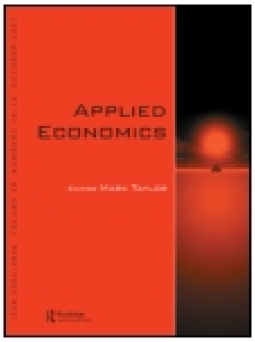

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Latent class model or mixed logit model? A comparison by transport mode choice data

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This article applies two recently stated choice survey datasets of Japan to investigate the difference between the Latent Class Model (LCM) and the Mixed Logit Model (MLM) for transport mode choice. A detailed comparison is carried out, focusing on comparing values of time savings, direct choice elasticities, predicted choice probabilities and prediction success indices. Furthermore, a test on nonnested model is also utilized to help determine which model is superior to another one. The results suggest that the LCM performs better than the MLM in both datasets.

I. Introduction

In the recent 30 years, analysts have made a great endeavour on developing different discrete choice models to relax the assumption of Independence from Irrelevant Alternatives (IIA) in the fundamental Multinomial Logit Model (MNL). Among these models, the MLM is probably the most flexible one (see, for instance, Revelt and Train, 1998; McFadden and Train, 2000; Persson, 2002; Bhat, 2001, 2003; Greene and Hensher, 2003; Bhat and Gossen, 2004; Viton, 2004; Kim *et al*., 2005, etc.). It generalizes a standard MNL by allowing its parameters associated with the observed variable to vary with a known population distribution across individuals. Alternatively, the Latent Class Model (LCM), which is frequently applied in marketing research, assumes that a discrete number of latent classes are sufficient to account for preference heterogeneity (see, for instance, Boxall and Adamowicz, 2002; Morey *et al*., 2006, etc.). Comparing with the MLM specification, the LCM has the advantage of being relatively simple, reasonably plausible and statistically testable. However, it is somewhat less flexible than the MLM since the parameters associated with each variable in each class are fixed. In contrast, the main disadvantage of the MLM is that the analysts should specify the assumption about the distribution of parameters. Due to the fact that each model has its virtues and limitations, it is meaningful to compare between these two advanced discrete choice models.

A recent study by Greene and Hensher (2003) compared the LCM with the MLM by using a dataset of road type's choice by car in New Zealand. After a detailed comparison on value of travel time savings, direct share elasticities, choice sensitivities to 50% increase in travel time, and choice probabilities, they concluded that although both the MLM and LCM offer attractive specifications than the MNL, it is inconclusive that which one is 'completely' superior to another despite some stronger statistical evidences support for the LCM in their dataset.[1] Remained as a future study implication, they mentioned that 'we encourage a greater effort to compare and contrast

[1] The inconclusiveness is due to the reason that these two models are nonnested, therefore, normal Likelihood Ratio (LR) test cannot be applied.

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such advanced models as one approach to searching for rules on stability in explanation and prediction' (Greene and Hensher, 2003).

Strongly encouraged by their study, we use two stated preference datasets of transport modal choice (monorail, car and bus) in Japan to make a comparison between the MLM and the LCM. Thus, the prime purpose of this article is to seek for whether or not the results of the comparison suggest that the LCM is to some extent superior to the MLM as Greene and Hensher (2003) mentioned in their study.

The rest of the article is organized as follows. Section II provides a brief introduction on the LCM and the MLM. Section III compactly describes our two stated preference datasets in Japan. Section IV presents a comparison between these two models and Section V draws conclusions of the article.

II. The Latent Class and Mixed Logit Models[2]

The latent class model

The LCM, unlike the MLM which specifies the random parameters to follow a continuous joint distribution, assumes that a discrete number of classes are sufficient to account for preference heterogeneity across classes. Therefore, the unobserved heterogeneity is captured by these latent classes in the population, each of which is associated with a different parameter vector in the corresponding utility. The LCM has often been used in marketing research instead of ML model, while there are few studies in other fields such as transportation and environmental economics.

The choice probability that an individual q of class s chooses alternative i from a particular set J, which comprises j alternatives, is expressed as:

$$P_{iq|s} = \frac{\exp(\beta_s' X_{iq})}{\sum_{j=1}^{J} \exp(\beta_s' X_{jq})} \quad s = 1, \ldots, S \tag{1}$$

where β_s' is the parameter vector associated with the vector of explanatory variables X_{iq}. Note that Equation 1 is a simple MNL specification in class s.

Additionally, one can construct a classification model as a function of some individual-specific attributes to explain the heterogeneity across classes. The LCM model simultaneously estimates Equation 1 for S classes and predicts the probability H_{qs} as individual q being in class s. Then, the unconditional probability of choosing the alternative i is given as:

$$P_{iq} = \sum_{s=1}^{S} P_{iq|s} H_{qs} \tag{2}$$

An issue to be noted is the choice of S, the number of classes. Since this is not a parameter, hypotheses on S cannot be tested directly. However, as Louviere *et al.* (2000, Ch. 10) mentioned that a number of methods to decide S have been used based on the Akaike Information Criterion (AIC) and its variants. AIC and Consistent AIC (CAIC), which are given in Equations 3 and 4, are used to guide model selection.

$$\mathrm{AIC} = -2[\mathrm{LL}(\hat{\beta}) - S \cdot K_s - (S-1)K_c] \tag{3}$$

$$\mathrm{CAIC} = -2\mathrm{LL}(\hat{\beta}) - [S \cdot K_s + (S-1)K_c - 1][\ln(2N) + 1] \tag{4}$$

where $\mathrm{LL}(\hat{\beta})$ is the log likelihood at the estimated parameters $\hat{\beta}$, K_s is the number of elements in the utility function of the class-specific choice models, K_c is the total number of parameters in the classification model and N is the number of observations in the sample. The value of S that minimizes each of the measures of AIC and CAIC suggests which model should be preferred (Louviere *et al.*, 2000, Chap. 10).

The mixed logit model

The MLM allows for a heightened level of flexibility by specifying taste coefficients to be randomly distributed across individuals. Additionally, superior to LCM, MLM can account for potential correlation over repeated choices made by each individual by imposing a first-order autoregressive (AR1) process.[3]

The model is a generalization of the MNL model, summarized as below:

$$P_{iqt} = \frac{\exp\left(\alpha' + \beta' X_{iqt} + \varphi' F_{iqt}\right)}{\sum_{j=1}^{J} \exp\left(\alpha' + \beta' X_{jqt} + \varphi' F_{jqt}\right)} \tag{5}$$

where α' is a vector of fixed or random Alternative-Specific Constants (ASCs) associated with $i = 1, \ldots, J$ alternatives and $q = 1, \ldots, Q$ individuals, and one of

[2] Since Greene and Hensher (2003) have provided a detailed description on the LCM and the MLM, therefore, we just give a brief introduction on these two models. For the other literature on the MLM and LCM, see Revelt and Train (1998), Louviere *et al.* (2000), McFadden and Train (2000), Bhat and Gossen (2004), Bishop and Provencher (2004), Greene (2003), Hensher *et al.* (2005), Train (2003), Train and Sandor (2004), Shen (2006), etc.

[3] Greene and Hensher (2003) mentioned that the LCM does not readily extend to autocorrelation, therefore, this aspect is left for future research.

Table 1. An example of choice set in Saito survey

	Monorail	Car	Bus
In-vehicle time including delay time caused by traffic jam (minutes)	15	40	50
Access time (minutes)	15	Almost 0	3
Frequency (minutes)	10	At any time	15
Generalized cost (JP yen)	360	800	280
Negative impact on the environment (such as CO_2 emission)	Low	3 times as monorail	2.5 times as monorail
Please choose one most preferable transport mode and ✓ in ☐	☐	☐	☐

these ASCs should be identified as 0. β' is a parameter vector that is randomly distributed across individuals. φ' is a vector of nonrandom parameters. X_{iqt} is a vector of individual-specific characteristics and alternative-specific attributes at observation t, and is estimated with random parameters. F_{iqt} is a vector of individual-specific characteristics and alternative-specific attributes at observation t, and is estimated with fixed parameters.

In this specification, a subset or all of α' and the parameters in the β' vector can be assumed to be randomly distributed across individuals.[4] These random parameters can then be defined as a function of characteristics of individuals and/or other attributes that are choice invariant. Based on these defined attributes, the mean and standard deviations of specified random parameters and contributions from these choice invariant attributes to random parameters are estimated by using Maximum Simulated Likelihood (MSL) method. The MLM is sufficiently flexible that it provides the modeler a tremendous range to specify individual unobserved heterogeneity. To some extent, this flexibility offsets the specificity of the distributional assumptions (Greene and Hensher, 2003).

III. Data

We use two survey datasets, which are collected in Osaka of Japan, to compare the LCM with the MLM. The first survey is based on a stated choice experiment carried out in July of 2005 on transport mode choices by the residents in the Saito and Onohara Area of Northern Osaka (hereinafter, called Saito survey). A prime purpose of this experiment is to investigate whether or not individual environmental consciousness is one of the determinants in transport modal choice. The transport modes in the choice set faced by each respondent consist of monorail, car and bus. This dataset is composed of 467 individuals with each answering eight choice sets, therefore, the total observations are 3736. Five attributes are used in the stated choice experiment as follows:

(A) In-vehicle time including delay time caused by traffic jam (in min)
(B) Access time (in min)
(C) Frequency (in min)
(D) Travel cost (in JP yen)
(E) Negative impact on the environment caused by transport modes

For each attribute, we adopted a two-level design except for access time and frequency in car and negative impact on the environment in monorail. Then, 32 choice sets were constructed by a fractional factorial design to reduce the number of choice sets to a manageable level. These 32 choice sets were further blocked into four versions avoiding a dominant selection. Each sampled individual was asked to answer one version. An example of the choice sets is provided in Table 1. Further details on the survey are given in Shen *et al.* (2007).

The second dataset is based on another stated choice survey on transport mode choice of the residents in Eastern Osaka (hereinafter, called Eastern Osaka survey), which was also carried out in July 2005. Different from the first one, this survey focused on both impacts of local natural environment and network accessibility on transport modal choice. Same experimental design strategy as that in Saito survey was used, except that the local natural environment and network accessibility were treated

[4] The distributions of random parameters can be considered, for example, normal distribution, lognormal distribution and triangular distribution, etc.

Table 2. An example of choice set in Eastern Osaka survey

	Monorail	Car	Bus
Average in-vehicle time for one section (minutes)	3	4	10
Average delay time due to congestion (minutes)	0	8	10
Average cost (JP yen)	100	200	60
Frequency (numbers/hour)	4	At any time	10
Local natural environment	Worse than current state	Worse than current state	Worse than current state
Network accessibility	Only monorail	Only monorail	Only monorail
Please choose one most preferable transport mode and ✓ in ☐	☐	☐	☐

as a common condition in each choice set, i.e. they were allowed to vary across choice sets but not across alternatives. A total of 453 valid responses, each with eight choice sets, produce 3624 observations. Table 2 shows an example of the choice sets, and Sakata *et al.* (2006) provides further details on this survey.

IV. A Comparison Between LCM and MLM

Tables 3 and 4 summarize the estimated results of the two datasets with the specifications of MNL, MLM and LCM.[5] We have specified a number of individual socioeconomic characteristics and added them into the estimated model. However, to conserve space, we omit these results in the tables.

With respect to the MLM, we have defined all time-associated attributes as random parameters and selected a *Normal* distribution for them. Specifying a given parameter to follow a *Normal* distribution is equivalent to making *a priori* assumption that both positive and negative values for this parameter may exist in the population. Concerning the possible positive signs of time-associated parameters, Hess *et al.* (2005) have noted that 'a negative measure for Value of Travel Time Savings (VTTS) for a given individual in effect suggests that this individual would be willing to pay for increases in travel-time. At first sight, this is counter-intuitive. However, several recent articles discuss zero (Richard, 2003) or positive (Redmond and Mokhtarian, 2001) elasticity with respect to travel-time. There are interesting statements like: 'I'd rather have an hour-plus commute than a five-minute commute. In the morning, it gives me a chance to work through what I'm going to do for the day. And it's my decompression time.' (Redmond and Mokhtarian, 2001)'. This citation indicates that if an individual is more satisfied with longer time-associated attributes due to some individual-specific reasons, the positive sign of time-associated attributes could be possible.[6]

AIC and CAIC given in Equations 3 and 4 were used to select the number of classes in the LCM. As a result, both AIC and CAIC were the lowest ones in the three latent classes for both datasets. Therefore, three-class LCMs were estimated for both Saito and Eastern Osaka surveys. From the results in Tables 3 and 4, based on the log-likelihood values, the hypothesis that the MNL model is in favour of either the MLM or the LCM can be safely rejected.

With respect to the comparison between MLM and LCM, we focus on contrasting indicators of willingness to pay, e.g. values of time savings, choice elasticities, predicted choice probabilities of each transport mode and prediction success index, respectively. In addition, a test on nonnested choice models which is based on the AIC proposed by Ben-Akiva and Swait (1986) is applied to help determine which model is relatively more superior in the two datasets applied in this study.

Table 5 summarizes the estimated Values of Time Savings (VOTS). For both datasets, the mean estimates of VOTS by the MLM specification differ substantially with the three latent classes for LCM, although in Saito survey, VOTS of in-vehicle time is similar to that in class 1 and VOTS of access time is similar to that in class 2. Overall, the results from the LCM indicate the fact that for either in-vehicle time, access time and frequency in Saito survey or in-vehicle time, delay time and frequency in Eastern

[5] All the results were estimated by NLOGIT 3.0 (Econometric Software, Inc., 2003).
[6] We have also estimated the MLM with a specification of triangular distribution on time-associated parameters. However, we did not find large differences between normal distribution and triangular distribution specifications on the estimated parameters, value of time savings choice elasticities, etc.

Table 3. Estimated results for Saito survey (*t*-statistics in parentheses)

Attribute	Alternative	MNL		MLM		LCM Class 1		LCM Class 2		LCM Class 3	
In-vehicle time	All	−0.0758	(−25.45)	−0.1668	(−17.12)	−0.0653	(−4.05)	−0.1160	(−36.34)	−0.0858	(−11.47)
Access time	All	−0.0265	(−2.08)	−0.0575	(−2.59)	−0.0270	(−3.78)	−0.0642	(−3.48)	−0.0088	(−2.94)
Frequency	All	−0.0155	(−3.57)	−0.0247	(−3.21)	−0.0228	(−2.04)	−0.0232	(−4.63)	−0.0097	(−2.82)
Travel cost	All	−0.0027	(−9.87)	−0.0049	(−10.13)	−0.0019	(−3.30)	−0.0056	(−15.42)	−0.0014	(−3.50)
Negative environmental impact	All	−0.7066	(−2.78)	−0.5100	(−3.06)	−3.1898	(−2.52)	0.3882	(1.273)	−3.1662	(5−5.97)
Monorail constant	Monorail	−0.7612	(−3.19)	−1.7252	(−3.22)	19.3000	(0.02)	−2.0457	(−7.90)	0.9842	(1.71)
Car constant	Car	−1.3935	(−4.41)	−3.4679	(−4.92)	0.4838	(0.00)	−18.5697	(−0.02)	4.1862	(5.48)
In-vehicle time standard derivation	All			0.1039	(11.17)						
Access time standard derivation	All			0.2109	(14.79)						
Frequency standard derivation	All			0.0848	(12.12)						
Latent class probability						0.14175	(7.15)	0.58520	(20.30)	0.27305	(10.781)
Log-likelihood		−2853.062		−2320.686		−1954.913					
Pseudo-R^2		0.1844		0.3366		0.4460					

Table 4. Estimated results for Eastern Osaka survey (*t*-statistics in parentheses)

						LCM					
Attribute	Alternative	MNL		MLM		Class 1		Class 2		Class 3	
In-vehicle time	All	−0.1251	(−8.65)	−0.2669	(−10.23)	−0.1365	(−5.51)	−0.2825	(−8.62)	−0.1915	(−3.55)
Delay time	All	−0.0606	(−8.10)	−0.1338	(−8.94)	−0.0672	(−5.10)	−0.1522	(−10.36)	−0.0501	(−2.10)
Frequency	All	−0.0328	(−3.18)	−0.1101	(−8.67)	−0.0710	(−3.97)	−0.0913	(−5.94)	−0.0377	(−2.21)
Travel cost	All	−0.0050	(−13.29)	−0.0083	(−15.52)	−0.0157	(−13.19)	−0.0062	(−10.70)	−0.0022	(−2.55)
Monorail constant	Monorail	1.3564	(7.25)	2.0211	(7.04)	1.0647	(2.42)	2.1905	(6.64)	−0.1073	(−0.18)
Bus constant	Bus	0.3930	(1.95)	0.9844	(3.43)	0.6429	(1.43)	0.3326	(0.77)	−1.3832	(−1.54)
Local natural environment	Monorail	0.4150	(1.85)	0.4396	(2.19)	−0.9100	(−1.55)	0.9895	(2.74)	1.3309	(2.24)
Network accessibility	Monorail	0.7705	(3.33)	0.9924	(2.60)	0.7249	(1.16)	1.2860	(3.66)	1.5493	(2.44)
Local natural environment	Bus	0.2396	(0.87)	0.1647	(0.42)	−0.9972	(−1.70)	−0.1079	(−0.14)	−5.9485	(−1.61)
Network accessibility	Bus	0.7990	(2.91)	1.0638	(2.60)	0.8712	(1.40)	−0.1265	(−0.16)	5.8119	(4.48)
In-vehicle time standard derivation	All			0.2799	(12.16)						
Delay time standard derivation	All			0.1620	(9.95)						
Frequency standard derivation	All			0.1993	(14.37)						
Latent class probability						0.35625	(12.60)	0.52661	(18.02)	0.11714	(6.43)
Log-likelihood		−2791.523		−2390.553		−1714.392					
Pseudo-R^2		0.0892		0.2200		0.4406					

Table 5. Values of time savings for Saito and Eastern Osaka surveys (JP yen per hour)

			LCM		
Time type	MNL	MLM (mean)	Class 1	Class 2	Class 3
Saito survey					
In-vehicle time	1684	2042	2062	1243	3677
Access time	589	704	853	688	377
Frequency	344	302	720	249	416
Eastern Osaka survey					
In-vehicle time	1501	1929	522	2734	5223
Delay time	727	967	257	1473	1366
Frequency	394	795	271	884	1028

Table 6. Direct choice elasticities for Saito and Eastern Osaka surveys (probability weighted)

Time type	MNL	MLM	LCM
In-vehicle time			
Monorail	−0.510 (−0.181)	−0.586 (−0.237)	−0.446 (−0.179)
Car	−1.304 (−0.276)	−1.367 (−0.398)	−1.361 (−0.306)
Bus	−1.418 (−0.676)	−1.343 (−0.666)	−1.374 (−0.776)
Travel cost			
Monorail	−0.397 (−0.243)	−0.400 (−0.263)	−0.423 (−0.313)
Car	−0.955 (−0.993)	−1.001 (−0.988)	−1.056 (−0.8699)
Bus	−0.375 (−0.331)	−0.398 (−0.419)	−0.455 (−0.785)

Note: Elasticities for Eastern Osaka survey are in the parentheses.

Osaka survey, three segments of low, medium and high VOTS can be found. This evidence supports the claim in Greene and Hensher's (2003) study that the latent influences are to some extent related to an individual's VOTS.

Summaries of the probability-weighted choice elasticities for common attributes (in-vehicle time and travel cost) in two surveys are provided in Table 6. The choice elasticities differ substantially between the MLM and the LCM, especially in Eastern Osaka survey. For response to changes in in-vehicle time, the LCM suggests less sensitivity for monorail and car but more sensitivity for bus than the MLM in both datasets, whilst the magnitude of sensitivity is relatively larger in Saito survey. With respect to changes in travel cost, the MLM predicts less-sensitive response for almost all the modes than the LCM in both datasets with the exception of car in Eastern Osaka survey.

A comparison of predicted choice probability between the LCM and the MLM for two surveys starts from the kernel density estimators of their ratios for each mode that are listed in Figs 1 and 2. From these figures, we may find that for both datasets, the distribution around 1 is skewed to the right for monorail and to the left for car and bus. This evidence indicates that at the individual level, the choice probability of monorail predicted by the LCM is relatively larger than that predicted by the MLM, whilst the choice probabilities of car and bus are relatively smaller than those predicted by the MLM. It is consistent to the result at the aggregate choice probability level for the sampled population. The respective aggregate probabilities for monorail, car and bus are in Saito survey LCM: 0.6784, 0.1881, 0.1335 and MLM: 0.6586, 0.1889, 0.1525, and in Eastern Osaka survey LCM: 0.5759, 0.1216, 0.3025 and MLM: 0.5369, 0.1456, 0.3175.

OLS regressions are further applied to investigate the relationship between the LCM probability and the MLM probability. The results of OLS regressions are provided in Table 7. From the relatively low R^2 for OLS regression, we may conclude that the relationship between the predicted choice probabilities under the LCM (for three latent classes) and the MLM (a normal distribution on the random parameters) is relatively weak at the individual level.

The prediction success indices suggested by McFadden (1979) are calculated and summarized in Table 8. From these indices, we found that in both datasets the LCM has more predictive capability than the MLM.

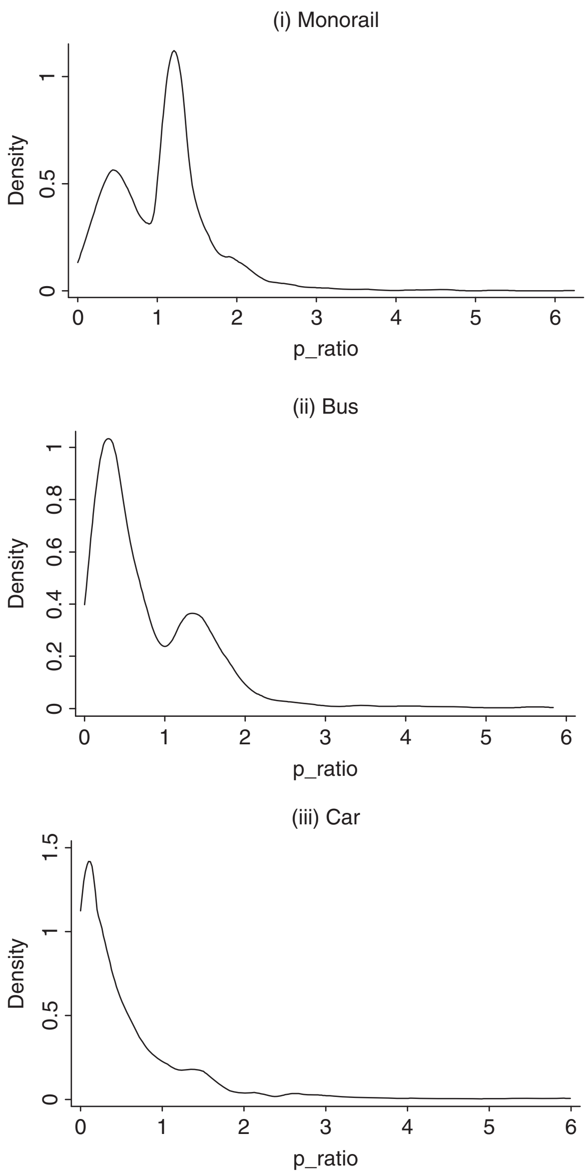

Fig. 1. Kernel density estimate for probability ratio of LCM to MLM in Saito survey

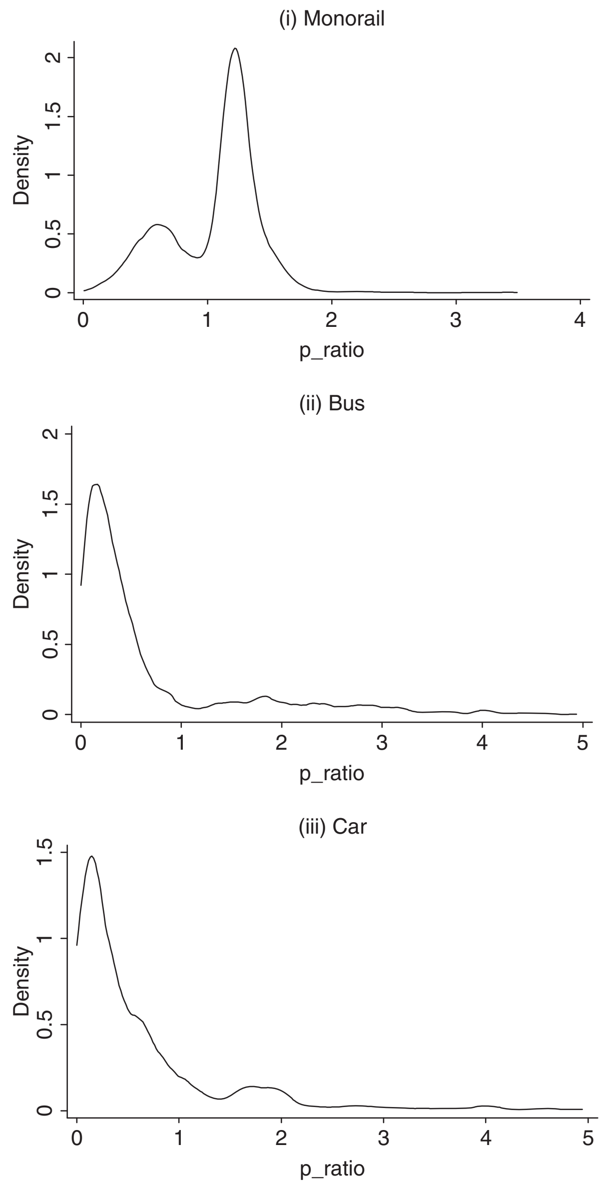

Fig. 2. Kernel density estimate for probability ratio of LCM to MLM in Eastern Osaka survey

Finally, we apply a test on nonnested choice models which is based on the AIC proposed by Ben-Akiva and Swait (1986). The test is carried out as follows. Suppose there are two nonnested Models 1 and 2. Model 1 explains choices using K_1 variables, while Model 2 explains the same choices using K_2 variables. Assume that $K_1 \geq K_2$ and either the two models have different functional forms or the two sets of variables are different by at least one element. Define the fitness measure for model j, $j=1,2$:

$$\rho_j^2 = 1 - \frac{L_j - K_j}{L(0)} \tag{6}$$

where L_j is the log-likelihood at convergence for model j and $L(0)$ is the log-likelihood for constants only. Ben-Akiva and Swait (1986) show that under the null hypothesis that Model 2 is the true model, the probability that the fitness measure in Equation 6 for Model 1 will be greater than that of Model 2 is asymptotically bounded by a function given in Equation 7:

$$\Pr\left(\left|\rho_2^2 - \rho_1^2\right| \geq Z\right) \leq \Phi\left(-\sqrt{-2ZL(0) + (K_1 - K_2)}\right) \tag{7}$$

where Z is the difference of the fitness measures between Model 1 and Model 2 and assumed larger

Table 7. OLS regressions of predicted probability estimated by the LCM and MLM

	Saito survey			Eastern Osaka survey		
	Monorail	Car	Bus	Monorail	Car	Bus
Constant	−0.03118	−0.01796	−0.0473	−0.1205	−0.03407	−0.04991
P_MLM	1.132968	1.012928	1.07295	1.253378	1.175096	1.046462
R^2	0.395	0.448	0.456	0.384	0.340	0.277

Note: Dependant variable is P_LCM. All the parameters are significant at 99.9% level.

Table 8. Prediction success indices for Saito and Eastern Osaka surveys

	MNL	MLM	LCM
Saito survey	0.1049	0.1440	0.3259
Eastern Osaka survey	0.0435	0.0622	0.2218

than zero, Φ is the standard normal Cumulative Distribution Function (CDF). Therefore, Equation 7 sets an upper bound for the probability that one incorrectly selects Model 1 as the true model although Model 2 is the true model.

Using the above definition, we calculate that the probabilities in Equation 7 for Saito survey and Eastern Osaka survey are $P \leq \Phi(-27.039) \approx 0$ and $P \leq \Phi(-36.773) \approx 0$, respectively, assuming that the MLM is Model 1 and the LCM is Model 2. Therefore, we may conclude that in both datasets to which we applied the test, the LCM is superior to the MLM.

V. Conclusions

This article provides a detailed comparison between two advanced specifications of discrete choice model, i.e. an LCM and an MLM. Following the study of Greene and Hensher (2003), the article compares the values of time savings, direct choice elasticities and predicted choice probability derived from these two models. In addition, the prediction success indices and a nonnested model test are further applied to investigate the difference between these two models, while these results indicate that the LCM performs statistically better than the MLM in our two datasets.

Although our results are consistent with those concluded from Greene and Hensher (2003), which claims that the LCM is supported by stronger statistical behaviours than the MLM in their dataset, we caution that it still cannot make this evidence as a conclusive suggestion that the LCM is definitely superior to the MLM in all cases. More and more studies on comparison between these two specifications are appreciated in future, because only after a number of accumulated studies, a systematical meta-analysis could be considered to seek for some rules on concluding which model specification is better or not.

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