Commuter Departure Time Choice Behavior under Congestion Charge: Analysis Based on Cumulative Prospect Theory

Abstract:

An often-overlooked problem in the evaluation and prediction of congestion charge policies is commuters' bounded rationality. Although some studies have sought to account for this using cumulative prospect theory (CPT), the specific behavioral parameters that reflect travelers' decision-making process in response to congestion charge scenarios are based on assumptions and lack empirical evidence. This paper aims to provide empirical evidence to define the shape parameters in CPT—while accounting for systematic heterogeneity due to commuters' characteristics—in order to build more realistic behavioral models for car commuters' departure time choice behavior under congestion charge scenarios. A stated preference (SP) experiment with four time-based congestion charge scenarios is designed to obtain commuters' departure time choices when facing uncertain travel conditions. A genetic algorithm (GA) is used to estimate the CPT coefficients that reflect car commuters' cognitive biases under the congestion charge. The results suggest that commuters' departure time choice under the congestion charge policy is consistent with the assumption of CPT. We find evidence of risk-averse and risk-taking behavior, loss aversion, and large distortion in probability weighting, and individuals' personal and commuting characteristics had heterogeneous effects on CPT coefficients. The results shed light on travelers' behavioral responses to congestion charge schemes and provide an important empirical reference.

Keywords: Cumulative Prospect Theory, Congestion Charge, Departure Time Choice, Genetic Algorithm.

1. Introduction

Private cars are an essential part of everyday life. Along with their convenience, however, the negative externality caused by excess travel demand over road capacity is steadily rising. Traffic congestion is a pervasive problem in most megacities around the world and impacts the quality of life by increasing air and noise pollution (e.g., Alvanchi et al., 2019; Armah et al., 2010; Chin, 1996; Greenwood et al., 2007); decreasing the safety of streets (e.g., Albalate & Fageda, 2019; Noland & Quddus, 2005); and, more directly, increasing travel time variability and arrival time uncertainty (Li & Hensher, 2012). According to the “2016 China Major Urban Traffic Analysis Report” released by AutoNavi Software Co., one-third of Chinese urban commuting trips are threatened by traffic congestion. The peak hour congestion delay index (which is total travel time divided by free-flow travel time) for cities such as Jinan, Harbin, and Beijing exceeded 2.0, which means that commuters in these cities spend more than twice as much commuting time due to traffic congestion as they would otherwise. Of the 60 major cities in the report, 32 have a peak hour congestion delay index greater than 1.8.

Traffic congestion is caused by the mismatch between travel demand and road capacity. In economics, the standard approach to internalize negative externalities from daily traffic is congestion charging (Pigou, 1920). Empirical evidence and analytical models in transportation have found that congestion charging is able to affect commuters’ travel behavior, including decisions related to departure time choice, route choice, and mode choice (e.g., Saleh & Farrell, 2005; Ubbels & Verhoef, 2006; Yamamoto et al., 2000; Börjesson et al., 2012). Some large cities worldwide have adopted congestion charging to alleviate urban traffic congestion and obtained notable results, such as Singapore (1975), London (2003), and Stockholm (2007). In contrast, other cities have failed to implement congestion charging (e.g., Edinburgh), and still others hesitated to implement it for a long time (e.g., Beijing). One of the main concerns of decision-makers is uncertainty regarding how travelers will respond to a congestion charge policy.

From a microeconomic standpoint, traffic demand and supply change stochastically, and travelers seek to make choices that will reduce their disutility of traveling (Lu et al., 2019). Experimental evidence in behavioral economics shows that individuals are boundedly rational and affected by cognitive biases when making decisions under risk and uncertainty (Kahneman & Tversky, 1982). On a daily basis, commuters make decisions in a highly variable environment and cope with the uncertainty of traffic conditions. Thus, commuters are expected to make travel choices that largely deviate from the predictions of standard economic theory (McFadden, 1999) due to multiple factors; these include a lack of road traffic information, a limited cognitive span to process numerous stimuli present in the traffic environment, and the complex pattern of risk attitudes exhibited by individuals in experimental studies. A congestion charge scheme renders traffic decisions more complex, and thus commuters become more sensitive to the uncertainty and unreliability of traffic conditions (Li & Hensher, 2010). Therefore, conducting systematic studies before the implementation of congestion charging and developing predictive models of travelers’ responses that account for their bounded rationality is critical for designing and evaluating ex ante a policy’s impact.

The majority of research on travelers’ behavior under congestion charging uses modeling frameworks that are consistent with expected utility theory (EUT) (e.g., Brownstone & Small, 2005; Small et al., 2005; Arellana et al., 2012; Lizana et al., 2021). Some work investigates the impact of bounded rational behaviors in the preference for congestion charge schemes, but still within the EUT framework (Thorhauge et al., 2019, 2020). However, since the early 1950s, the EUT framework has proved to not be a close representation of people’s decision-making process in reality (Starmer, 2000). Several empirical studies have found that actual choice behaviors appear to be inconsistent with EUT—notably, violations of the independence axiom of EUT discovered by Allais (1953), the preference reversal phenomenon observed by Lindman (1971), and the framing effect identified by Tversky and Kahneman (1981).

Given the limitations of EUT, some researchers have expanded the traditional scheduling model by embedding features from prospect theory, such as the fourfold pattern of risk attitudes (Li et al., 2012) and reference dependence (Fujii & Kitamura, 2004). Other decision-making theories developed in the behavioral sciences have been gained attention in the transportation field and have been used with the goal of enhancing travel behavior models (see Li & Hensher, 2019, for a review). In particular, prospect theory (PT) (Kahneman & Tversky, 1979) and cumulative prospect theory (CPT) (Tversky & Kahneman, 1992) have attracted great interest due to their advantages in modeling decisions under risk and uncertainty. PT has been applied to model a variety of transportation behaviors, including departure time choices (Jou et al., 2008; Schwanen & Ettema, 2009; Tian et al., 2012). In our view, the application of PT is crucial in accounting for cognitive biases triggered by the more complex and uncertain traffic environment that results from implementing a congestion charging scheme. Some studies have emphasized the importance of considering travelers' behavioral biases when evaluating the effectiveness of a congestion charge policy by using PT elements in theoretical modeling (Pan & Zuo, 2014; Xu et al., 2011a), but the specific behavioral parameters that reflect travelers' decision-making process in response to congestion charge scenarios are based on assumptions and lack of empirical evidence.

The purpose of this paper is to provide empirical evidence to define the shape parameters in CPT, while accounting for systematic heterogeneity due to commuters' characteristics, to build more realistic behavioral models for car commuters' departure time choice behavior under congestion charge scenarios. We aim to address the following three questions: (1) How can we build a more realistic behavioral model for travelers' time choices under congestion charge scenarios based on CPT? (2) What are the most relevant shape parameters in CPT to model departure time choices under congestion charge scenarios? (3) How will these CPT parameters change among commuters with heterogeneous characteristics? To answer these questions, the shape parameters in CPT functions are fitted using mixed logit models and data collected from a stated preference (SP) experiment. The parameter search was performed using a genetic algorithm (GA) to optimize a highly non-concave likelihood function.

The remainder of the paper is organized as follows. Section 2 reviews the literature on travelers' behavioral responses to a congestion charge and the application of PT in transportation studies. Section 3 introduces the model specification and estimation procedure. Section 4 describes the survey design, data collection, and descriptive statistics. Section 5 reports the estimated results. Section 6 concludes with a further discussion of the results and policy implications.

2. Literature review

2.1 Behavioral responses to a congestion charge

The idea of congestion charges can be traced back to the Pigouvian tax proposed by Pigou (1920). He argued for a tax on congestion to internalize the negative externality caused by travelers. By levying a specific charge for each road section based on its marginal cost, the user's equilibrium travel pattern can achieve the social optimum (Beckmann et al., 1956). Road traffic in cities that implemented congestion charge schemes provides empirical evidence of the effectiveness of this policy (Börjesson & Kristoffersson, 2018; Lehe, 2019). Hence, a number of studies support the use of congestion charges, and abundant research has been conducted to explore travelers' short-term and long-term behavioral responses to different congestion charge schemes (see Li & Hensher, 2012, for a review).

Looking at the methodology, previous work on congestion charging can be divided into three categories. The first category explores the effectiveness of congestion charge schemes for managing traffic flows using theoretical models and numerical examples. For example, Zhu et al. (2015) compared social welfare before and after imposing congestion charges on taxis and developed a bilevel programming model that solves the network equilibrium in the lower level and maximizes social welfare in the upper level. Knockaert et al. (2016) used a traditional bottleneck model and explored measures to improve the efficiency of a coarse charge by differentiating across heterogeneous travelers. De Palma et al. (2018) estimated the performance of a congestion charge in a parallel road and public transport network under uncertainty and compared its performance with a tradable credit scheme. They found that when the congestion charge can be adapted from day to day, it can be equivalent to a quantity instrument (i.e., tradable credits)—but when the congestion charge cannot be adaptive, it performs worse.

The second category of studies uses simulation-based approaches to evaluate and predict the practical impact of congestion charge schemes at city level. For example, Cipriani et al. (2019) designed and tested different zone-based pricing policies for Rome while accounting for equity. Zhang et al. (2019) proposed and tested a dynamic traffic assignment system that could precisely predict traffic conditions when applying a congestion charge in a real network. In their system, travelers made route choices based on discrete choice models, and toll revenue was the optimization object. He et al. (2021) evaluated a congestion charge plan using a multi-agent simulation model for New York City that can capture traffic dynamics and the substitution effects of multiple modes in different segments of the city. They found that the number of trip reductions evaluated by their model was more than the government proposal under the same charging scheme, even though the annual revenues collected were similar.

Empirical work has conducted SP experiments to study consumers' preference for congestion charge policies that are not currently in place. Compared with the above categories, this stream of research helps us better understand how individuals respond to congestion charge schemes from a behavioral perspective. The congestion charge mechanism analyzed mainly includes charges by transit times, charges by distance, flat time charges, and differentiated time charges (Siddique & Choudhury, 2017; Arellana et al., 2012; Tillema et al., 2010a, b; Ubbels et al., 2008). Most studies have shown that a dynamic charge that changes over time has the best effect on alleviating traffic congestion (Ubbels & Verhoef, 2006). In terms of the group charged, papers have mostly focused on car commuters (Andani et al., 2021; Arellana et al., 2012). In terms of charging area, a congestion charge scheme for the whole road network is considered to have the greatest impact (Siddique & Choudhury, 2017). Most studies have been conducted in European countries (such as the Netherlands, Greece, Denmark, the United Kingdom, and Sweden); a few countries in Asia (such as Singapore); Chile; and Australia, and travelers' responses to congestion charge policies are likely to differ depending on culture and political circumstances. Congestion charge studies that focus on Chinese contexts and Chinese travelers are still limited.

Some studies on behavioral departure time models have applied descriptive behavioral theories that consider travelers' bounded rationality in travel behavior research. For example, Koster and Verhoef (2010) took into account that travelers could treat the probabilities of arrivals in a nonlinear way, following rank-dependent utility theory. Koster et al. (2015) modeled commuters' scheduling choices with the assumption that individuals showed limited memory capacity, retrieval constraints, and anchoring, which was also termed "memory-based adaptive expectations." De Borger and Fosgerau (2008) developed a reference-dependent choice model to explain individuals' valuation of travel time within the framework of prospect theory. Using data from a large-scale choice experiment, they found that models that account for reference dependence had a better fit than their counterparts. Their parameter estimates also supported the presence of loss aversion. Hjorth and Fosgerau (2012) further extended the above research by reformulating the model proposed by De Borger and Fosgerau (2008) in a way that separates the value of travel time from value functions. They also identified and tested all model parameters using data from a new SP experiment in Norway.

In congestion charge contexts, Lindsey (2011) developed a model of reference-dependent preferences to analyze travelers' aversion to price variation based on the theory developed by Köszegi and Rabin (2006). He divided travelers' utility into two elements: an intrinsic utility and a gain-loss utility. Xu et al. (2011a) proposed a user equilibrium model with endogenous reference points based on PT and developed an optimal pricing model that could capture travelers' route choices in response to pricing signals under risk. They found that commuter decisions under congestion charge scenarios are affected by subjective factors, such as risk preferences. They argue that when commuters' bounded rational responses are considered in the design stage of a congestion charge policy, it is more likely to achieve the expected outcome. Pan and Zuo (2014) developed an improved stochastic user equilibrium model based on prospect theory. They proposed the concept of perceived prospect and assumed that the prospect of each route was constituted by a fixed term and a random one. Then, they analyzed optimal congestion pricing to manage users' route choices.

As suggested by theoretical work, when evaluating a congestion charge scheme with a differentiated toll—which could create more uncertainty for drivers (Li & Hensher, 2010)—it is crucial to understand travelers' bounded behavioral rules. However, the empirical evidence is still limited. Zou et al. (2016) provided empirical insight into travelers' bounded rational behavior under a time-flat congestion charge policy. The authors developed an agent-based choice model for travel mode and departure time in which travelers' searching and decision process is represented by a production rule based on fuzzy set theory. The model is validated using data collected from an online SP survey in Beijing in which respondents dynamically switched their choices based on the latest scenario after the last adjustment. This work considers travelers' bounded rationality when searching for the traffic equilibrium, but it does not consider the uncertainty or behavioral biases that travelers would face when making such choices. Other work has investigated the impact of bounded rational behavior on travelers' departure time choices in their preference for congestion charge schemes, such as habit-driven behavior or the effect of intention, but still within the EUT framework (Thorhauge et al., 2019, 2020).

Table 1 Key characteristics of reviewed studies on congestion charge

Study	Methodology	Whether behavioral biases for travel choices are considered	Whether behavioral parameters are estimated	Type of congestion charge	Behavioral choices	Country/City
Zhu et al., 2015	Modeling and numerical example	No	No	Link toll	Mode choice, route choice	None
Knockaert et al., 2016	Modeling and numerical example	No	No	Coarse charge	Time choice	None
de Palma et al., 2018	Modeling and numerical example	No	No	Tolls versus tokens	Number of trips	None
Cipriani et al., 2019	Simulation	No	No	Zone-based toll	Mode choice	Rome
Zhang et al., 2019	Simulation	No	No	Real-time proactive charging system	Route choice	Texas
He et al., 2021	Simulation	No	No	Time- and link-based toll	Mode choice	New York
Ubbels & Verhoef, 2006	SP experiment	No	No	Fixed, distance-based, and time-based charge	Mode choice and number of trips	Netherlands
Siddique & Choudhury, 2017	SP experiment	No	No	Trip duration and purpose-based toll	Mode choice	Dhaka

Andani et al., 2021	SP experiment	No	No	Link toll	Residential location, route, and mode choices	Indonesia
Arellana et al., 2012	Three-step RP–SP–attitudinal survey	No	No	Time-based charge	Mode choice and time choice	Santiago
Lizana et al. 2021	Forecasting RP-SP	No	No	Time-based charge	Mode choice and time choice	Santiago
Lindsey, 2011	Modeling and numerical example	Yes	No	State-dependent toll	Whether to use a congestible facility	None
Xu et al, 2011a	Modeling and numerical example	Yes	No	Link toll	Route choice	None
Pan & Zuo, 2014	Modeling and numerical example	Yes	No	Link toll	Route choice	None
Zou et al., 2016	SP experiment	Yes	No	Fixed toll	Mode, time, route, and number of trips change	Beijing
Thorhauge et al., 2019	SP experiment	Yes	No	Time-based toll	Time choice	Copenhagen
Thorhauge et al., 2020	SP experiment	Yes	No	Time-based toll	Time choice	Copenhagen

2.2 Applications of prospect theory in travel behavior modeling

Prospect theory is one of the most common frameworks used to study decision-making under risk and uncertainty (Kahneman & Tversky, 1979). Compared with EUT, PT is based on a new specification of the deterministic component of the utility function, which makes it more advantageous to describe travelers' decision-making under uncertainty (Avineri & Ben-Elia, 2015). PT models are typically estimated as random utility models in which the deterministic component of the utility function accounts for both the S-shaped value function and the probability weighting function. The CPT proposed by Tversky and Kahneman (1992) further generalizes PT by using a rank-dependent weighting function. Although the difference between PT and CPT is not significant, the application of CPT is expected to provide a more scientific and realistic approach to modeling commuters' choice behavior (Yang & Liu, 2018).

The systematic utility structure in PT and CPT can capture various kinds of behaviors that fail to be reflected in EUT, including:

- Reference dependence: In the EUT model, preferences do not depend on current assets but on states of wealth, which is a great simplification of the actual decision process (Tversky & Kahneman, 1991). To generalize the EUT model, a value function in which the outcomes are defined as gains and losses relative to a reference point is introduced in PT and CPT models (Kahneman & Tversky, 1979, 1984; Tversky & Kahneman, 1991).
- Loss aversion: Although EUT doesn't distinguish between different evaluations of gains and losses, the asymmetry between gains and losses has been observed in a variety of field data (Tversky & Kahneman, 1991). Hence, the principle that losses loom larger than corresponding gains has been applied in PT and CPT by using a steeper

value function for losses than for gains (Kahneman & Tversky, 1984; Tversky & Kahneman, 1992).

- Framing effect: The assumption of description invariance is implicit in EUT, which means that equivalent formulations of a choice problem should induce the same preference order (Arrow, 1982). However, widespread evidence has shown that variations in the framing of prospects can dramatically impact preference and choice (Tversky & Kahneman, 1981, 1986). As a result, PT embodied such violations of EUT based on the psychological principles of evaluation (Tversky & Kahneman, 1986).
- Risk seeking: Given the assumption of EUT, individuals' risk preference should be independent of the probability of losses and gains, which has been found to be inconsistent with empirical data (Starmer, 2000). Tversky and Kahneman (1992) proposed a distinctive fourfold pattern of risk attitudes in CPT, which considered both risk aversion and risk seeking. The pattern shows risk aversion for gains and risk seeking for losses of high probability, and risk seeking for gains and risk aversion for losses of low probability.
- Nonlinear probability weighting: According to EUT, the utility of a risky outcome is linear in its objective probability, and individuals' preferences should follow the independence axiom. However, the empirical evidence of Allais (1953) challenged this principle by demonstrating that a reduction of probabilities from 1.00 to 0.99 has more impact on preference and choice than from 0.11 to 0.10. This phenomenon was explained by Kahneman and Tversky (1979) as the certainty effect and is captured in the original PT. They introduced a nonlinear weighting function, which overweights small probabilities and underweights moderate and high probabilities. Considering that the separable decision weights cannot always satisfy stochastic dominance and be

extended to prospects with a large number of outcomes (Tversky & Kahneman, 1992), they further used a cumulative functional representation of probability in CPT.

A number of recent studies on travel behavior use PT or CPT (see Li & Hensher, 2011, for a review). Most of these studies highlight the advantages of PT and CPT in describing commuters' decision-making compared with EUT (e.g., Fujii & Kitamura, 2004; Huang, Burris, & Shaw, 2017; Yang & Jiang, 2014). In an attempt to challenge the premises of EUT in travel behavior models, Fujii and Kitamura (2004) hypothesized that (1) car commuters consider uncertain travel time as a time interval; (2) car commuters choose their departure time based on the time interval and use their preferred early departure time and preferred departure time as reference points. Their empirical data verified their hypotheses and refuted previous studies based on EUT that argue that travel time conforms to a subjective continuous distribution. The authors concluded that EUT is not suitable for describing car commuters' departure time choice behavior.

2.2.1 Exogenous versus endogenous estimation

Many early studies based on PT or CPT fix the shape parameters of the value and weighting functions using the estimates obtained by Tversky and Kahneman (1992) from financial experiments (Avineri, 2004; Avineri & Prashker, 2005; Gao et al., 2010; Tian et al., 2012). As Li and Hensher (2011) demonstrate, however, biased or even incorrect findings and conclusions may occur because PT parameters are highly context-dependent. For instance, Yang and Liu (2018) theoretically proved that different subjective gain-loss ratios highly influence the optimal solution of commuters' departure time choice. While some studies estimate the parameters of PT models using choice data, a subset of the parameters is always fixed arbitrarily, mainly for identification purposes. Using experimental data on route choice behavior, Xu et al. (2011b) estimate the risk preference parameter and loss aversion parameter in the value function of PT but fix the parameter in the weighting function to 0.74 based on results of previous studies. Using both revealed preference household travel survey data and empirically observed travel time data, Ghader et al. (2019) study travel mode behavior based on CPT. Since they model all outcomes as losses, the loss aversion parameter has been fixed to one and other parameters in CPT have been estimated using a logit model.

With increasing awareness of the particularity of travel behaviors in different contexts, few studies jointly estimate all CPT parameters based on their specific travel context. For example, Schwanen and Ettema (2009) explore the CPT parameters of employed parents' choice regarding collecting their child(ren) from the nursery by themselves at the end of the workday or letting their partner do it. They designed an SP experiment and set three reference points: (1) the time when most parents pick up children, (2) the time specified by the nursery, and (3) the nursery's closing time. They used a binary logit model and a GA to estimate the CPT parameters. Results show that the value function curve has an inverse "S" shape: slightly convex for gains (arrive early or on time) and concave for losses (arrive late). The results suggest that parents exhibit risk seeking behavior for gains and risk aversion for losses. Though this is opposite to Tversky and Kahneman's (1992) results, they consider their results plausible because arriving late for collecting children should become more objectionable as lateness increases. Also, individual characteristics, such as gender and share of collection duties, have significant effects on the parameters.

The use of more advanced discrete choice model techniques has also enhanced the development of PT models. Wen et al. (2019) estimate passengers' loss aversion, diminishing sensitivity, and probability-weighting coefficients for alternative travel arrangements when facing flight delays. They use an SP experiment to obtain empirical data on passengers' choices to retain the booked flight or the next available flight on the same airline, or to transfer to another airline. A mixed logit model combined with CPT is used to estimate passengers' preferences for each alternative. The results show that air travelers with different travel distances have different sensitivity to delay times.

2.2.2 Multiple reference points

The choice of reference points is a critical component of PT models, since they define whether time outcomes are framed as gains or losses in utility. Seminal work used PT defined a single reference point to model monetary decisions, but travel behavior models have extended this definition to allow for multiple reference points. Jou and Chen (2013) estimate CPT parameters to reflect the risk attitudes of freeway drivers in route choices. They use three reference points: free-flow travel time, average travel time, and longest travel time. CPT parameters are estimated using data from an SP survey and a logit model. Consistent with CPT, drivers were risk averse in the gain domain and risk seeking in the loss domain. Drivers exhibited loss aversion for travel time losses and distortion in probability weighting, especially in the loss domain. Moreover, drivers who usually encounter traffic congestion show higher sensitivity to gains. In another study, Jou et al. (2008) set three reference points: the earliest arrival time, the expected arrival time, and the work starting time. They divided the value function into two gain parts and two loss parts, then estimated the risk preference parameter and loss aversion parameter in PT using empirical data. Senbil and Kitamura (2004a) proposed two reference points for work activity: the earliest tolerable arrival time and the latest tolerable arrival time. A key assumption is that commuters perceive losses when arriving before the earliest acceptable arrival time and after the latest tolerable arrival time.

2.2 Research gaps and contribution of the present study

Overall, the evidence from previous studies suggests that travelers' preferences vary among different travel decisions in various travel contexts. The choice of reference points, the construction of travelers' utility functions, and the sociodemographic and traveling characteristics of samples may all lead to different estimates of CPT parameters. Evidence provided by theoretical work has shown that when assuming that travelers' utility function follows CPT, the traffic equilibrium condition can be far from a context that uses the EUT assumption (Pan & Zuo, 2014; Xu et al., 2011a). However, the numerical results of the above studies are directly applied to behavioral parameters estimated by previous studies in quite different contexts from ours, and thus might not correctly reflect commuters' departure time choice mechanisms under congestion charge scenarios. As a result, evaluation of the policy's effectiveness may be biased. Therefore, it is necessary to conduct more empirical studies to further examine travelers' behavioral responses to the congestion charge and calibrate CPT parameters in each context.

This study contributes to filling these gaps in three ways. First, it presents new evidence on congestion charging using an SP experiment that includes CPT-based scenarios and a time choice model with CPT. Second, it expands previous PT/CPT studies by empirically examining specific CPT parameters and Beijing commuters' value of time in congestion charge scenarios. In addition, the effects of commuters' heterogeneous characteristics on CPT parameters have been analyzed.

3. Model specification and estimation procedure

3.1 Cumulative prospect theory

3.1.1 Reference point

Following Senbil and Kitamura (2004a) and Jou et al. (2008), in this study we set up three reference points for commuters: Earliest Acceptable Arrival Time (TE), Work Starting Time (TW), and Latest Acceptable Arrival Time (TL). An important difference from previous studies that consider only the time change (e.g., Jou et al., 2008; Schwanen & Ettema, 2009) is that we consider both temporal and monetary change relative to reference points, and hence CPT is applied to gains and losses in multi-attribute utility.

3.1.2 Observable component of the utility function

Let's define v_s and t_s as the observable components of commuters' utility function and the reference time in the scenario $s = \{r, c\}$; and β_τ and β_{VOT} as commuters' travel cost coefficient and commuters' value of time, respectively. It should be noted that v_s is linear in the parameters utility function that does not account for loss aversion, reference dependence, or distortion in probability weighting, as in PT models.

The reference scenario $(s = r)$ corresponds to a pre-congestion charge situation in which net utility v_r is composed of a free toll with no charge $(\tau = 0)$ and the benefit attained by arriving at the reference arrival time (t_r). In the post-congestion charge situation $(s = c)$, each commuter needs to pay a congestion charge τ and the benefit of arriving at the actual arrival time (t_c) is based on their departure time choices under congestion charge scenarios, in which the actual arrival time is their arrival time in the congestion charge. Hence, when changing from the pre-congestion charge situation to the post-congestion charge situation, travelers will suffer a monetary loss from the congestion charge and will perceive a benefit or loss depending on the deviation $\Delta T = t_c - t_r$ between the actual and reference arrival time. Thus, the deviation of observable utilities Δv between the post-congestion charge situation v_c and the reference situation v_r is given by

$$\Delta v = v_c - v_r = \beta_\tau\big((\beta_{VOT} t_c) - \tau\big) - \beta_\tau(\beta_{VOT} t_r) = \beta_\tau(\beta_{VOT}(t_c - t_r) - \tau) = \beta_\tau(\beta_{VOT}\Delta T - \tau) \qquad (1)$$

Note that the weight between β_{VOT} and ΔT is by construction in monetary units, and the parameter β_τ multiplies the entire remainder of the function, which means that we seek to obtain direct estimates of β_{VOT} through working in the willingness-to-pay space (Train &

Weeks, 2005). Here, several important assumptions have been used to formulate Eq. (1): First, commuters' Value-of-Time (VOT) is assumed to be linear in travel time; second, income effects are assumed away by using the willingness-to-pay space. These assumptions can be empirically tested using the data. However, since this study focuses on the estimation of CPT parameters, we chose not to test these effects, which could be explored in future studies.

There are three possible arrival times after implementing the congestion charge: on-time, earlier, and later arrivals; however, in this study we focus on the late and on-time arrival cases (i.e., $t_c \geq t_r$). This is based on the following considerations. (1) The results of previous empirical studies show that offering three or more possibilities would confuse respondents in the test phase and lead to lower response rates (Schwanen and Ettema, 2009). (2) Although including both early arrival and late arrival is the most typical choice in scheduling models (e.g., Adnan, 2010; Arnott et al., 1990; Cantelmo & Viti, 2019; Feil et al., 2009), focusing only on the late one or the early one is still correct, because it depends on the context under study (e.g., Arnott & Kraus, 1993, 1995; Kraus & Yoshida, 2002; Kraus, 2003; van den Berg & Verhoef, 2014). These theoretical studies usually ignore the late arrival of commuters, under the assumption that the shadow value of time late is infinite, since commuters will incur a heavy penalty for arriving late. However, in this empirical study, late arrival is an important situation that will lead to additional time costs for commuters and affect their departure time choices. (3) We followed the setup of Senbil and Kitamura (2004), which considers only three parts of the decision frame rather than the whole picture of commuters' departure time decision frame. Two are loss regions, which are defined as when commuters arrive later than the work starting time or the acceptable latest arrival time. Another is a gain region, which is defined as when commuters arrive after the acceptable earliest arrival time. The CPT parameters are thus estimated for these three alternative decision frames.

Finally, we also note that Chinese workers live in a culture that promotes overtime work, which means that they cannot go home earlier if they start working earlier. This causes workers to have no incentive to arrive early, and instead prefer to arrive at work right on time. At the same time, workers who choose to arrive early may not perceive the loss as we assume, since arriving early can help them establish a good image in the mind of their supervisor. We are unclear whether early arrival is a gain or loss for workers. Thus, we treat early arrival and on-time arrival indifference in our work—and given that the value of schedule delay late is always more negative than the value of early arrival (i.e., Small, 1982; Arellana et al., 2012), we believe that the penalty of late arrival is important and sufficient to cause commuters to choose their departure time. Hence, in this study we assume that commuters will incur additional time costs for late arrival and no time cost for arriving on time, without designing detailed gains for arriving early.

It is important to note that the difference between the actual and the reference arrival time (ΔT) is a quantity that is assumed to be known and a result of the information presented to participants across the decision scenarios. For on-time arrivals, the actual arrival time t_c is assumed to be equal to the reference arrival time t_r, and thus the deviation ΔT is zero by construction (Eq. 1). For late arrivals, a predefined amount of lateness is assigned to ΔT and it is allowed to vary depending on the reference point. As a consequence, the outcome of on-time arrivals only depends on the congestion charge commuters would have to pay.

For late arrivals (i.e., arrivals after the reference arrival time), it is plausible to assume that commuters will perceive a loss when arriving late if TW or TL are used as reference points. This loss can be interpreted as the value of time loss for the schedule delay that corresponds to the reference time. In contrast, when using TE as the reference point, late arrival will be perceived as a gain. This is because arriving before TE will be too early and will be a loss for commuters who value staying at home more than waiting at the workplace for that amount of time. Conversely, arriving after TE will be perceived as a gain (Jou et al., 2008). Therefore, ΔT will be negative with respect to the reference arrival times TW or TL and positive with respect to TE. Hence, the absolute value of ΔT becomes equals to

$$|\Delta T| = \begin{cases} t_r - t_c, \ if \ t_r = TW \ or \ t_r = TL \\ t_c - t_r, \ if \ t_r = TE \end{cases} \tag{2}$$

3.1.3 CPT value function

According to the CPT, the value function is

$$V(x) = \begin{cases} x^{\alpha}, & \mathrm{x} \geq 0 \\ -\lambda x^{\beta}, & x < 0 \end{cases}$$

where x represents the deviation between an outcome value—e.g., monetary charge, travel time, or the utility of an alternative (Ghader et al., 2019)—and the reference point. Our model equates x with $\Delta v = v_c - v_r$, which is the difference between the observable utilities with and without a congestion charge. Thus, the CPT value function can be expressed as

$$V(v_r, v_c) = \begin{cases} (v_c - v_r)^{\alpha}, & v_c \geq v_r \\ -\lambda(v_r - v_c)^{\beta}, & v_c < v_r \end{cases} \tag{3}$$

When the post-congestion charge situation is better than the reference situation, commuters would perceive a gain ($v_c - v_r \geq 0$); when it is worse, commuters would perceive a loss ($v_c - v_r < 0$). If ($v_c - v_r$) is replaced by Eq. (1), the value function can be expressed in terms of T and τ as shown below:

$$V(T, \tau) = \begin{cases} [\beta_{\tau}(\beta_{VOT}\Delta T - \tau)]^{\alpha}, & v_c - v_r \geq 0 \\ -\lambda\{-[\beta_{\tau}(\beta_{VOT}\Delta T - \tau)]\}^{\beta}, & v_c - v_r < 0 \end{cases} \tag{4}$$

where α and β (0<α, β<1) are risk preference parameters and represent the corresponding degree of risk aversion or risk-seeking behavior in the gain and loss domains. λ is the loss-aversion coefficient, which is expected to be greater than 1 ($\lambda > 1$). Except for the case in which the reference point is set as the Acceptable Earliest Arrive Time (TE), we only consider the loss domain of the value function ($\Delta T \leq 0, \tau \geq 0$). In addition, to avoid overfitting the model, we set α=β, which means that a single parameter is fitted for the exponents of both the gain and loss domains of the value function (Tversky & Kahneman, 1992; Harrison & Rutström, 2008; Schwanen & Ettema, 2009).

To further explore commuters' heterogeneities of behavior under uncertainty, we also incorporated the interactions of each CPT parameter with social economics variables in the value function and the weighting function. The covariates interact with the parameters according to the following specification:

$$\alpha = \bar{\alpha} * (1 + \Delta\boldsymbol{\alpha} * \boldsymbol{X_i})$$

$$\lambda = \bar{\lambda} * (1 + \Delta\boldsymbol{\lambda} * \boldsymbol{X_i})$$

$$\gamma = \bar{\gamma} * (1 + \Delta\boldsymbol{\gamma} * \boldsymbol{X_i})$$

where $\bar{\alpha}$, $\bar{\lambda}$, $\bar{\gamma}$ are the means of parameters α, λ, γ. $\boldsymbol{X_i}$ is a vector of covariates, and $\Delta\boldsymbol{\alpha}$, $\Delta\boldsymbol{\lambda}$, $\Delta\boldsymbol{\gamma}$ are parameter vectors associated with characteristics X_i, which captures the heterogeneous impact of covariates on each CPT coefficient.

3.1.4 Probability-weighting function

In the original PT, the weighting function is

$$W(p)^{+} = \frac{p^{\gamma^{+}}}{\left(p^{\gamma^{+}} + (1-p)^{\gamma^{+}}\right)^{1/\gamma^{+}}} \text{ , } W(p)^{-} = \frac{p^{\gamma^{-}}}{\left(p^{\gamma^{-}} + (1-p)^{\gamma^{-}}\right)^{1/\gamma^{-}}} \tag{5}$$

where W^{+} and W^{-} indicate the decision weights in the gains and losses domains, respectively. In our application, p is defined as the probability of arriving on time or late, and thus γ^{+} and γ^{-} are estimable parameters that moderate the level of distortion in the probability judgment regarding on-time arrival. A common parameter is estimated for both gain and loss domains ($\gamma^{+} = \gamma^{-} = \gamma$) to avoid overfitting (Harrison and Rutström, 2008;

Harrison and Rutström, 2009; Schwanen and Ettema, 2009; Ghader et al., 2019). Also, following the setting of Schwanen and Ettema (2009), we assume that p is departure time-specific. This is to say that the probability of arriving on time or late will change along with the user's departure time choices. The earlier the user chooses to depart, the higher the probability they will arrive on time.

According to Tversky and Kahneman (1992), to define the cumulative weighting function, the outcome of each position should be arranged in increasing order. Then, decision weight π_i associated with an outcome i is the difference between the weight of outcomes that are strictly better/worse than the outcome i and outcomes that are at least as good/bad as outcome i. Then, the cumulative decision weight of outcome i can be deemed to be its marginal contribution. In this study, commuters only face two outcomes: arrive on time Δv^o or arrive late Δv^l. There are three types of situations:

1. When $\Delta v^o < 0 < \Delta v^l$, which occurs when using TE as the reference point,

$$\pi_O = W(p_O)^-,\ \pi_L = W(p_L)^+ \tag{6}$$

2. When $\Delta v^o < \Delta v^l \leq 0$ or $\Delta v^o > \Delta v^l \geq 0$,

$$\pi_O = W(p_O)^{+/-},\ \pi_L = 1 - W(p_O)^{+/-} \tag{7}$$

3. When $\Delta v^l < \Delta v^o \leq 0$ or $\Delta v^l > \Delta v^o \geq 0$,

$$\pi_L = W(p_L)^{+/-},\ \pi_O = 1 - W(p_L)^{+/-} \tag{8}$$

3.1.5 The prospect

In CPT, commuters' utility attained by some outcome (e.g., arriving late) is given by the cumulative prospect value (CPV) function. Similar to the expected utility function, $EU = \sum_I p_i u(x_i)$—i.e., the cumulative prospect value is the product of the subjective value (calculated by the value function) and the associated probability (calculated by the weighting function), which in this case is

$$CPV(T,\tau,p) = \pi_O V(\Delta v^o) + \pi_L V(\Delta v^l) \tag{9}$$

Since we didn't include early arrival in the experimental setup, only three parts of the decision frames have been considered, rather than the whole picture of commuters' departure time decision frame (Senbil & Kitamuta, 2004). Two are loss regions, which are defined as when commuters arrive later than the working starting time (TW) or the acceptable latest arrival time (TL). Another is the gain region, which is defined as when commuters arrive after the acceptable earliest arrival time (TE). CPT parameters are thus estimated for these three alternative decision frames.

3.2 Mixed logit model

The logit formulation has been widely used in studies that estimate travelers' behavioral choices based on PT/CPT (Ghader et al., 2019; Schwanen & Ettema, 2009; Wen et al., 2019). Given that respondents were asked a series of hypothetical choice questions on the SP survey, a mixed logit model was used to account for panel effects (Train, 2009). We specified the utility of alternative departure time j for individual n in scenario t as

$$CPU_{jnt} = CPV_{jnt} + \mu_{jn} + \varepsilon_{jnt} \tag{10}$$

where CPU_{jnt} is the CPV for individual n associated with alternative j in scenario t. μ_{jn} follows a normal distribution across individuals but is constant across all scenarios answered by the same respondent, which accounts for the panel correlation; ε_{jnt} is a random term with iid extreme value distribution.

Let us consider a sequence of alternatives, one for each scenario, $\mathbf{j} = \{j_1, \dots, j_T\}$. Once CPV_{jnt} is calculated for all of the alternatives using CPT, conditional on μ_{jn}, the probability that individual n makes this sequence of choices is the product of logit formulas (Train, 2009):

$$\boldsymbol{L}_{\boldsymbol{nj}}(\mu) = \prod_{t=1}^{T}[\frac{e^{(CPV_{jnt}+\mu_{jn})}}{\sum_j e^{(CPV_{jnt}+\mu_{jn})}}] \tag{11}$$

The unconditional probability is the integral of $\mathbf{L}_{\mathbf{nj}}(\mu)$ over the distribution of the random term μ:

$$P_{\boldsymbol{nj}} = \int \boldsymbol{L}_{\boldsymbol{nj}}(\mu) g(\mu|\Omega) d\mu \tag{12}$$

where $g(\mu|\Omega)$ is the probability density function of μ with a vector of parameters Ω.

Since the integral in Eq. (13) does not have a closed form, this is approximated by simulation. The simulated log-likelihood (SLL) function is given by

$$SLL(\Omega) = \sum_{n=1}^{N} ln\, [\frac{1}{R}\sum_{r=1}^{R} \boldsymbol{L}_{\boldsymbol{nj}}(\mu_{r,jn})] \tag{13}$$

where $\mu_{r,jn}$ is the r^{th} draw from $g(\mu|\Omega)$ for each alternative departure time j and individual n. R is the total number of draws.

To ease optimization of the highly non-convex likelihood function that arises due to the functional form of the CPT utility function, a GA is used in this study. A distinctive feature of this method is that it is gradient free and has been successfully applied in prior work using CPT to model departure time choices (Schwanen and Ettema, 2009). Details of the estimation procedure are provided in Appendix A. However, it is important to note here that when using a GA, solutions vary in different estimation runs. The estimation process must be repeated several times and estimated parameters of the best solutions in each run averaged. In this study, for the basic ML model, we repeated the estimation process 10 times. Each time we used R=500 draws for a total of 5,000 iterations. A disadvantage of the GA is that the estimation process is extremely time-consuming, and the estimation time increases exponentially with R. For these reasons, only results for the best ML model estimated, including panel effects and heterogeneity, is included.

4. Research design

4.1 Stated preference experiment

4.1.1 The design of congestion charge schemes

Since congestion charges have not been implemented in Beijing or in other Chinese cities, we used an SP experiment to collect data on how respondents would choose their departure time if hypothetical congestion charging scenarios were implemented. In designing the congestion charging scheme, the most important and basic aspects are charging type, charging time, and charging fee.

For the charging type and charging time, according to Jou et al.'s (2007) study of the acceptability of congestion charging for car and motorbike drivers in Taiwan, a time-based charge in a certain area is more acceptable than a fixed charge. Therefore, in this study, we designed a time-based congestion charge on congested roads.

For the charging fee, international experience has shown that the daily congestion charge is about 5%-10% of local residents' average daily disposable income (Lu & Cui, 2016). In 2017, Beijing's per capita disposable income was 57,230 yuan (about 7,390.91 euros). Thus, based on this research, a reasonable charging fee in Beijing would range between 10.96 and 21.92 yuan (about 1.42-2.83 euros) per day.

In addition, we chose 7:00 a.m. to 9:30 a.m. as the charging time, based on the morning peak hours used in the 2016 Beijing Transportation Development Annual Report. As shown in

Table 2, the charging time is evenly divided into five periods. The charging fee changes in each scenario and takes a symmetrical inverse-U shape, which means that the congestion fee is the highest during the most congested time. We designed four charging schemes, in which the charging fee gradually increases from scheme 1 to scheme 4.

Table 2 Congestion charge schemes

	Time when you reach the congested road	**Charging fee (¥)**			
		Scheme 1	**Scheme 2**	**Scheme 3**	**Scheme 4**
Time-based congestion charge	7:00 a.m. -7:30 a.m.	5	10	15	20
	7:30 a.m. -8:00 a.m.	10	15	20	25
	8:00 a.m. -8:30 a.m.	15	20	25	30
	8:30 a.m. -9:00 a.m.	10	15	20	25
	9:00 a.m. -9:30 a.m.	5	10	15	20

4.1.2 Design of arrival situations for multiple reference points

Three reference points—Acceptable Earliest Arrival Time (TE), Work Starting Time (TW), and Acceptable Latest Arrival Time (TL)—were considered in this study. Based on our pilot survey, we found that the majority of respondents were willing to accept being late within 10 minutes. Therefore, under each reference point we presented three possible arrival times: (1) arriving at the reference arrival time, (2) arriving 5 minutes late, and (3) arriving 10 minutes late. It is plausible that commuters could arrive later than the TE reference point. As shown in **Table 3**, the situation corresponding to a 5-minute late arrival was used for TW and TL, and the situation of a 10-minute late arrival was used for TE. When commuters arrived at the reference arrival time, the deviation between actual and reference arrival time is $\Delta T = 0$. When commuters arrive 5 minutes late, $\Delta T = -5$ for TW and TL. When commuters arrive 10 minutes late, $\Delta T = 10$ for TE.

Table 3 Reference points and possible arrival situations

Reference point	**Possible situation**	**Probability**
Acceptable Earliest Arrival time (TE)	Arriving at the company at the reference time.	50%
	Arriving at the company 10 minutes after the reference time.	50%
Work Starting Time (TW)	Arriving at the company at the reference time.	50%
	Arriving at the company 5 minutes after the reference time.	50%
Acceptable Latest Arrival Time (TL)	Arriving at the company at the reference time.	50%
	Arriving at the company 5 minutes after the reference time.	50%

Each outcome had an initial 50% probability (i.e., $p_O^* = p_L^* = 0.5$). This is based on respondents' feedback on the pilot survey. In the experiment, however, the probability of each outcome changes based on respondents' departure time choice. If they depart earlier, the probability of arriving late decreases and otherwise increases.

4.1.3 Scenarios and the questionnaire

The scenarios used in this study manipulated three components: reference points, possible arrival situations, and congestion charge schemes. We kept all combinations of the three reference points and four congestion charge schemes—i.e., 12 scenarios. To reduce cognitive effort and improve the accuracy of their answers, we blocked these 12 scenarios into three groups of four scenarios each. Each group contains four congestion charge schemes with one reference point; thus we have three types of questionnaires with different scenarios. Each respondent was randomly assigned one type of questionnaire. In each questionnaire, respondents were presented with four scenarios in sequence; each included two possible arrival situations and one congestion charge scheme (as shown in **Figure 2**). Note that learning effects may be observed in experiments that consider sequential choices. However, this effect is not strong, with only 4 sequential choices, since it usually appears with more iterations (Viti et al., 2005). Thus, we did not capture learning effects in our models.

Several measures have been used to encourage respondents to recall an actual commuting trip and reduce hypothetical bias as much as possible (Arellana et al., 2012). First, before the four scenarios, a general description was shown to respondents. For example, for respondents who were assigned to the questionnaire with TW as the reference point, the description was: "Assume that the Work Starting Time will be the reference arrival time for your morning commuting trip, and a time-different congestion charge policy will be implemented on the road you use. That is to say, the congestion charge fee that you are asked to pay varies based on the time you enter the congested road. Under the following four different congestion charge scenarios, when would you like to depart?" Second, before responding to the first scenario, we asked respondents to write down their reference arrival time for the morning commuting trip (e.g., work starting time for the questionnaire on TW). This is to say that the values of each reference point were customized with respect to the actual working time participants declared. Then, we asked them to report their regular departure time if they were using the above self-reported arrival time as a reference, in order to remind them of an actual commuting context.

1. Work starting time _______

2. When is your regular departure time? _______

	Scenario 1	
Reference time	Work starting time	
Arrival situations	**Possible arrival time**	**Probability**
	Arriving at the company at the reference time.	50%
	Arriving at the company 5 minutes later.	50%
Charging time-differentiated congestion fee	**The time when you reach the congested road section.**	**Charging level**
	7:00a.m.-7:30a.m.	5¥
	7:30a.m.-8:00a.m.	10¥
	8:00a.m.-8:30a.m.	15¥
	8:30a.m.-9:00a.m.	10¥
	9:00a.m.-9:30a.m.	5¥

3. According to the above scenario, will you change your departure time? (Every 10 minutes earlier/later, the probability of arriving on time will increase/decrease by 10%)

A. 50 and more than 50 minutes earlier **B.** 40 minutes earlier **C.** 30 minutes earlier
D. 20 minutes earlier **E.** 10 minutes earlier **F.** Not change
G. 10 minutes later **H.** 20 minutes later **I.** 30 minutes later
J. 40 minutes later **K.** 50 and more than 50 minutes later

Figure 2 A sample question in the SP experiment using TW as the reference point (translated from Chinese)

In each scenario, respondents made departure time choices. We assumed that the departure time change did not affect travel time itself, but rather the probability of being early or late (Noland & Small, 1995). Hence, the probability of arriving on time p_O and the probability of arriving late p_L in each scenario changed depending on respondents' departure time choice. They were also told that departing 10 minutes earlier or later increased/decreased p_O by 10%, and p_L correspondingly decreased/increased by 10%, which means:

$$p_O = \begin{cases} p_O^* + t10\% & if\ depart\ earlier \\ p_O^* - t10\% & if\ depart\ later \end{cases} \tag{14}$$

$$p_L = \begin{cases} p_L^* - t10\% & if\ depart\ earlier \\ p_L^* + t10\% & if\ depart\ later \end{cases} \tag{15}$$

where p_O^* and p_L^* are the initial probabilities of on-time and late arrivals, which are set to 50% based on respondents' feedback in the pilot survey, and t is the tenth digit of the advance or delay time. Also, the charging fee τ respondents would pay depends on the congestion charge scheme, their regular departure time, and the departure time change they chose. Respondents could immediately know the congestion charge cost and possible arrival situations when they made the choice decision for each scenario.

On the questionnaire, we also asked about individuals' socioeconomic, household, and commuting characteristics. The socioeconomic characteristics are gender, age, income, education, and job. The household characteristics are marital status, number of school-age children, car ownership, and need to pick up children/partner or not. The commuting characteristics are commuting distance, commuting time, commuting mode, residential location, and workplace; working time flexibility; transportation information: the quality of traffic information during their travel and road familiarity; and tolerance of lateness. These factors , which are likely to influence commuters' departure time choices, have been discussed in previous literature (Ben-Elia & Ettema, 2011; Hamed & Olaywah, 2000; Saleh & Farrell, 2005; Steed & Bhat, 2000).

For working time flexibility, we did not ask details about constraints at work (as recommended by Thorhauge et al., 2016), but instead whether respondents were fully flexible, not flexible at all, or if they could arrive up to 30, between 30 and 60, or between 60 and 90 minutes later/earlier[1]. The maximum late arrival respondents could tolerate also indicates the maximum late flexibility they can accept subjectively. In addition, we asked about their value of time: "Suppose that you depart 30 minutes earlier so as to avoid rush-hour congestion in your commuting trip. That means you have to give up time for resting or doing other things. Compared with half an hour's salary, how much do you think is the cost of departing half an hour early?"

4.2 Participants and data collection

The survey was conducted in November 2017, and questionnaires were distributed online and on-site. Network platforms such as Wechat, QQ (social software), and Wenjuanxing (a professional questionnaire distribution website) were used for online distribution. The target population was car commuters in Beijing. Two screening questions were included at the beginning of the questionnaire to exclude respondents who used travel modes other than a car ("What is your regular travel mode for morning commuting?"). Those who could set their working time themselves and work from home were also excluded, since they were not considered to be regular morning peak commuters. We collected a total of 400 questionnaires, of which 317 were valid after excluding respondents who met either of the above conditions. Since each respondent has 4 observations, we obtained 1,268 observations in total. This sample

[1] In Beijing, the morning peak can last for 3 hours (7 a.m. to 9 a.m.) in some places. It is thus possible that 90 minutes after the usual starting time is still within the morning peak.

size is in line with many SP studies on departure time (e.g., Arellana et al, 2012, use a sample of 357 respondents, and Thorhauge et al., 2016, used 286). Our sample is also larger than many previous studies that also estimated PT or CPT parameters. For example, Ghader et al. (2019) used 409 observations; Jou et al. (2008) used 152 respondents and 454 observations; and Senbil and Kitamura (2004) used 210 respondents and 630 observations. Since the CPT model is highly nonlinear, future studies could use even more respondents and observations to fit the models.

Table 4 Sample description

Variables	Categories	Percentage
Gender	male	53.0
	female	47.0
Age	20-25	12.6
	26-30	38.2
	31-40	29.3
	41-50	17.0
	>50	2.8
Education	≤ high school	8.8
	junior college	23.0
	college	48.6
	master	18.3
	Ph. D	1.3
Income per month	≤5,000 yuan	11.4
	5,000~10,000 yuan	39.1
	10,001~15,000 yuan	26.5
	15,001~20,000 yuan	14.8
	>20,000 yuan	8.2
Marital status	single	29.0

	married	71.0
Car ownership	0	.9
	1	73.2
	≥1	25.9
Working flexibility	no flexibility	71.3
	up to 30 mins earlier/later	17.4
	between 30 and 60 mins earlier/later	9.8
	between 60 and 90 mins earlier/later	1.6
Tolerance of lateness	0	56.8
	1~5 mins	19.2
	6~10 mins	11.7
	11~15 mins	6.9
	>15 mins	5.4

As shown in **Table 4**, the percentage of males (53%) is slightly higher than that of females (47%), which is consistent with the gender ratio of the population (male: 51.11%; female: 48.89%) in Beijing in 2017 (NBS, 2017). Most of our respondents are 26 to 40 years old, and more than 50% have a bachelor's degree or above. Also, 60.1% of respondents have a monthly income greater than 10,000 yuan, and about 26% have more than one car. According to the China Population and Employment Statistics Yearbook 2017 (NBS, 2017), 52.7% of urban employed persons in China are younger than 40 years old, 34.4% of employed persons in Beijing have a bachelor's degree or above, and the 2017 mean per capita monthly income for Beijing is about 8,467 yuan. Compared with the average employed population in Beijing, our sample is younger, higher educated, and richer. However, given that our sample only includes private car commuters, these results are not surprising. Also, 71.3% of respondents do not have flexible working time, and 56.8% can't tolerate any late arrivals. Of those who could tolerate arriving late, more than two-thirds report a tolerance within 10 mins, with the largest share being within 1~5 mins.

Table 5 Commuting characteristics

Variables	Categories	Mean	S.D.
Commuting time	10 mins, 20 mins, ……, 100 mins	33.18	41.04
Commuting distance	<2 km, 2~6 km, 6~10 km, ……, 26~30 km, >30 km	12.19	7.05
VOT (yuan/min)	0~5 yuan/half hour, 6~10, 11~15, 16~20, 21~30, 31~40, >40	0.69	0.53
Quality of traffic information	1 (Low) to 3 (High)	1.54	0.50
Degree of road familiarity	1 (very unfamiliar) to 7 (very familiar)	3.91	1.81
Degree of traffic congestion	1 (very uncongested) to 7 (very congested)	4.73	1.58

As shown in **Table 5**, the average commuting time and commuting distance are 33.18 minutes and 12.19 km separately. According to the Fifth Comprehensive Investigation Report of Beijing Urban Traffic (BMCT & BTI, 2016), the average commuting time and commuting distance by private car are 49.1 minutes and 13.5 km, which is slightly longer than what our sample reported. The average score for the quantity of traffic information they obtained during commuting is 1.54, with 14.8% of commuters choosing high and 31.5% choosing low. The average score for road familiarity is 3.91, and the percentage for commuters who are not familiar with the road network in Beijing is 45.1%. The average score for traffic congestion is 4.73, which shows that the majority (65.6%) believe that traffic is congested when they commute in the morning. The stated average value of time (VOT) for our sample is 0.69 yuan per minute, with the highest value of 1.67 yuan per minute and the lowest value of 0.17 yuan per minute.

4.3 Descriptive statistics

We first analyze the results using simple descriptive analyses. Results show that the majority (58.6%~67.8%) of car commuters would change their departure time under the congestion charge scenarios presented (shown in **Table 6** and **Figure 3**). With the increase in charging fees (from scenarios 1 to 4), the proportion of respondents who would not change their departure time gets smaller. Most commuters choose to depart early rather than late, which is in line with previous results in departure time choice models, and is related to constraints on work starting time (Thorhauge et al., 2016).

Table 6 Departure time change under different congestion charge scenarios

Departure time change		Scenario 1	Scenario 2	Scenario 3	Scenario 4
Early depart	≥50 mins	5.4%	6.9%	9.1%	12.6%
	40 mins	10.7%	13.2%	15.5%	13.6%
	30 mins	18.3%	19.2%	21.1%	21.1%
	20 mins	11.7%	13.2%	11.7%	10.7%
	10 mins	12.6%	11.4%	10.1%	9.8%
	Sum	58.6%	64.1%	67.4%	67.8%
Not change		30.6%	26.2%	21.5%	21.1%
Late depart	10 mins	3.2%	2.5%	3.8%	3.5%
	2 0mins	3.2%	2.8%	3.2%	2.5%
	30 mins	3.8%	3.5%	3.5%	4.1%
	40 mins	0.3%	0.6%	0.3%	0.6%
	≥50 mins	0.3%	0.3%	0.3%	0.3%
	Sum	10.8%	9.7%	11.15	11.15

With the increase in charging fees, the proportion of commuters who depart earlier increases faster than the proportion of those who depart later (see **Figure 3**). However, when the charging fee reaches a relatively high level (scenario 3), the changes are negligible. We can see that private car commuters prefer to depart early rather than late under congestion charge scenarios.

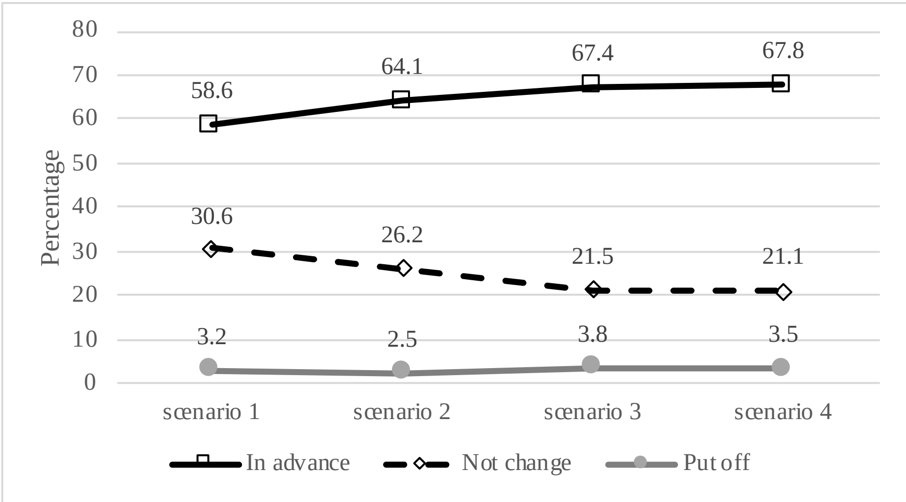

Figure 3 Departure time change under different congestion charge scenarios

We then compared the departure time choice among commuters with different degrees of work flexibility. The percentages of three departure time choices within each flexibility group are shown in **Figure 4**. From left to right, we can see that as work flexibility increases (from not flexible to "can arrive 60-90 mins earlier/later"), the percentage of respondents who chose to depart earlier decreases (from 70% to 40%) and the percentage of those departing later increases (from 10% to 40%). The percentage of respondents who did not change their departure time is similar among these four flexibility groups. This may imply that commuters with less work flexibility are more likely to depart earlier to avoid being late when the congestion charge is introduced. In contrast, those who have greater work flexibility have more choices; they can avoid rush hour congestion by departing either earlier or later.

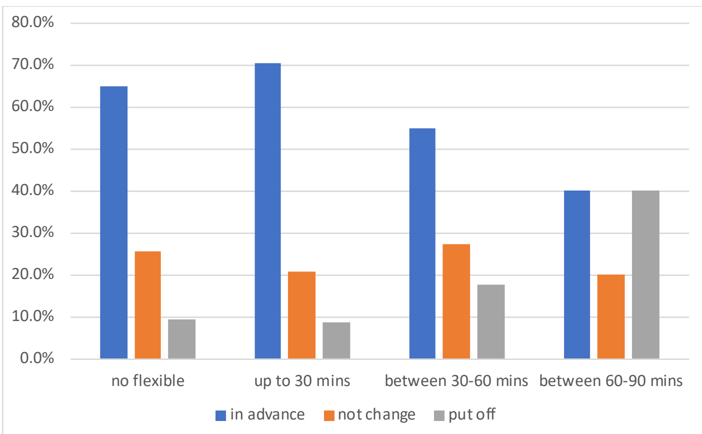

Figure 4 Departure time changes for commuters with different flexibility

5. Results

Table 7 shows the average value of each coefficient, the average value of the log-likelihood, and the corresponding BIC value over the multiple runs of GA in the basic ML model. A backward stepwise procedure has been implemented manually, whereby specifications have been assessed based on the improvement in log-likelihood and BIC, the statistical significance of each socioeconomic variable, and conceptual plausibility.

A one-tailed t-test was conducted for α, λ, γ, and β_{VOT} against 1 for the parameter's value and against zero for β_{τ}, the ASC of departing later, and the ASC of departing earlier. The alternative specific constants (ASCs) for departing later and earlier are significantly negative, which implies that commuters are more likely to keep their current departure time rather than departing earlier or later.

Table 7 Estimated coefficients for models with socioeconomic variables

Parameters	Values	(st. errors)
α	0.459***	(0.092)
λ	1.429**	(0.163)
γ	0.567***	(0.060)
β_{VOT}	0.605***	(0.084)
β_{τ}	0.248***	(0.056)
$\Delta\boldsymbol{\alpha}$_Male	0.891***	(0.292)
$\Delta\boldsymbol{\alpha}$_Need to pick up children/partner	-0.220**	(0.264)
$\Delta\boldsymbol{\lambda}$_School child(ren)	0.235**	(0.386)
$\Delta\boldsymbol{\lambda}$_Need to pick up children/partner	-0.367***	(0.388)
$\Delta\boldsymbol{\gamma}$_Degree of traffic congestion	0.033***	(0.035)
ASC of departing later	-6.684***	(1.210)
ASC of departing earlier	-3.298***	(0.804)

Standard deviation of μ	-1.358	(5.796)
Number of observations	1,268	
Log-likelihood	1,342.965	
BIC	2,757.382	

Note: The results of each model are the average results of 10 runs. ***p < 0.01, **p < 0.05.

5.1 CPT parameters

The estimation results provide evidence of risk-aversion/-seeking behavior, loss aversion, and probability distortion. Risk preference parameter α equals 0.459 and is significantly smaller than 1, which implies that commuters are not risk neutral. In line with previous studies (e.g., Senbil & Kitamura, 2004b, 2004a; Tversky & Kahneman, 1992), our results show that car commuters are risk averse when they perceive gains and risk seeking when they perceive losses under congestion charge contexts. **Figure 5** shows the resulting S-shaped value function, which is concave for time gains and convex for time losses. Loss-aversion parameter λ is significantly larger than 1, with a magnitude larger on departure time choices than in previous studies (Senbil & Kitamura, 2004b, 2004a). This result suggests that commuters are more sensitive to losses in a congestion charge scenario.

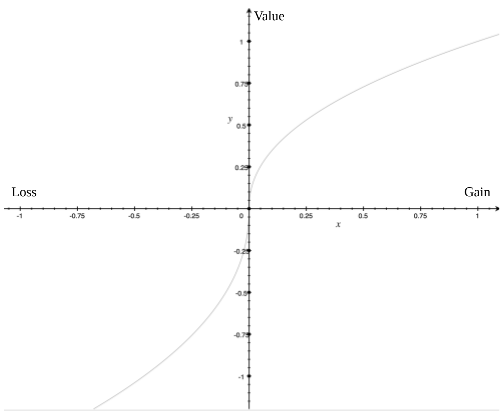

Figure 5 Estimated value function

Commuters exhibited a distortion in probability weighting when facing the uncertainty of the congestion charge context. The weighting function parameter γ equals 0.567, which is significantly lower than 1 and lower than the estimates (γ=0.61-0.69) obtained by Tversky and Kahneman (1992) in monetary experiments. As shown in **Figure 6**, the curvature of the estimated weighting function is far from a straight line. In fact, the largest gap between objective probability and decision weighting was about 0.5, which means that commuters overweight small probabilities and underweight larger probabilities; thus the degree of distortion is considerable. Note that this result is smaller than that of previous studies on road users' mode decisions (Ghader et al., 2019; Schwanen & Ettema, 2009). This suggests that commuters have a less accurate valuation of the objective probability (i.e., are more irrational) when making departure time choices. Given that effects such as inflating small probabilities become evident when losses are perceived as significant, we compared our results and in particular, the estimates of Schwanen and Ettema (2009). They use a similar setup for delay values (on-time, 5-minute delay, 10-minute delay) in their study of Dutch parents, but show lower weighting distortion. This demonstrates that our results reflect the special behavioral characteristics of Beijing commuters, rather than a bias caused by the setup using small delay values.

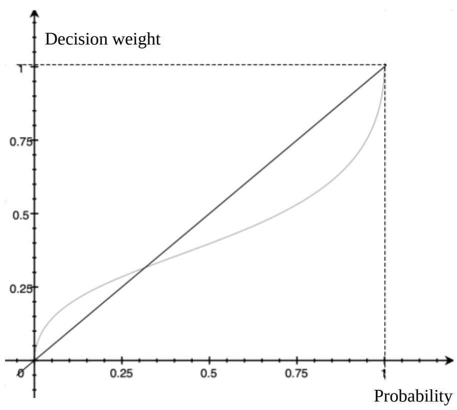

Figure 6 Estimated decision-weighting curve

Moreover, the average β_{VOT} of our samples equals 0.605 and is statistically significant at the 99% confidence level. This means that the average VOT across our sample is 0.61 yuan per minute—i.e., 36.6 yuan per hour—which is much lower than their stated value in the survey (0.69 yuan per minute). Given the average hourly wage in Beijing, calculated based on the average monthly wage in 2017 (BMHRSSB & BMBS, 2018) and the hourly wage conversion function used in China (MOHRSS, 2008)—50.81 yuan per hour—commuters would choose to spend 72% of their hourly wage to avoid a 1-hour travel delay.

5.2 Systematic heterogeneities in CPT parameters

Results show that the risk preference parameter α is the parameter most sensitive to commuters' heterogeneous characteristics. Factors such as gender and whether they need to pick up children or a partner are statistically significant in terms of affecting the value of α. The results show that gender (male=1, female=0) has a positive effect on α, which implies that male commuters are less risk averse; this result is consistent with Schwanen and Ettema's (2009) findings. Compared with female commuters, male commuters are closer to risk neutral. Commuting time has a significantly negative impact on α: The need to pick up children or a partner during commuting trips significantly decreases the value of α. Commuters who have to consider not only their own schedules but also others' schedules are more risk averse. This additional consideration has the largest impact on α of all the socioeconomic factors used in this study.

Compared with the risk preference parameter α, the parameters λ and γ are relatively consistent among commuters with different socioeconomic characteristics. The loss-aversion parameter λ is impacted by having or not having school-age child(ren) and by having or not having to pick up children/a partner. Commuters who have school-age child(ren) are more loss averse than others. However, this increase could be offset if commuters also need to pick up their children during commuting trips, since the need to pick up others can significantly decrease the value of λ. One possible explanation is that commuters share their losses with all passengers. Although they themselves suffer losses, their passengers may obtain gains from the same trip. Thus, commuters who also need to pick up other family passengers can be less sensitive to their own losses. The degree of traffic congestion has a positive effect on the weighting-function parameter γ. Commuters who regularly face congested commuting trips demonstrate a smaller degree of probability distortion—because they more are accustomed to coping with uncertain congestion than commuters who are used to smooth traffic—and this allows more accurate estimation of the objective probability of arriving late.

6. Conclusion and policy implications

This study contributes to the empirical estimation of travelers' behavioral mechanisms when making departure time choices under uncertain congestion charge scenarios. We conducted a stated preference experiment among commuters in Beijing to examine their departure time choice behavior under congestion charge scenarios based on cumulative prospect theory (CPT). Four time-differentiated congestion charge scenarios at different charging levels were designed for the experiment. Three reference points—Acceptable Earliest Arrival Time, Work Starting Time, and Acceptable Latest Arrival Time—were considered in the experiment. CPT utility functions and mixed logit models with panel effects have been used to estimate the departure time choice problem in congestion charge contexts. A genetic algorithm was adopted to estimate CPT parameters by maximizing the simulated log-likelihood function.

Our results are consistent with previous findings in the transport literature that apply CPT to travel decisions different from a congestion charge. Our findings support the presence of the bounded rational decision-making processes of commuters, which is more realistic and counters the assumption of perfect rationality used in expected utility theory. Our evidence suggests that car commuters exhibit cognitive biases when making departure time choices under congestion charge scenarios. Therefore, all parameters that define the shape of the CPT value function—the exponents that moderate the risk preferences, the level of probability distortion, and the linear parameter for loss aversion—are statistically significant. The estimated CPT parameters differ from the results obtained by Tversky and Kahneman (1992) in lab experiments and in the context of monetary decisions. The difference in the parameters' estimates could be attributed to the fact that commuters show different levels of behavioral biases when making departure choices in congestion charge contexts compared with other contexts. The parameters estimated by this study could yield more accurate predictions to model travel behavior in congestion charging contexts. Also, we found significant systematic heterogeneity, and particularly in the risk preference parameter. Commuters' characteristics, including gender, having school-age child(ren), commuting time, picking up child(ren)/a partner during the trip, the quantity of traffic information, and the degree of congestion during daily commuting trips significantly affect the value of CPT parameters. The results of this study could help decision makers better understand commuters' behavioral responses to congestion charges and provide an important empirical reference for the design of congestion charge schemes.

From a policy insight, given the loss-aversion preference, more behavioral change among real commuters—in contrast to when we assume they are *homo economicus*—can be achieved by congestion charge. If policymakers realize the cognitive biases of commuters in the policy design stage, they can achieve the same policy target with less congestion charge levying on commuters, which is better for public acceptability. Also, commuters' distortion in probability weighting is larger when making travel decisions under a congestion charge policy than previous estimations without policy incentives. This implies that commuters make their travel choices less rationally under uncertain traffic contexts when facing a congestion charge policy. Another thing to notice is that a higher congestion charge may not always lead to more behavioral changes, given the risk-seeking behavior elicited when outcomes are framed as losses. When commuters get used to a relatively high congestion charge level, it is harder for them to change their behavior under a higher charge level. In that case, the better way to manage road demand is not to blindly increase the charge level, but to adjust the charging structure, for example, or try other policy instruments.

Future studies could further expand on our findings by designing decision scenarios that consider not only travel delays but also travel time savings and that allow travel times to vary among different departure time choices and congestion charge scenarios. Also, given the reality of Chinese workers' norms and the complexity of potential experimental designs, we only offer on-time arrival and late arrival as two possible arrival situations in the scenario. Future studies could include the full combination of early arrival, on-time arrival, and late arrival. More values of early arrival and late arrival can be used to describe a more precise value function curve and weighting function curve for commuters. Fitting the CPT value functions for time and monetary attributes separately could also reduce variance in the parameter estimates, and thus increase confidence in the hypothesis testing. In addition, CPT parameters for time choice, mode choice, and route choice, as well as specific behavioral parameters for evaluating the value of departure time and the value of the charging price, could be allowed to differ. Moreover, future studies can seek to account for unobserved heterogeneities of CPT parameters among travelers. Latent class models can be used for such analysis. Other congestion charge schemes rather than a time-differential charge can be used to test travelers' behavior in response to different congestion charge schemes.

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Appendix A

A genetic algorithm (GA) is a metaheuristic algorithm that can identify optimal solutions through multiple iterations and transform the solution process into a process similar to the crossing and mutation of genes in biological evolution (Goldberg, 1989). It has been used in travel behavior studies (e.g., Schwanen & Ettema, 2009; Zong et al., 2012). Compared with conventional optimization algorithms, the advantage of GA is that can help to avoid falling into local optima. In addition, GA can find optimum solutions from the population with maximal probability, regardless of whether the fitness function is discontinuous and unstable or surrounded by great noise (Liu et al., 2007).

In this paper, we use the GA toolbox in MATLAB software. The procedure can be described as follows (Ettema & Timmermans, 2003; Goldberg, 1989) and is shown in **Figure 1**:

1) Population: Define Q sets of estimated coefficients, where Q indicates the number of candidate solutions and each candidate solution includes all coefficients that need to be estimated. Q has been set to 200 which is the default choice in MATLAB for models with more than five coefficients.
2) Parameter encoding: We used the double vector as our population type, which is also the default choice.
3) Fitness scaling: Calculate SLL values for each candidate solution and convert the raw fitness scores to values in a range that can be used by the selection function. Here, we used the rank scaling function. Candidate solutions are ranked. A candidate with rank r has a scaled score proportional to $1/\sqrt{r}$.
4) Selection: Choose candidate solutions as the parents to be propagated to the next iteration based on their scaled fitness scores. We used the reminder selection

function, which means that candidates with higher scaled value will be listed as parents more times.

5) Crossover: Combine two parents to form a new individual for the next generation. First, two solutions are randomly selected from the matching pool generated by propagation. Then, the binary solution strings are cut at a random point to cross over.
6) Mutation. Make small random changes in individuals to provide genetic diversity. Since all CPT parameters have their own constraints, the default adaptive feasible mutation function is chosen.
7) For procedures that cover propagated, crossed over, and mutated parameters, the SLL of each candidate solution is calculated and a new generation of populations is generated for iteration. Go back to step 3 and repeat steps 3-6 until all coefficients converge and output the coefficients.
8) Several criteria are used to decide when to stop the procedure. We used the default function tolerance and constraints tolerance. Also, the procedure will stop when it has repeated 100 times the number of parameters. If there is no improvement within 30 generations, the procedure will stop.

Given the above setting, the fitness function was calculated about 10,000 to 36,000 times to find the best solution for each generation. Then, the procedure was repeated 3 times (i.e., 3 generations) and stopped—given that the function tolerance and constraint tolerance had been reached—to obtain the best solution (i.e., the final point) for each run. Since the solutions of GA vary in different estimation runs (Schwanen & Ettema, 2009), for each model we repeated the estimation process 10 times. Then, t-tests of each coefficient were computed for the best solutions in each run.

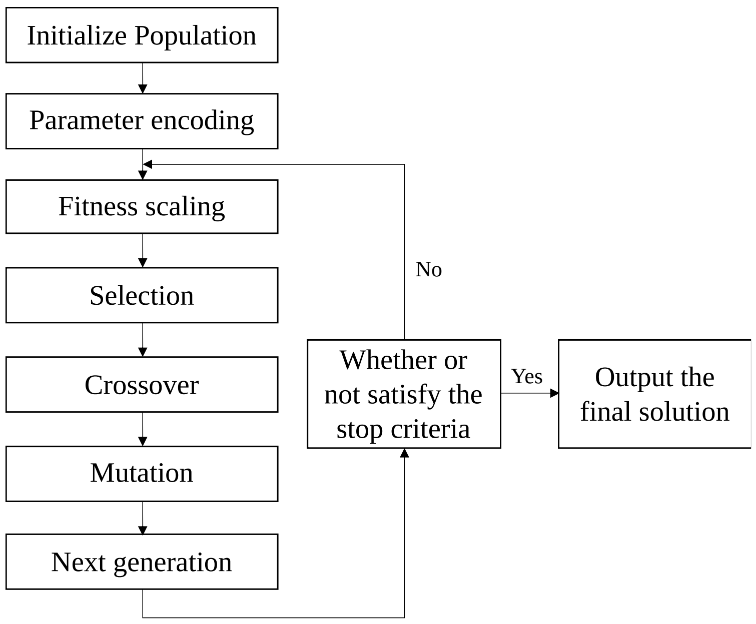

Figure A1 The procedure for parameter estimation by GA