■ 論 文 ■

Analysis of Repeated Measurement Problem in SP data

SP 데이터의 Repeated Measurement Problem 분석

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목 차

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요 약

SP 방법의 장점중 하나는 개인의 응답자로부터 다수의 응답(Repeated observations)을 받을 수 있는 점이다. 그러나 이렇게 얻은 개인의 다중응답을 각각의 응답이 독립적이라는 것을 가정하고 있는 단순한 모델링방법을 이용해서 분석하면 t값이 상향되는 문제를 가져올 수 있다. 이러한 문제를 다중응답의 문제(Reapeated Measurement Problem)라고 한다. 본 연구는 다양한 접근을 통해서 이러한 다중응답의 문제(Reapeated Measurement Problem)를 다루고, 단순한 모델링방법을 통한 모델추정치가 신뢰할 만한가를 검증하도록 한다.

다양한 접근중에서 본 연구에서는 Jackknife와 Kocurs 방법을 적용하였다. Jackknife 방법은 JACKKNIFE란 소프트웨어를 사용해서 분석하였다. Jackknife 추정치와 Kocurs 추정치를 단순한 모델링기법을 적용한 모델추정치와 비교하여서 다중응답의 문제(Repeated Measurement Problem)의 발생여부와 모델추정치에 어느정도 영향을 미치는 지를 분석하였다. 단순모델링의 추정치와 Jackknife 추정치의 표준오차도 비교하였다.

결과를 요약하면, Kocurs방법의 추정치의 t값은 단순한 모델링기법과 Jackknife 추정치의 t값보다 매우 낮게 나타났으며, 이는 Kocurs방법은 파라미터의 유의성을 지나치게 하향추정하는 것을 의미한다. Jackknife 방법의 추정치는 단순한 모델링기법의 추정치와 계수값은 거의 유사하나 t값이 다소 적은 것으로 나타났다. 이러한 결과들은 단순한 모델링기법의 계수값은 정확하나 유의정도가 다소 과장되는 것을 의미한다.

결론적으로 본 연구에서 사용한 데이터에는 다중응답의 문제가 존재하나 모델추정치에 유의하게 영향을 미치지 않는 것으로 나타났다. SP 방법을 사용한 데이터를 분석할 경우 다중응답의 문제(Reapeated Measurement Problem)를 분석하는 절차를 반드시 수행하여야 한다. 만약 단순한 모델링기법의 추정치가 다중응답의 문제로 인해서 영향을 받았다면 반드시 모델링 추정치를 보정하여야 한다.

Ⅰ. Introduction

One of the advantages of SP methods is the possibility of getting a number of responses from each respondent. All simple methods for analysing SP choice data require the assumption that each observation is independent. This assumption is not strictly valid when several repeated choices are made by each respondent. However, when the repeated observations from each respondent are analysed by applying the simple modeling method, a potential problem is created because of upbiased significance due to the repeated observation from each respondent. This repeated measurement problem have been generally either ignored in practice or confined to upward biased t-ratios, implying increased significance of explanatory variables(Ortuzar *et al.* 1997; Bates 1997). Simple estimation method which ignores the repeated measurement problem is here called the "uncorrected method".

This paper aims to investigate whether and the extent to which this repeated measurement problem affects model estimates. This also tests the robustness of the simple model estimates in which there is a possibility of biased results due to the repeated measurement problem.

The next section reviews alternative approaches to deal with the repeated measurement problem. After that, I apply Kocur's method and Jackknife methods to reestimate the models and then discusses the results, and compares them with those of simple estimates. Finally I summarises the results and draw a conclusion.

Ⅱ. Alternative Approaches

1. Alternative Approaches

A number of researchers(e.g. Cirillo *et al.* 1996; Ouwersloot and Rietveld 1996) have suggested correction methods against the upward biasing of t-ratios. The best known method involves dividing the t-statistic's of the uncorrected method by the square root of the number of repeated number of questions by each respondent(Kocur *et al.* 1982; Khattak *et al.* 1993a). But it reduces the value of t-ratios to reflect the influence of the repeated measurement problem on the significance of the estimates. This approach is based on the assumption that the amount of information from repeated choices by each respondent is only the same as the amount of information from only one observation from each respondent. In this paper, it is refined to as "Kocur's method".

Ouwersloot and Rietveld(1996) also applied a method to correct the repeated measurement problem. These method treat each observation separately, estimates separate models based on each subgroup one by one and combines these estimates to produce an overall parameter estimate using a 'minimum chi-square' method. Since only one observation per respondent is used in each model, there is no longer a correlation problem due to repeated observations. This approach seems to be ideal to cure the repeated observation problem. It is, however, very complicated to perform and requires a lot of computing.

Another potential approach is based on re-sampling. The purpose of re-sampling is to find out the true variance of the estimates affected by the repeated measurement problem and to observe the way coefficients change as the number of sub-samples changes. In general, smaller data samples would have more variance. The difference between the estimates obtained from small samples gives a more reliable estimate of the overall variance. Selecting the particular form of sample reduction gives the most efficient means of calculating the variance differences. Therefore, it is necessary to observe the differences between small-sample estimates that are also affected by the repeated measurements problem.

Two examples of re-sampling are "Jackknife" and "Bootstrap". Jackknife uses the same data set as the original data set but deletes small parts of the data in each Jackknife sample. Bootstrap creates a completely new sample each time for each Bootstrap sample by drawing randomly with replacement within the sample(Wonnacott and Wonnacott 1990; Cirillo *et al*. 1996; Shao and Tu 1995). Therefore, Jackknife requires less computational work than Bootstrap does(Wonnacott and Wonnacott 1990; Cirillo *et al*. 1996;). It was also reported by Shao and Tu(1995) that the Bootstrap variance estimator was down-biased and was not as efficient as the Jackknife variance estimator.

Cirillo *et al*.(1996) applied Jackknife and Bootstrap to logit model estimates using two real data sets and a simulated data set which had repeated measurement problem. The results of applying the Jackknife method confirmed that the uncorrected model produced good estimates of coefficients values. They suggested that the Jackknife method was theoretically slightly preferable to the Bootstrap method and recommended Jackknife for practical work because it is easy to implement and produce smoother estimates at low re-sampling rates.

2. Jackknife and Kocur's Method

The Jackknife method and Kocur's method are applied in this paper to deal with the repeated measurement problem. The uncorrected estimates ignore the repeated measurement problem, while the Kocur's method is based on assumption that amount of information from repeated choices by each respondent is the same as that of information when each respondent give only one choice. Thus the uncorrected estimates and the Kocur's estimates are at opposite ends of the spectrum. The Jackknife approach is between these too extremes. The Jackknife method is selected because of relatively easy computation due to a software program and recommendation by several studies(Ouwersloot and Rietveld 1996; Cirillo *et al*. 1996) for an application to a logit model.

3. Jackknife

The idea of Jackknife is to re-use the sample several times by dividing it into subgroups and by recombining these to assemble an estimate of the unknown parameter which has good sampling properties and perhaps more importantly, to produce an estimate of the variance of this statistic (Bissell and Ferguson 1975).

The Jackknife method proceeds as follows. Suppose that there is a random sample, $X_1, X_2, \cdots, X_n$ and the value of parameter, θ_0 is to be estimated.

First, the sample is divided into r sub-groups (at random if r < n) of each of size h. The maximum possible number of sub-groups should be used, although r=n(which implies h=1) may not always be computationally feasible.

Jackknife uses re-sampling vector $P_{(i)}$, where ith sub-group is deleted .

$$P_{(i)} = \left(\frac{1}{n-1}, \frac{1}{n-1}, \cdots, 0, \frac{1}{n-1}, \cdots, \frac{1}{n-1} \right) \tag{1}$$

It removes the first sub-group of data and re-estimates the first partial estimates, θ_{-1} from the remaining observations. Replacing the first sub-group, this estimation procedure is repeated after removing the second sub-group to obtain θ_{-2}.

After repeating this procedure r times, r partial estimates for each subgroup, $X_1, X_2, \ldots, X_r$, are produced and the jth estimates used the $h(r-1)$ observations.

$$\begin{array}{l} \theta_{-1}, \theta_{-2}, \theta_{-3}, \cdots, \theta_j, \cdots, \theta_{-n-1}, \theta_{-n} \\ X_1,\ X_2,\ X_3, \cdots, X_j, \cdots, X_{n-1}, X \end{array} \tag{2}$$

Then, the following formula is used to combine these partial estimates to get the Jackknife estimates.

$$\theta_{*Jack} = r\theta_0 - (r-1)\overline{\theta} = \theta_0 + (r-1)(\theta_0 - \overline{\theta}) \tag{3}$$

where

$$\bar{\theta} = \frac{1}{r} \sum_{j=1}^{r} \theta_{-j} \tag{4}$$

θ_{*Jack} : the final Jackknife estimate

θ_{-j} : the jth partial Jackknife estimate

θ_0 : the uncorrected estimate

$\bar{\theta}$: the mean of partial Jackknife estimates

r : the number of sub-samples

The Jackknife variance estimator (σ^2_{JACK}) is ;

$$\sigma^2_{JACK}(\theta) = \frac{n-1}{n} \sum_{i=1}^{n} (\theta_{-j} - \bar{\theta})^2 \tag{5}$$

The general properties of the Jackknife method are as follows(Bissell and Ferguson 1975). The magnitude of the bias of θ, determines whether the bias reducing property is useful in an application of Jackknife. The efficiency of the procedure depends on the form of the bias. The bias of practical estimators is usually approximately inversely proportional to sample size and the Jackknife will often produce a substantial improvement. The Jackknife estimate will generally have smaller bias than the uncorrected estimate θ_0, and often smaller variance also.

Jackknife often reduces variance slightly, especially if a large number of subgroups are used. Even if the variance is not actually reduced, the reduced bias is usually sufficient to effect an improvement in terms of mean squared error.

It is desirable to make r as large as possible. It improves the power of significance tests and reduces the expected length of confidence intervals, as well as make variance standard much more stable. A large r also tends to reduce the bias in standard errors which often seems to slightly overestimate variance when r is small. It can be a useful exercise in examining the robustness of an estimates from using the uncorrected methods.

In the past, a major disadvantage of Jackknife was the amount of computation required for its application. Fortunately the JACKKNIFE[1)] software recently developed by Hague Consulting Group makes the Jackknife produce much more straightforward to apply.

Ⅲ. Application of Jackknife and Kocur's Method

In this section, the Jackknife method and Kocur's method were applied and the results of the Jackknife and of Kocur's method were compared with those of the uncorrected method.

1. Data

A SP survey was conducted in Leeds city centre, which investigate route choice behaviours in responses to traffic information and variable road user charges. Detailed data description can be found elsewhere(Cho, 1998) The original valid number of data was a total of 2626 from 281 individuals' SP responses which contained maximum of nine observations from each respondent. The Jackknife method allows analysis of data which includes the same number of the repeated observations from each respondent. Observations which had come from respondents who yielded fewer than 9 observations were therefore excluded. The resulting valid number of observation was 2554.

2. Software

The Jackknife method has been implemented using a program "JACKKNIFE" and used in conjunction with a program "Alogit", which were developed by Hague Consulting Group. The program, "JACKKNIFE",

1) To differentiate the JACKKNIFE software from the Jackknife method, the former is expressed in upper case.

allows the choice of the number of sub-samples and modifies the control file of the estimation program to skip certain observations. Then "Alogit" program is then used to estimate sub-models based on the each sub-sample. Finally, "JACKKNIFE" combined all the sub-models to produce final Jackknife estimates.

3. Application

The number of sub-samples is important in Jackknife implementation because it improves the power of significance test and make variance standard stable. The ideal number of sub-samples is the number of samples(i.e. $r=n$). It was recommended to make the number of sub-samples, r as large as possible by Bissell and Ferguson (1975). It, however, was also suggested by Cirillo *et al.*(1996) for users to try different numbers of sub-samples and choose the lowest values of r where the estimates stabilise for the efficiency of the model estimates.

The program "JACKKNIFE" allows the number of sub-samples only between 2 and 99. In this study, total eleven models were estimated each with a different number of sub-samples; 5, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 99 which were chosen randomly.

The binary route choice logit model was estimated for this application of which the utility function as follows.

$$U_{route1} = \alpha * fttime_1 + \beta_1 * ndelay_1^2 + \beta_2 * exdelay_1^2 + \gamma_1 * fcharge + \gamma_2 * ttcharge + \gamma_3 * dtcharge \quad (6)$$

$$U_{route2} = \alpha * fttime_2 + \beta_1 * ndelay_2^2 + \beta_2 * exdelay_2^2 \quad (7)$$

where

fttime : in-vehicle free-flow travel time(minutes)
ndelay^2 : normal delay time(minutes^2)
exdelay : extra delay reported on VMS(minutes^2)
fcharge : fixed charge(pence) : the mid point of the range
ttcharge : total time-based charge(pence) : the mid point of the range
dtcharge: delay time-based charge(pence) : the mid point of the range

Ⅳ. Application Results

Model estimate results of the uncorrected model, the Kocur method and Jackknife are presented in the three tables : Jackknife estimates with 5, 10, 20, and 30 sub-samples in ⟨Table 1⟩ those with 40, 50, 60, and 70 sub-samples in ⟨Table 2⟩ and with 80, 90, 99 sub-samples in ⟨Table 3⟩.

First, the results of Kocur's method show that the t-ratio values are much lower than those of the uncorrected method and Jackknife estimates. This indicates that Kocur's method underestimates the significance of the coefficients. Therefore, the assumption of Kocur's method(that the amount of information from repeated observation by each

⟨Table 1⟩ Comparison of uncorrected method, Kocur's and Jackknife method (1)

	Uncorrected method		Kocurs	Jackknife 5 sub-samples		Jackknife 10 sub-samples		Jackknife 20 sub-samples		Jackknife 30 sub-samples	
	Coefficient	T-ratio	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio
fttime	-0.104	-11.6	3.87	-0.102	-8.42	-0.103	-10.32	-0.103	-11.31	-0.103	-10.33
ndelay	-0.017	-8.5	2.84	-0.016	-6.26	-0.016	-7.37	-0.016	-8.29	-0.016	-8.47
exdelay	-0.007	-6.4	2.13	-0.007	-4.93	-0.007	-5.64	-0.007	-6.95	-0.007	-6.85
fcharge	-0.027	-14.8	4.93	-0.026	-6.26	-0.026	-9.06	-0.026	-10.80	-0.026	-9.81
ttcharge	-0.023	-13.4	4.47	-0.022	-9.71	-0.022	-12.95	-0.022	-11.99	-0.022	-12.48
dtcharge	-0.024	-14.4	4.80	-0.024	-9.19	-0.024	-10.10	-0.024	-11.96	-0.024	-9.38

〈Table 2〉 Comparison of uncorrected method, Kocur's and Jackknife method (2)

	Uncorrected Estimates		Kocurs	Jackknife 40sub-samples		Jackknife 50 sub-samples		Jackknife 60sub-samples		Jackknife 70sub-samples	
	Coefficient	T-ratio	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio
fftime	-0.104	-11.6	-3.87	-0.103	-9.10	-0.103	-8.99	-0.103	-9.89	-0.103	-11.11
ndelay	-0.017	-8.5	-2.84	-0.016	-7.12	-0.016	-7.72	-0.016	-8.72	-0.016	-7.75
exdelay	-0.007	-6.4	-2.13	-0.007	-7.06	-0.007	-8.03	-0.007	-7.33	-0.007	-8.37
fcharge	-0.027	-14.8	-4.93	-0.026	-10.04	-0.026	-8.89	-0.026	-10.44	-0.026	-9.73
ttcharge	-0.023	-13.4	-4.47	-0.022	-11.32	-0.022	-11.75	-0.022	-12.23	-0.022	-11.42
dtcharge	-0.024	-14.4	-4.80	-0.024	-9.98	-0.024	-9.27	-0.024	-10.04	-0.024	-10.24

〈Table 3〉 Comparison of uncorrected method, Kocur's and Jackknife method (3)

	Uncorrected Estimates		Kocurs	Jackknife 80 sub-samples		Jackknife 90 sub-samples		Jackknife 99 sub-samples :	
	Coefficient	T-ratio	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio
fftime	-0.104	-11.6	-3.87	-0.103	-10.95	-0.103	-10.57	-0.103	-9.78
ndelay	-0.017	-8.5	-2.84	-0.016	-7.91	-0.016	-8.59	-0.016	-7.75
exdelay	-0.007	-6.4	-2.13	-0.007	-7.96	-0.007	-7.62	-0.007	-7.81
fcharge	-0.027	-14.8	-4.93	-0.026	-10.11	-0.026	-9.09	-0.026	-9.25
ttcharge	-0.023	-13.4	-4.47	-0.022	-12.55	-0.022	-12.40	-0.022	-12.06
dtcharge	-0.024	-14.4	-4.80	-0.024	-10.22	-0.024	-9.53	-0.024	-10.01

respondents is the only same as that of information when each respondent give only one choice) is clearly too strong.

Secondly, the Jackknife estimates show that, regardless of the numbers of sub-samples, most coefficients of Jackknife estimates are very close to those of uncorrected model estimates and that two coefficients of the Jackknife, *exdelay* and *dtcharge* are the same as those of uncorrected method. These results indicate that the coefficients of the uncorrected model estimates were very accurate despite of the repeated measurement problem.

Thirdly, t-ratio values of the Jackknife estimates are slightly lower than those of uncorrected model estimates, which indicates that the uncorrected method slightly overestimated the significance of the parameters.

Finally, as the number of sub-samples increases, there is little difference in coefficients of the Jackknife, while their t-ratio values are diminishing and stabilized.

In order to show the difference at a glance between Jackknife estimates and uncorrected model estimates and to test the significant difference of them, a test statistic was used to examine equality of parameters between the models. This statistics is discussed by Schulman(1992). The critical values for acceptance of the null hypotheses are 1.96% for a 5% level of significance and 2.575 for a 1% level of significance.

As shown in 〈Table 4〉, the test results of coefficients equality between the uncorrected model estimates and Jackknife estimates accept the null hypothesis in which the coefficient between two models are equal at the ±5% level of significance. This means that coefficients of two models are not significantly different and indicates that uncorrected estimates of these two coefficients are accurate regardless of the repeated measurement problem. In particular, Jackknife estimates of two parameters, *exdelay* and *dtcharge* are exactly the same as the uncorrected model estimates, which mean that these two parameters are very accurate and not influenced by the repeated measurement problem at all.

〈Table 4〉 Test for significant difference of individual parameters between uncorrected model estimates and Jackknife estimates

	Test results between Uncorrected and Jackknife method										
	5*	10*	20*	30*	40*	50*	60*	70*	80*	90*	99*
fftime	0.133	0.075	0.078	0.075	0.069	0.069	0.073	0.078	0.077	0.076	0.072
ndelay	0.308	0.339	0.360	0.363	0.332	0.347	0.368	0.348	0.352	0.366	0.348
exdelay	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
fcharge	0.220	0.294	0.331	0.311	0.316	0.290	0.324	0.309	0.317	0.295	0.298
ttcharge	0.352	0.414	0.398	0.406	0.386	0.394	0.402	0.388	0.408	0.405	0.399
dtcharge	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

* Number of sub-samples

〈Table 5〉 Comparison of Standard Errors between Uncorrected Model and Jackknife estimates

# of samples	original	5	10	20	30	40	50	60	70	80	90	99
fftime	0.010	0.013	0.011	0.010	0.011	0.012	0.012	0.010	0.009	0.009	0.010	0.011
ndelay	0.003	0.003	0.003	0.002	0.002	0.003	0.003	0.002	0.002	0.002	0.002	0.003
exdelay	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
fcharge	0.002	0.004	0.003	0.003	0.003	0.003	0.003	0.002	0.003	0.003	0.003	0.003
ttcharge	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
dtcharge	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.003	0.002
Mean of s.e.	0.003	0.004	0.004	0.003	0.003	0.004	0.004	0.003	0.003	0.003	0.003	0.004

In addition to the comparison of the coefficients and the t-ratios between uncorrected model estimates and Jackknife estimates, standard errors between them and standard error ratios were also compared in order to show the error estimates of them.

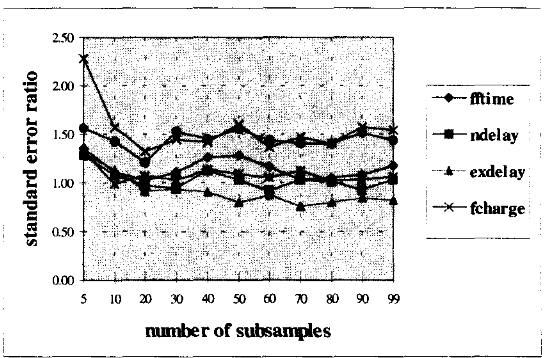
〈Table 5〉 reports the standard errors of the uncorrected original model and those of Jackknife estimates. The error estimates from the uncorrected model and Jackknife estimates are consistently very low except *fftime* parameter. The last row in the table presents the mean values of the standard errors over all coefficients in the models and indicates that the overall standard errors of the uncorrected model and Jackknife estimates are very similar regardless of the size of the sub-samples, even though there is some variation between parameters. 〈Table 5〉 shows that as the number of sub-samples increase, the standard errors of Jackknife estimates tend to stabilise.

$$\text{standard error ratio} = \frac{\text{standard error of jackknife estimates}}{\text{stadard error of uncorrected model estimates}} \quad (8)$$

〈Figure 1〉 show relative standard errors ratios which were quotients of standard error of each parameter of Jackknife estimates by those of uncorrected model estimate.

The results show that the values are consistently more than 1 and close to 1 which indicates that the uncorrected model estimates are accurate but slightly underestimate the errors.

As results of these analysis, the Jackknife estimates confirm that the coefficients of the un-



〈Figure 1〉 Comparison of standard error ratio corrected estimates are accurate, but that their significance is slightly overestimated. As the number of sub-samples increases, the Jackknife estimates are stabilised.

V. Summary and Conclusion

This paper has dealt with the "repeated measurement problem" which is caused by allowing several observations from each respondent and inflates the significance of explanatory variables. Several different approaches to correct the repeated measurement problem were reviewed : Kocur's method (Kocur *et al.* 1981), the approach by Ouwersloot and Rietveld(1996), and Jackknife and Bootstrap method (Cirillo *et al.* 1996).

Among those approaches, the Jackknife method and Kocur's method were applied to the SP results in order to treat the repeated measurement problem. The Jackknife method was implemented using a program 'JACKKNIFE'. The eleven Jackknife models were estimated with 5, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 99 of sub-samples.

The model estimate results of Jackknife method and Kocur's method were compared with those of the uncorrected estimates in order to test whether there was repeated measurement problem or not and the extent to which this problem affected the model estimates. The standard errors ratio of the uncorrected model estimates and Jackknife estimates were also compared.

The results reveals that the t-ratios of Kocur's are much lower than those of the uncorrected method and Jackknife estimates, indicating that Kocur's method underestimates the significance of the coefficients. Jackknife method produced the almost same coefficients as those of the uncorrected model but the lower t-ratios. These results indicate that the coefficients of the uncorrected method are accurate but that their significance are somewhat overestimated. This result is consistent with Cirillo *et al.*(1996). Therefore, I concluded that the repeated measurement problem did exist in our data, but that it did not affect the model estimation results significantly.

It is recommended that such a test should become a standard procedure. If it turns out that the analysis based on the simple uncorrected method are influenced by the repeated measurement problem, it should be corrected. One way of treating the problem is to re-estimate the model using Jackknife method used in this paper. The Jackknife is easy and simple method to correct the problem compared with other methods and the software 'JACKKNIFE' is available for this procedure.

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