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Travelers' Route Choice Behavior in Risky Networks

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TRAVELERS' ROUTE CHOICE BEHAVIOR IN RISKY NETWORKS

A Dissertation Presented

by

HENGLIANG TIAN

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Dedicated to my parents.

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Thank Dr Song Gao for her supervision and support during my four years' study at University of Massachusetts Amherst. Thank Dr John Collura and Dr Don Fisher, my thesis members, for their contributions to my dissertation. Thank my parents and friends for their always being there.

ABSTRACT

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The accurate modeling of travelers' route choice decision making when faced with unreliable (risky) travel times is necessary for the assessment of policies aimed at improving travel time reliability. Two major objectives are studied in this thesis. The first objective is to evaluate the applicability of a process model to route choice under risk where the actual process of decision making is captured. Traditionally, we adopt "as-if" econometric models to predict people's route choice decisions. The second objective is to investigate travelers' capability to incorporate future real-time traffic information into their current route choice decision making. Two separate stated preference (SP) surveys were conducted for each objective. The first SP survey used an interactive map in a computer based test. The second SP survey used a full-scale high-fidelity driving simulator.

Compared with econometric models, process models have been rarely investigated in travel decision making under risk. A process model aims to describe the actual decision making procedure and could potentially provide a better explanation to route choice behavior. A process model, Priority Heuristic (PH), developed by Brandstatter et al. (2006) is introduced to the travel choice context and its probabilistic version, Probabilistic Priority Heuristic (PPH), is developed and estimated in this study. With data collected from a stated preference (SP) survey which is based on an animated computer interface, one econometric model, Rank-Dependent Expected Utility (RDEU) model, and two other alternative models were compared with the PPH model in a cross validation test to investigate their data-fitting and predictive performance. Our results show that the PPH model outperforms the RDEU model in both data-fitting and predictive performance. This suggests that the process modeling paradigm could be a promising new area in travel behavior research.

With the advance of information and telecommunication technology, real-time traffic information is increasingly more available to help travelers make informed route choice decisions when faced with unreliable travel times. A strategic route choice refers to a decision taking into account future diversion possibilities at downstream nodes based on real-time information not yet available at the time of decision-making. Based on the data collected from a driving simulator experiment and a matching PC-based experiment, a mixed Logit model with two latent classes, strategic and non-strategic route choice, is specified and estimated. The estimates of the latent class probabilities show that a significant portion of route choice decisions are strategic and subjects can learn to make more strategic route choice as they have more experience with the decision scenarios. Non-parametric tests additionally show that network complexity adversely affects travelers' strategic thinking ability in a driving simulator environment but not in a PC environment and a parallel driving task only affects strategic thinking ability in a difficult scenario but not a simple one. In addition, we find that people's strategic thinking ability are influenced by their gender and driving experience (mileage) in the non-parametric analysis, but not in the modeling work. These findings suggest that a realistic route choice model with real-time traffic information should consider both strategic and non-strategic behavior, which vary with the characteristics of both the network and the driver.

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INTRODUCTION

1.1 Motivation

A traffic network is subject to significant delays resulting from crashes, constructions, inclement weather, special events, and so forth, and is inherently an uncertain system. Traffic delays will consume travelers' time, fuel and increase environmental pollution. Building more roads seems an immediate option, however, there are often a myriad of financial, political and environmental resistance. Furthermore, as a famous paradox in transportation engineering, Braess's paradox (Braess, 1968; Braess et al., 2005) is stated as: adding extra capacity to a network can sometimes reduce its overall performance. Therefore, infrastructure construction is not necessarily a good choice to address this problem. With advanced information and telecommunication technology, Intelligent Transportation Systems (ITS) could be an effective method to reduce traffic delays. The fundamental idea of ITS is making best use of current facilities and infrastructure with the help of information technologies, such as: sensors, cameras and Variable Message Signs (VMSs) along the road. Advanced traveler information systems (ATIS) is a key component of ITS which is used to provide travelers with real-time traffic information on prevailing and/or predictive traffic conditions and is designed with the premise that more information might help drivers make better route choice decisions that collectively might reduce the system costs associated with wasted travel time and pollution. Some studies show that the deployment of VMSs to inform drivers of traffic conditions has been proven successful in terms of improving network travel times (Chatterjee & McDonald, 2004). However this premise is not necessarily true in that real-time information could potentially degrade system performance (Gao, 2005) and thus the value of ATIS needs to be vigorously evaluated with sound models. While the presence of real-time traffic information affects each driver's route choice decisions, the collective of all drivers' route choice decisions in turn determines the overall performance of traffic systems. The complicated interaction between drivers' choice, the infrastructure, and the real-time information system needs to be captured to adequately assess the effectiveness of ATIS.

1.2 Scope of Thesis

To evaluate the role of ATIS, two major research questions need to be answered. First of all, we are interested in how people make route choice decisions when travel time distributions of alternatives are known while no real-time traffic information is provided. This is the basis of studying the impact of traveler information whose utility lies on reducing the level of uncertainty in the decision environment. Such behavior has been widely studied in economics and psychology and generally named "decision under risk". Classical econometric models assume people calculate the utilities of each alternative and the option with the highest utility will be chosen. Little emphasis has been placed on how people actually arrive at their route choice decisions. In this study, we will introduce a process model from the psychology literature to the route choice context, and develop a probabilistic version of the model for parameter estimation. Such a process model attempts to describe actual decision making process in people's mind. Furthermore, we will compare this model with three other competing models in terms of their estimation and prediction performance. Secondly, we are interested in how people respond to real-time traffic information which is implying future diversion possibilities. Most established route choice models assume people make a fixed route choice at the beginning of each trip and respond to real-time traffic information only when it is received. Planning ahead for such real-time information is not considered in these models. Through our experiments, we will investigate whether and how people respond to this real-time traffic information.

1.3 Research Summary

Two research topics are covered in this thesis. In the first part, a probabilistic process model is developed, where people's actual procedure to arrive at a route choice in a risky network is studied. In the second part, people's strategic route choice behavior where future diversion possibility is considered even before this real-time traffic information is received en route.

1.3.1 Process Model

How a traveler makes a route choice is the building block of any traffic forecasting model. For a simple scenario in transportation engineering, we are considering a route choice between two alternatives whose travel times and associated probabilities are given and there is a trade-off between fast travel time and risk. The situation that one route is dominated by another one is excluded from our analysis.

Different paradigms can be utilized to model a route choice decision. Econometric models assume that a utility is attached to each alternative and the alternative with higher utility is selected. The functional form of the utility is a research question. Expected utility (EU) model has been the mainstream model for decision under risk, where a value function, usually non-linear, is used to transform the objective outcomes into subjective values, which are then weighted by the objective probabilities and summed up to obtain an expected utility. For instance, if a route bears a half chance to be 20 minutes and another half to be 40 minutes and the value function is the travel time itself, the expected utility is 30 minutes. Many laboratory experiments have shown that this paradigm fails to predict choices. As a result, cumulative prospect theory (CPT) is proposed where people's perception towards probabilities is accounted by a non-linear function. To be specific, CPT supposes people have a S-shape perception curve towards outcomes and an inverted S-shape perception curve towards probability from 0 to 1. CPT is acclaimed in many situations.

A strikingly different paradigm is introduced by Brandstatter et al. (2006), the so called priority heuristic (PH) model. PH model is a process model and supposes that people make one or two and up to three comparisons in a decision making where two alternatives are involved and each alternative has two outcomes and associated probabilities. First, two minimum outcomes are compared and then two probabilities of minimum outcomes are compared and two maximum outcomes are compared at last. 1/10 is adopted as a aspiration level in each step. The proposers of PH model demonstrate in their paper that it exhibits advantages over many classic econometric models. We would like to make an adjustment with this deterministic model to improve its accuracy. The comparing order in the original PH model is not necessarily the only one. There are three reasons to be compared: minimum outcome, probability of minimum outcome and maximum outcome, and as a result, six possible comparisons should all be considered. A certain comparing order might be applied well in some specific conditions. The aspiration level of 1/10, is fixed in the original PH, but it is conceivable that this value changes with decision context. For example, after we change 1/10 to 1/5, we see a better model fit with our data set. This initial result prompted us to treat the aspiration level as a model parameter to be estimated.

To get a full picture about probabilistic priority heuristic (PPH) model's estimation and prediction performance, we conducted a cross validation. We prepare 10 independent data sets from the original data set. Each time, 2/3 subjects' route choice decisions are randomly selected as training set to estimate model parameters. The remaining 1/3 subjects' data are used for validation.

1.3.2 Strategic Route Choice Model

ATIS is able to provide travelers real-time traffic information to reduce the uncertainty of the decision environment. How people respond to this kind of real-time information is our interest in this topic. Traditional route choice model generally assumes that people make their route choices at the beginning of each trip and adjust their original route when real-time information is actually received. This assumption ignores the fact that some travelers can plan ahead for traffic information that is not yet available.

A strategic route choice is a route choice taking into account future diversion possibility which is not available when decision is made. Networks from the study of Razo & Gao (2010) are used here and we design one more complex map. One simple map is used to evaluate people's risk attitude and two more complex maps are used to investigate strategic route choice thinking. The difference between these two complex maps is network complexity which is the number of routes are considered when a decision is made. Cognitive load is often assumed to influence people's route choice behavior. It has been shown that people's route choice behavior in a paper-and-pencil test is different from that in a virtual environment (driving simulator) (Katsikopoulos et al., 2000). To conduct a field test is beyond the resources we have. Therefore, a PC-based test and a driving simulator test are implemented with exactly the same network situations to demonstrate people's difference in these two environments. To avoid learning effect across two environments, two different subject groups with similar background take part in these two tests.

Non-parametric analysis test is suitable for small data sets when a normal distribution assumption cannot be met. In the non-parametric analysis, we investigate whether people make strategic route choice decisions, how network complexity affects people's strategic route choice ability and how cognitive load affects people's strategic route choice behavior. Subjects' demographic information such as: age, gender and driving experience (years and mileage) are recorded in the questionnaire. Non-parametric analysis can help answer how these characteristics play a role in people's strategic route choice behavior.

Building a model enables us to make predictions based on the understanding of the drivers' choice behavior. A mixed Logit model with two latent classes, strategic and non-strategic, is developed and estimated. Modeling work is done with data from driving simulator test and PC-based test separately, as well as with the two data sets combined. Human beings learn from experience especially lessons or mistakes they have made. Route choices mostly happen in a daily commute context. Therefore, we are curious about whether people will change or improve their strategic route choice ability. A simple model where strategic route choice ability bearing a linear relationship with number of scenarios experienced is assumed and estimated.

1.4 Thesis Contributions

We contribute to the knowledge of process model in the travel behavior field in following aspects:

1. We introduce process model into travel route choice behavior analysis. Based on a comparison with three established models, we show that process model has satisfying data-fitting and predictive performance and should be given more emphasis.

2. Based on original PH model, we develop a stochastic PH model with data collected from a PC-based test. Some new findings which are different from original models, such as: different threshold values and different comparing orders, can be reasonably explained in our context. These findings provide a good guideline for future research in this direction.

Our contributions towards strategic route choice model are summarized as follows:

1. We extend the research in this direction from synthetic data and SP data of a PC-based test to our current driving simulator test. This is an important step to refine this model for the final applicability in our real life.

2. Since another PC-based test using the same networks was conducted, we are able to make a sound comparison between travelers' route choice behavior in these two environments where just the cognitive loads are different from each other. We find that a parallel driving task which is a reflection of cognitive load affect people's strategic thinking ability only in a difficult scenario but not a simple one.

3. Two strategic maps with different network complexities are involved in the driving simulator test and PC-based test. We conclude that network complexity affects people's strategic thinking ability in the modeling analysis in two test environments. However, in the non-parametric analysis, network complexity only affects people's strategic route choice behavior in driving simulator test but not in PC test environment.

4. From non-parametric analysis, we arrive at some interesting findings: at some occasions, people's gender and driving experience (milage) have an effect on their strategic route choice behavior.

1.5 Thesis Organization

This thesis is organized as follows. We first study the process model in a risky network and then investigate people's strategic route choice model.

In Chapter 2, we describe three tests whose route choice decisions will be utilized in the analysis of later chapters: PC-based test 1, driving simulator test and PC-based test 2. These three tests are conducted in different periods with different subjects. Test designs, pictures and information about subjects are recorded and presented.

In Chapter 3, we introduce the original PH and develop it into a stochastic version taking into account differences among the subject group. With data collected from PC-based test 1, a stochastic PH model is successfully estimated and explained. Finally, three other competing models are introduced for a cross validation to study these models' data-fitting and prediction performance.

In Chapter 4, we first do some analysis towards the test design and identify valid strategic route choice which are suitable for non-parametric analysis in each scenario. Since strategic route choice behavior is identified at a person level, the valid number of population in the data set for analysis is much smaller than that for modeling estimation. Therefore, non-parametric analysis is a suitable method to investigate subjects' route choice behavior. In this non-parametric analysis, we qualitatively tested some interesting topics, such as: whether subjects make strategic route choice decisions, how network complexity affects people's strategic thinking ability and whether a parallel driving task undermines travelers' strategic thinking ability.

In Chapter 5, a mixed Logit model with two latent classes is developed and estimated using data collected from the driving simulator test and PC-based test 2. A model combining data collected from the two tests was also estimated.

In Chapter 6, we give a summary of the work in this thesis and make a discussion towards future research directions.

CHAPTER 2

LITERATURE REVIEW

2.1 Process Model

2.1.1 Econometric Model

Understanding travel decision making in an uncertain environment and predicting travel choices in such an environment are important components in the overall goal of building a more reliable and efficient transportation system. Econometric (random utility) models are the generally accepted paradigm for choice modeling in transportation. They are adjusted to tackle the decision under risk problem, ranging from simply adding a risk measure (e.g., travel time standard deviation) to the utility function (Lam & Small, 2001), to probabilistic versions of non-expected utility models from behavioral economics that captures non-linear subjective perceptions of both probabilities and outcomes, such as Cumulative Prospect Theory (CPT) and Rank-Dependent Expected Utility (RDEU) theory (Schwanen & Ettema, 2009; Razo & Gao, 2013). Econometric models, such as CPT and RDEU applied in a travel decision making context, assume that decision makers integrate the outcomes and the associated probabilities of an alternative into one single measure of its worth (utility) and the alternative with higher utility will be chosen. See de Palma et al. (2008) for a review of the cross fertilization of the theories of decision under risk and discrete choice models.

CPT and Expected Utility Theory (EUT) both originated from the field of decision-making, not specialized for travelers' route choice behavior. Therefore, parameters of weighting function and value function used in CPT are still open to question about their accuracy when applied in route choice analysis. In Xu et al. (2011), it is shown that CPT model is more consistent with people's actual route choice behavior than EUT model. The authors re-estimated parameters of the value function based on an SP survey and final estimation results of this improved CPT model exhibited more advantage over the original CPT model whose parameters are borrowed from Wu & Gonzalez (1996). Compared with ordinary individual, commuters in the given study have a much greater degree of risk aversion when confronted with the prospect of gains, a greater degree of risk seeking when confronted with the prospect of losses, and a lesser degree of relative sensitivity of losses to gains. However, the weighting function is assumed to have a universal form for all kinds of decision making behavior (Tversky & Kahneman, 1992; Wu & Gonzalez, 1996).

In Thiene et al. (2012), Random Regret Minimization (RRM) model was established to investigate how people make a discrete choice among a selection of services provided by a Natural Park in Italy with stated preference data. RRM model is based on the notion that when choosing, people tend to minimize future regret rather than aiming to maximize future utility which is adopted in most econometric models. Regret is defined as what one experiences when a non-chosen alternative performs better than a chosen one. RRM models result in closed-form logit type choice probabilities and are suitable for the analysis of risky and riskless choices between multi-attribute alternatives in multinomial choice contexts. Its counterpart Random Utility Maximization (RUM) model was also developed and estimated for a comparison with RRM model.

With the purpose to enhance discrete choice model, psychological factors affecting decision making process should be considered and included. A hybrid model incorporating two parts: latent variable model and route choice model was proposed and estimated in Prato et al. (2012). Latent variables are defined as travelers' attributes as following: mnemonic ability, habit within the choice environment, familiarity with the choice environment, spatial ability and time saving skill. Structural equations in latent variable model associate the latent variables to individual characteristics such as gender, age, education level, family composition and etc. Meanwhile, structural equations of the choice model associate route utilities with route attributes and latent variables as perceived by each individual. Route attributes refer to distance, travel time, percentage of delay and etc. Simultaneous estimation was performed towards latent variable model and route choice model. Final results demonstrate that taking into account latent variables and traditional variables improve the comprehension of route choice behavior.

2.1.2 Priority Heuristic

One area in decision theory that is missing in travel behavior modeling is the process modeling paradigm, which aims to capture a decision maker's actual decision process, usually with efficient and frugal heuristics rather than correlating the choices with explanatory variables through complicated mathematical formula as in econometric models.

One of the popular process models is the parameter-free priority heuristic (PH) model proposed in Brandstatter et al. (2006). PH supposes that a decision maker does not make trade-offs between outcomes and probabilities, but uses information in a non-compensatory manner. The final decision is obtained through a series of comparisons of outcomes and/or probabilities (termed "reasons"). Specifically, in the situation of two alternatives with two outcomes (minimum and maximum in terms of the absolute values in the domain of gain or loss), the order of comparison is minimum outcome, probability of minimum outcome and maximum outcome.

- Step 1: compare two minimum outcomes. If the difference is larger than 1/10 (defined as the aspiration level) of the higher maximum outcome, the more attractive alternative (larger minimum outcome in the domain of gain, and smaller minimum outcome in the domain of loss) is chosen and the process stops. Otherwise, go to Step 2.

- Step 2: compare probabilities of two minimum outcomes. If the difference is larger than 0.1, the more attractive alternative (smaller minimum-outcome probability in the domain of gain, and larger minimum-outcome probability in the domain of loss) is chosen and the process stops. Otherwise, go to Step 3.

- Step 3: compare two maximum outcomes. The more attractive alternative (larger maximum outcome in the domain of gain, and smaller maximum outcome in the domain of loss) is chosen and the process stops.

We give an example to show how the PH works. Consider two alternatives in the domain of gain:

$$(4000, 0.2; 0, 0.8) \quad vs \quad (3000, 0.25; 0, 0.75).$$

At the first reason, both alternatives have the same minimum outcome (0), which is less than (1/10)*4000, and thus we move to the second reason. At the second reason, the difference between the probabilities of two minimum outcomes, 0.8 - 0.75, is less than 0.1, and thus we move to the third and last reason. At the third reason, the first alternative has a larger maximum outcome and thus it is chosen.

The priority heuristic is simple in several respects. It typically consults only one or a few reasons; even if all are screened, it bases its choice on only one reason. Probabilities are treated as linear (in contrast to the non-linear transformation of probabilities in CPT), and a 1/10 aspiration level is used for all reasons except the last, in which the amount of difference is ignored. No parameters for overweighting small probabilities and underweighting large probabilities or for the value function are built in.

Brandstatter et al. (2006) has shown that the PH can account for evidence at variance with expected utility theory, namely a) the Allais paradox, b) risk aversion for gains if probabilities are high, c) risk seeking for gains if probabilities are low (e.g., buying lottery tickets), d) risk aversion for losses if probabilities are low (e.g., buying insurance), e) risk seeking for losses if probabilities are high, f) the certainty effect, g) the possibility effect, and h) intransitivities. A wide range of choice problems were used in (Brandstatter et al., 2006) to compare the predictive performance of PH and other well-known theories of decision under risk, including CPT model (Tversky & Kahneman, 1992) and TAX (Transfer of Attention Exchange) model (Birnbaum, 1997). PH model gave comparable or superior performance in most situations.

Some researchers are skeptical of the PH. Johnson et al. (2008) conducted an experiment in web browsers running MouselabWEB (Willemsen & Johnson, 2012) to collect subjects' actual behavior during a decision making. Attentions and transitions across elements of each alternative were recorded. It was found that transitions between outcomes across alternatives were rare and outcomes-probabilities transitions were common. This finding contradicted with PH. In addition, it was hypothesized that when PH stopped at step 1, attentions between two minimums should be observed dominantly while attentions of two minimum-probabilities and maximums should not be observed or very few. The actual observations from experiment suggested that attentions were evenly distributed across outcomes and probabilities.

A recently published paper Schulte-Mecklenbeck et al. (2011) evaluated the contribution of process tracing data to the development and testing of models of judgement and decision making. Five different tools/models are mentioned: Active Information Search, Eye-tracking, MouselabWeb, Mouse-tracking and Thinking aloud. Three aspects of these models are discussed: core methodology, theoretical contribution and key results. In addition, this study discussed the issue of large data volumes resulting from process tracing and provided some remedies for handling those.

Glockner & Betsch (2008) pointed out that two strong restrictions have been imposed on the PH as described in Brandstatter et al. (2006): 1) the PH does not work in the situation where one alternative dominates the other one such as: (0, 1%, 1, 99%) vs (2, 50%; 30, 50%) (in the domain of gain) where PH model will make a wrong prediction. 2) The accuracy of the PH will decrease dramatically when the ratio of two alternatives' expected outcome values exceed 2, such as 20 vs (0, 1%; 100, 99%) (in the domain of gain). These two restrictions help the PH exclude more than 50% cases where it is not good at when all scenarios are randomly generated, and thus it is doubtful whether the PH can be used as a general theory of decision under risk.

While the debate about the PH is going on, we think it is worthwhile to investigate its applicability in a travel decision making context. The original PH is suitable for predicting majority choices, but appears to be less suited to provide proportional predictions. In order to predict the percentage of demand for each route in the traffic network, we construct a probabilistic PH model (Rieskamp, 2008). It is estimated using previously collected SP (stated preference) data (Razo & Gao, 2010).

2.2 Strategic Route Choice Model

2.2.1 Route Choice With Real-time Information

So far, most established route choice models are based on deterministic networks. They assume that a driver makes a complete route choice at the origin of a trip and does not account for any real-time information provided en-route. Examples of such models are Path Size Logit (Ben-Akiva & Ramming, 1998; Ben-Akiva & Bierlaire, 1999)e.g., C-Logit (Cascetta et al., 1996), Cross-Nested (Vovsha & Bekhor, 1998), and Logit Mixture (Ramming, 2001; Bekhor et al., 2002; Frejinger & Bierlaire, 2007)e.g..

There has been a plethora of studies in the literature showing that real-time traffic information could prompt drivers to change routes (Khattak et al., 1993; Adler et al., 1993; Emmerink et al., 1995; Polydoropoulou et al., 1996; Bonsall et al., 1997; Mahmassani & Liu, 1999; Lappin & Bottom, 2001; Srinivasan & Mahmassani, 2003;

Abdel-Aty & Abdalla, 2004; Bogers et al., 2005; Abdel-Aty & Abdalla, 2006; Bierlaire et al., 2006; Ben-Elia et al., 2008; Athena et al., 2009)e.g.,. However, most of the models focus on the switching behavior from a habitual route in a cross-sectional context or from the previous round's choice in a day-to-day learning situation, where only the on-the-spot response to real-time information is considered. Conceivably, real-time information provides a driver with more flexibility in route choices, as he/she does not need to commit to a particular route but can decide later at a switching point based on revealed traffic conditions and pick the route with a lower travel time for the remaining trip. The real-time information thus could make a collection of routes more attractive than those without the information, and influence route choice even before the information is available.

Saneinejad et al. (2012) built models to investigate how weather conditions impact residents' mode choice behavior in Toronto Canada. Five transportation modes are considered: auto driver, auto passenger, transit, bike and walk. Results of this study clearly demonstrate that people of different gender group or age group have different response for weather conditions. For instance, females' tendency to bike is about 1.5 times more negatively affected by low temperatures than males. In temperatures below 20°C cyclists below 55 years of age are negatively influenced by temperature. This negative influence is greatest for cyclists below 25 years of age, and gradually improves for older age groups. A web-based interactive experiment was designed and associated subjects were recruited in Eindhoven region Netherlands. People's socio-demographic information: age, gender and education level are used as covariate variables. Modeling results testified that people's activity rescheduling, route choice and information acquisition behavior are more affected by subjects' education level than their age and gender (Sun et al., 2012). Based on these two studies, we can reasonably expect that people's strategic route choice behavior are also influenced by these socio-demographic characteristics. In addition to age and gender, we also recorded each subject's driving experience: milage have driven and how many years holding license.

2.2.2 Strategic Route Choice behavior

Strategic route choice is defined as one that considers future diversion possibilities enabled by real-time traffic information.

While many studies have addressed the problem of optimal strategies (for a recent review, see Gao & Chabini (2006)), econometric models of strategic route choice have not been studied thoroughly. Such an econometric model was proposed by Gao (2005), but the estimation problem was not dealt with. Synthetic data were generated for validating strategic route choice models in Gao et al. (2008) and Gao et al. (2010). Stated preference (SP) data from a PC-based survey were gathered and a route choice model was estimated in Razo & Gao (2010) where two latent classes of route choice behavior, strategic and non-strategic, are both taken into account. The latent class method has been used previously in transportation research, e.g., to study travelers' air carrier decisions (Wen & Lai, 2010).

2.2.3 Cognitive Load in Different Test Environments

SP data from human subjects in a driving simulator test and a PC-based test are used to investigate people's strategic route choice behavior. Reviews of comparisons between driving simulator tests and our real life indicate that such a simulator is able to provide route choice data with high validity (Kaptein et al., 1995). In addition, Yan et al. (2008) demonstrates that driving simulator can also be used as a valid tool to assess traffic safety at signalized intersections. In this study, similar speed behavior and traffic risk patterns were observed in driving simulator test and real intersections. It is believed that this driving simulator environment could induce a more realistic level of cognitive load than a traditional paper-and-pencil or PC-based test. Research shows that subjects' route choice behavior in a driving simulator test that demands high cognitive load is different from that in a paper-and-pencil survey which demands low cognitive load (Szymkowiak et al., 1997; Katsikopoulos et al., 2000)e.g.,. Compared with paper-and-pencil surveys, the relative importance of expected travel time over travel time variability is more significant in the driving simulator test. It is also shown in some psychology studies that people's ability to make an informed intuitive judgment is impaired by concurrent involvement in a different cognitive task (Gilbert, 2002), which prompts us to investigate whether a parallel driving task affects people's ability to make an informed route choice decision.

CHAPTER 3

DATA COLLECTION

There are three stated preference surveys involved in this study: PC-based test 1, driving simulator test and PC-based test 2. Test design and participants of each test are described as following:

3.1 PC-based test 1

3.1.1 Test Design

The PC-based test 1 was conducted in 2009 and implemented by Adobe Flash in Windows OS. An abstract network is shown in Figure 3.1. A subject had a choice between a path with a random travel time (Path A with a high travel time of t_H with probability p and low travel time of t_L with probability $(1-p)$, the risky route), and a path with a deterministic travel time (Path B with a travel time of t_B, the safe route).

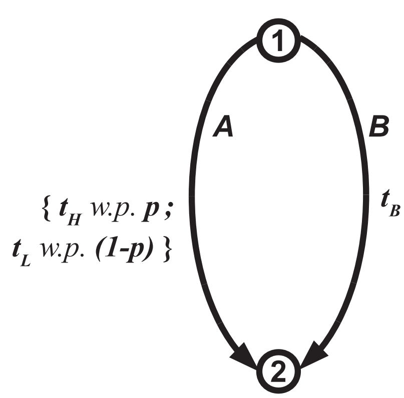

Figure 3.1 The Abstract Network.

With the advantage of simplicity and clarity as compared to describing the scenarios in written or verbal form, this survey was conducted using interactive graphical maps with a point-and-click interface (shown in Figure 3.2). Routes in green color are assigned as buttons for subjects to click. The white labels, 30 and 40, indicate the usual travel time of the adjacent route with the unit of minute. The yellow label beside the risky link indicates the probability of a delay and the full travel time of this path in the event of a delay. With a factorial design, the probability of delay (p) could be 20%, 50% and 80%. t_L is fixed at 30 minutes throughout all scenarios. t_H takes values 40, 50, and 60 while t_B takes values from 35 to 55 with a step size of 5 such that the safe route is not dominated by the risky route. Including introduction, paperwork and the survey, each session lasted 40 to 60 minutes for each subject.

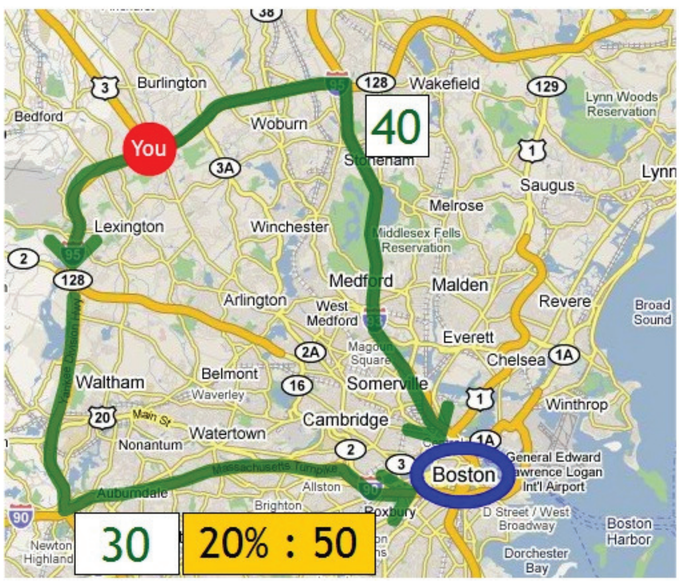

Figure 3.2 Screenshot of the Survey Interface.

This simple risk map used to test subjects' risk attitude is just a part of a survey which including another strategy map to investigate people's strategic route choice behavior. The strategy map is an extension of simple risk map by adding a detour (Link D) (as shown in Figure 3.3) and real-time information ("info" at Node 2) to the risky alternative. The real-time information notifies the subject of the actual travel time on Link C, before s/he must decide which link to take out of Node 2. This allows the subject to choose the faster of Links C and D and avoid large delays. t_M of Link C with probability p is designed as exceedingly larger than any other travel time on the map. The map can therefore measure the extent to which a subject recognizes and utilizes strategically advantageous real-time information. A screenshot of strategy map is shown as Figure 3.4. A blue "i" icon is shown at the node where the user will receive the information. When the user arrives at that node, the actual travel time of the risky link is revealed, and the user may choose whether to use the risky link (Link C) or the detour (Link D). More details of the complete survey which includes simple risk map and strategy map can be found in Razo & Gao (2010).

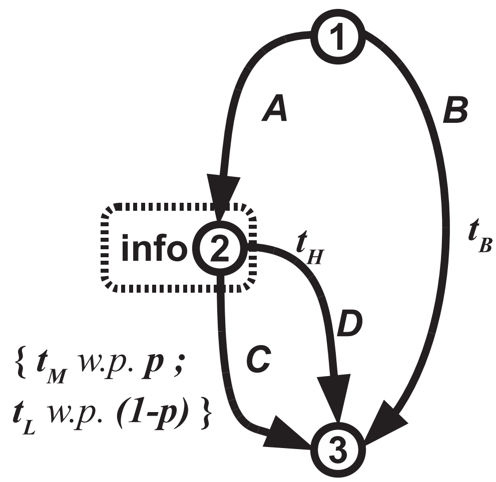

Figure 3.3 Abstract network for routing strategy tests

3.1.2 Participants

74 individual subjects were recruited from the University of Massachusetts Amherst students and staff community and surrounding areas. The mean age was 24.2 years and mean driving experience was 6.9 years. 54% of the subjects were male, 46% were female. Each subject made choices in 24 different scenarios in this simple risk map with a total of 1,767 observations (9 observations are missing due to problems in transmitting data).

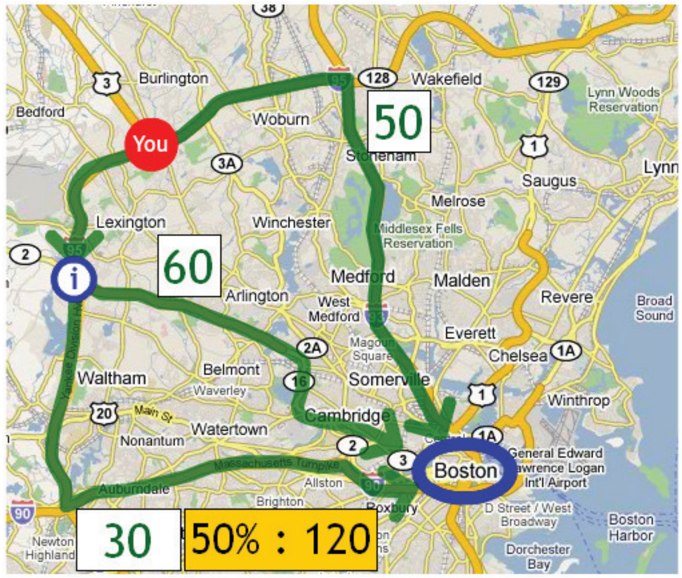

Figure 3.4 Example map interface with information and detour

3.2 Driving Simulator test

3.2.1 Test Design

The driving simulator is located in the Human Performance Laboratory at the University of Massachusetts Amherst. It consists of an actual car connected to three projectors that display a virtual traffic database (some photos of the given driving simulator can be found in Figure 3.5, 3.6 and 3.7). For each figure, the picture of network and travel times at the bottom is information subjects receive at each stage during the test.

There are three types of maps in this test, shown in Figure 3.8. A single number beside a route denotes a deterministic travel time, while (m, n) a random travel time with two ordered outcomes m or n $(m < n)$, each with probability 50%. From the origin node in each map, two options are available: either the safe Route 1 with a deterministic travel time t_b or the risky branch involving random travel times on one or more routes.

The risky branch gets more complicated in topology from Map A through C, containing one, two and three routes respectively. In Map A it contains one single

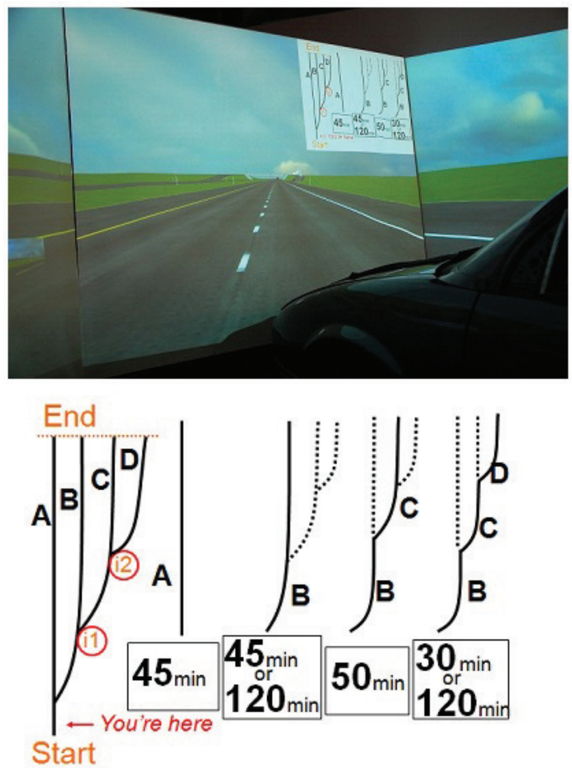

Figure 3.5 Origin of Map C.

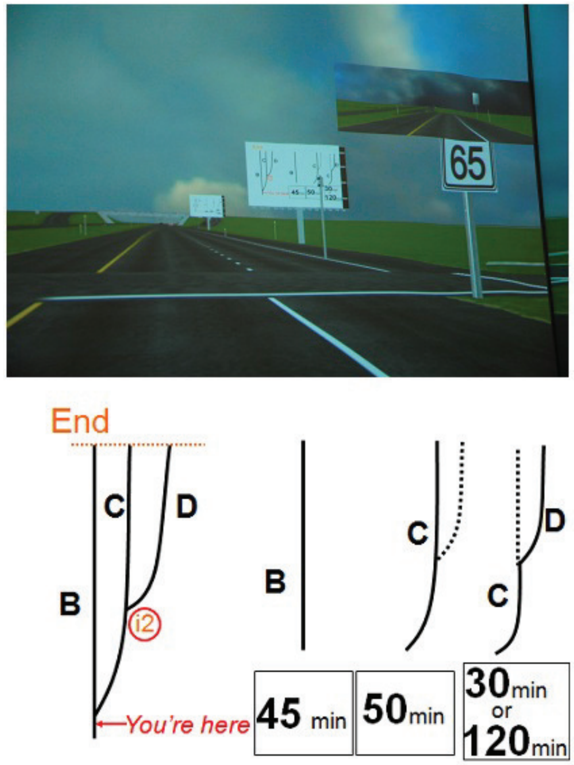

Figure 3.6 First information node in Map C.

Route 2, with a possible low travel time t_L and high travel time t_H. In Map B, a bifurcation is added to the risky branch, where the safe detour (Route 2) has a deterministic travel time t_H. The risky Route 3 has a low travel time t_L and a prohibitively long delay t_M, which could be due to an incident. At Node i, a subject receives real-time information on the realization of the travel time on Route 3. If t_M is realized, Route 2 can serve as a diversion from Route 3. A driver who takes into account the value of information at Node i when making the route choice at the origin is deemed as strategic. Map C adds another bifurcation to the risky branch, upstream of the one in Map B, with two possible outcomes t_b and t_M. Real-time information is available at Node i1 on the realized travel time on Route 2, and Node i2 on the realized travel time on Route 4. Similarly the information at either node could help drivers avoid the extremely high travel time t_M on Route 2 or 4, and a driver who takes into account these facts in route choice decisions at the origin is

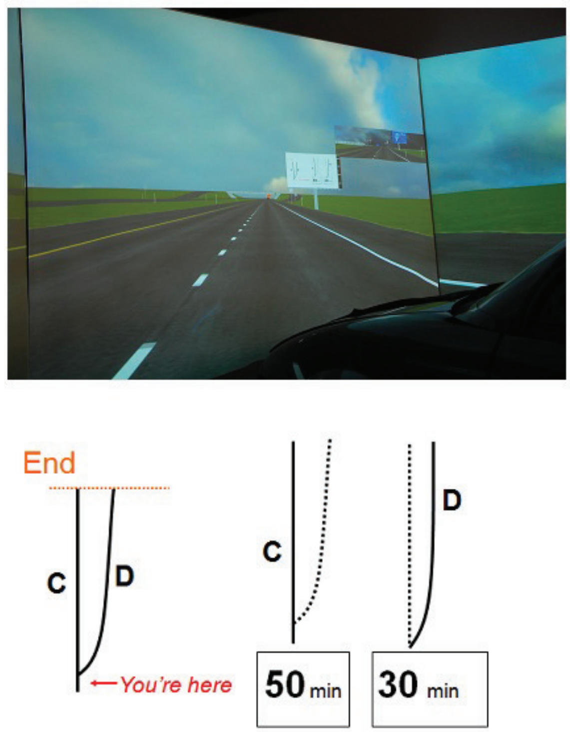

Figure 3.7 Second information node in Map C.

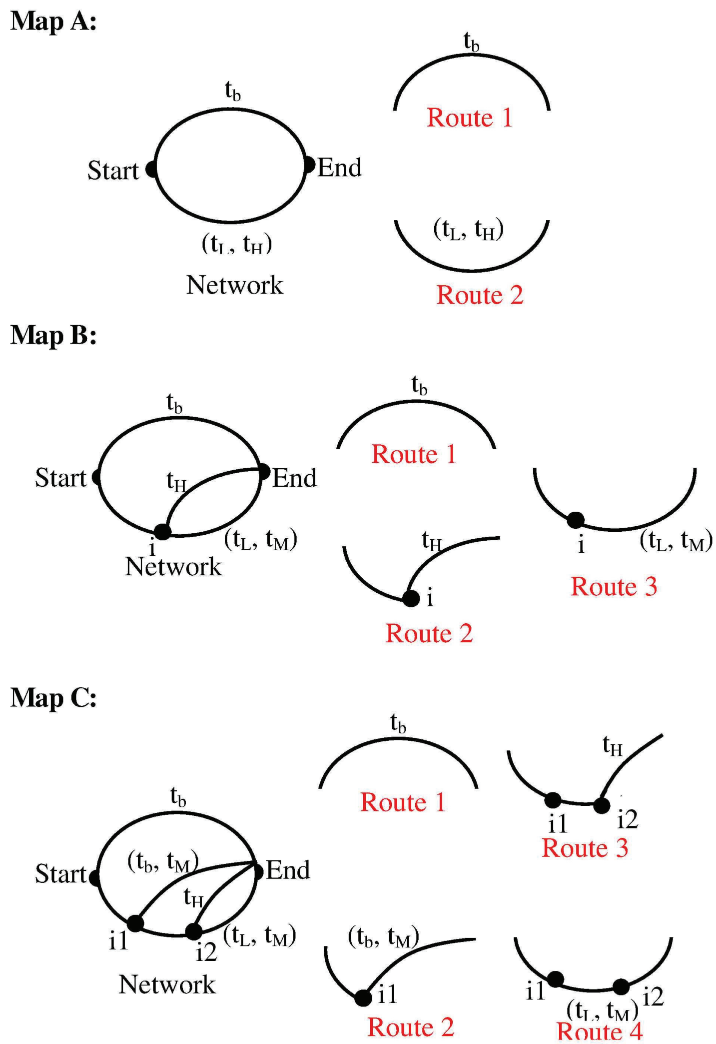

Figure 3.8 Three types of maps in the driving simulator test.

deemed as strategic. Note that a subject could behave strategically in one scenario and non-strategically in another, therefore strictly speaking we can only talk about strategic choices, not strategic subjects. However in the remainder of the paper, these two terms will be used interchangeably if no confusion will arise.

Each type of map appeared six times with different travel times as shown in Table 3.1. The relationships between travel times in each scenario are $t_L < t_b < t_H << t_M$ and $(t_L + t_H)/2 < t_b << (t_L + t_M)/2$. The rationale behind the travel time design is detailed in Section 5.8. Travel times denoted with the same symbol in three different map types have the same numerical value.

	t_L	t_H	t_b	t_M
#1	30min	50min	45min	120min
#2	30min	60min	50min	120min
#3	30min	60min	55min	120min
#4	30min	70min	60min	120min
#5	30min	70min	65min	120min
#6	30min	80min	70min	120min

Table 3.1 Travel time combinations in 6 groups of scenarios

The driving-simulator-based tests are set up with pre-fabricated blocks of road geometries and street scenes from the simulator program. Our subjects generally reported that they felt the experiences fairly close to real ones. Subjects were required to drive slowly at the beginning of each scenario to observe a map of the entire network with risky travel times before arriving at an intersection where a route choice decision had to be made. This map was shown as a picture on the up-right corner of the middle screen for exactly ten seconds (Figure 3.5). In addition, there were two identical roadside billboards shortly before each real-time information node in Maps B and C, namely Nodes i, i1 and i2, where the actual travel times on links immediately out of the information node were revealed, while risky travel times further downstream remained unchanged (Figure 3.6). The two identical billboards were intended for the subjects to have enough time to acquire the correct information. In order to implement different travel times for the same route, lead vehicles with pre-specified speeds were assigned in every intersection in each scenario, and subjects were instructed to follow lead vehicles. The simulator time that a subject actually spent on driving on any route in a map was scaled down from the displayed travel time by controlling the lead vehicle speeds. All route travel times in the same map were scaled by the same factor, so that subjects bore the consequences of their choices. Different maps had different scales due to the limitations of the simulator software, however we believe this would not affect subjects' understanding of the trade-offs between routes in the same map. On average, a subject spent two minutes in each scenario, and the complete test took around one hour including the time for instruction, rest and entry- and exit-questionnaires.

3.2.2 Participants

64 individual subjects were recruited from the University of Massachusetts Amherst students for the driving simulator test. The mean age was 22.2 years and mean driving experience was 3.4 years. 48% of the subjects were male, 52% were female. Each subject made choices in 13 different scenarios with a total of 819 observations. Data for one of the subjects were deleted due to a misunderstanding. Five other subjects exhibited extremely risk-seeking route choices behavior in the Map A scenario with highly risky travel times (t_L, t_M) on the risky branch.

3.3 PC-based test 2

3.3.1 Test Design

The PC-based test 2 was finished in 2012. It was also a PC-based test implemented by Adobe Flash. In order to investigate travelers' route choice behavior in two different environments: driving simulator and PC-based test, PC-based test 2 was developed. A screenshot can be found in Figure 3.9.

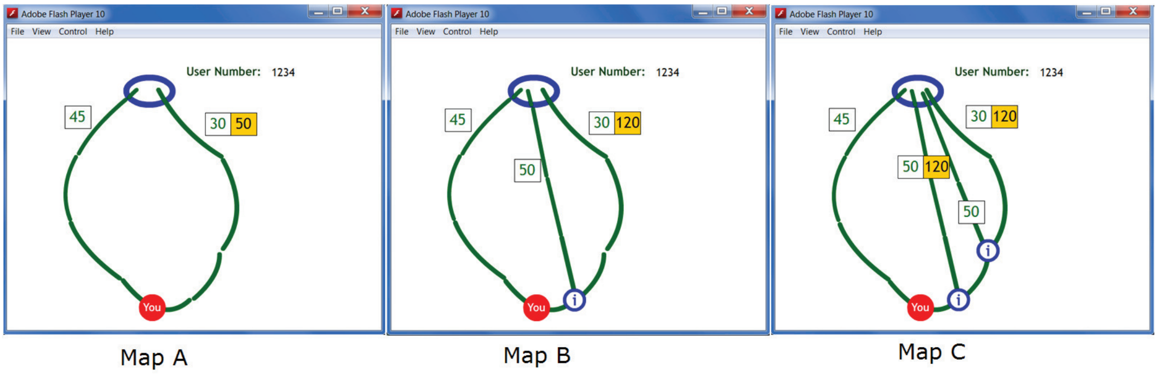

Figure 3.9 Three Maps in PC-based test.

PC-based test 2 was developed and conducted for a complete comparison between two test environments. Therefore, the test design of PC-based test 2 was quite similar to driving simulator test with minimal changes to eliminate biases in the experiments. In PC-based tests, subjects were required to view the map of the entire network with risky travel times for exactly ten seconds at the beginning of each scenario with all mouse or keyboard operations disabled. After ten seconds, all travel time labels disappeared and subjects then clicked on one of the routes to make a choice. An animated dot showed the movements along the routes, and upon the arrival at an information node, actual travel times on immediate outgoing links were revealed. Due to the technical limitation, there is a bias towards safe route in driving simulator test: safe route is always a straight line in all scenarios but risky branch is always comprised of uphill, downhill and intersections. In PC-based test, we specifically split the safe route into 4 links to keep a balance on number of clicks to finish each scenario, as shown in Figure 3.9. Actually, this balance is well kept for very route which means exactly 4 times clicks is needed to travel from origin to destination. The time spent in the PC-based tests for each subject was fixed and not proportional to the displayed travel time. However, we asked the subjects to put these travel times in their regular work-to-home commute context and make choices as they would in real life. On average, a subject spent twenty seconds in each scenario.

3.3.2 Participants

With purpose to eliminate potential learning from driving simulator test or vice versa, a completely different group of subjects were recruited for the PC-based tests. In order to draw conclusions from the comparison of driving simulator test and PC-based test, these two groups of subjects have very similar background, such as age, education and etc. 66 individual subjects were recruited from the University of Massachusetts Amherst students. The mean age was 20.5 years and mean driving experience was 3.3 years. 82% of the subjects were male, 18% were female. Each subject made choices in 13 different scenarios with a total of 858 observations.

3.4 Relationship between Driving Simulator test and PC-based test 2

As Table 3.2 shows, Driving Simulator test and PC-based test 2 can together be divided into four groups with respect to test environment and network complexity. For example, subjects in the *Sim_AB* subgroup were presented with six Map A scenarios and then six Map B scenarios in driving simulator. Two, three, and four warm up scenarios were scheduled before Map A, B, and C scenarios respectively to help subjects familiarize themselves with each route in these three maps and avoid explorative route choices later.

	Maps A&B	Maps A&C
Driving simulator	*Sim_AB*	*Sim_AC*
PC	*PC_AB*	*PC_AC*

Table 3.2 Two factors in the test design:test environment and network complexity.

In order to eliminate any potential bias resulting from any specific scenario sequence, the scenario sequence in each map was randomly assigned to each subject. The six scenarios were divided into three blocks, where the first block contained scenarios 1 and 4, the second block contained scenarios 2 and 5, and the third block contained scenarios 3 and 6. A randomization was applied to the three blocks with permutations of two scenarios in each block. This resulted in forty-eight different scenario sequences. There was one additional Map A scenario with travel time combination (t_L, t_M) on the risky route for the identification of extreme risk-seeking subjects, and thus the number of different scenario sequences was much more than 48. No randomization was conducted across map types, i.e., all Map A scenarios were presented before Map B or C scenarios.

CHAPTER 4

A PROCESS MODEL FOR ROUTE CHOICE UNDER RISK:PROBABILISTIC PRIORITY HEURISTIC (PPH) MODEL

4.1 Introduction

4.2 Model Development

In this chapter, route choice decisions collected from PC-bases test 1 used as data set for analysis and modeling. In this study, we develop a probabilistic version of the Priority Heuristic (PH) model similar to Rieskamp (2008) to predict the proportion of demand for each route in a traffic network, while the deterministic PH is only able to predict the majority choice. In the initial application of the PH to our data set, when the threshold used in the comparison of minimum outcomes changed from the default 10% to 20%, the predictive accuracy of the PH improved considerably. This finding suggests that the PH model could be improved by estimating threshold values rather than using the default 10%. Conceivably comparing minimum outcomes (min), probabilities of minimum outcomes (pr) and then maximum outcomes (max) is not necessarily the only comparing order. The other five potential orders should also be considered: 2) min, max and pr; 3) max, min and pr; 4) max, pr and min; 5) pr, max and min; 6) pr, min and max. The existence of different comparing orders has been discussed in Hilbig (2008).

We treat all travel times as losses and in the remainder of the paper we work in the domain of loss only. Consider two alternatives A and B, each with two probabilistic outcomes (in absolute values) and the associated probabilities in the domain of loss,

$$(A_{min}, A_{pr}; A_{max}, 1 - A_{pr}) \quad \text{and} \quad (B_{min}, B_{pr}; B_{max}, 1 - B_{pr}),$$

where the minimum (maximum) outcomes are defined by absolute values (e.g., a travel time of 10 minutes is a smaller loss than 15 minutes). Note that a lower loss (maximum or minimum) is more attractive, and a higher probability of the minimum loss is more attractive. Let R denotes a reason, and $R = min, max, pr$.

Error terms ϵ_{AR} and ϵ_{BR} are added to the objective values of reason R for the two alternatives respectively. Error terms for different reasons are independent, but do not necessarily have the same variance (scale).

If R is not the last reason, the probability of choosing A at reason R is the probability that the difference (the direction of taking the difference depends on the reason) between the noise-added reason values is greater than a threshold δ_R between 0 and 1, multiplied by the maximum outcome in the choice situation $M = max(A_{max}, B_{max})$.

$$P_R(A) = Prob(-[(A_R + \epsilon_{AR}) - (B_R + \epsilon_{BR})] > \delta_R M), R = max, min. \tag{4.1}$$

$$P_R(A) = Prob((A_R + \epsilon_{AR}) - (B_R + \epsilon_{BR}) > \delta_R M), R = pr. \tag{4.2}$$

Similarly, the probability of choosing B at reason R if R is not the last reason is

$$P_R(B) = Prob(-[(B_R + \epsilon_{BR}) - (A_R + \epsilon_{AR})] > \delta_R M), R = max, min. \tag{4.3}$$

$$P_R(B) = Prob((B_R + \epsilon_{BR}) - (A_R + \epsilon_{AR}) > \delta_R M), R = pr. \tag{4.4}$$

When δ_R is positive, $P_R(A) + P_R(B) < 1$, and the probability of not making a decision at reason R and moving to the next reason is $1 - P_R(A) - P_R(B)$. If δ_R is zero, the model collapses to a utility maximization one, and $P_R(A) + P_R(B) = 1$.

If R is the last reason, a decision must be made, and thus δ_R is set to 0. The probability of choosing A at the last reason R is thus

$$P_R(A) = Prob(-(A_R + \epsilon_{AR}) > -(B_R + \epsilon_{BR})), R = max, min. \tag{4.5}$$

$$P_R(A) = Prob(A_R + \epsilon_{AR} > B_R + \epsilon_{BR}), R = pr. \tag{4.6}$$

The probability of choosing B at the last reason R is $1 - P_R(A)$.

For a given reason R, the difference of the error terms $\epsilon_{AR} - \epsilon_{BR}$ effectively adds noises to the threshold of the reason $\delta_R M$, and captures the fact that different decision makers could have different thresholds. Other potential contributors to the noise include perception errors of outcomes and probabilities, and missing attributes. Theoretically if certain independent continuous distributions are assumed for the perception errors of the two outcomes of an alternative, the designations of the maximum and minimum outcome might be reversed for some realizations of the error terms, compared to the objective designation. We believe that such situations rarely happen in reality as decision makers generally can differentiate a good outcome from a bad outcome. Therefore we maintain the maximum and minimum outcome designation based on their objective values. The perception error, as only one part of the error term, is assumed to be not large enough to reverse the ordering.

The unconditional probability of choosing A is thus the sum of three components, each corresponding to a reason,

$$\begin{aligned} P(A) \quad = \quad & P_{R_1}(A) + & (\textbf{Reason 1}) \\ & P_{R_2}(A)(1 - P_{R_1}(A) - P_{R_1}(B)) & (\textbf{Reason 2}) \\ & P_{R_3}(A)(1 - P_{R_1}(A) - P_{R_1}(B))(1 - P_{R_2}(A) - P_{R_2}(B)) & (\textbf{Reason 3}) \end{aligned} \tag{4.7}$$

4.3 Discontinuity of the PPH Model

The choice probability of an alternative calculated from a PPH model can be discontinuous with respect to the outcomes and/or probabilities of the alternative outcome distributions, due to the discrete nature of defining the minimum and/or maximum outcomes. Two typical situations are discussed below, one with the probability and the other with the outcome.

Consider the comparing order of min, max, and pr. When the probability of the minimum outcome of alternative A, A_{pr} approaches 0 but remains a positive number, A_{min} remains the minimum outcome of alternative A. However when A_{pr} is exactly 0, the outcome distribution of alternative A collapse to a deterministic one $(A_{max}, 1)$ and the minimum outcome is the same as the maximum outcome A_{max}. The discontinuity in the change of the minimum outcome from A_{min} to A_{max} at $A_{pr} = 0$ will result in the discontinuity of the final probability of choosing A at the same location.

Consider again the comparing order of min, max, and pr. When A_{min} approaches A_{max} but is not equal to A_{max}, the probability of the minimum outcome remains A_{pr}. However when A_{min} is equal to A_{max}, the outcome distribution of alternative A collapse to a deterministic one, $(A_{min}, 1)$, and the probability of the minimum outcome becomes 1. The discontinuity in the change of the probability of the minimum outcome from A_{pr} to 1 at $A_{min} = A_{max}$ will result in the discontinuity of the final probability of choosing A at the same location.

The discontinuity could make it difficult to interpret model predictions at and close to the location of discontinuity. An example is shown later in Figure 4.2 with discussions provided in Section 4.6.1.

4.4 Model Specification

The PPH model developed in the previous section is a general model without specifications of the distributions of random error terms. It is adapted to the actual choice problem in the survey. An alternative-specific constant (ASC) is added to the risky route for each reason, $ASC_{min}, ASC_{max}, ASC_{pr}$. These variables are used to capture potential biases towards either one of the two routes, e.g., the risky route has two segments and could be viewed as less desirable due to the extra effort involved in clicking on the map.

The error terms are assumed to be i.i.d. Gumbel across observations and alternatives for the same reason. We simplify the variance structure across reasons, by assuming that error terms for min and max have the same standard deviation, and that the standard deviation of the error terms for pr is 1/60 of that for min and max (60 is an approximate magnitude of the travel times in the survey). These assumptions reduce the number of scale parameters to only one, λ for pr.

The probabilities of choosing A (risky route) and B (safe route) at reason R if R is not the last reason ($R = min, max$) are respectively

$$P_R(A) = \frac{1}{1 + \exp\{-(\lambda/60)[-(ASC_R + A_R - B_R) - \delta_R M]\}}, \tag{4.8}$$

$$P_R(B) = \frac{1}{1 + \exp\{-(\lambda/60)[-(B_R - ASC_R - A_R) - \delta_R M]\}}. \tag{4.9}$$

The probabilities of choosing A and B at reason pr if pr is not the last reason, are respectively

$$P_{pr}(A) = \frac{1}{1 + \exp\{-\lambda[(ASC_{pr} + A_{pr} - B_{pr}) - \delta_{pr} M]\}}, \tag{4.10}$$

$$P_{pr}(B) = \frac{1}{1 + \exp\{-\lambda[(B_{pr} - ASC_{pr} - A_{pr}) - \delta_{pr} M]\}}. \tag{4.11}$$

The probability of choosing A at the last reason $R = min, max$ is

$$P_R(A) = \frac{1}{1 + \exp\{-(\lambda/60)[-(ASC_R + A_R - B_R)]\}}. \tag{4.12}$$

The probability of choosing A at the last reason pr is

$$P_{pr}(A) = \frac{1}{1 + \exp\{-\lambda[ASC_{pr} + A_{pr} - B_{pr}]\}}. \tag{4.13}$$

The unconditional probability of choosing A, $P(A)$ can be obtained by substituting these probabilities into Eq. (4.7), and $P(B) = 1 - P(A)$.

To account for the panel effect that a subject made choices in multiple scenarios, the ASC for the first reason is treated as a normally distributed random variable across subjects and its mean and standard deviation are estimated.

Seven parameters are thus to be estimated: two threshold values for the first two reasons (δ_{min}, δ_{max}, δ_{pr} depending on which two are the first), one scale (λ), three ASCs for three reasons (ASC_{min}, ASC_{max}, ASC_{pr}), and the standard deviation of the first ASC.

The major differences of our model from that of Rieskamp (2008) include: 1) ASCs are included to capture innate biases in a travel choice context, while the choice scenarios used in Rieskamp (2008) are based on stated lotteries and do not entail ASCs in general; 2) The panel effect is accounted for while Rieskamp (2008) ignores it; 3) The error terms are Gumbel distributed instead of normal to enhance the tractability of the model.

4.5 Estimation Results

PPH models with all six potential comparing orders are estimated in BIOGEME Python 2.0 (Bierlaire, 2003, 2008) with 1,000 simulation draws for the normally distributed ASCs. Results are shown in Table 4.1. FLL stands for the final log likelihood. $\overline{\rho}^2 = 1 - (\text{FLL} - K)/L_0$ is the measure of fitness (Ben-Akiva & Lerman, 1985), where L_0 is the log likelihood of the naive (equal-probability) model, and K is the number of parameters. All parameters are significantly different from zero, except the standard

Table 4.1 Estimation Results of PPH models (Values in parentheses are robust standard errors. 74 subjects and 1,767 observations. 7 parameters for each model.)

	PPH_1 min,pr,max	PPH_2 min,max,pr	PPH_3 max,min,pr	PPH_4 max,pr,min	PPH_5 pr,max,min	PPH_6 pr,min,max
Scale λ	28.8 (2.30)	21.3 (1.23)	24.6 (1.41)	19.9 (0.989)	31.1 (1.99)	27.9 (1.82)
ASC_{min}	μ:-19.3 (1.29) σ:1.66 (0.261)	μ:9.51 (0.430) σ:2.09 (0.409)	-29.1 (1.93)	15.6 (0.408)	-72.0 (0)	8.91 (0.446)
ASC_{max}	-15.5 (0.711)	-11.0 (0.485)	μ:26.2 (0.737) σ:1.87 (0.397)	μ:-22.4 (0.582) σ:0 (0)	11.2 (1.09)	-7.79 (0.478)
ASC_{pr}	0.195 (0.00513)	0.334 (0.0293)	0.396 (0.0197)	0.514 (0.00920)	μ:0.517 (0.00537) σ:0.0239 (0.0071)	μ:0.517 (0.00594) σ:0.0284 (0.00915)
δ_{min}	0.627 (0.0243)	0.135 (0.00672)	0.802 (0.0336)	NA (NA)	NA (NA)	0.139 (0.0071)
δ_{max}	NA (NA)	0.111 (0.00879)	0.784 (0.0107)	0.391 (0.00677)	0.402 (0.0205)	NA (NA)
δ_{pr}	0.0323 (0.00589)	NA (NA)	NA (NA)	0.349 (0.00862)	0.338 (0.00595)	0.343 (0.00717)
FLL	-816.539	-826.779	-800.085	-880.671	-831.959	-828.892
$\overline{\rho}^2$	0.328	0.319	0.341	0.275	0.315	0.318

deviation of ASC_{max} in PPH_4. PPH_3 (max, min and pr) has the best model fit ($\overline{\rho}^2 = 0.341$) and the order is different from the original order (min, pr and max) posited in Brandstatter et al. (2006). This can be explained by the following two observations. 1) Travelers are generally very concerned about delays, and likely to consider the maximum outcome (delay on the risky route) first. 2) The survey scenarios were grouped by delay probability (for reasons not related to this study), and thus subjects were likely not paying attention to the probability while it remained constant.

Thresholds of min, pr and max differ very much in different models. Estimated values of δ_{min} and δ_{max} are 0.802 and 0.784 respectively for PPH_3, much higher than the original 0.1. Similar high values are found in previous studies (Rieskamp, 2008). It is not entirely clear why such high values of thresholds exist, and future research is needed to understand whether people truly use such high thresholds or they are the result of a wrong underlying theory.

It is not straightforward to interpret ASCs in a PPH model. In a typical utility maximization model such as the REDU model discussed in the next section, ASC is used to capture the bias towards a certain alternative and its sign indicate the direction of the bias. In the PPH model, however, the final probability of choosing a given alternative is a complex function of all three ASCs. Unless all three ASCs have the same sign, it is not straightforward what effect it will have on the choice probabilities. The only way to find out is to calculate the probability of choosing an alternative assuming the two alternatives have the same travel time distribution ("everything else equal"). However, "everything else equal" can be ambiguous. When the two alternatives have the same travel time distribution so that A_R and B_R cancel out for all reasons, the probability still depends on M, and thus varies across contexts.

4.6 Three Alternative Models

RDEU model and two other alternative models are introduced for comparison with the process model. The other two models have no underlying behavioral theories, and are designed for data fitting. They potentially can provide upper bounds on the goodness-of-fit and enable a more thorough assessment of the PPH model.

4.6.1 RDEU Model

One of the most popular non-expected utility (non-EU) theories (Starmer, 2000) is the rank-dependent expected utility (RDEU) theory (Quiggin, 1982; Schmeidler, 1989). A decision maker is supposed to maximize

$$V(\mathbf{x},\ \mathbf{p}) = \sum_{i=1}^{m} \pi_i u(x_i), \tag{4.14}$$

where $\mathbf{x}$ and $\mathbf{p}$ denote vectors of travel time outcomes (in absolute values) and associated probabilities respectively with a size of m.

$u(x)$ is a value function of outcomes and takes a power functional form.

$$u(x) = -x^{\beta}. \tag{4.15}$$

$\beta < 1$ indicates a decreasing sensitivity to outcome.

π_i is the decision weight for outcome i. It is related to the weighting function $w(p)$ that takes the form

$$w(p) = \frac{p^{\delta}}{(p^{\delta} + (1-p)^{\delta})^{1/\delta}}, \delta > 0.279, \tag{4.16}$$

and describes distorted perceptions of objective probabilities following Tversky & Kahneman (1992). A smaller δ suggests a more pronounced inverted S-shape. See Figure 4.1 for an illustration (red solid line). The blue dotted line shows a perfect perception with $\delta = 1$. $w(0) = 0$ and $w(1) = 1$ suggest that people have no problem perceiving impossibility and certainty. The sensitivity to probability diminishes when moving away from the two extreme points $p = 0$ and $p = 1$, represented by a flatter curve toward the middle point between 0 and 1.

With a sorted outcome sequence $x_1, x_2, \ldots, x_m$ by absolute values, the decision weight of outcome i is

$$\pi_i = w(p_i + p_{i+1} + \cdots + p_m) - w(p_{i+1} + \cdots + p_m), \tag{4.17}$$

and $\pi_m = w(p_m)$.

When the RDEU model is applied to a route choice scenario from the survey, the utility of risky route with the parameter vector $\boldsymbol{\phi} = \{ASC, \lambda, \beta, \delta\}$ is

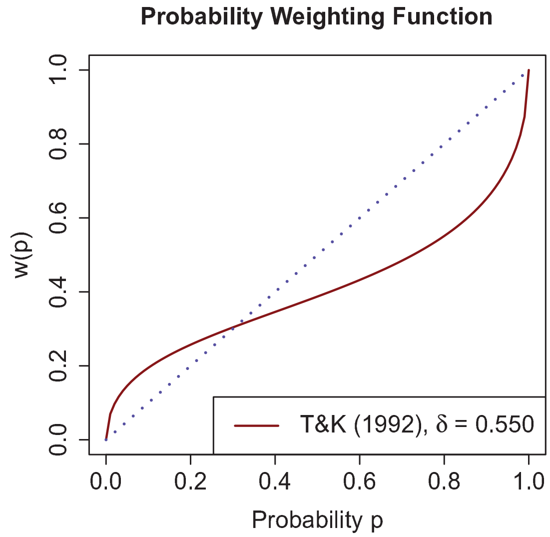

Figure 4.1 Probability Weighting Function

$$V(A) = ASC + \lambda\left[(t_H)^{\beta}w(p) + (t_L)^{\beta}\left(1 - w(p)\right)\right]. \tag{4.18}$$

Note that the negative sign before the power function in Eq. (4.15) is absorbed by the scale parameter λ. ASC denotes a bias towards the risky route, and is a normally distributed random variable across subjects to account for the panel effect.

The utility of the safe route is

$$V(\text{Safe}) = \lambda(t_B)^{\beta}. \tag{4.19}$$

The utilities are applied to a Logit function to yield the probability of a given choice observation.

$$P(i) = \frac{\exp(V(i))}{\sum_{j=A,B}\exp(V(j))} \tag{4.20}$$

Table 4.2 presents estimation results of the RDEU model with 1,767 route choice observations from 74 subjects. The negative sign of the mean of the ASC (μ = -0.933) indicates subjects' average preference towards the safe route when everything else is equal. The diminishing sensitivity to outcome is confirmed by $\beta < 1$, as well as an inverted S-shaped weighting function ($0.279 < \delta < 1$). Comparing Tables 4.2 and 4.1

we find that 5 out of 6 PPH models obtain better goodness-of-fit than the RDEU model. Note that the REDU model has already been shown to outperform a number of other models, including the mean-variance, mean-standard deviation models and their variations and the expected utility model (Razo & Gao, 2013).

Table 4.2 Estimation Results of the RDEU Model (Values in parentheses are robust standard errors.)

Risky Branch Bias $\boldsymbol{ASC}$	μ: -0.933 (0.144) σ: 0.529 (0.115)
Scale $\boldsymbol{\lambda}$	-1.48 (0.570)
Value Func. $\boldsymbol{\beta}$	0.720 (0.0749)
Weight. Func. $\boldsymbol{\delta}$	0.616 (0.0232)
Final LL	-840.872
$\overline{\rho}^2$	0.309

Figure 4.2 shows the probabilities of choosing the risky route calculated from the PPH_3 (green line) and REDU (red line) models as functions of the delay probability (0 to 1) in five situations. All five situations have the same travel time probabilistic outcomes on the risky route, 30 and 60. The travel time on the safe route varies from 35 to 55 with a step size of 5 across the five situations. The dots at 0 and 1 for the PPH_3 model indicate its discontinuity at those locations.

The general decreasing trends (except at $p = 1$ for the PPH model) are consistent with the intuition that a higher chance of delay on the risky route reduces its attractiveness. The shapes of the curves however are considerably different. The REDU curves seem smoother, while the PPH_3 curves have five distinctive sections: two discontinuous locations at 0 and 1, two relatively flat sections close to 0 and 1, and one decreasing section in the middle. The cause of discontinuity is discussed in Section 4.3. As such it is difficult to interpret PPH_3 model results at and close to the two extreme locations, which are consistent with the original PH's restrictions discussed in Brandstatter et al. (2006) that it models difficult decisions, not all decisions. It does not apply to pairs of alternatives in which one alternative dominates the other one (the delay probability is 0 or 1), and it also does not apply to "easy" problems in which the expected values are strikingly different (the delay probability is close to 0 or 1). It is of interest for future research to extend the PPH model so that it is applicable to extreme cases.

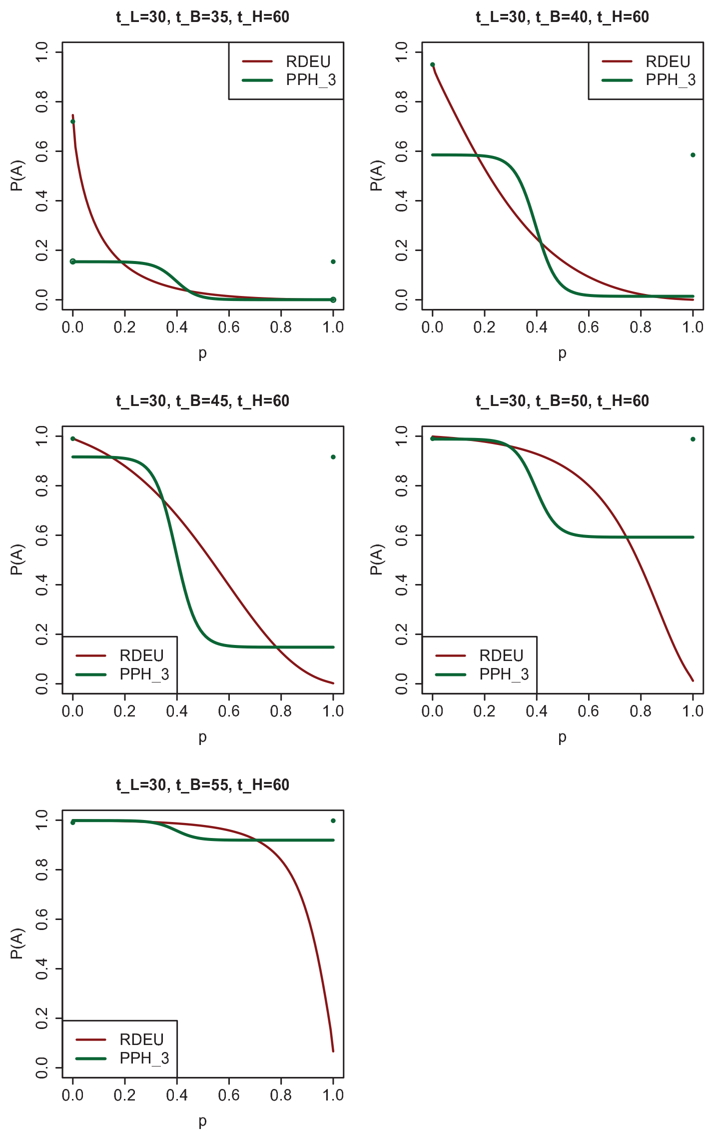

Figure 4.2 Probabilities of Choosing the Risky Route as Functions of the Delay Probability

4.6.2 Dummy Model

The other two models have no underlying decision theories and are simply fitting the data. Therefore they probably have better data-fitting performance and could produce an upper limit on the goodness-of-fit so that the performance of the PPH model can be better assessed.

The first of the two is a dummy model with a large number of dummy variables to fit the choice proportion for each possible scenario. It was proposed by graduate students from the Department of Statistics at the University of Massachusetts Amherst.

The utility of the safe route is assigned as 0. The utility of the risky route is:

$$\begin{aligned} V(A) = ASC + \beta_1 * 1_{p=0.5} + \beta_2 * 1_{p=0.8} + \beta_3 * 1_{t_H=50} \\ + \beta_4 * 1_{t_H=60} + \beta_5 * 1_{t_H=120} + \beta_6 * 1_{t_B=40} \\ + \beta_7 * 1_{t_B=45} + \beta_8 * 1_{t_B=50} + \beta_9 * 1_{t_B=55} \end{aligned} \tag{4.21}$$

ASC is a normally distributed random variable across subjects, following the same assumption in the PPH and RDEU models. 1_{event} is a 0-1 variables that is equal to 1 if the event is true and 0 otherwise.

The probability to choose the risky route over safe route is:

$$P(A) = \frac{1}{1 + exp(-V(A))} \tag{4.22}$$

4.6.3 EER Model

Another similar logit regression model was proposed by Ernan Haruvy and a winner in a choice prediction competition (Erev et al., 2010). The prediction competition produced two data sets, one for estimation that was provided to the competing groups and one for prediction that was not provided. Submitted models were estimated based on the estimation set only, and they competed in terms predictive accuracies based on the prediction set calculated by the organizers.

The utility of the safe route is assigned as 0. The utility of the risky route is

$$V(A) = ASC + \beta_1 * t_H + \beta_2 * t_L + \beta_3 * t_B + \gamma_1 * p + \gamma_2 * EXP \tag{4.23}$$

EXP is the expected travel time of the risky route. ASC is a normally distributed random variable across subjects. Eq. (4.22) can be applied here to calculate the probability to choose the risky route. The model is named EER after the first three authors of Erev et al. (2010).

4.7 Cross Validation

Cross validation is a method to assess different models' forecasting ability within the same data population. First, we generate 10 independent data sets from the original data set (1,767 observations of 74 subjects). Each time, 2/3 of the subjects' data are randomly chosen as the training set for model estimation, while the remaining 1/3 subjects' data are used as the validation set to test models' predictive performance. For example, in the 1st data set, 44 subjects with 1,054 observations are randomly chosen for model estimation. The remaining 30 subjects' 713 observations are used for validation.

4.7.1 Criteria

The mean squared distance (MSD) is used to compare the performance in addition to the adjusted rho squared. The squared distance (SD) is defined as the squared difference between the calculated probability to choose the risky route and the observed proportion of subjects that choose the risky route in one scenario. MSD is then an average of SDs over all scenarios.

4.7.2 Results

Table 4.3 Average Performance Measures of the Four Models

		Dummy	PPH_3	EER	RDEU
Average over 10 estimation data sets	FLL	-515.432	-535.013	-543.619	-561.170
	$\overline{\rho}^2$	0.355	0.336	0.328	0.306
	MSD	0.0075	0.0157	0.0189	0.0240
Average over 10 prediction data sets	FLL	-259.595	-268.095	-273.97	-281.778
	$\overline{\rho}^2$	0.338	0.327	0.318	0.299
	MSD	0.0136	0.0221	0.0256	0.0299
No. of Param.		11	7	5	5

Four competing models' estimation and prediction results in 10 data sets can be found in Tables 4.4 and 4.5. Average performance measures are presented in Table 4.3, and the ranking in terms of both estimation and prediction performance is (from best to worst): Dummy, PPH_3, EER and RDEU. In general we see a drop of performance level in the prediction set compared with the estimation set. The overall performance of PPH_3 model is better than that of the RDEU model. Surprisingly it is also better than the EER model, which is a winner of a choice prediction competition. It is not surprising that the dummy model gives an overall best performance, due to its data-fitting nature. These results suggest that the process modeling paradigm is a valid candidate for studying travel choice behavior under risk.

However, for a specific data set, the ranking does not necessarily hold. For example, in the 7th data set, the prediction FLL of the RDEU model (-258.51) is a little better than that of the PPH_3 model (-259.16) and EER model (-260.848). In the 9th data set, the prediction $\overline{\rho}^2$ of the dummy model (0.281) is a slightly worse than that of the PPH_3 model (0.290). In the 7th data set, the prediction MSD of the RDEU model (0.0208) is smaller than that of the EER model (0.0243). These confirm the notion that a model that best fits the data does not necessarily have the best prediction accuracy.

This cross validation is not a generalizability test - it simply tests the model robustness across subjects with the same set of scenarios. The general applicability of these four models can be ranked conceivably as: $RDEU > PPH > Dummy = EER$. RDEU is able to handle decisions of multiple alternatives with multiple outcomes and the estimated model can be applied to any other scenarios. PPH model is good at comparing two alternatives and the extension to multiple alternatives is feasible but not trivial. The dummy and EER models cannot be applied to scenarios other than those in the estimation set and are the most limited.

Table 4.4 Estimation Results of Four Models

		Dummy	PPH_3	EER	RDEU
1st data set estimation	FLL	-457.431	-482.961	-485.338	-499.542
	$\overline{\rho}^2$	0.359	0.329	0.329	0.309
	MSD	0.0072	0.0158	0.0181	0.0225
1st data set prediction	FLL	-320.256	-321.507	-333.477	-345.292
	$\overline{\rho}^2$	0.330	0.335	0.315	0.291
	MSD	0.0163	0.0195	0.0285	0.0339
2nd data set estimation	FLL	-522.492	-541.728	-556.421	-568.765
	$\overline{\rho}^2$	0.356	0.338	0.322	0.307
	MSD	0.0062	0.0137	0.0191	0.0225
2nd data set prediction	FLL	-250.761	-259.833	-260.195	-272.711
	$\overline{\rho}^2$	0.340	0.327	0.331	0.300
	MSD	0.0139	0.0219	0.0222	0.0298
3rd data set estimation	FLL	-559.192	-575.55	-578.36	-598.314
	$\overline{\rho}^2$	0.339	0.325	0.324	0.301
	MSD	0.0083	0.0151	0.0162	0.0219
3rd data set prediction	FLL	-214.849	-227.031	-238.878	-244.607
	$\overline{\rho}^2$	0.376	0.353	0.326	0.310
	MSD	0.0128	0.0297	0.0331	0.0363
4th data set estimation	FLL	-517.45	-541.252	-553.939	-569.253
	$\overline{\rho}^2$	0.361	0.338	0.325	0.306
	MSD	0.0066	0.0156	0.0203	0.0245
4th data set prediction	FLL	-256.699	-260.223	-263.172	-273.48
	$\overline{\rho}^2$	0.326	0.327	0.325	0.299
	MSD	0.0151	0.0229	0.0221	0.0286
5th data set estimation	FLL	-518.298	-538.256	-544.427	-559.936
	$\overline{\rho}^2$	0.347	0.328	0.323	0.303
	MSD	0.0074	0.0142	0.0178	0.0221
5th data set prediction	FLL	-255.333	-263.395	-272.097	-281.897
	$\overline{\rho}^2$	0.356	0.347	0.330	0.307
	MSD	0.0121	0.0249	0.0257	0.0314
6th data set estimation	FLL	-581.01	-597.095	-611.531	-626.835
	$\overline{\rho}^2$	0.349	0.336	0.322	0.305
	MSD	0.0075	0.0145	0.0190	0.0227
6th data set prediction	FLL	-192.864	-204.978	-204.939	-215.538
	$\overline{\rho}^2$	0.354	0.328	0.334	0.301
	MSD	0.0191	0.0302	0.0298	0.0379
No. of Param.		11	7	5	5

Table 4.5 Estimation Results of 4 Models. (Continued)

		Dummy	PPH_3	EER	RDEU
7th data set estimation	FLL	-526.821	-547.532	-556.79	-583.677
	$\overline{\rho}^2$	0.349	0.329	0.320	0.288
	MSD	0.0076	0.0182	0.0203	0.0286
7th data set prediction	FLL	-248.378	-259.16	-260.848	-258.51
	$\overline{\rho}^2$	0.349	0.332	0.333	0.339
	MSD	0.0149	0.0158	0.0243	0.0208
8th data set estimation	FLL	-464.62	-474.046	-483.669	-503.599
	$\overline{\rho}^2$	0.374	0.366	0.357	0.331
	MSD	0.0096	0.0149	0.0186	0.0245
8th data set prediction	FLL	-310.729	-329.422	-334.664	-339.654
	$\overline{\rho}^2$	0.308	0.277	0.270	0.259
	MSD	0.0081	0.0216	0.0257	0.0284
9th data set estimation	FLL	-513.691	-540.455	-550.812	-568.794
	$\overline{\rho}^2$	0.379	0.352	0.342	0.320
	MSD	0.0071	0.0178	0.0213	0.0263
9th data set prediction	FLL	-262.729	-263.146	-268.815	-275.883
	$\overline{\rho}^2$	0.281	0.290	0.280	0.262
	MSD	0.0131	0.0173	0.0212	0.0257
10th data set estimation	FLL	-493.319	-511.257	-514.907	-532.984
	$\overline{\rho}^2$	0.337	0.319	0.317	0.293
	MSD	0.0079	0.0174	0.0184	0.0242
10th data set prediction	FLL	-283.351	-292.253	-302.613	-310.206
	$\overline{\rho}^2$	0.365	0.355	0.337	0.320
	MSD	0.0110	0.0170	0.0232	0.0265
No. of Param.		11	7	5	5

CHAPTER 5

NON-PARAMETRIC ANALYSIS OF STRATEGIC ROUTE CHOICE WITH REAL-TIME INFORMATION

5.1 Introduction

PC-based test can be viewed as a replicate of driving simulator test in terms of network and associated travel time distributions. Thus, a fully comparison between these two environments can be made. In order to make a valid comparison, different subjects with very similar demographic characteristics were recruited. Mixed Logit model with two latent classes were built and estimated for driving simulator test and PC-based test. In addition, one more model was developed and estimated using data set from two tests. Within this research topic, there are three major research questions need to be addressed:

1. Do drivers think strategically when they plan for a trip in uncertain networks with probabilistic travel time distributions?

2. Does network complexity (the number of routes involved at the time a decision is made) affect drivers' strategic thinking ability?

3. Does a parallel driving task (pre-trip versus en-route) affect drivers' strategic choices?

Next we present the non-parametric analysis method and results towards the driving simulator test and PC-based test 2. The analysis relies on a deterministic method to identify a strategic route choice in Map B or C, which is generally complicated by a subject's risk attitude. Map A is utilized to control for risk attitude in the identification process and we discuss two situations based on the choice in Map A. We then comment on a troublesome situation with potential measurement errors and the resulting deletion of certain scenarios. The final counts of strategic route choices are then presented, and non-parametric statistic tests are performed to answer the three research questions posed before. In the end, we discuss the rationale of the experiment design at a high level, recognizing that strategic route choices are not directly observable.

5.2 Data Cleaning

In total we ran the experiment with 64 subjects in driving simulator test. Data for one of the subjects were deleted due to a misunderstanding and data for five other subjects were deleted because of the extremely risk-seeking route choices in the Map A scenario with highly risky travel times (t_L, t_M) on the risky branch. Meanwhile, we ran 67 subjects in PC-based test. Again, data for one of the subjects were deleted due to misunderstanding and data for twenty-two subjects were deleted because of the extremely risk-seeking in Map A scenario. The fact that much more risk-seeking subjects (5 vs.22) being found in PC-based test can be explained by much shorter actual travel time experienced for each scenario in PC-based test than that in driving simulator test (20 seconds vs. 2 minutes). To continue along this thought, we can reasonably expect fewer risk-seeking travelers in the daily commute. This finding is consistent with widely accepted assumption that people are generally risk averse. As will be shown later, the determination of a strategic route choice relies on the assumption that the subject is not extremely risk-seeking, as thus these subjects had to be deleted. After the first round of data cleaning, we had 58 subjects from driving simulator test and 44 subjects from PC-based test.

5.3 Identification of Strategic Route Choice

A strategic route choice is made with the consideration of a future diversion possibility, while a non-strategic route choice is not. Conclusions about strategic or non-strategic route choices only concern route choice decisions in Map B or C. Map A is used to test subjects' attitude towards risk and no strategic choices can be identified in Map A alone. However, all the conclusions about strategic route choices in Map B or C should take into account results in matched Map A scenarios. In this subsection we discuss the cases where the risky branch is strictly preferred in Map A, and in Section 5.4 those where the safe route is strictly preferred in Map A.

For subjects with Map A and B in driving simulator test and PC-based test 2, if he/she chose the risky branch in Map A but the safe route in Map B when these two maps used the same travel time combination in Table 3.1, we conclude that this route choice in Map B is non-strategic. The fact that this subject chose the risky branch in Map A implies that he/she considered the risky branch (t_L, t_H) more attractive than the safe route, t_b. (The case when a subject is indifferent between the two alternatives is discussed in Section 5.5.) If this subject realized that the real-time information at Node i could help avoid t_M in Route 3 and further help simplify the risky branch as a travel time combination (t_L, t_H), he/she would take the risky branch again in Map B. Assuming that a subject's risk attitude will not change in a short time period, the fact that a subject can tolerate the risk in Map A but appear not to in Map B suggests non-strategic thinking.

On the other hand, if a subject chose the risky branch twice in the paired Map A and B scenarios, we consider the route choice in Map B as a strategic route choice. Assume that he/she did not realize the value of real-time information at Node i, and thus three fixed routes were considered. The value of t_M in Map B was set to be very large so that Route 3 was much slower on average with a mean travel time $(t_L + t_M)/2$ and also involved an extremely high risk. Risk averse and risk neutral subjects would not take Route 3 because of the non-zero risk and slower mean travel time compared to the safe Route 1. Risk-seeking subjects also would be highly unlikely to choose Route 3 due to the extremely large risk involved. As mentioned before, in rare cases some subjects were indeed highly risk seeking and have been identified from corresponding Map A scenarios and deleted. Furthermore, the deterministic travel time on Route 2 (t_H) was longer than that on Route 1 (t_b). Therefore, only strategic thinking would lead one to choose the risky branch in Map B.

For subjects with Map A and C in driving simulator test and PC-based test 2, regardless of whether a subject realized the future diversion possibility provided by the real-time information at Node i1, Route 2 could not have added to the attractiveness of the risky branch. Route 2 of Map C served only as a decoy to make the route choice situation more complicated. Note that the strategic parts of Maps B and C (Routes 2&3 in Map B and Routes 3&4 in Map C) are the same. Route 2 of Map C hides the strategic part further downstream and a strategic route choice requires more forward thinking. Therefore similar analysis of strategic behavior could be conducted in Map C.

Specifically, if a subject chose the risky branch in Map A but the safe route in the paired Map C, we conclude that this route choice in Map C is a non-strategic. If one subject chose the risky branch twice in the paired Maps A and C, we consider the route choice in Map C as a strategic one.

Note that if t_b is realized on Route 2 and revealed to a subject at Node i1, he/she would essentially be facing the same decision problem as at the origin, except that the strategic parts (Routes 3&4) are immediately downstream. We would expect that if a subject is strategic at the origin, he/she would continue being strategic downstream at Node i1 and choose the risky branch again. However several Route 2 (safe) choices were observed in Map C in such situations, and the inconsistency in behavior might be explained by different amount of decision time (more time at the origin than en-route), among others. These choices are still considered strategic as our focus is on the behavior at the origin. The inconsistent behavior however will be an interesting topic for future research.

5.4 Map A Safe Route Chosen: Indeterminate Observations

If a subject chose the safe route in Map A, his/her route choice in the paired Map B or C cannot be determined as strategic or non-strategic. This subject did not accept the risk in Map A, and thus even if he/she was strategic in Map B or C and realized the risky branch in Map B or C presented the same travel time prospect as that in Map A, he/she was still not going to take the risk. In other words, the strategic behavior was confounded by the risk aversion behavior and could not be inferred. If he/she indeed took the risky branch in Map B or C, but not in A, there is an internal inconsistency in the behavior, which might be due to an innate bias towards flexible options even if no real benefit can be obtained. However in the current study with limited observed variables, it only complicates the strategic choice identification. Therefore we deleted any Map B or C observation with a matching Map A safe route choice.

5.5 Measurement Error

If a subject is indifferent between the deterministic travel time t_b and the risky travel time (t_L, t_H), a measurement error would occur that will lead to wrong conclusions about subjects' strategic route choices. In such a case, a strategic subject has a 50% chance of choosing either the safe or risky alternative in Map B or C. Following our logic in the previous section, we would conclude that out of the Map B or C observations with corresponding Map A risky choices, 50% of them are strategic. However 100% of them could be strategic, but just do not all appear so due to the indifference to travel times. This measurement error does not exist for non-strategic subjects, since they do not see the favorable prospect of the risky branch enabled by the information at the very first place, and no problems would result from the indifference towards it against the safe route.

In order to avoid this measurement error, certain travel time combinations should be deleted where the risky branch for a strategic subject is not exceedingly more attractive than the safe route. We observed non-negligible safe route choices in Map A with travel time combinations #1 and #4, which were subsequently deleted from further analysis.

5.6 Strategic Route Choice Counts

All the analysis above is summarized in Table 5.1. R refers to a choice of the risky branch and S the safe route.

Map A	Map B/C	Inference
R	R	Strategic
R	S	Non-strategic
S	R	N/A
S	S	N/A

Table 5.1 Inferences on strategic choices based on paired Map A and B/C choices

A subject might not select the risky branch in Map A in all the four remaining scenarios, even though the risky branch is exceedingly more attractive. We were concerned that such a subject tends to have a volatile risk attitude, which could undermine our method of identifying strategic choices that relies on the assumption of a stable risk attitude during the experiment. Furthermore, such a subject would provide fewer valid observations than other subjects due to deleted observations (see Section 5.4), which complicates the statistic analysis. Therefore we kept only subjects who chose the risky branch in the remaining four Map A scenarios. We then counted the number of times a subject was strategic in either Map B or C (a value between 0 and 4). Finally, we ended up with 22 valid subjects for each subgroup. The final results are shown as follows.

Sim_AB **subgroup:**

3, 4, 4, 4, 4, 3, 4, 4, 3, 4, 4, 4, 4, 1, 4, 0, 3, 1, 2, 4, 4, 4

Sim_AC **subgroup:**

4, 2, 4, 2, 4, 3, 1, 3, 0, 4, 2, 3, 3, 3, 4, 3, 3, 4, 4, 2, 0, 4

PC_AB **subgroup:**

2, 4, 0, 4, 4, 4, 2, 4, 4, 3, 1, 3, 4, 2, 4, 4, 4, 4, 4, 4, 2, 4

PC_AC **subgroup:**

4, 4, 0, 4, 4, 4, 3, 3, 2, 4, 0, 4, 4, 3, 4, 4, 4, 2, 2, 4, 4, 4

5.7 Results

1: Do drivers think strategically when they plan for a trip in uncertain networks with probabilistic travel time distributions?

If a driver does not think strategically in the risky network, he/she should always take the safe Route 1 with a deterministic travel time t_b in Map B or C. However, the final results show that a significant number of subjects take the risky branch in Map B or C. This is verified by a Wilcoxon Signed-Ranks Test on the counts of strategic route choices from 4 subgroups. The null hypothesis is rejected with a p-value of 3.388e-05 (one-sided),7.709e-05 (one-sided), 3.388e-05 (one-sided) and 4.725e-05 (one-sided) in these 4 subgroups respectively.

2: Does network complexity (the number of routes involved at the time a decision is made) affect drivers' strategic thinking ability?

By comparing the *Sim_AB* and the *Sim_AC* subgroup's strategic route choice counts in the driving-simulator-based tests, we could investigate whether network complexity affects drivers' strategic thinking. Map C is more complicated than Map B with Route 2 serving as a decoy.

We perform a Wilcoxon-Mann-Whitney test on strategic choice counts in two independent samples from Map B and C in the driving-simulator-based tests. The null hypothesis is rejected with a p-value of 0.0566 (one-sided). We thus conclude that network complexity adversely affects subjects' strategic thinking at the 0.10 significance level. This is consistent with intuition as recognizing the value of information from a part of the network that is further downstream is more difficult and imposes higher cognitive demand.

However, the same null hypothesis was rejected between the *PC_AB* and the *PC_AC* subgroup with p-value 0.5273 (one-sided). This result could quite possibly come from the lower cognitive load requied in PC-based test. In other words, PC-based test consumed relatively lower cognitive load and therefore subjects were still able to make informed route choices with complicated networks (Map C) as in simple networks (Map B).

An interesting future research topic would be to study a variety of more complicated networks and find some systematic relationship between the level of strategic thinking and network complexity. The result will be instrumental in estimating strategic route choice models from revealed preference data in real-life networks.

3: Does a parallel driving task (pre-trip versus en-route) affect drivers' strategic choices?

We gave each subject exactly ten seconds to observe the map topology and travel time distribution at the beginning of each scenario in both the driving-simulator and PC-based tests. In the driving-simulator-based tests, subjects were required to drive normally during the ten seconds while reading the map on the screen. This approximated an en-route decision-making context. In the PC-based tests, there were no parallel driving tasks during the ten seconds and subjects simply read the computer screen. This approximated a pre-trip decision-making context. Intuitively we would think that a parallel driving task will add to a subject's cognitive load, and cause him/her to be less strategic.

From a Wilcoxon Matched-Pairs Signed-Ranks Test, we cannot reject the null hypothesis that the numbers of strategic route choices in Map B with and without a parallel driving task have the same median (with p-value=0.5435). It is possible that Map B is simple enough such that, even if the driver's cognitive capacity has been consumed by the driving task to some extent, the remaining capacity is still enough for making a strategic decision.

However, as to Map C, this null hypothesis is rejected with p-value 0.0709 (one-sided) at 0.10 significance level. It seems that higher network complicity of Map C can help us to demonstrate the effect of parallel driving task.

In the entry-questionnaire, we collected each subject's demographic information, such as: gender, age and driving experience(mileage). The same methodology in the last subsection was utilized to test whether these characteristics influence people's strategic thinking ability. To be specific, subjects were divided into undergraduate student if he/she is equal to or less than 22 years old and graduate student otherwise. We set 3 categories for subjects' driving experience: less than 5,000 miles, more than 5,000 miles but less than 20,000 miles, more than 20,000 miles. With purpose to simplify our analysis, we finally adopted 20,000 miles as a threshold to distinguish inexperienced driver and experienced driver.

From the results of Wilcoxon-Mann-Whitney test, we find that in driving simulator test the subject with more driving experience tend to ended with more strategic route choices with p-value 0.06436 in both Sim_AB and Sim_AC groups. In the PC-based test, gender will only take effect in the PC_AC group: females tend to make less strategic route choice than males (with p-value = 0.0422). Age and driving experience do not influence people's strategic thinking ability. Although non-parametric analysis is robust for small sample cases, we still recommend that these conclusions should be tested with large sample size to guide our practice.

5.8 Experiment Design Revisited

In this section we discuss the design of the experiment at a high level. The previous discussions on data cleaning and strategic choice identification provide a basis for understanding the big picture in the design.

We do not directly observe a subject's thinking process, but only its outcome in different situations. Strategic route choices by definition include multiple outcomes contingent on revealed information. One way to investigate this process is to conduct in-depth personal interviews and ask the subjects to describe the process in detail. This method is suitable for an initial exploratory research phase, however not so much in large-scale data collection.

We adopt another approach where through carefully designed networks and travel time situations, we can equate strategic choices with choices of a certain alternative. Our definition of a strategic choice is one that takes into account the future information value on route switching, and thus Map B in Figure 3.8 is the simplest possible network for the study where the risky branch provides information and diversion possibility and the safe route provides an alternative to the risky branch. The idea is to make the risky branch more attractive for a strategic subject and the safe route more attractive for a non-strategic subject. As strategic planning is useful only when there are uncertainties, some travel times must be random. However with random travel times, subjects' decisions are also influenced by their risk attitudes, which we do not know ahead of time. The analysis in the previous subsections deal with the problem of disentangling strategic thinking from risk attitudes.

The travel time combination design is made with the above points in mind. To make the risky branch more attractive for a strategic subject than the safe route, it must have a smaller average travel time and thus $(t_L + t_H)/2 < t_b$. However this condition alone is not enough, so we make safe route travel time t_b very close to the higher travel time on the risky branch t_H so that the possible benefit of taking the risk is very high. However, some very risk-averse subjects might still prefer the safe route, and therefore we set up Map A to gauge a subject's risk attitude under the same travel time combinations, yet without the complications of information and the detour. Note that we cannot make t_b greater than t_H, in which case the fixed route with travel time t_H in the risky branch (Route 2 in Map B and Route 3 in Map C) is better than the safe route and even a non-strategic subject who only sees fixed routes will choose the risky branch.

To make the safe route more attractive for a non-strategic subject, we ensure the two fixed routes in the risky branch (Route 2 in Map B and Route 3 in Map C) are both worse than the safe route. The one with a fixed travel time t_H is trivial as $t_H > t_b$. The route with a possibly low travel time t_L has to be combined with an extremely high travel time t_M to make it highly unattractive. However some extremely risk seeking subjects might still want to take the risk, therefore we set up an additional scenario in Map A with the same high risk profile and delete a subjects if he/she takes the extreme risk.

CHAPTER 6

A LATENT-CLASS MODEL FOR ROUTE CHOICE WITH REAL-TIME INFORMATION

In addition to the non-parametric analysis, a mixed Logit model is estimated with random parameters over subjects and two latent classes for strategic and non-strategic thinking at the observation level. Eventually, we have 819 observations from driving simulator test (34 subjects from the *Sim_AB* subgroup and 29 subjects from the *Sim_AC* subgroup) and 858 observations from PC-based test (35 subjects from the *PC_AB* subgroup and 31 subjects from the *PC_AC* subgroup). All route choice observations are used for modeling except for those from subjects who misunderstood the instruction. For each subject, all 13 driving simulator scenarios are used (6 from either of the two maps and 1 additional Map A scenario to test extreme risk seeking), including those where the safe route is chosen in Map A, as we rely on the model estimation process to provide a best estimate of the probability that any observation is the result of strategic thinking. This is a different approach from that in the previous section, where a deterministic assessment has to be made for each observation pair from Maps A&B or A&C, and thus certain observations need to be removed if resulting in ambiguous assessments.

6.1 Model Specification

Expected Travel Time (ETT) and *Standard Deviation of Travel Time* (STD) are used as two explanatory variables in the model.

Based on the analysis in Section 5.3, non-strategic thinking will involve the prohibitively long delay, t_M, in the assessment of the risky branch. Meanwhile, strategic thinking will ignore this potential delay. Two separate utility functions can be established for the risky branch for strategic thinking and non-strategic thinking. The probability that each utility function applies to any single observation will be estimated.

For strategic thinking, the potential delay in Maps B and C, t_M, will be avoided with the help of information en-route. Therefore only t_L, the regular time of Route 3 in Map B and Route 4 in Map C, and t_H, the fixed travel time of Route 2 in Map B and Route 3 in Map C, will be considered. The utility of the risky branch for a strategic (S) individual n in scenario t is thus:

$$V_{nt}(Risky|S) = \beta_{ASC} - \beta_{ETT} * (t_L + t_H)/2 + \beta_{STD} * (t_H - t_L)/2 \tag{6.1}$$

Note that, this utility function is also valid for the risky branch in Map A. β_{ASC}, β_{ETT}, and β_{STD} are parameters to be estimated. β_{ASC} accounts for preference factors not directly related to expected travel time and standard deviation. In Maps B and C, non-strategic thinking will perceive the possible outcomes of risky branch as t_L and t_M. Since t_H is fixed and always higher than t_b, Route 2 in Map B and Route 3 in Map C are excluded from the choice set of a non-strategic thinker. In order to include the risky branch in Map A, a variable t_h_ns is defined. t_h_ns equals t_H in Map A and t_M in Maps B and C. Then, the utility of the risky branch for a non-strategic (NS) individual n in scenario t:

$$V_{nt}(Risky|NS) = \beta_{ASC} - \beta_{ETT} * (t_L + t\_h\_ns)/2 + \beta_{STD} * (t\_h\_ns - t_L)/2 \tag{6.2}$$

The utility of the safe route will be identical for strategic and non-strategic subjects in all maps.

$$V_{nt}(Safe|S) = V_{nt}(Safe|NS) = \beta_{ETT} * t_b \tag{6.3}$$

The utilities are applied within a Logit function to yield the conditional probability of a given choice observation.

$$P_{nt}(i_t|S,\Phi) = \frac{exp(V_{nt}(i_t|S,\Phi))}{\sum_{j_t} exp(V_{nt}(j_t|S,\Phi))} \tag{6.4}$$

is the likelihood of individual n choosing alternative i_t in scenario t, given strategic behavior and parameter vector Φ, and

$$P_{nt}(i_t|NS,\Phi) = \frac{exp(V_{nt}(i_t|NS,\Phi))}{\sum_{j_t} exp(V_{nt}(j_t|NS,\Phi))} \tag{6.5}$$

is the same likelihood given non-strategic behavior. We then define P_S as the probability of any given observation being the result of strategic thinking. We hypothesize that subjects learn to be more strategic with experience, and assume a linear relationship between P_S and the order of each scenario (starting at 1) as follows:

$$P_s = InitStratProb + SlopeStartProb * (order - 1) \tag{6.6}$$

As indicated in the non-parametric analysis, different levels of strategic thinking are present in Maps B and C. Therefore *InitStratProb* and *SlopeStartProb* can take two different values in Maps B and C, denoted as *InitStratProbB*, *InitStratProbC*, *SlopeStartProbB* and *SlopeStartProbC* respectively. Put the two probabilities in Eqs. (6.4) and (6.5) and the definition of P_S in Eqs. (6.6) into a latent-class model structure and we have

$$P_{nt}(i_t|S,\Phi)P_S + P_{nt}(i_t|NS,\Phi)(1 - P_S) \tag{6.7}$$

as the likelihood of individual n choosing alternative i_t in scenario t. Note that the risky branch has the same utility in Map A for strategic and non-strategic thinking as no diversion is available, and thus the value of the strategic probability will not affect the choice probability in Map A. The likelihood of individual n choosing the observed choices over all scenarios is:

$$\prod_{t} \left(P_{nt}(i_t|S,\Phi)P_S + P_{nt}(i_t|NS,\Phi)(1-P_S)\right) \tag{6.8}$$

The variations of β_{ASC}, β_{ETT}, and β_{STD} among subjects are accounted for by treating them as random parameters over subjects. The unconditional likelihood of the observed choices over all scenarios for individual n is the integral of the conditional probability over the probability density function of Φ:

$$\int_{\Phi} \prod_{t} \left(P_{nt}(i_t|S,\Phi)P_S + P_{nt}(i_t|NS,\Phi)(1-P_S)\right) d\Phi \tag{6.9}$$

and the log-likelihood of all observations over all individuals is:

$$\sum_{n} \ln \int_{\Phi} \prod_{t} \left(P_{nt}(i_t|S,\Phi)P_S + P_{nt}(i_t|NS,\Phi)(1-P_S)\right) d\Phi \tag{6.10}$$

which is maximized using simulation in the model estimation Train (2003).

6.2 Model Estimation

The model is estimated using BIOGEME Python 2.0 (for data from driving simulator test) and 2.2 (for data from PC-based test) (Bierlaire, 2003, 2008) with flexible specifications for latent variables. The results are shown in Table 6.1 and Table 6.2. 1000 simulation draws are performed.

6.2.1 Estimation Results of Driving Simulator test

In Table 6.1 (Driving Simulator test), the estimation results of two models are presented, one with learning effect and the other not. The two models have almost identical final log-likelihood, but since the model with learning has two additional

	With Learning Effect		**Without Learning Effect**	
Parameter	**Value (Robust std err)**		**Value (Robust std err)**	
β_{ASC}	μ: 0.539 (0.193)		μ: 0.669 (0.806)*	
	σ: 1.09 (0.204)		σ: 1.09 (0.239)	
β_{ETT}	μ of ln (β_{ETT}): -1.50 (0.266)		μ of ln (β_{ETT}): -1.48 (0.465)	
	σ of ln (β_{ETT}): 1.20 (0.344)		σ of ln (β_{ETT}): 1.26 (0.309)	
	InitStratProbB	0.762(0.0977)	*StratProbB*	0.879(0.0658)
	InitStratProbC	0.634(0.0976)	*StratProbC*	0.707(0.0792)
	SlopeStratProbB	0.0440 (0.0220)		
	SlopeStratProbC	0.0291 (0.0222)*		
No of Observations	819		819	
No of Individuals	63		63	
No of Parameters	8		6	
Initial Log-likelihood (equal probabilities)	-567.688		-567.688	
Final Log-likelihood	-368.678		-369.118	
$\bar{\rho}^2$	0.336		0.337	
Note:* means this parameter is not significant different from 0 at the 0.05 level.				

Table 6.1 Estimation Results of Driving Simulator test

	With Learning Effect		Without Learning Effect	
Parameter	**Value (Robust std err)**		**Value (Robust std err)**	
β_{ASC}	μ: 1.52 (0.292)		μ: 1.53(0.291)	
	σ: 1.46 (0.253)		σ: 1.45 (0.253)	
β_{ETT}	μ of ln (β_{ETT}): -1.75 (0.153)		μ of ln (β_{ETT}): -1.75 (0.154)	
	σ of ln (β_{ETT}): 0.315 (0.216)*		σ of ln (β_{ETT}): 0.321 (0.216)*	
	InitStratProbB	0.760(0.109)	*StratProbB*	0.815(0.0901)
	InitStratProbC	0.550(0.121)	*StratProbC*	0.650(0.0882)
	SlopeStratProbB	0.0236 (0.0185)*		
	SlopeStratProbC	0.0419 (0.0292)*		
No of Observations	858		858	
No of Individuals	66		66	
No of Parameters	8		6	
Initial Log-likelihood (equal probabilities)	-594.720		-594.720	
Final Log-likelihood	-332.198		-333.624	
$\bar{\rho}^2$	0.428		0.429	
Note:* means this parameter is not significant different from 0 at the 0.05 level.				

Table 6.2 Estimation Results of PC-based test

parameters, its $\bar{\rho}^2$ is slightly worse. Note that our objective is to gain an understanding of the learning effect, among other factors. Even though the model with learning effect does not provide a better model fit, it does shed light on the learning effect.

Including β_{STD} will lead to model estimation algorithm failure and therefore it is not included in the final model estimation results. The estimation of β_{ASC} and β_{ETT} are robust across the two models. One exception is that β_{ASC} is not significantly different from 0 in the model without learning, although numerically the values are very close in the two models.

The standard deviation of parameter β_{ASC} is significantly different from 0 and numerically almost twice as large as the mean. This suggests a large variation over subjects in terms of their bias towards the risky branch regardless of travel time. On one hand, the safe route is a straight road with no grade change, while the risky branch requires deviating from the direct road and a number of grade changes. Some subjects might prefer the direct safe route, as it requires less effort in driving. The safe route is also more straightforward with no deviations downstream and consumes less mental effort in information processing and decision-making, which might be viewed favorably by subjects. On the other hand, the risky branch might seem more interesting for some subjects to explore. The real-time information enables options downstream and even if it does not actually provide any travel time saving, subjects who like the feelings of having options might still prefer it.

We use a lognormal distribution for the parameter to the expected travel time, as we believe that a higher expected travel time makes the alternative less attractive and thus the parameter should be constrained as negative. In the model with learning effect, the median value of β_{ETT} is 0.223, mean value is 0.458, and the standard deviation is 0.823. The distribution of β_{ETT} is given in Figure 6.1.

In the model without learning, P_s is regarded as a constant within each group and takes two different values in Maps B and C, denoted as *StratProbB* and *StratProbC*

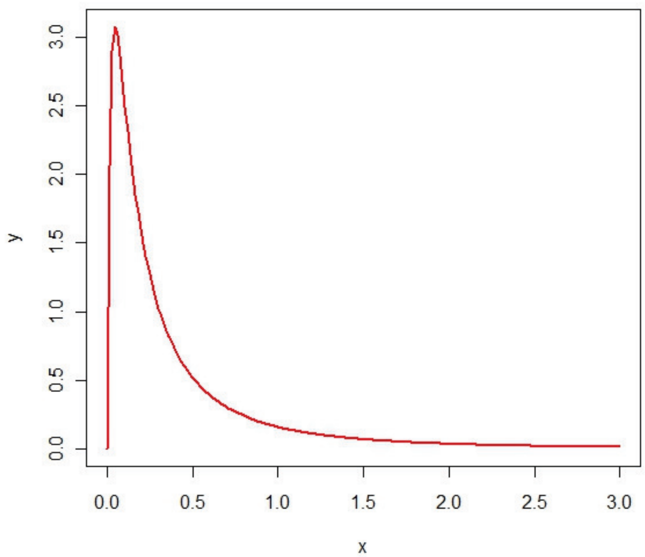

Figure 6.1 Density Function of Log-Normal Distributed β_{ETT}

respectively. The estimated value of *StratProbB* suggests that observations in the *Sim_AB* subgroup could be the result of strategic thinking with probability 87.9%. It is consistent with the result of the latent-class strategic model in Razo & Gao (2010) (84.1%). Due to a more complex network, observations in the *Sim_AC* subgroup have a chance of 70.7% being the result of strategic thinking. In the model with learning, the strategic probability in Map B starts from 76.2% in the first scenario and ends with 98.2% in the last scenario. Meanwhile, in Map C, this value ranges from 63.4% to 77.9%. This is consistent with the conclusion from the non-parametric analysis that network complexity adversely affects subjects' strategic thinking.

6.2.2 Comparison between Driving Simulator test and PC-based test 2

In Table 6.2, estimation of data from PC-based test are presented. With the same model specification, results from these two tables are quite close to each other. We noted that subjects generally assigned more value to β_{ASC} in PC-based test: 1.52 and 1.53 versus 0.539 and 0.669. The standard deviation of β_{ASC} is roughly multiplied by 1.5 times compared with that in driving simulator test. Again, a large variation of subjects' preference towards risky route is observed in PC environment. From the specific distribution of β_{ASC}, subjects from PC-based test exhibit more preference towards risky branch than their counterpart in driving simulator test.

The standard deviation of β_{ETT} in PC-based test is much smaller than that in driving simulator test which implies subjects in PC-based test tend to have similar perception for expected travel time. We assume that this phenomenon is possibly resulted from the fact that people tend to behave similarly in a familiar environment: PC-based test. One conclusion in Yan et al. (2008) is that subjects' speed behavior observed in driving simulator test showed a larger variability than that in the field. Compared with real life, driving simulator is unfamiliar with most people. Although driving simulator is accepted as an effective way to induce people's actual behavior in reality, subjects' driving experience in the given driving simulator is still far from their actual driving experience, such as: they cannot feel the acceleration or deceleration during the test. Subjects' strategic thinking probabilities in these two environments follow the similar pattern and are not significantly different from each other. We have two opposite conjectures for this finding. On one hand, the higher cognitive load in driving simulator test tend to make people less strategic. On the other hand, the more realistic environment might motivate people to be more thoughtful during the driving.

6.2.3 Combine Modeling with Driving Simulator and PC-based Data Sets

In the exit-questionnaire, each subject was asked to finish nine route choice scenarios using Map A. Compared with the design in driving simulator test and PC-based test where t_b is always higher than $(t_L + t_H)/2$, t_b could be equal to, higher than or less than $(t_L + t_H)/2$ in the exit-questionnaire. With purpose to avoid dominance, t_b is always between t_L and t_H in exit-questionnaire, driving simulator test and PC-based test. The exit-questionnaire thus provides larger data variability than the driving simulator test does. We initially plan to combine the driving simulator and exit-questionnaire data to obtain more efficient parameter estimates. The rationale is similar to that of the combined RP/SP estimation in the literature Ben-Akiva & Morikawa (1990a,b). When utility functions for RP/SP data have the common preference parameters that normally represent the trade-off ratios among the most important attributes, we can apply the combined RP/SP estimation method to estimate unknown parameters for both models. Since more observations and wider data range are involved, smaller variability of parameters' estimates are expected.

However, the standard deviation is not significant in the estimated model based on exit-questionnaire data either. The trade-off between expected travel time and standard deviation does not exist in either of these two decision situations, and the method to combine two data sources cannot be used in this situation.

However, data from driving simulator test and PC-based test can be combined together for a more accurate estimation. The methodology of combining RP/SP can be safely applied for this situation. β_{ASC_Sim} and β_{ASC_PC} are separately specified for two environments and estimated. In addition, one more parameter, Scaler, is specified for expected travel time in PC-based test. Estimation results can be found in Table 6.3. As a result of combination, we have 1677 observations from 129 subjects for model estimation. As to model's data-fitting performance, $\bar{\rho}^2$, the combined model (Table 6.3) lies between two separate models (Table 6.1 and Table 6.2). As expected, standard deviation of all parameters (values in parenthesis) in this table are smaller than that in separate driving simulator test and PC-based test. There is only 1 parameter in this combined model not significant different from 0 while there are 2 parameters in Table 6.1 and 4 parameters in Table 6.2. The conclusion that network complexity adversely affect travelers' strategic thinking ability can also be verified in this table no matter whether learning effect is involved. In the model without learning effect, strategic route choice probability in Map B is higher than that in Map C: 0.842 vs. 0.672. When learning effect is involved, the initial strategic probability in Map B 0.765 is still significantly higher than that in Map C 0.592.

	With Learning Effect		**Without Learning Effect**	
Parameter	**Value (Robust std err)**		**Value (Robust std err)**	
β_{ASC_Sim}	μ: 0.740 (0.164)		μ: 0.750 (0.164)	
	σ: 0.944 (0.159)		σ: 0.941 (0.161)	
β_{ASC_PC}	μ: 1.47 (0.302)		μ: 1.48 (0.302)	
	σ: 1.57 (0.282)		σ: 1.56 (0.284)	
β_{ETT}	μ of ln (β_{ETT}): -1.82 (0.159)		μ of ln (β_{ETT}): -1.83 (0.160)	
	σ of ln (β_{ETT}): 0.565 (0.206)		σ of ln (β_{ETT}): 0.573 (0.201)	
	InitStratProbB	0.765(0.0758)	*StratProbB*	0.842(0.0592)
	InitStratProbC	0.592(0.0785)	*StratProbC*	0.672(0.0619)
	SlopeStratProbB	0.0320 (0.0145)		
	SlopeStratProbC	0.0338 (0.0185)*		
Scaler	0.923(0.121)		0.919(0.122)	
No of Observations	1677		1677	
No of Individuals	129		129	
No of Parameters	11		9	
Initial Log-likelihood (equal probabilities)	-1162.408		-1162.408	
Final Log-likelihood	-702.842		-705.945	
$\bar{\rho}^2$	0.386		0.385	
Note:* means this parameter is not significant different from 0 at the 0.05 level.				

Table 6.3 Estimation Results of Driving Simulator & PC-based test

CHAPTER 7

CONCLUSION AND FUTURE DIRECTIONS

7.1 Research Summary

In this chapter, we present a summary towards our findings and conclusions in this thesis. A process model (Priority Heuristic) is introduced for studying travelers' decision making behavior in a route choice with risky travel times. A probabilistic version of the priority heuristic model is developed and estimated with an SP survey data set. According to our estimation results, the comparison order obtaining the best final log likelihood among six potential orders is different from that in the original PH model. In our test, subjects most likely compare two maximum outcomes first and then two minimum outcomes and finally two probabilities of minimum outcomes. This finding can be reasonably explained by our test design. Aspiration levels (threshold) used in each comparison step are far from the constant value 1/10 assigned in the original PH model. A cross validation test is conducted to compare PPH model, RDEU model and two other alternative models' data-fitting and predictive performance. These two alternative models have no underlying decision theories and are just fitting the data. Therefore they could possibly exhibit better data-fitting performance and serve as a upper limit in the cross validation test. We arrive at the conclusion that PPH model has superior estimation and prediction performance than a previously developed RDEU model, which itself has been shown to be better than a number of other models, including the mean-standard deviation and expected utility models. We believe that the process modeling paradigm is a valid candidate for studying travel behavior under risk. Note that the comparison is based on a particular dataset, specifically the subjects are mostly from the university student body, and therefore generalization to other situations should be made with caution.

Through the investigation concerning people's strategic route choice behavior in risky traffic networks, we show that travelers are able to plan ahead for future diversion possibilities downstream. This conclusion is a challenge towards basic assumption used by some existing route choice models that people's route choice are not affected by real-time traffic information until it is actually received. A driving simulator test and a PC-based test are conducted with a purpose to investigate people's strategic route choice behavior with different cognitive load. Different subject groups with similar background are recruited for these two tests. Non-parametric analysis suggests that a non-negligible portion of route choices are the result of strategic thinking in these two test environments. Network complexity adversely affects people's strategic thinking ability and a parallel driving task only undermines people's strategic thinking ability in a complex network but not a simple one. With more scenarios experienced before, subjects tend to make more strategic route choice. Although the model with learning effect does not gain much advantage over model without learning in two separate data sets: driving simulator test and PC-based test, this is still an enlightening research attempt in this direction. It is noted that as to combined data sets, the learning model is actually better than the model without learning. Additionally, we believe that people's strategic thinking ability has a relationship with their gender and driving experience, but not age in this context. As a conclusion, a more realistic route choice model in a risky network with real-time information should include both strategic and non-strategic behavior.

7.2 Future Research Directions

The research work towards travelers' route choice behavior, two topics covered in this thesis: Process Model and Strategic Route Choice, are far from complete and finished. Limited by time and resources, only a few aspects have been touched in this study. Being a reference for future research, some interesting directions in this field are suggested as following.

The PH is extended to multiple-outcome situations in Brandstatter et al. (2006) where decisions are based on maximum and minimum outcomes and their associated probabilities. Outcomes in the middle are not used in the decision making. In a travel choice context, it is more plausible to assume travelers recognize certain travel time categories (e.g., free flow, normal, congested, jam) rather than a continuous distribution of travel times. Observed travel time data are inherently discrete and thus support the categorization of travel time outcomes. Therefore the maximum and minimum travel times and their associated probabilities can be readily obtained, and the PPH model can be applied. Note that the assumption of only maximum and minimum outcomes are utilized need to be validated, and intermediate outcomes/probabilities might be added to the decision process.

The PH could also be extended to multiple-attribute situations. The PH effectively treats minimum outcome, maximum outcome and the associated probabilities as different attributes. The underlying assumption is that no systematic trade-off is made; rather, a series of comparisons over the different attributes are made and a choice is made if the difference of a certain attribute exceeds an aspiration level. In this sense, the PH follows the perspective of method of "elimination by aspect" proposed by (Tversky, 1972). The PH thus is well suited to handle multiple-attribute situations in travel choice, e.g, travel time and cost, and the order of comparison likely depends on the saliency or importance of an attribute.

The PPH model's deficiencies include the discontinuity and limited application in "easy" problems. Furthermore, for simplicity a decision with only two alternatives is investigated in this study. A decision with more than two alternatives is common in a travel decision context, and an extension of the PPH model is needed for its application in real life transportation problems.

We made a strong assumption in the PPH model that all subjects adopted the same comparing order for all scenarios during the survey. It is reasonable to suppose that subjects can make use of more than one comparing order, and the comparing orders vary across subjects and contexts. Moreover, we hypothesize that different decision strategies, such as RDEU and PPH might be used in different contexts and/or by different people. Therefore, it will be worthwhile to combine these two paradigms (and possibly others) and investigate which strategies are more likely to be used in different decision contexts. This combination could also potentially resolve the aforementioned problem of the PPH model not working well with "easy" problems and the discontinuity at extreme points.

All the probabilities in the survey were directly presented to subjects. In real life, however, travelers experience outcomes and delays and perceive event frequencies without explicit descriptions of probabilities. Research has shown a difference between decision from description and decision from experience (Rakow & Newell, 2010), for example, small probabilities are underweighted in decision from experience, in contrast to the overestimation in decision from description. Future research should focus on decision from experience as travelers learn about the uncertain environment through experience in most situations. The fact that travelers' choices collectively affect the network performance through congestion effects should also be adequately captured (Lu et al., 2011; Ben-Elia et al., 2013). There are indeed situations where a combination of both theories is desired, such as for modeling choice behavior when real-time traffic information describes event probabilities, and a traveler has the decision environment both experienced and described.

In the study towards travelers' strategic route choice behavior, we find that network complexity adversely affects drivers' strategic thinking ability. The network complexity involved in the driving simulator test could be different from the situation experienced by drivers in their everyday lives. While alternatives' travel time distributions in real life are generally obtained by drivers' own experience after a long time period, travel times situations in this experiment are directly presented in a schematic map to the subjects at the beginning of each scenario. In order to achieve a better understanding of drivers' strategic route choice behavior in different network complexities that are closer to what they experience in real life, a series of tests that involve day-to-day learning are planned for future research. Current studies in the literature focus on generating optimal strategies in a general network. However, an optimal strategy can be extremely complicated and thus behaviorally unrealistic. Questions such as what is the limit of a driver's strategic planning capability and whether a driver simplifies a network to allow for a high-level strategic planning would be interesting topics for future research.

Non-parametric analysis shows that subjects' strategic thinking ability has relationship with their gender and driving experience to some extent, but not age. This phenomenon is possibly due to a short range of subjects' age in our test. To future investigate whether people's age play a role in strategic thinking, a new subject group with large range in age variable should be recruited. With purpose to simulate our real-life, the distribution of subjects' age variable should be consistent with the actual situation on the road.

The significance of the study towards strategic route choice behavior implies a solid progress in this logic trajectory: synthetic data, PC-based test and driving simulator test. With no doubt, conducting this research in a filed test would be an important step to study how people actually behave in the real traffic systems. Safety and efficiency are two major issues we need consider in a field test design. Finding a location with exact networks which are suitable for our research is another difficulty we need to think about.

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