Why do drivers divert? Impact of Graphical Route Information Panels

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Abstract: This study applied a stated preference survey method to investigate the impact of Graphical Route Information Panels (GRIPs) on taxi drivers' diversion decisions. A cross-sectional ordered logit model and a panel data ordered logit model were developed. Main findings are: Taxi drivers and mid-age drivers with high urban freeway use frequency are more likely to divert; drivers are more likely to divert if the original ramp is jammed and an accident occurs; employer-provided car drivers are less sensitive to accident and less likely to divert. On the modelling aspect, the panel data model does not provide substantially different model coefficients but more robust statistical inferences; the cross-sectional model tends to seriously overestimate *t*-test values for explanatory variables changing across drivers and tends to slightly underestimate *t*-test values for explanatory variables changing across trip scenarios and interaction terms. The findings have implications for GRIP assessment and for future response behaviour modelling effort.

Keywords: GRIP; graphical route information panel; mobile communication; diversion; ordered logit; panel data; stated preference.

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1 Introduction

Internationally, benefiting from rapidly growing ‘wireless communication’ (Baek et al., 2011) and ‘intelligent transportation systems’ (Gan and Wei, 2012) technologies, transportation agencies are more interested in installing GRIPs to enhance traffic information services. GRIPs use graphical information to represent current traffic conditions of a particular area within the road network to convey traffic messages. They help drivers make better route choices.

Since the effect of GRIPs essentially depends on how drivers respond to information, there is a need to correctly understand drivers’ behaviour in response to GRIPs. This understanding can facilitate better investment, design and operation of GRIPs. Because of the lack of research on modelling drivers’ behaviour to GRIPS via economic models, the objective of this study is to investigate freeway user’s diversion response to GRIPs through establishing econometric models. Specifically, this study is intended to identify factors that influence drivers’ response to GRIP and obtain insightful results, which have implications for future driver response modelling as well. The topic of this study, in essence, is a topic on human-computer interaction (Chang, 2010). In the context of this study, ‘human’ is drivers, ‘computer’ is an expressway information system and ‘interface’ is GRIP.

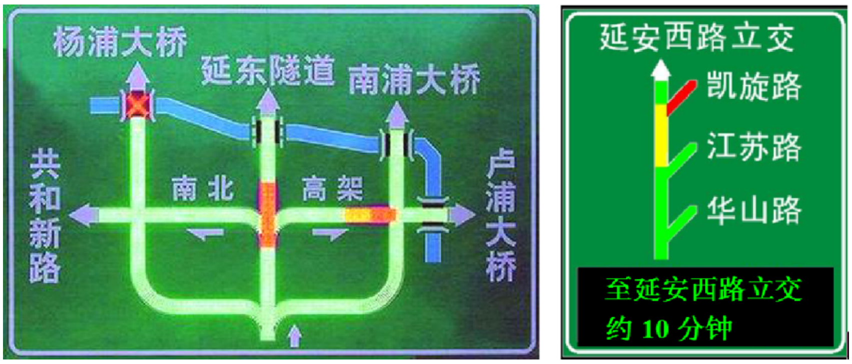
In contrast to Gan et al. (2008), this study develops both a cross-sectional and a panel data ordered logit model for predicting diversion probabilities under GRIP. The panel data model aims to account for correlations among repeated observations from the same respondent, which previous GRIP studies neglected. In addition, unlike most previous information response studies that mainly concentrated on private car drivers, this study mainly targets taxi drivers. Since the percentage of taxies on urban roads in big Chinese cities such as Shanghai is quite high (e.g., 5~40% varying with time of day and site of road), research results of this study are expected to facilitate better assessment of GRIPs.

The remainder of this paper is organised as follows. In Section 2, literature review is presented. Section 3 describes a survey for collecting behavioural data on drivers' response to GRIPs. Then, it uses the collected data to develop both a cross-sectional and a panel data ordered probit model for predicting diversion probabilities under GRIP, which is followed by discussions on model estimation results given in Section 4. Finally, in Section 5, concluding remarks are given.

2 Literature review

A number of researchers have conducted GRIP-related studies. In Japan, questionnaire surveys (Hirokazu and Mitsuru, 2000) were conducted to investigate drivers' attitudes towards GRIPs (e.g., awareness, legibility, readability and usefulness). The survey results showed that GRIPs were well accepted. In Germany, Schönfeld et al. (2000) reported extensive research including questionnaire surveys, laboratory computer-aided cognitive experiments and full-scale driving simulator experiment. Their work aimed to obtain a better panel design of GRIP. In the Netherlands, Alkim and Schenk (2001) reported studies investigating motorists' reaction to GRIPs via full-scale driving simulator experiment, and their research results showed the advantage of GRIP over regular Variable Message Sign (VMS). Dicke-Ogenia and Brookhuis (2008) reported a real-world experiment of a new freeway GRIP on A12 Motorway in the Netherlands and investigated the impacts of GRIP on driver travel behaviour. Their study showed that GRIPs were successful in attracting the attention of drivers. In the UK, Richards et al. (2004) reported a laboratory research that examined whether the content of GRIP information could be readily understood by a simple driving simulator. On the basis of the test of a series of different sign designs, some successful sign design types were identified. In Australia, the Drive Time System uses roadside signs with colour strips to indicate the level of congestion between roadway sections and display travel time to main road exits (Kloot, 1999). In Taiwan, Lai tested different kinds of GRIPs ('road colour only', 'road colour + traffic speed' and 'road colour + travel time') through examining optimum route choice percentage and response time of respondents, and suggested 'road colour only' should be used (Lai, 2012). In USA, Aitken et al. (2012) designed several prototype GRIPs and conducted an internet-based survey to assess initial reception of GRIPs and their potential usefulness to US drivers. Their work showed that driver age, gender, familiarity with road network and the presence of travel time information were more likely to influence GRIP understanding and use. In China, Gan et al. (2006) and Gan (2010) described methods of generating colour-coded Level-Of-Service (LOS) information and predicting travel time for GRIPs on urban freeways. Shanghai's freeway GRIPs contain two types: Type-L Sign and Type-M Sign (see Figure 1). 'Type-L Sign' displays a LOS map. 'Type-M Sign' displays both LOS map and text information (e.g., travel time and accident alert).

Figure 1 Shanghai GRIPs: (a) Type-L Sign and (b) Type-M Sign (see online version for colours)



(a) (b)

Previous GRIP studies, however, mainly concerned issues of panel design, or drivers' attitude towards and perception of GRIPs (e.g., readability, understanding, usefulness and legibility), or operational aspects (e.g., GRIP information generation). Relatively fewer studies developed econometric models (e.g., discrete choice models) to describe driver route choices or diversion responses to GRIPs. Hato et al. (1999) developed a route choice model to show the relationship between drivers' reactions to multiple information sources (including GRIPs), latent psychological factors, external travel constraints and certain information characteristics in the context of Tokyo, Japan. Gan et al. (2008) developed a multinomial logit model to quantify the impact of GRIPs (Type-M Signs) on freeway users' decision about diverting to arterial streets in the context of Shanghai, China. Obviously, further modelling efforts need to be made to obtain a better understanding of drivers' behaviour in response to GRIPs.

3 Methodology

3.1 Background

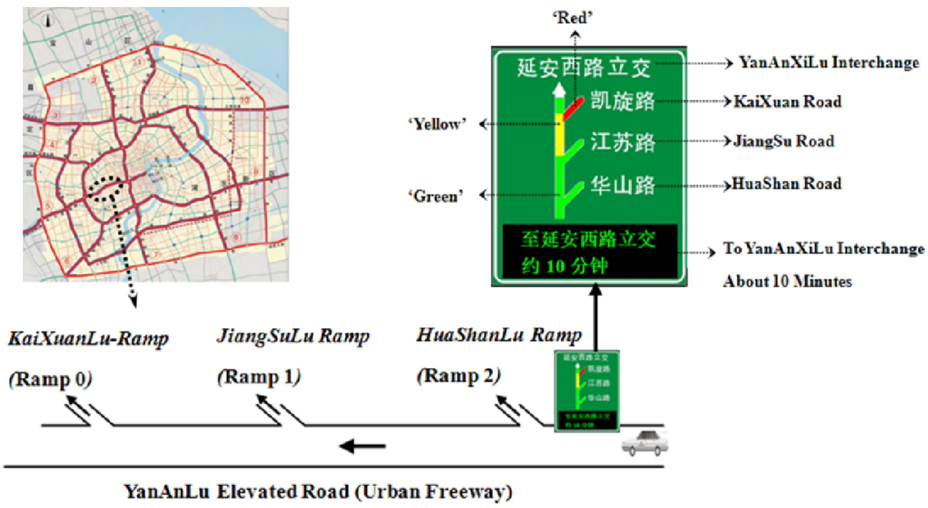
In Shanghai, GRIPs on urban freeways are operated by Shanghai urban freeway Traffic Management Center (TMC). Type-M Signs (Figure 1) are installed on the urban freeway upstream of key off-ramps. They display a colour-coded LOS map of a freeway section (usually covering 2 or 3 off-ramps) and text information (e.g., incident alert, congestion warning and travel time). They are used to help drivers make informed off-ramp selection decisions and avoid congestions. A three-colour scheme is used to indicate traffic conditions: Green (free flowing), Yellow (mild congestion) and Red (heavily congested). For more technological details of Shanghai GRIPs, the readers are referred to Gan et al. (2006) and Gan (2010).

Since it is unsafe to do real-world experiments to collect behavioural data through intentionally displaying information about non-existing unexpected events, this study applied the stated preference (SP) survey approach to collect data about drivers' response to GRIPs.

3.2 Survey design

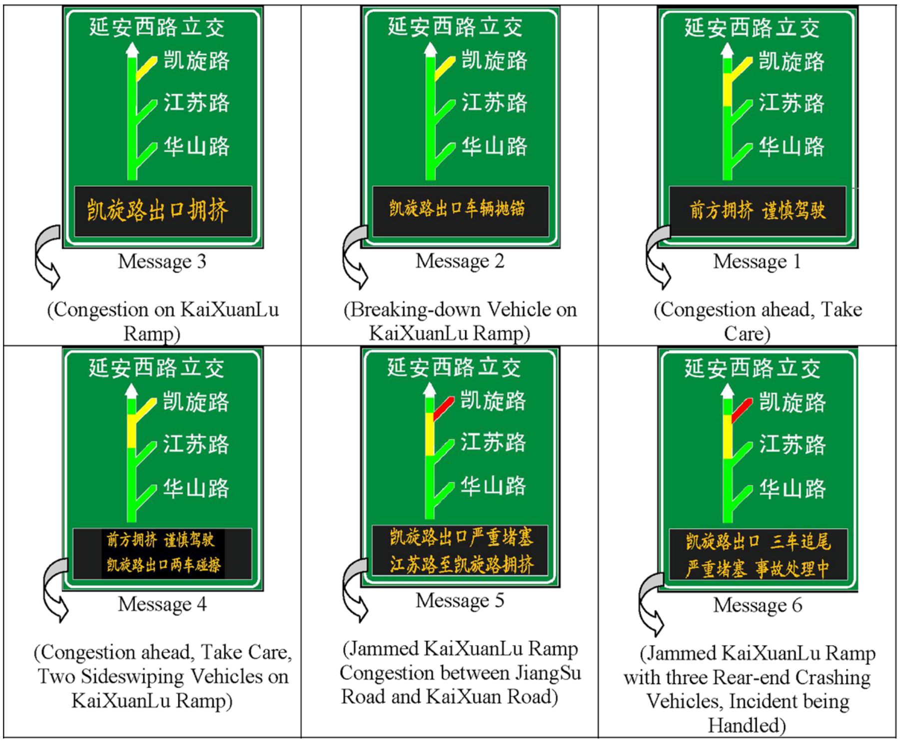
The SP experiment was designed based on a hypothetical journey on a section of the westbound YanAnLu Elevated Road (an un-tolled urban freeway in the downtown). The urban freeway section specified in the SP experiment is depicted in Figure 2. The upper left part of Figure 2 is the urban freeway network in Downtown Shanghai. The lower part of Figure 2 is the urban freeway section, which covers three off-ramps and one real-life roadside GRIP (Figure 2). The upper right part of Figure 2 is an illustration of GRIP for which Chinese words on the panel are translated in English. The three off-ramps in the urban freeway section from downstream to upstream are ‘KaiXuanLu Ramp’, ‘JiangSuLu Ramp’ and ‘HuaShanLu Ramp’, which are denoted by Ramp 0, Ramp 1 and Ramp 2, respectively. The GRIP is installed immediately upstream of ‘Ramp 2’. Respondents were asked to assume that they were travelling on YanAnLu Elevated Road in the off-peak period in a weekday, and their destination was right on the arterial road under the freeway immediately downstream of Ramp 0. In real life, Ramp 0 is naturally the respondent’s intended off-ramp. When the respondent approaches Ramp 2, he or she sees the GRIP displaying information about traffic conditions ahead. Respondents were required to make a diversion decision, i.e., make a choice among Ramp 0, Ramp 1 and Ramp 2.

Figure 2 Travel scenario of the survey (see online version for colours)



GRIP messages in the SP experiment were designed based on GRIP message records in TMC and discussions with TMC operators, so that respondents could understand GRIP message contents easily and had a more realistic feeling of the journey. Following the principle of factorial design, six GRIP messages were designed (Figure 3). There are two attributes controlling the design: problem type and problem severity. Problem type has two levels: ‘no incident’ and ‘incident’. It is reflected by the text message part of the GRIP. Problem severity has three levels in the increasing order of degree of severity: ‘S1’, ‘S2’ and ‘S3’. It is reflected by the graphical part of the GRIP. As shown in Figure 3, Messages 1, 3 and 5 belong to ‘no incident’, whereas Messages 2, 4 and 6 belong to ‘incident’. Messages 2 and 3 belong to ‘S1’, Messages 1 and 4 belong to ‘S2’, and Messages 5 and 6 belong to ‘S3’. In the survey, the messages were specified in random order to avoid potential directional biases for messages. These six messages accord to six choice questions (travel scenarios) in the questionnaire. The text message part of GRIP information is translated from Chinese into English.

Figure 3 Pictorial presentation of GRIP messages (see online version for colours)



3.3 *Data collection and survey results*

An SP questionnaire survey was conducted to collect behavioural data with the consideration of budget. The questionnaire consists of two parts:

- information on driver characteristics such as gender, age, driver type, years of driving experience and frequency of using urban freeway
- drivers’ response to GRIP.

The survey was conducted in May 2008 in the parking lot at PuDong International Airport where both taxi drivers and other types of driver are relatively easy to access. 108 drivers were randomly interviewed and surveyed. As the result of a check for data completeness, 85 questionnaires are found valid and used for further analysis.

Table 1 provides a descriptive analysis of the sample. Since the survey mainly targets taxi drivers, about 75% of respondents are taxi drivers while about 14% and 11% of them are, respectively, employer-provided car drivers and private car drivers. Male drivers and drivers who frequently use freeway dominate the sample. ‘Age’ and ‘Yeas of driving experience’ are more evenly distributed among the sample.

Table 1 Driver characteristics of the sample

Attributes	*Statistical results*
Sex	'Male': 96.5%; 'Female': 3.5%
Age (in yrs)	'21–30': 23.5%; '31–40': 37.6%; '41–60': 38.8%
Yeas of driving experience(in yrs)	'Less than 2': 8.2%;'3–5': 30.6%; '6–10': 29.4%; 'over 10':31.8%
Driver Type1	'Taxi driver': 75.3%; 'Employer-owned car driver': 14.1%; 'private car drivers': 10.6%
Frequency of expressway use	'Almost every day': 92%; '2~3 days per week': 4%; 'Seldom use': 4%

[a]Years of driving experience indicate for how many years the driver has been driving.

[b]Employer-provided Car is not owned by a driver but assigned by his or her employer for business purpose.

[c]Private Car is owned by a driver himself or herself.

Table 2 summarises the GRIP information in each scenario and drivers' choices. In all the scenarios, the information includes yellow signs indicating congested freeway or ramp, red sign indicating jammed ramp, texts indicating occurrence of accident on ramp caused by one breaking-down vehicle, two sideswiping vehicles or three rear-end crashing vehicles, as listed in the upper left part of in Table 2. The upper right part of Table 2 uses either '1' or '0' code to indicate whether the relevant information is delivered. For example, in Scenario 6, there are yellow sign indicating congested mainstream, red sign indicating jammed ramp and texts indicating occurrence of accident caused by three rear-end crashing vehicles on the ramp.

Table 2 Analysis of GRIP information and drivers' choices

Travel scenarios / *GRIP information*	*1*	*2*	*3*	*4*	*5*	*6*
Delivered information						
Yellow sign indicating congested mainstream	1	0	0	1	1	1
Yellow sign indicating congested ramp	1	1	1	1	0	0
Red sign indicating jammed ramp	0	0	0	0	1	1
Texts indicating an accident caused by one breaking-down vehicle occurs on the ramp	0	1	0	0	0	0
Texts indicating an accident caused by two sideswiping vehicles occurs on the ramp	0	0	0	1	0	0
Texts indicating an accident caused by three rear-end crashing vehicles occurs on the ramp	0	0	0	0	0	1
Drivers' choices						
Exiting from the original ramp	15.3%	16.5%	69.4%	7.1%	12.9%	2.4%
Exiting one ramp upstream	80.0%	74.1%	29.4%	77.6%	72.9%	35.3%
Exiting two ramps upstream	4.7%	9.4%	1.2%	15.3%	14.1%	62.4%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*

The lower part of Table 2 gives distributions of drivers' choices among three alternatives. Among all the six scenarios, Scenario 6 has the greatest impact on drivers. Under that scenario, only 2.4% of drivers still choose the original ramp. On the contrary, Scenario 3 has the least impact on drivers since 69.4% of drivers still choose the original ramp. The statistics look intuitive because the situation in Scenario 6 is the most severe but that in Scenario 3 seems to be the least severe.

In Scenarios 1, 2, 4 and 5, about 70–80% of drivers choose to divert one ramp upstream. However, in Scenario 6, only 35.3% of drivers choose to divert one ramp upstream but 62.4% of them choose to divert two ramps upstream. We conjecture that this may be caused by drivers' anticipation based on their experience. In case of a serious accident as in Scenario 6, congestion will propagate backward, and when a driver approaches Ramp 1, the mainstream upstream of Ramp 1 may also be congested. Therefore, most drivers (62.4%) chose to divert two ramps upstream. To further investigate how different drivers respond to GRIP, econometric models will be developed in the next section.

3.4 Model development

Ordered choice models are developed to estimate a driver's diversion probability under GRIP using the SP data since the choices faced by drivers are ordered in nature. Considering that the SP data belongs to panel data (each individual responded to six different scenarios), both cross-sectional and panel models will be developed and compared with each other to show their similarities and differences.

3.4.1 The cross-sectional ordered probit model

The authors use the ordered probit modelling method to model drivers' choice behaviour. It starts from an assumption that driver '*i*' makes decision based on a random utility function U_i^*, which can be formulated as:

$$U_i^* = x_i \beta + \varepsilon_i. \tag{1}$$

In this equation, '*i*' is an index variable for each driver in the sample; x_i is a row vector of explanatory variables of interest (e.g., GRIP information and driver characteristics); β is a column vector of coefficients associated with the explanatory variables; ε_i is a random variable to take account of unspecified or unobserved explanatory variables in U_i^*, which is assumed to be I.I.D. standard normally distributed. Two threshold values μ_1 and μ_2 ($\mu_1 < \mu_2$) are specified. If U_i^* is less than μ_1, driver '*i*' will still choose Ramp 0; if U_i^* value falls between μ_1 and μ_2, driver '*i*' will choose Ramp 1; if U_i^* value is greater than μ_2, driver '*i*' will choose Ramp 2. The probabilistic function of each choice can be formulated as

$$P(y_{0i} = 1) = P(U_i^* < \mu_1), \tag{2}$$

$$P(y_{1i} = 1) = P(\mu_1 < U_i^* < \mu_2), \tag{3}$$

$$P(y_{2i} = 1) = P(U_i^* > \mu_2), \tag{4}$$

where y_{0i}, y_{1i} and y_{2i} are three dummy variables indicating whether driver 'i' chooses Ramp 0 ($y_{0i} = 1$), Ramp 1 ($y_{1i} = 1$) or Ramp 2 ($y_{2i} = 1$). Since ε_i is assumed to be standard normally distributed, one may obtain that

$$P(y_{0i} = 1) = 1 - \Phi(x_i\beta - \mu_1), \tag{5}$$

$$P(y_{1i} = 1) = \Phi(x_i\beta - \mu_1) - \Phi(x_i\beta - \mu_2), \tag{6}$$

$$P(y_{2i} = 1) = \Phi(x_i\beta - \mu_2), \tag{7}$$

where $\Phi(.)$ represents the cumulative distribution function of standard normal distribution. In summary, the probabilistic function for the choice of the driver 'i' can be formulated as

$$P_i = [1 - \Phi(x_i\beta - \mu_1)]^{y_{0i}} [\Phi(x_i\beta - \mu_1) - \Phi(x_i\beta - \mu_2)]^{y_{1i}} [\Phi(x_i\beta - \mu_2]^{y_{2i}}. \tag{8}$$

If the nature of panel data is ignored, the log-likelihood function for the entire observations can be formulated as:

$$LL = \sum_{i=1}^{N} \ln(P_i) \tag{9}$$

where N is the sample size. The log-likelihood function can be maximised for estimating all the model coefficients in vector β, μ_1 and μ_2.

3.4.2 The panel data ordered logit model

The data used for modelling analysis belongs to panel data since each individual in the survey responded to 6 different scenarios. Strictly, the econometric model can be formulated as:

$$U_{it}^* = x_{it}\beta + \rho v_i + \varepsilon_{it}. \tag{10}$$

In the utility function, 'i' is the driver index and 't' is the scenario index; x_{it} is a vector of explanatory variables including some variables changing across drivers but not changing across scenarios (e.g., age). We call those variables as '*individual variables*'. The vector x_{it} may also include some variables changing across scenarios but not changing across drivers (e.g., yellow sign, red sign or accident information). We call those variables as '*scenario variables*'. In addition, the vector x_{it} may include some interactive terms between individual variable and scenario variable to distinguish the degree of sensitivity of different drivers. 'v_i' is a random effect changing across drivers but not changing within the same driver. 'v_i' is specified to capture common unobserved random variables that affect choice behaviours of the same driver. 'β' is a vector of model coefficients and 'ρ' is a coefficient indicating the variance of the common unobserved random variable for drivers. 'ε_{it}' is a random variable changing across both individuals and scenarios.

To make cross-sectional and panel models comparable, we re-specify the ordered probit model for panel data to avoid scaling up model coefficients:

$$U_{it}^* = x_{it}\beta + \rho v_i + \sqrt{1-\rho^2}\,\varepsilon_{it}. \tag{11}$$

In the equation, both 'v_i' and 'ε_{it}' are assumed to be standard normally distributed. The variance of the random component in the utility function is exactly 1, which is equal to the variance in the ordered probit model for cross-sectional data. Then, model coefficients from panel and cross-sectional models can be easily compared with each other. The probabilistic functions conditional on the random variable 'v_i' can be formulated based on comparisons between U_i^* and μ_1 or μ_2:

$$P(y_{0it} = 1 \mid v_i) = P(U_{it}^* < \mu_1 \mid v_i), \tag{12}$$

$$P(y_{1it} = 1 \mid v_i) = P(\mu_1 < U_{it}^* < \mu_2 \mid v_i), \tag{13}$$

$$P(y_{2it} = 1 \mid v_i) = P(U_{it}^* > \mu_2 \mid v_i). \tag{14}$$

Then, based on the standard normal distribution of 'ε_{it}', one may obtain that

$$P(y_{0it} = 1 \mid v_i) = 1 - \Phi\left(\frac{x_i\beta - \mu_1 + \rho v_i}{\sqrt{1-\rho^2}}\right), \tag{15}$$

$$P(y_{1it} = 1 \mid v_i) = \Phi\left(\frac{x_i\beta - \mu_1 + \rho v_i}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{x_i\beta - \mu_2 + \rho v_i}{\sqrt{1-\rho^2}}\right), \tag{16}$$

$$P(y_{2it} = 1 \mid v_i) = \Phi\left(\frac{x_i\beta - \mu_2 + \rho v_i}{\sqrt{1-\rho^2}}\right). \tag{17}$$

Equations (15)–(17) can be summarised as:

$$\begin{aligned} P(y_{it} \mid v_i) = {} & \left[1 - \Phi\left(\frac{x_i\beta - \mu_1 + \rho v_i}{\sqrt{1-\rho^2}}\right)\right]^{y_{0it}} \left[\left(\frac{x_i\beta - \mu_1 + \rho v_i}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{x_i\beta - \mu_2 + \rho v_i}{\sqrt{1-\rho^2}}\right)\right]^{y_{1it}} \\ & \left[\Phi\left(\frac{x_i\beta - \mu_2 + \rho v_i}{\sqrt{1-\rho^2}}\right)\right]^{y_{2it}}. \end{aligned} \tag{18}$$

For an unconditional probabilistic function, the conditional probabilistic function needs to be integrated for all the scenarios over the probability density function of 'v_i', $\phi(v_i)$:

$$P_i = \int_{-\infty}^{+\infty} \phi(v_i) \prod_{t=1}^{T} P(y_{it} \mid v_i)\, \mathrm{d}v_i. \tag{19}$$

$T = 6$ in this study, representing 6 different scenarios for each driver. Gaussian-Hermite integral method is employed to evaluate the integral in equation (19) as:

$$P_i \approx \sum_{k=1}^{K} \left[w_k \phi(z_k) \prod_{t=1}^{T} P(y_{it} \mid z_k) \right]. \tag{20}$$

In this study, 10 points are chosen to support the integral evaluation (i.e., $K = 10$). Values for w_k and z_k can be found in Appendix. Finally, the log-likelihood function for the entire sample can be formulated as:

$$LL = \sum_{i=1}^{N} \ln(P_i). \tag{21}$$

The log-likelihood function can be maximised for estimating all the model coefficients in vector β, μ_1, μ_2 and ρ.

4 Model estimation results and discussions

4.1 Comparisons between cross-sectional and panel models

Table 3 provides model estimation results of both panel and cross-sectional models. In Table 3, the panel model is listed in the left block. As seen in Table 3, the estimated coefficient ρ is 0.6153, which appears highly significant (t-value = 11.5). Meanwhile, the goodness-of-fit of the panel model is also substantially better than that of the cross-sectional model based on the improvement in likelihood ratio indices (e.g., 0.3971 vs. 0.3532). These statistical results show that the panel modelling method accommodating error correlation among the same individual is more appropriate than the cross-sectional modelling method.

However, it can be found that magnitudes of model coefficients are not obviously different between these two models. These results verify the econometric theory that both cross-sectional and panel models can obtain statistically consistent coefficient estimators; therefore, there is no great difference between those two sets of model coefficients. The advantage of a panel model is that it can provide more reliable statistical inferences for coefficient estimators than a cross-sectional model. Apparent differences can be found in t-tests and p-values between the estimation results of two types of model in Table 3.

It can be calculated that t-test values for individual variables' (e.g., age) coefficients are overestimated by 40~47% in the cross-sectional model relative to those in the panel model. On the contrary, the t-test value for the scenario variable 'red sign indicating jammed ramp' is underestimated by about 12% in the cross-sectional model relative to that in the panel model. These findings are similar to those in our earlier study (Gan and Ye, 2012).

In contrast to the work of Gan and Ye (2012), this study specifies interactive terms of scenario variable and individual variable to examine the differences in t-tests and p-values between cross-sectional and panel models. Without modelling practice, it is hard to tell whether t-test values will be under- or over-estimated in a cross-sectional model. Through the authors' modelling effort, it turns out that t-test values for all the interactive terms are actually underestimated by 6~18% in the cross-sectional model relative to those in the panel model.

These above-mentioned findings suggest that we should lower the standard of t-test values, to some extent, for scenario variables and interactive terms of scenario variable and individual variable when a cross-sectional model is applied to screen variables in an initial modelling effort. This is because their t-test values tend to be underestimated in a cross-sectional model and will be expanded and show significance in a panel model.

Table 3 Model estimation results

	Panel model			*Cross-sectional model*		
Variables	*Coefficient*	*t-test*	*p-value*	*Coefficient*	*t-test*	*p-value*
Age (Years)	0.2192	1.743	0.0813	0.2136	2.495	0.0126
Age Square (Years^2)	–0.0030	–1.713	0.0868	–0.0029	–2.394	0.0167
Taxi driver	0.3648	1.613	0.1067	0.3744	2.370	0.0178
Using freeway almost every day	–0.6004	–1.619	0.1055	–0.6025	–2.381	0.0173
Red sign indicating ramp jam	0.3055	1.852	0.0640	0.3104	1.630	0.1031
Sign indicating an accident on ramp caused by a breaking-down vehicle	1.6209	8.610	0.0000	1.6263	7.767	0.0000
Sign indicating an accident on ramp caused by two sideswiping vehicles	0.4805	2.861	0.0042	0.4908	2.547	0.0109
Sign indicating an accident on ramp caused by three rear-end crashing vehicles	1.4403	8.091	0.0000	1.4357	7.269	0.0000
Employer-provided car driver × Sign indicating an accident on ramp caused by a breaking-down vehicle	–0.8522	–2.427	0.0152	–0.7960	–1.984	0.0473
Age × Yellow sign indicating freeway congestion	0.0856	4.458	0.0000	0.0890	4.088	0.0000
Age Square × Yellow sign indicating freeway congestion	–0.0012	–2.785	0.0054	–0.0013	–2.614	0.0090
μ_1	4.0349	1.781	0.0748	3.9747	2.592	0.0095
μ_2	6.4283	2.818	0.0048	6.3861	4.109	0.0000
ρ	0.6153	11.512	0.0000	–	–	–
LL(β)	–323.7852			–349.3780		
Adj. $\rho^2(0)$	0.3971			0.3532		
Adj. $\rho^2(c)$	0.2932			0.2414		

4.2 Discussions of model coefficients

On the basis of the estimation results of the panel model, implications of model coefficients are as follows:

Age: ‘Age’ and ‘Age square’ are specified into the model to quantify the non-linear effect of age on the utility value for the route choice decision. The Age term takes a positive coefficient while the Age Square term takes a negative coefficient, indicating that a parabola opening down can be used to express the relationship between age and the utility value. The peak point occurs at 36.5 years old (=0.2192/0.0030/2), indicating the highest probability to divert from freeway earlier at that age. Drivers younger or elder than that age are less likely to divert under GRIP. Plausible interpretation is that middle-aged drivers take on more social roles and their schedules tend to be heavier, and therefore are more sensitive to congestion or accident information from GRIP than young and old drivers. Interestingly, this finding confirms to a recent study, which found that middle-aged drivers were more likely to divert from a freeway to a local street when they receive travel time information displayed by VMSs, and found the peak point occurs at 37 years (Gan and Ye, 2012).

Taxi drivers: 'Taxi driver' takes a positive coefficient, which indicates that taxi drivers are more likely to leave the freeway than private car drivers and employer-provided car drivers under the influence of GRIPs. This is presumably because leaving the freeway to avoid delays will both satisfy their 'time-saving route' pursuing customers and benefit their business. It is noted that in Shanghai most of the people who take taxi will let the taxi driver choose a route with short time. Statistically, the significance level of variable 'Taxi driver' is relatively high (10.67%) in the panel data model. But in the cross-sectional model, 'Taxi driver' takes a statistically significant coefficient (p-value is 0.0178). In this study, considering that the dominance of taxi drivers (more than 75%) in the sample tends to lower the significance level, the authors retained 'Taxi driver' in the final model specification.

Frequent freeway users: The dummy variable indicates that the driver using freeway almost every day takes a negative coefficient in the model. Although it does not appear quite significant (p-value is about 0.11), the variable is retained considering that 93% of drivers are frequent freeway users in the sample. The negative coefficient indicates that drivers using freeway almost every day are less willing to leave from freeway earlier. The plausible interpretation is that these drivers using freeway almost every day may be heavily dependent on freeway; therefore, they show less tendency to choose ramps upstream the original ramp. These findings confirm to Gan and Ye (2012).

The red sign indicating ramp jam: This variable takes a positive coefficient, indicating that drivers are more likely to choose to leave freeway early upon seeing the red sign indicating ramp jam. This result is intuitively reasonable. In real life, if the original ramp is jammed, drivers will usually leave from freeway earlier to avoid delays.

Text messages indicating accident occurrence on the ramp: All the three variables indicating accident occurrences take significantly positive coefficients, showing that accident information will greatly increase the probability of early leaves. Among all these three coefficients, the coefficients for accidents caused by one breaking-down car and three rear-end crashing cars are close whereas the coefficient for an accident caused by two sideswiping cars is relatively small. It is probably that drivers may consider that it takes less time to deal with two-car-sideswiping accidents than the other two types of accidents and are, therefore, less sensitive to that information.

Interactive terms between age and freeway congestion information: The significance of those coefficients reflects that drivers at different ages are not sensitive to freeway congestion information in the same way. The coefficient of the term interactive with 'Age' is positive and that with 'Age Square' is negative, which indicates that middle-aged drivers are the most sensitive to congestion/accident information, when compared with young and old drivers. The plausible explanation for these findings is that middle-aged drivers are more sensitive to delays than young and old drivers given their multiple social roles and heavy time schedules.

Interactive term between employer-provided car driver and accident information: This interactive term takes a negative coefficient, indicating that employer-provided car drivers are less sensitive to a GRIP message that indicates accident caused by a breaking-down vehicle. It is presumably because employer-provided car drivers are less sensitive to delays caused by accidents than other drivers. This finding confirms to a recent study in Shanghai, which found employer-provided car drivers are less sensitive to delays indicated by VMSs (Gan and Ye, 2012).

5 Concluding remarks

Internationally wireless communication and ITS technologies are facilitating the improvement of traffic information services via GRIPs. However, previous GRIP studies rarely developed econometric models describing drivers' responses to GRIPs. This paper investigated the impact of GRIPs on drivers' en-trip decisions about diverting from the freeway to the local street. The current study developed both the cross-sectional ordered logit model and the panel data ordered logit model for predicting diversion probabilities, using the behavioural data collected from the SP survey of Shanghai taxi drivers.

Main findings regarding GRIP impacts are:

- Taxi drivers are more likely to divert than private car and employer-provided car drivers
- mid-age drivers are more likely to divert
- drivers using urban freeway frequently are more likely to divert
- a jammed original ramp increases diverting probabilities
- drivers are more likely to divert if congestion is caused by accident
- employer-provided car drivers are less sensitive to accident-induced delay and less likely to divert.

This study has practical implications for transportation management. The estimated diversion probability models may be incorporated within a dynamic traffic assignment and simulation framework to assess network-level impacts of GRIPs, based on which GRIP benefits can be estimated. The results from the current research may help the government make better decisions on GRIP investment, design and operations, e.g., determination of the optimal number or locations of GRIP in a road network.

On the modelling aspect, it was shown that

- the panel data model does not provide substantially different model coefficients but more robust statistical inferences when compared with the cross-sectional model
- the cross-sectional model tends to seriously overestimate *t*-test values for explanatory variables changing across drivers (i.e., individual variables)
- the cross-sectional model tends to slightly underestimate *t*-test values for explanatory variables changing across trip scenarios (i.e., scenario variables) and interaction terms of individual variable and scenario variable.

These findings have implications for future effort on driver response modelling.

One limitation of this research is that the number of employer-provided car drivers and private car drivers in the sample is not large. The future study will collect more behavioural data about employer-provided car drivers and private car drivers and estimate more robust econometric models describing driver responses to GRIPs.

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Appendix

The Gauss-Hermite integral method uses the Hermite polynomials to deal with the integration interval of (–∞, +∞). The Gauss-Hermite integral method is formulated as:

$$\int_{-\infty}^{+\infty} f(x)\,\mathrm{d}x \approx \sum_{k=1}^{K} w_k f(z_k).$$

In the formula, z_k and w_k are abscissae and weights. Table 4 provides 10-point abscissae and weights being used in this study.

Table 4 10-point abscissae and weights

k	z_k	w_k
1	–3.436159119	1.025451691
2	–2.532731674	0.820666126
3	–1.756683649	0.741441932
4	–1.036610830	0.703296323
5	–0.342901327	0.687081854
6	0.342901327	0.687081854
7	1.036610830	0.703296323
8	1.756683649	0.741441932
9	2.532731674	0.820666126
10	3.436159119	1.025451691