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□論 文□

混成「로-짓」模型의 檢証

AN EMPIRICAL TEST OF THE BLENDING LOGIT MODEL

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要 約

本 硏究는 1980年 Moses-Anas에 의해 提案된 「混成로-짓模型」의 有效性을 서울市의 出勤通行實態 資料를 利用하여 檢證하기 위한 것으로, 「混成로-짓模型」에 의한 推定結果와「傳統的로-짓模型」에 의한 推定結果를 統計的 觀點에서 相互 比較하였다. 利用된 資料는 1981年 6月 10日부터 6月 16日까지 一週日間의 出勤通行實態資料이며 調査標本數는 約 2000餘標本이었다.

「混成 로-짓模型」에 의한 推定結果는 「傳統的로-짓模型」에 의한 경우보다 統計的으로 優越한 것으로 나타났으며, 特히 通行時間 및 通行費用에 대한 選擇確率의 彈力性은 「混成模型」에 의해 推定된 結果가 더욱 合理的인 것으로 判明되었다.

I. Introduction

Since the early sixties economists have been interested in modeling travel demand, and more specifically in the modeling of choice among an alternative travel modes for commuting to work. The earliest research into disaggregate, mode-choice models was published in 1962 by Warner who used household files from the Chicago Area Transportation Study to develop a set of three-mode choice models for both work and nonwork trips.

A great contribution has been made to the application of economics to travel modeling by Kelvin J. Lancaster (1966) who developed a concept of "abstract modes" which stated that demand for travel by a mode is not dependent on the name of the mode, but on the characteristics that describe

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the level of service that each mode offers. A number of pioneering efforts were published in the period 1967 through 1969. Different mathematical calibration procedures have been used for each travel demand model, for example, discriminant analysis by David A. Quarmby, probit analysis by Thomas E. Lisco, and regression and logit analysis by Peter R.Stopher.

But the behavioral theory of travel demand did not become clearly formulated until recent contributions by McFadden (1973, 1974) and Domenich and McFadden (1975). In this literature the commuter is viewed as a rational utility maximizing consumer who must choose among discrete travel alternatives such as automobile, bus, train, walking etc. The choice of mode is governed by the characteristics of the various modes, by income constraints and by preference of the commuter. Viewed in this way the problem of travel mode choice does not differ from other economic choice situations where a consumer must choose from discrete but substitutable alternatives.

Recently a number of developments and extensions have been made in the area of mode-choice models by David A. Hensher, Peter L.Watson, Moshe E. Ben-Akiva, Antti P. Talvitie, Peter S.Liou, Steven R. Lerman, etc.

Leon N. Moses and Alex Anas (1979) formulated a different kind of mode-chocie theory on the basis of two fundamental observations which had gone unnoticed in the above literature. First, the the typical commuter faces an external constraint on the number of days he or she should work per week or month, and in many cases a further constraint on the number of hours that should be spent at work on any given work day. Second, it was observed that work travel is a negative good for most, if not all, commuters.

In the paper, "Disutility, work constraints and travel demand theory", the authors incorporated three realistic assumptions to develop a new theoretical model. Which are (1) travel to work enters utility negatively and that travel by transit is inferior to travel by auto, (2) the typical commuter is constrained to make a minimum number of work trips per week or month, and (3) commuting must be planned over an extended period such as a week or a month. In this theory the demand for transit is positively sloped, which means that the number of transit trips is reduced by a fare cut.

Although the demand theory by professor Leon N. Moses and Alex Anas is different from those of the traditional theory in which travel demand is negatively sloped, it is not the intention of this paper to test the new theoretical model or to compare it with traditional model. The objective is to empirically test the multinomial logit model suggested by the authors as an econometric approach for testing their theoretical model and to compare it with traditional logit model.

So attempts were made to estimate the coefficients of the utility function using the proposed multinomial logit model with work constraints, to compare the estimated coefficients with those of the traditional myopic logit models, to determine whether the travel plan choice model has superior explanatory power and whether they produce better predictions of modal choice patterns. Futhermore, elasticities of the new logit model and those of the conventional logit model were estimated.

Week-diary travel data was collected for a sample survey in Seoul city, Korea. The estimation was carried out by QUAIL program

II. Model

Conventional Logit Model

The structure of disaggregate choice model is derived from economic and psychological theories of human behavior. These model structures relate the probability of making a particular choice to the attractiveness of the available alternatives.

The basic assumption behind the conventional logit is that the random component of the utility function, E_{it} and E_{jt}, are independent and identically distributed (IID), and that the distribution of each is Weibull (or Gumbel).

The logit model is written as follows:

$$P(i{:}A_t) = \frac{e^{U_i(X_i, S_t)}}{\sum_{j \in A_t} e^{U_j(X_j, S_t)}} \quad \cdots\cdots (1)$$

where

t = a behavioral unit. t = 1, 2, ---- T

A_t = the set of relevant alternatives for behavioral unit t

$P(i : A_t)$ = the probability that individual t will choose alternative i out of the set A_t

$U_i(X_i, S_t)$ = the utility of alternative i to individual t

X_j = a vector of variables describing alternative j

S_t = a vector of socioeconomic variables describing individual t.

Thus, the probability of an individual choosing an alternative from a set of available alternatives is a function of the attributes of each alternative and characteristics of the individual. The attributes of the alternatives could include the price, travel time to the alternative, the parking charge or congestion at that alternative, or some measure of its attractiveness, such as the number of employees. The socioeconomic characteristics of the individual include income and other variables, such as family size, education, sex, etc, which can account for difference in tastes etc.

Blending Logit Model

The weekly utility of a commuter randomly drawn from the population and taking A auto and T transit trips is expressed as,

$$V(A,T) = V(M(A,T), Q_1(A,T), \cdots, Q_k(A,T)) + E(A,T) \cdots\cdots (2)$$

where

$M(A,T) = I - AC_a - TC_t$ is the part of the commuter's weekly income, I, that can be spent on other consumption if the commuter takes A auto and T transit trips priced at C_a, C_t, respectively.

$Q_i(A,T)$ = A Q_{ia} + T Q_{it}, $i = 1 .... k$ is the weekly level of the ith attribute for a commuter choosing A auto and T transit trips.

Q_{ia}, Q_{it} = denote the amount of the ith attribute suffered in a single trip taken by auto (a) and transit (t), repsectively.

$V(\cdot)$ = the part of utility which is common to all commuters in the population.

$\varepsilon(A,T)$ = The part of utility for travel plan (A,T) which varies randomly among commuters due to personal idiosyncrasies or unmeasured attributes.

For a week of six workdays each commuter faces a choice among six discrete travel plans given by (A,T) = ((5, 0), (4, 1), (3, 2), (2, 3), (1, 4), (0.5)).
These six travel plan will be indexed in above order as $i = 1, ... 6$.
The probability that a commuter randomly drawn from the population will choose a specific weekly travel plan is P_i ;

$$P_i = \text{probability } (V_i + \varepsilon_i > V_j + \varepsilon_j ; V_i \neq j) \quad : i = 1 .... 6 \qquad \cdots\cdots (3)$$

A choice model is derived by specifying the joint multivariate distribution of the elements of the random terms

$$\bar{\varepsilon} = (\varepsilon_1 , ... \varepsilon_6) \qquad \cdots\cdots (4)$$

The authors derived the multinomial logit model (MNL) by assuming that each ε_i is independently and identically distributed according to the extreme value distribution with mean zero and variance σ^2.
The multinomial logit model is

$$P_i = \frac{e\left(\frac{\Pi/\sqrt{6}}{\sigma}\right) V(M_i , Q_{ii}, ... Q_{ki})}{\sum_{j=1}^{6} e\left(\frac{\Pi/\sqrt{6}}{\sigma}\right) V(M_i, Q_{ij}, ... Q_{kj})} \qquad \cdots\cdots (5)$$

$$j = 1, ... 6$$

If the commuter is myopic and decides each day's travel separately the possible travel plan are only two and expressed as (A,T) = ((0, 0), (0, 1)), i.e., the binary logit model.

III. Data

The blending logit model needs travel diary data set for an extended period such as a week or month and sampling has to be limited to a population of commuters who make work trips. The week-diary travel data was collected from Seoul, Korea, where commuters are used to blending modes for travel.

Data was collected by messenger survey method. Survey had been carried out through students of Jinsun woman's highschool located in the residential area in the southern suburbs of the Seoul city. The total number of students amount to about 2,000 students. Questionaires had been given to the students by their teachers. Then students took the questionaire home and asked their household head or member of household who had a occupation to answer the questions. In Seoul, students are required by law to enroll in a school near their home. So the data collected represents persons who live in a certain area but have different work places. All transportation modes are available to this sampling area.

The sample survey was made for six work days from July 10 to July 16, 1981, excluding sunday, July 12. A questionaire for a week-diary work travel data were distributed to 400 household heads and returned, but only 340 were suitable for this study.

The questionaire was designed to obtain data for one-way-trip, i.e., home-to-work trip, work-to-home trip, every day for six work days a week, and the general informations contained in the questionaire are as follows.

General data (Socioeconomic Characteristics)

For Household : Household income; Household monthly expenditure (foods, housing cost, utility cost, clothes, transportation cost, etc.); Household size; Number of the employed; Number of car owned.

For Household head : Home address and address of work place; Sex; Age; Driver's License?; Occupation; Average number of work days per month.

Travel data (For Household head) :Origin-destination or work trips; Travel time: in vehicle time, out of vehicle time (vehicle access time); Travel cost; Travel distance; Mode used; Reason of the mode chosen; Rank of the mode;

The frequency distribution of mode choice for all 340 observations is summarized as in Table 1. For the simplicity of work, the study classified the choice market only for taxi-bus blending observations (148 observations, hereafter TBGRP) in which commuters use taxi and public bus alternatively. Table 2 shows the statistics of level of service variables. The data set, TBGRP, was used to calibrate the conventional and blending logit model, respectively.

Table 1. Distribution of mode choice

1. Single Mode

	No. of observation		%
• Auto only	57		(16.8)
• Taxi	7		
• Private commuter bus	5		
• Microbus	7	119	(35.0)

• Public bus	99		
• Subway	1		
• Bicycle	1		
• Walking	22		
Sub – Total	199		(58.5)
2. Mode Blending			
Auto ⟷ Other Modes	21		(6.2)
• Auto – Taxi	7	11	(3.2)
• Auto – Microbus	1		
• Auto – Public bus	2		
• Auto – Subway	1		
• Auto – Taxi, Commuter bus	1	10	(3.0)
• Auto – Taxi, Public bus	2		
• Auto – Taxi, Microbus	2		
• Auto – Taxi, Public bus, Subway	1		
• Auto – Taxi, Microbus, Public bus	1		
• Auto – Public bus, Subway	2		
• Auto – Public bus, commuter bus, Subway	1		
Taxi → Other Modes	87		(25.6)
• Taxi – Commuter bus	3	62	(18.2)
• Taxi – Microbus	13		
• Taxi – Public bus	42		
• Taxi – Subway	2		
• Taxi – Walking	2		
• Taxi – Public bus, Microbus	12	25	(7.4)
• Taxi – Public bus, Subway	3		
• Taxi – Public bus, Commuter bus	4		
• Taxi – Microbus, Commuter bus	3		
• Taxi – Public bus, Microbus, Commuter bus	1		
• Taxi – Public bus, Microbus, Subway	2		
Between Other Modes	33		(9.7)
• Commuter bus – Microbus	5		
• Commuter bus – Public bus	2		
• Microbus – Public bus	18		
• Public bus – Subway	5		
• Public bus – Walking	1		
• Public bus – Bicycle	1		
• Microbus – Public bus, Subway	1		
Sub – Total	141		(41.5)

The reasons that use only 148 observations of taxi and public bus users are as follows: First, the previous data analysis shows a strong tendency that most of the auto owners use auto only for work trip and do not use other modes for their work trip. So most of the mode blending for work trip occurred between taxi users and bus users in Seoul. Second, the data also shows that taxi is considered as a superior mode to public bus. Most of the household heads did not answer that auto is superior to taxi or public bus because an auto is unavailable to them. So it would be appropriate to use taxi as a superior mode instead of auto to public bus. Third, many of the auto owners did not report the travel cost of their each work trip.

There were 148 TBGRP commuters who use public bus, taxi, public bus and taxi for their work trips, 99 for public bus, 7 for taxi and 42 for public bus and taxi blend.

Table 2. Statistics of level of service variable (TBGRP : 148 observations)

Variables		Mean	Standard Error	Standard Deviation	Minimum	Maximum
Bus	In-Vehicle time (minutes)	31.510	1.008	12.220	6.000	74.000
	Out-of vehicle time (minutes)	11.524	0.412	4.995	3.00	27.00
	Out-of-pocket cost (won)	155.054	5.567	67.501	100.000	500.000
Taxi	In-vehicle time (minutes)	18.190	0.649	7.868	3.000	40.000
	Out-of-vehicle time (minutes)	6.211	0.206	2.497	0	20.000
	Out-of-pocket cost (won)	1601.721	68.545	831.067	600.000	6000.000
Travel Distance (km)		9.857	0.538	6.523	1.000	45.000

IV. Estimation

1. Selection of Variables

The basic problem of variable selection is the trade-off between the level of detail and relative ease of use in forecasting. In general variables are classified into generic variables and alternative specific variables. The Table 3 gives the definition of independent variables used in my estimation.

Generic Variables

The following variables were selected as generic variables of utility function for both blending logit model and conventional logit model. Since the variables for transportation level of service to work influence directly the primary worker's choice of travel mode to work, the study decided to use the traditional level-of-service measures commonly included in modal-choice models : in-vehicle-time (IVTT), out-of-vehicle time (OVTT), total travel time (TTIME), out-of-pocket cost (COST).

Socioeconomic variables are a special class of attributes in that they do not vary across travel-mode-to-work alternatives. For this reason, these variables must some-how be transformed in the utility function either by combining them with other variables or by making them alternative specific. Household income plays an important role in choosing travel mode to work. Here the variable ICOST was selected as an socioeconomic variable. ICOST was defined as cost/household monthly income. Another variable introduced is OVTDIST which represent the out of vehicle time measured relative to trip distance. This corresponds to the hypothesis that time spent out of vehicle may be viewed as a fixed charge, the effect of which is less important on long trip than on short ones.

Alternative Specific Variable

As discussed earlier, trip means one-way-trip (e.g. home-to-work trip or work-to-home trip) in this study. For a week of six workdays each commuter faces a choice among thirteen discrete travel plan. If these thirteen travel plan were indexed in the above order as alternative i = 1, 2,. ... 13, then we have thirteen alternatives. So we can define twelve alternative specific dummy variable. But here the study decided to use only seven alternative specific variable, ALT1, ALT2, ALT3, ALT4, ALT5, ALT6, ALT13, which are defined in the Table 3. The multinomial logit model was run using all the twelve alternative specific dummy variables, but the iterations did not converge. Six alternatives of which were chosen with a frequency of 0, 1 or 2 were deleted leaving the seven alternatives show in Table 3.

Table 3. Definition of independent variables

Variable	Definition
1. IVTT	Reported in-vehicle time per one way work trip for household head (in minutes)
2. OVTT	Reported out-of-vehicle time per one way work trip for household head (in minutes). (including the waiting time and walking time to each mode, station, home and work place, etc)
3. TTIME	Total travel time equal to IVTT + OVTT (in minutes)
4. COST	Reported out-of-pocket cost per one way work trip for household head (in won) Auto = including parking fee, tolls and gasoline cost only Taxi, Bus = taxi fare, bus fare paid per one way trip
5. YNCOME	Household monthly income (in won)
6. ICOST	Cost/YNCOME (ratio)
7. DIST	Travel distance of one way work trip (in km)
8. OVTDIST	OVTT/DIST
9. ALT 1	Alternative dummy variable 1 = 1 if alternative 1 (Bus = 12, Taxi = 0) were chosen = 0 otherwise
10. ALT 2	Alternative dummy variable 2 = 1 if alternative 2 (Bus = 11, Taxi = 1) were chosen = 0 otherwise
11. ALT 3	Alternative dummy variable 3 = 1 if alternative 3 (Bus = 10, Taxi = 2) were chosen = 0 otherwise
12. ALT 4	Alternative dummy variable 4 = 1 if alternative 4 (Bus = 9, Taxi = 3) were chosen = 0 otherwise
13. ALT 5	Alternative dummy variable 5 = 1 if alternative 5 (Bus = 8, Taxi = 4) were chosen = 0 otherwise
14. ALT 6	Alternative dummy variable 6 = 1 if alternative 6 (Bus = 7, Taxi = 5) were chosen = 0 otherwise
15. ALT 13	Alternative dummy variable 13 = 1 if alternative 13 (Bus = 0, Taxi = 12) were chosen = 0 otherwise
16. TAXIDUM	Mode dummy variable = 1 if Taxi were chosen = 0 otherwise

On the other hand one mode dummy variable was selected for the conventional logit model. That is TAXIDUM which is also defined in the Table 3. The conventional model represent the binary logit model in this study, while blending model represents multinomial logit model.

2. Estimation of the Blending Logit Model

Model Formulation

It is assumed that commuter must choose a weekly travel pattern which is composed of trips taken by taxi and public bus. It is also assumed that trip is a one-way trip. So for a week of six workdays each commuter faces a choice among thirteen discrete travel plan given by

(Bus, Taxi)= [(12, 0), (11, 1), (10, 2), (9, 3), (8, 4), (7, 5), (6, 6), (5, 7), (4, 8), (3, 9), (2, 10), (1, 11), (0, 12)]

If these thirteen travel plan are indexed in the above order as i=1, ... 13, the probability that a commuter will choose a specific weekly travel plan, P_i, can be calculated by blending logit model. This is a multinomial logit model.

$$P_i = \frac{e^{U_i}}{\sum_{j=1}^{13} e^{U_j}} \quad \cdots\cdots (6)$$

U_i = utility function of the commuter choosing alternative i.

U_j = utility function of the commuter choosing alternative j, j = 1, ... 13. U_i, U_j are linear in parameters.

The 10 different model specifications are formulated as in Table 4, for the estimation of the blending model. To save the estimation cost and time one preferred model among the above ten models was chosen according to the estimation results and it's model specification was applied to the estimation of the conventional model.

Evaluation and Interpretation of the results

The Table 4 gives the summary of the estimated results and statistics of the blending logit model.

To evaluate the models presented above, we can focus on the following statistics and econometric meaning of the coefficients : i) signs and the magnitude of the coefficient, ii) standard error or t-value of the coefficients and test results whether the coefficient is significantly different from zero or not, iii) likelihood ratio index, iv) likelihood ratio tests of the fitted models, v) percent correctly predicted (PCP).

Table 4. Estimation results of blending logit model

DV: CHO

Model / IV	1	2	3	4	5	6	7	8	9	10
IVTT (t-value)	-0.001504 (-0.3466)	-0.000818 (-0.1857)	-0.002015 (-0.4741)	-0.001085 (-0.2493)	-0.001484 (-0.3418)	0.0004873 (-0.1101)				
OVTT			0.02173 (2.320)	0.02038 (2.186)						
TTIME							0.003674 (0.9599)	0.003938 (0.9999)	0.001618 (0.3907)	0.0031 0.777
COST	-0.0001084 (-2.078)		-0.000113 (-2.139)		-0.0001383 (-2.424)		-0.00008741 (-1.774)		-0.0001211 (-2.076)	
I COST		-0.000113 (-2.139)		-0.02759 (-1.519)		-0.03226 (-1.757)		-0.02240 (-1.300)		-0.025 (-1.39
OVTDIST					0.05023 (3.316)	0.02553 (0.7803)			0.04157 (1.086)	0.0178 (0.550
ALT 1	3.591 (5.256)	3.915 (6.052)	2.798 (3.756)	3.253 (4.652)	2.953 (3.728)	3.657 (5.162)	3.123 (4.277)	3.448 (4.984)	2.786 (3.593)	3.363 (4.772
ALT 2	1.216 (1.712)	1.494 (2.175)	0.5433 (0.7244)	0.9324 (1.296)	0.6638 (0.8425)	1.269 (1.738)	0.8057 (1.087)	1.086 (1.516)	0.5167 (0.6674)	1.012 (1.396)
ALT 3	1.573 (2.434)	1.807 (2.872)	1.013 (1.504)	1.340 (2.057)	1.104 (1.564)	1.615 (2.436)	1.222 (1.827)	1.457 (2.242)	0.9772 (1.410)	1.395 (2.123
ALT 4	1.478 (2.354)	1.670 (2.707)	1.025 (1.592)	1.291 (2.050)	1.090 (1.632)	1.510 (2.360)	1.185 (1.847)	1.278 (2.190)	0.9841 (1.496)	1.327 (2.092
ALT 5	1.130 (1.721)	1.283 (1.970)	0.7780 (1.171)	0.9870 (1.501)	0.8222 (1.209)	1.155 (1.736)	0.8962 (1.350)	1.048 (1.595)	0.7375 (1.096)	1.007 (1.526
ALT 6	1.248 (1.965)	1.362 (2.153)	0.9914 (1.554)	1.145 (1.803)	1.018 (1.573)	1.265 (1.976)	1.072 (1.680)	1.185 (1.866)	0.9548 (1.486)	1.154 (1.81
ALT 13	2.307 (3.879)	2.187 (3.174)	2.586 (4.265)	2.408 (4.032)	2.582 (4.155)	2.294 (3.816)	2.520 (4.182)	2.388 (4.017)	2.667 (4.343)	2.424 (4.058
L (0)	-379.6	-379.6	-379.6	-379.6	-379.6	-379.6	-379.6	-379.6	-379.6	-379.6
L ($\hat{\beta}$)	-195.7	-196.7	-192.4	-193.8	-194.6	-196.4	-195.3	-196.2	-194.5	-196.0
PCP	66.89	66.89	66.89	66.89	66.89	66.89	66.89	66.89	66.89	66.89
ρ^2	0.4843	0.4818	0.4818	0.4895	0.4875	0.4827	0.4855	0.4831	0.4875	0.483
-2 [L(0)- L ($\hat{\beta}$)]	367.3	365.8	365.8	371.6	370.1	366.5	368.6	366.8	370.1	367.1
# of cases	1776	1776	1776	1776	1776	1776	1776	1776	1776	1776

The sign of the coefficients of the independent variable IVTT, OVTT, TTIME, and COST should be negative, because these variable reflect the disutility of travel time and travel cost. All else being eqúal travellers would prefer lower travel time and cost alternatives in commuting. Variable ICOST and OVTDIST also should have negative sign. The increase of travel cost for a given income and the increase of out-of-vehicle time at the same distance would decrease the utility of the travellers.

The alternative specific dummy variable ALT1, ALT2, ALT3, ALT4, ALT5, ALT6, ALT13, represents a constant term added to each utility function. A different constant term can be intorduced into all but one of the utilities. These constants measure pure alternative effects, that is, the attributes of the alternative relative to the one without a constant term that are not measured in all the other variables. In this study a constant term was introduced into each utility except for the case of alternative 7, 8, 9, 11, and 12 as discussed earlier.

The sign of the constant should be positive, because the alternative 1, 2, 3, 4, 5, 6, and 13 reflects the preference for alternative 7, 8, 9, 10, 11, and 12. This can be explained by the following choice structure of each household head to each alternatives.

Table 4 shows that the coefficients of the IVTT, COST, ICOST, and constant term, have correct sign in all models, while the coefficients of the OVTT, TTIME, and OVTDIST, have wrong sign. Only Model 1 and Model 2 shows that all the coefficients have correct sign.

Table 5. Alternatives and their frequencies

Alternative	Frequency chosen	Percent chosen
1	99	66.89
2	8	5.405
3	10	6.757
4	8	5.405
5	5	3.378
6	5	3.378
7	2	1.351
8	2	1.351
9	0	0
10	1	0.6757
11	0	0
12	1	0.6757
13	7	4.730
Total	148	100.0

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The critical value of t statistic at 5% level of significance is $t_{0.05,1776} = 1.645$ and $t_{0.1,1776} = 1.282$, respectively. Although the coefficient of variable IVTT has correct sign, it is insignificant in all model. But if we increase the number of observations, it would be improved. The coefficient of the OVTT is significant at 5% level of significance but has wrong sign. The TTIME has wrong sign and insignificant in the coefficient of all model. The coefficient of ICOST has correct sign and are significantly different from zero in all model. The coefficient of OVTDIST has wrong sign in all model and is insignificant in all model except Model 5.

The coefficients of the constant term ALT1 and ALT13 are significant at 5% level of significance and also has correct sign. The other constant term ALT2, ALT3, ALT4, ALT5, ALT6 has also correct sign. However, not all the coefficient estimates are significantly different from zero at the usual 5% or 10% levels of significance in all model. We can infer from the coefficient of the constant term that commuter in the data set prefer the alternative 1 and alternative 13 to the other alternatives relatively. In other words the commuter in this sample prefer the taxi only or bus only to the blending of the taxi and bus. We can conclude that the Model 1 and Model 2 are superior to other models in terms of sign and t-value of the coefficient.

The likelihood-ratio test of the fitted models for the equal shares hypothesis can be done by using the likelihood ratio statistics ($-2\ [L(0) - L(\beta)\ ]$) of the preceding table. The value of the likelihood ratio statistics varies from 365.8 to 374.5 with degrees of freedom 9-10. The critical value of X^2 with 9 degree of freedom and that of X^2 with 10 degree of freedom at 5% level of significance are $X^2_{0.05,9} = 16.9$ and $X^2_{0.05,10} = 18.3$, respectively. So we can say that all the models can be considered to be significantly better than the equal share model with 5% of type 1 error.

The likelihood-ratio index for each model varies from 0.4818 to 0.4933, which is almost the same for each model. As dissussed before, these values are quite excellent, and we can conclude that each model replicate the real data very well.

The percent correctly predicted which accounts for the predictive capabilities of the model shows that each model predicts the observed dependent variable with a 66.89% of correctness.

Judging from the previous evaluation of each model in terms of signs and t-value of the each coefficient, auxiliary statistics, and goodness of fit statistics, the Model 1 and Model 2 are superior to other models. But the t-value of the coefficients and likelihood ratio index and likelihood ratio statistics shows that Model 1 is a little superior to the Model 2. Thus I would select Model 1 as the most preferred one.

3. Estimation of the Conventional Logit Model

Model Formulation

Since it is assumed in conventional logit model that the commuter is myopic and decides each day travel separately, the possible travel plan has only two choices for the same commuter as that of blending logit model. This travel plan can be expressed as (Bus, Taxi) = [(1, 0), (0, 1)].

The probability that a commuter will choose a travel plan i, P_i, can be calculated by binary logit model. The binary logit model can be written as follows:

$$P_B = \frac{e^{U_B}}{e^{U_B} + e^{U_T}} \quad \text{or} \quad P_T = \frac{e^{U_T}}{e^{U_B} + e^{U_T}}$$

where

P_B, P_T = probability of commuter choosing Bus, Taxi, respectively.

U_B, U_T = utility function of commuter choosing Bus, Taxi, respectively. It is assumed to be linear in parameter.

In order to compare the estimation results of the blending model with that of the conventional model, the study selected the specification of Model 1 which is believed to be the most preferred one for the blending model and also used the same 148 observations i.e., TBGRP. The fifteen models, 12 day-model and 3 pooled model, was formulated and estimated. Table 6 gives the summary of the estimation results and some statistics of the model estimated.

Table 6. Estimation results of conventional model

DV: CHOSEN

Model \ IV	IVTT	COST	TAXI-DUM	L (0)	$L(\hat{\beta})$	PCP	$\rho^2 = 1 - \frac{L(\hat{\beta})}{L(0)}$	$-2[L(0) - L(\hat{\beta})]$	# of cases	Taxi chosen
MONM	-0.062 (01.245)	-0.002489 (-3.108)	-0.2382 (-0.3450)	-102.5	-40.51	89.86	0.6051	124.1	148	15 (10.1)
MONA	0.04984 (1.374)	-0.0001358 (0.3724)	-1.094 (-1.904)	-102.6	-55.22	87.16	0.4617	94.72	148	19 (12.8)
TUEM	0.01259 (00.3124)	-0.002011 (-3.049)	0.1869 (0.2912)	-102.5	-48.64	87.84	0.5258	107.9	148	19 (12.8)
TUEA	0.05778 (1.601)	-0.00111 (-2.243)	0.1236 (0.2148)	-102.6	-51.41	88.51	0.4989	102.4	148	20 (13.5)
WEDM	-0.02361 (0.6402)	-0.001206 (-2.435)	-0.5472 (-0.9576)	-102.6	-58.08	85.14	0.4338	89.0	148	22 (14.9)
WEDA	-0.0129 (-0.4314)	-0.0002846 (-0.8285)	-1.585 (-2.772)	-102.6	-60.03	85.81	0.4148	85.11	148	21 (14.2)
THURM	-0.03345 (-0.8419)	-0.001553 (-2.778)	-0.4705 (-0.7379)	-102.6	-51.24	87.16	0.5005	102.7	148	29 (12.9)
THURA	-0.001303 (-0.0425)	-.00004025 (-1.090)	-1.338 (-2.270)	-102.6	-57.89	86.49	0.4357	89.40	148	20 (13.5)

FIRM	-0.04559 (-1.137)	-0.001994 (-3.135)	0.03039 (0.0516)	-102.6	-55.14	85.14	0.4625	94.90	148	23 (15.5)
FRIA	0.06664 (1.896)	0.00001012 (0.03117)	-0.9921 (-1.902)	-102.6	-58.05	85.81	0.4341	89.07	148	23 (15.5)
SATM	0.002491 (0.07609)	-0.000654 (-1.636)	-0.8116 (-1.454)	-102.6	-62.04	84.46	0.3953	1084	148	21 (14.2)
SATA	0.06232 (2.054)	-0.0001035 (-0.3696)	-0.5325 (-1.210)	-102.6	-65.92	82.43	0.3574	73.43	148	23 (15.5)
MORN-POOL	-0.02374 (-1.520)	0.001483 (-6.683)	-0.3734 (-1.526)	-615.5	-321.3	86.37	0.4781	588.5	148	26 (17.6)
AFTER-POOL	0.03847 (2.926)	-0.0002712 (-1.931)	-0.9356 (-1.192)	-615.5	-355.3	85.70	0.4228	520.4	888	121 (13.5)
POOL	0.01547 (1.611)	-0.0007153 (-5.889)	-0.7200 (-4.393)	-1231.0	-689.3	86.04	0.4401	1084	1776	127 (14.3)

Evaluation of the Results

The meaning of the signs of IVTT and COST was already discussed. The positive sign of the coefficient of the constant term, TAXIDUM, reflects the relative preference for the taxi mode, while negative sign reflects the relative preference for the bus mode. The sign of the coefficient of TAXIDUM is expected to be postive because taxi reflects the positive effects to the utility of the commuter by comfort and time saving in comparison with public bus.

The singns of the coefficient of the independent variables are not consistent in all model. The models which have wrong sign in the coefficient of IVTT are all significant at 10% level of significance, while the models which have correct sign in the coefficient of IVTT are all insignificant. On the other hand, the coefficient of COST have correct sign and are significant at 5% level of significance in all model except the MONA, WEDA, THURA, and SATA which are insignificant. The only FRIA model have wrong sign of estimated coefficient of COST, but this is insignificant. The results of the sign of the coefficient of IVTT and COST indicates that the commuters in this sample consider the cost more important than time relatively.

The sign of the constant, TAXIDUM, are expected to be positive, but only the three model, i.e. TEUM, TUEA, and FRIM have positive sign. Futhermore, the coefficient of the constant in this three model are all insignificant. The other model have negative sign in the coefficient of constant, but are significant at 10% level of significance except MONM, WEDM, and THURM. The reason why the coefficient of the constant has a negative sign in most of the models can be explained by missing variables. This results from the following reasons: First, the sample that we are now analyzing represents the commuters who 93% of them spend less than 50,000 won per month and are forced to choose public bus rather than expensive taxi for their work trips. Table 6 shows that only

10-15% of commuters choose taxi for their work trip everyday. Second, the commuters consider the cost more important than the time. So people in TBGRP prefer the bus to the taxi mode which is expensive but fast. Third, it is very difficult to take the taxi expecially at rush hours in Seoul. So the commuters who want to take taxi are forced to take public bus.

However, the day-model refects the variations in statistics in each model. It would be clearer to explain this by the pool-model. The model MORNPOOL have correct sign in the coefficients of IVTT and COST, but has a negative sign of the constant term and all coefficients are significant at 10% level of significance. The model AFTERPOOL has a wrong sign in the coefficient of IVTT and a negative sign of coefficient of COST and constant and also all the coefficients are significant at 10% level of significance. These two model imply that the commuter give greater relative importance to the time in the morning than in the afternoon. So the commuter wants to take taxi more frequently in the morning than in the afternoon, which can be explained by the magnitude of the constant term.

The model POOL have wrong sign in the coefficient of IVTT and also negative sign in the coefficients of COST and constant. All the coefficients are significantly different from zero at 5% level of significance. We can say that the commuter gives greater relative importance to the cost than the time and prefer bus to the taxi. This result might be caused by the missing variables. If we include more important variables in the estimation model, the results may be different from the above.

The likelihood ratio index (ρ^2) for each model varies from 0.3574 to 0.6051, indicating differences between models. But these values are quite excellent and each model replicate the real data well.

The likelihood ratio statistics varies from 73.43 to 124.9 in day-model and varies from 520.4 to 1084 in pooled model with degrees of freedom of k=3. This indicates that we can reject the null hypothesis that all the parameters are zero at the 0.005 level of significance. In other words all the models can be considered to be significantly better than the equal share model with 0.5% level of type I error.

4. Comparision of the Results

For the convenience the study compare the blending model with POOL model which represents the aggregated form of the day-model, because day-model shows variations of statistics in each model.

The blending model has correct sign in the coefficient of all independent variable. The coefficient of the COST and constant term in significantly different from zero, while the coefficient of IVTT is insignificant. The POOL model has wrong sign in the coefficient of IVTT but it is significantly different from zero at 5% level of significance. The coefficient of COST and constant has negative sign and are significantly different from zero at 5% level of significance.

The other statistics i.e., likelihood ratio index, percent correctly predicted, likelihood ratio statistics, are excellent and are almost same in both blending model and the POOL model.

The conventional day-model shows that there are variations in sign and other statistics in each model. But the blending model has consistent correct sign and significant coefficient in each constant term, alternative dummy variables.

As far as this model specification is concerned, there is a little statistical superiority in blending model over the conventional model. But further studies are needed to compare superiority of the blending model and conventional model by using another model specification.

5. Weakness and Strength of the Blending Model

The weakness of the blending model is, first, we can not find the optimal travel plan period of the commuters by the blending model. In other words, we don't know which is the appropriate travel plan period of the commuters according to the blending model. In order to get the optimal or standard travel plan period, It is necessary to test blending model by changing the travel plan period which is one week in this analysis. For example, we can pool the data from Monday to Tuesday and from Thursday and Saturday, also extend the period from one week to two week or one month. If we extend the travel plan period, the results of the analysis would be improved, especially, the stability of the model would be increased. Second, there is a possibility of incorrect data in collecting a week or month diary data. Some people are inclined to answer their travel behavior the same for everyday in a week or month. Third, as all the other models do, it is difficult to coordinate the model with the transportation system, because the physical transportation system changes over time.

On the other hand, the strength of the blending model is that the estimation results of the blending model is quite stable in comparision with the traditional model.

6. Elasticity

The elasticity of the logit model can be defined as the percentage change in the probability of choosing a given alternative k due to a one percent change in one of the variable in the utility function of the particular alternative.

The elasticities can be calculated for the blending model and conventional model separately as follows:

Elasticity of the Blending Logit Model

Since it is assumed that utility function is linear in parameters, the utility function can be written as;

$$U_i = \alpha t_k^i + \beta C_j^i \tag{6}$$

where

U_i = utility function of individual i choosing alternative k
t_k^i, c_k^i = travel time, travel cost of alternative k chosen by individual i
$\mathcal{L}$, β = coefficient.

Then the probability that individual i will choose alternative k among 13 alternatives can be written as equation (7).

$$P_k^i = \frac{e^{\alpha t_k^i + \beta C_k^i}}{\sum_{k=1}^{13} e^{\alpha t_k^i + \beta C_k^i}} \qquad (7)$$

So
$$\frac{\partial P_k^i}{\partial t_k^i} = \alpha P_k^i (1 - P_k^i) < 0 \qquad (8)$$

Now the aggregate elasticity of the new model is:

$$\&t = [\sum_{k=1}^{13} \sum_{i=1}^{148} \frac{\partial P_k^i / \partial t_k^i}{P_k^i / t_k^i} \cdot P_k^i \;] / {}_{148} \qquad (9)$$

Substituting equation (8) into equation (9) we get

$$\&_t = [\sum_{k=1}^{13} \sum_{i=1}^{148} \frac{\partial P_k^i (1 - P_k^i)}{1} \cdot \frac{t_k^i}{P_k^i} \;] / {}_{148}$$

$$= [\sum_{k=1}^{13} \sum_{i=1}^{148} \alpha P_k^i (1 - P_k^i) \cdot t_k^i \;] / {}_{148} \qquad (10)$$

where
$\&_t$ = aggregate travel time elasticity of choice probability

In similar way we can get aggreate travel cost elasticity.

Elasticity of the Conventional Logit Model

$$\&_t = [\sum_{i \in T}^{148} (\frac{\partial P_T^i / \partial t_T^i}{P_T^i / t_T^i}) P_T^i + \sum_{i \in B}^{148} (\frac{\partial P_B^i / \partial t_B^i}{P_B^i / t_B^i}) P_B^i \;] / {}_{148} \qquad (11)$$

$$= [\sum_{i \in T}^{148} \pounds . P_T^i (1 - P_T^i) t_T^i + \sum_{i \in B}^{148} \pounds P_B^i (1 - P_B^i) t_B^i] / {}_{148} \qquad \text{(11)}$$

where

$\&_t =$ aggregate travel time elasticity of choice probability

$$P_T^i = \frac{e^{\pounds t_T^i + \beta c_T^i}}{e^{\pounds t_T^i + \beta c_T^i} + e^{\pounds t_B^i + \beta t_B^i}} \qquad \text{(12)}$$

= probability that individual i will choose taxi (T)

$$P_B^i = \frac{e^{\pounds t_B^i + \beta c_B^i}}{e^{\pounds t_T^i + \beta c_T^i} + e^{\pounds t_B^i + \beta c_B^i}} \qquad \text{(13)}$$

= probability that individual i will choose bus (B)

t_T^i , C_T^i = taxi travel time, taxi travel cost, respectively

t_B^i , C_B^i = bus travel time, bus travel cost, respectively.

The aggregate elasticity is in fact a weighted sum of the individual elasticities using the individual probabilities as the weights.

Estimation Results of the Elasticities

The aggregate elasticities with respect to choice probability by using the coefficient estimates of the utility function are shown in Table 7.

The elasticities calculated by the blending model show that the choice probability is inelastic to the changes of the travel time, and travel cost. But the choice probability is more elastic to the changes of the travel cost than to the changes of the travel time. This implies that the choice behavior of the commuter is more sensitive to changes of travel cost than by changes of travel time. In other words commuter gives greater relative importance to travel cost than to travel time.

On the other hand the elasticities calcualted by the conventional model also show that the choice probability is inelastic to the travel cost and travel time. But the numerical value of the elasticities is not negative in all models. The positive value of the elasticities result from the wrong positive sign of the coefficient of the IVTT and COST of the utility function which I estimated in the previous section. The positive value of the elasticities means that as the travel time and travel cost increase the choice probability increases. This doesn't make sense. The value of the time and cost elasticity should be negative because commuter will decrease frequencies of the mode choice as the travel time and travel cost increase.

Table 7. Estimation results of elasticities

Elasticity / Model	ε_{Tt}	ε_{Bt}	ε_{Tc}	ε_{Bc}	ε_{t}	ε_{c}
BLENDING MODEL					-0.2611286	-0.2954409
CONVENTIONAL MODEL						
MONM	-0.077222	-0.1276136	-0.2041607	-0.0311919	-0.1998856	-0.2353525
MONA	0.0952714	0.1588446	-0.0211936	-0.0225973	0.2541159	-0.0234535
TUEM	-0.0179876	-0.0316128	-0.2151336	-0.299323	-0.0496005	-0.2450659
TEUA	0.0941968	0.1555306	-0.1336927	-0.0169026	0.2497274	-0.1505953
WEDM	-0.0442072	-0.0773945	-0.1784458	-0.0203998	-0.1216017	-0.2000116
WEDA	-0.0275436	-0.0492391	-0.0509616	-0.0053132	-0.0767827	-0.056278
THUM	-0.0512847	-0.0910426	-0.1866903	-0.0238621	-0.1423274	-0.2105524
THUA	-0.0025897	-0.0046453	-0.0653584	-0.0070632	-0.007235	0.0724216
FRIM	-0.0781374	-0.1404379	-0.2576939	-0.0340437	-0.2185753	-0.0917365
FRIA	0.1404236	0.2256765	0.0017672	0.000178	0.3661001	0.0019452
SATM	0.0052506	0.0090283	-0.1123843	-0.0125129	0.0142789	-0.1048972
SATA	0.2132283	0.3478755	-0.0294835	-0.0290453	0.5611037	-0.032388
MORN-POOL	-0.2354703	-0.4143663	-1.1353218	-0.1453951	-0.6498365	-0.2807169
AFTER-POOL	0.4814868	0.8070168	-0.2727102	-0.0293754	1.2885036	-0.3050855
POOL	0.3524161	0.6039445	-1.2912497	-0.1502728	0.9563606	-1.4415524

Note : ε_{Tt} : time elasticity of choosing taxi (T)
ε_{Bt} : time elasticity of choosing bus (B)
ε_{Tc} : cost elasticity of choosing taxi
ε_{Bc} : cost elasticity of choosing bus
ε_{t} : aggregate time elasticity of choice probability
ε_{c} : aggregate cost elasticity of choice probability

Most of the elasticity of the conventional day-model is smaller than that of blending model. Model MORNPOOL and POOL show that the choice probability is elastic to the changes of travel cost but inelastic to the changes of the travel time. The AFTERPOOL shows that the choice probability is elastic to the changes of the time but inelastic to the changes of the travel cost. However, the sign of the elasticity of AFTERPOOL and POOL is positive. The numeric value of the elasticity the blending model is smaller than that of pooled model (MORNPOOL, AFTERPOOL, POOL). In conclusion the elasticities calculated by the conventional model show variations in signs and numerical value between models.

V. Conclusion

In concluding the study attempted to empirically test the conventional logit model and blending logit model suggested by professor, Leon N. Moses and Alex Anas by the data collected in Seoul. The estimation results of the utility function of the blending model shows a little statistical superiority over the conventional model. Futhermore the elasticities of choice probability with respect to travel time and travel cost shows that the blending model is more reasonable than the conventional model which shows variations in sign and values of the elasticities in each model.

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