高速公路駕駛人交通資訊影響下路徑選擇行為之研究 -應用累計期望理論

Freeway drivers' route choice behavior under the influence of real-time traffic information – application of CPT mdoel

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1. Introduction

Route choice behavior has been extensively investigated in the past decades. Several main streams in the route choice models can be classified, which include random utility maximization models (Khattak et al., 1993; Abdel-Aty et al., 1997; Chen & Jovanis, 2003), bounded rationality models (Mahmassani & Chang, 1986; Mahmassani & Liu, 1999; Jou et al., 2005) and (cumulative) prospect theory (PT) models (Kahneman & Tversky, 1979; Kahneman, 2003; Tversky & Kahneman, 1981, 1986, 1992; Schwanen & Ettema, 2009).

Meanwhile, some economists and psychologists have verified that the expected utility theory (EUT) axiom is inapplicable to many empirically realistic decisions, and could even be violated in reality (Allais, 1953; Kahneman & Tversky, 1979). Models based on the bounded rationality principle and PT framework have been developed to avoid the shortcomings of the EUT axiom and shown their capability of captured realistically the driver’s decisions.

PT has been widely applied in various studies. For example, it has been used to test the suitability of EUT modeling for route choice behavior (Avineri, 2004; Avineri & Prashker, 2004, 2005；Viti et al., 2005). Some have focused on presenting risk route choice behavior by using a simple two-node route with known travel time of route (Katsilopoulos et al., 2000; Katsikopoulos et al., 2002; Avineri & Prashker, 2004; Avineri & Prashker, 2005). More recently, Ben-Elia and Shiftan (2010) applied the concept of PT with a logit model to demonstrate the combined effect of information provision and learning experiences on a driver’s route choice. Gao et al. (2010) demonstrated the flexibility of the cumulative prospect theory (CPT) model when presenting varying degrees of risk aversion and risk seeking dependent on the outcome probabilities.

Other studies also applied the concept of risk attitude in PT (or CPT) to capture drivers’ behaviors, such as the coefficients in the value and weighting functions are estimated to reflect drivers’ risk attitude on departure times (Fuji & Kitamura, 2004; Senbil & Kitamura, 2004; de Palma & Picard, 2005; Jou et al., 2008), bus line decisions (Avineri, 2004), marketing and competitiveness analyses of different brands of drink and chocolate (Klapper et al., 2005), and even parents’ behavior when chauffeuring their children (Schwanwn & Ettema, 2009).

This study aims to investigate the driver’s route choice behavior by applying CPT framework with provision of real time information (predicted travel time and its probability) on two alternative freeways. Surveys are conducted in the rest areas along freeways to gather the required data. Different markets are segmented in terms of section (location), trip purpose and traffic condition. Parameters of CPT models for different markets are estimated to investigate the risk attitude of Taiwanese freeway drivers.

This paper is organized as follows: Section 2 explains the model framework of cumulative prospect theory model. Section 3 describes the questionnaire design and presents data analysis results. Section 4 provides the estimation results of CPT. Conclusions are proposed in Section 5.

2. Model Framework

Two phases are used to evaluate lotteries in prospect theory. The first is editing phase, this step establishes the reference points for attributes and then maps the lotteries as gains or losses. Such a reference point may be the current asset position. The second phase is evaluation phase, it utilizes a value function $v(\cdot)$ and a probability weighting function $\pi(\cdot)$. A lottery includes three outcomes: (a) x with a probability p, (b) y with a probability q, (c) the status quo with a probability $1–p–q$. Then the prospect value of the lottery is given by:

$$\pi(p)v(x)+\pi(q)v(y) \tag{1}$$

Figure 1 presents the possible of value functions, where gains are assumed to be concave and losses are convex with a turning point at the reference point. A sharper slope ratio in losses than in gains is assumed to capture loss aversion, i.e., people tend to be more sensitive to decreases in their wealth than to increases. (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

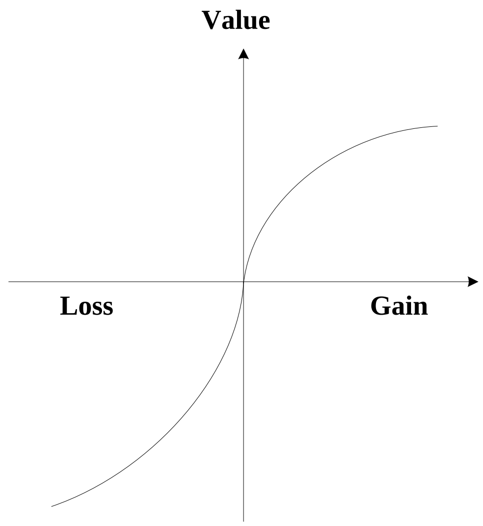

Figure 1 CPT value function

Figure 2 shows the weighting function, a reverse S-shaped curve instead of a 45-degree line. The overweighting of small probabilities implies that individuals are prone to risk seeking when offered low-probability with high-reward lotteries, whereas under a high-probability low-reward offering, decision makers will be prone to risk aversion (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

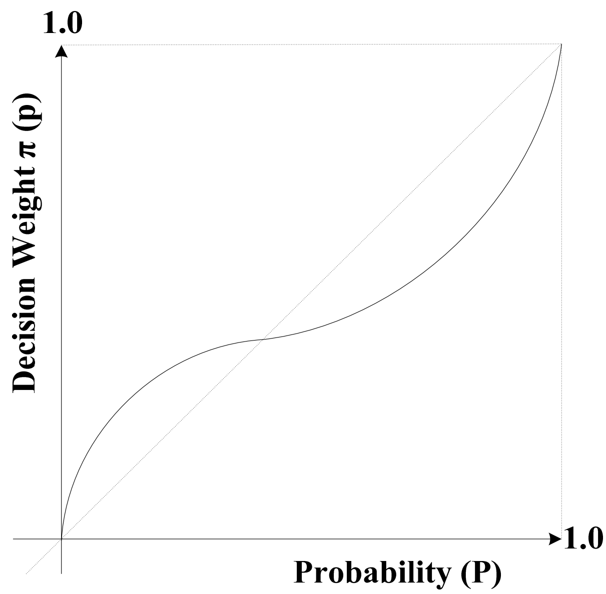

Figure 2. PT weighting function

To develop CPT, Kahneman and Tversky (1992) employed cumulative, instead of separable decision weights in the version of PT. It was intended to deal with any number of outcomes and separately applies the cumulative function to gains and losses. Suppose a prospect f is represented as follows:

$$
\begin{aligned}
&v(f) = v(f^{+}) + v(f^{-}) \\
&v(f^{+}) = \sum_{i=0}^{n} \pi_i^{+} v(x_i) \\
&v(f^{-}) = \sum_{i=-m}^{0} \pi_i^{-} v(x_i)
\end{aligned}
\tag{2}
$$

where $v(f^{+})$ is the prospect gains value, $v(f^{-})$ is the prospect losses value, $\pi^{+}(f^{+}) = (\pi_0^{+},\ldots,\pi_n^{+})$ are the decision weights of the gains, and $\pi^{-}(f^{-}) = (\pi_{-m}^{-},\ldots,\pi_0^{-})$ are the decision weights of the losses. Positive subscripts are used to denote positive outcomes, negative subscripts to denote negative outcomes, and zero subscript to indicate a neutral outcome.

Decision weights are further defined by

$$
\begin{aligned}
&\pi_n^{+} = w^{+}(p_n),\ \pi_{-m}^{-} = w^{-}(p_{-m}) \\
&\pi_i^{+} = w^{+}(p_i \cup \ldots \cup p_n) - w^{+}(p_{i+1} \cup \ldots \cup p_n),\ 0 \le i \le n-1 \\
&\pi_i^{-} = w^{-}(p_{-m} \cup \ldots \cup p_i) - w^{-}(p_{-m} \cup \ldots \cup p_{i-1}),\ \text{1-m} \le i \le 0
\end{aligned}
\tag{3}
$$

where w^{+} and w^{-} are strictly increasing functions from the unit interval into itself satisfying $w^{+}(0) = w^{-}(0) = 0$; $w^{+}(1) = w^{-}(1) = 1$.

Tversky and Kahneman (1992) proposed the following value function and weighting function which fit the CPT assumptions.

$$
v(x) = \begin{cases} x^{a} & ,\text{if } x \ge 0 \\ -\lambda(-x)^{\beta} & ,\text{if } x < 0 \end{cases}
\tag{4}
$$

In the value function, the parameter $\lambda \ge 1$ describes the degree of loss aversion and $\alpha = \beta = 1$ represents the case of pure loss aversion: Equation 5 represents the weighting function for gains and losses respectively:

$$
\begin{aligned}
w^{+}(p) &= \frac{p^{\gamma}}{[p^{\gamma} + (1-p^{\gamma})]^{1/\gamma}} \\
w^{-}(p) &= \frac{p^{\delta}}{[p^{\delta} + (1-p^{\delta})]^{1/\delta}}
\end{aligned}
\tag{5}
$$

The parametric values of γ and δ define the curvature of the weighting function, as well as the point where it crosses the 45 degree line. Decreasing γ and δ causes the weighting function to become more curved and to cross the 45 degree line farther to the right.

Tversky and Kahneman (1992) estimated those parameters and found that the best fits of model are $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$. The findings from other empirical studies are similar (Fennema & Van Assen, 1998; Abdellaoui, 2000). Wu and Gonzalez (1996), Camerer and Ho (1994) and Senbil and Kitamura (2004), also tested the fitness of these parameters and obtained values of α between 0.26 and 0.31.

An example will help to illustrate the CPT model used in this study. Assume that a driver needs to make a choice between routes 1 and 2 based on the reference point (for example, average travel time). Suppose that the prospect values on route 1 yields the payoffs (-15, -5, 5, 10, 13), with probabilities (0.05, 0.05, 0.05, 0.1, 0.75). Therefore, using Equations (1)–(5), we can obtain the prospect value of route 1:

$$
\begin{aligned}
v(f) &= v(f^{+}) + v(f^{-}) \\
&= v(5)[w^{+}(0.05+0.1+0.75) - w^{+}(0.1+0.75)] \\
&\quad + v(10)[w^{+}(0.1+0.75) - w^{+}(0.75)] \\
&\quad + v(13)[w^{+}(0.75) - w^{+}(0)] \\
&\quad + v(-15)[w^{-}(0.05) - w^{-}(0)] \\
&\quad + v(-5)[w^{-}(0.1) - w^{-}(0.05)]
\end{aligned}
\tag{6}
$$

The SP questionnaire was used to collect data and to estimate the coefficients of the CPT model. A logit formulation was employed for the parameter estimation. The probability of driver *i* choosing route 1 can be represented as:

$$
P_i\left(route\ 1\right) = \frac{e^{CWV_1}}{e^{CWV_1} + e^{CWV_2}} \tag{7}
$$

where $CWV_i = v(x)_{i1} \cdot w(p)_{i1} + v(x)_{i2} \cdot w(p)_{i2}$ represents the cumulative weighted value for route i (i=1.2) and subscripts $i1$ and $i2$ indicate two possible lotteries (travel times and their respective probabilities) on route i. Moreover, the log-likelihood function of a driver's route choice is shown as:

$$\log L(\alpha,\ \beta,\ \lambda,\ \gamma,\ \delta,\ \eta) = \sum_k \log P_k \tag{8}$$

in which, P_k denotes the choice probability of route being chosen by the kth driver, α and β are the parameters of gains and losses corresponding to the value function, λ is the loss aversion coefficient, γ and δ are the parameters of gains and losses corresponding to the weighting function, and parameter η represents the alternative-specific constant.

This study demonstrates that CPT not only captures the risk attitude of drivers, but also obtains the best-fit values of parameters related to Taiwanese freeway drivers.

3. Survey Design and Data Analysis

3.1 Survey Design

A computer-aided field survey was conducted on freeway rest areas (Taian service area and Chingshui service area) and freeway drivers were the main interviewees. The survey duration was from May 10 to 18, 2011, which covered weekdays and weekends. A total of 550 respondents were interviewed and 539 valid questionnaires were returned. The survey includes three parts.

1. Socioeconomic characteristics: this part includes gender, age, education, marital status, job position, working hours, and monthly personal income.
2. Driver's trip characteristic: this part includes the most frequent trip purpose of driving on the freeway, sections of driving and their corresponding reference points (average travel times), frequency of freeway usage monthly, the traffic condition most encountered on the freeway, on-board navigation device and its usage on the freeway, familiarity with other alternative local routes, and the error tolerance of travel time prediction.

3. Experimental scenarios: geographic areas of three sections are first identified by system interchanges (switching points) and they are north area (from Xizhi to Hsinchu), central area (from Hsinchu to Changhua), and south area (from Changhua to Dingjin) (as shown in Figure 3). Scenarios of travel time distributions, including travel times and their respective probabilities, for two freeways are provided to respondents.

Appendix A depicts the screen shot of one scenario of the computer-aided survey. With the predicted travel times and their corresponding probabilities provided, the respondent can make a choice between Freeway No. 1 and Freeway No.3. Note that the reference point is the value filled in by the respondent in part b of the survey. Each respondent has to answer nine scenarios resulting in 539x6=3234 samples. Travel times assumed in different levels of reference points in different sections are shown in

Table 1. These three levels of reference points are calculated from historical data (from Nov. 2009 to Nov. 2010) (High=free flow travel time; Medium=average travel time; Low=the slowest travel time).

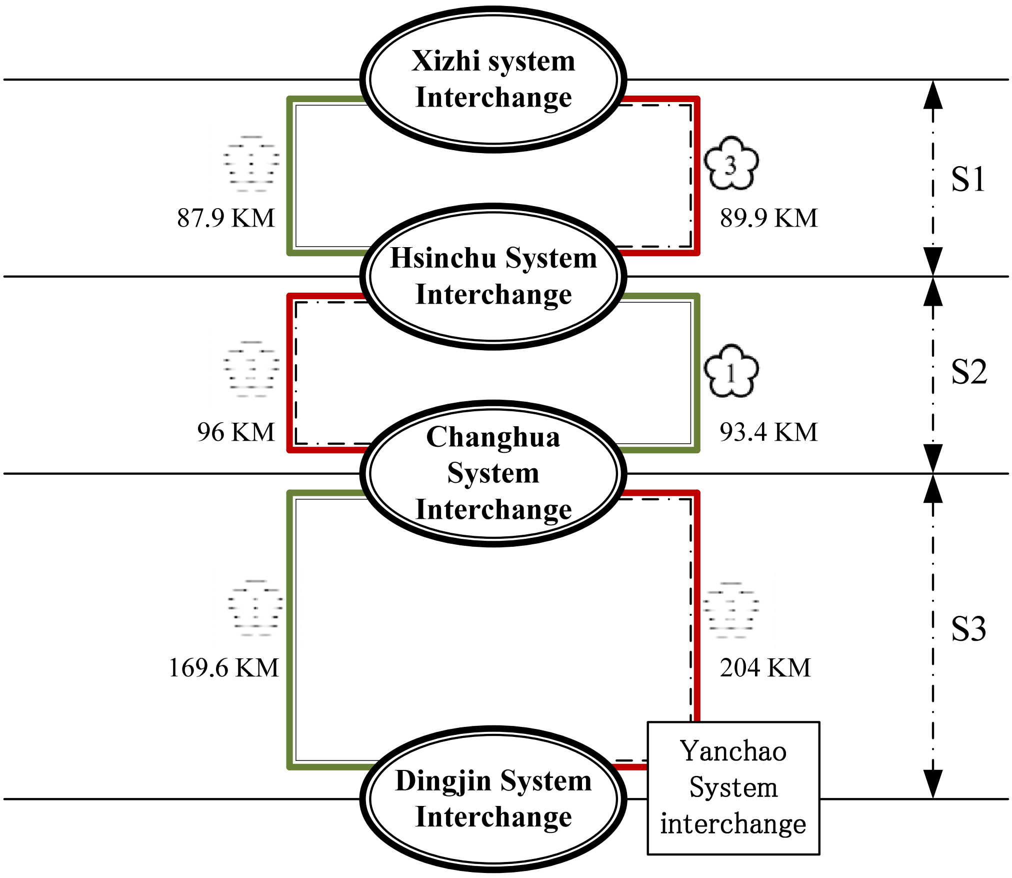

Figure 3. Study area of freeway systems in Taiwan

Table 1 Assumed travel times in different levels of reference points in different sections (unit: minutes)

Section	High	Medium	Low
North area (S1)	52	63	89
Central area (S2)	52	67	95
South area (S3)	102	132	187

It shall be noted that four levels are used as the first predicted travel times for both freeways. There are free flow travel time (fftt) of the freeway section, 1.25 fftt, 1.5fftt and 1.75fftt. The second predicted travel time can be randomly generated by certain percentages of the first one, and they are +30%、+15%、0%、-15%、-30%. The probabilities of these two predicted travel times are generated from 0, 0.1, 0.3, 0.5, 0.7, 0.9 and 1.0. All scenarios were obtained by full factorial orthogonal design, and the unreasonable scenario combinations, travel times less than free flow travel time and greater than historical longest travel time, were deleted based on the priori knowledge.

3.2 Data Analysis

Around 84% of the drivers were male and the majority were between 18 and 40 years old (65%). A large proportion of the drivers (58%) had a college education. In terms of marital status, 65% were married. Concerning working hours, the fixed type accounted for approximately 69%. Monthly personal incomes were mostly between 38,001 and 58,000 NT[1] dollars (33%), and the average monthly personal income was 48,293 NT dollars.

Trip characteristics of drivers are summarized in

Table 2. 46% of respondents their trip purpose was leisure, followed by visiting (22%), and business trips (19%). Most drivers travelled in the north area and the central area, accounting for 44% and 41%, respectively. In contrast, a less proportion drove through the south area (15%). This result may be explained by the fact that a trip through the south area is longer than the other two sections, meaning that fewer drivers traverse its full section, i.e., most of the drivers get on and off the freeway

[1] 1 US$=30NT$.

within this section. Fifty-seven percent of drivers travelled on the freeway during weekends; for the majority (70%), freeway usage is lower than four times per month. A total of 73% of drivers usually experienced smooth or very smooth traffic conditions on the freeway.

Furthermore, more percentages of drivers were familiar with alternative freeways than local route; this implies that more traffic information shall be offered to alter the driver to use alternative local routes. Otherwise, once a driver has driven on the freeway, they would generally not be inclined to choose a local route. Moreover, approximately 55% of drivers equipped their vehicle with a navigation device. Around 30% of these drivers also equipped a TMC (Traffic Message Channel) function. Almost half of those who had equipped navigation devices (49%) used them mostly or every time whenever they were driving on the freeway. In addition, the majority of drivers (65%) perceived the error tolerance of travel time prediction as between 3%–10%; whereas 9.3% perceived 0% error tolerance. This implies that most drivers may recognize the perfect travel time prediction cannot be possible.

Table 2 Trip characteristic analysis

Variable	Item	Sample (%)	Variable	Item	Sample (%)
Trip purpose	Leisure	247(45.8)	Familiarity with alternative local routes	Completely unfamiliar	16(3)
	Business	103(19.1)		Unfamiliar	226(41.9)
	Visiting	117(21.7)		Normal	172(31.9)
	Work	67(12.4)		Familiar	112(20.8)
	Others	5(0.9)		Completely familiar	13(2.4)
Sections of travel on freeways	North area(S1)	271(44.3)	Familiarity with alternative freeways	Completely unfamiliar	10(1.9)
	Central area(S2)	248(40.5)		Unfamiliar	166(30.8)
	South area(S3)	93(15.2)		Normal	174(32.3)
Days of travel on freeway	Monday to Friday	233(43.2)		Familiar	169(31.4)
	Weekend	306(56.8)		Completely familiar	20(3.7)
Frequency of monthly freeway usage	Less than 4	375(69.6)	Error tolerance of travel time prediction	0%	50(9.3)
	5-12	88(16.3)		3%	103(19.1)
	13-20	42(7.8)		5%	122(22.6)
	More than 21	33(6.1)		10%	123(22.8)

Traffic conditions encountered on freeway	Very crowded	13(2.4)		15%	48(8.9)
	Crowded	115(21.3)		20%	52(9.6)
	Normal	216(40.1)		Never mind	48(8.9)
	Smooth	175(32.5)	Frequency of Navigation device used on freeway	Never use (0/10)	22(7.4)
	Very smooth	20(3.7)		Seldom use (2/10)	80(26.8)
On-board navigation device	Equipped with TMC	88(16.3)		Normal (5/10)	48(16.1)
	Not equipped with TMC	210(39)		Mostly use (8/10)	56(18.8)
	None	241(44.7)		Every time	92(30.9)

Different reference points based on different market segmentations are presented in Table 3. The results indicate that most respondents in northern area (41%) choose free flow travel time (High) as their referent point, while average travel times are the preferred reference points in other two areas. As for trip purpose, the reference points of most respondents in business and work trips (43.3% and 56.8%, respectively) are free flow travel times. It could due to the need of punctuality in work and business trips. On the other hand, drivers without an on-time need are likely to use average travel times as their reference points, as shown by the trip purposes of leisure (46%) and visit (38%). Finally, drivers who usually experienced smooth traffic on freeways mostly use average travel time as their reference points (43%), while drivers who usually encountered congestion traffic tend to choose average or shortest travel times as their reference points (41%).

Table 3 Analysis of different reference points based on different segmentations (%)

Segmentation＼Reference point	High	Medium	Low	Total
Travel section				
North area (S1)	111(41.0)	101(37.2)	59(21.8)	271(100)
Central area (S2)	93(37.5)	108(43.5)	47(19.0)	248(100)
South area (S3)	35(37.6)	45(48.4)	13(14.0)	93(100)
Trip purpose				
Leisure	96(35.3)	126(46.3)	50(18.4)	272(100)
Business	58(43.3)	55(41.0)	21(15.7)	134(100)
Visit	44(32.4)	51(37.5)	41(30.1)	136(100)
Work	42(56.8)	24(32.4)	8(10.8)	74(100)
Most encountered traffic				
Smooth	49(32.0)	66(43.1)	38(24.8)	153(100)

Congestion	193(41.2)	190(40.6)	85(18.2)	468(100)

4. Estimation Results of CPT Model

Two kinds of CPT models are estimated in this study, including single-attribute and multi-attributes models. In the former one, different models (restricted CPT model and unrestricted CPT model) are estimated by three segmentations, section, trip purpose and traffic condition. The latter one estimates a full model with significant variables included.

4.1 Single-attribute model results

There are also two kinds of models estimated in the single-attribute CPT models. In the first kind of models, the parameters in value function and in weighting probability function are restricted to be the same (alpha= beta; delta=gamma) to investigate the risk aversion of drivers in different markets; no restrictions are forced in the second kind of models.

1. Restricted single-attribute model results

The detailed results of the restricted single-attribute CPT models are presented in the Appendix B and summarized in Table 4; the figures of value and weighting functions are presented in Figures 4-8. All parameters are significant and the signs of coefficients are correct. The estimated coefficients of value and weighting functions confirm that the EUT axioms are violated systematically in different segmentations. However, it shall be noted that risk-aversion behavior is not supported in southern area (S3). This may because the travel distance in S3 is the longest and drivers are likely to switch routes in that section. Moreover, drivers in business and work trips show no risk aversion behavior either. This could due to the reasons mentioned above (in Table 4). In addition, driver usually encountered congestion traffic on freeways are discovered with risk-aversion attitude on the route choice behavior.

Table 4 Estimation results of restricted single attribute models

	$\alpha = \beta$	λ	$\gamma = \delta$
Travel section			
ALL sample	0.982	1.142	0.580
S1	1.119	1.080	0.689

S2	0.971	1.199	0.520
S3	1.128	0.902	0.510
Trip purpose			
Business	0.940	0.646	0.662
Work	1.058	0.831	0.574
Visit	0.799	1.521	0.526
Leisure	1.017	1.332	0.662
Usually encountered traffic			
Smooth	0.971	0.976	0.635
Congestion	0.853	1.091	0.481

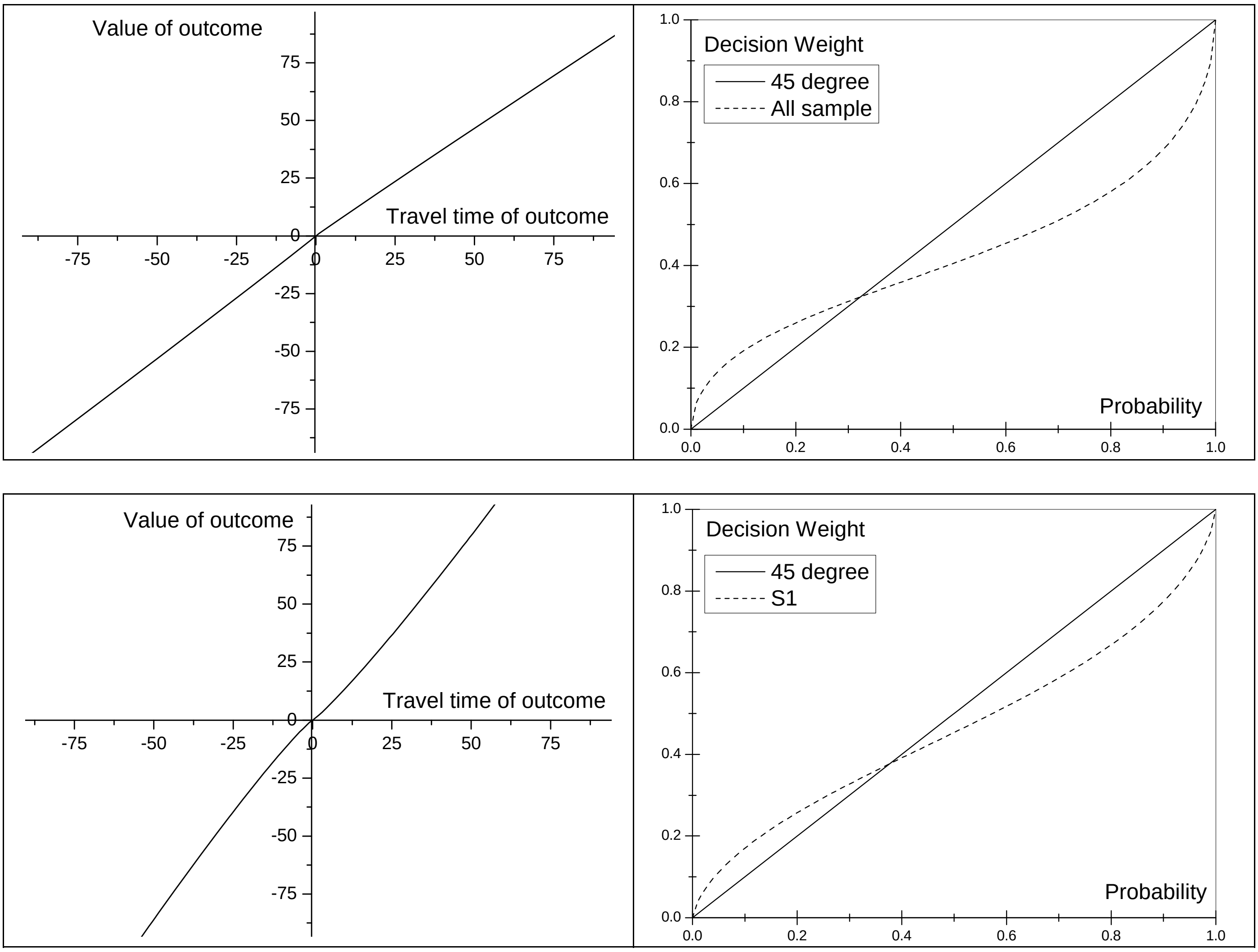

Figure 1 Value and weighting functions of travel section segmentations (restricted)

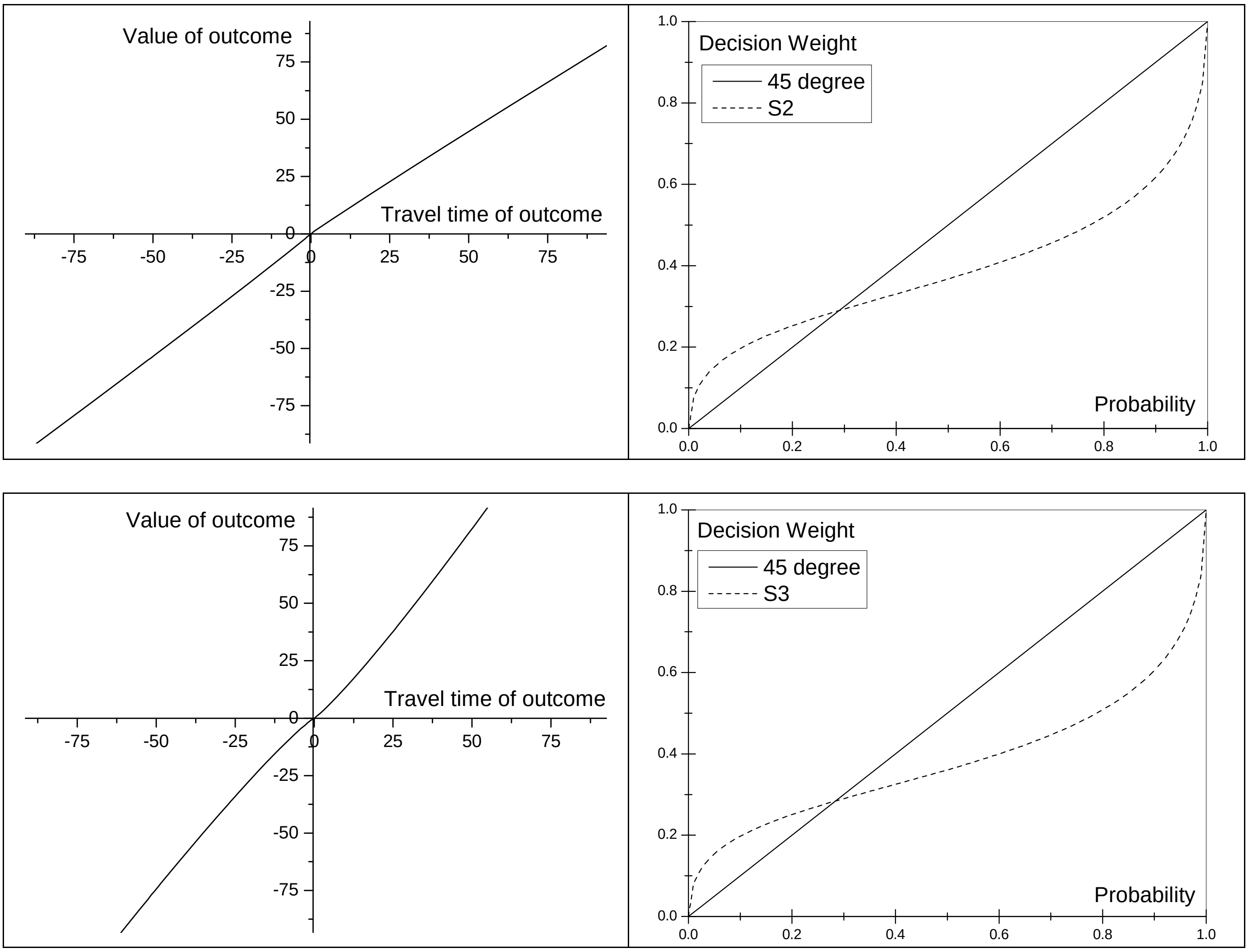

Figure 2 Value and weighting functions of travel section segmentations (restricted) (cont.)

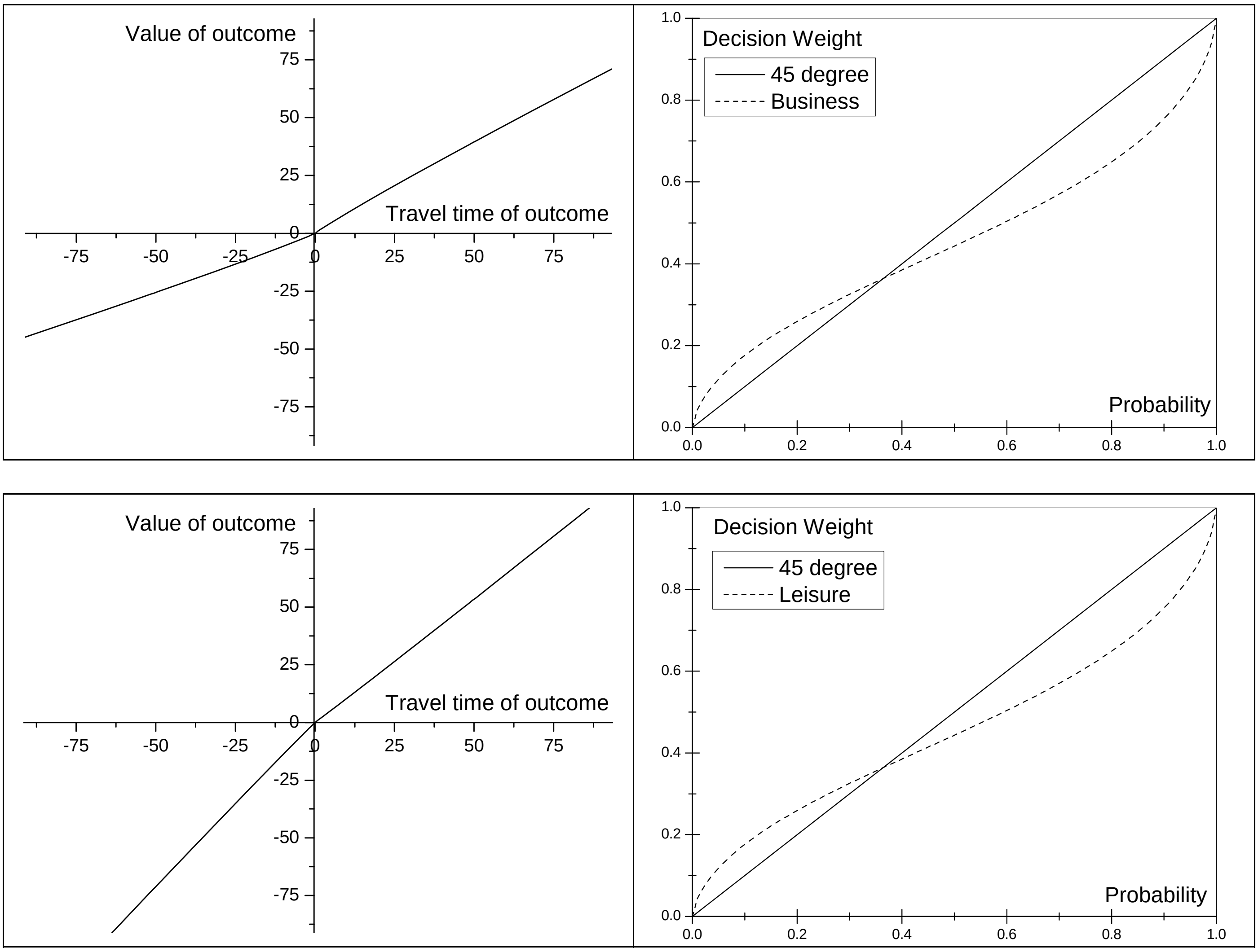

Figure 3 Value and gain functions of trip purpose segmentation (restricted)

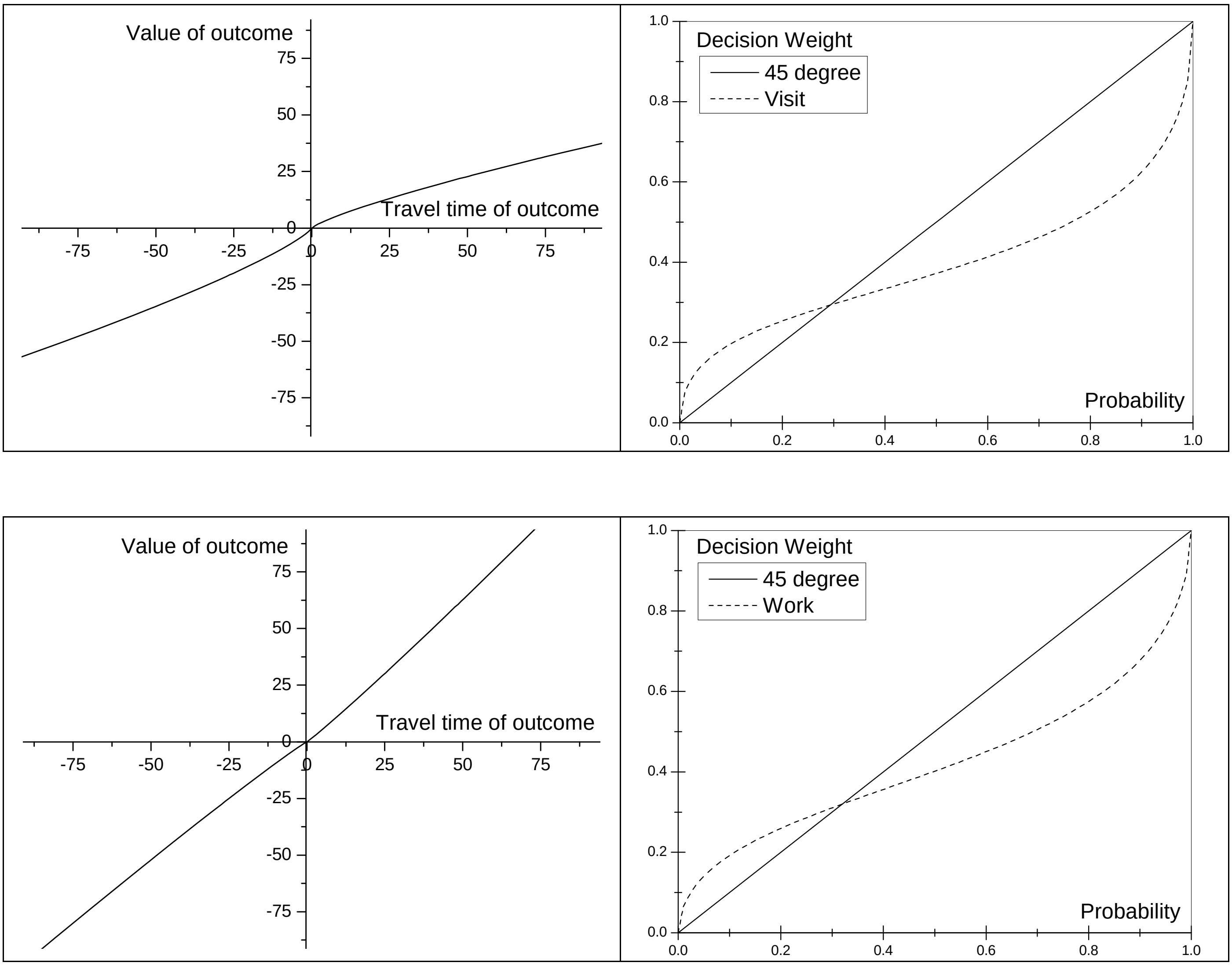

Figure 4 Value and gain functions of trip purpose segmentation (restricted) (cont.)

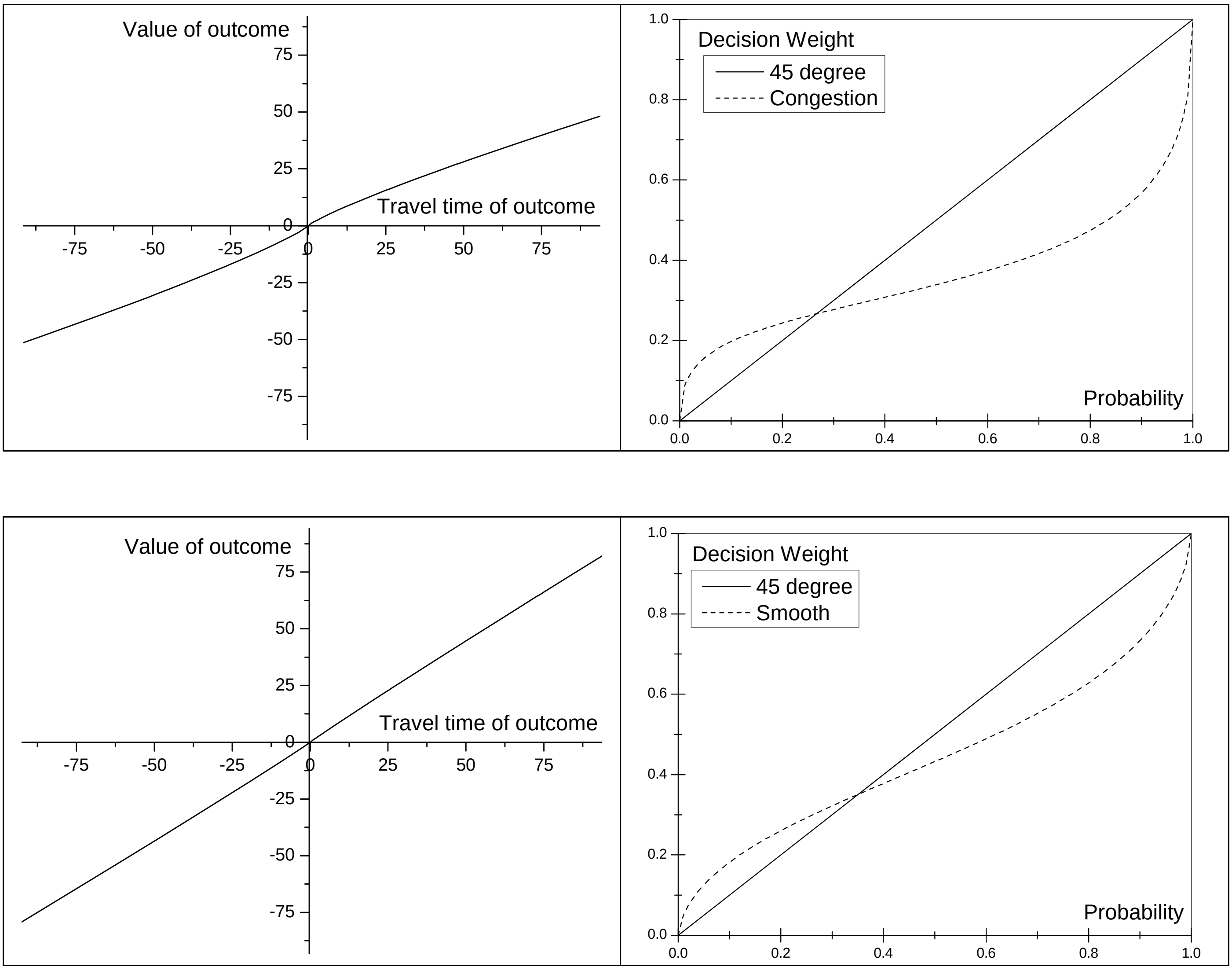

Figure 5 Value and gain functions of trip purpose segmentation (restricted)

2. Unrestricted single-attribute model results:

The detailed results of the unrestricted single-attribute CPT model are presented in the Appendix C and summarized in Table 5; the figures of value function and weighting function are presented in Figures 9-13. Most of the estimated parameters are statistically significant and the signs are consistent with prior expectation. In the model estimation results, the slops in the loss region are steeper than the ones in the gain region (except in congestion case). The results reveal that Taiwanese freeway drivers are loss-sensitive in the route choice behavior with the provision of real-time traffic information. Furthermore, risk seeking, distorted perception of probabilities and non-liner preferences are evidenced in all the weighting functions.

In summary, the results of unrestricted single-attribute models demonstrate how freeway drivers adopt a risk attitude after receiving real-time traffic information under specified market segmentations. Furthermore, the coefficients of γ are larger than δ and closer to one in the weighting function for the majority of market segmentations. The results indicate the driver is risk-insensitive in the gain's weighting function (since γ is closer to one). That is, the driver is neither prone to risk seeking, nor prone to risk aversion (please refer to Figure 2).

Table 5 Estimation results of unrestricted single attribute models

	α	β	λ	γ	δ
Travel section					
ALL sample	0.721	1.096	1.000	0.782	0.568
S1	0.829	1.267	0.903	0.758	0.620
S2	0.858	1.008	1.152	0.992	0.479
S3	0.727	1.559	0.559	0.619	0.524
Trip purpose					
Business	0.502	1.193	0.377	0.573	1.241
Work	0.935	1.074	1.239	0.849	0.645
Visit	0.586	0.870	1.397	0.806	0.516
Leisure	0.669	1.267	0.649	0.797	0.544
Usually encountered traffic on freeway					
Smooth	0.580	1.139	0.800	0.804	0.620
Congestion	1.033	0.948	1.083	0.813	0.458

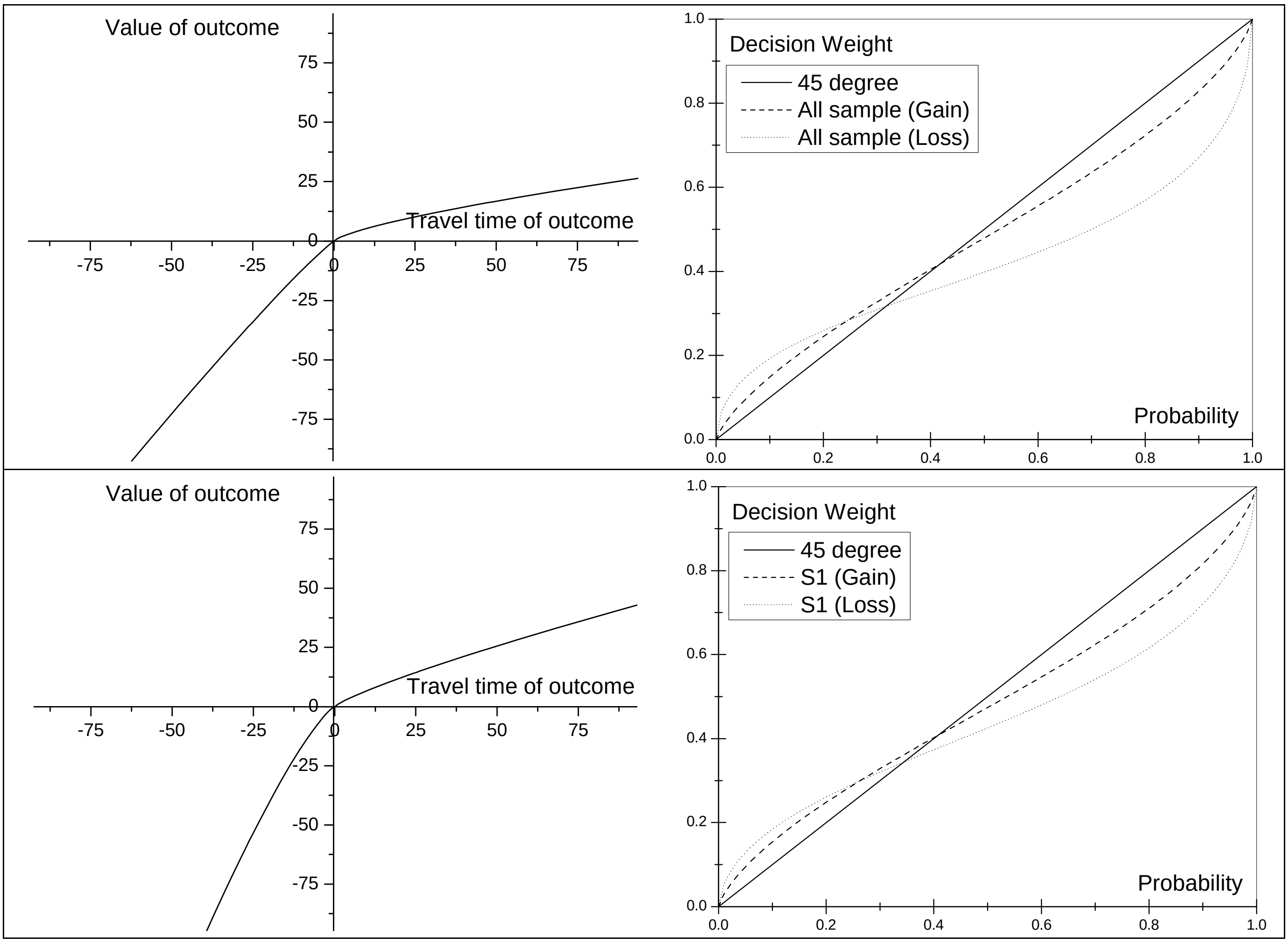

Figure 6 Value and weighting functions of travel section segmentations (unrestricted)

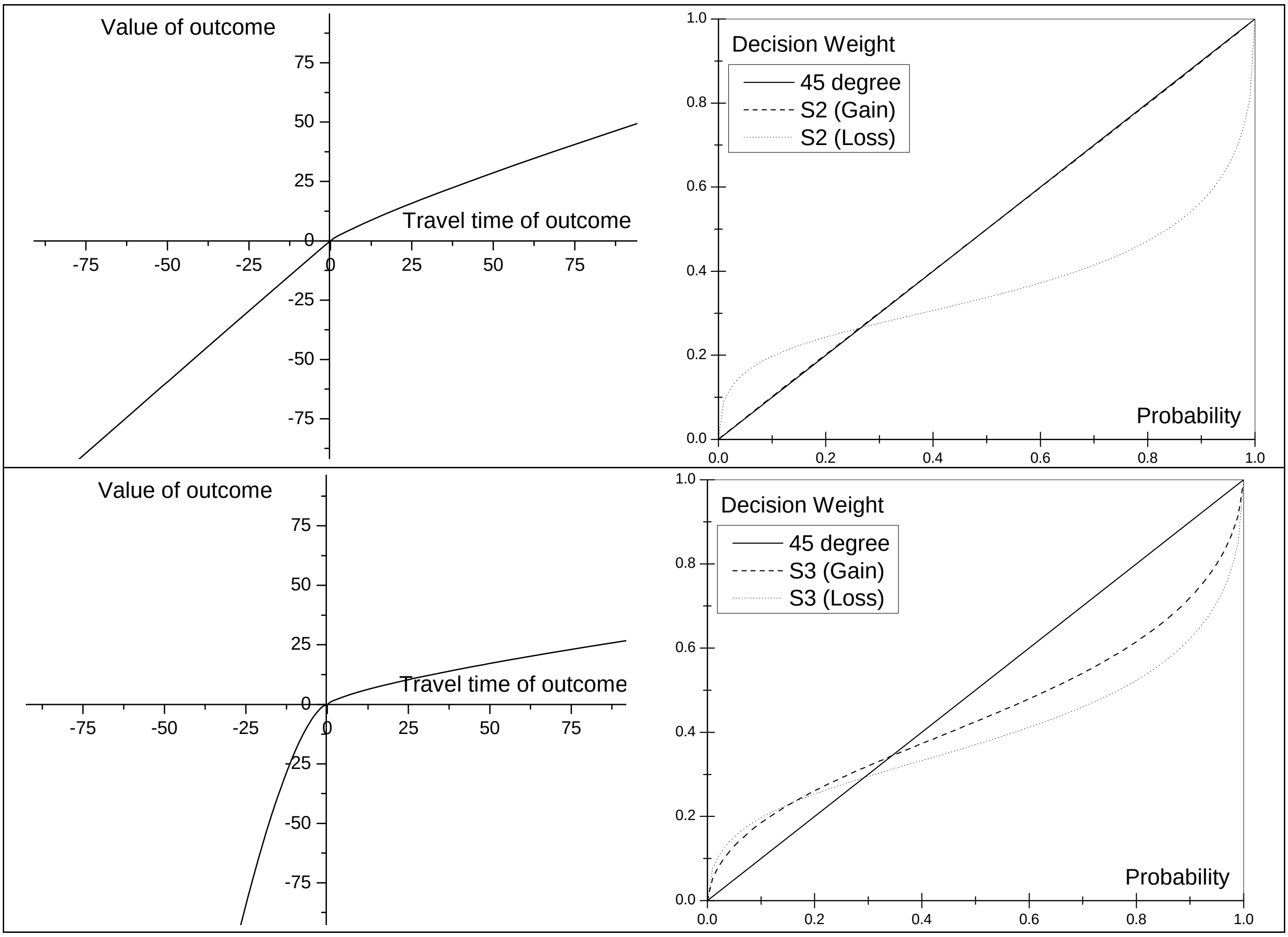

Figure 7 Value and weighting functions of travel section segmentations (unrestricted) (cont.)

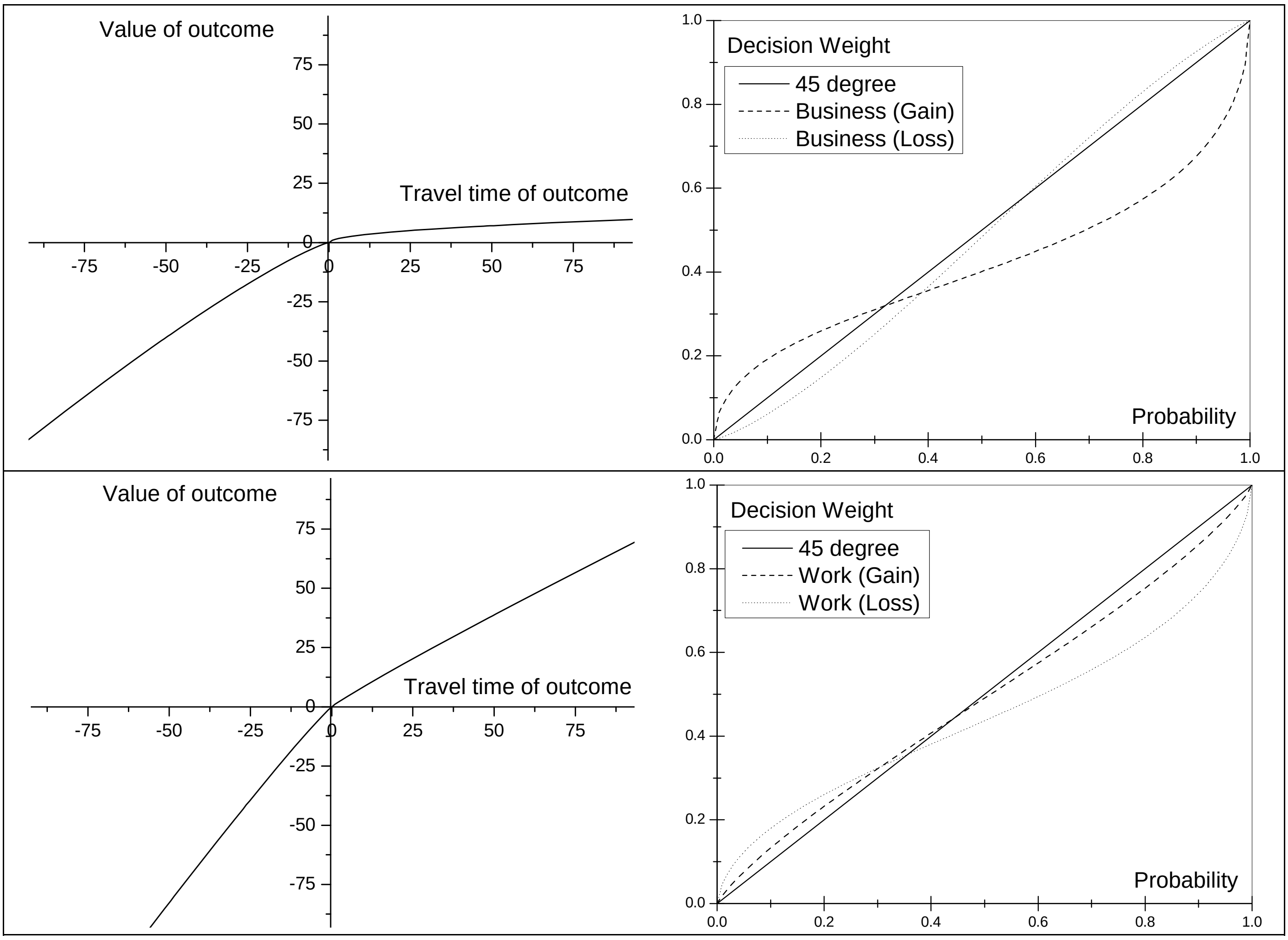

Figure 8 Value and weighting functions of trip purpose segmentations (unrestricted)

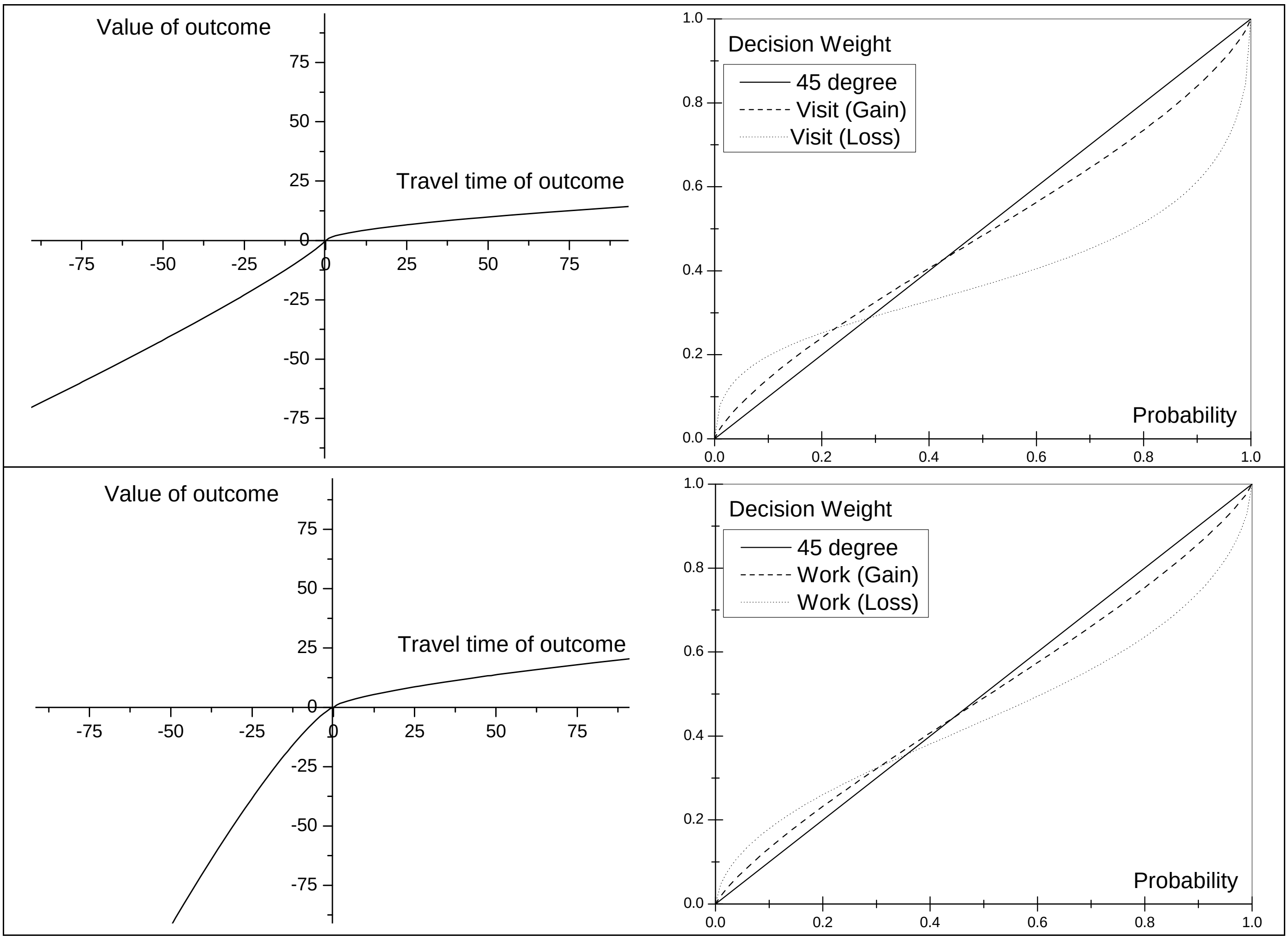

Figure 9 Value and weighting functions of trip purpose segmentations (unrestricted) (cont.)

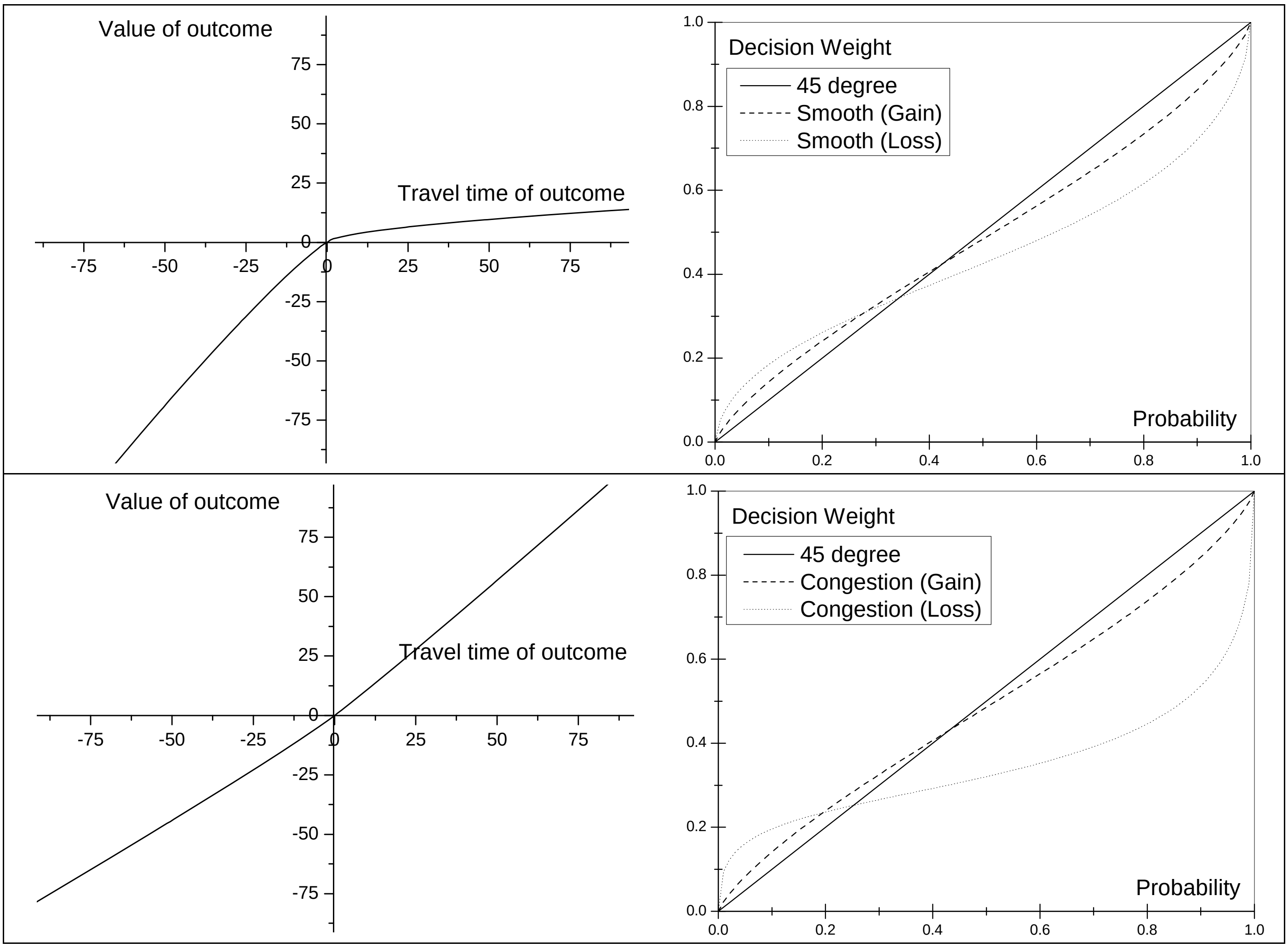

Figure 10 Value and weighting functions of usually encountered traffic segmentations (unrestricted)

4.2 Multi-attribute model results

In this section, the effects of various variables on value and weighting functions are investigated and the estimation results are summarized in 6. Drivers who usually encounter traffic congestion on freeways are likely to have a positive effect on gain's value function, i.e., gain-sensitive. This is reasonable because drivers are more sensitive to travel time savings (gain) if they often encounter congestion, especially with the provision of real-time traffic information.

On the other hand, driving on a habitual freeway, a business trip and a leisure trip all have effects on loss's value function. Drivers driving on their habitual freeways are more sensitive to travel time loss (loss), while drivers in business and leisure trips are less loss-sensitive. This could be drivers driving on habitual freeways are more knowledgeable with the traffic conditions, and consequently, react more strongly to travel time loss. As for these two trip purposes, drivers in the business trip could reserve a buffer for late arrivals and drivers in the leisure trip normally are more relaxing. Both cases are less-sensitive to travel time loss.

As expected, drivers requiring real-time traffic information predicted precisely and with high monthly personal income are more loss-aversive. This may due to their high expectation on the travel time variability and high value of time. However, drivers driving on habitual freeways are less loss-aversive, which can be confirmed by the result of its effect on loss value function, i.e., they react more strongly to travel time loss.

In the gain's weighting function, the driver in work trip is more risk-sensitive (either prone to risk seeking or prone to risk aversion). The main reason is that work trips always need to meet the working start time at workplace. On the other hand, in the loss's weighting function drivers in the leisure trip do not have the restriction to be on-time arrivals, and therefore are less risk-sensitive. Finally, drivers who usually encountered congestion are also less risk-sensitive, i.e., they are not either prone to risk seeking or risk aversion, although they are more sensitive to travel time savings (in gain's value function).

Table 6 Estimation results of Multi-attributes models

Parameter	Estimate(t-value)	95% confidence interval	
α (Value function- Gain scope)			
Constant	0.628(3.84)	0.307	0.9487
Usually encountered traffic on freeway	0.365(1.30)	-0.185	0.9149
β (Value function- Loss of scope)			
Constant	1.513(8.35)	1.1578	1.868
Driving on habitual freeways	0.296(1.86)	-0.0167	0.609
Trip purpose – Business	-0.335(-2.2)	-0.6336	-0.0359
Trip purpose – Leisure	-0.192(-1.63)	-0.423	0.0385
λ (Loss aversion)			
Constant	1.832(5.73)	1.2058	2.4591
Acceptance information prediction error – precisely	0.46(2.76)	0.1336	0.7869
Monthly personal income above population mean	0.284(1.66)	-0.0519	0.619
Driving on habitual freeways	-1.599(-5.11)	-2.212	-0.9859
γ (Weighting function- Gain scope)			
Constant	0.776(8.07)	0.5877	0.9649
Trip purpose – Work	1.076(1.5)	-0.3299	2.4821
δ (Weighting function- Loss of scope)			
Constant	0.706(11.01)	0.5802	0.8314
Trip purpose – Leisure	-0.148(-2.11)	-0.2859	-0.0105
Usually encountered traffic on freeway	-0.221(-2.97)	-0.3661	-0.075
η (Alternative-specific constant)			
Constant	0.017(0.45)	-0.0577	0.0921
Log pseudo-likelihood			-2027.6963
Samples			3184

5. Conclusions

This study has applied the CPT framework to investigate Taiwanese freeway drivers' risk attitude in route choice behavior with the provision of real-time traffic information. The estimated results provide valuable insights into freeway drivers' responses to travel time's gain and loss in different market segmentations. The results of both single- and multi-attribute CPT models show that Taiwanese freeway drivers' behavior can be captured by CPT's features, such as reference dependence, loss aversion, framing effects, risk seeking and distorted perception of probabilities and non-linear preferences under different market segmentations. The estimated coefficients of CPT's value and weighting functions confirm that the EUT axioms are violated systematically.

The results of the multi-attribute CPT model are more comprehensive and therefore are used as illustration of conclusions. The results show that drivers usually encounter congestion, which increases the expected value of gains in the value function. Driving on a habitual freeway, a business trip and a leisure trip all have effects on loss's value function as well. Concerning loss aversion, drivers requiring real-time traffic information predicted precisely and with high monthly personal income are more loss-aversive, while drivers driving on habitual freeways are less loss-aversive. In terms of the gain's weighting function, the driver in work trip is either prone to risk seeking or prone to risk aversion, while this is not the case for the driver in leisure trip in the loss's weighting function. Drivers who usually encountered congestion are not either prone to risk seeking or risk aversion.

Some directions can be considered in the further study. Driving on different networks may facilitate the comparison of different risk attitudes in decision-making, such as the route choice behavior between local streets and freeways. This could help to promote better real-time information experiences; it is therefore worthy of further research. Based on the findings of this study, the provision of real-time traffic information incentivizes drivers to switch to freeways.

Finally, not all of the risk attitude issues have been discussed in this study. For example, the effects of habitual decision behaviors, as well as how to assess or quantify the different risk attitude in minutes (or other units), requires more investigation. Moreover, the application of the CPT model could further investigate drivers' risk attitudes relating to different traffic policies and then address feasible ways to advocate and implement them in Taiwan.

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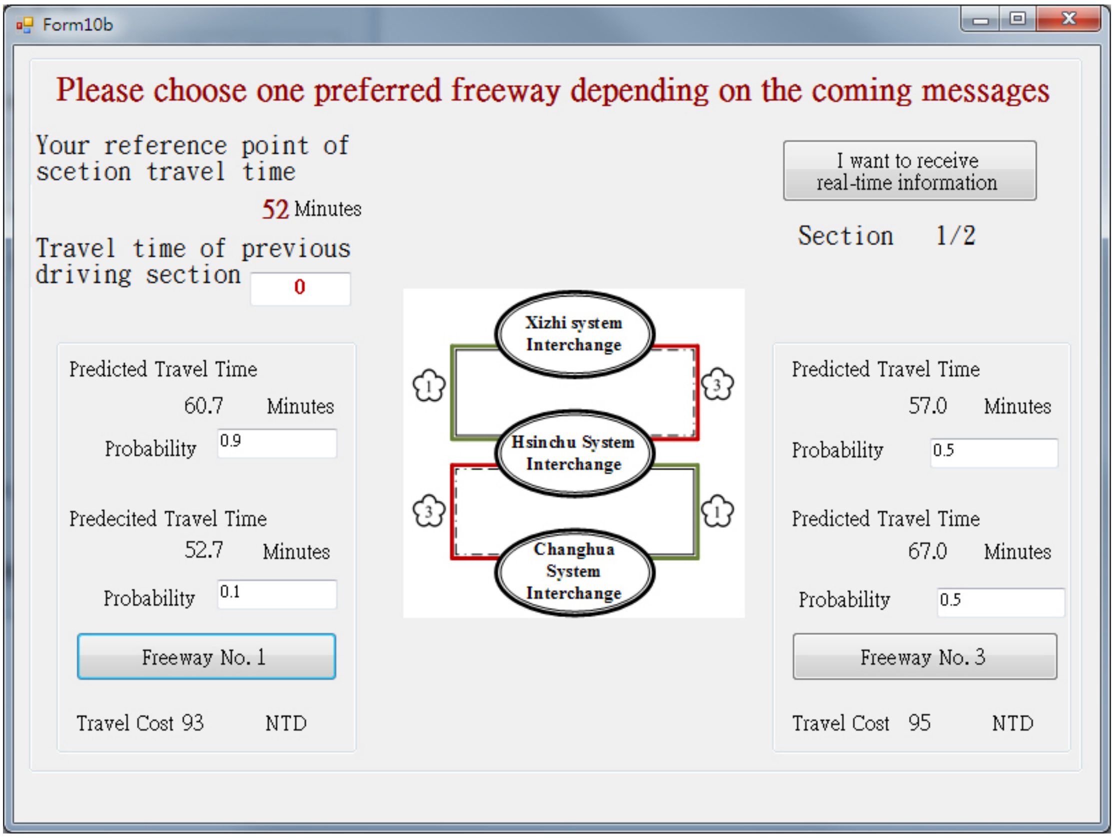
Appendix A

Screen shot of computer-aided survey



Appendix B

Table B-1 Restricted single-attribute CPT model results (travel section)

Parameter	Estimate(t-value)	95% confidence interval	
Travel section (All sample)			
α (Value function)	0.982(16.19)	0.863	1.101
λ (Loss aversion)	1.142(9.89)	0.916	1.369
γ (Weighting function)	0.580(16.37)	0.511	0.650
η (Alternative-specific constant)	0.029(0.76)	-0.046	0.103
Log pseudo-likelihood	-2068.270		
Samples	3184		
Travel section (S1)			
α (Value function)	1.119(12.89)	0.948	1.289
λ (Loss aversion)	1.080(7.04)	0.779	1.380
γ (Weighting function)	0.689(12.79)	0.532	0.725
η (Alternative-specific constant)	0.208(-3.54)	-0.323	-0.925
Log pseudo-likelihood	-952.991		
Samples	1508		
Travel section (S2)			
α (Value function)	0.971(8.74)	0.753	1.188
λ (Loss aversion)	1.199(6.19)	0.819	1.578
γ (Weighting function)	0.520(10.03)	0.419	0.622
η (Alternative-specific constant)	0.183(2.95)	0.061	0.304
Log pseudo-likelihood	-808.671		
Samples	1243		
Travel section (S3)			
α (Value function)	1.128(6.43)	0.784	1.471
λ (Loss aversion)	0.902(3.93)	0.451	1.351
γ (Weighting function)	0.510(7.13)	0.370	0.650
η (Alternative-specific constant)	0.271(2.62)	0.068	0.474
Log pseudo-likelihood	-281.649		
Samples	433		

Table B-2 Restricted single-attribute CPT model results (trip purpose)

Parameter	Estimate(t-value)	95% confidence interval	
Trip purpose (Business)			
α (Value function)	0.940(5.88)	0.626	1.253
λ (Loss aversion)	0.646(3.40)	0.274	1.019
γ (Weighting function)	0.662(3.70)	0.311	1.013
η (Alternative-specific constant)	0.093(1.29)	-0.049	0.235
Log pseudo-likelihood	-567.046		
Samples	848		
Trip purpose (Leisure)			
α (Value function)	1.058(11.59)	0.879	1.237
λ (Loss aversion)	0.831(6.51)	0.581	1.081
γ (Weighting function)	0.574(10.51)	0.467	0.681
η (Alternative-specific constant)	0.186(3.65)	0.086	0.286
Log pseudo-likelihood			
Samples			
Trip purpose (Visit)			
α (Value function)	0.799(7.15)	0.580	1.018
λ (Loss aversion)	1.521(6.35)	1.051	1.991
γ (Weighting function)	0.526(9.32)	0.415	0.637
η (Alternative-specific constant)	0.190(2.61)	0.047	0.333
Log pseudo-likelihood	-546.826		
Samples	873		
Trip purpose (Work)			
α (Value function)	1.017(6.85)	0.726	1.308
λ (Loss aversion)	1.332(4.13)	0.700	1.963
γ (Weighting function)	0.662(7.77)	0.495	0.828
η (Alternative-specific constant)	0.071(0.73)	-0.119	0.260
Log pseudo-likelihood	-311.833		
Samples	502		

Table B-3 Restricted single-attribute CPT model results (usually encountered traffic)

Parameter	Estimate(t-value)	95% confidence interval	
Smooth traffic			
α (Value function)	0.971(14.96)	0.844	1.098
λ (Loss aversion)	0.976(9.11)	0.766	1.186
γ (Weighting function)	0.635(13.46)	0.543	0.728
η (Alternative-specific constant)	0.237(6.06)	0.161	0.314
Log pseudo-likelihood	-1921.892		
Samples	2949		
Congestion traffic			
α (Value function)	0.853(6.78)	0.677	1.228
λ (Loss aversion)	1.091(4.96)	0.660	1.523
γ (Weighting function)	0.481(7.30)	0.352	0.611
η (Alternative-specific constant)	-0.155(-2.32)	-0.286	-0.024
Log pseudo-likelihood	-686.703		
Samples	1041		

Appendix C

Table C-1 Single-attribute CPT model results (travel section)

Parameter	Estimate(t-value)	95% confidence interval	
Travel section (All sample)			
α (Value function- Gain scope)	0.721(5.2)	0.4492	0.9933
β (Value function- Loss of scope)	1.096(13.15)	0.9323	1.259
λ (Loss aversion)	1.000(7.79)	0.7483	1.2513
γ (Weighting function- Gain scope)	0.782(8.32)	0.5976	0.9659
δ (Weighting function- Loss of scope)	0.568(15.84)	0.4979	0.6386
η (Alternative-specific constant)	0.029(0.76)	-0.0455	0.1027
Log pseudo-likelihood	-2064.715		
Samples	3184		
Travel section (S1)			
α (Value function- Gain scope)	0.829(3.67)	0.3865	1.2709
β (Value function- Loss of scope)	1.267(9.74)	1.0123	1.5222
λ (Loss aversion)	0.903(5.21)	0.5636	1.2429
γ (Weighting function- Gain scope)	0.758(3.82)	0.3694	1.1472
δ (Weighting function- Loss of scope)	0.620(12.74)	0.5246	0.7153
η (Alternative-specific constant)	-0.201(-3.47)	-0.3154	-0.0875
Log pseudo-likelihood	-951.001		
Samples	1508		
Travel section (S2)			
α (Value function- Gain scope)	0.858(3.39)	0.3617	1.3546
β (Value function- Loss of scope)	1.008(8.00)	0.7613	1.2556
λ (Loss aversion)	1.152(5.52)	0.743	1.5605
γ (Weighting function- Gain scope)	0.992(9.92)	0.7965	1.1885
δ (Weighting function- Loss of scope)	0.479(10.17)	0.3865	0.571
η (Alternative-specific constant)	0.18(2.91)	0.0586	0.3006
Log pseudo-likelihood	-805.7513		
Samples	1243		
Travel section (S3)			
α (Value function- Gain scope)	0.727(2.38)	0.1276	1.3268
β (Value function- Loss of scope)	1.559(3.50)	0.6869	2.4312
λ (Loss aversion)	0.559(1.74)	-0.0713	1.1894
γ (Weighting function- Gain scope)	0.619(3.99)	0.3153	0.9232
δ (Weighting function- Loss of scope)	0.524(5.97)	0.3518	0.696
η (Alternative-specific constant)	0.261(2.54)	0.06	0.4627
Log pseudo-likelihood	-280.2217		
Samples	433		

Table C-2 Single-attribute CPT model results (trip purpose)

Parameter	Estimate(t-value)	95% confidence interval	
Business			
α (Value function- Gain scope)	0.502(0.99)	-0.4924	1.4971
β (Value function- Loss scope)	1.193(4.89)	0.7147	1.6708
λ (Loss aversion)	0.377(2.53)	0.0847	0.6691
γ (Weighting function- Gain scope)	0.573(2.13)	0.0452	1.1017
δ (Weighting function- Loss scope)	2.241(2.71)	0.6203	3.8621
η (Alternative-specific constant)	0.093(1.29)	-0.0485	0.2344
Log pseudo-likelihood	-566.1359		
Samples	848		
Work			
α (Value function- Gain scope)	0.935(2.50)	0.2005	1.6686
β (Value function- Loss scope)	1.074(5.99)	0.7223	1.4255
λ (Loss aversion)	1.239(3.51)	0.5465	1.9312
γ (Weighting function- Gain scope)	1.849(2.49)	0.3949	3.304
δ (Weighting function- Loss scope)	0.645(8.42)	0.4947	0.795
η (Alternative-specific constant)	0.076(0.79)	-0.1133	0.2656
Log pseudo-likelihood	-311.3744		
Samples	502		
Visit			
α (Value function- Gain scope)	0.586(2.36)	0.0997	1.073
β (Value function- Loss scope)	0.870(6.27)	0.5979	1.1412
λ (Loss aversion)	1.397(5.33)	0.8835	1.9114
γ (Weighting function- Gain scope)	0.806(4.51)	0.4557	1.1569
δ (Weighting function- Loss scope)	0.516(8.79)	0.4008	0.6308
η (Alternative-specific constant)	0.190(2.63)	0.0484	0.332
Log pseudo-likelihood	-563.7720		
Samples	873		
Leisure			
α (Value function- Gain scope)	0.669(3.04)	0.2372	1.1013
β (Value function- Loss scope)	1.267(9.15)	0.9953	1.5377
λ (Loss aversion)	0.649(4.64)	0.3751	0.923
γ (Weighting function- Gain scope)	0.797(9.17)	0.6266	0.9671
δ (Weighting function- Loss scope)	0.544(9.54)	0.4322	0.6555
η (Alternative-specific constant)	0.184(3.63)	0.0844	0.2831
Log pseudo-likelihood	-1133.9662		
Samples	1723		

Table C-3 Single-attribute CPT model results (usually encountered traffic)

Parameter	Estimate(t-value)	95% confidence interval	
Smooth			
α (Value function- Gain scope)	0.58(3.61)	0.2657	0.8952
β (Value function- Loss scope)	1.139(12.6)	0.9615	1.3157
λ (Loss aversion)	0.800(7.00)	0.5758	1.0235
γ (Weighting function- Gain scope)	0.804(7.19)	0.5852	1.0237
δ (Weighting function- Loss scope)	0.62(12.95)	0.5263	0.714
η (Alternative-specific constant)	0.235(6.02)	0.1582	0.3111
Log pseudo-likelihood	-1917.469		
Samples	2949		
Congestion			
α (Value function- Gain scope)	1.033(3.91)	0.5149	1.5515
β (Value function- Loss of scope)	0.948(5.9)	0.6332	1.2626
λ (Loss aversion)	1.083(4.6)	0.6213	1.5446
γ (Weighting function- Gain scope)	0.813(3.39)	0.3432	1.2819
δ (Weighting function- Loss of scope)	0.458(7.12)	0.332	0.5843
η (Alternative-specific constant)	-0.154(-2.32)	-0.2844	-0.024
Log pseudo-likelihood	-685.71803		
Samples	1041		