A Positive Model of Departure Time Choice

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1. INTRODUCTION

Departure time choice is an important component of the travel decision-making process. Travelers’ preference toward alternative departure times is an important dimension for transportation demand and policy analysis when peak spreading is of concern. The normative behavioral theory, which assumes substantial rationality, complete information, and utility maximization, has been applied extensively in modeling departure time choice.

This paper develops a novel positive approach to departure time choice modeling, focusing on how the departure decisions are actually made. The choice is theorized as a continual search process with several key concepts defined and operationalized including spatial-temporal travel knowledge, adaptive learning, subjective search gain, perceived search cost, search starting and stopping conditions, search rules, and decision rules. In order for the estimation of the proposed model, a practical memory-recall survey method with relatively low respondent burden is also designed in this research and employed for behavior process data collection. In practice, there is imperative need for incorporating departure time choices into both microscopic traffic operations analysis and micro/macro-level travel demand studies. The proposed positive model tracks the departure time changes of each individual user in the transportation system, and therefore is especially suitable for integration with microscopic traffic simulators, simulation-based dynamic traffic assignment models, and activity/agent-based travel demand models.

Section 2 reviews literature and contrasts normative and positive travel behavior theories. Section 3 presents the positive theoretical framework and model development. Section 4 summarizes the fully operational model and concludes the paper.
2. LITERATURE REVIEW

Rational behavior theory assumes that individuals can identify all feasible alternatives, measure all of their attributes, and choose the alternative that maximizes their utility (Samuelson, 1947). There have been extensive research efforts applying this approach to departure time choice analysis.

Vickrey (1969) examined a single bottleneck and derived supply-demand equilibrium conditions with departure time considerations. Several researchers, including Arnott et al. (1990) and van Vuren et al. (1999), have developed continuous departure time modeling frameworks, collectively referred to as the “Equilibrium Scheduling Theory” (EST).

The second line of research based on rational behavior theory focuses on discrete departure time choice modeling. Small (1982) adopted the multinomial logit (MNL) approach. However, the underlying assumption of independence from irrelevant alternatives (IIA) in MNL may not hold. Nested logit (NL) models have been used to address the correlated departure time intervals. Small (1987) tested the NL and ordered generalized extreme value model, and concluded they performed better than MNL. Cross-nested logit models, which allow more flexible substitution patterns, were also explored by researchers, including Vovsha (1997) and Ben-Akiva and Bierlaire (1999). More recently, Lemp et al. (2010) introduced the continuous cross-nested logit model, which considers correlations across alternatives in a way similar to the continuous response variable approach.

Tversky and Kahneman (1974) argued that individuals rely on mental shortcuts or heuristics that “are highly economical and usually effective but … lead to systematic and predictable errors.” This is especially true when making choices among a large number of alternatives (e.g. departure time choice) because individuals obviously cannot obtain complete information for every feasible departure time interval. The choice set generation process in the context of departure time analysis is the search for alternative departure times, which is often assumed away in previous research. Search theory, originally developed in economics (Stigler, 1961), may be applied here. It theorizes the process in which individuals search for alternatives with various behavioral and environmental constraints.

As individuals identify new departure time alternatives from the search process, they need to decide whether or not they will use them. This requires a set of decision rules in departure time models. While maximizing utility acts as the decision rule for rational behavior analysis, positive departure time models need to focus on how individuals actually make departure time choice decisions. Several knowledge representation methods, such as machine learning and logical
programming, can estimate a set of decision rules based on observed decision outcomes and
decision environment (Durkin, 1994, Arentze and Timmermans, 2000).

3. MODEL

The proposed theoretical framework for positive departure time choice analysis is illustrated in
Figure 1.

![Theoretical Framework for Positive Departure Time Choice Analysis](image)

**FIGURE 1. Theoretical Framework for Positive Departure Time Choice Analysis**

3.1. Survey Methods and Data for the Positive Approach

The target population consists of drivers traveling on the D.C.’s Capital Beltway during weekday
morning and afternoon peak periods. Drivers were intercepted when they were waiting at traffic
lights on several off-ramps. A flyer was distributed to the drivers, and the link to a web-based
joint revealed/stated preference survey on departure time and route choices was provided in the
flyer. The final sample herein consists of 151 commuters.
The survey consists of three parts. The first part includes a list of revealed preference questions about the current daily travel patterns of the respondents including the characteristics of their commute trips. Socio-economic and demographic information was also collected.

Then, a series of carefully designed memory-recall questions were employed to gather behavior process data related to the search for alternative departure times. Each respondent was asked to recall the order of alternative departure times they had considered and actually tried, as well as the travel conditions corresponding to those choices. As reflected by the data, about 10% of the respondents had only experimented with just one alternative, while most individuals had considered two to three alternatives. About 20% had tried more than four alternatives. In the subsequent modeling section, the reported search characteristics and travel conditions are used to model the search process and the distribution of perceived search costs.

The third part is based on stated preference, wherein the respondents were asked to make choices in seven scenarios. Unique alternatives were designed for each respondent based on her/his reported trip attributes in the first part. Each situation included three departure time alternatives with different travel conditions, schedule delay, and monetary costs. Information collected here was used to estimate decision rules that commuters employ to select departure times.

3.2. Knowledge and Learning

The individual’s knowledge about departure times can be quantified as a single-dimension vector \( K(n_1, \ldots, n_i, \ldots, n_I) \). According to Bayesian learning rules, the perceived weights of past observations are the same. For instance, when a new alternative departure time is experienced and the associated utility falls into category \( i \), the updated knowledge becomes: \( (n_1, \ldots, n_i+1, \ldots, n_I) \). Let vector \( P(p_1, \ldots, p_i, \ldots, p_I) \) represent an individual’s subjective beliefs, where \( p_i \) is the subjective probability that an additional search would lead to an alternative departure time with utility level \( u_i \). We assumed that individuals’ prior beliefs follow a Dirichlet distribution to establish a quantitative relationship between knowledge \( K \) and beliefs \( P \). The posterior beliefs will also be a Dirichlet distribution (Rothschild 1974). This assumption is equivalent to assuming Equation 1, where \( N \) denotes the total number of observations \( (N=\text{Sum}(n_i)) \).

\[
p_i = n_i / N
\]

3.3. Search Gain and Search Cost

The decision to search is based on the relationship between subjective search gain and perceived search cost. Let an individual’s utility on the currently used departure time be \( u \). The search gain \( g \) is based on subjective beliefs, \( P \), and defined as the expected utility improvement from an additional search:
\[ g = \sum_{i \in \{u_i > u\}} p_{i} \cdot (u_{i} - u) \]  

where \( u \) is the maximum of all observed/experienced utility levels (\( u_{\text{max}} \)) because individuals can selected from all tried departure times.

Let \( u^* \) be the theoretically maximum utility level under free-flow travel condition, and assume all individuals initially believe there is no congestion. As the search process proceeds, the subjective probability of finding a departure time with utility level \( u^* \) after \( N \) searches is \( 1/(N+1) \). Therefore, Equation (2) can be further simplified as Equation (3).

\[ g = \left( u^* - u_{\text{max}} \right) / (N + 1) \]  

Perceived search cost represents both the variety-seeking propensity of individuals and the perceived mental/monetary cost associated with search. If we empirically observe that an individual stops searching after \( n \) rounds of search, the perceived search cost for that individual must be lower than the subjective search gain after \((n-1)\) searches such that search \( n \) is meaningful (Equation 4-a), and must be higher than the subjective search gain after \( n \) searches such that search \((n+1)\) does not occur (Equation 4-b).

\[ c_{\text{LOW}} = g_{n} = \frac{u^* - u_{\text{max},n}}{n + 1} \]  

\[ c_{\text{HIGH}} = g_{n-1} = \frac{u^* - u_{\text{max},n-1}}{n} \]  

\[ c = \frac{1}{2} \left( c_{\text{LOW}} + c_{\text{HIGH}} \right) \]  

We also allow perceived search cost to vary for different trips because it may be more different to search for alternatives for certainly trips than for other trips. The method is to empirically estimate the relative perceived search cost (\( c^* = c/u^* \)). In order to empirically derive the distribution of relative perceived search cost, information about searched alternatives, the order by which alternatives are searched, and attributes of each alternative departure time was extracted from the memory-recall survey. The estimated cumulative density distribution function of \( c^* \), as well as its lognormal and Weibull approximations, is plotted in Figure 2.
3.4. Search Rules

Part 2 of the survey data on search processes are used to derive search rules. The variables used in the search rule induction model include: arrival schedule delay early \((ASDE)\), arrival schedule delay late \((ASDL)\), travel time \((TT)\), and free flow travel time \((TT^*)\). Equation 6 defines the arrival schedule delay variables (i.e. \(ASDE\), \(ASDL\), and \(Delay\)), which is consistent with the definition in previous research. \(PAT\) denotes the preferred arrival time, \(AT\) the actual arrival time, \(Delay\) the difference between actual travel time \((TT)\) and free flow travel time \((TT^*)\).

\[
\begin{align*}
ASDE &= \max \left(0, PAT - AT\right) \\
ASDL &= \max \left(0, AT - PAT\right) \\
Delay &= \left(\frac{TT - TT^*}{TT^*}\right)
\end{align*}
\]  

Various machine learning algorithms (Witten and Frank, 2000) are able to derive if-then rules from behavior process survey data. We have tested four proven algorithms including C4.5
(Quinlan, 1986), PRISM (Cendrowska, 1987), PART (Frank and Witten, 1998), and RIPPER (Cohen, 1995), and selected PART based on predictive accuracy of the derived search rules on a validation dataset. The complete departure time rule sets are presented below:

Search 30-60 min earlier, if
   
   \[ 45 < ASDL \leq 70 \]  
   Rule 2

Search 0-30 min earlier, if
   
   \[ ASDL > 0 \text{ AND } Delay > 0 \]  
   Rule 3

Search 0-30 min later, if
   
   \[ 0 < ASDL \leq 30 \text{ AND } Delay > 40\% \]  
   OR\[ASDL \leq 10 \text{ AND } ASDE \leq 40 \text{ AND } Delay \leq 50\% \text{ AND } TT \leq 65 \]  
   Rule 4

Search 30-60 min later, if
   
   \[ ASDL = 0 \]  
   Rule 5

Search 60+ min later, if
   
   \[ ASDE > 75 \]  
   Rule 6

OR\[ASDE > 45 \text{ AND } Delay > 10\% \]  
   Rule 7

Otherwise, search 0-30 min earlier.  
   Rule 8

3.5. Decision Rules

Once an individual found a new departure time alternative with the search rules, the individual after experimenting with the new alternative will either change or not change departure time. Subjects’ actual departure time changing behaviors are observed in Part 3 of the survey, which allow us to extract decision rules with machine learning algorithms. The decision rule set consists of 6 rules, presented below. RIPPER is chosen for its superior predictive performance on validation dataset, and the clear physical meaning of the derived behavioral rules. The explanatory variables in the decision rules include: preferred arrival time (PAT), departure time (DT), preferred departure time (PDT), travel time (TIME), household income (INCOME), trip purpose (PURPOSE), fuel cost (FC), and toll cost (TC). The variable none-peak is a dummy variable that is equal to one if the trip occurs during off-peak hours, and zero otherwise. \( \Delta \) denotes changes or percentage changes from attributes of current departure time choice.

Switch to the alternative departure time, if
   
   \[ \Delta TIME \leq -35\% \text{ and } \Delta FC \leq -8\% \]  
   Rule 1

\[ \Delta TC \leq 2.5 \text{ and } \Delta ASDL \leq -48\% \]  
   Rule 2

\[ \Delta TC \leq 2.4 \text{ and } INCOME \geq $150K \text{ and } \Delta ASDL \leq -31\% \]  
   Rule 3

\[ none-peak = 1 \text{ and } PURPOSE = Other \text{ and } \Delta TIME \leq -8\% \text{ and } \Delta ASDL \leq 53\% \]  
   Rule 4

\[ \Delta ASDE \leq -20\% \text{ and } \Delta TC \leq 0.7 \]  
   Rule 5

Otherwise, continue to use the current departure time.  
   Rule 6
4. CONCLUSIONS

This research develops a fully operational departure time choice model based on the positive theory and other aforementioned positive travel behavior research. The main contribution of the paper lies in the originality of the model and the development of associated survey and implementation methods. The theoretical framework removes assumptions of perfect information and maximum utility. Instead, travelers’ spatial knowledge, learning, subjective beliefs, perception, search for alternatives, and decision-making with limited computational abilities are explicitly theorized and modeled with empirical data. The proposed positive approach enhances both our understanding of the travel decision-making process and the realism of departure time choice models.

The model is ready to be integrated with traffic models or demand models for various transportation operations and planning applications that require peak spreading analysis. A numerical example presented elsewhere (Zhang and Xiong 2011) highlights the capabilities of the positive model in estimating rich behavioral dynamics, such as day-to-day evolution of congestion by departure time intervals and individual-level learning, search, and decision-making processes over time. Another possible future research direction lies in the application of the positive theoretical framework and modeling methods to multidimensional travel decision-making analysis (i.e. not just departure time choice, but integrated routing, scheduling, mode, destination, and trip frequency decisions).
REFERENCE