Transferability and Updating of Disaggregate Travel Demand Models

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In recent years much work has gone into the development of disaggregate travel demand models. However, little has been done to evaluate the ability of these models to predict travel behavior in locations other than the area for which the model was estimated. Unlike aggregate models, the parameters of disaggregate models are not dependent on a particular zonal system and therefore have the potential for transferability. The motivation behind transferring is clear-if a model estimated in one area can be transferred to another, the cost of conducting transportation studies could be greatly reduced. Several possible approaches for transferring are developed and discussed from a theoretical perspective. For an empirical evaluation, a work-trip modal-split model estimated on Washington, D.C., data is transferred to New Bedford, Massachusetts, using each of the proposed approaches. The results of estimating the original model on Los Angeles data are also represented. The most significant result is the exceptional performance of the original Washington work mode choice model on both New Bedford and Los Angeles data. This is noteworthy in view of the extreme differences of the means for several variables between these cities. Of the several approaches for transferring that were developed, Bayesian updating based on combining the existing model coefficients with the estimation results from a new sample gave the best overall performance. The results of this study indicate that the potential transferability of disaggregate travel demand models can be realized.

Traditional aggregate models of travel demand, which are based on existing relationships between aggregate variables, tend to be correlative rather than causal, and often are insensitive to proposed changes in transportation policy. Recently, travel demand models based on disaggregate data (i.e., individual observations of travel behavior) have been developed. These models can include the causal relationships between transportation level of service, household socioeconomic characteristics, and travel behavior and, therefore, provide a more meaningful analysis of various transportation policy options.

Often, particularly in small urban areas, there is neither the time nor the money to develop a travel demand model. This makes desirable the development of a travel demand model that could be transferred from one area to another. Disaggregate models are most likely to be transferable because they represent the average behavior of the individual traveler, and it is reasonable to expect individual travel behavior to be essentially the same in one area as in another. Moreover, the estimation of disaggregate models does not rely on a particular zonal aggregation so that a correctly specified disaggregate model that properly explains travel behavior in one area should be valid (or at least more valid than a comparable aggregate model) for predictions of travel behavior in other areas.

This paper discusses the theoretical justification for the transferability of disaggregate models. The results of transferring an existing disaggregate mode choice model for work trips, developed using 1968 data from Washington, D.C., to data sets representative of New Bedford, Massachusetts, in 1963 and Los Angeles, California, in 1967 are presented. Several possible approaches for updating are developed, compared from a theoretical standpoint, and evaluated empirically using the New Bedford data base. The most useful product of the research is a procedure for travel demand model development suitable for low-budget or short-duration transportation planning studies.

PROPERTIES OF DISAGGREGATE MODELS

Before empirical updating procedures are developed, the theoretical justification for the transferability of these models should be established by identifying the attributes that affect any model's ability to be transferred from one area to another. Clearly, all those factors that affect the reliability of predictions will also affect the transferability. If a model cannot successfully predict travel behavior in the area for which it was estimated, there is no reason to expect it to function better in any other area. To be transferable, then, it is not enough that the model merely fit existing data; it must also explain why travel behavior changes as conditions change. Rather than simply correlating existing travel behavior with socioeconomic characteristics and transportation level of service, the model specification must represent the causal relationships between these variables. Thus, the causal specification of a model is a precondition to its consideration for transferability.

From a practical point of view, no model is ever perfectly specified. Some variables that should be included in the model often must be excluded (e.g., when the estimation data set does not contain sufficient variability of these variables). In particular, when data for model development are taken from one urban area and applied to another, there may be cultural differences between the two areas that are not explicitly represented in the model. These peculiarities of the data will be implicitly hidden in the model coefficients and so the coefficients estimated in one area will not be valid for the other. For a model to be perfectly transferable its coefficients must be free from contextual factors.

What are the differences between aggregate and disaggregate models that affect their potential transferability? If we assume that the model specification is given, what effect does the use of aggregate or disaggregate data in its estimation have on its potential transferability? An implicit assumption in using aggregated data is that the characteristics of households within zones are relatively homogeneous as compared to the differences between zones. However, several studies have shown the opposite to be true-there is more variation within zones than between them (1, 2). Because of this, problems such as the loss of variability in the data, collinearity between variables, and the risk of an ecological fallacy (3) can arise in the estimation of aggregate models and adversely affect their predictive ability and, hence, their transferability.

Suppose for a moment that these problems have been considered and do not affect the estimation of an aggregate model. One serious problem that still remains is the linkage of the coefficients of the aggregate model to the zonal structure of the area for which it was estimated. This linkage is directly observed from the definition of an aggregate demand model. If the disaggregate model is denoted as $f(X, \theta)$ where X is a vector of independent variables and θ is a vector of the coefficients of the disaggregate model, the aggregate demand is the sum of the disaggregate demands and therefore the aggregate model is

$$\int_{\mathbf{X}} f(\mathbf{X},\boldsymbol{\theta}) h(\mathbf{X}, \overline{\mathbf{X}}, \boldsymbol{a}) \, \mathrm{d}\mathbf{x} \tag{1}$$

where $h(X, \overline{X}, \alpha)$ is the distribution function of the independent variables for the group on which the aggregation is performed, \overline{X} is the vector of means of the independent variables, and α denotes other parameters (or higher moments) of $h(X, \overline{X}, \alpha)$. The result of this integral is an aggregate demand model that could be expressed as $F(\overline{X}, \alpha, \theta)$, where the function $F(\overline{X}, \alpha, \theta)$ does not necessarily have the same analytical form as $f(X, \theta)$. Traditional aggregate models do not explicitly include all the parameters of the within-zone distributions , $h(X, \overline{X}, \alpha)$, and therefore these parameters are implicit in the resulting coefficents of the model. Since these distributions would certainly differ from one area to another (4) they would have to be reflected in the model in order for it to be transferred successfully. However, existing aggregate models are not capable of this and so are less likely to be transferable than disaggregate models that are estimated on observations of individual behavior and have model coefficients that are not bound to any particular zonal structure. Thus, a disaggregate model is always more transferable than a comparable (i.e., same set of variables) aggregate model.

TEST OF TRANSFERABILITY

As an initial test of the transferability of disaggregate demand models, the specification of an existing mode choice model developed on 1968 Washington, D.C., data was reestimated on data sets representative of New Bedford, Massachusetts, in 1963 and Los Angeles, California, in 1967. The model coefficients from this reestimation and the statistical significance of the differences between these and those of the original model are discussed below.

Existing Model

The model selected for this test (and the subsequent empirical evaluation) is a multinomial logit mode choice model (1) that has been modified and extensively tested (5, 6, 7) [the multinomial logit formulation itself is described in many places (8, 9, 10, 11).] This model predicts the probability of a commuter driving alone, sharing a ride (i.e., two or more persons in a car), or using transit for the home-to-work trip. The model specification is given in Table 1.

The model contains all the normally expected variables-in-vehicle travel time, out-of-vehicle travel time, out-of-pocket costs, income, and automobile availability - plus some special variables to differentiate between alternative modes. A primary worker dummy variable is included for the drive alone mode under the hypothesis that the head of household has some priority in using any available automobile. The CBD dummy variables for the drive alone and shared ride modes express the added inconvenience of driving an automobile into the Washington, D.C., CBD above that reflected in the level-of-service variables. Three additional variables are included to account for the choice of the shared ride mode. These variables are a government worker variable (GW) that serves as a proxy for employer provided incentives for forming car pools, the destination employment density times one-way trip distance variable (DTECA), and the number of workers in the household variable (NWORK).

In transferring this model to the New Bedford and Los Angeles data sets, the specifications of the independent variables are identical to those of the original model with the exceptions that both CBD variables and the government worker variable are excluded. In the case of the CBD variables, the congestion and inconvenience associated with driving into the CBD of a large, dense city such as Washington are real factors in choosing between automobile modes and transit. In a small city such as New Bedford or in a very diffuse city such as Los Angeles, however, the distinction between CBD and non-CBD trips would probably have little effect on this choice. Therefore, the DCITY variables are assumed to have a value of zero. Similarly, the effects of large organizations offering incentives to car pool do not exist in either New Bedford or Los Angeles and the government worker variable also has a value of zero.

Estimation Results

The coefficients and statistics of the models estimated on the Washington, New Bedford, and Los Angeles data sets are given in Table 2. (The data base is given below.)

City	No. of Observa- tions	No. of Alterna- tives	Log Likelihood at Zero	Log Likelihood at Conver- gence	
Washington	1114	2924	-1054.0	727.4	
New Bedford	453	1208	-436.4	-256.5	
Los Angeles	879	2549	-930.0	-391.2	

The coefficients of the original Washington model all have the correct signs, and, for the most part, are highly significant (i.e., having large t-statistics). The coefficients of the New Bedford model also have the correct signs. The t-statistics, however, are not nearly as large as those of the original model, although for only three coefficients (in-vehicle travel time, shared ride automobile availability, and employment density times distance) are they seriously low. This relatively poor statistical performance may be related to the smaller sample size (453 versus 1114 observations) and the much lower variability observed for several of the level-ofservice variables. (Data were available only for those trips having both origin and destination within the city of New Bedford itself.) The coefficients for the Los Angeles model also have the correct signs. In this case the overall statistical performance is much better than in the New Bedford case due in part to the larger sample size (879 observations).

Comparison of Coefficients

The three sets of coefficients are remarkably similar. The significance of the differences in coefficient values that do exist can be evaluated from two viewpoints: the practical policy analysis and the statistical. From the point of view of transportation policy evaluation the concern is with the consequences of the differences for transportation planning decisions, i.e., differences be-

Table 1. Work mode choice model: definition of variables.

Variable	Definition 1, for drive alone 0, otherwise					
D,						
D,	1, for shared ride					
	0, otherwise					
OPTC/INC	Round trip out-of-pocket travel cost (#) household annual income (\$)					
IVTT	Round trip in-vehicle travel time (min)					
OVTT/DIST	Round trip out-of-vehicle travel time (min) one-way distance (miles)					
AALD.	Number of automobiles licensed drivers, for drive alone 0, otherwise					
AALD,	Number of automobiles licensed drivers, for shared ride 0, otherwise					
BW.	 if worker is head of household, for driver alone otherwise 					
GW,	 if worker is a civilian employee of the federal govern- ment, for shared ride otherwise 					
DCITY,	1, if work place is in the CBD, for drive alone 0, otherwise					
DCITY,	1, if work place is in the CBD, for shared ride 0, otherwise					
DINC, .	Household annual income - 800 × number of persons in the household (\$), for drive alone and shared ride 0. otherwise					
NWORK.	Number of workers in the household, for shared ride 0, otherwise					
DTECA,	Employment density at the work zone (employees per commercial acre) < one-way distance (miles), for shared ride 0, otherwise					

tween coefficient values for level-of-service variables. As given in Table 2, with the exception of the travel cost coefficient for the New Bedford model, all level-ofservice coefficients are sufficiently similar to warrant the conclusion that, even if the model as a whole may not be transferable, the level-of-service coefficients of the Washington model are.

The difference between two sets of coefficients can be tested by using the likelihood ratio test (12) where the null hypothesis is that the two sets of coefficients are equal. To perform this test it would be necessary to estimate the model with the two data sets pooled together in addition to the two separate estimations presented here. This was not done primarily because in an actual planning situation access to raw data cannot be assumed. Therefore, the original Washington coefficients were taken as constants (rather than random variables), and the likelihood ratio test was performed with the new data set only. The test statistic is given by

$$2[L^*(\theta_{\text{WASH}}) - L^*(\theta_{\text{NB}})]$$
(2)

where

$L^*(\theta_{ND}) =$	the log likelihood of the New Bedford
NB	coefficients on the New Bedford data
	(= -256.5), and
$L^{*(\theta_{WASH})} =$	the log likelihood of the Washington co-

efficients on the New Bedford data (= -262.4).

From this, the value of the statistic is 11.8; it is chisquare distributed with 11 degrees of freedom. The probability of this statistic exceeding 11.8 is 38.3 percent. Therefore, the null hypothesis cannot be rejected, and the two sets of coefficients are not significantly different for the New Bedford data.

Rather than comparing sets of coefficients, the differences between individual coefficients can be evaluated by expressing the significance of the difference between the New Bedford or Los Angeles coefficients and the Washington coefficients as the t-statistic for the absolute difference. The test statistic used is the difference of the two coefficients divided by the square root of the sum of the variances of the two coefficients, and for large samples is normally distributed. Only for two of these coefficients (AALD_c and AALD_c) are the differences significant at the 90 percent level.

The facts that the original specification gave a reasonable model in other areas and that the sets of coefficients taken together and key level-of-service coefficients are not significantly different are encouraging. The differences between several of the coefficients indicate areas in which more research on improved specification could be fruitful, and show that the comparison of coefficients

Table 2. Transferability of work mode choice model to different cities.

Variable	Washington		New Bedford		Lus Angeles		
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	
D.	-3.24	-6.86	-2,198	-2.648	-2.746	-4.85	
D.	-2.24	- 5_60	-1.535	-1.535	-1.830	-3.95	
OPTC INC	-28.8	-2.26	-87.33	-1.576	-24.37	-2.07	
IVTT	-0.015 4	-2.67	-0.019 9	-0,4849	-0.014 65	-2.25	
OVTT DIST	-0.160	-4.08	-0.101 3	-2 903	-0.186 0	-4.02	
AALD.	3.99	10.08	2.541	3 674	3.741	7.19	
AALD.	1.62	5.31	0.449 9	0.847 8	0.609 3	1.58	
BW.	0.890	4.79	1.026	3.769	0.810 1	3.28	
GW.	0.287	1.78	-	-	-	-	
DCITY.	-0.854	-2.75	-	-	-	-	
DCITY.	-0.404	-1.36	-	-		-	
DINC.	0.000 07	3.46	0.000 072	1.279	0.000 083	2.31	
NWORK.	0.098 3	1.03	0.187 4	1.249	0.081 0	0.46	
DTECA.	0.000 63	1.34	0.000 60	0.766 5	0.000 27	2.23	

estimated for two different data sets is a powerful method of detecting specification errors. But, whatever improvements are implemented, no model will be perfectly specified and therefore perfectly transferable, hence the motivation for the application of updating procedures for the model coefficients.

PROCEDURES FOR UPDATING

This section develops several approaches for transferring a model from one area to another. Since the motive for transferring is to provide a reasonable travel demand model while meeting stringent resource constraints, the level of effort required for each of these approaches will be an important factor in evaluating their effectiveness. In terms of level of effort required, these approaches can be divided into two broad categories: those that require a disaggregate sample from the area in question and those that do not.

Transferring With No Disaggregate Sample

The simplest approach requiring the minimum level of effort is to use the existing model with its original coefficients. This assumes that all factors relevant to the choice process are embodied in the model, an assumption that will never be fully justified. For example, the specification of most models contains constant terms to account for factors not explicitly explained by the model. The presence of these constants indicates that in fact the model has not captured all aspects of the choice process and, because these other factors can vary between areas, the value of such a constant estimated in one area may or may not be appropriate for another. Therefore, although there is a theoretical basis for transferring the relationships estimated between time, cost, income, automobile availability, and such, there is no such basis for transferring these constant terms. Fortunately, in most applications data on existing conditions are available and the model will be used to predict changes in travel behavior that result from changes in the independent variables. For incremental predictions, therefore, the constant terms have no effect on the results. In some situations, however, data on existing conditions are not uniformly available at the required level of detail and the constants must be modified.

A suitable approach to this might be to use the existing model with adjustments of these constants. In this approach, the coefficients other than the constants are accepted and aggregate data on travel patterns in the new area are used to adjust the constants to better reflect the existing situation. The adjustment is performed by applying the model to the new area in the way in which it will be applied for forecasting. The results are aggregated to the level for which data (e.g., aggregate mode splits for work trips for the model tested in this paper) are available and the constants then adjusted until the model replicates the existing aggregate data. This improves the goodness of fit to the existing data, but the use of areawide averages for the independent variables could result in poorer estimates of the constants because of an aggregation bias. The primary criticism of this approach is that, in practice, other coefficients are not perfectly transferable and adjusting only the constant terms will compensate for these errors.

Transferring With a Disaggregate Sample

In this category, it is assumed that at least a small sample of observations on individual trip-making behavior representative of the study area will be available for use in updating the original model. The sample should be selected such that it could be used to reestimate the original model. (The effect of sample size on the performance of each approach is discussed later.) The most straightforward approach is to use the small disaggregate sample to reestimate all the coefficients of the original specification, reasoning that, since the model specification was successful in one area, it should work in another, and that, by using the coefficients estimated on data from the area where the model is to be used, none of the original coefficients need be accepted. However, because a model specification results in good statistical performance on one particular data set does not guarantee that estimating it in another area would result in reasonable coefficients. Even if the specification were correct, the use of a small sample for estimation is a potential source of problems. The maximum likelihood estimation technique used for these models gives coefficient estimates that have asymptotically optimal properties. For the small samples used in this approach, it is possible that the resulting biases and standard deviations will be large.

Another approach is to reestimate only the constant terms. In this approach, a single coefficient that modifies the scale of the other coefficients could also be estimated. This would retain the original trade-offs among the independent variables and should give a better goodness of fit on existing data. Forecasting accuracy for changes of individual variables should increase for those coefficients that benefit from the single scale coefficient and decrease for the others.

A better approach is to combine the original coefficients with those estimated on the small sample. Ideally, this should be done in such a way that all of the original coefficients are modified and at the same time any adverse effects resulting from the small sample available for the new area are minimized. Updating the original coefficients by using sample information should result in a model that better reflects travel behavior in the new area.

Bayesian Updating

The methodology used for combining sample information with prior information was that of Bayesian statistics (13), which relates the posterior distribution in an unknown parameter, θ , to the prior distribution in θ and the sample likelihood function by

/Posterior \		/likelihood		
probability	- 0	of the	(prior probability)	(2)
of θ given	= C x	sample	× \ofθ /	(3)
\the sample/		\given θ /		

(The normalizing constant, C, is to ensure that the resulting posterior distribution is a proper set of probabilities.) The estimated coefficients of the original model are random variables that, for large samples, are normally distributed: This is the prior distribution. The data for the small sample for the new area are next used to reestimate the model to obtain a different distribution of the model coefficients: This is the sample distribution. These two distributions are then combined to obtain the posterior, or updated, distribution of the coefficients. This is shown in Figure 1 for the single coefficient case.

Since both the prior and the sample distributions are normal and the variance is assumed to be known, the mean and standard deviations for the posterior distribution in the single coefficient case are

$$\theta_2 = \left[(\theta_1 / \sigma_1^2) + (\theta_s / \sigma_s^2) \right] / \left[(1 / \sigma_1^2) + (1 / \sigma_s^2) \right]$$
(4)

and

 $\sigma_2 = [(1/\sigma_1^2) + (1/\sigma_1^2)]^{-1/2}$

where

- θ_1 = original coefficient,
- $\theta_{\bullet} = \text{sample coefficient},$
- θ_2 = updated coefficient,
- σ_1 = standard deviation of the original coefficient,
- σ_{0} = standard deviation of the sample coefficient, and
- σ_2 = standard deviation of the updated coefficient.

Thus, θ_2 , the updated coefficient, is a weighted average of the original coefficient, θ_1 , and the coefficient estimated from the new sample, θ_{s} , the weights being the inverse of their respective variances. The extension to the multivariate normal case is given by Raiffa and Schlaifer (13, p. 310). For the case shown in Figure 1, in which the prior information is reliable and a relatively small sample is used, the posterior distribution of θ will be based primarily on the prior information. For the case shown in Figure 2 in which the prior information is not very reliable and a relatively large sample is used, the posterior distribution of 0 will be based primarily on the sample information. In both cases, the variance of the posterior distribution will always be less than that of both the prior distribution and the sample likelihood distribution.

This procedure also offers an opportunity to introduce subjective judgments into the model estimation process. Consider the case in which the data used to estimate the original model are thought to be inaccurate: The variance of the original coefficients can be increased to reduce the weight of these estimates in the updating process. Similarly, if the original estimation has been done a long time earlier, the relative weight placed on the prior distribution can be reduced.

It should be stressed that the key advantage of the Bayesian updating procedure is economic. By combining new sample information with prior information, it permits the use of small sample surveys that, by themselves, would not be statistically adequate for updating models. This procedure approximates the pooling of the sample used to estimate the existing model with the new sample but obviates the need to go back to the original sample data. It also has the advantage of being able to subjectively alter the weight of the prior sample with relative ease.

EMPIRICAL EVALUATION OF UPDATING PROCEDURES

This section describes an empirical evaluation of these approaches using New Bedford data. Two measures of effectiveness, goodness of fit on existing data and forecasting ability, are used to compare the models resulting from the various procedures of transferring. Each procedure is evaluated in terms of both; the results of this empirical evaluation indicate which method dominates at a given level of effort.

Goodness of Fit

One way of measuring how well a particular model fits the existing data is to use the log likelihood of the coefficients of that model for the New Bedford data to determine a value for a goodness of fit measure such as ρ^2 , which equals the fraction of the log likelihood explained by the model, and is defined as $\rho^2 = 1 - [L^*(\hat{\theta})] / [L^*(0)]$

(5)

 $L^*(\theta)$ = the log likelihood of the sample for $\theta = \hat{\theta}$ and $L^*(0)$ = the log likelihood of the sample for $\theta = 0$.

This approach has the advantage that it provides a single measure by which to rank the various models. However, ρ^2 is an abstract measure and it is difficult to grasp what differences in ρ^2 actually mean in terms of model performance.

Another approach is to compare the observed mode split of the data set with that predicted by the model by using values for the independent variables given in the data set. This is done by calculating individual probabilities of choosing available modes for each observation using the particular model being evaluated. These individual probabilities are then summed and compared with the observed mode split for the entire data set. These differences between observed and predicted mode splits provide a more specific measure of the goodness of fit of a model.

Forecasting Ability

To assess the forecasting ability of the models resulting from the transferring methods, the predicted changes in mode split resulting from policy changes are compared with the true changes predicted by the New Bedford model. The true changes are obviously unknown, but the model estimated with the entire New Bedford data set provides the best estimate available of the New Bedford conditions and therefore the best estimate of the true changes. The responses to policy changes are determined by recalculating the choice probabilities for each observation in the data set to account for the changed variables. These probabilities are then summed for each mode to find the forecasted mode shares. The policy selected to evaluate forecasting ability was that of assigning preferential lanes for multiple occupancy vehicles, resulting in a 15 percent decrease in shared ride and transit in-vehicle travel time.

EVALUATION OF APPROACHES FOR TRANSFERRING

The following models are used in this empirical evaluation:

1. True New Bedford model - the model estimated on the entire New Bedford data set (453 observations),

2. Washington model-the original model estimated on Washington data.

3. Washington model with updated (aggregate) constants—the original Washington model with the constant terms adjusted by use of aggregate mode split data,

4. New Bedford small sample models — models estimated on small random samples taken from the New Bedford data set [the size of the sample is indicated by the number of observations (44, 89, or 177)],

5. Washington model with updated (disaggregate) constants—models resulting from using disaggregate samples to reestimate the constant terms and a scale factor for all other coefficients, and

6. Model resulting from Bayesian updating—models resulting from Bayesian updating with the inverse of the variance-covariance matrix as the weighting factor.

Before discussing the evaluation results, a point should be made concerning the bias introduced into the



Table 3. Evaluation of approaches for transferring.

Updating Procedure	No. of Observations	p²	Predicted - Observed Mode Shares* (4)			Predicted - True Changes in Mode Shares' (4)		
			Drive Alone	Shared Ride	Transit	Drive Alone	Shared Ride	Transit
True New Bedford model		0.412	0	0	0	0	0	0
Washington model		0.399	-0.39	-0_7	1.09	0,25	-0.24	0.01
Washington model with updated (aggregate) constants		0.398	-1.90	0.96	0.94	0.22	-0.21	-0_01
New Bedford small sample models	44	0_291	-4.91	3,55	1.36	-1.04	1.09	-0.05
	89	0 382	-1.69	0.31	1.37	-2.30	2.28	0.02
•	177	0.397	-1.20	-0.58	1.78	0.82	-0.78	-0.04
Washington model with	44	0.396	-3.51	4,22	-0.71	0.37	-0.34	-0.03
updated (disaggregate)	89	0 401	-1.33	0.83	0.50	0.36	-0.34	+0.02
constants	177	0.398	-1.95	0.35	1.59	0.26	-0.26	0.0
Models resulting from	44	0.399	-2.20	1.26	0.91	0.27	-0.26	-0.01
Bayesian updating	89	0.400	-0.39	-1.16	1.56	0.24	-0 25	0.01
	177	0.400	-0 51	1.03	1.54	0.20	0,20	0.0

*Observed mode shares are drive alone = 55 12, shared ride = 37 76, transit = 7 12%

"True mode share changes are drive alone = 1.01, shared ride = 0.96 transit = 0.05%

evaluation measures. Because the observations for the small samples used in some of the transferring methods are taken from the data set that was used as the standard for New Bedford, the resulting measures of effectiveness for these approaches are biased toward indicating better performance, especially for the models estimated directly on these small samples. The magnitude of this bias varies with the sample size: For example, the bias for the model using 44 observations is relatively small since 409 observations (90 percent of the full data set) are different from those used in estimating the model. For the model using 177 observations, however, the bias may not be negligible since only 276 observations (61 percent of the full data set) are different.

The ρ^2 values for the different models are listed in Table 3. For sample sizes of less than 89 observations, performance is very poor: the small sample approach requires a sample size of at least 180 observations. In general, the Bayesian updating approach is best.

The comparison of predicted versus observed mode shares for the existing data is given in Table 3 for the entire data set. As observed with the o^2 values, below 89 observations the performance decreases for all approaches to transferring that require a disaggregate sample. The pattern of errors is not the same for all three modes and no general pattern of dominance emerges. Overall, the Washington model and the Bayesian updating models performed better than other approaches, particularly for the drive alone mode. The performance of the different approaches in predicting changes in mode shares due to a preferential lanes policy is also given in Table 3. The Bayesian updating approach in general performs better than the other approaches; the Washington model is superior to small sample models.

CONCLUSIONS

The most interesting result of this empirical study is the surprisingly good performance of the original Washington model on both the New Bedford and Los Angeles data sets. This is remarkable in view of the fact that the New Bedford and Los Angeles data sets represent very different conditions than those existing in the Washington data set. Although differences in individual coefficients between the models were observed, only three of these differences can be considered significant. Of all the approaches to updating the original model, Bayesian updating gives consistently better results. The small sample approach resulted in models that were inferior to the original Washington model for every measure of effectiveness and is clearly unreliable for the purposes of transferring.

Two approaches were taken to updating the constants: one using aggregate mode split data and the other using a small sample. For the first approach, because the original model had fit the data so well, the resulting model performed more poorly than the Washington model. Although slight improvements in some measures were observed for reestimating the constants, these improvements were insignificant when compared with those resulting from Bayesian updating. Therefore, the approach of reestimating the constants, like the small sample approach, is an inefficient use of the disaggregate sample for updating.

However, the superior performance of the Bayesian updating approach to that of the small sample models can be attributed to the good performance of the Washington model by itself for the New Bedford data. If the Washington model had had serious specification errors the small sample models would probably have performed much better relative to the Bayesian updating models. Thus, it is clear that a credible specification is a precondition to any attempt to transfer a model.

In summary, three important conclusions are indicated from the empirical results:

1. A well-specified disaggregate mode choice model is transferable.

2. It is useful to update the model coefficients when transferring.

3. The Bayesian updating procedure using a small disaggregate sample is the most effective procedure for transferring well-specified models.

The empirical results reported in this paper are based on a model for the conditional probability of mode choice, which is only one component of the entire travel demand model system. These results are indicative but further work is needed in other aspects of travel demand for which model development effort has been significantly lower.

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