Modelling Trip Frequency with Longitudinal GPS Data Collected by Mobile Phone

Lei GONG[1], Toshiyuki YAMAMOTO[2] and Ryo KANAMORI[3]

[1]Non-member of JSCE, Researcher, Institutes of Innovation for Future Society, Nagoya University
(Furo-cho, Chikusa-ku, Nagoya, Japan 464-8603, Japan)
E-mail:Leigongchi@gmail.com
[2]Member of JSCE, Professor, Institute of Materials and Systems for Sustainability, Nagoya University
(Furo-cho, Chikusa-ku, Nagoya, Japan 464-8603, Japan)
E-mail: yamamoto@civil.nagoya-u.ac.jp
[3]Member of JSCE, Designated Associate Professor, Institute of Innovation for Future Society, Nagoya University
(Furo-cho, Chikusa-ku, Nagoya, Japan 464-8603, Japan)
E-mail: kanamori.ryo@nagoya-u.jp

Censors attached on smart phone make it easier to collect trip and activity data of mobile phone holders. However, it also brings challenges of analyzing the obtained data. How to treat the days with zero trip is one of them. With the only information of GPS trajectories, it is difficult to distinguish whether a zero-trip day is a day when the phone holder did not make any trips or a day when the person forgot to bring the phone. Traditional ordered probit (OP) model cannot distinguish these zero-trip days. In this research, we applied zero-inflated ordered probit (ZIOP) model to analyze the influencing factors over the number of trips in a day with GPS trajectories collected by mobile phones in Hakodate. The results show ZIOP outperforms traditional OP model which does not consider to treat possible causes of zero-trip days in separate ways. In addition, the weather features can be analyzed in a more specific way in ZIOP models.

Key Words: *trip rate, trip frequency, GPS data, zero-inflated ordered probit (ZIOP) model, ordered probit model*

1. INTRODUCTION

Trip frequency (or trip rate) is a fundamental concept regarding trip generation (in a disaggregated or aggregated way) used in the transportation demand prediction. Traditional household travel survey usually investigates the trip frequency in the urban area on a selected day. However, travel demand is not a fixed variable but varying according to a couple of factors. Mobile phone with GPS censors provide a chance of collecting trip and activity data from a longitudinal perspective since this kind of data collection method can greatly relieve the burden of being involved in the survey. Although this advanced technology can obtain a higher accuracy on data collection in the temporal and spatial perspectives, some existing problems should not be ignored, such as forgetting to bring the phone when traveling out, running out of the battery before getting a plug-in somewhere for recharging. Forgetting to bring the phone when traveling out marks a zero-trip result on that day, which is the same result as not going out. It is confusing to deal with two types of zero-trip days which are mixed together when building the trip generation model for the demand analysis. This paper provides a zero-inflated ordered probit (ZIOP) model to solve the problem when modeling the trip generation, since it can treat the zero-trip days in two separate ways: one is forgetting to bring the mobile phone when traveling out which means the person did not attend the survey, and the other one is not traveling out which means that the person attended the survey but had a real zero-trip day.

Due to mobile phone GPS data collected in an easier way, multi-day travel data collection may become more popular in the future. So it is very likely to obtain a high proportion of zero-trip days in the data set. And including the distinction of zero-trip days in the trip frequency model is essential since the reasons resulting the same zero-trip day are totally different. The contribution of this paper is providing an appropriate way to deal with zero-trip days in longitudinal data collection and it is an essential component of analyzing dynamic travel demand. The rest of this paper is structured as follows. Section 2 offers a brief introduction related to achievements of influencing factors exploration to trip rate or trip frequency. Data used in this research are described in section 3 followed by the model specification in section 4 which provides the model structure and explanations of ZIOP and its variant, ZIOPC (zero-inflated ordered probit considering correlations between error terms). Section 5 shows the estimation results of ZIOP(C) models and compares these results with ordinary ordered probit (OP) model. Conclusions are drawn in section 6.

2. LITERATURE REVIEW

Trip frequency is a traditional topic; it determines the number of trips (daily or longer time period) generated for each individual. This section only reviews the achievements related to persons, not the trucks or freight[1; 2].

From last century, trip frequency has been analyzed from different dimensions and various aspects. Here, we only focus on influencing factors and its intra-person or intra-household variability, which are most related to this paper, although other issues related to trip frequency such as transferability of trip generation models[3; 4] and sharing bike trip generation models[5] were also investigated in the literature.

As far back as in 1980s, the number and distribution of daily person trips were directly examined by gender, marital and family status and the number of workers in the household in the metropolitan area in the US[6] by Gordon et al. Hjorthol et al. found employment status is an influencing factors to trip frequency from the data collected in the national travel surveys in Denmark, Norway, and Sweden[7]. Their results also show that commuting and work-related trips decline after retirement, while shopping and leisure trips do not start to decline before extreme old age. Regarding gender, Pooley et al. found that males travel more than females in all age groups and time periods[8].

Certain groups, such as the elderly, disabled and vulnerable groups are the ones attracted more attention. Household structure, income, car ownership, possession of a driver's license, difficulty for walking, and other disabilities are found to affect trip frequency to the elderly and the disabled people through applying ordered probit models on travel survey data in London[9]. Shimizu analyzed trip frequency together with other characteristics of travels of persons with visual impairments in Japan[10]. Their trip frequencies are found to be much lower than that of sighted persons. Roorda et al. focused on trip generation of three vulnerable groups: single-parent families, low income households, and the elderly in three Canadian urban areas[11]. An ordered probit model with spatially expanded coefficients was applied on these persons. Spatial expansion shows that there are spatial mobility trends for the elderly and low-income populations. It provides clues as to where vulnerable populations may experience greater degrees of social exclusion. Focusing on physical activities for the elderly, Davis et al. conducted a seven-day trips log recording on the elderly and concluded that trip frequency was associated with gender, age, physical function, walking-aid use, educational attainment, number of amenities within walking distance and cars in the household[12].

With multiple-day data collection, intra-person and intra-household variability of trip frequency have also been explored. Pas and Koppelman empirically investigated intrapersonal variability in daily trip frequency with data collected by 145 persons in seven days[13]. Their results confirmed that employment status, role in the household, presence of children, availability of travel-related resources are influential variables having impact on the variability of daily trip frequency. Pas and Sundar concluded considerable day-to-day variability in the trip frequency with a three-day travel data collected by 150 households in Seattle, US[14]. Their results show that the level of day-to-day variability is about the same for home-based and non-home-based trips. Tarigan and Kitamura examined variability of frequency of leisure trips per week with a six-week diary survey in Germany with a two-stage method consisting of a tobit and an ordinary least squares approaches[15]. Intra-household travel variability was examined with vehicle trips collected by approximate 500 vehicles in 260 households in Georgia, US[16] by Elango et al. They found that demographic variables significantly affect the day-to-day variability in the total number of household trips per day.

More recently, due to the popularity and easy access of social media, social media related factors have also been included in the analysis. Parady et al. checked the relationship between social factors with leisure trip frequency. The relation between social networks, social interactions and out-of-home leisure was analyzed via a multi-level SEM model in the context of Japanese society[17].

3. DATA DESCRIPTION

The data set used in this research was collected in Hakodate city, Hokkaido. 20 persons provided their daily GPS trajectories by a smart mobile phone which collected the longitude, latitude, time stamp etc. every 30 seconds. The data were collected in two periods (Dec. 2012-Apr. 2013 and Jun. 2013-Oct. 2013) which cover winter and summer; it means the weather's influence on the trip frequency can also be investigated. Finally, 16 persons' data were used in the study, since the other four persons only have very limited days of attending the survey or most of the days are with incomplete trip chains.

Here we show the proof of existence and necessity of distinguishing two types of zero-trip days in our data set. We demonstrate whether each day (horizontal axis) for each person (vertical axis) is a zero-trip day or non-zero-trip day in Fig. 1 by pink cube and green cube with black dot respectively. It is obvious some persons have a much longer continuous period of zero-trip days which cannot be reasonably explained as being at home for more than 10 days. The possible reason of such a long duration of zero-trip days is the person did not bring the mobile phone in that period due to the issues such as privacy concerns in that period or business trips making the person not in Hakodate or nearby cities.

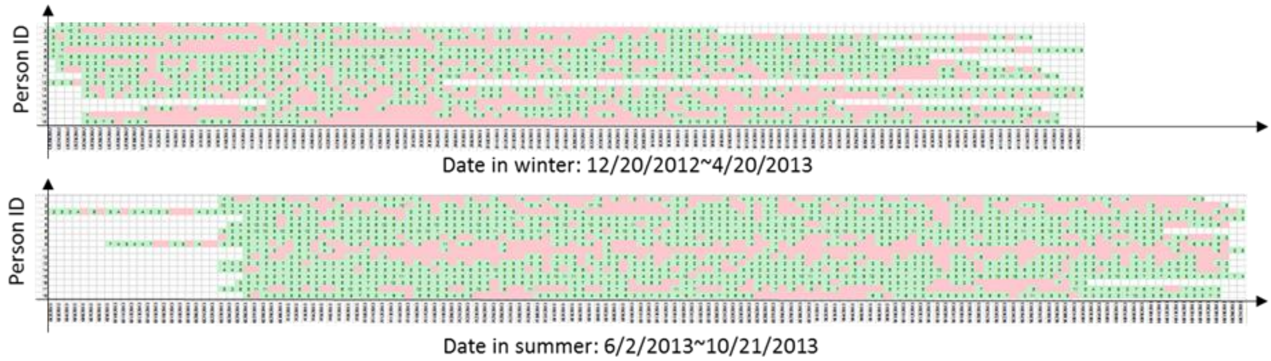

Fig. 1 Zero-trip days (pink) and non-zero-trip days (green with black dot)

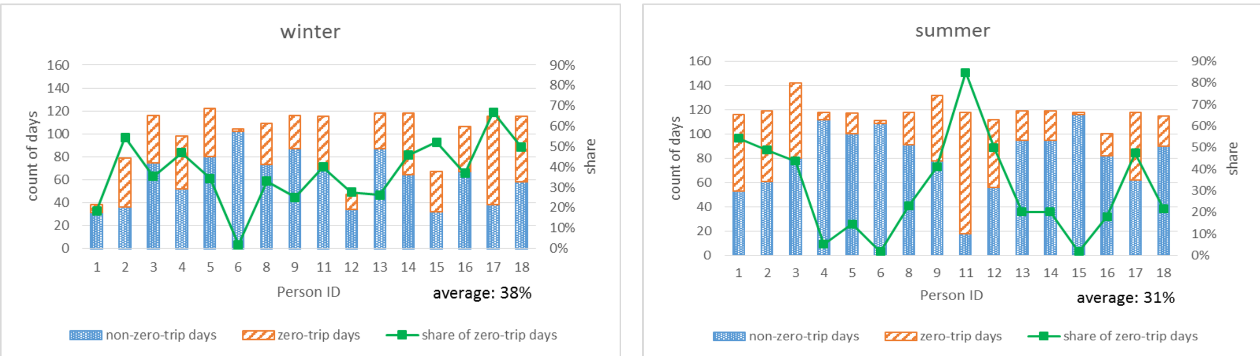

Fig. 2 Constitution of person-day types and share of zero-trip day for each person in winter (left) and summer (right)

Fig. 2 shows composition of person-days by indicating the number of zero-trip days and non-zero-trip days as well as the share of zero-trip days for each person in two seasons. The share of zero-trip days fluctuates a lot among persons and the average share is 38% in winter and 31% in summer. It reflects that persons' characteristics may influence whether attending the survey or having a zero-trip day conditional on attending the survey.

Usually one or two consecutive zero-trip days can be reasonably explained by being home due to bad weather, illness, or bad mood. In order to check the reasonability of duration of consecutive zero-trip days, the distribution of duration of continuous zero-trip days was drawn as shown in Fig. 3. It uncovers that the majority of continuous zero-trip days lasts for 1 or 2 days. It is reasonable since some people may not go out during that short period. For the rest of the durations of zero-trip days which are longer than 2 days, it is highly probable that the person did not bring the mobile phone which means not attending the survey.

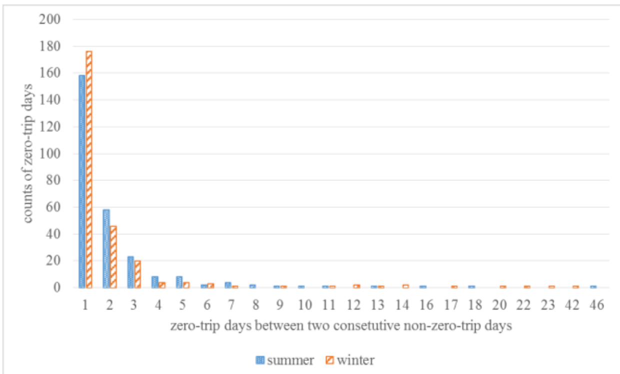

Fig. 3 Distribution of the number of consecutive zero-trip days between two non-zero-trip days

4. METHODOLOGY

ZIOP model is an effective one when fitting data set with excessive zero values in the dependent variable, whose application can be found in a couple of topics, such as individual problem of smoking tobacco[18], sports participation[19], conflict & peace issues[20], and mushroom consumption[21]. Our data set got an average share of more than 30% of zero values which means ZIOP model is an appropriate option.

This paper estimates the daily trip frequency considering the possible influencing variables from demographic, weather, trip and time dimensions. Trip frequency was converted from count variable to ordinal variable before further analysis since daily trips on some days are more than 9 and not consecutively distributed.

Both ZIOP and ZIOPC models are two-step models. In the first step, a binary split model whose outcomes (1 for attending the survey while 0 otherwise) are decided by the propensity for a sample of person-day i $(i = 1, \dots, N)$ as follows.

$$r_i^* = \boldsymbol{z_i}\boldsymbol{\gamma} + \varepsilon_i \tag{1}$$

where $\boldsymbol{z_i}$ is the corresponding explanatory variable vector for coefficients $\boldsymbol{\gamma}$; ε_i is the error term assumed to follow a standard normal distribution.

The result of the formula (1) will decide whether the person attended the survey on a day (i.e. $r_i = 1$) or not (i.e. $r_i = 0$) as follows.

$$r_i = \begin{cases} 1\ if\ r_i^* > 0 \\ 0\ if\ r_i^* \le 0 \end{cases} \tag{2}$$

The probability of a selection of attending the survey is given by formula (3).

$$\Pr(r = 1|\boldsymbol{z_i}) = \Pr(r_i^* > 0|\boldsymbol{z}) =$$
$$\Pr(\varepsilon_i > -\boldsymbol{z_i}\boldsymbol{\gamma}|\boldsymbol{z}) = 1 - \Phi(-\boldsymbol{z_i}\boldsymbol{\gamma}) = \Phi(\boldsymbol{z_i}\boldsymbol{\gamma}) \tag{3}$$

where Φ is cdf of univariate standard normal distribution.

Conditional on the outcome is equal to 1 in the first step, the second step is derived from an ordered probit model which is as follows.

The propensity of selection of an ordinal trip frequency for sample i is defined by the following formula.

$$\tilde{y}_i{}^* = \boldsymbol{x_i}\boldsymbol{\beta} + \mu_i \tag{4}$$

where $\boldsymbol{x_i}$ is the corresponding explanatory variable vector for coefficients $\boldsymbol{\beta}$; μ_i is the error term assumed to follow a standard normal distribution.

Conditional on attending the survey, the discrete variable $\tilde{y}$ $(\tilde{y} = 0,1,\dots,J)$ is mapped by

$$\tilde{y}_i = \begin{cases} 0 & if\ \tilde{y}_i{}^* \le \kappa_0^x, \\ j & if\ \kappa_{j-1}^x < \tilde{y}_i{}^* \le \kappa_j^x, \\ J & if\ \kappa_{J-1}^x < \tilde{y}_i{}^* \end{cases} \tag{5}$$

There are J+1 outcomes in the second step which need J thresholds $(\kappa_0^x, \dots, \kappa_{J-1}^x)$.

$\boldsymbol{z}$ and $\boldsymbol{x}$ are explanatory variables that can be same or partially same in propensity functions. Samples are assumed to be independent from each other. ε_i and μ_i can be correlated or not, which results in ZIOP model and ZIOPC model respectively as follows.

(1) ZIOP model

When error terms ε_i and μ_i are not correlated, the full probability of y_i is given by formula (6). If additionally denote $\kappa_{-1}^x = -\infty$ and $\kappa_J^x = \infty$, which are treated as two additional thresholds, then we get J+1 thresholds and the above probability can be written as formula (7).

$$\Pr(y_i) = \begin{cases} \Pr(y_i = 0|\boldsymbol{z_i},\boldsymbol{x_i}) = [1 - \Phi(\boldsymbol{z_i}\boldsymbol{\gamma})] + \Phi(\boldsymbol{z_i}\boldsymbol{\gamma})\Phi(\kappa_0^x - \boldsymbol{x_i}\boldsymbol{\beta}) \\ \Pr(y_i = j|\boldsymbol{z_i},\boldsymbol{x_i}) = \Phi(\boldsymbol{z_i}\boldsymbol{\gamma})\left[\Phi\left(\kappa_j^x - \boldsymbol{x_i}\boldsymbol{\beta}\right) - \Phi\left(\kappa_{j-1}^x - \boldsymbol{x_i}\boldsymbol{\beta}\right)\right], (j = 1,\dots,J-1) \\ \Pr(y_i = J|\boldsymbol{z_i},\boldsymbol{x_i}) = \Phi(\boldsymbol{z_i}\boldsymbol{\gamma})\left[1 - \Phi\left(\kappa_{J-1}^x - \boldsymbol{x_i}\boldsymbol{\beta}\right)\right] \end{cases} \tag{6}$$

$$\Pr(y_i|\boldsymbol{z_i},\boldsymbol{x_i}) = [1 - \Phi(\boldsymbol{z_i}\boldsymbol{\gamma})]\cdot \mathbb{I}(y_i = 0) + \prod_{j=0}^{J}\left\{\Phi(\boldsymbol{z_i}\boldsymbol{\gamma})\cdot\left[\Phi\left(\kappa_j^x - \boldsymbol{x_i}\boldsymbol{\beta}\right) - \Phi\left(\kappa_{j-1}^x - \boldsymbol{x_i}\boldsymbol{\beta}\right)\right]\right\}^{\mathbb{I}(y_i=j)} \tag{7}$$

where $\mathbb{I}$ is the indicator function whose result is 1 when the condition in the parenthesis is satisfied and 0 otherwise.

(2) ZIOPC model

This model assumes error terms ε_i and μ_i are allowed to be correlated. If additionally denote $\kappa_{-1}^x = -\infty$ and $\kappa_J^x = \infty$, similar to formula (7), we can get J+1 thresholds and the probability in formula (8).

$$\Pr(y_i|\boldsymbol{z_i},\boldsymbol{x_i}) = [1 - \Phi(\boldsymbol{z_i}\boldsymbol{\gamma})]\cdot \mathbb{I}(y_i = 0) + \prod_{j=0}^{J}\begin{bmatrix}\Phi_2\left(\boldsymbol{z_i}\boldsymbol{\gamma}, \kappa_j^x - \boldsymbol{x_i}\boldsymbol{\beta}, -\rho\right) - \\ \Phi_2\left(\boldsymbol{z_i}\boldsymbol{\gamma}, \kappa_{j-1}^x - \boldsymbol{x_i}\boldsymbol{\beta}, -\rho\right)\end{bmatrix}^{\mathbb{I}(y_i=j)} \tag{8}$$

where Φ_2 is the cdf of bivariate standard normal distribution; ρ is the correlation between error terms in two phrases.

Given the simplified assumption of independence over samples, the simulated maximum likelihood (SML) estimator is the value $\boldsymbol{\theta}$ that maximizes:

$$\hat{\theta}_{SML} \equiv \underset{\boldsymbol{\theta}\in\boldsymbol{\Theta}}{\arg max} \sum_{i=1}^{N} \log P_i(\boldsymbol{\theta}) \tag{9}$$

5. RESULTS AND DISCUSSION

The estimation results of ZIOP, ZIOPC and OP models are shown in Table 1. It is clear that the ZIOPC model can best fit the data, whose log-likelihood value and AIC as well as BIC value outperform the other two. And the overall performance of ZIOP model is also better than OP model. So two-step decision process seems to be more suitable in modeling daily trip frequency. In addition, the correlation between the error terms in these two steps in ZIOPC model was found to be significant with a value of 0.261; it means that the error terms in two phrases are indeed correlated with each other in our data set.

In the following paragraphs, we first explain the results estimated by ZIOP(C) models; then discuss the manifest difference between ZIOP(C) models and OP model.

ZIOP and ZIOPC models almost got the similar trends in the estimation results. Two parts of difference related to the identified significant explanatory variables are precipitation and certain family types which were found significant by ZIOPC model. Here we use the results from ZIOPC as demonstration. Longer duration of zero-trip days before current zero-trip day make less propensity in the first step formula and induce more likely to be a day not attending the survey. Higher average temperature makes larger probability of attending the survey while more precipitation causes the converse results. Compared to no-precipitation weather condition, rain causes less trips conditional on attending the survey; while weather condition has no significant contribution to whether the person attending the survey or not. Male is found to be more likely not to attend the survey; however, if attending the survey, male has more trips than female. Regarding age group, compared to the referred 20s group, persons in 30s and 50s have a higher probability of attending the survey while persons in 30s prefer to have less trips and persons in 60s prefer to have more trips conditional on attending the survey. Driving frequency is also found significant in both phrases of the model; compared to driving almost every day, almost not driving and driving sometimes, both of them show a larger probability of attending the survey and having less trips conditional on attending the survey. About the contribution of family type, referred to couple with kids, single person is more probable of attending the survey; however, persons from single-person and three-generation household have less daily trips conditional on attending the survey. Average travel distance in previous 4 days was not confirmed as a significant variable in the second phrase model while averaged out-of-home time is found to be a significant variable whose value larger result more daily trips conditional on attending the survey.

Table 1 Estimation results

variables	Model I: ZIOP binary F.	Model I: ZIOP ordered F.	Model II: ZIOPC binary F.	Model II: ZIOPC ordered F.	Model III: OP
constant	**1.580** ***	---	**1.396** ***	---	---
# of zero-trip days	**-0.437** ***	---	**-0.443** ***	---	---
Day type					
Working day	ref.	ref.	ref.	ref.	ref.
Holiday	**-0.278** ***	0.047	**-0.260** ***	0.019	**-0.136** ***
Average temperature	**0.013** *	0.001	**0.013** *	0.002	**0.006** *
Precipitation	-0.008	-0.003	**-0.009** *	-0.004	**-0.006** *
Snowfall	0.018	-0.004	0.016	-0.002	0.006
Average humidity	-0.010	0.003	-0.008	0.002	-0.005
Wind speed	-0.042	0.015	-0.036	0.008	-0.016
Max precipitation	0.011	0.032	0.015	0.030	0.025
Daytime weather Cond.					
Other	ref.	ref.	ref.	ref.	ref.
Rain	0.048	**-0.223** **	0.029	**-0.195** **	-0.085
Snow	0.042	-0.111	0.043	-0.104	-0.036
Gender					
Female	ref.	ref.	ref.	ref.	ref.
Male	**-0.217** **	**0.274** ***	**-0.204** **	**0.261** ***	-0.027
Age group					
20s	ref.	ref.	ref.	ref.	ref.
30s	**0.867** ***	**-0.866** ***	**0.794** ***	**-0.724** ***	**-0.324** ***
40s	0.041	-0.115	0.025	-0.024	0.062
50s	**0.391** ***	0.062	**0.379** ***	0.171	**0.387** ***
60s	-0.488	**0.651** ***	-0.433	**0.603** ***	**0.239** *
Driving frequency					
Almost everyday	ref.	ref.	ref.	ref.	ref.
Almost do not drive	**1.313** **	**-1.580** ***	**1.133** *	**-1.479** ***	**-0.368** ***
Some times	**1.125** **	**-1.046** ***	**1.018** **	**-0.863** ***	**0.246** **
Family type					
Couple with kids	ref.	ref.	ref.	ref.	ref.
Couple without kids	**0.981** *	-0.235	0.905 *	-0.086	**0.324** *
Single	**0.288** *	**-0.613** ***	**0.268** *	**-0.580** ***	**-0.426** ***
Three generation	0.078	-0.302	-0.003	**-0.284** *	**0.226** *
Aver. travel dist.	---	-0.001	---	-0.001	-0.001
Aver. out-of-home tim	---	**0.001** ***	---	**0.001** ***	**0.002** ***
ρ	---		**0.261** *		---
LL	-5947		-5945		-6233
AIC	11993		11991		12524
BIC	12086		12086		12578
CAIC	11968		11966		12510
Sample size	3347		3347		3347

significance level: *** 0.001 **0.01 *0.05

The estimation results also show OP model does not always get consistent results with ZIOP(C) models. A possible reason is the split two-step decision process in ZIOP(C) models makes more reasonable fitting to the reality. OP model did not find daytime weather condition as a significant one influencing the trip frequency. It did not find gender as a significant one, either; while ZIOP(C) models did and their results are consistent with the findings[8)] by Pooley et al. Another problem of using OP model is the contradictory results with regard to driving frequency. OP model returns opposite direction of contribution of almost not driving and driving sometimes when referred to driving almost every day. However, ZIOP(C) models return reasonable results regarding this variable and their results are consistent with existing findings that driving more causes more trips due to higher mobility[9; 13]. It is a proof that ZIOP(C) models not only can fit the data set better but also show reasonable results due to the two-phrase structure model which is a more appropriate one for modeling the process of making trips.

Note that we only got 16 persons in the estimation and increasing the number of persons in the survey may cause different conclusions.

6. CONCLUSIONS

This paper applied ZIOP(C) models on the data of daily trip frequency to check its relationship with explanatory variables from demographic, trip, weather and time dimensions. In the context of easier data collection along with multiple days which may return large proportion of zero-trip days than a reasonable level, this proposed two-phrase model structure can better fit the decision process of making trips and return more reasonable results compared to traditional OP model which treats zero-trip days an identical way. Although our data set was collected during almost eight months, it should also be noted that limited number of participated persons in the survey may cause the demographic diversity issue which can be solved in the future by recruiting more persons in the survey to diversify the demographic information. Another concern is treating all sampled person-day as pooled data set instead of panel data, which means the random effects should also be considered and included in the model in the future to make the model more appropriate.

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