provide an accurate representation of intermodal competition in the corridor. In this complex multimodal environment characterized already by extremely heavy transit usage, policy makers and planners had to know not just how many commuters might be attracted to a new service, but also from where they would be drawn. To contribute to the solution of the trans-Hudson crisis, a transportation improvement had to draw commuters out of automobiles and other low-occupancy vehicles, and not simply cannibalize existing transit ridership.

How the model was developed and the problem of intermodal competition are described in this paper. The next section describes in general terms the form and specification of the model. The mathematical properties of this specification are then analyzed, and formulas are derived for own- and cross-elasticities of demand and contrasted with the formulas of the more common multinomial logit (MNL) model. A fourth section discusses empirical results. In the conclusion, the implications of this work for travel demand forecasting are considered.

MODEL SPECIFICATION

The model allocates travel demand across seven distinct travel modes. These include automobile, three combinations of conventional transit (bus, commuter rail with a PATH trans-Hudson link, and commuter rail to Manhattan), two fringe park-and-ride modes (using either bus or PATH for the trans-Hudson segment), and local PATH (which as a mode in itself is defined to be available only within an inner core area along the Hudson River).

The explanatory variables used to define the level of service along each trip segment are those traditionally found in mode choice models. These include variables describing ease of access and egress, wait time, transfer time, cost, and line-haul time. To take into account the multimodal trans-Hudson environment, the model incorporates separate coefficients for the different types of line-haul time to capture the distinctly different characteristics of the different line-haul technologies.

The model was formulated as a set of logistic regression equations estimated across origin-destination (O-D) pairs *(1)*. The dependent variable in each equation consisted of the log of the ratio of the transit share for the mode in question for that O-D pair, divided by the corresponding automobile share. Six

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equations were estimated—one for each transit mode. The automobile mode was thus used as the reference mode, and the automobile share was computed from the log-odds ratio predictions using the constraint that the estimated shares had to sum to one. The mathematical form of the resulting model is expressed in Equation 1.

$$\log(S_i/S_a) = a_0 + a_1X_1 + \ldots + a_nX_n \tag{1}$$

where

S_i = share for Transit Mode i;
S_a = share for automobile mode,
X_i = explanatory Variable i and
a_i = estimated Coefficient i.

Each demand equation contains three sets of independent variables: measures describing the service offered by the subject mode; measures describing the service offered by competing alternatives (which include the reference automobile mode); and measures describing characteristics of the O-D pair itself. The latter category includes selected socioeconomic variables, as well as dummy variables specifying whether or not specific modes are available for trips between that origin and destination.

The definitions of the variables included in the model, as well as the data sources and procedures used for model estimation, are described in more detail in another paper by Neels and Mather in this Record.

PROPERTIES OF THE MODEL

The principal advantage of this formulation is its explicit representation of the attributes of the competing modes. The presence of these variables permits a pair of modes to be either close or distant substitutes. The degree of competition between them can vary continuously between these two extremes, and be estimated empirically. Thus, both the independence of irrelevant alternatives problem that characterizes the MNL model and the sometimes arbitrary groupings that are often found in nested logit models can be avoided. In this respect, the trans-Hudson model represents a considerable advance in the analysis of travel behavior in multimodal environments.

The ability of the model to capture complex patterns of intermodal competition can best be illustrated by an examination of the formulas it implies for the own- and cross-elasticities of demand with respect to level-of-service variables. The formulas for these elasticities of demand are derived in this section. The next section presents values for selected elasticities derived from the model coefficients.

Elasticity of demand for travel with respect to some level-of-service variable I is defined as

$$n_{Im} = \frac{dT_m}{T_m} \div \frac{dI}{I} \tag{2}$$

where

n_{Im} = elasticity of demand for Mode m with respect to level-of-service variable I;
T_m = volume of trips made by Mode m, and
I = a level-of-service variable such as automobile travel time or bus cost.

In the multimodal framework of the model, I can describe an aspect of the level of service offered by Mode m, or a measure of the level of service offered by any competing mode.

The modal split model assumes implicitly that the total number of trips remains constant, and that any change in the level of demand for a particular mode is the result of modal shifts. Equation 2 can thus be rewritten as

$$n_{Im} = \frac{dS_m}{S_m} \div \frac{dI}{I} \tag{3}$$

where S_m is the share of trips made by Mode m.

In calculating elasticities with respect to the level-of-service variable I, all other level-of-service variables are held constant. This assumption implies that

$$dS_m = \frac{\partial S_m}{\partial I} dI \tag{4}$$

Substituting Equation 4 into Equation 3 yields

$$n_{Im} = \frac{\partial I}{\partial S_m} \cdot \frac{S_m}{I} \tag{5}$$

To complete the derivation of the formula for the demand elasticity, the particular functional form of the line haul mode share model must be considered and the partial derivative $\partial S_m/\partial I$ must be evaluated.

The line-haul mode share model takes the general form

$$\ln(S_i/S_A) = a_0 + b_1I_1 + \ldots + b_nI_n \tag{6}$$

where

S_i = share of trips for Transit Mode i,
S_A = share of trips for automobile mode, and
$I_1, \ldots, I_n$ = explanatory variables.

The overall mode will include one such equation for each of the six line-haul transit modes. The explanatory variables can refer to the level of service offered by the subject mode, or by any competing mode. For the purposes of this derivation, all six demand equations are assumed to contain the same set of explanatory variables but different variable coefficients. Some coefficients, of course, can be equal to zero.

In computing the partial derivative, all explanatory variables except the one of interest are held constant. Thus, the explanatory variables can be folded into the constant term, and without loss of generality the system of equations can be expressed as

$$\ln(S_i/S_A) = c_i + b_iI \qquad (i = 1, \ldots, 6) \tag{7}$$

referring to the six transit modes; and c_i, b_i are the constant terms and coefficients of variable I in Equation 7.

The share for automobiles can be computed as a residual. Solving the set of equations for S_A yields

$$S_A = \frac{1}{1 + \sum_{j=1}^{6} \exp(c_j + b_j I)} \tag{8}$$

From Equations 7 and 8 it can be shown that

$$S_i = \frac{\exp(c_i + b_i I)}{1 + \sum_{j=1}^{6} \exp(c_i + b_i I)} \tag{9}$$

Therefore,

$$\frac{\partial S_i}{\partial I} = \frac{b_i \exp(c_i + b_i I)}{1 + \sum_{j=1}^{6} \exp(c_j + b_j I)} - \frac{\left[\sum_{j=1}^{6} b_j \exp(c_j + b_j I)\right] \exp(c_i + b_i I)}{\left[1 + \sum_{j=1}^{6} \exp(c_j + b_j I)\right]^2} \tag{10}$$

With the help of Equations 8 and 9, this expression can be simplified to

$$\frac{\partial S_i}{\partial I} = S_i \left(b_i - \sum_{j=1}^{6} b_j S_j\right) \tag{11}$$

Substitution of Equation 11 into Equation 5 then yields

$$n_{Ii} = I \left(b_i - \sum_{j=1}^{6} b_j S_j\right) \tag{12}$$

where n_{Ii} is the elasticity of demand for Travel Mode i with respect to level-of-service variable I.

The specification used for the trans-Hudson mode choice model includes the MNL model as a special case. In the standard MNL context, a demand equation of the form shown in Equations 1 and 6 for a transit mode would include only level-of-service variables associated with that mode and the reference mode of automobiles. As a result, in the formula shown in Equation 12,

$$b_j = 0 \qquad \text{for all } j \neq i. \tag{13}$$

If I represents a level-of-service variable associated with Mode i, Equation 12 reduces to

$$n_{Ii} = I b_i (1 - S_i) \tag{14}$$

which is the formula for the own-elasticity of demand implied by the multinomial logit model.

If I represents a level-of-service variable associated with some Mode $i \neq j$, Equation 12 reduces to

$$n_{Ii} = -I b_j S_j \tag{15}$$

which is, of course, the formula implied for the cross-elasticity of demand implied by the MNL model.

Note that the formula shown in Equation 15 is independent of i. Thus, the cross-elasticity of demand with respect to level-of-service Variable I will, in the MNL model, be the same for all other modes. If one mode is improved, the MNL model predicts that it will draw share from all other modes in proportion to their current shares. In the trans-Hudson context, where there are seven distinct modes, some of which are closely related, this is a restrictive and unrealistic assumption.

RESULTS

Because the value for the elasticity depends on both modal shares and the value taken by the level-of-service variable, it was necessary to select a reference point in order to calculate what values the model implies for own- and cross-elasticities of demand. The point chosen represents average conditions in the Newark Division—the portion of New Jersey served by NJ Transit commuter trains running through Newark and on to Penn Station, New York. Values calculated for selected own-elasticities of demand using the formula shown in Equation 12 and the estimated mode coefficients are presented in Table 1.

The different modes presented in Table 1 differ dramatically in their sensitivity to changing levels of service. With their low modal shares, the two park-and-ride modes show the greatest sensitivity to changes in level of service. This sensitivity is especially pronounced in connection with access time, which constitutes a large fraction of the total trip time for these modes. In contrast, the two commuter rail modes show much less sensitivity to changes in the level of service. Automobiles and buses fall between these two extremes.

The elasticity values reflect the geometry of the transportation system. Although demand for direct rail is less sensitive than demand for rail with transfer to PATH to changes in travel time or travel cost, it is much more sensitive to changes in ease of access. Their differing responses to changes in access time reflect the fact that whereas rail with transfer to PATH is relatively ubiquitous, direct rail service to Penn Station, New York, is available only in the Newark Division. Demand for direct rail service from an area is thus strongly influenced by that area's proximity to the lines offering that service.

In general, the elasticity values presented in Table 1 are considerably higher than those normally found in travel demand research. This higher level of sensitivity is attributable to the large number of alternatives that are available in this region and represented in the model.

Table 2 presents own-elasticities of demand for the different modes with respect to cost, broken down by geographic area. The Newark Division, which was described briefly earlier, constitutes the southern portion of the study region. The Hoboken Division, which is served by NJ Transit commuter rail services terminating in Hoboken, constitutes the northern portion of the study region. The local PATH area, which comprises the remainder, consists of the portions of Hudson and Essex counties served directly by the PATH system.

TABLE 1 SELECTED OWN-ELASTICITIES OF DEMAND, BY MODE, NEWARK DIVISION

Mode	Elasticity of Demand with Respect to: Line Haul Time	Cost	Access Time
Auto	-2.69	-2.21	N.A.
Bus	-1.10	-0.64	-0.89
Auto-to-Bus	-0.95	-2.04	-9.21
Rail-to-PATH	-0.93	-0.58	-0.89
Auto-to-PATH	-1.02	-1.25	-7.73
Direct Rail	-0.37	-0.24	-1.61

SOURCE: Calculations from mode split model coefficients and level of service data.

TABLE 2 OWN-ELASTICITIES OF DEMAND WITH RESPECT TO COST, BY MODE AND GEOGRAPHIC AREA

Mode	Hoboken Division	Newark Division	PATH Area
Auto	-1.52	-2.21	-1.57
Bus	-0.38	-0.64	-0.30
Auto/Bus	-1.55	-2.04	-1.07
PATH	N.A.	N.A.	-0.19
Rail/PATH	-0.49	-0.58	N.A.
Auto/PATH	-1.14	-1.25	N.A.
Direct Rail	N.A.	-0.24	N.A.

SOURCE: Calculations from mode split model coefficients and level of service data.

TABLE 3 OWN- AND CROSS-ELASTICITIES OF DEMAND WITH RESPECT TO LINE-HAUL TIME: NEWARK DIVISION

	With Respect to Line Haul Time of:					
Demand For:	Auto	Bus	Auto/Bus	Rail/PATH	Auto/PATH	Rail
Auto	-2.69	0.04	0.01	0.30	0.15	0.07
Bus	0.20	-1.10	0.01	0.36	0.15	0.07
Auto-to-Bus	1.65	0.04	-0.95	0.30	0.15	0.07
Rail-to-Path	0.22	1.13	0.01	-0.93	0.15	0.09
Auto-to-Path	1.58	0.04	0.01	0.30	-1.02	0.09
Direct Rail	0.21	0.04	0.01	0.36	0.15	-0.37

SOURCE: Calculations from mode split model coefficients and level of service data.

The elasticity values in the Newark Division, where more alternatives are available, are without exception higher in absolute value than the corresponding values for the Hoboken Division. This fact emphasizes once again the effect that the presence of a large number of alternatives has on individual elasticity values. Conversely, elasticities are lower in the local PATH area because of the smaller number of trans-Hudson modes available there. In addition, the price elasticity of demand for PATH is low because of the huge share of the market that PATH commands in that area. In effect, there are few trans-Hudson commuters left to be diverted to PATH.

Table 3 presents the own- and cross-elasticities of demand with respect to line-haul time that the model implies for the Newark Division. Here the ability of this specification to provide a flexible treatment of a large number of travel alternatives is apparent. The first column of the table shows that an improvement in automobile travel time will have a major effect on demand for the two park-and-ride modes, and much less effect on demand for the more traditional transit alternatives. The second column shows that improvements in regular bus service are likely to have a much bigger effect on use of the rail with transfer to PATH option than on other transit modes. This result confirms impressions formed by NJ Transit staff based on recent shifts in patterns of demand. The third column, however, indicates that a change in automobile-to-bus travel time would be likely to have a uniform effect on the demands for other modes. The competing mode terms in Equation 1 were insignificant for automobile-to-bus mode, providing direct statistical support for the appropriateness in this case of the IIA assumption. A similar result was found in the case of the automobile-to-PATH mode. Changes in travel time for either rail with transfer to PATH or direct rail would have differential effects on demands for the other modes, although in these cases the differences are not pronounced.

CONCLUSION

The results presented are intuitively plausible, and generally conform closely to the expectations of knowledgeable observers of recent developments in the trans-Hudson travel corridor. They demonstrate the ability of this model form to provide a sensitive, accurate treatment of the complex multimodal environment of the northern New Jersey to Manhattan market. With seven primary modes and an empirically estimated pattern of intermodal competition, this model represents a considerable advance in the ability to deal with markets of this type. It has proven to be a useful, flexible tool for evaluating potential solutions to the trans-Hudson crisis.

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Modeling Mode Choice in New Jersey

KEVIN NEELS AND JOSEPH MATHER

In this paper, a mode choice model developed for NJ Transit and the Port Authority of New York and New Jersey to assist in the evaluation of proposals for increasing the capacity and use of the existing Hudson River crossing connecting Manhattan and northern New Jersey is described. The model focuses on the choices of a.m. peak period eastbound commuters. It allocates demand across seven primary modes, including automobile, bus, two park-and-ride modes (automobile to bus and automobile to PATH), and three rail modes (commuter rail to Penn Station, commuter rail with transfer to PATH, and local access to PATH). The emerging trans-Hudson crisis that provided the impetus for the model development effort, the planning program of which it was a part, the data sources used in the effort, the specification of the model, the procedures used to estimate the model coefficients, the statistical results of the model estimation, and the model's forecasting performance are also discussed.

In this paper, the mode choice model developed by NJ Transit, the Port Authority of New York and New Jersey, and Charles River Associates is described. This model is explicitly designed to be sensitive to the presence and comparative quality of the large number of travel alternatives available in that market. With the large number of modes it handles (seven) and the flexible way in which it captures intermodal competition, it represents one of the most ambitious efforts to date to forecast travel demand in a complex, multimodal environment.

The model was developed to help NJ Transit and the Port Authority to deal with the trans-Hudson crisis. Over the past several years, the growth in service employment in Manhattan has stimulated a rapid increase in journey-to-work travel. Largely a result of its high-quality and comparatively inexpensive housing stock, New Jersey has provided a growing share of the workers filling these new jobs. According to the Bureau of the Census, in 1980, 10 of every 100 Manhattan jobs were held by New Jersey residents. However, recent Port Authority estimates suggest that of the new Manhattan jobs being created in the late 1980s, 34 of every 100 jobs will be held by New Jersey residents. Already in the first half of the decade, trans-Hudson commuters have experienced lengthening backups and delays at the Hudson River crossings and passenger loadings that strain the capacity of trans-Hudson transit links. The trans-Hudson crisis is due to the system's inability to serve current demand and the constraint this places on New Jersey's economic development.

Because of the problems the model was intended to address, the development team had to strike a balance among a number of distinct and sometimes conflicting goals. There were a number of important features that were incorporated into the model, including

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- Statistical estimation of model parameters,
- Accurate representation of intermodal competition,
- Appropriate responses to policy changes,
- High levels of forecast accuracy, and
- Ease of estimation and use.

The primary requirement was that the model parameters be estimated statistically from locally collected data. This procedure was the only way to achieve the best fit to the data, to ensure that the model parameters fully reflected local patterns of behavior, and to guarantee the objectivity of the model results.

It was also critically important that the model be able to deal with the large number of modal alternatives that are available in the trans-Hudson commuter market and provide an accurate representation of the complex patterns of competition that exist among them. In this complex, multimodal environment characterized already by extremely heavy transit usage, policy makers and planners had to know not just how many commuters might be attracted to a new service, but also from where they would be drawn. To contribute to the solution of the trans-Hudson crisis, a transportation improvement had to draw commuters out of automobiles and other low-occupancy vehicles, and not simply cannibalize existing high-capacity transit ridership.

It was decided early in the development effort to build into the model appropriate responses to key policy variables. The most important goal of the calibration effort was to produce a model that would provide appropriate and accurate predictions of the responses of trans-Hudson commuters to changes in service levels or modal attributes. To achieve this goal, the process had to build into the model appropriate values for the key behavioral parameters. Specifically, the model had to imply reasonable values for self- and cross-elasticities of demand. It also had to be sensitive to the service attributes that were important from a policy point of view.

Because the output of the model would be used to evaluate the financial feasibility of alternative capital improvements and to make key engineering decisions regarding capacity and station location, it was essential that the model be able to reproduce and forecast patterns of travel behavior with a high degree of accuracy.

Because this model was to be a working model that would be used on an ongoing basis to analyze and solve practical planning problems, it was important that the model be easy to estimate and easy to use. The goal was to develop an easily applied forecasting tool that could be used by all agencies to analyze trans-Hudson travel. It was also necessary to develop a model that could be updated by NJ Transit or Port Authority staff or reestimated as better or more recent data became available. These goals led to a decision to rely on microcomputers to build and run the model.

The remainder of this paper is divided into four sections. The section that follows presents the form and specification of the model that emerged from this effort. The third section of the paper describes the sources of data that were used in the model estimation. The fourth section describes procedures used to estimate the model coefficients. The final section presents estimation results and summarizes what was learned.

MODEL SPECIFICATION

The model was formulated as a set of logistic regression equations estimated across origin-destination (O-D) pairs *(1)*. The dependent variable in each equation consisted of the log of the ratio of the transit share for the mode in question for that O-D pair, divided by the corresponding automobile share. Six equations were estimated—one for each transit mode. Automobiles were thus used as the reference mode, and the automobile share was computed from the log-odds ratio predictions using the constraint that the estimated shares had to sum to one. The mathematical form of the resulting model is shown in Equation 1.

$$\log(S_i/S_a) = a_0 + a_1X_1 + \ldots + a_nX_n \qquad (1)$$

where

S_i = share for Transit Mode i;
S_a = share for automobile mode,
X_i = explanatory Variable i and
a_i = estimated Coefficient i.

Each demand equation is composed of three sets of independent variables: measures describing the service offered by the subject mode, measures describing the service offered by competing alternatives (which include the automobile reference mode), and measures describing characteristics of the O-D pair itself. The last category includes selected socioeconomic variables, as well as dummy variables specifying whether or not specific modes are available for trips between an origin and destination.

The principal advantage of this formulation is its explicit representation of the attributes of the competing modes. The presence of these variables permits a pair of modes to be either close or distant substitutes. The degree of competition between them can vary continuously between these two extremes, and can be estimated empirically. Thus, both the IIA problem that characterizes the multinomial logit (MNL) model and the sometimes arbitrary groupings that are often found in nested logit models can be avoided. In this respect, the trans-Hudson model represents a considerable advance in the analysis of travel behavior in multimodal environments.

One of the thorniest problems lay in the definition of the modal alternatives. Mode definition was difficult not only because many different transportation technologies were available in the trans-Hudson market, but also because these technologies were used by commuters in such varied and complex ways. A standard technology-based approach to mode definition in this region might have resulted in only three modes: automobile, bus, and rail. However, a close look at the way in which these traditional modes manifest themselves within the region quickly reveals the inadequacy of this simple trichotomy.

Consider, for example, rail. A substantial number of commuters drive long distances to access PATH, the rapid transit system connecting northern New Jersey and Manhattan. The PATH systems serves two other distinct markets as well: local walk-on or bus access riders, and commuter rail riders who transfer to PATH for the final trans-Hudson leg of their journey. The commuter rail riders transferring to PATH, in turn, make up a different market from that of the commuters who travel directly to Penn Station, New York, on NJ Transit or Amtrak trains.

In order to understand patterns of travel demand in this market it was important to account both for the characteristics of the technology and the way in which it was used by commuters. For this reason, the model was based on modal definitions that reflect distinct patterns of travel behavior, rather than distinct vehicle or guideway technologies. The model allocates travel demand across seven distinct travel modes. These include automobile, three combinations of conventional transit (bus, commuter rail with a PATH trans-Hudson link, and commuter rail to Manhattan), two fringe park-and-ride modes (using either bus or PATH for the trans-Hudson segment), and local PATH (which as a mode in itself is defined to be available only within an inner core area along the Hudson River).

The explanatory variables used to define the level of service along each trip segment are those traditionally found in mode choice models. These include variables describing ease of access and egress, wait time, transfer time, cost, and line-haul time. In a further effort to take into account the multimodal trans-Hudson environment, separate coefficients for the different types of line-haul time were incorporated into the model to capture the distinctly different characteristics of the different line-haul technologies.

Measures of ease of access were constructed using a parallel impedance formulation. This formulation, which is based on an analogy to electrical circuit theory, was used because of its ability to deal with situations in which multiple-access modes are available. The parallel impedance formula reflects both the number of access options available as well as their quality. It has the property that the addition of a new access mode always improves ease of access, regardless of the quality of the new option. Hence it avoids the feeder bus paradox in which the introduction of a new but inferior access mode increases average access time and decreases the share of the line-haul mode that has been improved. The exact formula used is shown in Equation 2 for a two-access mode example.

$$A = \left(\frac{1}{T_w} + \frac{1}{T_a}\right)^{-1} \qquad (2)$$

where

A = ease of access,
T_w = walk access time, and
T_a = automobile access time.

In exactly the same way, egress parallel impedances were calculated for representation of the egress alternatives in this region.

DATA SOURCES

The data set used for estimation of the model coefficients was constructed from two primary sources. A comprehensive set of travel surveys administered by the Port Authority and NJ Transit provided information on patterns of demand and selected socioeconomic characteristics of commuters. A combination of published schedules, time tables, and field measurements provided travel times, cost, frequency, and other level-of-service measures.

The funneling of the entire target travel market through the Hudson River crossings created an environment in which surveying commuters was relatively easy. Partly for this reason, a large body of recently collected travel survey data was available for the model development effort. Within the 2 years preceding the initiation of the project, on-board surveys were administered to bus riders, commuter rail passengers, and users of the PATH system. In addition, comprehensive surveys of users of automobile facilities were available. Usable responses were obtained from approximately 50 percent of all eastbound peak-period trans-Hudson commuters.

Level-of-service variables were developed from schedules, timetables, and field measurements. Starting with times, costs, and frequencies for individual bus and rail lines, the data were first summarized to the minor civil division level for bus and the station level for rail. Subsequent aggregations summarized the information at an O-D level using zone definitions developed specifically for this project.

An early decision was made to rely on an aggregate approach to model development and forecasting. In contrast to many recent model development efforts, the project was carried out in a data-rich environment. Hence, the economies in estimation that disaggregate modeling can offer were not needed. The use of data based on zonal level averages offered a number of advantages. First, the aggregate data structure made it possible to carry out all calibration and forecasting on a microcomputer and thereby realize significant time and cost savings. Second, the small datasets and microcomputer-based processing permitted by an aggregate approach gave the model the potential for wide distribution and easy use. Third, the use of aggregate data permitted the manual generation of much of the initial input data. This last feature was a great advantage in the early stages of the effort, before much progress towards automating the process of developing model inputs was made.

Because the focus of the modeling effort was entirely on peak-period trans-Hudson travel, the trip table was structured to contain one-way (eastbound) trip flows from origins west of the Hudson to destinations east of the Hudson. Working within a practical limit of approximately 1,000 trip interchanges, the study region was divided into a relatively coarse zone system. This zone system used the region's transportation network as a skeletal framework. The commuting region west of the Hudson River was divided into 23 radial corridors. Each corridor was defined around either a rail line, a bus service corridor, or a concentration of automobile users. Within each corridor, variations in residential density and demographic characteristics were used to define three to four concentric sectors, as appropriate. The final zone system in New Jersey was composed of 68 origin zones, each containing an average of 2,916 peak-period trips in an area of 74 mi^2.

The destination area east of the Hudson River was segmented into 10 Manhattan central business district (CBD) analysis zones, with four additional external destination zones to maintain consistency with overall trip control totals. The 10 destination zones considered in the analysis are all in Manhattan, south of 60th Street. These zones were defined from smaller Port Authority zones primarily on the basis of proximity to Manhattan's various transportation terminals.

ESTIMATION

In this section, the procedures followed in calibrating the trans-Hudson mode split model are outlined. Calibration is defined as the full process of bringing up an operational model for practical use. Thus, calibration includes but is not limited to the use of statistical procedures to estimate model coefficients. Much of the hard work involved in achieving the ambitious goals set for this effort actually took place in the calibration process.

Ordinary least squares estimation was used in initial exploratory work. This procedure was consistent with the basic form of the model and with the use of aggregate demand and service data. It generated results quickly and cheaply, and permitted both establishing the basic outlines of the model and refining the data procedures.

In an effort to build the desired policy sensitivity into the model, a number of cross-coefficient constraints were imposed on the various demand equations. These constraints typically set the coefficient for one service attribute to be a multiple of the coefficient for a related service attribute. They were made necessary by the limited amount of variation in these service measures contained in the base data set, and the consequent difficulty of obtaining precise coefficient estimates directly.

Such constraints were relied on heavily in the PATH equation and in the equations for the two park-and-ride modes. For example, in the case of PATH it was important for the sake of completeness and consistency with other modes to consider separately line-haul time, wait time, and transfer time. The PATH system is not extensive, however, and has relatively little variation in service frequency. The only transfer in the entire system is an insignificant across-the-platform transfer at the Journal Square Station. Rather than drop these two variables from the model, relationships found in travel demand literature were used and these two coefficients were set at twice the line-haul time. In this way, the desired policy sensitivity was built into the model.

The use of cross-coefficient constraints solved another potential problem associated with this particular model specification. The incorporation of the competing mode variables presented estimation problems in that there was a large number of such variables. Including all of them could have quickly exhausted the available degrees of freedom. Because all that was sought by including these variables was a general indication of how attractive the alternatives were, the detailed level of service variables for each competing mode were combined into a summary measure of the generalized cost of that mode.

This generalized cost was the sum of the travel cost and the dollar equivalent of a weighted sum of access, waiting, line-haul, transfer, and egress travel times for the competing mode. Access impedance was weighted at three times the value of line-haul time; and waiting, transfer, and egress times were tendency to overestimate shares for these minor modes. To compensate for this problem, a set of threshold limits was estimated that set a lower bound for the estimated share for each mode. These thresholds were set at the values for each mode that best distinguished between zero and nonzero share O-D pairs in the baseline dataset. In applications, mode shares below the threshold limit are set to zero. In effect, the mode split model is applied conditionally, given a prior judgment about which modes will have nonzero shares. That judgment, in turn, is based on the relative attractiveness of the different modal options. This procedure is consistent with the way in which the coefficients of the model were estimated, because in using a logistic regression approach O-D pairs with a zero mode share were eliminated from the estimation dataset.

RESULTS

The following list presents goodness-of-fit and summary statistics for the regression carrying out the simultaneous estimation of the six demand equations.

Statistic	*Value*
R^2	0.6530
Corrected R^2	0.6484
F statistic	142.8
Number of observations	1,999

Despite the large number of primary modes and the complexity and diversity of the region the model describes, the percentage of variation explained by the model is relatively high. The model coefficients are highly significant.

Tables 1–6 present the estimated coefficients of the six individual transit demand equations. As a result of the rich set of data available for model estimation and the use of a priori information in the form of cross-coefficient and cross-equation constraints, the individual coefficient estimates are, as a rule, extremely precise. Standard errors are small.

The ability of the model to replicate the baseline demand data varies somewhat by mode. Automobile and PATH modes are forecast with the highest accuracy. Prediction errors for these modes are about one-third the average number of trips per interchange. The model deals well with these two modes

TABLE 4 REGRESSION RESULTS FOR RAIL-TO-PATH EQUATION IN MODAL-SPLIT MODEL

Variable	Coefficient	Standard Error	T-Statistic
Rail-to-PATH Service Variables:			
Rail-to-PATH Cost	-.2162	.0054	-39.828
Rail-to-PATH Rail Time	-.0301	.0008	-39.828
Rail-to-PATH PATH Time	-.0301	.0008	-39.828
Rail-to-PATH Wait Time	-.0602	.0015	-39.828
Rail-to-PATH Transfer Time	-.0903	.0023	-39.828
Rail-to-PATH Access Impedance	-.1230	.0096	-12.825
Rail-to-PATH Egress Impedance	-.1748	.0217	-8.037
Competing Mode Variables:			
Auto Time	.0364	.0018	20.715
Auto Cost	.2871	.0137	20.927
Bus Generalized Cost	.1840	.0167	11.041
Direct Rail Generalized Cost	.0026	.0004	6.906
Modal Availability Flags:			
Local PATH Market Area Flag	-.1353	.3000	-0.451
Direct Rail Market Area Flag	-.0874	.0127	-6.906
Other Terms:			
Intercept	-2.9703	.5066	-5.863

NOTE: The standard error shown for the intercept term is based upon an approximate calculation that ignores the covariance between the intercept term for the pooled regression and the intercept shift for this equation

SOURCE: Regression Analysis of Travel Demand and Level of Service Data

TABLE 5 REGRESSION RESULTS FOR NONLOCAL PATH EQUATION IN MODAL-SPLIT MODEL

Variable	Coefficient	Standard Error	T-Statistic
Nonlocal PATH Service Variables:			
Nonlocal PATH Cost	-.4835	.0322	15.012
Nonlocal PATH Line Haul Time	-.0623	.0041	-15.012
Nonlocal PATH Wait Time	-.1246	.0083	-15.012
Nonlocal PATH Transfer Time	-.1246	.0083	-15.012
Nonlocal PATH Access Impedance	-.1869	.0124	-15.012
Nonlocal PATH Egress Impedance	-.1246	.0083	-15.012
Competing Mode Variables:			
Auto Time	.0535	.0030	17.639
Auto Cost	.4156	.0236	17.639
Direct Rail Generalized Cost	.0042	.0005	7.970
Modal Availability Flags:			
Direct Rail Market Area Flag	-.1392	.0175	-7.970
Other Terms:			
Intercept	-2.7571	.5361	-5.143

NOTE: The standard error shown for the intercept term is based upon an approximate calculation that ignores the covariance between the intercept term for the pooled regression and the intercept shift for this equation.

SOURCE: Regression Analysis of Travel Demand and Level of Service Data

TABLE 6 REGRESSION RESULTS FOR DIRECT RAIL EQUATION IN MODAL-SPLIT MODEL

Variable	Coefficient	Standard Error	T-Statistic
Direct Rail Service Variables:			
Direct Rail Cost	-.0779	.0254	-3.068
Direct Rail Line Haul Time	-.0104	.0034	-3.068
Direct Rail Wait Time	-.0208	.0068	-3.068
Direct Rail Transfer Time	-.0312	.0102	-3.068
Direct Rail Access Impedance	-.1593	.0141	-11.324
Direct Rail Egress Impedance	-.2367	.0290	-8.176
Competing Mode Variables:			
Auto Time	.0363	.0018	20.663
Auto Cost	.2865	.0137	20.884
Rail-to-PATH Generalized Cost	.0098	.0079	1.248
Modal Availability Flags:			
PATH Market Area Flag	-.1301	.4525	-0.287
Other Terms:			
Northeast Corridor Flag	1.4130	.2180	6.483
Intercept	-.9501	.6480	-1.466

NOTE: The standard error shown for the intercept term is based upon an approximate calculation that ignores the covariance between the intercept term for the pooled regression and the intercept shift for this equation.

SOURCE: Regression Analysis of Travel Demand and Level of Service Data

weighted at twice the value of line-haul time. Time was converted to dollars by using one-half the average hourly wage rate of the users of the competing mode as reported in on-board surveys.

In subsequent refinements of the model a procedure was adopted that permitted estimating the coefficients of all six equations simultaneously. To do this, the estimation datasets for the six demand equations were concatenated and slope shift variables were introduced to allow each equation to take a different set of coefficients. Use of this procedure allowed the imposition of cross-equation constraints on coefficients and use of generalized least squares to correct for cross-equation correlation of error terms in subsequent reestimations.

The ability to impose cross-equation constraints on coefficients permitted more efficient estimation of model coefficients and ultimately improved the policy sensitivity of the model. These constraints were used in two ways: to incorporate prior information about relationships between modes, and to place bounds on the cross-elasticities of demand between modes.

An example of the first use occurred with the two commuter rail modes, where there was ample reason to believe that an extra minute of commuter rail time was viewed in the same way by users of either mode. The coefficients on rail time in the two equations were constrained to be the same, thereby improving the precision of the overall model estimate.

We also used cross-equation constraints to correct a number of instances in which the estimated cross-elasticities of demand between modes were slightly negative. This typically occurred in cases where the modes in question were not close substitutes and where the estimated cross-elasticity was not significantly different from zero. With such constraints, these elasticities could be constrained to remain strictly, though only slightly, positive.

As part of the calibration process, two adjustments to the raw regression results were carried out to improve the model's accuracy in practical applictions.

The first such adjustment corrected for functional form bias. Because the ordinary least squares method was used in connection with a log-odds transformation of the underlying dependent variable, the means of the model's predicted shares did not necessarily equal the means of the raw data. This potential bias was corrected by adjusting the constant terms. A set of mode-specific factors was estimated to adjust the total predicted demand for each mode to the total actual demand found in the base trip table. This procedure resulted in a distribution of over and under predictions at the zone level that summed to zero by mode and were, therefore, unbiased. An iterative process estimated the values of these mode-specific adjustment factors.

The second adjustment improved forecasts of minor share modes. Minor share modes (those attracting less than 2 percent of the trips within an interchange) result from the method used to define the analysis zones. Because these zones are defined around major transportation facilities, they tend to be dominated by a single mode. Hence, at least one of the competing modes typically assumes a small share. For the two park-and-ride modes, which had small shares regionwide, shares at an O-D level would often be zero. Because the log form of the model prevents estimates of a zero share, the model had a

TABLE 1 REGRESSION RESULTS FOR BUS EQUATION IN MODAL-SPLIT MODEL

Variable	Coefficient	Standard Error	T-Statistic
Bus Service Attributes:			
Bus Cost	-.1946	.0164	-11.882
Bus Line Haul Time	-.0182	.0015	-11.882
Bus Wait Time	-.0364	.0031	-11.882
Bus Access Impedance	-.2141	.0303	-7.060
Bus Egress Impedance	-.0364	.0031	-11.882
Competing Mode Variables:			
Auto Time	.0363	.0018	20.629
Auto Cost	.2865	.0137	20.884
Rail/PATH Generalized Cost	.0098	.0079	1.248
Modal Availability Flags:			
Local PATH Market Area Flag	.1921	.1710	1.123
Rail/PATH Market Area Flag	-.3928	.3147	-1.248
Other Terms:			
Percent of All HH's In High Income Category	-.0492	.0052	-9.519
Intercept	-.0233	.3240	-0.072

SOURCE: Regression Analysis of Travel Demand and Level of Service Data

TABLE 2 REGRESSION RESULTS FOR LONG-HAUL AUTOMOBILE-TO-BUS EQUATION IN MODAL-SPLIT MODEL

Variable	Coefficient	Standard Error	T-Statistic
Auto-to-Bus Service Variables:			
Auto-to-Bus Cost	-.5089	.0904	-5.631
Auto-to-Bus Line Haul Time	-.0567	.0101	-5.631
Auto-to-Bus Wait Time	-.1135	.0202	-5.631
Auto-to-Bus Access Impedance	-.1702	.0302	-5.631
Auto-to-Bus Egress Impedance	-.1135	.0202	-5.631
Competing Mode Variables:			
Auto Time	.0545	.0099	5.509
Auto Cost	.4890	.0888	5.509
Other Terms:			
Intercept	-3.8394	.6760	-5.679

NOTE: The standard error shown for the intercept term is based upon an approximate calculation that ignores the covariance between the intercept term for the pooled regression and the intercept shift for this equation.

SOURCE: Regression Analysis of Travel Demand and Level of Service Data

TABLE 3 REGRESSION RESULTS FOR LOCAL PATH EQUATION IN MODAL-SPLIT MODEL

Variable	Coefficient	Standard Error	T-Statistic
Local PATH Service Variables:			
Local PATH Cost	-1.0370	.0917	-11.314
Local PATH Line Haul Time	-.0773	.0068	-11.314
Local PATH Wait Time	-.1545	.0137	-11.314
Local PATH Transfer Time	-.1545	.0137	-11.314
Local PATH Access Impedance	-.2318	.0205	-11.314
Local PATH Egress Impedance	-.1545	.0137	-11.314
Competing Mode Variables:			
Auto Time	.0342	.0015	22.849
Auto Cost	.2831	.0117	24.235
Bus Generalized Cost	.0447	.0046	9.614
Other Terms:			
Intercept	2.6844	.5717	4.695

NOTE: The standard error shown for the intercept term is based upon an approximate calculation that ignores the covariance between the intercept term for the pooled regression and the intercept shift for this equation

SOURCE: Regression Analysis of Travel Demand and Level of Service Data

because each captures a significant number and consistent share of the trips within its market area.

Bus park and ride and PATH park and ride are handled least well. The primary motivation for defining these travel paths as modes was to remove the influence of fringe park-and-ride users from bus and local PATH coefficient estimates. In doing so, two small share modes were created, neither of which had a strong facility orientation. They drew a small market share from a wide region, and were difficult to predict. However, the accuracy of Auto-Bus and Auto-PATH forecasts was judged adequate given the small number of trips these modes attract both across the region and within each interchange. It should also be noted that other modeling efforts are under way at NJ Transit to deal more specifically with the park-and-ride modes and to supplement the more aggregate forecasts of this model.

The uniform forecast accuracy among the conventional transit modes is a positive characteristic of the model. Bus, direct rail, and rail with transfer to PATH are all replicated well by the model. Predictions for these modes are only marginally less accurate than the automobile forecasts. The model is not biased toward any of the conventional transit modes. The model also does not exhibit any strong geographic bias in predictive accuracy. Root mean square errors by mode within the northeast test area (Hoboken Division) are consistent with those throughout the region. Predictive accuracy within the southwest (Newark Division) is generally consistent with the region, though the treatment of automobiles there is somewhat less accurate.

The model has been applied extensively by NJ Transit and the Port Authority of New York and New Jersey, as well as by a variety of consultants to analyze options for improving access, travel times, and capacity in the trans-Hudson corridor. It has proven itself to be a sensitive and flexible tool that has made an important contribution towards resolution of the trans-Hudson crisis.

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North Carolina Procedure for Synthesizing Travel Movements

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A procedure for synthesizing travel movements in small and medium-sized urban areas begun in 1961–1963 by the planning staff of the North Carolina Department of Transportation is described. Four methods are used, depending on the extent of travel surveys done as part of the transportation study. Method 1 uses data from an external-cordon, origin and destination (O-D) survey and small-sample, internal, O-D survey. Method 2 procedures are followed if only an external-cordon, O-D survey is done. Method 3 requires only travel data from an internal O-D survey. Method 4 is followed if no O-D surveys are done. All four methods require comprehensive traffic volume counts and comprehensive inventories of employment, commercial vehicles, and dwelling units. The North Carolina procedure has greatly reduced the time and cost required for the travel-modeling phase of transportation studies and has enabled more time and effort to be devoted to travel forecasting and transportation plan development and evaluation. A brief history of the evolution of the synthesis procedure is included.

If every land area had a sufficient variety of required natural resources; if people had uniformly adequate basic skills; and if people were satisfied with a relatively fixed level of goods, foods, and other benefits, there would be no need for travel. However, natural resources are not evenly distributed, and people have fundamental desires to increase their individual benefits and happiness. These factors have led people to specialize in various endeavors to increase productivity and benefits. This specialization or division of labor and increased benefits have increased the need to travel—in order to trade, work, play, and obtain required services. Today's complex urban society requires extensive travel to fulfill the needs of its population and its economic activity.

Prediction of future travel desires is a basic prerequisite for developing an adequate transportation plan for any urban area. Conventional techniques for travel forecasting have generally involved the development of a series of models that describe travel in terms of major components: *(a)* trip generation, *(b)* trip distribution, and *(c)* transportation system. From inputting of specific future assumptions about factors that create travel, the models produce estimates of future travel. The procedure for travel model development and travel forecasting has traditionally included inventories of travel, socioeconomic data, and transportation facilities; data validation; trip generation model development; transportation system coding and calibration of through-traffic assignment; trip distribution modeling; modal-split modeling; and projection of future travel through projection of future socioeconomic data and input of the data into the travel models. The process has been expensive and time-consuming, particularly in the inventory, data validation, and model development phases.

The purpose of this paper is to describe the synthesis procedure developed by the planning staff of the North Carolina Department of Transportation over more than two decades to shorten, simplify, and reduce the cost of travel forecasting. In the following sections, evolution of the synthesis procedure and current methods of approach is described.

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EVOLUTION OF SYNTHESIS PROCEDURE

The North Carolina experience in transportation planning began with the 1959 General Assembly and the enactment of general statutes requiring cooperative major street planning. These general statutes *(a)* required state and municipal development of a thoroughfare plan; *(b)* provided for state and municipal adoption of the plan; *(c)* required state and municipal agreement on street and highway responsibilities on mutual adoption of the plan; *(d)* defined state and municipal responsibilities; and *(e)* provided for mutual revision of the plan. The statutes applied to all municipalities, but did not affect counties because counties in North Carolina have no road construction or maintenance authority.

In 1958–1962, consultants were used for studies in the larger cities that generally included comprehensive internal-home-interview and external-cordon, origin and destination (O-D) traffic surveys. The basic techniques for projection of travel were the growth factor method *(1)* and the combination growth factor and modified gravity model *(2)*.

Beginning in 1961–1963, travel synthesis was initiated in smaller cities *(3, 4)*. The technique was based on the Iowa gravity model procedures *(5)* using data from a small-sample, home interview, O-D survey and employment data. An external-cordon traffic survey was done. All gravity model computations and traffic assignments were manual.

Following the enactment of the federal transportation planning regulation in 1962, comprehensive studies were required for cities over 50,000 population in the 1964–1971 period. The studies, which were expensive, included comprehensive O-D surveys, extensive gathering of land use and socioeconomic data, use of regression analysis techniques to develop estimating equations for trip productions and attractions, and use of the gravity model for trip distribution.

For smaller urban areas, during 1964–1976, the synthesis procedure for estimating travel was refined in an effort to reduce the cost of planning studies. The refinement included the standardization of procedures, building of a data bank for trip generation rates and trip length frequency curves from internal O-D surveys in 17 urban areas of various size, development of specialized computer programs, and research on procedures for synthesis of through-travel. The cost of internal O-D surveys was reduced in urban areas of less than 50,000 by reducing the sample size to 5 percent based on research by Horn et al. *(6)* and Parsonson and Horn *(7)*. In 1968, Cochrane *(8)* evaluated the ability of the synthesis approach to duplicate traffic volumes on the street system for Mooresville, North Carolina, and concluded the synthesis method had better duplicating ability than did a uniformly upgraded O-D survey. In 1971, Modlin *(9)* developed a method for estimation of external and through-travel that provided means for reducing costs associated with external-cordon traffic surveys. Studies for Marion, North Carolina *(10)*, and Ahoskie, North Carolina *(11)*, were the two earliest studies that used borrowed trip generation rates and trip distribution curves as means for modeling and synthesizing travel movements. A study for Wilkesboro-North Wilkesboro, North Carolina *(12)*, involved the first complete synthesis of all travel patterns—internal, external, and through.

During 1974–1984, dependence on the synthesis methodology and its application to urban areas over 50,000 population increased.

NORTH CAROLINA PROCEDURE FOR MODELING TRAFFIC MOVEMENTS USING A SYNTHESIS APPROACH

The steps involved in the North Carolina modeling procedure followed the conventional sequence of *(a)* study area and traffic zone definition, *(b)* inventory of existing conditions, *(c)* model development, and *(d)* model validation. Procedures varied depending on whether travel data were totally absent or partially available.

Study Area and Traffic Zones

Subdivision of the planning area into traffic analysis zones is the first step in segregation of travel into component parts for model development. Care in delineation of the planning area and zones minimizes potential problems in the synthesis procedure. It is important that the planning area boundary include all the land area that may become urban in character during the usual 20-year design period, that it follow easily defined topographic features, and that it be located so as to minimize the number of street crossings. If an external traffic survey is to be done, it is desirable to minimize the number of external stations to reduce survey cost, or to minimize analysis required if external and through-movements are to be synthesized. An external survey done previously in the area would also be considered.

Traffic analysis zones should define areas of similar lane use, be of regular shape, and contain an area not to exceed 1 mi^2. Typical urban areas have traffic zones that vary in size from 10–15 acres in densely developed areas to 500–600 acres in sparsely developed areas. Considerations in establishing traffic zone boundaries include census tract boundaries; local planning zone boundaries; topographic features; the existing and proposed street system; existing transit routes; and unique or significant travel generators such as airports, shopping centers, sports complexes, hospitals, schools, and universities. Because travel, from the standpoint of the travel forecast models, in theory originates and terminates at centroids of traffic zones, the analyst delineates zones considering the forecast models. The establishment of a large number of small zones means that traffic assignment models are more refined but that more error is likely in estimation of trip generation on a zonal basis. Contrariwise, larger zones produce greater confidence in trip generation estimates on a zonal basis, but less confidence in assignment model results.

One or two screenlines are normally defined that completely bisect the planning area. The screenlines are used to check and validate the travel models. They should follow natural topographic features, cut as few streets as possible to minimize travel inventories, and should be common to traffic zone boundaries.

Inventories

Travel inventories conducted to validate and assist in travel model calibration include *(a)* comprehensive traffic volume counts on segments of the major street network and at external-cordon and screenline stations; and *(b)* some vehicular classification counts at selected external-cordon and screenline stations. Traffic volume counts on street segments are usually taken by automatic traffic counters for minimum periods of 48 hr. Counts at external-cordon and screenline stations are preferably hourly machine counts taken over a 2-week period. Vehicular classification counts at selected screenline stations and external cordon stations are to determine trip distribution by hour of day and vehicle classification. Classification counts may be taken for 8-, 16-, or 24-hr periods.

A small-sample, internal, home interview, O-D survey or external-cordon O-D survey may be done depending on the scope of the study, funds available, and time constraints. An external-cordon traffic survey is usually avoided if at all possible because of the high cost and time required. A small-sample, internal survey of 400–600 dwelling units is needed occasionally to update information in the trip data bank on dwelling unit trip generation rates, trip purpose distribution, and trip length frequency.

Socioeconomic data inventories required for synthesis of travel are employment and number of dwelling units. The employment inventory consists of a survey of all employers in the planning area to determine number of employees and number of trucks, commercial automobiles, and taxis. The dwelling unit inventory identifies the number of dwelling units in each zone by five housing classes—excellent, above-average, average, below-average, and low. A sixth category of housing can be used to identify population in group quarters such as military bases and college campuses.

The employment survey is obtained by field survey by either city staff, state staff, or by temporary employment of a local person by the state or city. The last method has proved to be cost-effective. Two recent inventories were done using this approach for urban areas of 18,000 and 25,000 for less than $1,000 each.

Two procedures have been used to stratify dwelling units into the five housing classifications. If a recent tax assessment had been done for an area, property tax records and maps were used to determine dwelling unit numbers and classes in a cost-effective manner. Because tax reassessment is usually not frequent or recent, the most consistently used procedure for completing the dwelling unit inventory has been to do site inspections of all households and classify them based on specified criteria.

Travel Modeling

Travel modeling is accomplished by one of four methods depending on whether travel inventory data are obtained. The four methods are illustrated by the four flowcharts shown in Figures 1–4.

Method 1

Figure 1 shows the procedure followed if an external-cordon, O-D survey and a small-sample, internal, O-D survey are done as part of the transportation study. The internal O-D survey provides areawide information on dwelling unit trip generation rates, distribution of trips by purpose, and trip lengths. The external O-D survey provides a through-trip table, a summary of external-trip generation and attraction, a total number of internal trips generated by vehicles garaged outside the study area, and information on external trip length.

In Method 1, a multiple linear regression analysis is done to relate external trip attractions to employment and dwelling units. The usual regression form is

$$Y = a + bX_1 + cX_2 + dX_3 + eX_4 + fX_5 + gX_6 \quad (1)$$

where

Y = external trip ends,
X_1 = industrial employment,
X_2 = retail and wholesale employment,
X_3 = highway retail employment,
X_4 = office employment,
X_5 = service employment, and
X_6 = number of dwelling units.

The resulting equation is used as an estimator for external trip attractions and internal, nonhome-based (NHB) trip attractions and internal, other-home-based (OHB) trip attractions.

An internal data summary (IDS) computer program is a key program in the North Carolina synthesis procedure. Inputs to the program are *(a)* occupancy per dwelling unit class; *(b)* trip generation rates for dwelling unit classes; *(c)* trip generation rates for trucks, commercial automobiles, and taxis; *(d)* percentage of internal trips remaining inside the cordon; *(e)* percentage of home-based work (HBW), NHB, and OHB trips; *(f)* number of occupied dwelling units in each class in each zone; *(g)* number of trucks, commercial automobiles, and taxis in each zone; *(h)* total number of internal trips generated by traffic garaged outside the study area; and *(i)* trip attractions by zone. Trip attractions for HBW trips are total zonal employment. Trip attractions for other trips (NHB and OHB) are the factors from the regression equation. The IDS program does the following:

1. Computes total internal trips generated by dwelling units, trucks, commercial automobiles, and taxis for each zone.
2. Reduces the trips generated by the percentage of internal trips that cross the cordon.
3. Separates the remaining trips into HBW, NHB, and OHB trip purposes by zone.
4. Sums NHB trips and adds to internal NHB trips generated by external traffic.
5. Reallocates NHB trip productions to internal zones based on NHB trip attraction factors.
6. Factors HBW, NHB, and OHB attractions to equal productions.

Outputs of the IDS program are *(a)* zonal totals of trip productions and attractions by purpose (HBW, NHB, and OHB), *(b)* zonal and areawide totals of trips; *(c)* zonal and areawide totals of population and employment; and *(d)* zonal and areawide totals of dwelling units, trucks, commercial automobiles, and trips.

Several checks for reasonableness are made on the output of the IDS program. The total trips generated by dwelling units divided by the total number of dwelling units should approximate the areawide trip generation rate. The distribution of dwelling units according to housing condition should be a normal and reasonable distribution. Population estimate totals within corporate limits or townships should be checked against Bureau of the Census data or other independent estimates.

In Method 1, trip data from the small-sample, internal, O-D survey and external-cordon survey are both processed through the trip length distribution (TDIST) computer program that assigns trip data to the existing street network and tabulates the number of trips occurring in each time increment. The output of the TDIST program is plotted and smooth curves are derived from the data.

Two programs in the FHWA battery of computer programs used to calibrate a gravity model and estimate internal and external trips are the gravity model calibration (GMCAL) program and the gravity model (GM) program.

The procedure requires the processing of data through these two programs and validation of the results through assignment of output trip tables to the existing street network.

The standard gravity model form is

$$T_{ij} = P_i A_j F_{ij} K_{ij} + \sum_{j=1}^{n} (A_j F_{ij} K_{ij}) \quad (2)$$

where

T_{ij} = trips produced at i and attracted to j;
P_i = total trip production at i (may be by purpose, mode, etc.);
A_j = total trip attraction at j (may be by purpose, mode, etc.);
F_{ij} = calibration term for interchange ij (travel time factor);
K_{ij} = socioeconomic adjustment factor for interchange ij;

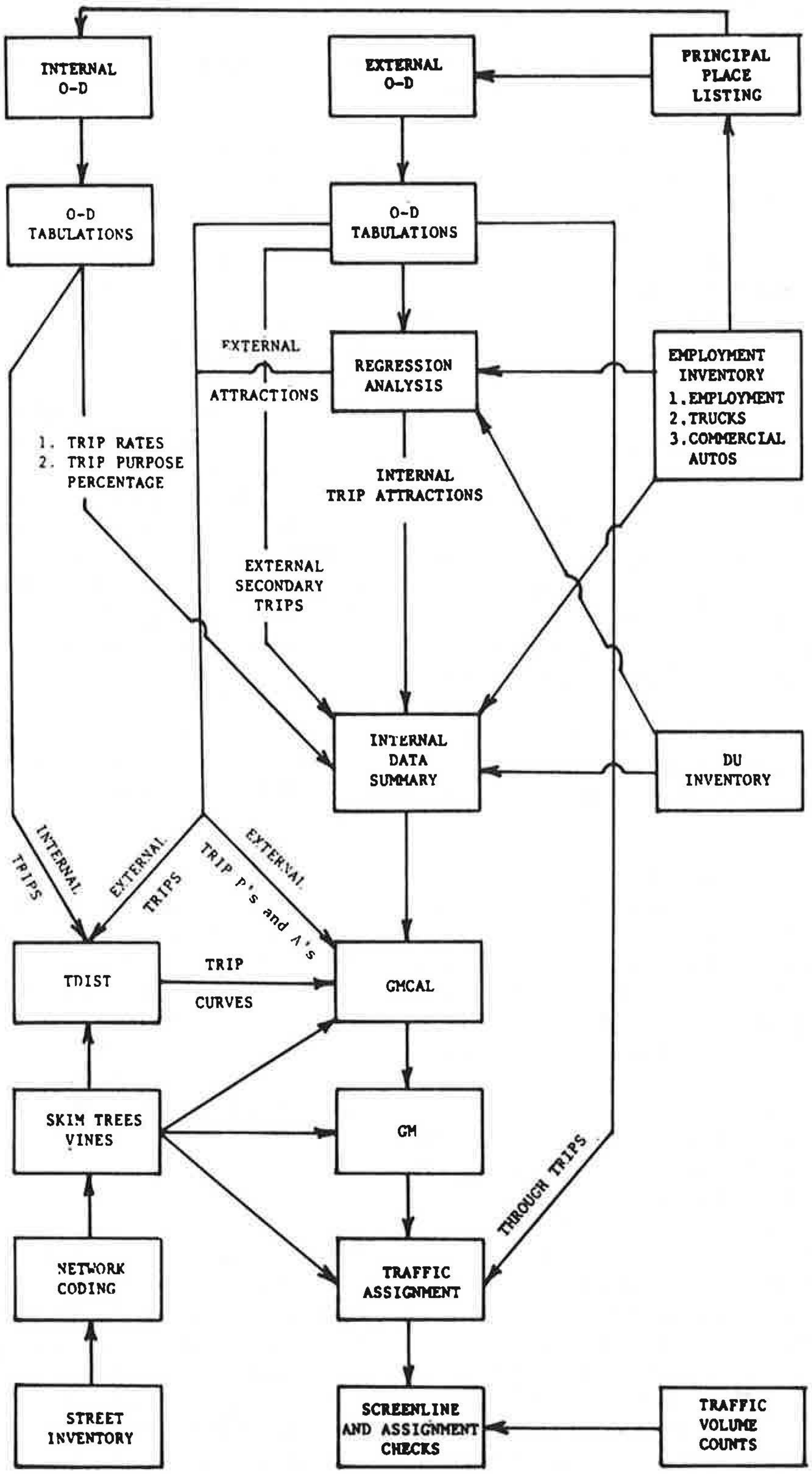

FIGURE 1 Synthesis of travel with small-sample, internal, O-D travel survey and external-cordon, O-D traffic survey.

i = origin zone number ($i = 1, 2, \ldots, n$);
j = destination zone number ($j = 1, 2, \ldots, n$); and
n = number of zones.

The GMCAL program repeatedly adjusts travel time factors (F_{ij}) until a satisfactory match is achieved between the desired areawide trip distribution curve and the output of the gravity model. Input to the program includes the zone-to-zone travel times (termed "skim trees" and "vines"), zonal productions and attractions from the IDS program, and trip length distribution for the trip purpose being analyzed. The user may also supply an initial trial set of F factors and specify the number of iterations desired. For proper operations of the GMCAL program, input must satisfy the following conditions for each trip purpose:

Total P trips = total A trips
= total trips in given distribution curve

One iteration of the GMCAL program involves

1. Computation of trip distribution based on given P and A trips, skim trees and vines, and given, or assumed, F factors.
2. Comparison for each time increment of trips distributed by gravity model to desired trips (input trip distribution).
3. Computation of adjusted F factors on basis of comparison.
4. Smoothing of adjusted F factors by fitting to a smooth curve using the least squares technique.
5. The smooth F factors are subsequently input to the second iteration.

There are opposing views as to whether F factors should conform to a smooth curve. For a large urban area with a large number of analysis zones and extensive transportation network, F factors can reasonably be expected to conform to a smooth curve; but, for smaller urban areas of the size typically found in North Carolina, this expectation may not be reasonable. Distortions in impedances resulting from network configuration or spatial location of travel generators tend to have a more significant effect in distorting impedances.

In North Carolina, the best procedure for accomplishing the GMCAL calibration phase has been to run three iterations of the GMCAL program and selected adjusted F factors from the best iteration for input to a second run of the program. A second run usually results in adequate calibration. F factors chosen should generally adhere to a decreasing number set with the exception of the first and second minutes.

The result of the GMCAL calibration process is a set of F factors for input to the GM program. The objective of the GM program is to produce trip tables that reasonably duplicate the travel patterns existing in the study area. Calibration is achieved in the GM program by holding F factors constant and making adjustments in input attraction factors (A's) until output trips attracted equal desired attractions. Input to the program includes the zone-to-zone travel times (skim trees and vines), zonal productions and attractions, and F factors derived from the GMCAL process.

One iteration of the GM program involves

1. Computation of trip distribution based on given P and A trips, skim trees and vines, and F factors.
2. Comparison by zone of actual trips attracted to desired input attractions.
3. Computation of adjusted attractions on basis of comparison for input to second iteration.

If socioeconomic adjustment factors K_{ij} are used, their need may first appear during the GM calibration phase. Unlike the F factor term, the K_{ij} term applies only to interchange i and j or other points specified. If used, it may be necessary to recycle through the GMCAL calibration phase. A 1972 FHWA manual *(13)* provides good documentation for using K factors.

Trip tables from the GM calibration and through trips are assigned to the existing street network and compared to actual volumes on the system as a check of the ability of the synthesis procedure to reproduce travel. Checks consist of both screenline comparisons and comparisons on an individual link bases. COMPARE, an FHWA computer program, may be used to make the link comparisons.

Some additional network calibration, that is, adjustment in speeds on various links, may be required at this stage. This additional network calibration may require that several of the steps in gravity model calibration be retraced because such changes result in changes in output of the skim trees and vines that is input to the calibration programs. Whether or not such retracing is required depends on the magnitude of changes made in the network.

Care must be exercised during the synthesis process to ensure that the models are not forced to duplicate givens too precisely during calibrations. Throughout the process it is important to remember that there are few if any absolute givens. For example,

1. O-D surveys are only estimates of existing travel;
2. Traffic volume counts and screenline counts are estimates of actual travel on the system;
3. Regression equations and trip rates provide estimates of attractions and productions; and
4. The gravity model provides estimates of travel patterns.

When discrepancies occur, data inputs as well as model performance must be examined before a decision is made as to what is in error.

Method 2

Figure 2 shows the procedure followed if only an external-cordon O-D traffic survey is done as part of the transportation study. The major difference between Method 1 and Method 2 is that borrowed trip generation rates and estimated percentage of internal trip purposes must be used as input to the IDS program. It is also necessary that estimated or borrowed HBW, NHB, and OHB trip distribution curves be used as input to the GMCAL gravity model program.

Average family income from the Bureau of the Census and areawide employment base is normally used as a guide in selecting trip generation rates and trip purpose distribution. The trip generation rates may need to be adjusted for changes in vehicle ownership, vehicle usage, and persons per dwelling unit if the borrowed rates are several years old. Adjustments to

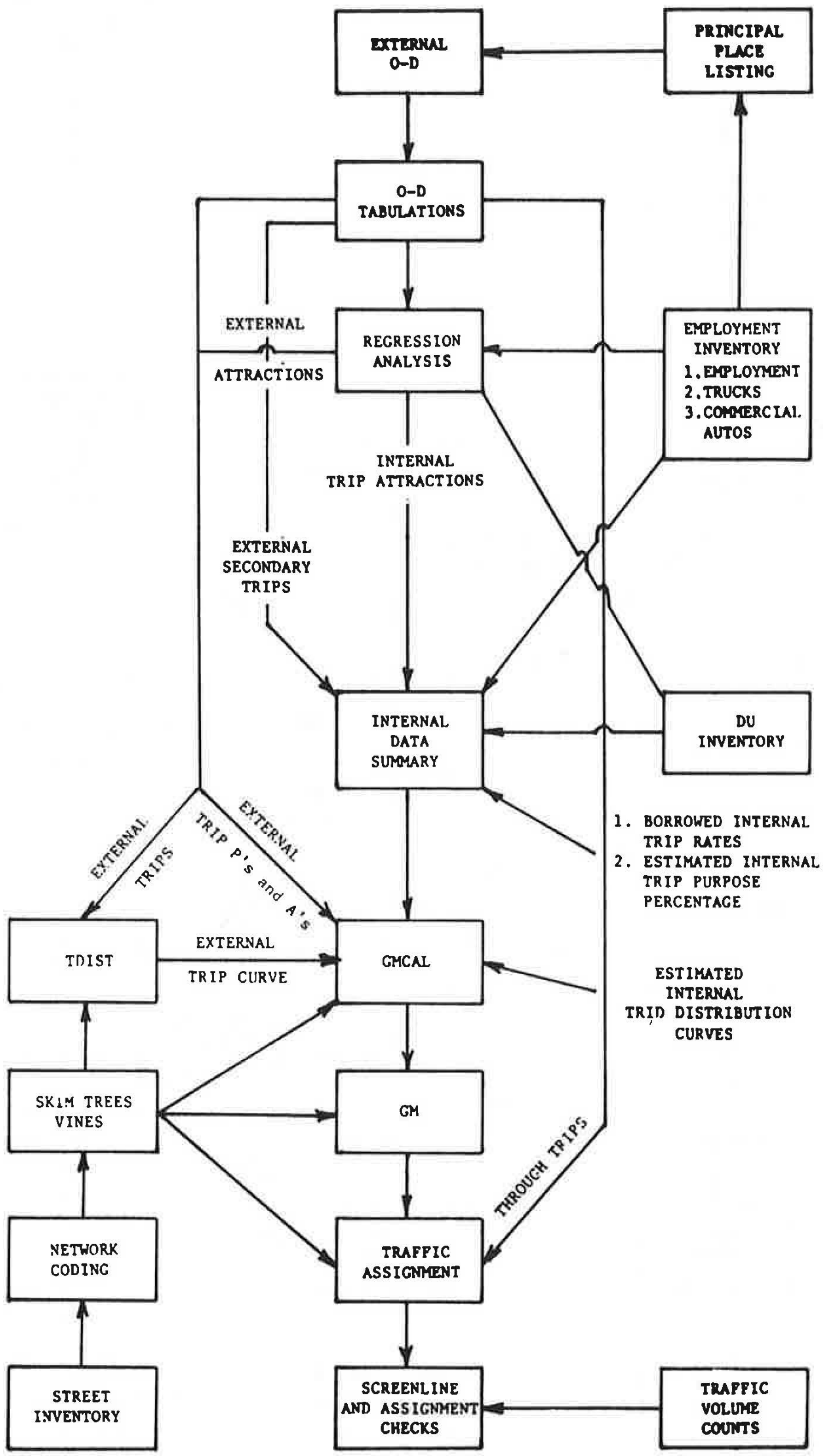

FIGURE 2 Synthesis of travel with an external-cordon, O-D traffic survey.

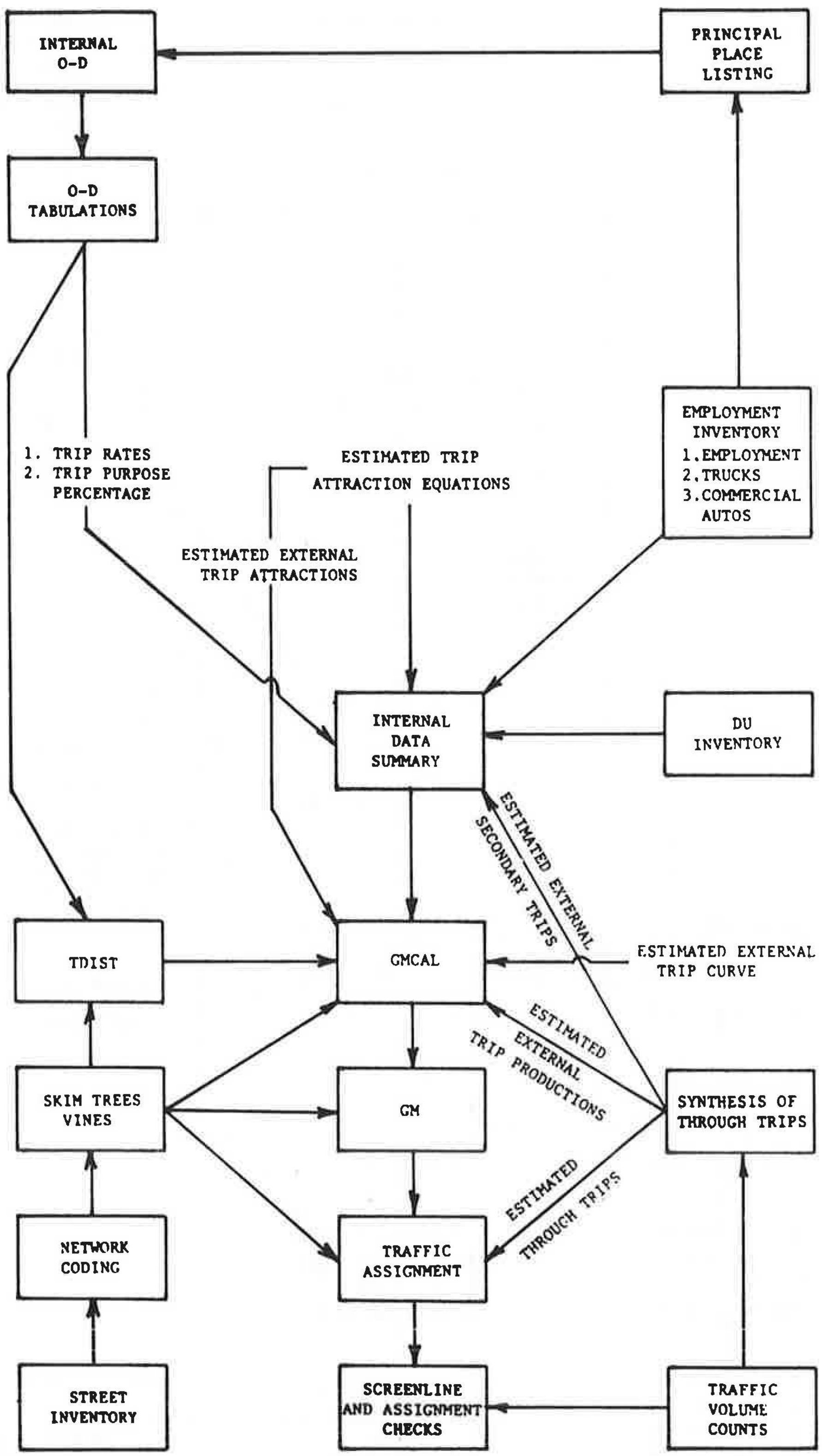

FIGURE 3 Synthesis of travel with a small-sample, internal, O-D travel survey.

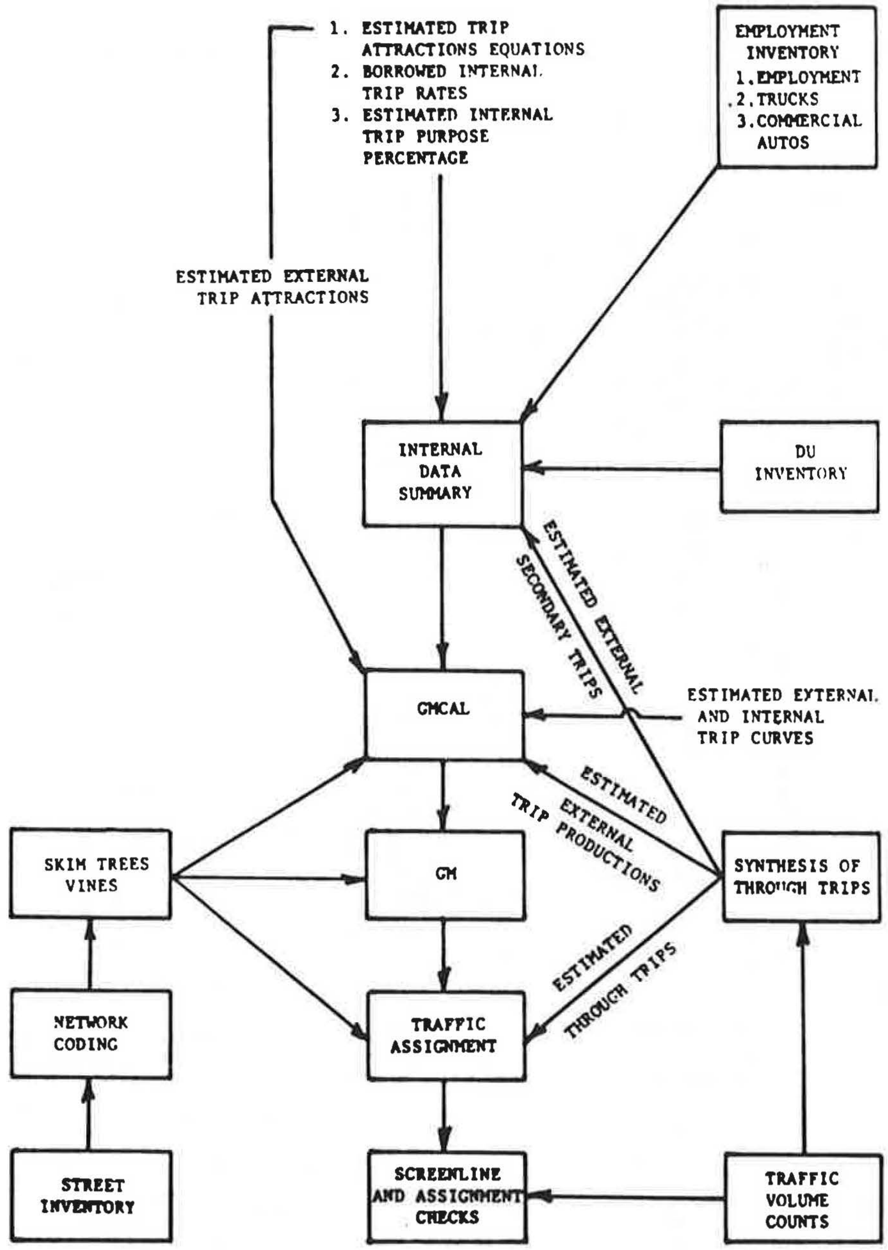

FIGURE 4 Synthesis of travel with no O-D travel surveys.

rates are made by factoring the areawide average and adding the incremental difference to each rate category.

The remainder of the synthesis procedure under Method 2 follows in a manner similar to Method 1. However, it is important in Method 2 to carefully examine the first iteration trip generation curve output of the GMCAL program. Because the internal trip distribution curves have been borrowed, they may not adequately represent the travel patterns of the area under study. The first-iteration output of the GMCAL program sometimes signals that adjustments may be needed in the trip distribution curves.

Method 3

Figure 3 shows procedures that are followed if only a small-sample, internal, O-D survey is done as part of the transportation study. In this procedure, a borrowed trip attraction equation is used to estimate trip attractions for NHB, OHB, and external trips. If an external-cordon, O-D survey was done for the area in prior years, it would serve as a basis for synthesis of through-travel movement and external-travel productions. If information on through- and external-travel data is totally absent, the synthesis procedure for estimation of through-travel, developed and updated by Modlin *(9, 14)*, is used to estimate through- and external-travel productions. An estimated or borrowed external trip distribution curve must be used in the GMCAL program in this method.

Method 4

Figure 4 shows the procedure followed if neither an external-cordon nor internal, home interview, O-D survey is done as part of the transportation study. The only inventoried data used

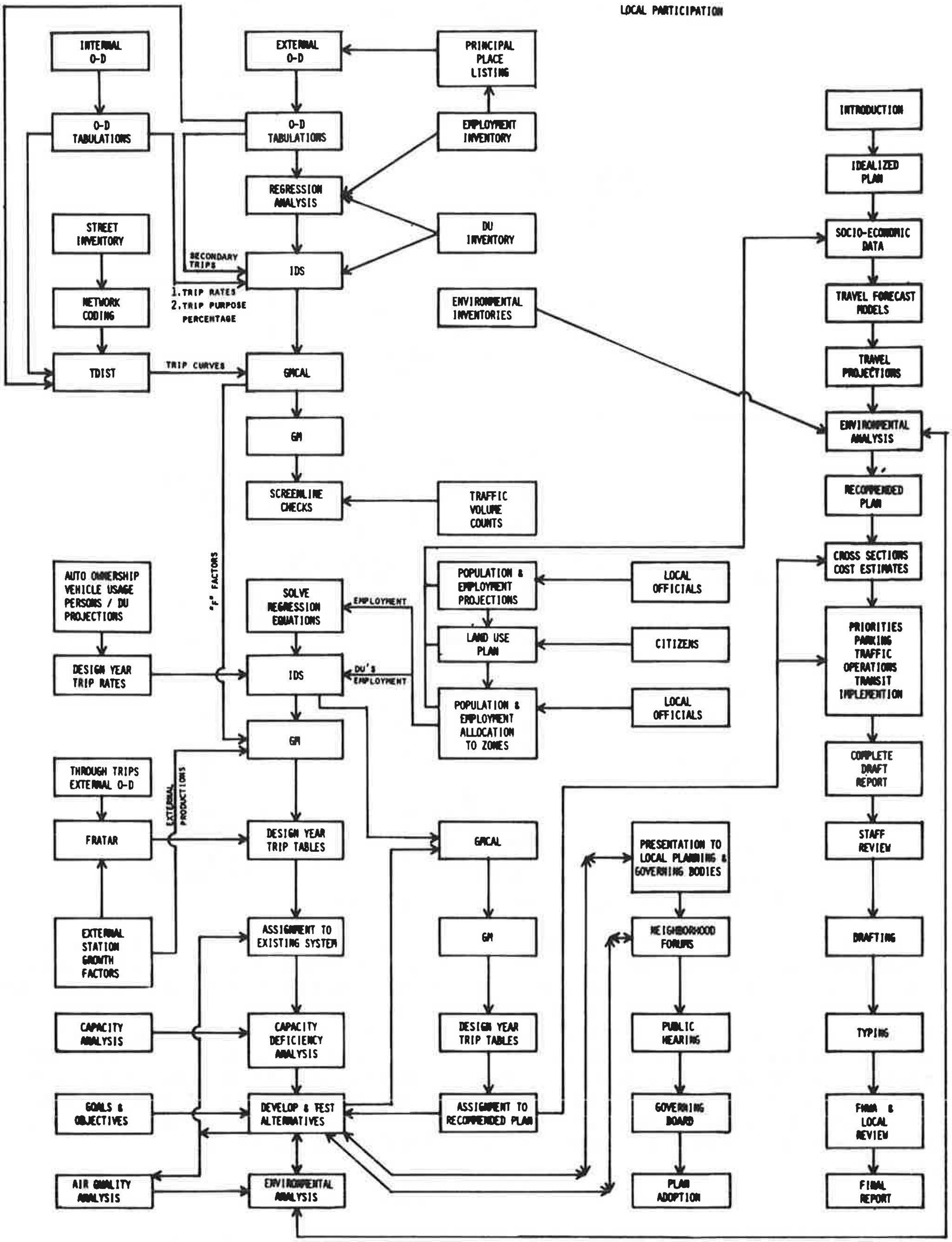

FIGURE 5 Transportation plan development flowchart.

in the synthesis process in this procedure are data from employment and dwelling unit inventories, and from traffic counts. Borrowed or previously developed trip attraction equations must be used to estimate trip attractions for NHB, OHB, and external trips. Estimated trip generation rates and estimated percentage of internal trip purposes must be used as input to the IDS program. It is also necessary that estimated or borrowed HBW, NHB, and OHB trip distribution curves be used as input to the GMCAL gravity model program. Through and external travel must be estimated generally as described in Method 3.

Method 4 requires careful checks on reasonableness of data and output at each step of the process because assumptions are much more extensive in number.

SELECTION OF SYNTHESIS METHOD

Since the early 1960's, North Carolina has completed 69 studies applying one of the four synthesis procedures. Currently, selection of one procedure over an alternative depends on *(a)* perceived transportation problems, *(b)* extent of prior studies completed for the area, *(c)* study time constraints, *(d)* cost, and *(e)* staff availability. In general, Method 4 typically requires 1–3 months to complete traffic counts and the employment and dwelling unit inventories, and 2–4 months to complete the synthesis of travel. If a small-sample, internal O-D survey is done as in Method 3, an additional 3–6 months are needed to plan, conduct, and tabulate the survey data. Methods 1 and 2 have typically required 12–18 months to plan, complete, and tabulate data from O-D surveys.

In some cases, locally preconceived ideas as to the cause of the transportation problem may dictate the synthesis method used. For example, it may be perceived locally that the major travel problem is through traffic. In this case, it may be desirable to include a partial or full, external, O-D survey to obtain hard data on through traffic. In another situation, local officials may feel internal travel characteristics of the area are significantly unique, or have changed. In this case, it may be necessary to schedule a small-sample, home interview, O-D survey as a part of the study to ensure local confidence in the study.

The extent of travel data obtained in a prior study, problems encountered in prior travel modeling, and the type of travel modeling used in a prior study may influence the decision on which procedure to use. In most instances, if O-D surveys have been done earlier for an area, Method 4 is the preferred procedure for travel synthesis for an update study.

In recent years, cost and staff availability have been controlling factors in the decision process. Staff and monies have just not been available for conducting O-D surveys. In 1985, a thoroughfare planning study was completed for Reidsville, a city in north-central North Carolina with an estimated planning area population of 23,700. Method 4 was used in the study and the total study cost was $24,000. If a small-sample, internal, O-D survey was done, an estimated additional cost of $10,300 would have been incurred. If an external-cordon, O-D survey was done, the estimated additional cost would have been $68,000.

SUMMARY

The North Carolina procedure for synthesis of travel discussed herein is but one part of several sequential steps involved in the transportation plan development process (Figure 5). Historically, considerable time and monies have been expended in data inventories and travel modeling. The North Carolina procedure has greatly reduced the time and cost required for this part of the transportation study and allowed more time and effort to be devoted to travel forecasting and plan development and evaluation.

The procedure was developed for use in small- to medium-sized cities where transit has not been a major consideration. In urban areas where it has been desirable to consider transit, procedures developed by Modlin et al. *(15)* have been used to estimate transit travel and its impact on automobile driver travel.

A data bank of information on trip generation rates, trip attractions, trip purpose distribution, and trip length frequency is needed to apply the synthesis procedure. In North Carolina, this information was gathered over a number of years. Method 1 procedures that included an external-cordon, O-D survey and a small-sample, internal, home interview, O-D survey were widely used in the 1960s. Today, Method 4, which involves no O-D surveys, is the procedure used almost exclusively. Method 3, which entails a small-sample, internal, O-D survey, is occasionally followed in order to add to the data bank new information on trip generation rates, trip purpose distribution, and trip length frequency.

The synthesis procedure requires detailed inventories of dwelling units, employment, and traffic counts. No substitute has been found for a comprehensive inventory of employment numbers, trucks, and commercial automobiles. Attempts at using alternative sources for employment data have proved to be inefficient, costly, time-consuming, and inadequate.

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Characteristics of Urban Transportation Demand: An Updated and Revised Handbook

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In this paper, a selection of updated data on a wide variety of statistics pertaining to urban travel demand, and how they have been integrated into the UMTA report, *Characteristics of Urban Transportation Demand: An Update*, are discussed. This report presents a compilation of almost exclusively post-1970 data on travel demand for all major urban modes. It is designed to be used by transportation planners and analysts as a source of data to check the validity and reasonableness of local forecasts developed from either conventional or emerging planning and modeling techniques, or as a cross-check on the similarity of travel statistics from one locality to another. Certain data also may be used as default values for modeling purposes, when such information is not available locally or would require new or extensive data collection efforts. Another application is in examining how key statistics have changed over time and transferring these changes from one area to another. Much of the information contained in the report was obtained from reports, documents, and memoranda produced by or for each study area contacted. A main criterion of the study was that the information collected be based on surveys, measurements, counts, and so forth, and not be synthesized results from analytical modeling efforts. Many source documents have not been circulated widely, adding to the usefulness of the data contained in this report.

In urban transportation planning, an analyst must often borrow a particular factor related to travel demand, especially when such estimates or factors are not available locally or, if available, are believed to be out of date. This situation is typically encountered when results are needed in a quick-response time frame (sometimes referred to as "yesterday"). Alternatively, after a fairly complex and laborious exercise of forecasting the volume of vehicle- or person-trips that may be made on a proposed system is completed, it may be useful to undertake a reasonability check by comparing such forecasts to actual volumes observed elsewhere. To help meet these needs, UMTA released the report *Characteristics of Urban Transportation Demand—A Handbook for Transportation Planners* (CUTD) in April 1978 *(1)*. A description of the overall objectives and use of the original CUTD Handbook was presented by Levinson *(2)*.

The original CUTD Handbook *(1)* drew heavily from facts contained in the comprehensive, large-scale, urban transportation planning studies that were conducted in many localities during the 1950s and 1960s. While providing a rich source of data that has not been duplicated, the information contained in these studies generally reflects travel behavior before 1970. Since these early studies, many changes have occurred in the nation's transportation system (e.g., fuel price increases, transit retrenchment, and expansion) and in the socioeconomic characteristics of travelers and households; for example, household sizes have generally declined over time and the availability of automobiles has continued to increase. It is therefore reasonable to expect that changes have also occurred in many of the travel demand factors presented previously.

In this paper, the results of a study to update and reorganize data on a wide variety of statistics related to urban travel demand characteristics *(3)* are described. Except for a paucity of recent data on urban truck travel, the CUTD Update *(3)* presents a compilation of almost exclusively post-1970 data on travel demand. It is designed to be used by transportation planners and analysts as a source of data to check the validity and reasonableness of local forecasts using either conventional or emerging planning and modeling techniques, or as a cross-check on the similarity of travel statistics in various localities. Certain data may also be used as default values for modeling purposes when such information is not available locally, or would require new or extensive data collection efforts. Another use for the CUTD Update *(3)* is in examining how key statistics have changed over time and transferring these changes from one area to another.

DATA SOURCES

Since 1970, few urban areas have conducted comprehensive transportation studies of the type undertaken in the 1950s and 1960s. Many areas, however, have conducted small-scale data collection efforts either to update earlier data for model validation purposes or for some specialized (rather than area-wide) planning purposes. As might be expected, those localities that have available more recent data on travel demand statistics tend to be the larger metropolitan areas that are able to support an ongoing transportation planning staff. Thus, the updated travel demand data available for small- to medium-sized urban areas are not as voluminous as those in the 1978 CUTD Handbook *(1)*.

Much of the updated information on travel demand characteristics was obtained from reports, documents, and memoranda produced by or for each study area contacted. A main criterion was that the information collected be based on

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surveys, measurements, counts, and so forth, and not be synthesized results from analytical modeling efforts. Many of these source documents have not been circulated widely, which should add to the usefulness of the data contained in the CUTD Update *(3)*. One objective of the work undertaken was to summarize useful travel demand statistics that may not be readily available elsewhere. Therefore, little information was reproduced from many other widely circulated but potentially relevant publications *(4–9)*.

ORGANIZATION AND USE OF THE UPDATED CUTD REPORT *(3)*

As an aid to using and locating data within the CUTD Update *(3)*, tables were grouped into the following nine sections in a sequence consistent with the traditional cooperative, comprehensive, and continuing (3C) transportation planning process:

A. Socioeconomic Characteristics for Study Areas,
B. Trip Generation–Person and Vehicle Trips,
C. Trip Length and VMT Data,
D. Mode Choice and Automobile Occupancies,
E. Temporal Distribution of Travel,
F. CBD Characteristics and Travel Statistics,
G. Truck Travel,
H. Transit Usage Statistics, and
I. Highway and HOV Usage Statistics.

Presented in the following is an overall description of the types of data that can be found in Sections A–I, along with selected tables that highlight the updated travel demand data that have been collected.

Section A: Socioeconomic Characteristics for Study Areas

Section A of the CUTD Update *(3)* contains data on population, land areas, and densities for cities, urbanized areas, and standard metropolitan statistical areas (SMSAs) along with vehicle availability statistics from the 1980 Census for major urbanized areas in the United States. Users of the CUTD Update *(3)* can refer to this information to determine which other cities are most comparable to their own locality in terms of area, density, and vehicle availability. Vehicle availability can be viewed as a proxy for the amount of transit available or the relative income level of the study population. The attractiveness of these data is that the geographical boundaries are defined according to a consistent set of census definitions. This is rarely the case for the geographical areas traditionally used in regional transportation planning studies.

Once one or more comparable cities have been identified, the user should refer next to the table that presents key socioeconomic statistics about many of the study areas for which data are presented in subsequent tables of the report. In particular, this table identifies for these study areas: *(a)* the year the information was collected, *(b)* the size (i.e., population) or boundaries for the study area examined, and *(c)* the socioeconomic characteristics of the study area. Generally (but with some exceptions), information on study areas from this table can then be matched with information on study areas in any other table for which the study area name, year, and study area description are the same.

In addition to these factors, certain travel demand data can be expected to change over time. Even though the inclusion of data before 1970 has been minimized, there is a time span of at least 15 years between the earliest and latest entries. An even longer time span exists if comparisons are made to data contained in the original CUTD Handbook *(1)*. Consequently, to assist users in transferring data between two points in time, selected key socioeconomic characteristics taken from the 1960, 1970, and 1980 censuses are presented *(9)*. For example, it is evident that the work force has expanded as a result of population growth and the increase in the number of women who work outside the home. Automobile ownership levels have increased, bringing about increases in the percentage of commuter trips made by automobile at the expense of mass transit modes. An understanding of the implications of these types of trends for travel demand should assist users of the CUTD Update *(3)* in examining or transferring data between different points in time.

Certain tables in the CUTD Update *(3)* also present summary statistics on average nationwide travel demand characteristics from the 1969 and 1983 Nationwide Personal Transportation Study (NPTS) reports. These statistics are useful in highlighting how a given travel factor may have changed over time. The NPTS results can also be used as a reference point to determine how similar factors from a particular study area compare to a nationwide estimate. Users should note, however, that differences in definitions, questionnaire designs, and relatively small sample sizes associated with the 1983 NPTS may not always yield a true comparison.

Section B: Trip Generation—Person and Vehicle Trips

Section B of the CUTD Update *(3)* presents data on total person and vehicle trip rates for selected study areas in the United States. Trip rates are further cross-classified by pertinent factors such as number of automobiles per household, income, size of household, and trip purpose. Depending on local practice, certain trip purpose factors are presented according to the home-based and nonhome-based convention, which classifies trips according to both the origin and the destination purpose, whereas other tables use only destination purpose to assign trip purpose. In some instances, transit trip rates are also presented.

Given information on population and average trip rates for either an entire area or disaggregated by a particular market segment, it is possible to compute an approximate estimate of the total number of trips made in an area. Caution must be exercised regarding the basic definition of trips; for example, do they include walking or only motorized modes, trips by trucks, trips by persons of all ages, and are they linked or unlinked (particularly for transit)?

Table 1 presents motorized trip generation rates per person and per household for selected study areas. For each study area, Table 1 indicates (as do all tables) the year and study area description (either the population or a common term for the

TABLE 1 TRIP GENERATION: PER PERSON, PER HOUSEHOLD

Study Area	Year	Study Area Description	Person Trips per: Person	Person Trips per: Household	Persons per Household	Persons per Vehicle	Vehicles per Household
Atlanta	1972	1,640,000	2.49	7.20	2.9	2.1	1.38
Baltimore	1977	T.P.A.	2.9	8.3	2.8	---	---
Buffalo	1973	1,234,000	2.5	7.5	3.0	2.5	1.2
Chicago	1979	City	1.6	4.6	2.9	---	---
Chicago	1979	SMSA	2.4	7.2	3.0	---	---
Dallas	1984	T.P.A.	3.40	8.68	2.6	1.4	1.84
Denver	1971	T.P.A.	2.83	8.76	3.10	2.21	1.40
Fresno/Clovis	1972	295,000	3.00	8.25	2.74	2.27	1.21
Los Angeles	1976	6 County	2.99	8.15	2.8	1.8	1.6
Louisville	1975	Urban Area	2.19	6.34	2.90	1.91	1.52
Philadelphia	1977	SMSA (+)	2.45	7.66	2.5	2.45	1.27
Phoenix	1980	T.P.A.	2.44	6.58	2.7	---	---
Portland	1977	SMSA	3.67	8.66	2.4	---	---
Rochester	1974	735,000	2.56	8.03	3.14	2.75	---
Sacramento	1978	3 County	3.39	9.34	2.6	1.6	1.6
San Diego	1977	County	3.5	9.8	2.8	1.71	1.64
San Francisco	80/81	CMSA (-)	3.40	8.71	2.56	1.52	1.70
Washington, DC	1968	2,714,000	2.17	---	---	2.58	---

SOURCE: Reports from individual study areas.

TABLE 2 PERSON-TRIPS GENERATED PER HOUSEHOLD BY AUTOMOBILE OWNERSHIP

Study Area	Year	Study Area Description	Autos per Household: 0	1	2	3+	All Households
Buffalo	1973	1,234,000	1.6	6.9	11.5	16.9	7.5
Chicago[a]	1979	City	1.9	5.3	7.7	9.5	4.6
Chicago[a]	1979	SMSA	1.7	6.4	10.7	12.7	7.2
Fresno	1971	295,000	1.3	6.7	-----12.0-----		8.2
Los Angeles	1976	6 County	2.0	5.8	-----11.0-----		8.1
Milwaukee	1972	7 County	1.9	7.0	11.5	16.0	7.9
Minneapolis/St. Paul	1982	7 County	1.8	6.5	11.1	16.4	9.1
Portland	1977	SMSA	3.0	6.8	-----11.5-----		8.7
Rochester	1974	735,000	2.2	7.1	11.1	14.0	8.0
San Diego[b]	1977	County	3.0	6.6	-----13.0-----		9.8
San Francisco	80/81	CMSA (-)	4.0	6.3	10.1	13.4	8.7

Key to Notes

a — Shown are person trips per occupied dwelling unit.
b — Person trips not including motorcycle, bicycle, walking.

SOURCE: Reports from individual study areas.

geographic boundary, or, if neither are available, the local transportation planning area) that applies to the data item listed. Many travel demand factors can differ simply because of differences in study area sizes. For example, as given in Table 1 for Chicago, the number of person-trips made per household in the city of Chicago compared to the larger SMSA varies considerably because of differences in automobile availability, income, and household composition.

Table 2 shows how person-trip rates per household increase with the number of automobiles owned per household (which implicitly would also reflect increases in the number of individuals per household). For the cities shown, households with no automobiles average about 2 person-trips/day, increasing to about 10.5 person-trips/day for households with 2 automobiles. From Table 3, the vast majority of trips made are home based, although over time it appears that the percentage of trips that are home based has declined. Work trips still represent the largest category of home-based trips.

As given in Table 4, a much higher percentage of transit trips represents home-based trip purposes. This difference is largely due to the increased likelihood of individuals using transit for work and school trips, offset partially by the decreased likelihood of their using transit for home-based trips made for shopping, social, and recreational purposes.

Section C: Trip Length and VMT Data

Section C of the CUTD Update *(3)* represents the output of the trip distribution phase of travel demand analyses. Data are reported on average trip length characteristics for all trips and disaggregated by trip purpose and by mode. Where possible, trip lengths are reported in miles or minutes, or both. For example, Table 5 presents average trip lengths by trip purpose expressed in miles and minutes. (Differences in the definitions of trips and whether or not trip times include line-haul as well as access or transfer times can affect the transferability of the data.) As is typically observed, home-based work trips are the longest—measured in terms of either miles or minutes. Average trip lengths for home-based nonwork and nonhome-based trips, while shorter than for work trips, are more nearly equal to each other.

Categorized by motorized modes, the longest trips are made on commuter rail, followed by rapid transit, automobile, bus, and taxi. Table 6 also presents a comparison of average trip length from individual cities to average trip length reported in

TABLE 3 HOME-BASED PERSON-TRIPS BY TRIP PURPOSE

Study Area	Year	Study Area Description	Home-Based Trips as % of All Trips	Percent of Home-Based Trips to & from: Work	School	Shop	Soc/Rec	Other	Total Home-Based Trips per HH
Dallas	1984	T.P.A.	74.7	36.1	---	---	---	63.9	6.4
Denver	1982	Urbanized Area	79.2	31.8	---	21.5	---	46.7	---
Detroit	1980	7 County	74.1	27.4	---	---	---	72.6	5.5
Detroit	1965	4,042,000	77.6	20.8	17.0	19.8	22.2	22.0	6.6
Detroit	1953	2,969,000	87.0	41.6	6.3	13.9	20.1	18.1	4.7
El Paso	1970	363,000	75.6	26.0	14.0	19.0	17.0	24.0	6.6
Fresno	1971	245,000	69.3	24.8	---	18.3	---	56.9	5.9
Louisville	1975	Urban Area	80.7	33.0	---	21.6	21.2	24.2	---
Philadelphia	1977	SMSA (+)	78.0	29.5	---	---	---	70.5	---
Philadelphia	1960	4,007,000	85.4	34.8	6.6	12.7	17.1	28.8	3.9
Phoenix	1980	T.P.A.	79.2	32.4	11.4	20.5	---	35.7	---
San Diego	1977	County	71.0	22.3	---	18.2	---	59.5	7.0
San Francisco	80/81	CMSA (-)	73.2	29.6	14.9	---	19.8	35.7	6.4
Washington, DC	1968	2,714,000	87.2	28.0	8.0	23.4	17.7	22.9	6.3

SOURCE: Reports from individual study areas.

TABLE 4 TRANSIT PERSON-TRIPS BY TRIP PURPOSE

Study Area	Year	Study Area Description	Mode	Trip Definition	Home-Based Transit Trips: Work	School	Shop	Soc/Rec	Other	Nonhome-Based	Total
Atlanta	1980	7 County	Rapid Rail	Linked	50.4	19.5	1.8	7.2[b]	9.7	11.4	100
Atlanta	1980	7 County	Bus	Linked	50.0	16.3	4.8	9.8[b]	7.8	11.3	100
Atlanta	1980	7 County	All	Linked	50.1	17.4	3.7	8.9[b]	8.5	11.4	100
Boston	1978	79 Cities	Bus	Unlinked	48.5	18.3	8.1	4.4	10.4	10.4	100
Boston	1978	79 Cities	Rapid Rail	Unlinked	53.6	12.6	---	---	17.5	16.3	100
Cincinnati	1978	T.P.A.	Bus	Linked	40.1	17.6	---	---	24.8	17.5	100
Detroit	1980	7 County	Bus	Unlinked	36.7	---	---	---	50.0	13.3	100
Denver	1978	4 County	Bus	Unlinked	49.9	15.6	8.4	4.5	7.6	14.0	100
Indianapolis	1973	T.P.A.	Bus	Unlinked	58.2	13.6	11.9	---	16.3	---	100
Minn./St. Paul	1982	7 County	Bus	Linked	36.8	a	---	41.4	---	21.8	100
Philadelphia	1977	SMSA (+)	All	Linked	55.4	---	---	---	34.0	10.6	100
Portland	1977	SMSA	Bus	Linked	31.9	18.9	---	9.9	22.1	17.2	100
San Diego	1977	County	All	Unlinked	35.0	24.4	10.8	----19.4----		10.4	100
San Francisco	80/81	CMSA (-)	Bus	Linked	36.9	22.6	15.2	8.0	c	17.3	100

Key to Notes

a -- School bus trips not included.
b -- Personal business.
c -- Included in "shop."

SOURCE: Reports from individual study areas.

TABLE 5 AVERAGE PERSON-TRIP LENGTH BY TRIP PURPOSE

Study Area	Year	Study Area Description	Home-Based Work Miles	Home-Based Work Minutes	Home-Based Nonwork Miles	Home-Based Nonwork Minutes	Nonhome-Based Miles	Nonhome-Based Minutes	All Trips Miles	All Trips Minutes
Baltimore	1977	T.P.A.	6.6	---	4.0	---	4.9	---	4.9	---
Dallas	1984	T.P.A.	10.1	---	5.3	---	6.5	---	6.9	---
Indianapolis	1970	T.P.A.	---	19.0	---	12.9	---	14.2	---	14.5
Minn./St. Paul	1982	7 County	8.1	---	5.0	---	5.4	---	5.7	17
Philadelphia	1977	SMSA (+)	---	22.1	---	16.6	---	15.0	---	17.5
Phoenix	1980	T.P.A.	---	18.9	---	12.8	---	13.0	---	14.4
Portland	1977	SMSA	6.6	---	4.1	---	4.1	---	5.0	---
San Diego	1977	County	8.9	14.3	4.9	8.4	4.9	8.3	5.5	9.3
San Francisco	80/81	CMSA (-)	---	26.6	---	17.6	---	16.7	---	19.3
Seattle	1977	T.P.A.	---	22.1	---	---	---	15.4	---	---
Tucson	1977	T.P.A.	---	17.7	---	12.3	---	10.9	---	13.0

SOURCE: Reports from individual study areas.

TABLE 6 AVERAGE TRIP LENGTH BY MODE

Study Area	Year	Study Area Description	Auto	All Transit	Commuter Rail	Rapid Transit	Bus
Baltimore	1977	T.P.A.	5.0	4.1	---	---	4.1
Chicago	1970	7,593,000	5.0	---	18.5	7.9	3.9
Chicago	1979	SMSA	4.5[a]	6.4	---	---	---
Denver	1982	Urbanized Area	5.3	4.7	---	---	4.7
Minn./St. Paul	1982	7 County	5.9	5.0	---	---	5.0
New York	1983	City	---	---	22.1	7.0	2.4
Philadelphia	1977	SMSA (+)	6.2	4.9	18.4	4.8/7.5[b]	2.6[c]
Portland	1977	SMSA	4.9	6.0	---	---	6.0
San Diego	1977	County (-)	5.5	---	---	---	3.2
Washington, DC	1980	SMSA (-)	7.5	---	---	---	---
NPTS	1983	USA	7.6	---	19.4	10.6	6.1

Key to Notes

a — Measured in airline miles.
b -- For Subway Elevated/PATCO High Speed.
c — Includes surface trolley.

SOURCE: Reports from individual study areas.

TABLE 7 AVERAGE DAILY PERSON-TRIPS BY MODE

			Total	Percent of Person Trips by Mode						
Study Area	Year	Study Area Description	Trips (000's)	Auto Driver	Auto Passenger	Transit	Truck	Walk	Other	Notes
Atlanta	1972	1,640,000	4,087	61.2	28.4	10.4	---	---	---	a
Baltimore	1977	T.P.A.	3,408	--------89.3--------		10.7	---	---	---	
Chicago	1979	City	---	50.6	18.4	29.7	---	---	1.3	
Chicago	1979	SMSA	---	65.0	21.5	10.4	---	---	3.1	
Denver	1982	Urbanized Area	6,025	58.0	20.0	2.5	19.5	---	---	b
Los Angeles	1976	6 County	---	59.7	22.0	3.1	---	11.9	2.6	
Louisville	1978	835,000	1,858	--------92.3--------		7.7	---	---	---	
Milwaukee	1972	7 County	4,505	64.3	27.2	8.0	---	---	0.5	
Minn./St. Paul	1982	7 County	---	68.8	20.4	3.8	---	---	7.0	b
Philadelphia	1977	5,123,900	12,690	--------92.0--------		8.0	---	---	---	
Portland	1977	SMSA	3,550	60.7	22.8	7.1	---	7.9	1.5	b
Sacramento	1978	3 County (-)	---	57.7	23.7	4.3	0.5	9.3	4.5	b
San Diego	1977	County (-)	---	59.1	22.6	4.1	0.6	10.1	3.5	b
San Francisco	80/81	CMSA (-)	17,168	60.0	18.2	6.4	---	11.4	4.0	
NPTS	1969	USA	145,146,000	--------85.1--------		8.3	5.6	---	1.0	b
NPTS	1983	USA	205,811,000	--------81.5--------		5.6	11.6	---	1.3	b

Key to Notes

a -- Does not include trips by motorcycle, bicycle, walking.
b -- Transit includes school bus trips.

SOURCE: Reports from individual study areas.

the 1983 NPTS *(10)*. In general, NPTS trip lengths are longer because the total linked length of a particular O-D trip is reported even though more than one mode may be used for the trip in question. Following the convention of the Bureau of the Census, when more than one mode is used, the mode with the longest unlinked trip segment measured according to distance is the one reported. Thus, a 2-mi bus trip followed by an 8-mi trip on rapid transit appears in the data as a 10-mi-long rapid transit trip.

Section D: Mode Choice and Automobile Occupancies

In Section D of the CUTD Update *(3)*, information is provided on total person and vehicle trips by mode (as well as vehicle type for vehicle trips) and by trip purpose. Because mode shares are sensitive to the size of the geographic area under consideration, one table shows modal shares for journey-to-work trips based on the consistent urbanized area definition used in the 1980 census of population. Also presented in Section D are average automobile occupancies by time of day and by trip purpose, separately. Again, trip purpose is defined according to the home-based and nonhome-based trip-end convention as well as by the purpose at the destination end.

Table 7 lists the number of total daily trips made for various study areas along with modal shares (which if multiplied together produces the average number of daily trips made by each mode). Also presented for comparative purposes is equivalent trip information from the 1969 and 1983 NPTS surveys. If statistically valid, the NPTS data suggest that the total number of daily trips made increased by 42 percent between 1969 and 1983, whereas the share of public transit trips declined by 24 percent, from 3.4 to 2.6 percent *(11)*. (Table 7

TABLE 8 AUTOMOBILE OCCUPANCY BY TRIP PURPOSE

Study Area	Year	Study Area Description	Home-Based Work	Home-Based Nonwork	Nonhome-Based	Total
Dallas	1984	T.P.A.	1.13	1.55	1.39	1.36
Honolulu	1981	County	1.20	1.65	1.54	1.52
Kansas City	1970	8 County	1.11	1.61	1.56	1.51
Los Angeles	1976	6 County	1.15	1.71	1.65	1.54
Minn./St. Paul	1982	7 County	1.15	1.40	1.24	1.31
Portland	1977	SMSA	1.13	1.56	1.65	1.50
Sacramento	1978	3 County(-)	1.06	1.54	1.75	1.50
San Diego	1977	County (-)	1.08	1.63	1.58	1.50
San Francisco	1980	9 County	1.07	1.52	1.51	1.41
Tucson	1977	T.P.A.	1.18	1.55	1.37	1.42

SOURCE: Reports from individual study areas.

shows modal shares for public transit and school bus combined.) However, over this period the absolute number of transit trips made nationwide increased by over 8 percent, according to NPTS data.

Table 8 presents average automobile occupancy data by trip purpose. The lowest occupancies are home-based work trips, reflecting the greater propensities of individuals to commute to work in single-occupant automobiles. Both home-based nonwork and nonhome-based trip purposes have similar but significantly higher occupancies, indicative of the underlying shopping and recreational trip activities that are being undertaken.

Section E: Temporal Distribution of Travel

Section E of the CUTD Update *(3)* presents statistics on the temporal distribution of person and transit trips over the course of an average weekday. Factors are also provided so that the relative magnitude of person-trips taken on weekdays versus weekend days by mode and by trip purpose can be compared or computed from other available data. Based on the hourly distribution of trips made on four rapid transit systems and vehicle driver-transit trips made in San Francisco, transit trips exhibit sharper peaks compared to those for the automobile.

Section F: CBD Characteristics and Travel Statistics

Section F of the CUTD Update *(3)* presents statistics concerning person, vehicle, and truck travel as related to the central business districts (CBDs) of urban areas. However, there are multiple definitions of the geographic boundaries of a CBD that can have a major influence on the interpretation of the statistics presented. Although the CBD area as defined by the Bureau of the Census can be easily ascertained, few areas choose to use this definition, as it encompasses too small an area of interest. Where possible, the local acronym for the central area (e.g., Boston proper) has been used in place of the term "CBD"; however, only the lack of a local convention prevents wider use of this approach. Although many of the data pertain to CBDs, the term might better be translated to mean central, built-up areas of cities.

Also presented in this section of the CUTD Update *(3)* are summaries of cordon counts for persons and vehicular trips taken over an entire day (or nearly so) and during the peak hour. These data tend to be based on actual counts rather than on samples. Comparisons of cordon counts over time are possible when the geographic boundaries are the same. Although rare, the inclusion of an artery or expressway with much through traffic can distort the comparability of the cordon data. Similarly, because of the traditionally high peaking characteristics of transit trips to the CBD, peak mode shares based on two-way flows artificially reduce the importance of transit trips compared to measurements based on the one-way peak direction.

Table 9 presents the peak-hour percent of person trips by transit and nontransit modes crossing the CBD cordon for cities of various sizes and, in some instances, over time for the same city. Generally, high concentrations of transit trips to the CBD are associated with large cities (New York, Chicago), high-CBD employment, and cities with dense, downtown-oriented rapid transit systems. Some large but nonrail cities (e.g., Houston) have, as a result, relatively low transit mode shares destined to the CBD. In the case of Houston, however, the share of transit trips to the CBD in the peak hour has increased with the overall growth of the central core. Conversely, from the early 1970s to the early 1980s, there has actually been a decline in the proportion of transit trips being made in New York and Chicago.

Section G: Truck Travel

Section G of the CUTD Update *(3)* contains data concerning truck travel. Following the basic outline of the entire handbook, statistics are presented for average truck trip rates per day, average trip length, percentage of trips that are made by trucks, trip rates by trip purpose, and hourly variation of truck trips for all trips and by facility type. Many of the data are drawn from studies conducted in the 1960 because few studies of this kind have been undertaken since that time.

Section H: Transit Usage Statistics

Section H of the CUTD Update *(3)* presents statistics on the usage characteristics of transit facilities. Annual ridership data and selected productivity statistics (e.g., person-trips per revenue-car-mile operated) are reported on all commuter rail, rapid rail, light rail, and streetcar transit systems except for those cities that only recently began partial service, and for major bus systems. Peak-hour volumes on selected lines are reported for various rapid rail, light rail, and streetcar systems. Modes of access at the systemwide level and by selected stations and terminals are also provided. From the data collected, it is clear

TABLE 9 PEAK-HOUR PERSON-TRIPS BY TRANSIT TO CENTRAL BUSINESS DISTRICTS

City Rank 1980 Census	Study Area	1980 City Population (000s)	Year of Count	Peak-Hour One-Way Persons (000s)	Peak-Hour Percent	
					Auto/Other	Transit
1	New York	7,072	1971	805	8	92
			1974	738	10	90
			1982	748	12	88
2	Chicago	3,005	1971	210	19	81
			1974	200	18	82
			1983	152	23	77
3	Los Angeles	2,967	1970	99	69	31
			1974	93	63	37
			1980	88	64	36
5	Houston	1,595	1971	55	86	14
			1980	66	82	18
6	Detroit	1,203	1974	39	67	35
7	Dallas	904	1971	50	72	28
			1983	88	71	29
11	San Antonio	786	1979	21	73	27
15	Washington, DC	638	1983	169	68	32

SOURCE: Reports from individual study areas.

TABLE 10 COMMUTER RAIL RIDERSHIP STATISTICS

Study Area	Annual Ridership	Passengers per Revenue Car Mile	Passenger Miles per Revenue Car Mile	Implied Average Trip Length (Miles)
Boston (1987)	14,649,000	1.7	29.6	17.2
Chicago (1987)	66,505,000	3.0	63.5	21.2
New Jersey (FY1987)	43,773,000	1.2[a]	28.2[a]	23.4[a]
New York (1987)				
Metro-North	53,802,000	1.7	46.3	27.5
LIRR	74,938,000	1.4	38.7	27.5
Philadelphia (FY1987)	22,933,000	2.2	29.6	13.5
Pittsburgh (FY1987)	236,000	0.9	15.5	17.2
San Francisco (FY1987)	5,422,000	2.3	54.9	23.7
Washington (FY1987)				
Baltimore (Amtrak)	713,000	--	--	--
Baltimore (CSX)	337,000	1.4	30.0	21.8
Martinsburg (CSX)	772,000	--	--	--

a -- NJT District only (i.e., less NEC Adj. and NY)

SOURCE: Individual rail systems or transportation agencies, except where noted.

that access modes at outlying stations in the morning differ considerably from access modes at center city stations on the return trip in the evening. Thus, access mode shares can be expected to vary significantly, depending on whether they are given as a.m. in-bound only, systemwide, or by station or terminal. The distribution of access modes at stations and terminals is heavily dependent on parking availability and cost, feeder bus service, and neighborhood characteristics.

In Table 10 annual ridership statistics for all areas in the United States currently served by commuter rail are summarized. The CUTD Update *(3)* provides additional details for various commuter rail line and branch segments. Because average trip lengths on commuter rail are relatively long (about 25 mi), passengers per revenue-car-mile average only about 1.9 with a range between 0.9 and 3.0. However, differences in operating procedures (e.g., pertaining to carrying passengers on trains moving in the reverse-haul direction), may lead to artificial differences in how revenue-car-miles are computed, potentially affecting precise comparison between systems.

On rapid rail systems in the United States, unlinked trips per vehicle-mile-traveled (VMT) have a weighted average of 5.0 using the data in Table 11. This number contrasts with the weighted average of 7.6 for streetcar and light rail transit lines and about 4.4 for large bus transit systems *(3)*. Expressed on the basis of linked trips per VMT, these statistics would be lower.

TABLE 11 RAIL RAPID TRANSIT: RIDERSHIP AND SYSTEM PROFILES (1986)

Study Area	System	Directional Route Miles (One-Way)	Number of Stations	Maximum Revenue Vehicles in Service	Annual Revenue VMT (000s)	Annual Unlinked Rides (000s)	Unlinked Rides per Station (Avg. Weekday[a])	Unlinked Rides per VMT
Atlanta	(MARTA)	51.5	25	115	11,741	65,548	8,740	5.6
Baltimore	(MTA)	14.4	9	42	1,792	11,567	4,280	6.5
Boston	(MBTA)	76.6	50	252	17,543	143,747	9,580	8.2
Chicago	(CTA)	191.0	143	925	46,401	145,348	3,390	3.1
Cleveland	(RTA)	38.2	18	35	2,065	5,671	1,050	2.7
Lindenwold	(PATCO)	30.5	12	90	3,829	10,367	2,880	2.7
Miami	(DCTA)	39.7	20	66	4,442	7,668	1,280	1.7
New Jersey	(PATH)	27.6	13	241	11,344	53,794	13,790	4.7
New York City	(NYCTA)	481.2	463	4,889	290,493	1,591,526	11,460	5.5
Philadelphia	(SEPTA)	80.4	74	283	15,572	88,357	3,980	5.7
San Francisco	(BART)	142.0	34	321	30,490	63,959	6,270	2.1
Washington	(WMATA)	139.1	64	446	26,859	145,149	7,560	5.4

Key to Notes

a -- Average weekday trips computed by dividing annual trips by 300. Note that this statistic may be deceptively high for systems with relatively large numbers of rail-to-rail transfers.

SOURCE: U.S. Department for Transportation, National Urban Mass Transportation Statistics, 1986 Section 15 Annual Report (UMTA-VA-06-0127-88-1), June 1988; computations by Charles River Associates.

TABLE 12 PEAK-HOUR VEHICLE VOLUMES ON URBAN FREEWAYS AND EXPRESSWAYS

Study Area	Facility	No. of Lanes	Year	Average Daily Traffic (2-Way)	Peak Directional Volumes: Vehicles (One-Way)	Peak Directional Volumes: % of ADT
Atlanta, GA	I-20 E. of CBD @ Moreland Ave.	8	1984	99,900	7,794	7.8
	I-85 N. of I-75 @ Monroe Dr.	8	1984	95,300	6,765	7.1
Boston, MA	S.E. Expwy. @ Southampton St.	6-8	1982	143,300	6,860	4.8
	I-95 -- East of 128 N. of Middlesex	8	1984	125,050	7,282	5.8
Denver, CO	I-25 South of I-70	8	1983	175,000	7,500	4.3
	US 6 West of Federal Blvd.	6	1985	112,000	5,835	5.2
Detroit, MI	Jeffers Fwy. (I-96) & Warren	8	1980	67,600	6,270	9.3
	Lodge @ East Grand Blvd.	6	1981	111,450	4,660	4.2
Houston, TX	I-10 - East of Taylor St.	10	1985	151,000	7,600	5.0
	I-610 - @ Ship Channel	10	1985	103,200	5,540	5.4
Milwaukee, WI	N-S Fwy @ Wisconsin	8	1984	118,080	5,370	4.5
	Airport Fwy @ 68th	6	1984	81,020	3,940	4.9
New York City, NY	Holland Tunnel	4	1982	73,200	2,700	3.7
	Lincoln Tunnel	6	1982	110,700	5,150	4.7
San Francisco, CA	Oakland-Bay Bridge (I-80)	10	1984	223,000	8,898	4.0
Washington, DC	Anacostia Fwy (Howard Road)	6	1984	121,700	---	5.0

SOURCE: Reports from individual study areas.

Section I: Highway and HOV Usage Statistics

Section I of the CUTD Update *(3)* presents statistics on the usage characteristics of major highways and high-occupancy vehicle (HOV) facilities located on freeways. Flows on the network are a key output of any demand modeling project. For comparative purposes, average daily traffic (ADT) and percentage of ADT occurring in the peak hour as measured at maximum load points are provided for selected freeway facilities (Table 12). For HOV sites, peak-hour volumes on the general-purpose and HOV lanes by carpool or bus are given as measured approximately 1 year after implementation and as most recently available (typically, for the years 1982–1985). Information is not presented on changes in travel volumes due to the introduction of HOV treatment *(12)*; rather, the statistics presented are most useful for comparison with other forecasts.

CONCLUSIONS

In this paper, an overview of the various types of data on urban travel demand characteristics that have been assembled and incorporated into the newly revised CUTD Update *(3)* has been presented. The CUTD Update *(3)* is designed to provide a handy reference for analysts who need to borrow particular statistics not otherwise available locally, or who would like to compare forecasts of travel demand to actual volumes experienced elsewhere. At various points, potential pitfalls in accomplishing this task have been described. Overall, the CUTD Update *(3)* is viewed as an addition to the literature on urban travel behavior that will be progressively updated as more data become available. In this way it should continue to be a useful reference to urban transportation planners.

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