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Automobile drivers' willingness to pay for moving violation behaviour—Compared to motorcyclists

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ABSTRACT

A triple-bounded dichotomous choice (TBDC) structure and Spike models are applied to investigate the amount of money Taiwan automobile drivers are willing to pay for five types of moving violations, including local street speeding, expressway and freeway speeding, red light running, right turn on red, and drink-driving. Face-to-face survey was conducted at freeway rest areas by targeting passenger car drivers. The Spike model, superior to other tradition models by capturing excessive zero responses, is applied and the estimated results show that speeders would accept willingness to pay (WTP) of US$37 and US$48,[1] respectively, for local roads and expressways and highways, while red-light runners would accept a WTP of US$44, drivers who turn right on red would accept a lower WTP of US$9, and drunk drivers will accept a WTP as high as US$597. Interestingly, the difference in WTP for drunk driving between drivers and motorcyclists is significant, while others are not.

1. Introduction

By the end of 2009, the number of registered motor vehicles in Taiwan[2] totalled 21.37 million (an increase of 31% from a decade earlier), of which 6.67 million were passenger cars. Official statistics show that, in 2009, police issued 957,000 citations for moving violations, down from 1.337 million citations in 2003, but the accident rate for all motor vehicles increased from 31.67 accidents per 10,000 vehicles in 2000 to 81.39 accidents per 10,000 vehicles in 2008.

The rate of moving violations is related to the strength of the police enforcement of traffic regulations. Normally, there are two ways to deter violations[3]: by increasing the probability of getting caught or increasing the fine. Given police staffing constraints and manpower limitations, the former, however, is unfeasible and therefore not considered in this study.[4] The latter, while imposing a relatively modest social burden, has different deterrent effects on drivers of different levels of relative wealth, and may or may not deter violations.

Although a certain amount of research has been conducted on factors contributing to rule breaking by automobile drivers (Broughton et al., 2009; Scott-Parke et al., 2009; Fernandes et al., 2010), little research has focused on analysing automobile drivers' willingness to pay (WTP) for moving violations. Without objective criteria to set fines for moving violations, it is not clear whether current fines are too high or too low. Polinsky and Shavell (1991) and Chu and Jiang (1993) showed that, in societies with unequal wealth distribution, setting fines too high or too low will result in an ineffective social deterrent. Hence, finding an appropriate level of fines is important to setting a fine that will serve as a deterrent to the greatest number of people. Analysing the WTP for moving violations will result in more realistic fines, thus increasing the likelihood that the potential drivers will accept the corresponding fine.

The WTP is defined as the amount of money a driver is willing to pay each time he/she decides to freely engage in the violation. As such, the WTP can be compared to the current fine for a certain violation, as both are measured in the same unit (a one-time

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[1] 1 US$ = 30 NT$.

[2] The data presented in the first two paragraphs are quoted from International Road Federation (IRF) (2000–2010).

[3] Deterrence theory assumes drivers assess legal threats based on the perceived risk of punishment, including the perceived risk of being caught and the perceived certainty, severity, and swiftness of legal sanctions (Leal et al., 2009; Homel, 1988; Cameron et al., 1992; Watson, 2003; Vingilis, 1990).

[4] It should be noted that the impacts of the level of enforcement or probability of apprehension and fine is not necessarily the same at a given level of expected cost to the violator. Some studies show that the probability of apprehension has stronger deterrent effects.

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violation). That is, the former is the driver's willingness to pay when he/she decides to commit a traffic violation, while the latter is the actual amount of money the driver must pay whenever he/she is caught engaging in the given violation.

Because rule-breaking behaviour is not a market good, it cannot be traded through market mechanisms to establish its economic value. One widely used approach for assessing non-market goods is the contingent valuation method, which has an advantage in assessing the value of non-market goods in the conversion of the value of goods, primarily through surveys or similar interview methods. The contingent valuation method asks respondents to subjectively determine the dollar value of non-market goods and determines what maximum sum the respondents would be willing to pay for a given good.

Logit or probit models are most commonly used in prior research to establish (WTP) (see, for example, Hanemann, 1984; Salvador, 2001; Jou and Chen, 2011). However, because of the high likelihood that respondents will respond with "zero" (either not willing to pay or unlikely to commit the violation[5]) when asked what they would be willing to pay, numerous studies have adopted the Spike model as an alternative to avoid creating bias in the model (e.g., Kristroöm, 1997; Saz-Salazar and Garcia-Menendez, 2001; Yoo et al., 2006; Bengochea-Morancho et al., 2005; Hu, 2006; Jou et al., 2011, 2012, 2013). The results from these studies have shown that the Spike model is an appropriate approach to handling a large number of zero responses in the WTP survey data and can incorporate other WTP factors as well. Therefore, the Spike model provides a more realistic picture.

The aim of this study is to investigate the WTP of Taiwan automobile drivers for moving violations. In addition to providing a better understanding of the factors influencing the WTP for automobile drivers, the results of this study can also provide a reference for the setting of fines. In the survey conducted for this study, 31% of respondents answered that their WTP would be zero for local street speeding and expressway and freeway speeding, 43% for running red lights, 41% for making a right turn on red, and 53% for driving drunk. Regardless of the type of violation, zero WTP accounts for at least 30% of the responses, which justifies the use of the Spike model. In the end of this study, the WTP results of drivers are compared with the ones of motorcyclists[6] to gain possible similarities and differences among the two groups.

The remainder of this paper is as follows. The next section presents the data survey and analysis, followed by the model framework for the Spike model. Model estimation results are addressed in Section 4, with Section 5 discussing the difference between the WTP and the current fines. Conclusions are summarised at the end of the paper.

2. The Spike method

As the contingent valuation method applied in this study uses the TBDC structure, eight types of answers will be generated in the end (please see Fig. 1). However, if respondents consecutively answer "no" to all three questions, the respondents may actually have two possible WTP situations: the respondent may be unwilling to pay any price, in which case the response for the WTP price is US$0 (see the last line of Eq. (1)), or the respondent has a certain willingness to pay, but the WTP amount is lower than the amount indicated on the questionnaire (i.e., 0 < WTP < A). Thus, to avoid situations where the WTP is overestimated, that is, when respondents are unwilling to accept the final price situation, they are asked to specify the maximum they would be willing to pay (the resulting amount will be lower than the price in the final level) (see the second to last line of Eq. (1)). Therefore, when these two situations are included, the total number of possible cases is nine, as in Eq. (1).

$$
\begin{aligned}
I^{YYY} &= 1\{Yes - Yes - Yes\}\\
I^{YYN} &= 1\{Yes - Yes - No\}\\
I^{YNY} &= 1\{Yes - No - Yes\}\\
I^{YNN} &= 1\{Yes - No - No\}\\
I^{NYY} &= 1\{No - Yes - Yes\}\\
I^{NYN} &= 1\{No - Yes - No\}\\
I^{NNY} &= 1\{No - No - Yes\}\\
I^{NNNY} &= 1\{No - No - No - Yes\}\\
I^{NNNN} &= 1\{No - No - No - No\}
\end{aligned}
\tag{1}
$$

Among these, the indicator I^{ijk} shows the actual answer. i, j and k are, respectively, the first-, second- and third-level price responses. Suppose that the first level price is B_1^O. If the second-level recommended price is higher, it is $B_2^{U_1}$; otherwise, it is $B_2^{D_1}$. If the third-level recommended price is higher than the second-level price, it is $B_3^{U_2}$; otherwise, it is $B_3^{D_2}$. Therefore, the probability of YYY in Eq. (1) can be obtained by Eq. (2).

$$
\begin{aligned}
&\Pr(I^{YYY}(B_1^O, B_2^{U_1}, B_3^{U_2})) = \Pr(WTP \geq B_1^O, WTP \geq B_2^{U_1}, WTP \geq B_3^{U_2})\\
&= \Pr(WTP \geq B_1^O, WTP \geq B_2^{U_1} | WTP \geq B_3^{U_2}) Pr(WTP \geq B_3^{U_2})\\
&= Pr(WTP \geq B_3^{U_2}) = 1 - F_{WTP}(B_3^{U_2}; \theta)
\end{aligned}
\tag{2}
$$

where $F_{WTP}(B_3^{U_2}; \theta) = \Pr(WTP \leq B_3^{U_2}) = \Pr(\text{not willing to pay})$.

Derived from the same concept, for I^{NNNN} the probability value can be derived by Eq. (3):

$$
\begin{aligned}
&\Pr(I^{NNNN}(B_1^O, B_2^{D_1}, B_3^{D_2}, 0))\\
&= \Pr(WTP < B_1^O, WTP < B_2^{D_1}, WTP < B_3^{D_2}, WTP \leq 0)\\
&= \Pr(WTP < B_1^O, WTP < B_2^{D_1}, WTP < B_3^{D_2} | WTP \leq 0) \times \Pr(WTP \leq 0)\\
&= 1 \times \Pr\{WTP \leq 0) = F_{wtp}(0; \theta)
\end{aligned}
\tag{3}
$$

Similarly, the probability of I^{YYN} can be expressed by Eq. (4):

$$
\begin{aligned}
&\Pr(I^{YYN}(B_1^O, B_2^{U_1}, B_3^{U_2})) = \Pr(B_2^{U_1} \leq WTP < B_3^{U_2}) = \Pr(WTP < B_3^{U_2})\\
&- Pr(WTP < B_2^{U_1}) = F_{wtp}(B_3^{U_2}; \theta) - F_{wtp}(B_2^{U_1}; \theta)
\end{aligned}
\tag{4}
$$

Finally, the sequence of six answers develops as follows:

$$
\begin{aligned}
&\Pr(I^{YNY}(B_1^O, B_2^{U_1}, B_3^{D_2})) = \Pr(B_3^{D_2} \leq WTP < B_2^{U_1}) = F_{wtp}(B_2^{U_1}; \theta) - F_{wtp}(B_3^{D_2}; \theta)\\
&\Pr(I^{YNN}(B_1^O, B_2^{U_1}, B_3^{D_2})) = \Pr(B_1^O \leq WTP < B_3^{D_2}) = F_{wtp}(B_3^{D_2}; \theta) - F_{wtp}(B_1^O; \theta)\\
&\Pr(I^{NYY}(B_1^O, B_2^{D_1}, B_3^{U_2})) = \Pr(B_3^{U_2} \leq WTP < B_1^O) = F_{wtp}(B_1^O; \theta) - F_{wtp}(B_3^{U_2}; \theta)\\
&Pr(I^{NYN}(B_1^O, B_2^{D_1}, B_3^{U_2})) = Pr(B_2^{D_1} \leq WTP < B_3^{U_2}) = F_{wtp}(B_3^{U_2}; \theta) - F_{wtp}(B_2^{D_1}; \theta)\\
&\Pr(I^{NNY}(B_1^O, B_2^{D_1}, B_3^{D_2})) = \Pr(B_3^{D_2} \leq WTP < B_2^{D_1}) = F_{wtp}(B_2^{D_1}; \theta) - F_{wtp}(B_3^{D_2}; \theta)\\
&Pr(I^{NNNY}(B_1^O, B_2^{D_1}, B_3^{D_2}, 0)) = Pr(0 \leq WTP < B_3^{D_2}) = F_{wtp}(B_3^{D_2}; \theta) - F_{wtp}(0; \theta)
\end{aligned}
\tag{5}
$$

The Spike model uses the maximum likelihood estimation (MLE) method, and accordingly, the likelihood function of the nine cases can be expressed as in Eq. (6).

[5] The latter case is excluded in this study to avoid underestimating the WTP.

[6] The results were summarized from previous study by Jou and Wang (2012).