

■ 論 文 ■

Inherent Random Heterogeneity Logit Model for Stated Preference Freight Mode Choice

SP 화물수단선택을 위한 Inherent Random Heterogeneity 로짓 모형 연구

KIM, Kang-Soo

(Research Fellow, The Korea Transport Institute)

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Key Words : SP, Logit, Random, Heterogeneity, IIA

요 약

화물수단선택모형 구축은 화물 및 물류관련 연구에 있어서 중요한 역할을 차지한다. 그러나 이러한 화물수단 선택 모형을 구축하기 위해 실제 관측되는 자료(Revealed Preference:RP)를 이용하는 데는 한계가 존재하며 따라서 선호의식 기법을 활용한 Stated Preference(SP) 자료가 화물수단 선택 모형을 구축하는데 중요한 자료로 사용된다. SP 자료는 이처럼 화물교통 자료의 현실적인 한계를 극복할 수 있지만 SP 자료를 이용하여 구축되어지는 화물수단모형인 경우 조사기법의 한계로 RP자료에는 존재하지 않는 편익이 발생한다.

본 논문은 SP 자료를 이용하여 수단선택모형 구축 시 발생하는 편익 제거에 대한 연구이다. 특히 본 논문에서는 시뮬레이션 방법을 이용하여 개인의 다양한 선택행태 다양성(heterogeneity)과 이러한 다양성이 SP 다음 질문에 전이되는 문제점을 극복하는 새로운 개념의 화물수단 선택 로짓모형을 제시한다. 또한 단순 로짓모형이 갖고 있는 IIA 특성을 극복하는 화물수단 선택모형도 제시한다. 본 연구를 통해 화물교통에 존재하는 화주의 다양한 선택행태 분석뿐만 아니라 SP 수단선택 모형이 갖는 편익 극복에 본 연구가 일조하기를 기대한다.

I. Introduction

Freight mode choice models are essential to the analysis of many transport research topics such as intermodal competition, the importance of service quality and the forecasting of flows that are carried by existing or new freight transport modes. However, observations of actual market choices have only been made in a limited number of situations. Therefore, stated preference(SP) techniques have emerged as an alternative source of actual market choices to be used for estimating freight mode choice models. However, little consideration has been given to potential estimation bias in SP data, and there are still many other issues to be explored.

This paper has been motivated by the theoretical side of estimating discrete choice models, in particular stated preference(SP) modelling, and it focuses on a case study of freight mode choice. Specifically, this paper deals with the following two problems. The first is how to consider the effect of individual heterogeneity in SP choice modelling, and the inheritance of this heterogeneity to the next choices. The second is the uniform elasticity problem in the standard multinomial logit models(MNL).

This paper consists of several sections. Following this introductory section, section II reviews and identifies weaknesses in the existing approaches to the treatment of individual heterogeneity in MNL and in the treatment of correlation of the unobserved error in MNL. Two inherent random heterogeneity logit models(HL) models are developed to overcome these problems respectively in the subsections. These two HL models are distinguished by having different degrees of decomposition of errors. Section III explains the freight mode choice database for the estimation of the HL and section IV displays the estimation results. Finally, conclusions are presented in section V.

II. Background

Consider the utility function in SP freight

mode choice of an individual p for the alternative i at observation t . If we assume that the utility function has a linear functional form, then it can be written explicitly as

$$U_{pit} = V_{pit} + \varepsilon_{pit} = \beta X_{pit} + \varepsilon_{pit} \quad (1)$$

where p refers to an individual respondent, $p=1, 2, \dots, P$ and t refers to each element of SP responses for the individual p , $t=1, 2, \dots, T_p$. i is the set $A(p)$ which is a feasible choice set for each individual p . V_{pit} is an observable component. The ε_{pit} is an unobserved random component. X_{pit} is a vector of the observed variables. β is a coefficient vector for X_{pit} .

The multinomial logit(MNL) model is derived by assuming that the unobserved error terms are mutually independent and identically(IID) Gumbel distributed with a common scale factor μ (McFadden, 1974). The MNL is given by

$$\Pr_{pit}(i) = \frac{\exp(\mu V_{pit})}{\sum_{j \in A(p)} \exp(\mu V_{pit})} \quad (2)$$

μ is a scaling parameter that is related to the variance σ^2 of the error term ($\mu = \frac{\pi}{\sqrt{6}\sigma}$) and is usually normalised to be equal to one, as it cannot be estimated separately from the coefficients. $A(p)$ is a feasible choice set for each individual.

However, the IID Gumbel assumption on the unobserved error terms leads to the MNL model having three main weaknesses, and these have been discussed in the literature.

The first problem in the MNL model is that it ignores each individual's heterogeneity. It treats the individual heterogeneity as the unobserved error component, and produces the same taste parameter for the whole population for each explanatory variable.

The second problem in the MNL model concerns the assumption on independence of the unobserved

error component of each observation. This assumption may not be valid when SP data is used for discrete choice modelling.

The third problem in the MNL model is the well-known property of independence from irrelevant alternatives(IIA). The problem has been identified and discussed extensively(see the famous red bus-blue bus paradox in Mayberry, 1973).

1. The Inherent Random Heterogeneity Logit Model(HL1) : Incorporating a Random Individual Specific Error Component

This section presents two alternative models to overcome the problems in the MNL model mentioned in the previous section.

In order to include the unobserved individual heterogeneity in SP repeated observations from each individual, a *random inheritance heterogeneity variable* (ξ_{pi}) is included in the utility function. Then, the utility function of individual p for alternative i at observation t becomes

$$U_{pit} = V_{pit} + \varepsilon_{pit} \rightarrow U_{pit} = V_{pit} + \theta \cdot \xi_{pi} + \varepsilon'_{pit} \quad (3)$$

where ξ_{pi} is a stochastic unobserved random term that represents the person's heterogeneity. It has mean zero and a specified functional distribution over people. θ is an unknown coefficient for ξ_{pi} . ε'_{pit} is also an unobserved random component with mean zero. In the utility function, for any given individual p , ξ_{pi} will be same for each observation. This means that, for any given individual, the repeated observations are correlated, but they may not be correlated from person to person.

To derive the probability of choosing alternative i , based on the above utility function, both the distribution for ξ_{pi} and the distribution for ε'_{pit} need to be defined. If the value of $\xi_p = (\xi_{p1}, \xi_{p2}, \dots, \xi_{pA})$ is given, the conditional probability of choosing

alternative i is simply a standard MNL model, provided the error, ε'_{pit} , is independent and identical Gumbel(IID Gumbel) distributed(as we have already assumed).

$$\Pr_{pi}(i | \xi_p) = \text{pro}(U_{pit} > U_{pj}; i, j \in A, \text{ and } i \neq j | \xi_p) = \frac{\exp(\beta X_{pit} + \theta \cdot \xi_{pi})}{\sum_{j \in A(p)} \exp(\beta X_{pj} + \theta \cdot \xi_{pj})} \quad (4)$$

However, the value of ξ_p is not known. Thus the unconditional probability is the integral of $\Pr_{pi}(i | \xi_p)$ over all possible values of ξ_p , weighted by the density function, $f(\xi_p)$. Therefore the unconditional probability is

$$\Pr_{pi}(i) = \int_{-\infty}^{+\infty} \frac{\exp(\beta X_{pit} + \theta \cdot \xi_{pi})}{\sum_{j \in A(p)} \exp(\beta X_{pj} + \theta \cdot \xi_{pj})} f(\xi_p) d\xi_p \quad (5)$$

where $f(\xi_p)$ is the joint conditional density of ξ_p . Furthermore, for the special case of SP models, the probability of each individual's sequence of observed choice is modelled as the product of the probability of each response.

$$\Pr^{sp}(c_p) = \prod_{t=1}^{T_p} \Pr_{pi}(i_t) \quad (6)$$

where i is a sequence of choice and $c_p = i_1, i_2, \dots, i_{T_p}$. Equation(5) is still a logit model even though the probability is expressed by a combination of a logit model and an integral over a certain distribution(the mixing distribution).

MacFadden and Train(1997) refer to this model as a mixed logit model(because of the mixing distribution) and they proved that most discrete choice models, including even MNP, could be approximated by an appropriate specification of the mixing distribution. If the mixing distribution is normally distributed, and the elements of ε

are IID Gumbel, BenAkiva and Bolduc(1996) refer to this model as a probit model with logit kernel.

Finally, the log-likelihood function for estimating the unknown parameters follows after applying equation(6) to equation(5), and then summing the sequence of logged probabilities across respondents (where i is only for the chosen alternative).

$$L(\beta, \theta) = \sum_{p=1}^P \ln \left[\prod_{t=1}^{T_i} \int_{-\infty}^{+\infty} \frac{\exp(\beta X_{pit} + \theta \cdot \xi_{pi})}{\sum_{j \in A(p)} \exp(\beta X_{pjt} + \theta \cdot \xi_{pj})} f(\xi_p) d\xi_p \right] \quad (7)$$

1) Estimation of the HL1 : Simulation Method

$Pr_{pi}(i)$ in equation(5) must be calculated to estimate the unknown parameters in equation(7). The integral in the probability $Pr_{pi}(i)$ has no closed form expression and thus can not be evaluated analytically. Therefore, the integral is evaluated by either a numerical approximation or by a simulation method.

To evaluate the improper integral, Monte Carlo simulation(see Lerman and Manski, 1981, McFadden, 1989, Pakes et al., 1989, Hajivassiliou, 1993 and Hajivassiliou and Rudd, 1994) is employed. It is useful for multi-dimensional integrals. The following procedures have been derived to summarise and illustrate the evaluation of the improper integrals and the direct simulation maximum likelihood estimation.

[Step 1]

Values of ξ_{pi} are drawn ($\xi_p = (\xi_{p1}, \xi_{p2}, \dots, \xi_{pA})$) from random generators for $f(\xi_p)$. We assume that the $f(\xi_p)$ is a standard normal distribution.

[Step 2]

Using these generated numbers for $f(\xi_{pi})$, a conditional probability

$$Pr_{pi}(i | \xi_p) = \frac{\exp(\beta X_{pit} + \theta \cdot \xi_{pi})}{\sum_{j \in A(p)} \exp(\beta X_{pjt} + \theta \cdot \xi_{pj})} \quad (8)$$

is calculated based on logit specification with given coefficients θ and β .

[Step 3]

A sequence of choice probability of each individual is calculated. This is the product of probability of each response.

$$Pr'^{sp}(c_p | \xi_p) = \prod_{t=1}^{T_i} Pr_{pi}(i_t | \xi_p) \quad (9)$$

[Step 4]

Go back to [Step 1] and repeat this procedure many times. In our experiment, we repeated this procedure 300 times

[Step 5]

The conditional probabilities are averaged

$$APr_{pi}(i) = \frac{1}{R} \sum_{r=1}^R Pr'^{sp}(c_p | \xi_p) \quad (10)$$

where $APr_{pi}(i)$ is an averaged probability and R is the number of repeated times. The average probability ($APr_{pi}(i)$) is taken as an approximation of the choice probability.

[Step 6]

To estimate unknown parameters, the averaged probability $APr_{pi}(i)$ is inserted in a log-likelihood function. That is $L(\beta, \theta) = \sum_{p=1}^P \ln Pr'^{sp}(c_p)$ is approximated by the simulated log-likelihood function.

$$L^{simulated}(\beta, \theta) = \sum_{p=1}^P \ln APr_{pi}(i) \quad (11)$$

where $L^{simulated}$ denotes a simulated log-likelihood function.

(Step 7)

The $L^{simulated}(\beta, \theta)$ is maximised to find parameter vectors. In other words, β and θ is changed and go back to Step 1 to maximised to the simulated log-likelihood function

This procedure was programmed using the GAUSS (Aptech Systems, 1994) programming language. The program was tested by setting the individual heterogeneity coefficient parameter to zero, and assuming that each response is pseudo individual.

2. The Inherent Random Heterogeneity Logit Model 2(HL2) : Normally Distributed Coefficients Logit Model

In the above section, an individual heterogeneity error component variable is used to absorb some of the individual unexplained variance(see equation(3)). However, although the specification can overcome the individual heterogeneity and its inheritance problems, the unobserved utility component ($\theta \cdot \xi_{pit} + \epsilon'_{pit}$) is still independent across alternatives. In this section, the problem of independence across alternatives is tackled by decomposing the original IID Gumbel error into several error components which are depended on the observed attributes.

Let the original stochastic unobserved part of the utility be written as

$$\epsilon_{pit} = \sum_{k=1}^K \theta_k (\xi_k X'_{kpit}) + \epsilon'_{pit} \tag{12}$$

where each ξ_k is a random term with mean zero, and density function $f(\xi_k)$. The subscript k denotes the number of error components. θ_k are estimates of the k_{th} error coefficients. ϵ'_{pit} is a random term with mean zero that is IID Gumbel over all alternatives. Note that the error components are assumed to depend on an observed data matrix X' .

If we further assume that X'_{kpit} is equal to the

vector of the observed variables, X_{pit} (so that the number of error components k is equal to the number of coefficients), then the utility function can be expressed as

$$U_{pit} = bX_{pit} + \theta \cdot \xi \cdot X_{pit} + \epsilon'_{pit} \\ = (b + \theta \cdot \xi)X_{pit} + \epsilon'_{pit} \tag{13}$$

Note that this expresses the coefficient vectors as the sum of the mean value, b , of the population and the stochastic deviation, $\theta \cdot \xi$ which represents variations relative to the mean value of the population(in MNL $b=\beta$ and $\theta \cdot \xi=0$). ξ is a standard normal deviate with standard deviation of one and θ is a coefficient of ξ that represents its standard deviation. That is, $\theta \cdot \xi$ is a normal random term with zero mean and standard deviation of θ . Furthermore, the utility function shows that the unobserved utility component is correlated over alternatives because the same values of $\theta \cdot \xi$ occur for different alternatives.

Based on the above utility function, the unconditional probability of choosing alternative i is expressed, as before, as a combination of a logit model and integrals over mixing distributions of ξ . It is the same as equation(5) except the dimension of the integrals and distributions is now greater than one. The parameters b, θ can be also estimated using a maximum likelihood approach and the log-likelihood function for estimating parameters becomes(where i is only for the chosen alternative).

$$L(\beta, \theta) = \sum_{p=1}^P \ln \Pr^{sp}(c_p) = \sum_{p=1}^P \ln \left[\prod_{i=1}^{T_k} \int_{-\infty}^{+\infty} \frac{\exp(bX_{pit} + \theta \cdot \xi \cdot X_{pit})}{\sum_{j \in A} \exp(bX_{pit} + \theta \cdot \xi \cdot X_{pit})} f(\xi) d\xi \right] \tag{14}$$

where the dimension of the integrals and the distributions of ξ is equal to the number of coefficients to be estimated. The procedures of the evaluation of the improper integrals are the same

as that of the HL1 except that now we generate multi-dimensional random variables. As noted, the assumption that the unobserved utility component is depended on the observed variable X_{pit} allows the HL2 model to overcome the IIA property because the unobserved utility component is correlated over alternatives.

III. Description of Data : Channel Tunnel Data

In order to test the models proposed in section 2 we shall consider their application to a model of freight mode choice between the UK and Europe. The Channel Tunnel surveys (Tweddle et al., 1995, 1996) were performed before and after the Channel Tunnel was opened to normal traffic. Unitised cargo was concentrated in the survey. Bulk commodities were excluded since the bulk freights were unlikely to be transported through Channel Tunnel. The unitised cargo meant goods vehicles the drivers of which travel with the goods vehicle on the Ferry or Shuttle. New services resulting from opening of the Channel Tunnel were also included in the survey and these were rail wagons and intermodal services. In particular, this survey uses programmed adaptive SP experiments. In these programmed adaptive SP experiments, each respondent chooses a typical international flow of freight traffic between UK and continental Europe. Each respondent was then asked to express their preference, by rating four alternatives (Ferry(F), New Ferry (NF), Le Shuttle(SH) and Through Rail(RAIL)) which consist of three variables (cost, arrival time and reliability). For the Le Shuttle (SH) mode the haulier transfers the accompanied road vehicle to rail just for the journey through the Channel Tunnel, implying intermodal traffic. For the Through Rail(RAIL) mode the load is carried entirely by rail, implying rail wagon traffic.

The cost variable in the SP experiment was

related to the information given by the respondent. The typical flow cost of the respondent's company was given index value 100. This simplifies the complexities of the variety of units and transport costs per unit that apply to the wide range of products moved.

We define 'arrival time' to be the scheduled arrival time. The unit of time we use is two hours (between 07:00 and 19:00) and four hours (between 19:00 and 07:00). Hence each day is divided into nine units.

Reliability was denoted by the percentage of 'on time' arrivals, that is, arrivals not later than the scheduled arrival time.

IV. Estimation Results

1. HL1 Model

This section uses the HL1 model to capture the individual heterogeneity and its inheritance. We simply assume that the highest rated alternative is chosen. There are 361 observations which can be transformed to the choice data. To specify the utility function, three variables: cost, time and reliability are taken as generic variables for the four alternatives (Ferry, New Ferry, Shuttle and Through Rail). The Shuttle and Through Rail dummies, denoted by ASC(SH) and ASC(RAIL) respectively, also enter into their utilities specifications. Note that the cost was expressed as a percentage of the freight rate for given a typical flow. Table 1 provides the estimated result of the HL1 model along with that of MNL. We specify the individual heterogeneity variable to vary according to a normal distribution in the HL1 model, and θ denotes the unknown parameter for this variable.

In line with our expectation, <Table 1> shows negative signs for parameters of cost and time and a positive sign for reliability. It shows that cost and reliability variables are significant for all the models, while the time variable is only significant

(Table 1) Standard Logit and Inherent Random HL1 Estimates with a Normally Distributed Heterogeneity Variable

PARAMETERS		MNL(t-ratio)	HL1(t-ratio)
COST		-0.0097(-4.46)	-0.0128(-4.80)
TIME		-0.0448(-1.61)	-0.0779(-2.39)
RELIABILITY		-0.1350(2.98)	-0.1444(3.09)
ASC(SH)		-0.1331(-1.00)	-0.1508(-0.95)
ASC(RAIL)		-0.1829(-1.18)	-0.2493(-1.39)
θ		-	1.8447(3.66)
Statistics	$K(0)$	-500.45	-500.45
	$l^*(\theta)$	-488.07	-480.34
	Rho-squared(θ)	0.025	0.0401
	No. of Obs.	361	361
Value of Time		4.62	6.08
Value of Reliability		-13.92	-11.28
Value of Shuttle		13.72	11.78
Value of Rail		18.86	19.48

Note : $l^*(\theta)$ means a final log-likelihood function value at convergence.

at the 5% significance level in the HL1 model. ASCs can have either positive or negative signs according to the tastes of the respondents. Negative coefficients of ASCs indicate that respondents choose the Ferry or New Ferry more readily than can be explained by cost, time and reliability. However, the t-ratios of ASCs are not significant. It is noteworthy that the absolute value of ASC(RAIL) is greater than that of ASC(SH) implying that respondents relatively prefer Shuttle to Rail.

The significance of θ (t-statistics : 3.66) illustrates that the correlation among repeated observations for each individual affects that individual's mode choice. Note that if θ is equal to zero, the HL model is exactly same as MNL. This suggests that this factor should be incorporated in the estimation.

The coefficients in the HL1 are consistently larger than those of the MNL. These results show that the individual heterogeneity random parameters (ξ) absorb some amount of the variance in the unobserved utility, as we expected

We next investigated the values respondents placed on possible changes in the services. Values

of attributes in the last row of (Table 1) imply a willingness to pay for improvements in service time and reliability. In particular, we interpret values of ASCs(VO(SH) and VO(RAIL)) as the discount rate of transport charges that could induce respondents to switch from Ferry to Shuttle or Through Rail. The reason is that the cost variable was expressed as a percentage of the freight rate. It appears that respondents would pay 4.62% more to reduce time 1 unit in the MNL and 6.08% more in the HL1 model. Also, the willingness to pay for a 1% increase in reliability is 13.92% of freight rate in the MNL, and 11.28% of freight rate in the HL1 model. Respondents require 13.72% discount to the freight rate to change mode to Shuttle in the MNL and 11.78% in the HL1 model. The HL1 model presents higher valuations than the MNL for VOT and VO(RAIL), but smaller valuations for VOR and VO(SH), however, they are not significant.

The value of the log-likelihood function rises when the individual heterogeneity variable is incorporated, indicating that the explanatory power of the HL1 model is greater than that of the standard MNL. A log-likelihood ratio test statistic is 15.47(the log likelihood value of the restricted model(MNL) is -488.07 and -480.34 for the unrestricted model, HL1) which is significant at any reasonable level when compared to a chi-squared statistic with one degree of freedom. Therefore, the inclusion of heteroscedastic error components (as in HL1) is justified, and this suggests that there is heteroscedastic variance in the unobserved part of the utility, and the improvement of the explanatory power is significant.

2. The Inherent Random Heterogeneity Logit Model 2(HL2)

(Table 2) provides the estimation result of the HL2 model, along with the result of MNL. We specify all coefficients(cost, time, reliability, ASC

〈Table 2〉 Standard Logit(MNL) and HL2 Estimates with all Normally Distributed Coefficients

PARAMETER		MNL	HL2
COST	Mean Coeff	-0.0097 (-4.46)	-0.0514 (-5.78)
	Std. Of Coeff	-	0.0322 (4.07)
TIME	Mean Coeff	-0.0448 (-1.61)	-0.4507 (-4.08)
	Std. Of Coeff	-	-0.6087 (-4.71)
RELIABILITY	Mean Coeff	0.1350 (2.98)	1.0082 (3.52)
	Std. Of Coeff	-	1.0526 (3.10)
ASC (SH)	Mean Coeff	-0.1331 (-1.00)	-0.4296 (-1.66)
	Std. Of Coeff	-	0.8565 (3.64)
ASC (RAIL)	Mean Coeff	-0.1829 (-1.18)	-1.1120 (-2.53)
	Std. Of Coeff	-	2.0649 (4.83)
Statistics	$\lambda(0)$	-500.45	-500.45
	$\lambda^*(\theta)$	-488.07	-417.89
	Rho-squared(θ)	0.025	0.16
	Observation	361	361
Value of Time		4.62	8.78
Value of Reliability		-13.92	-19.63
Value of Shuttle		13.72	8.37
Value of Rail		18.86	21.66

(SH) and ASC(RAIL)) to be normally distributed in the HL2 model.

The mean coefficients in the HL2 model are consistently larger than those of MNL. These results show that the error components of the HL2 model have decomposed the unobserved portion of utility. The fact that the parameters increase by five times or more implies that the random parameters (ξ) absorb a very large amount of the variance in the unobserved utility.

In the HL2 model, the size of the estimated standard deviations are large(except that of the cost coefficient) relative to the estimated means of coefficients. This implies that different people respond quite differently to these variables. The estimated standard deviations of coefficients are also highly significant, indicating that these parameters do indeed vary in the population. In particular, the coefficient of time has a mean of -0.4507 and a standard deviation of 0.6087, which implies that some population have positive time coefficients, which looks implausible. However, for the case of low value commodities, long transit time can be a good strategy for shippers to reduce total logistic

cost, thus some shippers prefer the long transit time.

Shuttle and Through Rail dummies enter the utility specification as alternative specific constants. Their mean coefficients indicate that, on average, respondents choose the Ferry or New Ferry more readily than can be explained by cost, time and reliability. However, the standard deviations indicate that different respondents have quite different preferences. For example, the mean coefficient for the ASC(SH) has a negative sign but is not significantly different from zero, while the standard derivation is fairly large and highly significant. These results indicate that there are a wide variety of views held by respondents about Le Shuttle.

Additionally, the likelihood ratio index rises by allowing the parameters to vary, indicating that the explanatory power of the random coefficients logit model is greater than the standard logit model. The log-likelihood ratio test statistic is 124.88(the log-likelihood value of the restricted model(MNL) is(488.07 and -417.90 for the unrestricted model (HL2)) which is significant at any reasonable level when compared to a chi-squared statistic with five degrees of freedom. Therefore, the loglikelihood

test showed that the improvement of the log-likelihood value was very significant.

The values respondents placed on possible changes of services are investigated. It appears that respondents would pay 4.62% more to reduce one time unit in the MNL and 8.78% more in the HL2 model. Also the willingness to pay for a 1% increase in reliability is 13.92% of freight rate in the MNL, while it is 19.63% of freight rate in the HL2. Respondents require 13.72% discount to the freight rate to change mode to Le Shuttle in the MNL and 8.37% in the HL2 model. Overall, the HL2 model presents higher valuations than MNL except for the valuation of Shuttle(VO(SH)). Following this, the substitution patterns of the MNL and HL2 model are investigated.

〈Table 3〉 gives the aggregate change in the probabilities of choosing alternatives, that results from the change in the cost of Ferry. We assume that the cost of Ferry is reduced by 20%. It should be noted that disaggregate cross-elasticities in MNL are simply averaged without weights. As expected, the MNL predicts that respondents change proportionately to each of the other alternatives because of the IIA property. However, the HL2 model shows that respondents change more readily from Shuttle than from Rail. This shows that the HL2 model does not exhibit the IIA property.

〈Table 3〉 Percent Change in Probability

Scenario*	MNL	HL2
Ferry	10.93 %	29.12%
New Ferry	-3.5%	-8.16%
Shuttle	-3.5%	-11.07%
Rail	-3.5%	-7.72%

* Scenario : Decrease cost of Ferry by 20%

V. Conclusion

Freight mode choice models are essential to the analysis of many transport research topics such as intermodal competition, the importance of service quality and the forecasting of flows that are carried

by existing or new freight transport modes. However, observations of actual market choices have only been made in a limited number of situations. Therefore, stated preference(SP) techniques have emerged as an alternative source of actual market choices to be used for estimating freight mode choice models. However, notwithstanding successful applications of SP models, little consideration has been given to potential estimation bias in SP data.

This paper has been motivated by the theoretical side of estimating discrete choice models, in particular stated preference(SP) modelling, and it focuses on a case study of freight mode choice. The developed models consider individual heterogeneity and its inheritance to the next choices, and overcome the IIA property. Specifically, recently developed direct simulator and simulated maximum likelihood methods are used to construct inherent random heterogeneity logit models.

The conclusion arising from our analysis is that the unobserved influences affecting a specific individuals mode choice are correlated from one of his or her selections to the next SP repeated questions. Therefore, this variance should be incorporated in the estimation and the suggested SP freight mode choice models, considering individual heterogeneity and its inheritance to the next choices, should be applied. It is also found that large taste variations exist in freight mode choice. The estimated standard deviations of coefficients are highly significant and there is wide variation in the values of parameters and attributes.

This paper contributes to the development of models dealing with the heterogeneity and its inheritance, and sheds light on the heterogeneity of SP freight transport mode choice.

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