Hindawi
Journal of Advanced Transportation
Volume 2019, Article ID 7219047, 14 pages
https://doi.org/10.1155/2019/7219047

Research Article

Estimating Productivity Loss Cost according to Severity of Vehicle Crash Injury

Rong-Chang Jou and Tzu-Ying Chen

Department of Civil Engineering, National Chi Nan University, No. 1, University Rd, Puli, Nantou County 54561, Taiwan

Correspondence should be addressed to Tzu-Ying Chen; tychen.ncnu@gmail.com

Received 9 April 2019; Revised 28 August 2019; Accepted 20 September 2019; Published 12 December 2019

Academic Editor: Eneko Osaba

Copyright © 2019 Rong-Chang Joum and Tzu-Ying Chen. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This study estimates the productivity loss cost according to the severity of vehicle crash injury. A contingent valuation survey was conducted to estimate the willingness to pay (WTP) of vehicle crash offenders in Taiwan. In addition, a Double-Hurdle model was used to deal with the large number of zero WTP responses. The results show that the estimated productivity loss cost of vehicle crash ranges from 2,000 USD to 47,000 USD. In addition, as expected, the individuals' WTP is positively related with education, average monthly income, share of vehicle crash responsibility, experience of moderate or worse vehicle crash injury, work days lost after a vehicle crash, and experience of receiving compensation for productivity loss from a vehicle crash. This study also demonstrates that the Double-Hurdle model was statistically superior to the Tobit model.

1. Introduction

Injuries and deaths from vehicle crashes are a global problem, and current trends show that by 2030, vehicle crash injuries will become the fifth leading cause of death. Such injuries burden low- and middle-income countries with an estimated US$100 billion per year [1]. Owing to this significant economic burden, in addition to the increasing numbers of injuries and fatalities, methods to estimate vehicle crash costs have increasingly become important.

The economic costs of vehicle crashes have been extensively studied [2–6]. Although BRS and TRL [7] reports have indicated the crash costs of traffic road include property damage, medical costs, lost output, human costs, and administrative costs, most studies focus on the short-term medical costs of vehicle crash victims. Blincoe et al. [8] show that lost market and household productivity due to vehicle crashes in the U.S. accounted for $93 billion of the total $277 billion economic costs, but fewer studies discuss costs related to reduction in quality of life [9–12] and lost output, such as the temporary disability, long-term productivity loss, and productivity loss from death [13–16]. Our previous study show that productivity loss cost accounts for up to 50 per cent of vehicle crash costs in Taiwan [17]. In addition to injuries and deaths, vehicle crash victims can also incur a disability, which involves partial or total loss of an individual's value, or ability to function. These outcomes mean that victims who die can no longer work for or offer their services to their families or companies, and victims who become disabled incur increased long-term care expenses. Therefore, if we cannot estimate the productivity loss from disability and death, we will underestimate the total vehicle crash costs. Since productivity loss from vehicle crashes is substantial, it should be estimated from vehicle crash costs appropriately and separately to give decision makers (e.g. policymakers, courts, insurance companies, and individuals involved) sufficient and clear information about the impact of different injury levels.

Taiwanese courts have not yet clearly defined compensation for productivity loss, so the public is not familiar with this type of compensation and does not know whether it is possible to make a claim for this type of compensation. In order to monetise the productivity loss cost of vehicle crashes, this study estimates individuals' Willingness To Pay (WTP) for productivity loss cost according to the severity of vehicle crash injury. We distributed 100,000 questionnaires to offenders and victims who had been involved in a vehicle crash in 2010 to inquire about the compensation they paid and received, respectively, for productivity loss in order to understand their perceptions of reasonable compensation levels.

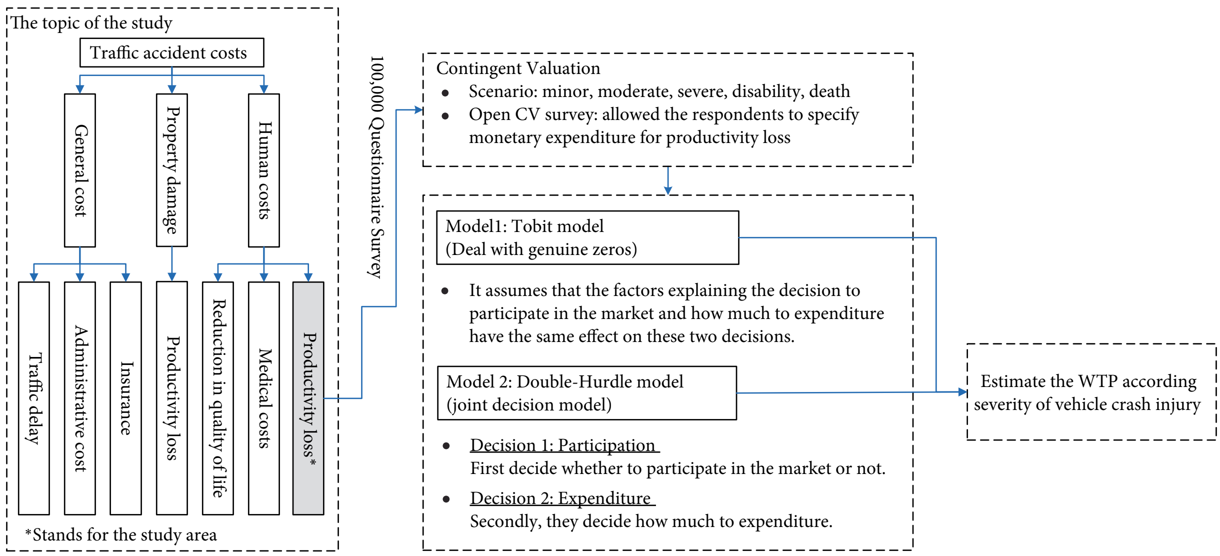


Figure 1: The comprehensive framework of the study.

On the other hand, Contingent Valuation (CV) is a stated preference method that has been widely used to reveal information about the values associated with public and nonmarket goods. As individual preferences for the provision of nonpriced goods and services are not readily determined from observable behaviour, CV is a useful tool that allows values to be associated with such goods and services [18]. It is an assessment method based on hypothetical questions aimed at allowing the calculation of the monetary value of public goods or policies [19]. CV can be implemented through four formats: open-ended, iterative bidding, multiple-bounded dichotomous choice, and payment card. It has been broadly applied in different areas, such as environment [20–22] and transportation, including for vehicle crash costs [14, 23], carbon offsets [24–26], and air pollution [27, 28]. In this study, because sanctions for productivity loss of different severity caused by traffic vehicle crash have not been implemented in Taiwan, the economic cost of such measures to the parties involved cannot be evaluated. Thus, this study utilised the CV method to obtain interviewees' subjective valuation of compensation for productivity loss caused by vehicle crashes; allows interviewees to express their WTP based on their experience or knowledge but determining the maximum amount of money that respondents are willing to pay as compensation for productivity loss caused by a vehicle crash as to obtain a more effective WTP.

In our surveys on WTP, we have identified a large number of respondents who are not willing to pay (zero WTP) for vehicle crash, generating a large proportion of observed values censored at zero and resulting in samples that apparently do not follow normal distributions. That is, in determining the compensation amount, responses with a zero WTP price are considered to address the complications from many zero WTP price responses. The classic ordinary least squares regression could not provide consistent and unbiased estimates of parameters [29]. To address this issue, some studies have used the Tobit model [30], which was developed to recognise that WTP values are censored at zero and to minimise the bias and inconsistency of parameter estimates.

Although the Tobit model is suitable for handling the problem of censored dependent variables, it has two limitations. First, it assumes that the zeros arise purely, that is, are a corner solution, since it also assumes that the zeros are the result of the respondent's economic circumstances [31]. Second, it assumes that the individual's zero response is generated from the same process by which the same variables affect the probability of a nonzero observation (the participation decision), as well as the level of a positive observation (the expenditure decision), and moreover, with the same sign. In order to address these shortcomings, this study uses the Double-Hurdle model developed by Cragg [32] and previously applied by Eakins [33]. The model postulates that two hurdles must be overcome before we can observe a positive expenditure amount. The first hurdle corresponds to factors affecting participation in the market for the good, and the second to the level of expenditure on the good. That is, the model may be more reasonable in allowing the factors of the two decisions to be different.

The application of the Double-Hurdle model in empirical research began with the works of Jones [34], Yen and Su [35, 45], Goodwin et al. [36], and can be seen in more recent studies [37]. Their studies indicate that with the Double-Hurdle model, an individual has to overcome two hurdles in order to have a positive expenditure. First, the individual decides whether or not to participate in the market, a stage known as the participation stage (of a potential consumer). Next, the individual decides the level of expenditure, a stage referred to as the expenditure stage.

This study aims to offer a comprehensive framework (Figure 1) for estimating productivity loss cost and to compare the costs for different injury levels using two estimation methods. In this study, we apply CV to estimate the productivity loss incurred by vehicle crash victims. Apart from estimating productivity loss cost, this study considers that the samples may include a high proportion of zero responses by offenders, that is, a high proportion of offenders who are not willing to pay for productivity loss compensation. Therefore, two econometric models are applied. First, we apply the Tobit model, which assumes that all the respondents are willing to pay for productivity loss from a vehicle crash. Second, for comparison, we apply the Double-Hurdle model to deal with the issue of zero responses and take into account the many individuals who are willing to participate in this market and willing to pay for productivity loss from a vehicle crash.

The rest of this paper is structured as follows. Section 2 describes the construction of the Double-Hurdle model. Section 3 describes the data and analysis. Section 4 shows the results of the model estimation and the analysis of elasticities. Finally, Section 5 presents the conclusions and recommendations.

2. Econometric Methodology

2.1. Tobit Model. This study aims to discuss the WTP of parties for productivity loss caused by traffic accidents. It is very common that many observations are with zero values because not every party has the same experience of compensation for these types of loss, nor is there a prescribed fine, especially for the death party of a vehicle crash. The standard Tobit model assumes that all respondents have the same needs for compensating the cost caused by traffic crashes, and in the mind of respondent i, he/she is willing to pay Y_i^* to compensate for the damage caused by an crash. The function is described in Equation (1). If there are n respondents in total, the mean of errors (ε_i) is zero, σ^2 is the variance, and the samples follow Independent and Identical Distributed (IID) normal distribution.

$$Y_i^* = \beta X_i + \varepsilon_i,\ \varepsilon_i \sim N\left(0, \sigma^2\right), \quad (1)$$

where Y_i^* is the dependent variable and also a random variable (WTP to compensate for the productivity loss caused by a crash); β is a vector of coefficients to be estimated; X_i is a vector of explanatory variables (socioeconomic and accident related characteristics). When Y_i^* is greater than zero, the WTP of respondent i, Y_i, will be equal to the WTP in his or her mind, and in that case, the actual WTP in his or her mind can be observed. If the WTP in the mind of respondent i is less than or equal to zero, then WTP is zero, which is the lower limit of WTP. That is, the value of zero may be either an actual WTP or the observed value of a WTP with a negative value, as shown in the following Equation (2) (Since the designed scenarios provided to respondents were assumed that they were all perpetrators, there has no possibility that Y^*<0. Nevertheless, the way equation (2) is formulated will not affect results since the cumulative probability of Y^*<0 is always zero.):

$$Y_i = \begin{cases} Y_i^*, & \text{if } Y_i^* > 0 \\ 0, & \text{if } Y_i^* \leq 0. \end{cases} \quad (2)$$

When the WTP of respondents is greater than zero, the probability density function of the sample can be expressed as follows:

$$\text{Prob}\left(Y_i > 0\right) f\left(Y_i Y_i \middle| > 0\right) = \frac{1}{\sigma}\phi_i\left(\frac{Y_i - \beta X_i}{\sigma}\right), \quad (3)$$

where ϕ_i is the standard normal probability density function. When observed values are censored at zero, the function of the continuous random variables is not a probability density function. Therefore, the probability distribution of observed values of zero WTP follows a cumulative distribution function. That is, when respondents' WTP (Y_i) is zero, the actual WTP in their minds may be either zero or less than zero, and thus, the probability function of the sample can be expressed as follows:

$$\text{Prob}\left(Y_i = 0\right) f\left(Y_i \leq 0\right) = 1 - \Phi_i\left(\frac{\beta X_i}{\sigma}\right). \quad (4)$$

In Equation (4), Φ_i is the standard normal cumulative distribution function. Next, the likelihood function of the standard Tobit model can be derived from Equations (3) and (4), as shown in Equation (5):

$$L = \prod_{Y_i=0}\left[1 - \Phi_i\left(\frac{\beta X_i}{\sigma}\right)\right] \times \prod_{Y_i>0}\left[\frac{1}{\sigma}\phi_i\left(\frac{Y_i - \beta X_i}{\sigma}\right)\right]. \quad (5)$$

2.2. Double-Hurdle Model. Jones [38] was the first to define the structure of the Double-Hurdle model, but we, nevertheless, describe the model in this subsection to help ensure clarity. For observation i, let D_t^* be defined as an unobserved variable representing the decision whether to participate or not (willingness or unwillingness to pay for productivity loss). Let Y_t^* be the latent variable representing the value of an individual's actual WTP. The two latent variables are described as follows:

$$D_i^* = x_{1i}\alpha_i + u_i,\quad u_i \sim N\left(0, \sigma^2\right) \quad \text{Participation decision}, \quad (6)$$

$$Y_i^* = x_{2i}\beta_i + v_i,\quad v_i \sim N\left(0, \sigma^2\right) \quad \text{Expenditure decision}, \quad (7)$$

where $\left(u_i, v_i\right) \sim BVN(0, \Sigma)$, $\quad \Sigma = \begin{bmatrix} 1 & \sigma\rho \\ \sigma\rho & \sigma^2 \end{bmatrix}$, and x_i is a vector of variables representing a set of individual characteristics explaining the participation and expenditure decisions, respectively. In this study, we assume that the participation and expenditure decisions have the same set of explanatory variables, that is, $x_{1i} = x_{2i} = x_i$. α and β are vectors of parameters that enter the first and second hurdles. The observed expenditure, Y_i, relates to the latent variables Y_i^* and D_i^*, which can be expressed as follows:

$$\begin{aligned} Y_i = Y_i^*, &\quad \text{if } Y_i^* > 0 \text{ and } D_i^* > 0 \\ = 0, &\quad \text{if } Y_i^* \leq 0 \text{ and } D_i^* > 0 \\ &\quad \text{or } Y_i^* > 0 \text{ and } D_i^* \leq 0 \\ &\quad \text{or } Y_i^* \leq 0 \text{ and } D_i^* \leq 0. \end{aligned} \quad (8)$$

Using 0 to denote zero observations and + to denote positive observations, this study writes the model's sample likelihood as

$$L = \prod_{0} \{1 - F(u_i < -x_{1i}\alpha, v_i < -x_{2i}\beta)\} \prod_{+} \{F(u_i < -x_{1i}\alpha, v_i < -x_{2i}\beta) f(v_i u_i| < -x_{1i}\alpha, v_i < -x_{2i}\beta)\}. \quad (9)$$

According to Gao et al. [39], Equation (9) can be simplified as

$$L = \prod_{0} \left\{1 - \Phi\left(-x_{1i}\alpha_i, -\frac{x_{2i}\beta_i}{\sigma}, \rho\right)\right\} \times \prod_{+} \left\{\Phi\left(x_{1i}\alpha_i + \frac{\rho}{\sigma_i} \frac{(Y_i^* - x_{2i}\beta_i)}{\sqrt{1-\rho^2}}\right) \frac{1}{\sigma}\phi\left(\frac{(Y_i^* - x_{2i}\beta_i)}{\sigma_i}\right)\right\}, \quad (10)$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the cumulative distribution function (cdf) and standard normal probability density functions (pdf), respectively, for a standard normal random variable.

2.3. Verification. Following Goodwin et al. [36], we compare the models by the values of the log-likelihood functions of the Tobit, Probit, and truncated models and determine whether the Double-Hurdle model outperforms the Tobit model (Equation (11)). Assuming the three equations have the same set of explanatory variables, λ will be viewed as a χ^2 distribution with degrees of freedom equal to the number of explanatory variables under the null hypothesis that the Tobit model is the correct specification:

$$\lambda = -2(L_{\mathrm{T}} - L_P - L_{\mathrm{TR}}), \quad (11)$$

where L_{T} is the likelihood value for the Tobit model, L_P is the likelihood value for the Probit model, and L_{TR} is the likelihood value for the truncated model.

2.4. Elasticities. Following Anastasopoulos et. al. [40], the expectation of the standard Tobit model can be expressed as:

$$E[Y] = \beta X F\left(\frac{\beta X_i}{\sigma}\right) + \sigma f\left(\frac{\beta X_i}{\sigma}\right), \quad (12)$$

where $\beta X_i/\sigma$ is z-score for an area under, which follows the normal distribution, $F(\beta X_i/\sigma)$ is the cumulative normal distribution function and is related to the proportion of events greater than zero, $f(\beta X_i/\sigma)$ is the probability density function, and σ is the standard deviation of the error term. If $E[Y']$ is the expectation of observed values that are greater than zero, then $E[Y]$ can be expressed as:

$$E[Y] = F\left(\frac{\beta X_i}{\sigma}\right) E[Y']. \quad (13)$$

Refer to the Amemiya [41, 42], the impact of explanatory variables on expectations can be calculated using the first derivative of Equation (12) and is shown as follows:

$$E[Y'] = E[Y | Y > 0] = E[Y \varepsilon > -\beta | X_i] = \beta X_i + \frac{\sigma f(\beta X_i/\sigma)}{F(\beta X_i/\sigma)}. \quad (14)$$

The first-order partial derivative of the specific explanatory variables (X_k) in Equation (13), derived by McDonald and Moffitt [43], is shown in Equation (15):

$$\frac{\partial E[Y]}{\partial X_k} = F\left(\frac{\beta X_i}{\sigma}\right)\left(\frac{\partial E[Y']}{\partial X_k}\right) + E[Y']\left(\frac{\partial F(\beta X_i/\sigma)}{\partial X_k}\right). \quad (15)$$

$\partial E[Y]/\partial X_k$ is the change in the overall expectation with respect to the explanatory variable; $\partial E[Y']/\partial X_k$ is the change in the expectation of observed values greater than zero with respect to the explanatory variable (by weighting the probability of observed values that are greater than zero); $\partial F(\beta X_i/\sigma)/\partial X_k$ is the change in the cumulative probability of observed values greater than zero with respect to the explanatory variables (by weighting the expectation of observed values that are greater than zero) [44]. Equation (15) can be derived by estimating $\partial E[Y']/\partial X_k$ and $\partial F(z)/\partial X_k$ using β_k and σ and then integrating with $F(\beta X_i/\sigma)$, $f(\beta X_i/\sigma)$ and $\beta_k X_k$ (X_k is the mean of the observed values). Equation (16) shows that changes in the expectation of observed values greater than zero with respect to the explanatory variable is:

$$\frac{\partial E[Y']}{\partial X_k} = \beta_k\left[1 - \frac{\beta X_i}{\sigma} \times \frac{f(\beta X_i/\sigma)}{F(\beta X_i/\sigma)} - \frac{f(\beta X_i/\sigma)^2}{F(\beta X_i/\sigma)^2}\right] \quad (16)$$

when $X = \infty$, $F(\beta X_i/\sigma) = 1$, and $F(\beta X_i/\sigma) = 0$ [43]. However, the range of WTP in our study is not infinite, and thus, Equation (16) should be used to calculate the marginal effect of observed values that are greater than zero.

Secondly, following Yen and Su [35, 45], we rewrite the probabilities of participation and expenditure of Double-Hurdle model as

$$P(D_i^* > 0) = \Phi(x_{1i}\alpha_i), \quad (17)$$

$$P(Y_i > 0) = \Pr(D_i^* > 0, Y_i^* > 0) = \Phi(x_{1i}\alpha_i)\Phi\left(\frac{x_{2i}\beta_i}{\sigma_i}\right). \quad (18)$$

The marginal effects represent the probability change when the explanatory variable is the dummy variable, which shifts from zero to one, holding all the other variables constant. Based on the maximum likelihood estimated (MLE) parameters, several types of elasticities can be calculated: the so-called elasticity of participation, elasticity of the probability of expenditure, and finally, elasticity of the unconditional level of expenditure or the total elasticity [46].

The derivative of the participation probability (17) with respect to x_{ij} is

$$\frac{\partial P(D_i^* > 0)}{\partial x_{ij}} = \frac{\partial \Phi(x_{1i}\alpha_i)}{\partial x_{ij}} = \phi(x_{1i}\alpha_i)\alpha_j. \quad (19)$$

The marginal effect of x_{ij} on the probability of expenditure is

$$\frac{\partial P(Y_i > 0)}{\partial x_{ij}} = \frac{\partial \Phi(x_{1i}\alpha_i)\Phi(x_{2i}\beta_i/\sigma_i)}{\partial x_{ij}} = \Phi\left(\frac{x_{2i}\beta_i}{\sigma_i}\right)\phi(x_{1i}\alpha_i)\alpha_j + \Phi(x_{1i}\alpha_i)\phi\left(\frac{x_{2i}\beta_i}{\sigma_i}\right)\sigma_i^{-1} \times \left[\beta_j - \left(\frac{x_{2i}\beta_i}{\sigma_i}\right) \times \frac{\partial \sigma_i}{\partial x_{ij}}\right]. \quad (20)$$

From Equations (18) and (20), it is obvious that the probability of expenditure depends on both the first-hurdle (α) and second-hurdle parameters (β). According to Amemiya [42], the conditional mean of Y_i is

$$E[Y_i|Y_i^* > 0] = x_{2i}\beta_i + \sigma_i\left(\frac{\phi(x_{2i}\beta_i/\sigma_i)}{\Phi(x_{2i}\beta_i/\sigma_i)}\right). \quad (21)$$

Another elasticity, the conditional mean of Y_i with respect to x_{ij}, can then be calculated as follows [35, 45]:

$$\begin{aligned}\frac{\partial E(Y_i|Y_i > 0)}{\partial x_{ij}} &= \beta_j + \left[\frac{\phi(x_{2i}\beta_i/\sigma_i)}{\Phi(x_{2i}\beta_i/\sigma_i)}\right]\frac{\partial\sigma_i}{\partial x_{ij}} \\ &- \left[\frac{\phi(x_{2i}\beta_i/\sigma_i)}{\Phi(x_{2i}\beta_i/\sigma_i)}\right] \times \left[\beta_j - (x_{2i}\beta_i/\sigma_i)\frac{\partial\sigma_i}{\partial x_{ij}}\right] \\ &\times \left[\left(\frac{x_{2i}\beta_i}{\sigma_i}\right) + \frac{\phi(x_{2i}\beta_i/\sigma_i)}{\Phi(x_{2i}\beta_i/\sigma_i)}\right]. \end{aligned} \quad (22)$$

3. Data Analysis

Generally speaking, the crash analyses in Taiwan usually use the crash database of the National Police Administration. The traffic accident records contain information regarding the crash, vehicle, and driver characteristics such as the crash times and locations, weather conditions, and road geometry features. Unfortunately, in the database, there is no driving behaviour and habit of perpetrators. In 2014, we had a special opportunity to sample and investigate the incident (including accident and the driving behaviour) of perpetrator in the crash event. It's a large-scale mailing questionnaire survey over the year of crashes for perpetrators in Taiwan. Of the 218,814 suitable samples, we mailed 100,000 questionnaires that asked offenders and victims about their accident history, along with the amount of compensation paid and received, respectively. From the responses, incomplete answers on driver behaviour and habit questions and erroneous records were discarded, resulting in a final sample of 4,089 valid questionnaires; the overall recovery rate of questionnaire was approximately 4%. Excluding the respondents whose questionnaires had incomplete responses to WTP questions (did not provide WTP data), the final effective questionnaires consisted of 2,122 respondents. The process of questionnaire survey is shown in Figure 2. The questionnaire was divided into three parts: the respondents' socioeconomic characteristics, traffic crash history, and WTP. In part 3, in those scenario questions, we assume that the respondent is the perpetrator, and the crash caused a certain level of bodily injury, we then query the respondent's WTP for productivity loss compensation. The respondents answered questions based on injury severity in hypothetical scenarios: minor injury, moderate injury, severe injury, disability, and death (Minor injury: includes general head, chest, abdominal, lumbar, upper limb, and lower limb injuries, as well as multiple traumas. Moderate injury: includes head fractures; thoracic, abdominal and lumbar fracture, and dislocation; upper limb fracture and dislocation; and lower limb fracture and dislocation. Serious injury: includes serious head injuries; major chest, abdominal and lumbar organ injuries; and injury to the central nervous system and spinal cord. Disability: includes serious injury but qualifies for disability certificate or disability. Death: loss of life). The open CV survey allowed the respondents to specify monetary expenditure for productivity loss. The respondents' WTP was elicited through the part 3 questionnaire framework. For example, the minor injury scenario is described as follows.

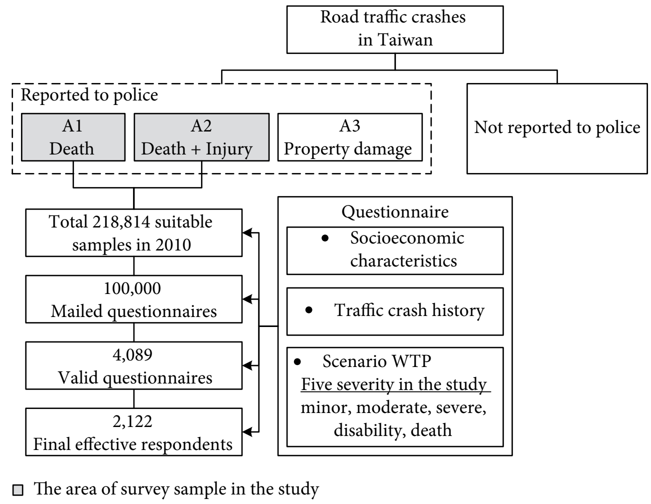
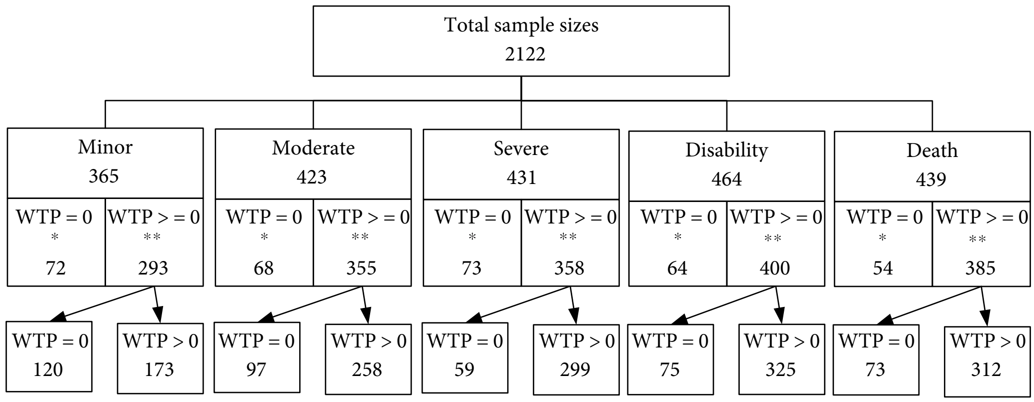


Figure 2: The process of a questionnaire survey.

> *Assume that you are responsible for a vehicle crash that caused a victim's minor injury. Tobit and Double-Hurdle modelsy for the victim's productivity loss (the reference values of court verdicts for minor injuries are US$2,305 for productivity loss).*
>
> (a) *Would you be willing to pay for the productivity loss?*
>
> ☐ *NO*
> ☐ *YES*
>
> (b) *If 'YES', how much would you be willing to pay?*
>
> ☐ *Willing to pay, but zero amount (cannot afford the expenditure).*
> ☐ *Willing to pay, and the highest amount is US$________.*

The questionnaire asked the respondents whether they were willing to pay for the productivity loss. Figure 3 presents the total sample size and subsample sizes according to the different scenarios. The respondents with a zero WTP fell into two categories: with and without protest. Figure 4 presents the sample distribution in the decision market according to existence of protest (with and without protest) and average WTP according to injury severity. Figure 4(a) shows the distribution for the entire sample, Figure 4(b) for the without protest sample within WTP ≥ 0, and Figure 4(c) for the without protest sample within WTP > 0 in the market. Figure 4(a) shows that the protest sample had a higher percentage of minor and moderate injuries (17.201% and 19.934%, respectively), but Figures 4(b) and 4(c) show that the without protest sample had a higher percentage of a severe or worse injury. We expect that respondents will be more willing to pay if they are aware of the injury severity that caused the significant productivity loss.



Note: *stands for nonparticipation, **stands for participation, and WTP stands for willingness to pay.

Figure 3: Sample sizes according to different scenarios (injury severity; with and without protest).

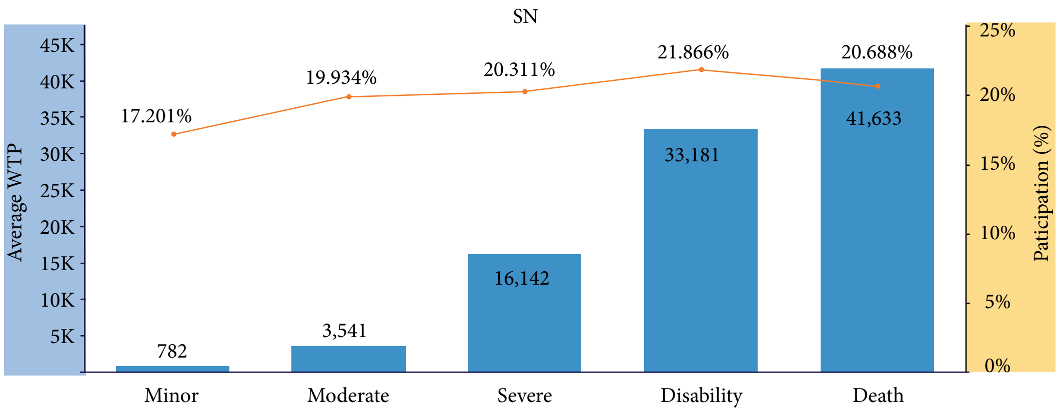
The average WTP increased with severer injury levels. The average positive WTP of the without protest sample is US$1,644, US$5,806, US$23,269, US$47,372, and US$58,579, respectively, for each. The average WTP of the without protest sample for severe injury, disability, and death increased significantly (by over 40%), from US$16,142, US$33,181, and US$41,633, respectively, in the full sample to US$23,269, US$47,372, and US$58,579, respectively, in the positive WTP sample. However, the average WTP was higher for the sample without protest. Even though there have not been actual cases of productivity loss compensation in Taiwanese courts, it is still necessary to discuss the monetary value that vehicle crash perpetrators place on their victims' injuries that result in productivity loss.

The analysis results for the respondents' WTP for productivity loss according to their socioeconomic characteristics are shown in Table 1. First, we verified the procedure of questionnaires to be effective and assumed to follow a population distribution. The homogeneity test according to the characteristics of age, gender, and injury experience were following the population distribution and did not reject the null hypothesis. That is, the distribution of received back of mailed questionnaires was consistent with the sample population. In order to distinguish between the results for with and without protest, the table divides the samples into two categories, one for the sample of respondents who did not want to participate in the market (with protest) and another for the sample of respondents who wanted to participate (without protest), including both respondents with a zero WTP and those with a positive WTP. From the table, it can be observed that the majority of the total sample was female (55.1%), of whom a relatively high proportion had a positive WTP for productivity loss. The 20 or younger age group had a high proportion of respondents who protested (28.7%), while the other age groups had high proportions of respondents with a zero WTP and a positive WTP. Respondents with a university degree or above had a higher proportion of those with a positive WTP (71.8%), compared to those without such a degree. Meanwhile, respondents with an average individual monthly income of US$1,460 or higher had a greater proportion of those with a positive WTP (22.2%), compared to those with a lower monthly income. Most of those who protested were concentrated in the under-US$1,460 individual monthly income bracket (85.8%). The proportions of those with a positive WTP for productivity loss increased with the level of household monthly income, with the highest proportion in the over-US$2,305 household monthly income bracket (37.0%). The proportions of those who protested decreased with the level of household monthly income.

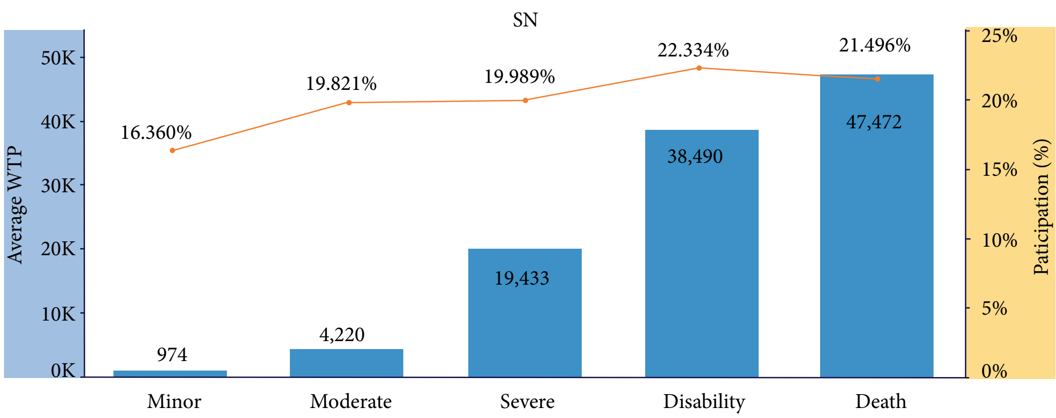
Table 2 presents the characteristics of vehicle crash injuries. Respondents who had third-party liability insurance for their car had the highest proportion of positive WTP (83.0%). In addition, among respondents who wanted to participate in the market, those who had a zero WTP and those who did not have third-party liability insurance had higher proportions of respondents with a positive WTP (59.8% and 63.2%, respectively). Respondents who took full responsibility for a vehicle crash had a higher proportion of positive WTP (36.5%) than zero WTP (17.2% and 10.4%), while respondents who took no responsibility for a vehicle crash had a large proportion of the protest sample (36.0%). The respondents were asked to state the severity of the injury they sustained in a previous vehicle crash, and the results show that most of the injuries were either minor or moderate (93.2%). However, respondents who indicated a severe or worse injury had the highest proportion of positive WTP (7.5%), and respondents who were unable to work for more than 30 days had higher proportions of participation in the market (16.8% and 16.2%) than non-participation in the market (6.3%). Although the percentage of respondents who received no compensation was still quite high (86.7%), the results show that respondents who received compensation in a previous vehicle crash had a higher proportion of positive WTP (16.5%). This finding suggests that these respondents were willing to pay for productivity loss because they experienced receiving compensation in a previous vehicle crash and therefore, had a better understanding of the importance of compensation.

4. Model Estimation Results and Discussion

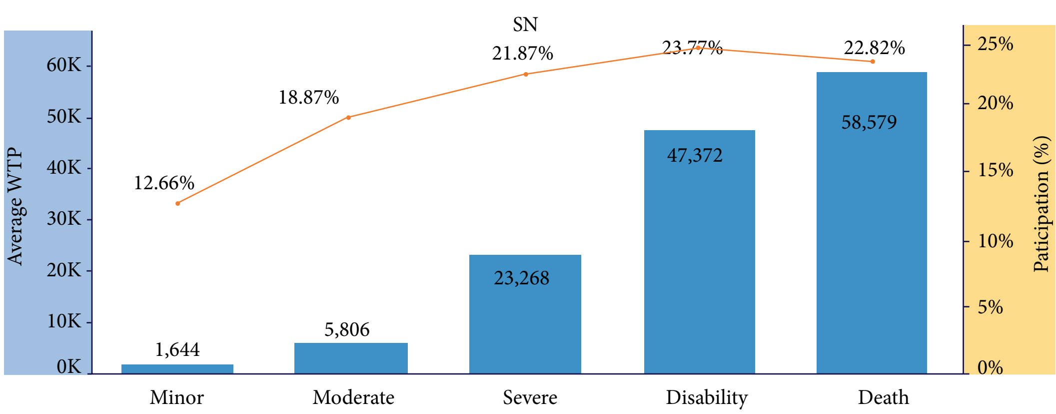
4.1. Variable Definition. The definitions of variables used, and the means for the entire sample, and the positive expenditure



(a) WTP ≥ 0, Average WTP, full sample, with protest



(b) WTP ≥0, Average WTP, without protest



(c) WTP > 0, Average positive WTP, without protest

Figure 4: Participation rates and average WTP by injury severity. Note: WTP stands for willingness to pay.

samples are presented in Table 3. The dependent variable is the WTP stated by the respondent in the open-ended question, while the independent variables include an educational level of university or above, an average individual monthly income of higher than US$1,460, an average household monthly income of higher than US$2,305, third-party liability insurance, experience of moderate or worse vehicle crash injury, over 50% share of vehicle crash responsibility, work days lost after a vehicle crash, experience of receiving compensation for productivity loss, and eight dummy variables that are equal to one if the interview was conducted in the sections called 'EDU', 'GIN', 'HIN', 'INST', 'EXP', 'RESP', 'DAY', and 'COMP' (please refer to Table 3 definition). The mean of the entire sample's WTP is US$782–US$41,633. However, the mean for the subsample that indicated a positive WTP for productivity loss according to injury level and fatality is US$1,644–US$58,579.

4.2. Model Estimation Results. We compare the performances of the Tobit and Double-Hurdle models, where the same set of explanatory variables was used. (The coefficients of the variables used in our previous study [12] were insignificant and

Table 1: WTP according to socioeconomic characteristics.

Item	Nonparticipation		Participation				Total sample	(%)
	Protest	(%)	Zero	(%)	Positive	(%)		
Gender *pearson chi-square test* = 2.85 < $\chi^2_{1, 0.05}$								
Female	183	(55.3)	229	(54.0)	768	(56.2)	1169	(55.1)
Male	148	(44.7)	195	(46.0)	599	(43.8)	953	(44.9)
Age *pearson chi-square test* = 8.73 < $\chi^2_{5, 0.05}$								
20 or younger	95	(28.7)	101	(23.7)	222	(16.2)	410	(19.3)
21–30	103	(31.1)	151	(35.6)	505	(36.9)	755	(35.6)
31–40	53	(16.0)	74	(17.5)	296	(21.7)	428	(20.2)
41–50	36	(10.9)	41	(9.7)	181	(13.2)	260	(12.3)
51–60	24	(7.3)	33	(7.8)	106	(7.8)	166	(7.8)
61 or older	20	(6.0)	24	(5.7)	57	(4.2)	103	(4.8)
Education								
Below university	155	(46.8)	282	(66.5)	385	(28.2)	719	(33.9)
University or above	176	(53.2)	142	(33.5)	982	(71.8)	1403	(66.1)
Individual monthly income								
1,459 or lower	284	(85.8)	400	(94.3)	1064	(77.8)	1748	(82.4)
1.460 or higher	47	(14.2)	24	(5.7)	303	(22.2)	374	(17.6)
Household monthly income								
1,317 or lower	114	(34.5)	169	(39.9)	367	(26.8)	645	(30.4)
1,318–2,305	111	(33.5)	153	(36.1)	495	(36.2)	755	(35.6)
2,306 or higher	106	(32.0)	102	(24.0)	505	(37.0)	722	(34.0)
Total sample	331		424		1367		2122	

Note: The percentage of respondents in each category is given in parentheses.

Table 2: Respondents' accident history.

Item	Nonparticipation		Participation				Total sample	(%)
	Protest	(%)	Zero	(%)	Positive	(%)		
Third-party liability insurance								
No	198	(59.8)	268	(63.2)	232	(17.0)	698	(32.9)
Yes	133	(40.2)	156	(36.8)	1135	(83.0)	1424	(67.1)
Vehicle crash responsibility								
0%	119	(36.0)	169	(39.8)	523	(38.3)	811	(38.2)
25%	58	(17.5)	85	(20.0)	184	(13.5)	327	(15.4)
50%	54	(16.3)	66	(15.6)	82	(6.0)	202	(9.5)
75%	43	(13.0)	60	(14.2)	78	(5.7)	181	(8.5)
100%	57	(17.2)	44	(10.4)	500	(36.5)	601	(28.4)
Injury experience *pearson chi-square test* = 2.86 < $\chi^2_{1, 0.05}$								
Minor or moderate	316	(95.5)	397	(93.6)	1265	(92.5)	1978	(93.2)
Severe or worse	15	(4.5)	27	(6.4)	102	(7.5)	144	(6.8)
Work days lost								
0	121	(36.6)	207	(48.8)	500	(36.6)	867	(38.0)
1–30	188	(56.8)	146	(34.4)	645	(47.2)	979	(46.1)
31 or more	22	(6.3)	58	(16.8)	222	(16.2)	315	(14.9)
Experience receiving compensation								
No	305	(92.1)	393	(92.7)	1142	(83.5)	1840	(86.7)
Yes	26	(7.9)	31	(7.3)	225	(16.5)	282	(13.3)
Total sample	331		424		1367		2122	

Note: The percentage of respondents in each category is given in parentheses.

Table 3: Summary statistics.

Variable	Description	Injury level	Entire sample Ave.	Entire sample Min.	Entire sample Max.	Participation sample Ave.
Expend	Individual's WTP for productivity loss (US$)	1	782	0	21,404	1,644
		2	3,541	0	46,101	5,806
		3	16,142	0	1,136,064	23,269
		4	33,181	0	987,882	47,372
		5	41,633	0	658,588	58,579
Dummy variables (yes = 1; 0 otherwise)						
EDU	1 If individual had university degree or above, 0 otherwise	1	0.59	0	1	0.85
		2	0.61	0	1	0.82
		3	0.65	0	1	0.71
		4	0.63	0	1	0.74
		5	0.80	0	1	0.88
GIN	1 If individual's average monthly income was higher than US$1,459, 0 otherwise	1	0.16	0	1	0.18
		2	0.15	0	1	0.24
		3	0.16	0	1	0.18
		4	0.14	0	1	0.15
		5	0.27	0	1	0.35
HIN	1 If household's average monthly income was higher than US$2,305, 0 otherwise	1	2.02	0	1	2.05
		2	2.13	0	1	2.24
		3	2.24	0	1	2.27
		4	2.25	0	1	2.36
		5	2.33	0	1	2.48
INST	1 If individual has third-party liability insurance, 0 otherwise	1	0.50	0	1	0.92
		2	0.58	0	1	0.83
		3	0.64	0	1	0.71
		4	0.77	0	1	0.90
		5	0.82	0	1	0.82
EXP	1 If individual had experience of moderate or worse vehicle crash injury, 0 otherwise	1	0.13	0	1	0.16
		2	0.06	0	1	0.07
		3	0.05	0	1	0.06
		4	0.05	0	1	0.06
		5	0.07	0	1	0.05
RESP	1 If individual's share of vehicle crash responsibility was higher than 50%, 0 otherwise	1	0.21	0	1	0.28
		2	0.17	0	1	0.21
		3	0.16	0	1	0.22
		4	0.14	0	1	0.15
		5	0.15	0	1	0.16
DAY	1 If individual's work days lost after a vehicle crash was higher than 30 days, 0 otherwise	1	0.39	0	1	0.39
		2	0.40	0	1	0.38
		3	0.63	0	1	0.69
		4	0.49	0	1	0.52
		5	0.40	0	1	0.38
COMP	1 If individual had experience of receiving compensation for productivity loss from a vehicle crash, 0 otherwise	1	0.12	0	1	0.18
		2	0.15	0	1	0.20
		3	0.13	0	1	0.14
		4	0.12	0	1	0.14
		5	0.15	0	1	0.17

Note: 1: Minor injury, 2: Moderate injury, 3: Severe injury, 4: Disability, 5: Death.

incorrectly signed in this study. In addition, the resulting WTP from our models is either overestimated or underestimate. For these reasons, the variables of the Double-Hurdle model were not used to develop the Tobit model in this study.)

Table 4 presents the estimation results from the Tobit model and Table 5 from the Probit and Truncated regressions of the Double-Hurdle model. As expected, the results for the Tobit and Double-Hurdle models indicate that the WTP was

Table 4: Estimation results for WTP for productivity loss (Tobit model).

Variable	Minor injury Coef. (t-value)	Moderate injury Coef. (t-value)	Severe injury Coef. (t-value)	Disability Coef. (t-value)	Death Coef. (t-value)
Constant	−1.33 (−8.52**)	−5.23 (−10.95**)	−1.70 (−6.88**)	−1.13 (−4.05**)	−0.15 (−4.59**)
EDU	1.19 (7.60**)	2.44 (4.49**)	0.33 (1.73*)	0.90 (2.92**)	0.15 (4.69**)
GIN	—	1.92 (5.01**)	0.56 (2.23**)	1.27 (3.07**)	0.12 (4.38**)
HIN	—	—	—	1.09 (2.85**)	0.07 (2.66**)
INST	—	2.73 (5.17**)	0.42 (2.06**)	—	—
EXP	0.57 (2.87**)	4.20 (6.59**)	0.80 (3.72**)	2.60 (3.94**)	0.08 (2.73**)
RESP	—	1.34 (3.99**)	0.83 (4.30**)	—	—
DAY	0.42 (2.56**)	1.29 (2.99**)	0.67 (2.50**)	1.33 (3.27**)	0.11 (2.86**)
COMP	0.59 (3.16**)	1.28 (3.23**)	0.89 (3.20**)	1.58 (3.83**)	0.09 (2.742**)
σ	1.05 (18.22**)	2.58 (21.08**)	1.76 (24.02**)	2.74 (25.17**)	0.24 (24.37**)
Log-likelihood function	−338.43	−580.53	−648.49	−896.69	−783.22
LM test [df] for Tobit	235.00 [5]	181.44 [8]	668.48 [8]	350.44 [7]	256.48 [7]
Observations	365	423	431	464	439

Note: **indicates a significance level of 0.05; *indicates a significance level of 0.1.

significant and positive and the magnitude of the regression coefficients was influenced by their respective variables. The results show that for an educational level of a university degree or higher, an average individual monthly income was higher than US$1,459, an average household monthly income was higher than US$2,305, third-party liability insurance, experience of moderate or worse injury in a vehicle crash, over 50% share of vehicle crash responsibility, work days lost after a vehicle crash was overhigher than 30 days, and experience of receiving compensation for productivity loss from a vehicle crash had a positive impact on WTP for productivity loss according to injury level.

The Double-Hurdle model can be divided into two parts. The first part, the Probit model, represents an individual's decision to participate (pay for the expenditure), and the second part, the truncated model, represented the individual's WTP. Table 5 shows that as expected, the minor injury scenario yielded the least number of significant variables, perhaps because a minor injury does not significantly affect an individual's income. In the minor and moderate injury scenarios, the coefficients of an educational level of a university degree or higher were 1.54 (t-value = 9.61) and 1.61 (t-value = 7.44), respectively, showing that the variable had the greatest impact on the decision to participate. Meanwhile, in the level of expenditure model, the coefficients of experience of moderate or worse vehicle crash injury were 2.72 (t-value = 2.51) and 10.35 (t-value = 5.30), respectively. In the severe injury and disability scenarios, the coefficients of experience of receiving compensation for productivity loss from a vehicle crash were 4.67 (t-value = 5.13) and 8.27 (t-value = 4.77), respectively, indicating that this variable had the greatest impact on the level of expenditure. In the fatality scenario, in both the participation and expenditure models, the coefficients of work days lost were 1.18 (t-value = 2.96) and 0.99 (t-value = 2.62), respectively, indicating that this variable had the greatest impact on the models for this scenario.

According to Goodwin [36], 'a comparison of the maximized log-likelihood function values allows formal statistical testing of the alternative estimators' (p. 8). For this reason, we found that the log-likelihood function value of the Tobit (−338.43, −580.53, −648.49, −896.67, and −783.22, respectively) estimates was much smaller than that of the Double-Hurdle (−55.3, −350.55, −138.09, −420.05, and −244.43, respectively) estimates, an outcome that overwhelmingly rejects the Tobit specification. Moreover, we can compare the specification testing results of the Tobit and Double-Hurdle models. Table 6 presents the estimated WTP for the two models according to injury level and shows that the specification testing of the Tobit model against the Double-Hurdle model can be accomplished using the statistic given by Equation (9). The table shows that the λ value for the minor injury, moderate injury, severe injury, disability, and fatality scenarios were 178.13, 219.86, 652.30, 454.35, and 240.40, respectively. The critical value of the chi-square for the different injury levels showed values between 18.48 and 20.09 at the α = 0.01 level of significance, which strongly rejected the Tobit specification in favour of the Double-Hurdle model. The results suggest that individuals' decisions to participate in the market and their WTP for productivity loss are generated by different processes. that is, Double-Hurdle models consider whether or not to participate; the willingness to pay for productivity loss is indeed superior to Tobit that only determines the positive WTP values as well as fits the sample data realistically.

Table 7 shows the marginal probability results for the Double-Hurdle model according to injury severity. The first column presents the marginal probability effects of participation and nonparticipation indicated by the changes in the explanatory variables, which are calculated from the means of the first-stage model's explanatory variables. The second column presents the marginal probability effects for the second-stage model's explanatory variables on the probability of the expenditure. Finally, the last column presents the marginal

Table 5: Estimation results for WTP (Double-Hurdle model).

Variable	Minor injury		Moderate injury		Severe injury		Disability		Death	
	Probit	Truncated	Probit	Truncated	Probit	Truncated	Probit	Truncated	Probit	Truncated
	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)	Coef. (t-value)
Constant	−1.27 (−8.80**)	−7.26 (−3.90**)	−2.04 (−10.67**)	−17.07 (−3.94**)	−0.85 (−5.10**)	−0.54 (−10.59**)	0.16 (1.33)	−22.0 (−6.22**)	−0.59 (−3.65**)	−3.67 (−7.88**)
EDU	1.54 (9.61**)	2.17 (1.55)	1.61 (7.44**)	3.14 (1.02)	0.37 (−5.10**)	4.06 (4.69**)	0.37 (2.68**)	7.49 (3.06**)	0.86 (5.13**)	0.72 (−7.88**)
GIN	—	—	1.59 (2.86**)	6.49 (4.38**)	1.14 (4.10**)	1.20 (1.28)	0.39 (1.79*)	6.76 (3.47**)	0.75 (3.79**)	0.88 (2.83**)
HIN	—	—	—	—	—	—	0.34 (1.67)	3.34 (1.78*)	0.87 (4.34**)	0.25 (1.13)
INST	—	—	1.18 (5.89**)	2.57 (0.63)	0.45 (2.88**)	2.00 (2.22**)	—	—	—	—
EXP	0.51 (2.00**)	2.72 (2.51**)	1.01 (2.04**)	10.35 (5.30**)	0.69 (3.77**)	3.29 (0.25)	1.00 (1.89*)	6.80 (3.19**)	0.57 (2.77**)	0.51 (1.66)
RESP	—	—	0.88 (3.52**)	2.74 (2.03**)	1.01 (6.71**)	0.20 (3.70**)	—	—	—	—
DAY	0.64 (3.11**)	0.86 (0.85)	0.72 (2.41**)	4.65 (2.78**)	1.27 (3.69**)	2.51 (2.43**)	0.45 (2.01**)	6.98 (3.86**)	1.18 (2.96**)	0.99 (2.62**)
COMP	0.84 (3.33**)	1.51 (1.48)	1.02 (3.52**)	2.52 (1.69)	0.22 (0.86)	4.67 (5.13**)	0.35 (1.61)	8.27 (4.77**)	0.39 (1.72)	0.71 (2.14**)
σ	—	1.81 (10.70**)	—	4.29 (11.31**)	—	2.30 (19.07**)	—	4.45 (14.65**)	—	0.66 (9.06**)
Log-likelihood function	−83.21	−55.31	−120.05	−350.55	−261.30	−138.09	−253.77	−420.05	−200.81	−244.43
Pseudo R^2	0.67	—	0.59	—	0.29	—	0.06	—	0.21	—
Expected WTP excluding 0 (US$)	—	1,940	—	4,781	—	19,985	—	45,513	—	47,129
Observations	365		423		431		464		439	

Note: **indicates a significance level of 0.05; *indicates a significance level of 0.1.

Table 6: Compare with Double-Hurdle versus Tobit models.

Scenario	χ^2 test result	Tobit model WTP	Double-Hurdle model WTP
Minor injury	$\lambda = 178.13 > \chi^2(7) = 18.48$	2,865	1,940
Moderate injury	$\lambda = 219.86 > \chi^2(8) = 20.09$	5,752	4,781
Severe injury	$\lambda = 652.30 > \chi^2(8) = 20.09$	22,591	19,985
Disability	$\lambda = 454.35 > \chi^2(7) = 18.48$	108,405	45,513
Death	$\lambda = 240.40 > \chi^2(7) = 18.48$	60,185	47,129

*Estimated WTP excluding 0 (US$).

probability effects indicated by the changes in the explanatory variables for each scenario (injury level), with the positive WTP as the means of the explanatory variables.

Table 7 also presents the effects of significant dummy variables. These effects suggest that in the minor injury scenario, an individual with a university degree or above are about 61.4% more likely to participate in the market, 1.6% more likely to pay for the productivity loss, and if the individual is indeed willing to pay, they spend about US$404 more than those without a university degree. The effects of other dummy variables can be interpreted in the same manner.

In the moderate injury scenario, an individual who has third-party liability insurance is 58.5% more likely to participate in the market and 71.5% more likely to be willing to pay for

Table 7: Marginal probability results from Double-Hurdle model.

Variable	Minor injury			Moderate injury			Severe injury			Disability			Death		
	MP1	MP2	MP3	MP1	MP2	MP3	MP1	MP2	MP3	MP1	MP2	MP3	MP1	MP2	MP3
EDU	0.614	0.016	404	0.595	0.518	4,003	0.105	0.123	12,916	0.118	0.0148	23,112	0.343	0.371	21,879
GIN	—	—	—	0.585	0.715	8,260	0.320	0.324	3,809	0.123	0.0135	20,883	0.298	0.334	26,680
INST	—	—	—	0.435	0.395	3,266	0.126	0.135	6,376	—	—	—	—	—	—
HIN										0.107	0.0068	10,304	0.345	0.352	7,545
EXP	0.201	0.016	505	0.372	0.831	13,169	0.193	0.207	10,478	0.318	0.0143	20,992	0.226	0.246	15,324
RESP	—	—	—	0.324	0.345	3,493	0.284	0.284	650	—	—	—	—	—	—
DAY	0.254	0.006	160	0.264	0.427	5,919	0.356	0.366	7,997	0.141	0.0140	21,545	0.468	0.507	29,926
COMP	0.334	0.010	281	0.375	0.359	3,208	0.062	0.082	14,840	0.112	0.0163	25,521	0.154	0.184	21,581

*MP1 : represent $\partial P(D_i^* > 0)/\partial x_{ij}$, MP2 : represent $\partial P(Y_i > 0)/\partial x_{ij}$, MP3 : represent $\partial E(Y_i|Y_i > 0)/\partial x_{ij}$.

productivity loss. The result is similar to that for the educational level variables. The results for this scenario also suggest that an individual with an average monthly income higher than US$1,416 pays more for productivity loss (by US$8,260). An individual who has experience of moderate vehicle crash injury is 83.1% more likely to be willing to pay for productivity loss and pays the most for productivity loss (US$13,169). In the severe injury scenario, an individual who has previously received compensation for productivity loss from a vehicle crash is willing to pay more (by US$14,840) for productivity loss.

In the disability and death scenarios, WTP is significantly influenced by the same explanatory variables. An individual's experience with moderate or worse vehicle crash injury has a significant impact on the marginal probability effects on the individual's decision to participate. An individual who has experience of receiving compensation for productivity loss is 1.63% more likely to be willing to pay for productivity loss and is willing to pay the highest amount (US$25,521). In the death scenario, an individual with an average household monthly income higher than US$2,305 is 34.5% more likely to participate in the market. Moreover, in both the severe injury and death scenarios, an individual who has lost over 30 work days after a vehicle crash is 35.6% and 46.8% more likely to participate in the market, and 36.6% and 50.7% more likely to be willing to pay for productivity loss. Likewise, an individual in either of these scenarios is willing to pay more (US$29,926).

5. Conclusions

In this study, several conclusions are obtained. First, the results provide important information regarding the calculation of productivity loss compensation for vehicle crash victims, especially in five injury levels were designed to analyse the compensations of productivity loss. As the results showed compensations were increased as injury severity increased. Secondly, the open-ended contingent valuation bids are employed to estimate parties' productivity loss expenditure in Taiwan; therefore, the results of the survey can well capture the nature zero bids.

Third, the compensation for productivity loss for different injury levels is estimated using Tobit and Double-Hurdle models, and the results showed compensations were increased as injury severity increased. We summarize the detail results of the Double-Hurdle model as follows: educational level, individual monthly income, household monthly income, third-party liability insurance, experience of severe or worse injury from a vehicle crash, individual's share of vehicle crash responsibility, work days lost from a vehicle crash, and experience of receiving compensation for productivity loss from a vehicle crash are all significant variables affecting the WTP for productivity loss. Of the 2,122 individuals in the sample, 331 (15.6%) reported that they were not willing to pay. Excluding these respondents with a zero WTP, the estimated amounts the individuals were willing to pay for productivity loss were US$1,940, US$4,781, US$19,985, US$45,513, and US$47,129, for minor injury, moderate injury, severe injury, disability, and death, respectively.

Fourth, a comparison of the results from the two models shows that the Double-Hurdle model was more flexible compared to the Tobit model in that it distinguishes between the process for discrete decision (determining whether individuals are willing to pay in the market) and how much they are willing to pay for productivity loss from a vehicle crash. Fifth, in addition to estimating the effects of participation and WTP, we calculated the significant elasticities of the variables. The overall elasticities show that the experience of severe injury had the highest positive WTP means of the explanatory variables in the minor and moderate injury scenarios. For the severe injury and death scenarios, a change in lost workdays of more than 30 days after a vehicle crash had a strong effect on the mean of a positive WTP. For the moderate or worse injury and fatality scenarios, a change in an individual's monthly income had a much larger effect on the probability of a positive WTP.

Finally, the study's methodology differs from that of civil court verdicts in Taiwan in that it estimates productivity loss compensation not only based on an individual's monthly income, but also on injury level (minor, moderate, and severe injuries), disability, and death; moreover, it identifies the significant factors affecting such compensation. The results highlight the importance of precise information in determining the individual's actual WTP and in turn, in capturing the individual's perceptions of reasonable compensation for productivity loss from vehicle crashes in Taiwan.

The study has two recommendations. First, Taiwanese courts do not have an actual framework for calculating compensation for vehicle crash death. In the study, we constructed the hypothesis scenario and estimated the productivity loss value of death. Moreover, the study captures the individuals' productivity loss value of vehicle crash victims' rights according to different type injury severity. That is, for the victim fairness and justice, not only the government of Taiwan, but international countries should better consider the productivity loss of different injury level in the future similar studies and related policies. Secondly, according to the methodology of the study, D-H model was provided for the representative references for accident compensation. We suggest that different countries could refer to the model and update the study's vehicle crash questionnaire to use it to estimate the overall economic losses caused by productivity loss according to injury severity.

Data Availability

The data that support the findings of this study are available from the Ministry of Transportation and Communications of Taiwan but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the Ministry of Transportation and Communications of Taiwan.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Funding

This study was sponsored by the Institute of Transportation, MOTC (contract number: 103-2221-E-260-015-MY3 and 105-2811-E-260-003).

References

[1] Centers for Disease Control and Prevention, CDC, "Centers for Disease Control and Prevention. Global Road Safety," 2016, http://www.cdc.gov/Features/GlobalRoadSafety/.

[2] W. Wijnen, W. Weijermars, A. van den Schoeters et al., "An analysis of official road crash cost estimates in European countries," *Safety Science*, vol. 113, pp. 318–327, 2019.

[3] A. M. Hezaveh, R. Arvin, and C. R. Cherry, "Geographically weighted regression to estimate the comprehensive cost of traffic crashes at a zonal level," *Accident Analysis and Prevention*, vol. 131, pp. 15–24, 2019.

[4] M. Ayuso, M. Guillén, and M. Alcañiz, "The impact of traffic violations on the estimated cost of traffic accidents with victims," *Accident Analysis & Prevention*, vol. 42, no. 2, pp. 709–717, 2010.

[5] L. B. Connelly and R. Supangan, "The economic costs of road crashes: Australia, states and territories," *Accident Analysis & Prevention*, vol. 38, no. 6, pp. 1087–1093, 2006.

[6] R. Elvik, "How much do road accidents cost the national economy?" *Accident Analysis & Prevention*, vol. 32, no. 6, pp. 849–851, 2000.

[7] BRS and TRL, "Guidelines for estimating the costs of road crashes in developing countries," Babtie Ross Silcock & Transport Research Laboratory, 2003.

[8] L. J. Blincoe, T. R. Miller, E. Zaloshnja, and B. A. Lawrence, "The economic and societal impact of motor vehicle crashes," National Highway Traffic Safety Administration, Washington, DC, 2010, (Report No. DOT HS 812 013).

[9] W. Suwanrada, "The cost of road accidents in Thailand- an analysis of the efficiency of road safety budget and risk behavior by road users," submitted to the Office of the Thai Health Promotion Foundation (in Thai), 2005.

[10] Bureau of Infrastructure, "Transport and Regional Economics," Cost of Road Crashes in Australia, 2006, Report 118.

[11] R. C. Jou, "The amount of consolation compensation in road traffic accidents," *Accident Analysis and Prevention*, vol. 67, pp. 21–29, 2014.

[12] R. C. Jou and T. Y. Chen, "The willingness to pay of parties to traffic accidents for loss of productivity and consolation compensation," *Accident Analysis & Prevention*, vol. 85, pp. 1–12, 2015.

[13] T. Harmon, G. Bahar, and F. Gross, "Crash costs for highway safety analysis," DCUSDOT FHWA Office, Washington, 2018.

[14] R. C. Jou and T. Y. Chen, "The willingness to pay of parties to traffic accidents for loss of productivity and consolation compensation," *Accident Analysis & Prevention*, vol. 85, pp. 1–12, 2015.

[15] H. Naci and T. D. Baker, "Productivity losses from road traffic deaths in Turkey," *International Journal of Injury Control and Safety Promotion*, vol. 15, no. 1, pp. 19–24, 2008.

[16] Department of Highways, "The study of traffic accident cost in Thailand Report," Bangkok, 2007.

[17] T. Y. Chen, R. C. Jou, Y. T. Lin, C. W. Kuo, and Y. C. Chiou, "A study on the compensation of road traffic accidents: An approach using civil court verdicts," in *Proceedings of the 12th Road Safety and Simulation International Conference*, Rome Italy, 2010.

[18] R. C. Ready, J. C. Buzby, and D. Hu, "Differences between continuous and discrete contingent value estimated," *Land Economics*, vol. 72, no. 3, pp. 397–411, 1996.

[19] S. Del Saz-Salazar and L. Garcia-Menendez, "Willingness to pay for environmental improvements in a large city: evidence from the spike model and from a nonparametric approach," *Environmental and Resource Economics*, vol. 20, no. 2, pp. 103–112, 2001.

[20] S. V. Ciriacy-Wantrup, "Capital returns from soil-conservation practices," *Journal of Farm Economics*, vol. 29, no. 4, pp. 1181–1196, 1947.

[21] S. Del Saz-Salazar and P. A. Rausell-Köster, "Double-Hurdle model of urban green areas valuation: dealing with zero responses," *Landscape and Urban Planning*, vol. 84, no. 3– 4, pp. 241–251, 2008.

[22] E. Thunberg and L. Shabman, "Determinants of landowners' willingness-to-pay for flood hazard reduction," *Journal of the American Water Resources Association*, vol. 27, no. 4, pp. 657–665, 1991.

[23] R. C. Jou and T. Y. Chen, "External costs to parties involved in highway traffic accidents: the perspective of highway users," *Sustainability*, vol. 7, no. 6, pp. 7310–7332, 2015.

[24] R. Brouwer, L. Brander, and P. Van Beukering, "A convenient truth': air travel passengers' willingness to pay to offset their

CO2 emissions," *Climatic Change*, vol. 90, no. 3, pp. 299–313, 2008.

[25] J. L. Lu and Z. Y. Shon, "Exploring airline passengers' willingness to pay for carbon offsets," *Transportation Research Part D: Transport and Environment*, vol. 17, no. 2, pp. 124–128, 2012.

[26] G. J. MacKerron, C. Egerton, C. Gaskell, A. Parpia, and S. Mourato, "Willingness to pay for carbon offset certification and co-benefits among (high-)flying young adults in the UK," *Energy Policy*, vol. 37, no. 4, pp. 1372–1381, 2009.

[27] F. Lera-López, J. Faulin, and M. Sánchez, "Determinants of the willingness-to-pay for reducing the environmental impacts of road transportation," *Transportation Research Part D: Transport and Environment*, vol. 17, no. 3, pp. 215–220, 2012.

[28] H. Wang and J. Mullahy, "Willingness to pay for reducing fatal risk by improving air quality: a contingent valuation study in Chongqing, China," *Science of The Total Environment*, vol. 367, no. 1, pp. 50–57, 2006.

[29] T. Amemiya, "Tobit models: a survey," *Journal of Econometrics*, vol. 24, no. 1–2, pp. 3–61, 1984.

[30] J. Tobin, "Estimation of relationships for limited dependent variables," *Econometrica*, vol. 26, no. 1, pp. 24–36, 1958.

[31] R. Martínez-Espiñeira, "A Box-Cox Double-Hurdle model of wildlife valuationThe citizen's perspective," *Ecological Economics*, vol. 58, no. 1, pp. 192–208, 2006.

[32] J. G. Cragg, "Some statistical models for limited dependent variables with application to the demand for durable goods," *Econometrica*, vol. 39, no. 5, pp. 829–844, 1971.

[33] J. Eakins, "An application of the double hurdle model to petrol and diesel household expenditures in Ireland," *Transport Policy*, vol. 47, pp. 84–93, 2014.

[34] A. M. Jones, "A Double-Hurdle model of cigarette consumption," *Journal of Applied Econometrics*, vol. 4, no. 1, pp. 23–39, 10.1002/jae.3950040103, 1989.

[35] S. T. Yen and S. J. Su, "Modeling U.S. butter consumption with zero observations," *Agricultural and Resource Economics Review*, vol. 24, no. 1, pp. 47–55, 1995.

[36] B. K. Goodwin, L. A. Offenbach, T. T. Cable, and P. S. Cook, "Discrete/continuous contingent valuation of private hunting access in Kansas," *Journal of Environmental Management*, vol. 39, no. 1, pp. 1–12, 1993.

[37] W. Wijnen and H. Stipdonk, "Social costs of road crashes: an international analysis," *Accident Analysis and Prevention*, vol. 94, pp. 97–106, 2016.

[38] A. M. Jones, "A note on computation of the Double-Hurdle model with dependence with an application to tobacco expenditure," *Bulletin of Economic Research*, vol. 44, no. 1, pp. 67–74, 1992.

[39] X. M. Gao, E. J. Wailes, and G. L. Cramer, "Double-Hurdle model with bivariate normal errors: an application to US rice demand," *Journal of Agricultural and Applied Economics*, vol. 27, no. 2, pp. 363–376, 1995.

[40] P. Ch Anastasopoulos, A. P. Tarko, and F. L. Mannering, "Tobit analysis of vehicle accident rates on interstate highways," *Accident Analysis and Prevention*, vol. 40, no. 2, pp. 768–775, 2008.

[41] T. Amemiya, "Regression-analysis when dependent variable is truncated normal," *Econometrica*, vol. 41, no. 6, pp. 997–1016, 1973.

[42] T. Amemiya, *Advanced Econometrics*, MAHarvard University Press, Cambridge, 1985.

[43] J. F. McDonald and R. A. Moffitt, "The uses of Tobit," *AnalysisThe Review of Economics and Statistics*, vol. 62, no. 2, p. 318, 1980.

[44] D. W. Roncek, "Learning more from Tobit coefficients: extending a comparative analysis of political protest," *American Sociological Review*, vol. 57, no. 4, p. 503, 1992.

[45] S. T. Yen and S. J. Su, "Modeling U.S. butter consumption with zero observations," *Agricultural and Resource Economics Review*, vol. 24, no. 1, pp. 47–55, 1995.

[46] A. M. Angulo, J. M. Gil, and A. Gracia, "The demand for alcoholic beverages in Spain," *Agricultural Economics*, vol. 26, no. 1, pp. 71–83, 2001.


Journal of Engineering
The Scientific World Journal
International Journal of Rotating Machinery
Journal of Sensors
Advances in Multimedia
Advances in Civil Engineering
Journal of Control Science and Engineering
Hindawi
Submit your manuscripts at
www.hindawi.com
Journal of Robotics
Journal of Electrical and Computer Engineering
Advances in OptoElectronics
VLSI Design
International Journal of Navigation and Observation
Modelling & Simulation in Engineering
International Journal of Aerospace Engineering
International Journal of Chemical Engineering
International Journal of Antennas and Propagation
Active and Passive Electronic Components
Shock and Vibration
Advances in Acoustics and Vibration