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Diverging effects of subjective prospect values of uncertain time and money

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ABSTRACT

Studies from behavioral economics show that the subjective prospect value of money has diminishing sensitivity to losses/gains, represented by an S-shape, and this has been applied in representing the subjective prospect value of time in many transportation studies such as travel behavior modeling and network equilibrium. In this study, we demonstrate that the prospect value of time has an increasing sensitivity to losses/gains and can be represented by an 8-shape, which contrasts that of money. We further explain the rationality of this surprising finding based on psychological and behavioral theories and discuss extensive practical implications. The correlations between sensitivities to gains and losses in terms of magnitude are revealed as well to shed light on potential underlying correlated behavioral principles. Substantial loss-aversion features are observed in the empirical analysis, supporting endowment effects. Implications of the findings on decision-making and other areas that utilize time as a key indicator have been discussed. The findings may revolutionize many research areas that utilize time as a key indicator such as transportation engineering.

1. Introduction

The old saying "time is money" has been widely used to emphasize the value of time. However, do we really perceive time in the same way as money? Can we directly apply the rules from financial decision-making about monetary outcomes in representing time? In this study, we utilize systematic investigation on travel behavior for commuting to explore the different functions of subjective prospect values of uncertain time and money.

The principles concerning how human evaluates and judges attributes of available options in decision-making have been very important topics in behavioral economics. Prospect Theory (PT) and the extension Cumulative Prospect Theory (CPT) proposed by Kahneman and Tversky (1979) are two of the most influential theories. Based on laboratory and monetary experiments, Tversky and Kahneman (1992) obtained diminishing sensitivity of monetary gains and losses, a noticeable loss aversion feature, and an inverse S-shaped weighting function implying that decision-makers overweight the low probabilities and underweight the high probabilities. Over the past decades, researchers from different fields have extensively applied PT or CPT to various areas, such as finance and insurance (Krefeld-Schwalb et al., 2019; Barseghyan et al., 2013), health care (Ogdie and Asch, 2019), marketing (Heidhues and Kőszegi, 2014), labor organization (Crawford and Meng, 2011), engineering design (Klotz et al., 2018), and almost any other activity related to human decision-making (Helversen et al., 2020). PT and CPT have indeed offered an epoch-making contribution to the description of decision processes, and was decisive in causing Kahneman to be awarded the Nobel Prize for Economic Sciences in 2002. There is no doubt that the behavioral principles discovered from monetary experiments could reflect decision-makers' judgments and evaluations about money in economics. However, it is imperative to involve multiple attributes besides monetary outcomes in diverse decision contexts. The question is whether decision-makers edit and evaluate other behavioral factors in the same way, or follow the same principles as when evaluating monetary outcomes. It is likely for there to be differences in the evaluation principles for different attributes (Abdellaoui and Kemel, 2014). Time is another common and crucial factor influencing people's decision-making in diverse contexts, such as travel, insurance strategies, investment, purchasing behavior, and health care (Jonas et al., 2008; Chen et al., 2015). How decision-makers evaluate uncertain time is a vital question in determining the strategies in the above domains.

As per the conventional economic theory, it is supposed that "time is money" and thus the decisions concerning time under risk should comply the similar principles as monetary decisions under risk (Becker, 1965). However, psychological and behavioral science suggests that decision-makers may present divergent evaluation principles for time

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and money (Leclerc et al., 1995; Weber and Milliman, 1997; Zauberman and Lynch Jr, 2005), namely "time is not money". How is time different from money? There are several fundamental differences, which would make time follow a different line from money. Firstly, time, as a resource, is not fungible (Leclerc et al., 1995). It is more difficult to make up for time loss than money loss, which can prompt more risk aversion when individuals are facing time loss. Secondly, time is easier to be aggregated than money. It is normally perceived as a flow rather than a stock, and it is hard to save (Leclerc et al., 1995; Zauberman and Lynch Jr, 2005; Okada and Hoch, 2004). This may lead to divergent evaluation principles to time gain/loss as compared to monetary outcomes. In this regard, we address a crucial question: How do decision-makers judge and evaluate uncertain time as compared to monetary outcomes?

The studies about evaluations of monetary outcomes have absolutely dominated the decision science literature. Fewer efforts have been made to empirically investigate decision-makers' perception principles concerning uncertain time. Leclerc et al. (1995) examined whether consumers treated time like money when they made decisions in several aspects, including context effects, the integration of losses, and risk-seeking for losses based on laboratory experiments. They indicated that participants were more risk-averse for time than for monetary losses (i.e., increasing marginal utility for time losses) (Leclerc et al., 1995). Weber and Milliman (1997) reported risk aversion for time losses as well and found risk seeking for time gains (i.e., an increasing marginal utility for time gains) using lottery equivalence experiments. Festjens and Janiszewski (2015) studied the risk preferences for time in riskless situations of decontextualized settings, contextualized but unfamiliar settings, and naturalistic settings. They indicate time valuation shows increasing marginal utility (i.e., risk-seeking for gains and risk aversion for losses) when there is a time deficit but diminishing marginal utility when there is a time surplus. In contrast, some studies report inverse findings. Kroll and Vogt (2008) using lottery experiments about waiting time and Zushi et al. (2009) following the experimental design of Leclerc et al. (1995), both report that risk seeking for time losses. However, the experiments and analysis in the above-mentioned research apply qualitative investigations of the model-free risk attitudes without estimating all components of PT; they do not consider risky situations or the effects of decision-makers' distorted perceptions of probabilities (i.e., probability weighting functions in analysis). The risk attitudes under risky situations are not solely determined by the values functions, but should be interpreted by all components including the value functions, the probability weighting functions, and the loss aversion feature (Abdellaoui et al., 2008; Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). There are mere two attempts to measure the value functions for time and monetary outcomes under risk by fully considering all components of PT. Abdellaoui and Kemel (2014) elicited the prospect theory components (value functions, probability weighting, and loss aversion) for money and time. They used laboratory experiments and the Certainty Equivalence (CE) elicitation method of several two-outcome gambles (e.g., subjectively reporting a certain time gain that is equivalent to the prospect of 50% chance of gaining 60 min and 50% chance of gaining 0 min; time gains and losses are defined as leaving an experimental session earlier or later than the previously informed experimental period). They focused on the difference between time and monetary outcomes, and concluded less concave utility and smaller loss aversion for time than for money. Festjens et al. (2015) followed the experiments and elicitation methods of Abdellaoui and Kemel (2014), but improved the size effects in experimental designs by distinguishing small and large time and monetary outcomes. Their results demonstrated constant marginal utility for time and monetary gains, and increasing marginal utility for both time and monetary losses. They also report that small time losses are more painful than small money losses, but this pattern is reversed when the outcomes are larger. Nonetheless, the experimental investigations of the certainty equivalents of prospects confined either to the negative or to the positive domain in the two studies, rather than the mixed prospects characterizing most actual choice situations, are questioned (Levy and Levy, 2013). The "certainty effect" may strongly affect choices (Allais, 1953; Tversky and Kahneman, 1981). Therefore, in the certainty equivalent approach, it remains unclear whether the subjects' choices are derived from the value functions, the distortion of probability, or both. Different elicitation methods including Probability Equivalence (PE), Certainty Equivalence (CE), Value Equivalence (VE), Probability Lottery Equivalence (PLE), and Value Lottery Equivalence (VLE), lead to endogenous differences of estimated results due to the natural properties of the methods themselves (Bleichrodt et al., 2007). Moreover, in the experimental settings of the two studies (Abdellaoui and Kemel, 2014; Festjens et al., 2015), no explicit hints or clues are provided about how the saved (or lost) time can be utilized (or compensated) for other activities, the choice scenarios are laboratory settings without naturalistic contextualization and the participants are university students. It is implied that how decision-makers value the time highly relates to the contexts in terms of whether the time can be fully utilized to contribute to future planning (Leclerc et al., 1995) of other activities and the actual opportunity costs (e.g., the saved/lost time is for work or leisure) (Festjens and Janiszewski, 2015; Okada and Hoch, 2004).

In sum, the existing literature regarding evaluation principles of time-based decisions presents mixed findings, and no shared conclusions are reached. This may be a consequence of differences across different studies in terms of elicitation methods (e.g., PE, CE, VE, PLE, and VLE), experimental and estimation procedure (e.g., risky or riskless situations; estimate value functions and weighting functions sequentially or jointly), the choice context/scenario settings (e.g., decontextualized, contextualized but unfamiliar, and naturalistic context settings; scenarios where the saved time can be explicitly used for other activities or the utility of saved time is ambiguous for future usage), the identification of reference points (e.g., time losses refer to waiting time or larger waiting time than expected) and the specific participants (e.g., students). More importantly, all the relevant literature uses laboratory experiments (even though some use contextualized settings) with assumptive scenarios that participants are not familiar with or are not in accord with their participants' daily choice contexts. The participants are explicitly informed that they are taking behavioral experiments, and the collected behavior data is obtained by self-reporting (e.g., CE), potentially leading to reporting biases such as the Hawthorne effect. It is argued that the behavioral principles found in laboratory experiments may be informative about behavior in realistic settings due to hypothetical scenarios deviating from real choice contexts (Falk and Heckman, 2009; Levitt and List, 2009), especially where decision-makers have much experience in making the decisions.

This research adds value to the strand of relevant studies with regard to evaluation principles of the uncertain time in several ways. First, the emphasis of this study is placed on the potential differences in the evaluations of uncertain time and money. Especially, we aim to test whether the evaluation principles about money from behavioral economics can be transplanted to time-based decisions. Second, the analysis is based on non-laboratory experiments, in which the scenarios are real-world settings unobtrusively without any research purpose hints, individual-specific and in line with participants' familiar choice contexts. Another advantage of the used scenarios is that decision-makers have explicit clues about how the time gains (or losses) can be utilized (or compensated) as per their daily time scheduling. Third, we explore the evaluation principles concerning time and money simultaneously in the same decision process by taking advantage of the multi-attribute decision scenarios where both time and monetary outcomes play crucial roles, rather than investigate the two behavioral determinants separately. This ensures straightforward comparisons between money and time by controlling the confound effects of using different experimental scenarios for different determinants. Fourth, the results are attained based on explicit individual-specific reference points and behavioral data from respondents with a wide coverage of demographic characteristics for reducing potential sample biases.

The remaining parts are organized as follows. Section 2 introduces the details of experiments and used data. Section 3 presents the analysis

methods. The results are provided in Section 4, followed by discussion in Section 5. Lastly, Section 6 summarizes the main findings.

2. Experiments and data description

2.1. Experiments

The used experiment concerns travel behavior for commuting trips. The non-laboratory experiments are real-world settings unobtrusively without any research purpose hints, individual-specific, and in line with participants' familiar choice contexts. In the commuting travel scenarios, decision-makers have explicit clues about how the time gains (or losses) can be utilized (or compensated) as per their daily time scheduling. Moreover, the same decision process involves the evaluations of time and monetary outcomes simultaneously as both time and monetary outcomes play crucial roles in daily commuting travel behavior (Eliasson, 2021). This enables straightforward comparisons between money and time by controlling the confound effects of using different experimental scenarios for different determinants and investigating them separately. The experiment contained two stages, and the process is demonstrated in Fig. 1(a). At the beginning of the experiments, we gather the respondent's current commuting trip information, including his/her frequently used commuting transport mode in the past half of a year, the common commuting time range, the overall monetary cost of commuting (including fuel, tolls, and parking), commuting distance, and other information during commuting (i.e., in-vehicle crowding). Besides, the information of other feasible transport modes for commuting purposes in the respondent's real commuting contexts was collected as well. For instance, a respondent commonly uses a private car for commuting, whilst he/she could choose metro and bus for commuting as well. The information about all the available commuting choices in his/her real travel contexts was collected.

Afterward, stated preference (SP) experiments were created based on collected actual information for each participant using cloud-based programming and presented to the same respondent using tablet computers. In the SP experiments, respondents were asked to finish several SP scenarios, in which several external changes were assumed in their real commuting contexts. The scenarios for a participant were generated based on his/her specific travel contexts and thus individual-specific. These aimed to guarantee that the designed experiment contents (e.g., travel time) in scenarios were in line with the participant's real commuting contexts, and to avoid unrealistic scenarios and reporting biases. The used scenario is a choice between the current commuting transport mode and a new hypothetical alternative. To investigate choice behavior in different situations, scenarios assume several reasonable changes in travel choices and show variations in level-of-service variables as shown in Table 1. The assumed changes were potential transport instruments in Shanghai, China (i.e., the experiment place). For instance, an example of the used SP scenario for the car user is shown in Fig. 1(b). In the SP scenario, we assume the cost of using a private car for commuting increases due to road pricing policy, and a new bus line is open for commuting. The attributes of using the car and the bus for commuting are explicitly presented, as shown in Fig. 1(b). The respondent chooses which transport mode he/she would choose after deliberations as per their subjective judgment.

Four commonly used commuting transport modes (i.e., private car, metro, bus, and taxi) were considered in the experiment. The considered level-of-service variables were monetary cost, travel time, and comfort features (i.e., in-vehicle crowding). In the design process, the uncertain travel time was reflected by two attributes: mean travel time and variation in travel time due to dynamic traffic situations (measured by the standard deviation of travel time). For the presentation of uncertain travel time in SP scenarios, piecewise travel time internals were used according to Li et al. (2010). The probabilities of travel time in Fig. 1(b) are generated based on the mean travel time and variation of travel time (i.e., standard deviation) given in Table 1, referring to Gao et al. (2018).

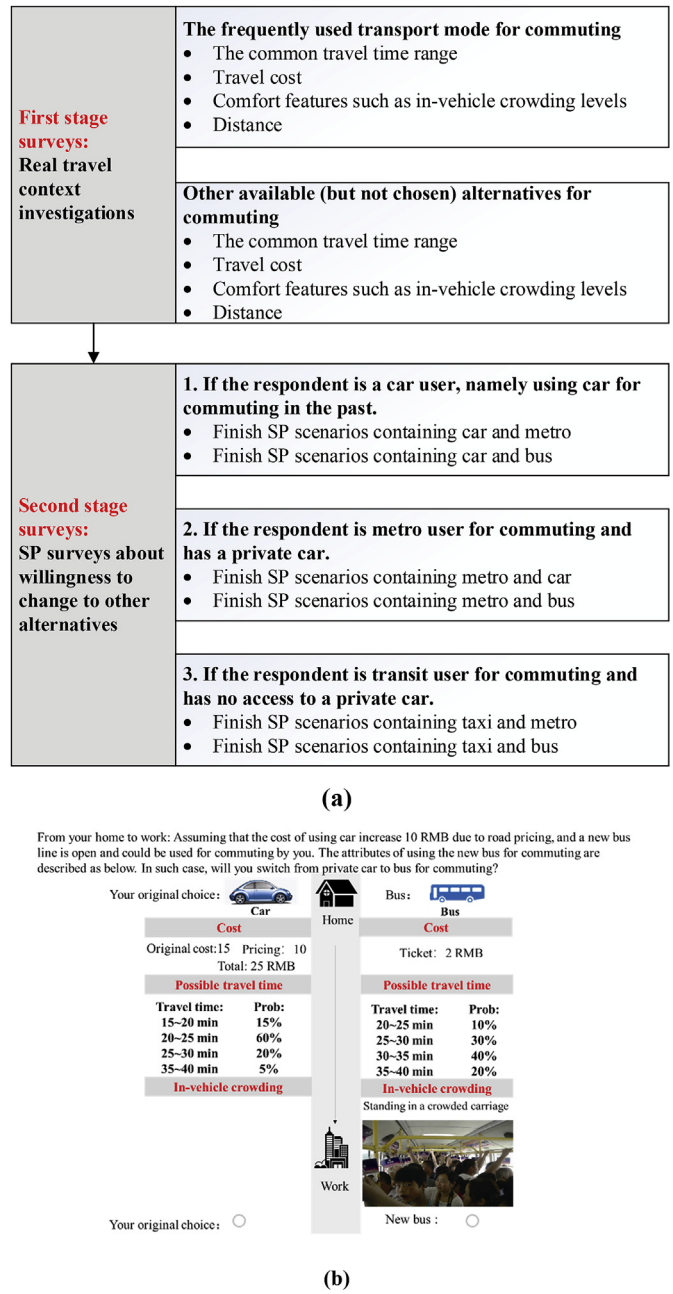


Fig. 1. (a) The survey process and (b) an example of SP scenario used.

The settings of the attribute levels for the SP scenario design were based on the collected information in the first stage and knowledge from practitioners, which are summarized in Table 1. The content design of the SP scenarios used the efficient design method to guarantee orthogonality and utility balance among alternatives in a scenario (Rose et al., 2008; Gao et al., 2020). Four scenarios for a choice situation[1] were randomly selected from the generated database of each situation to give out to each respondent. Pilot experiments were conducted in advance to test the validity of the experiment design, which indicated the designed experiments could be easily understood by respondents.

[1] It should be noted that a respondent finished SP scenarios in two choice situations. For instance, a car user finished the SP scenarios about car and metro and SP scenarios about car and bus.

Table 1
Influencing factors and their levels in SP scenario content design.

	Alternative	Attributes	Levels	Unit
For car users	Car (current commuting mode)	Mean travel time	MTT_{real} (the mean travel time in current travel contexts collected in the first stage)	min
		Monetary cost (petrol, parking fare, tolls)	TC_{real} (the current travel cost collected in the first stage) + {5, 15, 25, 40}	CNY
		Variation of travel time	$VTTC_{real}$ (the standard deviation of travel time in current travel contexts collected in the first stage)	min
		Comfort feature (crowding inside the car)	None	
	Metro	Mean travel time	{0.8, 1.1, 1.4} × MTT_{real}	min
		Monetary cost (ticket)	{3, 4, 5, 6}	CNY
		Variation of travel time	{1, 3, 5}	min
		Comfort feature (crowding inside metro)	{Level 1, Level 2, Level 3}	
	Bus	Mean travel time	{1, 1.3, 1.6} × MTT_{real}	min
		Monetary cost (ticket)	{2, 4, 6}	CNY
		Variation of travel time	{3, 7, 10}	min
		Comfort feature (crowding inside bus)	{Level 1, Level 2, Level 3}	
For metro users	Metro (current commuting mode)	Mean travel time	MTT_{real}	min
		Monetary cost (ticket)	TC_{real} + {2, 6, 10}	CNY
		Variation of travel time	$VTTC_{real}$	min
		Comfort feature (crowding inside metro)	$IVCL_{real}$ (the in-vehicle crowding of using metro collected in the first stage)	
	Bus	Mean travel time	{0.75, 1, 1.25}× MTT_{real}	min
		Monetary cost (ticket)	{2, 4, 6}	CNY
		Variation of travel time	{3, 7, 10}	min
		Comfort feature (crowding inside bus)	{Level 1, Level 2, Level 3}	
	Car	Mean travel time	{0.7, 0.9, 1.1}× MTT_{real}	min
		Monetary cost (petrol, parking fare, tolls)	Petrol fee + {5, 10, 20}	CNY
		Variation of travel time	{3, 5, 8}	min
		Comfort feature (crowding inside the car)	None	
	Taxi/ ridesharing	Mean travel time	{0.7, 0.9, 1.1} × MTT_{real}	min
		Monetary cost	{T1, T2, T3}	CNY
		Variation of travel time	{3, 5, 8}	min
		Comfort feature (crowding inside the taxi)	{Level 1, Level 2, Level 3}	

Note: Crowding Level 1: uncrowded with seats; Level 2: standing in the non-crowded carriage; Level 3: standing in a crowded carriage. The cost of taxi is calculated according to the pricing rules of taxi in Shanghai: T_1 (hitchhiking) = distance × 1.6, T_2 (ridesharing with others) = 0.8 × (distance × 2.3 + travel time × 0.5), T_3 (ride without sharing) = (distance × 2.3 + travel time × 0.5). The petrol fee denotes the cost of used petrol for the trip, which is estimated based on the travel distance. The table refers to Gao et al. (2021).

2.2. Sample

A total of 4,136 observations were collected from 517 valid respondents. The respondents' statistical attributes are outlined in Table 2. The experiments were carried out at public locations in Shanghai of China (e.g., transit hubs and vehicle management departments). The vehicle management departments in Shanghai are the official institutions responsible for car-related services such as annual checks of vehicles, renewing driving licenses, and administrating traffic violations. Investigators (college students at universities) were recruited to conduct face-to-face and one-to-one experiments for the sake of data validity using tablet computers. Travelers or customers who were waiting for their services in the public locations were randomly invited to participate in the experiments during workdays. In such a way, the participants in this study were randomly selected and had wide coverage of socio-economic attributes without biases, as depicted in Table 2. Once the respondent agreed to participate, the investigator gave the table computer to the respondent. The respondents were required to read and understand the questions attentively and answer the questions as per their own subjective predilection and judgments. The investigators actively checked whether the respondent was responsible for answering the designed questions (e.g., observing if the respondent finished the experiments extremely fast without deliberations), standing by the side of the respondent. Respondents who showed irresponsibility in finishing questions (e.g., finished questions in less than 5 min) were stopped and excluded. The experiment took around 20 min to finish. Each participant is provided with a monetary incentive of 20 CNY to increase the participation rate and appreciation for supporting the experiments. Consents from the university and public management department were obtained to conduct experiments in the public locations. As for the sample size, the collected sample includes 4,136 observations from 517 respondents with various socio-economic attributes, which is over four times as compared to the sample size in relevant studies (Abdellaoui and Kemel, 2014; Festjens et al., 2015). The collected sample is more representative as compared to the relevant literature, whose participants were all students (Abdellaoui and Kemel, 2014; Festjens et al., 2015). More importantly, most of the investigated behavioral parameters in the estimated results are statistically significant at the confidence level of 95%, indicating that the collected sample is plausible to provide reliable behavioral analysis.

3. Methodology

The analysis method was based on the framework of CPT. However, we relax two propositions from the original version of CPT in economics. First, we relax the diminishing sensitivity to be non-linear sensitivity; second, we relax the weighting function from the restricted inverse S-shaped function. The subjective prospect value of an influencing factor with n possible values, $\boldsymbol{E} = \{p_1, x_1; \ldots; p_k, x_k; \ldots; p_n, x_n\}$ is calculated as per CPT by

$$V(\boldsymbol{E}) = \sum_{k=1}^{n} \psi(p_k)\varphi(x_k, x_0) \tag{1}$$

where p_k is the probability of obtaining the outcome x_k,$\varphi(x_k, x_0)$ is a monotonic value function to obtain the prospect of the outcome x_k based on the reference point x_0. $\psi(p_k)$ is the weighting probability function for calculating the subjectively perceived probability based on the objective probability p_k. CPT treats gains and losses differently and the $\varphi(x_k, x_0)$ is calculated by

$$\Delta x_k = x_k - x_0 \tag{2}$$

Table 2
Statistical summary of valid participants.

Personal attributes	Statistics
Age	Less than 30 years old (47%), 30–40 (41%), 40–50 (10%), more than 50 years old (2%)
Education level	Lower than undergraduate (25.3%), undergraduate (57.7%), master (14.5%), doctor (2.5%)
Monthly income (CNY)	Less than 3,000 (2.1%), 3,000–6,000 (14.9%), 6,000–10,000 (33.1%), 10,000–20,000 (29%), more than 20,000 (12.4%), skipped (5.9%).
Gender	Male (65.5%), female (34.5%)
Marital status	Yes (49.6%), no (46.5%), skipped (3.9%)
Occupations	State-owned enterprise (29.8%), private enterprise (43.8%), individual business (14.3%), others (12.1%)
Commuting distance	Less than 5 km (10.8%), 5–10 km (36.7%), 10–20 km (35.9%), over 20 km (16.6%)
Current commuting mode	Private car users (53.8%), metro users (46.2%)

$$\varphi(x_k, x_0) = \begin{cases} \varphi^+(\Delta x_k) = (\Delta x_k)^\mu & \text{if } \Delta x_k \text{ is a gain} \\ -\beta \times \varphi(-\Delta x_k) = -\beta(-\Delta x_k)^\tau & \text{if } \Delta x_k \text{ is a loss} \end{cases} \tag{3}$$

In our studied case, influencing factors include travel time, monetary cost, and in-vehicle crowding. Longer travel time or cost as compared to the reference point is a loss rather than again, which should be noted in the calculation. The parameter β is the loss aversion coefficient and should be larger than one to fit the loss aversion assumption. The $\varphi^+(\Delta x_k)$ and $\varphi^-(-\Delta x_k)$ can be any defined formulations with separate parameterizations to measure how the decision-makers evaluate losses and gains. We adopted the power value function as per the literature (Tversky and Kahneman, 1992; Stott, 2006). For the probability weighting function, CPT uses the cumulative probability rather than the probability of a single outcome, so the possible outcomes should be arranged in descending order of gains for calculation (Tversky and Kahneman, 1992). The subjectively perceived probabilities for gains and losses are calculated separately by cumulative probability instead of individual probabilities (Tversky and Kahneman, 1992), as shown in Eq. (3). Assuming that an attribute has n possible outcome $x_1 < \ldots < x_{m-1} < x_m < \ldots < x_n$ with corresponding probability $(p_1, \ldots, p_{m-1}, p_m, \ldots, p_n)$ in a descending order of gains where x_m is a gain and x_{m-1} is a loss. The subjective perceived weighting as per CPT is

$$\begin{aligned} \psi(p_1) &= \varpi(p_1) \\ \psi(p_n) &= \varpi(p_n) \end{aligned} \tag{4}$$

$$\psi(p_k) = \begin{cases} \varpi\left(\sum_k^n p_{wi}\right) - \varpi\left(\sum_{k+1}^n p_{wi}\right) & \text{if } n-1 \geq k \geq m \\ \varpi\left(\sum_1^k p_{wi}\right) - \varpi\left(\sum_1^{k-1} p_{wi}\right) & \text{if } m-1 \geq k \geq 2 \end{cases}$$

where ϖ is a probability weighting function for capturing the distorted perceptions of probability. We adopted a Prelec I probability weighting function (Stott, 2006). The Prelec I was used instead of the famous Tversky–Kahneman probability weighting function as it offers a more flexible fitting space (Stott, 2006). Therefore, the calculation equations can be given by

$$\varpi(p) = \frac{1}{e^{(-lnp)^\vartheta}} \tag{5}$$

Different from the existing studies (Abdellaoui and Kemel, 2014; Festjens et al., 2015), commuting travel choice in our empirical analysis is a typical multi-attribute decision making involving multiple attributes (i.e., monetary cost, travel time, and in-vehicle crowding). In other words, the decision-maker evaluates multiple influencing factors rather than a single influencing factor in the decision process. An attribute with uncertainty can be expressed as Eq. (6). The above-mentioned model specifications of CPT can be fully applied to depict travelers' evaluation process for every attribute of each alternative.

Table 3
Modeling results.

Parameters	Coefficient	Standard error	Robust t-test	P-value
$IM(cost)$	0.977	0.218	4.48	< 0.001
$IM(cost)_{caruser}$	−0.602	0.145	−4.16	< 0.001
$IM(bus\ travel\ time)$	0.0277	0.0106	2.61	0.01
$IM(car\ travel\ time)$	0.101	0.0492	2.04	0.04
$IM(metro\ travel\ time)$	0.0243	0.0063	3.86	< 0.001
$IM(taxi\ travel\ time)$	0.0137	0.0049	2.79	0.01
$IM(crowding\ level\ 2)$	0.566	0.148	3.82	< 0.001
$IM(crowding\ level\ 3)$	1.25	0.244	5.12	< 0.001
Effect of frequently using car in the past	−0.119	0.748	−0.16	0.87
Effect of frequently using metro in the past	2.75	0.696	3.94	0.00
Error component between metro and bus	3.02	0.229	13.20	0.00
ASC_{car}	−1.07	0.697	−1.53	0.12
ASC_{metro}	−2.51	0.661	−3.79	< 0.001
ASC_{bus}	−4.58	0.642	−7.13	< 0.001
ASC_{taxi}	0	–	Fixed	
$\mu(time)_{mean}$	1.651	0.238	6.93	< 0.001
$\mu(time)_{SD}$	0.632	0.147	4.31	< 0.001
$\tau(time)_{mean}$	1.303	0.219	5.95	< 0.001
$\tau(time)_{SD}$	0.325	0.117	2.78	0.01
β_{mean}	2.315	0.486	4.76	< 0.001
β_{sd}	1.915	0.532	3.60	< 0.001
$\mu(money)_{mean}$	0.422	0.065	6.49	< 0.001
$\mu(money)_{SD}$	0.167	0.044	3.82	< 0.001
$\tau(money)_{mean}$	0.542	0.046	11.89	< 0.001
$\tau(money)_{SD}$	0.198	0.029	6.94	< 0.001
ϑ	1.42	0.410	3.46	< 0.001
No. of parameters	25			
Final log-likelihood	1,929.335			
Akaike Information Criterion (AIC)	3,908.671			
Bayesian Information Criterion (BIC)	4,066.858			
Observation	4,136			

Note: The smaller AIC and BIC indicates a better model fit. The weight of cost is $IM(cost)_{mean} + IM(cost)_{caruser} \times$ Caruser where "Caruser" is 1 if the respondent frequently uses car for commuting in the past, otherwise 0. This aims to consider the fact that car users in Shanghai are generally richer and thus have higher value of time.

$$\begin{pmatrix} \boldsymbol{E}_{ij} \\ \boldsymbol{p}_{ij} \end{pmatrix} = \begin{pmatrix} e^1{}_{ij}, & \cdots, & e^r{}_{ij}, & \cdots, & e^n{}_{ij} \\ p^1{}_{ij}, & \cdots, & p^r{}_{ij}, & \cdots, & p^n{}_{ij} \end{pmatrix} \tag{6}$$

The prospect value of option i's attribute j with possible outcomes (e^1_{ij}, …, e^r_{ij}, …, e^n_{ij}) and corresponding probabilities (p^1_{ij}, …,p^r_{ij}, …, p^n_{ij}) can be obtained based on CPT using Eqs. (1)–(5). We further add a random error ε_{ij} to consider the unobserved subjective evaluation errors in the evaluation process. Therefore, the prospect value for attribute j of option i is

$$PV_{ij}\left(\boldsymbol{CPT}_j, \boldsymbol{E}_{ij}, \boldsymbol{p}_{ij}, e_{0ij}\right) = \sum_{r=1}^{n} \psi\left(p^r{}_{ij}\right)\varphi\left(e^r_{ij}, e_{0ij}\right) + \varepsilon_{ij}$$
$$\boldsymbol{CPT}_j = \left(\mu_j, \beta_j, \tau_j, \upsilon_j\right) \tag{7}$$

where e_{0ij} denotes the reference point for attribute j of option i and $\boldsymbol{CPT}_j$ is the vector containing all parameters in Eqs. (3)–(5) for attribute j. On account that one option has several attributes, the overall subjective prospect of option i is attained using Simple Additive Weighting (Hobbs, 1986), which is popular and widely used in practical applications due to its merits. Consequently, the subjective prospect of option i is

$$PV_i(CPT, IM^i, E_i, P_i, E_{0i}) = \sum_{j=1}^{T} IM^i_j \cdot \left(\sum_{r=1}^{n} \psi\left(p^r{}_{ij}\right)\varphi\left(e^r_{ij}, e_{0ij}\right) + \varepsilon_{ij}\right) + ASC_i + IP_i = \sum_{j=1}^{T}\sum_{r=1}^{n} \psi\left(p^r{}_{ij}\right)\varphi\left(IM^i_j, e^r_{ij}, e_{0ij}\right) + ASC_i + IP_i + \varepsilon_i$$
$$\varphi\left(IM^i_j, e^r_{ij}, e_{0ij}\right) = \begin{cases} IM^i_j \cdot \left(e^r_{ij} - e_{0ij}\right)^{\mu}, & if\ c^r_{ij} - c_{0ij}\ is\ a\ gain \\ -\beta \cdot IM^i_j \cdot \left[-\left(e^r_{ij} - e_{0ij}\right)\right]^{\tau}, & if\ c^r_{ij} - c_{0ij}\ is\ a\ loss \end{cases} \quad \varepsilon_i = \sum_{j=1}^{T} IM^i_j \varepsilon_{ij} \tag{8}$$

where IP_i denotes the influence of past choice behavior on current choice preference and is added in the model formulations to reduce external biases of estimated CPT behavioral parameters as per Cantillo et al. (2007). $\boldsymbol{CPT} = \{\mu_j, \lambda_j, \tau_j, \upsilon_j \big| j = 1, 2, ..., T\}$ is the parameter vector for all influencing factors, $\boldsymbol{IM}^i = \{IM^i_j \big| j = 1, 2, ..., T\}$ is the weighting vector representing the importance weights of the attributes of option i, $\boldsymbol{E}_{0i} = \{e_{0ij} | j = 1, 2, ..., T\}$is the reference point vector for attributes of option i, $\boldsymbol{E}_i = \{e^r_{ij} \big| j = 1, 2, ..., T;\ r = 1, 2, ..., n\}$ and $\boldsymbol{P}_i = \{p^r_{ij} \big| j = 1, 2, ..., T;\ r = 1, 2, ..., n\}$ are the matrix concerning attributes of alternatives and corresponding probabilities for option i in a choice scenario, respectively, and ASC_i is the constant preference for alternative i. The parameters in the value functions of CPT are set to be random parameters rather than constant to further consider the heterogeneity among decision-makers. More specifically, the parameters are assumed to follow lognormal distributions. This is also aimed to ensure that the parameters remain the correct sign in the estimation (e.g., the parameters in CPT functions should be positive), so lognormal distributions (e.g., $\mu = \exp\left(u_{\text{mean}} + u_{\text{sd}} \times N\right)$ where N is the standard normal distribution) are used to constrain the parameters to be positive. In calculating the subjective prospect, reference points are very crucial as per Eq. (8). In the experiments, different decision-makers have significantly distinct actual commuting contexts in terms of commuting costs, travel time, and distance. These instinctively results in the phenomenon that every single decision-maker has his/her own reference point in the evaluation process (Schwartz et al., 2008). Hence, we make the best of the collected revealed commuting information to use individual-specific reference points for analysis rather than homogeneous reference points across different decision-makers. The value of an attribute of a respondent's actual commuting trips is selected as the reference point of CPT in his/her evaluation process about the attribute (De Borger and Fosgerau, 2008). For instance, if a respondent's currently common commuting time is 40 min, this value is used as the reference point for evaluating time in the SP experiments. Then, the prospect value of option i for a decision-maker d is

$$PV_{id}\left(\boldsymbol{CPT}, \boldsymbol{IM}^{id}, \boldsymbol{E}_i, \boldsymbol{P}_i, \boldsymbol{E}^d_{0i}\right) = \sum_{j=1}^{T}\sum_{r=1}^{n} \psi\left(p^r_{ij}\right)\varphi\left(IM^i_j, e^r_{ij}, e_{0ij}\right) + ASC_i$$
$$+ IP_{id} + \varepsilon_{id}\ DPV_{id}\left(\boldsymbol{H}, \boldsymbol{W}^i, \boldsymbol{C}_i, \boldsymbol{P}_i, \boldsymbol{C}^d_{0i}\right)\boldsymbol{E}^d_{0i} = \left\{ e^d_{0ij} \middle| j = 1, 2, \ldots, T \right\}\boldsymbol{IM}^{id}$$
$$= \left\{ IM^{id}_j \middle| j = 1, 2, ..., T \right\} \tag{9}$$

where $\boldsymbol{E}^d_{0i}$ is the vector that contains reference points for attributes of option i for decision-maker d. For the sake of calculation robustness, the error terms ε_{id} in Eq. (9) are set to be identical and independent Gumbel distributions. The decision-maker prefers the option with the largest subjective positive prospect. Hence, we can obtain the probability of selecting option i by Eq. (10).

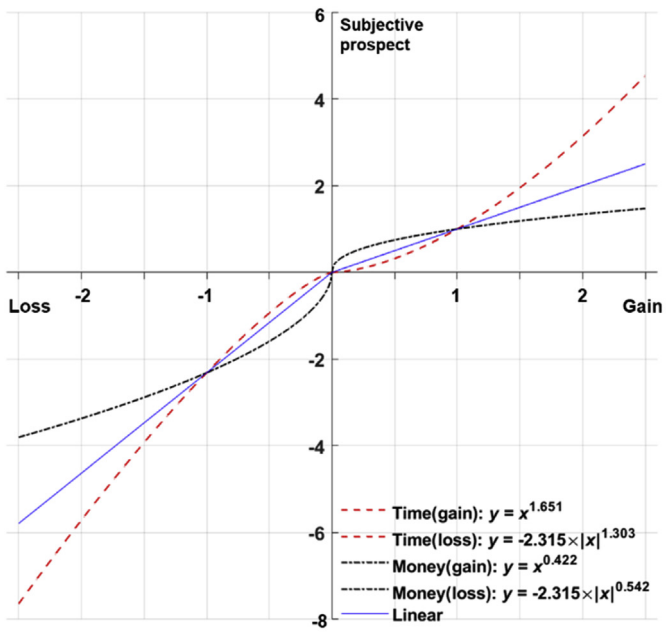
$$Prob_{if} = \int_{\boldsymbol{\beta}} \theta(\boldsymbol{\beta}) f(\boldsymbol{\beta}) d(\boldsymbol{\beta})$$
$$Prob_{if} = \frac{e^{DPV_{id}}}{\sum_{i=1}^{Z} e^{DPV_{id}}} \tag{10}$$

where $\boldsymbol{\beta} = \{\mu_j, \beta_j, \tau_j, \upsilon_j, IM^i_j \big| j = 1, 2, ..., T;\ i = 1, 2, ..., Z\}$ is the vector, including all parameters to be estimated in the model specifications. To estimate the parameters in the model, maximum simulated likelihood optimization is applied because there are random parameters and no close-form solutions. Monte Carlo simulations are used to generate 500 draws for each random parameter (Train, 2009). In the model specifications, different sensitivity parameters (i.e., μ and τ) are used for the time and monetary outcomes. The in-vehicle crowding levels are categorical variables rather than continuous, so they do not require specific CPT parameters in the analysis. Two dummy variables are used to model different crowding levels. The value of crowding level 2 is one when the in-vehicle crowding is level 2 and zero otherwise. The same goes for in-vehicle crowding level 3. Crowding level 1 is regarded as the reference situation. The loss aversion parameter β is set to be identical across different attributes. On account of the fact that each respondent finished several SP scenarios in the experiment, the panel data process was performed in the estimation to ensure the preference homogeneity of one respondent over several SP scenarios (Train, 2009). Several nested structures among modes are examined using error component models. It turned out that there was a nested correlation between the metro and the bus.

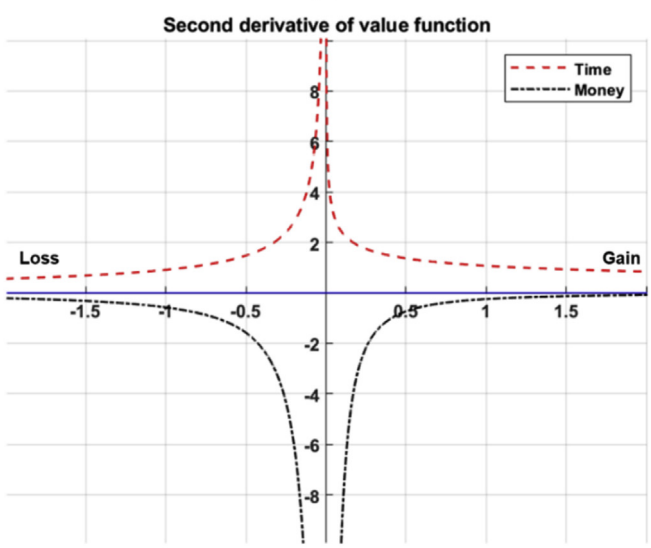
4. Results

4.1. Divergent evaluations regarding time and monetary outcomes

The analysis results are summarized in Table 3. The mean value of the sensitivity parameter (the key parameter of the curve) for monetary gains u_{money}, is 0.422 (< 1) and significantly different from 0 to 1 at the confidence level of 99% (i.e., $\alpha = 0.01$). The estimated standard deviation (SD) of the sensitivity parameter for monetary gains u_{money} is 0.167, which is also significant (as compared to 0) at the confidence level of 99% and implies the noticeable heterogeneity among different decision-makers. The estimated mean value of u_{money} is significantly less than 1.



(a)



(b)

Fig. 2. (a) Value functions and (b) second-order derivatives of value functions for time and monetary outcomes.

The result demonstrates that the subjective positive prospect shows diminishing sensitivity with increasing monetary gains, as illustrated in Fig. 2(a). In other words, the marginal utility of a large monetary gain is smaller than that of a small monetary gain. For the sensitivity parameter for monetary losses, τ_{money}, the estimated mean value is 0.542 (< 1) and significantly different from 0 to 1 ($\alpha = 0.01$). This result indicates that decision-makers also show decreasing sensitivity to monetary losses, as shown in Fig. 2(a). We further comparatively explored the evaluation principles regarding time. The estimated mean value of the sensitivity parameter for gains in time, u_{time}, is 1.651 (> 1) and significantly larger from 1 ($\alpha = 0.01$). The estimated SD of u_{time} is 0.632 and significantly different from 0 as well. As demonstrated in Fig. 2(a), this result about u_{time} illustrates that decision-makers show increasing sensitivity with increasing time gains. Namely, the marginal utility of large gains is perceived to be larger than the marginal utility of small gains in time, as displayed in Fig. 2(a). Meanwhile, the mean value of sensitivity parameter for time losses, τ_{time}, is 1.303 and significantly larger than one as well ($\alpha = 0.01$). This means that decision-makers also show an increasing sensitivity to losses in time (Fig. 2(a)). The SD of τ_{time} is estimated to be 0.325, which is significantly different from 0 ($\alpha = 0.01$) and hints the heterogeneity among decision-makers. These findings reveal that decision-makers exhibit increasing sensitivities to losses and gains in time, rather than the diminishing sensitivity that they show with respect to monetary outcomes.

To explicitly compared the sensitivities regarding gains and losses in time and monetary outcomes, Fig. 2(b) shows the second-order derivatives of the value functions. That for gains in time is always positive and indicates increasing marginal utility, while that for monetary gains stays negative and shows decreasing marginal utility. These findings explicitly demonstrate decision-makers' distinct (even opposite) evaluation sensitivities concerning gains in time and money. Similarly, divergent sensitivities can be observed for losses in time and money. The divergence is more remarkable for losses due to the loss aversion feature. Apparent asymmetric patterns can be observed in the sensitivities to gains and losses of time, as per Fig. 2(b), which could be attributed to the loss aversion in decision making and distinctions in the gradient of the changing sensitivities for losses and gains. Through this result, we demonstrate that the outcome from monetary studies cannot be applied to represent the evaluation process of time which has an increasing sensitivity (not diminishing sensitivity).

4.2. Individual-level analysis

The above section presents the results at the sample-average levels, which may cover the impacts of large variations of the parameters on obtained results and thus biases in behavioral interpretations (Sillano and Ortúzar, 2005; Train, 2009). For instance, some people have a sensitivity parameter to monetary outcomes of less than 1 (i.e., diminishing sensitivity), whilst others have a sensitivity parameter to monetary outcomes of larger than 1 (i.e., increasing sensitivity) and the sample-average sensitivity parameter (influenced by the collected sample) is smaller than 1. If so, the sample-average result indicates diminishing sensitivity. However, the conclusion may overturn in another sample with a large proportion of individuals with large sensitivity parameters (i.e., larger than 1). To eliminate such potential biases, we further utilize posterior estimations based on the Bayesian paradigm to obtain individual-level parameters instead of sample-average results (Sillano and Ortúzar, 2005; Train, 2009). As the individual-level results are conditioned on the choices by each individual rather than sample-average choices, they can reflect the real distributions of a parameter without predefined assumptions (Sarrias, 2020). The results are displayed in Fig. 3. As can be seen in Fig. 3, the parameter distributions do not resemble a certain distribution (e.g., a normal or log-normal distribution). Hence, potential biases may occur if a certain distribution is assumed in analysis. Fig. 3(a) and (b) show that the sensitivities to gains and losses in monetary outcomes indeed have noticeable variation among different individuals, which are in line with the estimated standard deviations of the parameters in Table 3. Irrespective of the large variations, the values of sensitivities to gains and losses (i.e., $\mu(money)$ and $\tau(money)$) in monetary outcomes are always less than 1 (i.e., diminishing sensitivity) as shown in Fig. 3(a) and (b). The results further corroborate the findings about the diminishing sensitivities to monetary outcomes that are discussed in last section, after eliminating the potential biases in sample-average analysis. The individual-specific results regarding sensitivities to gains and losses in time are presented in Fig. 3(c) and (d). Again, large variance can be observed. Nevertheless, 99.6% of individuals have a sensitivity parameter to time gains (i.e., $\mu(time)$) of larger than 1, and 99.2% individuals have a sensitivity parameter to time losses (i.e., $\tau(time)$) of larger than 1. The "outliers" (i.e., the sensitivity parameter to time outcomes is less than 1) are all very close to 1. The results further provide solid evidence for the declared

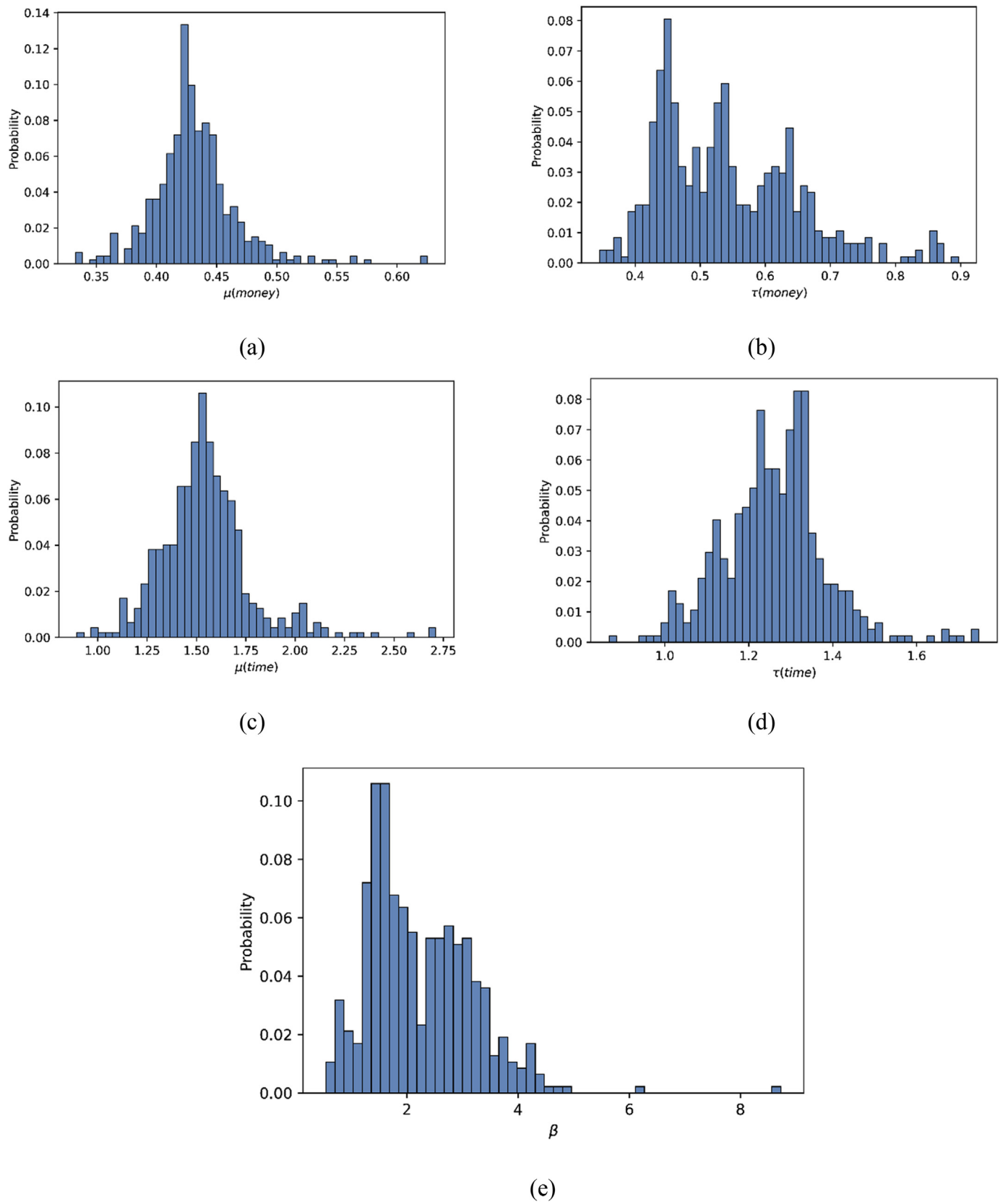


Fig. 3. Individual-level parameters based on Bayesian posterior estimation.

Table 4
Correlations among parameters in value functions for time and monetary outcomes.

			$\mu(time)$	$\mu(money)$	β	$\tau(time)$	$\tau(money)$
Spearman	$\mu(time)$	Correlation coefficient	1.000	0.084	0.192**	0.179**	0.048
		Sig. (2-tailed)		0.067	0.000	0.000	0.300
	$\mu(money)$	Correlation coefficient		1.000	0.316**	−0.258**	0.235**
		Sig. (2-tailed)		.	0.000	0.000	0.000
	β	Correlation coefficient			1.000	−0.016	0.503**
		Sig. (2-tailed)			.	0.730	0.000
	$\tau(time)$	Correlation coefficient				1.000	−0.004
		Sig. (2-tailed)					0.932
	$\tau(money)$	Correlation coefficient					1.000
		Sig. (2-tailed)					
Kendall	$\mu(time)$	Correlation coefficient	1.000	0.055	0.131**	0.123**	0.029
		Sig. (2-tailed)		0.072	0.000	0.000	0.348
	$\mu(money)$	Correlation coefficient		1.000	0.218**	−0.175**	0.156**
		Sig. (2-tailed)			0.000	0.000	0.000
	β	Correlation coefficient			1.000	−0.011	0.339**
		Sig. (2-tailed)				0.715	0.000
	$\tau(time)$	Correlation coefficient				1.000	−0.005
		Sig. (2-tailed)					0.879
	$\tau(money)$	Correlation coefficient					1.000
		Sig. (2-tailed)					

**: Correlation is significant at the 0.01 level (2-tailed). The sample size is 517.

findings of increasing sensitivities to time, excluding the potential biases of sample-average analysis. As for the loss aversion parameter in Fig. 3(e), the estimated results of 95% individuals are larger than 1, demonstrating and verifying the well-known loss aversion feature in CPT. The results of very few individuals (5%) do not fit the loss aversion feature and may be attributed to behavior habits and special evaluation principles of minor individuals.

Making the best of the individual-level results, we further explore the correlations among different behavioral aspects during the evaluation process. The results of Spearman and Kendall's rank correlation analysis are summarized in Table 4. The sensitivity to time gains $\mu(time)$ is positively related to the sensitivity to losses in time $\tau(time)$, which is statistically significant at the confidence level of 99% ($\alpha = 0.01$). This means that individuals who have larger increasing sensitivities to time gains, also show larger increasing sensitivities to time losses. This same positive relation is identified among the sensitivities to gain $\mu(money)$ and losses $\tau(money)$ in monetary outcomes. If an individual presents more pronounced diminishing sensitivities to monetary gains (i.e., larger risk aversion), he/she is expected to have more marked diminishing sensitivities to monetary losses (i.e., larger risk seeking) as well. The results show that people present behavior unitarity in the evaluation process for gains and losses of time (or cost) in terms of the magnitude of sensitivities. The results in Tversky and Kahneman (1992) reported the risk aversion for monetary gains and risk seeking for monetary losses but did not elucidate their potential relations at the individual levels. The results herein are pioneering work to reveal the underlying linkages between the sensitivities to gains and losses of time (or money) based on individual-level analysis. The results are plausible as people who more appreciate large time gains generally also show high aversion to large time losses. The loss aversion is found to be significantly and positively associated with sensitivities to gains in time and monetary outcome as well as losses in monetary outcomes. The hint of the results is that it is rather important to consider all components of CPT to reveal behavioral principles correctly. Many relevant studies (e.g., Abdellaoui and Kemel, 2014; Festjens et al., 2015) elicits the different aspects (e.g., loss aversion and sensitivities to gain or loss) separately or sequentially based on different experiments, due to complexity to elicit all aspects simultaneously. However, ignoring some components in the analysis may result in obscure biases in other results on account of the correlations. For instance, if the loss aversion of monetary outcomes is neglected, an individual's large loss aversion feature may be reflected as a large sensitivity to monetary loss or a small sensitivity to monetary gains due to their correlations in Table 4. If so, such results may cause misleading behavioral interpretations.

5. Discussion

Despite some challenges to practical applications of CPT, such as the reference identification issue and the questioning of its accuracy outside laboratory scenarios (List, 2004), it is widely agreed that theories like CPT derived from behavioral economics have made differences in economic analysis as well as other domains. However, many studies in other areas outsides of economics (e.g., transportation engineering) have directly referred to the results from monetary experiments without verifying the applicability of the results to different behavioral determinants and choice contexts. This study examines decision-makers' evaluating principles concerning uncertain time outcomes in contexts other than economics, based on a relaxed framework based on CPT and well-designed empirical experiments.

Under decision situations where time is a key behavioral determinant, decision-makers indeed exhibit some anomalies that are contradictory to findings in economics. The results demonstrate that the perception principles for time and monetary outcomes are divergent. Our empirical analysis reveals the same behavioral mechanisms in the evaluating of monetary outcomes as having been found in economic experiments. Tversky and Kahneman (1992) reported that the median values of the sensitivity parameters for both gains and losses were 0.88, based on monetary experiments. Here, our empirical results corroborate the diminishing sensitivities to monetary gains and losses (i.e., the value function parameters for monetary gains and losses are 0.422 and 0.542, respectively), but identify a more obvious diminishing sensitivity as compared to Tversky and Kahneman (1992). Nevertheless, the difference in absolute values is not relevant given the divergent choice contexts and datasets. The underlying mechanisms of diminishing sensitivity in evaluating monetary outcomes are explained by the concave pattern of psychological response to the magnitude of change in monetary outcomes (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

More importantly, it is observed that decision-makers show increasing sensitivity to gains or losses in time, which is contrary to the evaluation principles regarding monetary outcomes. The underlying behavioral mechanisms of the increasing sensitivity of time gains or losses may be the fact that time is not easy to be aggregated and utilized jointly as compared to money. For instance, if a decision-maker obtains a small time gain (e.g., merely10 min) every day in a week, the saved time is separated into pieces every day and is hard to be used effectively for finishing other new activities and thus for increasing subjective prospects

noticeably (Cantillo et al., 2006). In contrast, if the decision-maker can save 70 min in one day of a week (rather than 10 min every day), the large time saving is more likely to create large subjective prospects by allowing them to optimize their time allocation (e.g., adding a new activity) that produces a more subjective positive prospect. The same principle applies to time losses as well. When a decision-maker encounters small time losses (e.g., 5 min), the loss is not remarkable and can be easily resolved and acceptable in most cases. This results in more trivial negative prospects as small time loss generally will not influence the decision maker's schedules. However, if the decision-maker suffers a large time loss, the time loss is large and has to be compensated by reducing the time (or cancel) that they plan for other activities, which consequently leads to more negative prospects. The subjective prospect of obtaining gains in time comes from the ability to conduct other tasks by leveraging the gained time. This is also consistent with the Gestalt principles (Wertheimer and Riezler, 1944). Many social, medical, and perceptional dimensions share the phrase "the whole is greater than the sum of parts" that can be attributed to Aristotle (Cohen, 2016). We propose that this principle applies in particular to the perceived outcomes of gains and losses in time. The subjective prospect of a whole period of time (e.g., 1 h) can be fully utilized to carry out an activity continuously and create noticeable outcomes. However, in the case of six segmented 10-min time slices (in total 1 h), each separate time slice is not adequate to finish a task that can produce noticeable outcomes. Therefore, the perceived outcome of a continuous 1-h time is more pronounced than that of six segmented 10-min time slices. In another word, the subjective prospects from gains and losses in time have accumulated effects due to the fact that a period of time is required to fully finish a task in most situations. Another potential explanation for increasing sensitivity in evaluating time is Increasing-Returns Learning Curve (Habermeier, 1989). The rate of progression is slow at the beginning and gradually rises over time with attaining experience, knowledge, and being proficiency for finishing a task (Habermeier, 1989; Hoffmann et al., 2019). In the process of finishing a task, the progression in per-unit time increases over time. Thus, the marginal rate of positive prospect evaluated by decision-makers, from utilizing the gained time to finish other tasks, is increasing with the scale of gained time. These lead to the phenomenon that decision-makers show higher sensitivity to the large gains in time as compared to small gains in time.

Our analysis is based on a dataset of travel behavior, as the scenario in our experiments is an important component of shaping sustainable transport systems and a typical situation in which both time and monetary outcomes are vital determinants. The identified results provide strong empirical evidence that decision-makers indeed show distinct behavioral mechanisms in their perceptions of time, as compared to findings of the evaluation of monetary outcomes in economics. These findings do not argue against the exceptional work carried out in behavioral economics and quite different decision experiments (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), but alert us the fact that decision-makers' perceptions regarding uncertainty do not always follow the patterns found in money gambling experiments in economics in diverse domains. Researchers should be aware of the risk of directly transplanting the conclusions from economics into diverse domains where time is a vital determinant.

6. Conclusions

The concept of "time is money" has made transplanting behavioral principles about financial (or money-related) decision making to time-based decision making instinctively nature, especially in many transportation research. However, it is hardly doubted that if it is plausible to directly apply the rules from financial decision-making to time-related decision making. This study targets to address how decision-makers judge and evaluate uncertain time as compared to monetary outcomes, and reveals their essential differences. We base this research on a more general framework derived from CPT and non-laboratory experiments in which the scenarios are real-world settings and both time and monetary outcomes play crucial roles. The results reveal that decision-makers show substantially distinct evaluation principles for monetary and time outcomes. The findings are beyond the differences in the magnitude of sensitivities to monetary and time outcomes, but uncover the divergent evaluation principles for the two different attributes. Contrary to the decreasing sensitivities to gains and losses in monetary outcomes drawn from behavioral economics, increasing sensitivities to gains and losses in time are empirically obtained, which is contrary to the principles of monetary decision-making. The findings are corroborated by both sample-average and individual-level analyses. We demonstrate that the outcomes from monetary studies cannot be directly utilized to represent the evaluation process of time, at least in some choice contexts. Moreover, the individual-level results find that the magnitude of the sensitivity to time gains is positively linked to that of sensitivity to time loss. The same pattern goes for sensitivities to money gains and loss as well. Time is one of the most important attributes in transport-related studies. The new finding herein potentially renovates the paradigm of directly using findings about monetary outcomes from economics or behavior economics based on monetary experiments into transport study.

This study still has some future work to be addressed. Although we have tried our best to design the experiments where both time and monetary outcomes make difference in the decisions and collect comprehensive data, the current findings are derived from data about commuting travel behavior. It could be concluded that the evaluation principles about monetary outcomes cannot be directly used for the time-related decision in commuting travel choices. However, more behavioral data in other choice contexts, where time is a key determinant (e.g., health care, consumer behavior and insurance), should be used to further make solid conclusions about whether the findings are applicable in general (Zheng, 2021). This is challenging work as it requires sound experiments to collect reliable and enough data in different choice areas. Moreover, even though our sample is enough for analysis, this study can be always improved by more comprehensive data, which is a common dilemma in behavioral experiments. In addition, the scale effect of time (e.g., at the scales of hour, day, or year) and monetary outcomes (e.g., hundreds, thousands, or millions) may also have influences on the results (Abdellaoui and Kemel, 2014) and could be further controlled using more adequate datasets. Lastly but not at least, we did not explicitly distinguish different users (e.g., car and transit users) in the analysis as we focus on general results about differences in evaluation about monetary and time outcomes. However, we indeed observe substantial heterogeneity in CPT parameters among different users in Fig. 3. Beyond the findings in this study, it is an interesting future work to decipher the evaluations among different users for further explaining behavioral heterogeneity.

Declaration of competing interest

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper.

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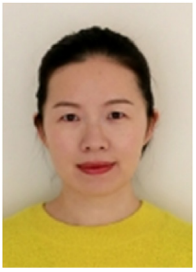

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