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# Cognitive Cost in Route Choice with Real-Time Information: An Exploratory Analysis

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## Abstract

Real-time traffic information is increasingly available to support route choice decisions by reducing the travel time uncertainty. However it is likely that a traveler cannot assess all available information on all alternative routes due to time constraints and limited cognitive capacity. This paper presents a model that is consistent with a general network topology and can potentially be estimated based on revealed preference data. It explicitly takes into account the information acquisition and the subsequent path choice. The decision to acquire information is assumed to be based on the cognitive cost involved in the search and the expected benefit defined as the expected increase in utility after the search. A latent class model is proposed, where the decision to search or not to search and the depth of the search are latent and only the final path choices are observed. A synthetic data set is used for the purpose of validation and ease of illustration. The data are generated from the postulated cognitive-cost model, and estimation results show that the true values of the parameters can be recovered with enough variability in the data. Two other models with simplifying assumptions of no information and full information are also estimated with the same set of data with significantly biased path choice utility parameters. Prediction results show that a smaller cognitive cost encourages information search on risky and fast routes and thus higher shares on those routes. As a result, the expected average travel time decreases and the variability increases. The no-information and full-information models are extreme cases of the more general cognitive-cost model in some cases, but not generally so, and thus the increasing ease of information acquisition does not necessarily warrant a full-information model.

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## 1. Introduction

Real-time traffic information is increasingly available to support route choice decisions pre-trip and en-route. Travelers can, for example, listen to radio broadcasts for incident information or check websites displaying actual speeds on highways and main arterials. They can also consult other information sources, for instance, weather forecast or special event schedules. By acquiring information travelers can estimate the actual travel time for a given

path and departure time instead of relying on the average travel time (e.g. gained through experience or given by a travel information system using links' mean travel times). Due to time constraints and limited cognitive capacity, a traveler cannot assess all available information on all alternative routes.

The focus of this paper is the modeling of information acquisition and the subsequent path choice. We explicitly model cognitive cost by adapting the directed cognition (DC) model (Gabaix et al., 2006) to path choice. The DC model is shown to perform better than perfectly rational models in experiments involving complex decision context and costly information acquisition. The paper is methodological and its main objective is to present and illustrate the proposed model. For this reason we use synthetic data for the model estimations.

The DC model is a type of bounded rationality model, which in general describes a decision maker choosing a satisficing rather than optimal solution due to constraints on available information, cognition capacity and time. Bounded rationality is applied to route choice in a traffic assignment context in Mahmassani and Chang (1987), where a traveler is assumed to choose a path within a given threshold of the shortest path travel cost. The labeling approach proposed by Ben-Akiva et al. (1984) may also be viewed as a boundedly rational one. The cognitive process leading to such behavior is however not described in these studies. Some similarities exist with the work of Chorus et al. (2010) (extended in Chorus et al., In review) who model the value of information in terms of the difference between current utility and the anticipated utility after the information acquisition. They use data collected in a simulator and include a monetary cost of information whereas we are interested in the cognitive cost. Moreover, we define a model that is consistent with a general network topology and that can potentially be estimated based on revealed preference (RP) data.

Hato et al. (1999) model information acquisition and reaction to travel information and use RP data for the estimation. Their model includes latent variables – cognitive involvement and information processing capability – but the model does not capture the benefit of information in terms of the difference between current utility and the anticipated utility after the information acquisition. We refer the reader to Chorus et al. (2006) for an in-depth review of approaches for modeling travel information search.

Modeling optimal information acquisition poses conceptual challenges as well as computational ones due to the curse of dimensionality (Gabaix et al., 2006). The DC model recognizes decision makers' limited cognition capacity and makes some simplifying assumptions to make it both behaviorally sound and tractable. It assumes that in a choice context where each alternative has a large number of components that contribute to its utility (e.g. a TV with multiple attributes such as price, size, warranty etc.), individuals do not acquire information for all the components. Instead, they are partially myopic and choose to learn about some components of one or several alternatives that bring them the most useful information.

The main contribution of this paper is an adaptation and extension of the DC model to the route choice problem. We propose a model estimated on path choice observations where information acquisition is an integral yet latent part. Compared to the original DC model, we model the choice of information acquisition as stochastic rather than deterministic; the model is estimated on final path choices rather than intermediate information acquisition processes that are generally unobservable in RP route choice data from the field.

## **2. Model Specification**

A traveler  $n$  associates a link additive deterministic utility with each path  $j$  in his/her choice set  $C_n$ . Before searching any information, the traveler is assumed to know the mean travel time of each path. A traveler can make repeated information searches in order to learn the actual realized travel times on relevant parts of the network and improve his/her forecast of one or several paths' travel times. It comes however at the cost of searching for the information. An information search stage is denoted  $t$  and the initial state where average travel times for all paths in  $C_n$  are known is  $t = 0$ .

Although it would be convenient from a modeling point of view, it is not behaviorally realistic to assume that travelers search information link-by-link. Indeed, a link-node representation is the analyst's model of the network rather than the travelers'. Instead we assume the existence of information search cases that correspond to different classes of the population who have different ways of searching for information. Note that in RP data, the class membership is in general not observed. The search sequence for an origin-destination (OD) pair from a given information provider is determined by the information provider following its information display logic. We do not explicitly model the information provider's logic here; rather we assume the search sequence is given. The ordered

search sequence over the whole network for an individual  $n$  of class  $s$  is unique  $\mathbf{H}_n^s = \{H_{n1}^s, H_{n2}^s, \dots, H_{nT_n^s}^s\}$  (at stage  $T_n^s$  all available information for class  $s$  has been searched). The search operation  $H_{nt}^s$  at any stage  $t$  is broadly defined as an action to acquire information, e.g., checking Google Maps to get recommended path travel times, construction work schedules, sports event schedules and so forth. A search operation is characterized by the conditional joint distribution of relevant path travel times given the operation. One search operation can give information on more than one path alternative.

Stopping at  $t = 1$  means no search and this is a specific class. It is labeled “no search” in the remainder of the paper and the class index  $s$  refers to a class where at least one search is performed. At each stage  $t > 1$ , the traveler can choose to stop or to continue the search. Since stopping at  $t = 1$  is a specific class, the traveler must search once if in another class, that is, it is not possible to stop the search at  $t = 1$ . The search stops at  $t = t'$  but  $t'$  is in general not observed.

The probability that individual  $n$  of class  $s$  searches until  $t = t'$  and chooses path  $j$  is

$$P(j, t' | C_n, \mathbf{H}_n^s) = P(j | t'; C_n, \mathbf{H}_n^s) P(t' | \mathbf{H}_n^s). \tag{1}$$

$P(t' | \mathbf{H}_n^s)$  is the probability of continuing the search until  $t'$ , or equivalently stopping the search at  $t' + 1$ :

$$P(t' | \mathbf{H}_n^s) = \left(1 - P(H_{n,t'+1}^s | \mathbf{H}_n^s)\right) \prod_{t=1}^{t'} P(H_{nt}^s | \mathbf{H}_n^s), \tag{2}$$

where the search probability at stage 1 is 1 for any class where a search is performed, that is,  $P(H_{n1}^s | \mathbf{H}_n^s) = 1$ , and the stopping probability beyond the final stage is 1, that is,  $P(H_{n,T_n^s+1}^s | \mathbf{H}_n^s) = 0$ .

This is a “stop-and-go” Logit model (see e.g., Ben-Akiva and Lerman, 1985) starting from stage 2 and the utility of continuing the search at stage  $t$ , hence choosing  $H_{nt}^s$  includes the expected benefit and cognitive cost of the search.

Since  $t'$  and  $s$  are latent we have

$$P(j | C_n) = P(j | C_n; \text{no search}) P(\text{no search}) + \sum_s \sum_{t'=1}^{T_n^s} \underbrace{P(j | t'; C_n, \mathbf{H}_n^s)}_{\text{Eq. 4}} \underbrace{P(t' | \mathbf{H}_n^s)}_{\text{Eq. 5,6,8,9}} \underbrace{P(\mathbf{H}_n^s)}_{\text{Eq. 10}}, \tag{3}$$

where  $P(\mathbf{H}_n^s)$  is the probability of an individual  $n$  belonging to class  $s$ . In the following section we present an example showing how the model can be specified in practice. The equations that are referenced in Equation (3) correspond to this example.

### 3. Model Specification

#### 3.1. Network

We use an example of a commuter from Brookline, MA to his workplace, MIT. There are three alternative paths. Paths 1 (MassAve, right path in green), 2 (BU, middle path in red) and 3 (River St, left path in blue) that is a long detour in case of congestion on the previous two paths. We assume travel times on paths 1 and 2 are normally distributed truncated at one standard deviation below the mean (approximating free-flow travel times) and three standard deviations above the mean (approximating highly congested travel times), and the travel time on path 3 is a

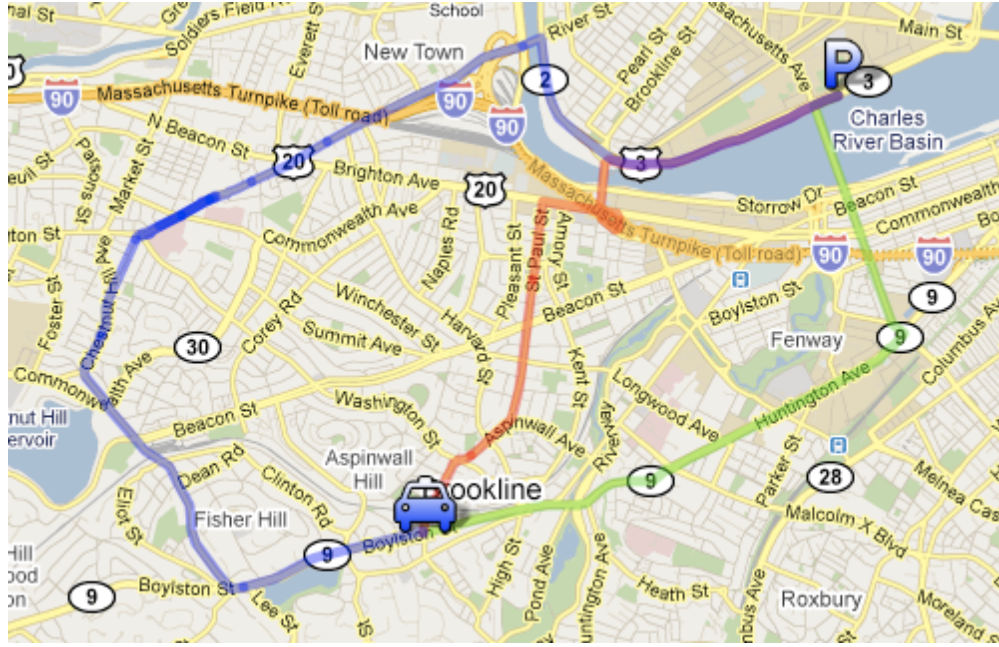


Figure 1: The Map

fixed value. Note that path travel times are not necessarily independent. However an individual traveler might or might not realize this correlation.

### 3.2. Path Size Logit

We use a Path Size (PS) Logit model (Ben-Akiva and Ramming, 1998) for the path choice. The systematic utility of path  $j$  for individual  $n$  from class  $s$  at stage  $t'$  is linear with two predictors: the mean and standard deviation of travel time given the searches performed up to stage  $t'$ . When no search is performed, the unconditional path travel time mean and standard deviation are used. If some searches are performed, the conditional mean and standard deviation are calculated based on the search results. The PS variable is included to take into account the overlapping of alternative paths.

$$V_{njt'}^s = \ln PS_{nj} + \alpha_{\text{Mean}} \text{MeanTT}_{njt'}^s + \alpha_{\text{std}} \text{TTstd}_{njt'}^s \quad (4)$$

Note that the PS attribute represents a traveler's long-term perception of route overlapping and is based on distances only. There is a 1-mile overlapping between paths 2 and 3, and  $PS_{n1} = 1, PS_{n2} = 0.85, PS_{n3} = 0.92, \forall n$ .

### 3.3. Information Search Classes

There are two search classes:

1. No search
2. Search by path. The ordered search sequence is 1, 2, since Google Maps first suggests path 1, and then the traveler can choose to drag (i.e. move a point on path 1 so that it passes the bridge of path 2) and get path 2, given that path 2 is the traveler's habitual route (observable from a survey) but not shown by Google Maps. A searched path has a mean equal to the actual travel time and a zero standard deviation. Path 3 has a fixed travel time, so there is no need to search. We assume travelers in this class are not aware of the correlation between paths 1 and 2, i.e. the actual travel time on path 1 does not tell the travelers anything about that on path 2.

The number of latent classes is however three instead of two. Travelers who choose to search by path could stop the search at either stage 2 or 3, meaning that they search either path 1 or both paths 1 and 2.

A stop-and-go Logit model is applied for the search operations. Specifically at each search stage  $t$ , a binary Logit is used with two alternatives: going (searching  $H_{nt}^s$ ) or stopping. The systematic utilities are specified as follows:

$$Y(H_{nt}^s) = \beta_{\text{CognitiveCost}}^s + \beta_{\text{Benefit}} B_{nt}^s(\text{go}) \tag{5}$$

$$Y(\text{stop}) = \beta_{\text{Benefit}} B_{nt}^s(\text{stop}) \tag{6}$$

The alternative specific constant (ASC)  $\beta_{\text{CognitiveCost}}^s$  represents the cognitive cost of one search operation, and depends on the search class.  $B_{nt}^s(\text{go})$  is the average (over search outcomes) expected (over individuals) maximum (over alternatives) utility of searching at stage  $t$  for an individual  $n$  from class  $s$ , and  $B_{nt}^s(\text{stop})$  is the expected maximum utility of stopping the search at stage  $t$ . Since a Logit model is used for the path choice, the expected maximum utility is the logsum. Let  $D_{nt}^s$  be the set of paths affected by the search operation of individual  $n$  of class  $s$  at stage  $t$ , and  $f_{nt}^s(\{\text{MeanTT}_{nlt}^s\}, \{\text{TTstd}_{nlt}^s\}, l \in D_{nt}^s)$  the conditional joint distribution of affected path travel time means and standard deviations given the said search operation.

$$B_{nt}^s(\text{go}) = \int_{\{\text{MeanTT}_{nlt}^s\}, \{\text{TTstd}_{nlt}^s\}} \left\{ \ln \sum_{j \in C_n} \exp(V_{nlt}^s(\text{MeanTT}_{nlt}^s, \text{TTstd}_{nlt}^s)) f_{nt}^s(\{\text{MeanTT}_{nlt}^s, \text{TTstd}_{nlt}^s\}, l \in D_{nt}^s) \right\} \underbrace{d\text{MeanTT}_{nlt}^s d\text{TTstd}_{nlt}^s}_{l \in D_{nt}^s} \tag{7}$$

$$B_{nt}^s(\text{stop}) = \ln \sum_{j \in C_n} \exp(V_{nj,t-1}^s) \tag{8}$$

If no search is performed at stage  $t$  (implicitly searches have been performed in all previous stages), the logsum is calculated based on the information on paths that are covered by searches up to stage  $t - 1$ . If the traveler searches by path, realized link travel times will be used as the means in path utilities and the standard deviation is zero.

Since the search at stage  $t$  has not been performed at the time of search decision, the travel time means and standard deviations at stage  $t$ ,  $\text{MeanTT}_{nlt}^s$  and  $\text{TTstd}_{nlt}^s$  on paths affected by the search operation depend on the unknown search result and are random variables. Therefore Equation (7) involves an integration of the logsum over the probability distribution of the search results.

In the case of searching by path, the continuous normal density functions are used. We calculate the integral by the Gauss-Hermite quadrature method, which is suitable for approximating the value of integrals of the following kind:

$$\int_{-\infty}^{+\infty} \exp(-x^2) f(x) dx.$$

In this specific case, each path search operation contains only one path. Let  $j_t$  be the index of the path to be searched in stage  $t$ , and thus the expected maximum utility for a path search can be re-written as:

$$\begin{aligned}
 B_{nt}^{\text{path}}(\text{go}) &= \frac{1}{0.84\sqrt{\pi}} \sum_{k=1}^m w_k \ln \sum_{j \in C_n} \exp(V_{njt}^{\text{path}}(x_k)) \\
 &= \frac{1}{0.84\sqrt{\pi}} \sum_{k=1}^m w_k \ln \left\{ \exp\left(\alpha_{\text{Mean}}(\text{OriginalMean}_{nj,t-1}^{\text{path}} + \sqrt{2}\text{OriginalSTD}_{nj,t-1}^{\text{path}}x_k)\right) \right. \\
 &\quad \left. + \sum_{j \in C_n \setminus \{j_t\}} \exp\left(\alpha_{\text{Mean}}\text{MeanTT}_{nj,t-1}^{\text{path}} + \alpha_{\text{std}}\text{TTstd}_{nj,t-1}^{\text{path}}\right) \right\}. \tag{9}
 \end{aligned}$$

OriginalMean $_{nj,t-1}^{\text{path}}$  and OriginalSTD $_{nj,t-1}^{\text{path}}$  are the parameters of the original normal distribution (not the truncated one) of the travel time along the path under consideration in the previous stage  $t - 1$ . 0.84 is the probability mass between the two truncating points of a standard normal random variable.  $m$  is the number of sample points,  $x_k$  are the roots of the Hermite polynomial of degree  $m$ , truncated between -1 and 3, and the associated weights  $w_k$  are calculated based on given formula. Specifically we use thirty sample points for a normal distribution to obtain ten points for the truncated normal between -1 and 3.

### 3.4. Class Membership Function

We specify a class membership function in this section and start by defining two attributes that may be plausible in a real setting. On the one hand, a traveler who is not particularly familiar with the network might be interested to ask a route generation system, such as Google Maps to recommend one or more routes. On the other hand, a commuter who is familiar with the network might falsely feel safe because of his/her experience and does not search for information at all. We use the number of years of commuting, YEARS, to represent network familiarity.

The search decision may also depend on the arrival time flexibility of the trip. People may be more likely to search if the arrival time is less flexible, as the consequence of being late is more serious. The length of the arrival time window, WINDOW, is used to represent the flexibility.

Both variables are categorical in order to allow an interpretation of the associated parameters in terms of behavioral change from one category to another rather than from one year or one minute to another. Each category (0, 1, 2, 3) of the variable YEARS represents a 5-year commuting experience, with 0-5 years as the least experienced commuter and 15 years and above the most experienced. Each category of the variable WINDOW represents a 10-minute time window, starting from 0-10 minutes as the least flexible, and 30 minutes and above as the most flexible. Note that the categories are set up for illustrative purpose. In a real application, the categories should be determined from the context and the data, or the attributes could be continuous.

We use a Logit model for the class membership with the following systematic utility functions.

$$\begin{aligned}
 W_n^{\text{no search}} &= \gamma_{\text{Benefit}} B_{n1}^{\text{no search}}(\text{stop}) \\
 W_n^{\text{no path}} &= \text{ASC}^{\text{path}} + \gamma_{\text{Benefit}} B_{n1}^{\text{path search}}(\text{go}) + \gamma_{\text{YEARS}} \text{YEARS}_n + \gamma_{\text{WINDOW}} \text{WINDOW}_n \tag{10}
 \end{aligned}$$

$B_{n1}^{\text{no search}}$  and  $B_{n1}^{\text{path search}}$  are the benefits of no search and one path search, under the assumption that travelers have limited cognitive capacity and cannot calculate the full benefit of performing a series of path searches (Gabaix et al., 2006). They are calculated the same way as are the benefits in the stop-and-go Logit from Section 3.3 using Equations (8) and (9).

An ASC can be interpreted as the average preference towards a particular alternative if the explanatory variables are held equal for all alternatives. In this specific context, the ASC can be viewed as the average preference towards search over no search for a new commuter (YEARS = 0) with a rigid arrival time window (WINDOW= 0) where the benefits of search and no search are the same. We postulate that such a traveler tends to search given the unease a new commuter (usually a new employee) may feel about being on time for work. The ASC includes the cognitive cost of searching, but we note that it is not separable from other unobserved factors that it may also capture. Therefore the sign of the ASC is not necessarily negative.

This cognitive cost of performing a search compared to no search at all could be different from that in the stop-and-go Logit, in the sense that a traveler making the decision between search and no search might consider some initial set-up cost, such as subscribing to a game schedule notice, tuning in to the traffic radio station, acquiring a route guidance system with real-time information, and so forth. The cognitive cost in the stop-and-go Logit is purely a marginal cost of each additional search operation.

#### 4. Numerical Results

The objectives of the numerical results presented in this section are to (1) show that the proposed cognitive-cost model can be consistently estimated, and (2) study the prediction bias that is introduced if a full-information or no-information model is used when the travelers actually behave according to the cognitive-cost model. In order to fulfill the first objective we need to estimate the cognitive-cost model on data for which we know the true model parameters. For the second objective we need a choice and information search setting that is simple enough to allow us to clearly analyze the predictions of the three models in question.

For the numerical results presented in this section, we therefore use the small network presented previously. We postulate a cognitive-cost model and generate a synthetic data set for estimation. The cognitive-cost model corresponds to the postulated one and should therefore have consistent parameter estimates. The full-information and no-information models are estimated based on the same data. The estimated models are used for prediction and the results are analyzed in Section 4.2.

##### 4.1. Data Generation and Model Estimation

A synthetic data set is used for the purpose of validation and ease of illustration. In this section we first describe how the synthetic observations are generated (values of the model parameters and the attributes) and then present the estimation results obtained using these observations.

We postulate the true parameters,  $\alpha_{\text{Mean}} = -0.08$ ,  $\alpha_{\text{std}} = -0.03$ ,  $\beta_{\text{CognitiveCost}}^{\text{path}} = -0.2$ ,  $\beta_{\text{Benefit}} = -0.1$ ,  $\text{ASC}^{\text{path}} = 0.5$ ,  $\gamma_{\text{Benefit}} = 0.1$ ,  $\gamma_{\text{YEARS}} = -0.2$ ,  $\gamma_{\text{WINDOW}} = -0.2$ . The choices of these values are based on empirical results and judgment as described in the following.

The travel time mean and standard deviation parameter values are postulated based on route choice model estimation results using RP data in the literature (see, e.g., Ramming, 2002; Frejinger and Bierlaire, 2007; Bierlaire and Frejinger, 2008; Lam and Small, 2001), namely, the travel time (in minutes) coefficient varies in magnitude between 0.001 to 0.1, and the travel time standard deviation coefficient is in the same magnitude as the travel time coefficient but generally smaller in absolute value. The magnitude of the cognitive cost is postulated based on the empirical evidence from an SP survey reported in Chorus et al. (2010), where the non-monetary cost of information search is approximately one magnitude larger than the travel time (in minutes) coefficient. The magnitude of the benefit coefficient is close to the cognitive cost so that neither the cognitive cost nor the search benefit will dominate the choice and thus avoids obscuring the trade-off between the two factors. The magnitude of the coefficient for YEARS or WINDOW is chosen to be similar to others.

The network topology is fixed with three paths between one OD pair, and a constant overlapping ratio between paths 2 and 3. The major variables are means and standard deviations of the path travel times. We sample uniformly the means of the un-truncated Normal distribution for paths 1 and 2 between 10 and 160. The fixed travel time on path 3 is uniformly sampled between 1.5 and 2 times the larger of path 1 and 2 means. The standard deviation of the un-truncated travel time Normal distribution is uniformly sampled between 2 and 2.5 times the corresponding travel time mean.

We also need to sample realized path travel times. We generate the correlation between paths 1 and 2 by sampling first a congestion event with two possible outcomes, congestion or no congestion. Travel time distributions under the two events are separated by a threshold represented as the number of standard deviations higher than the mean. The travel time given a congestion situation is distributed as a truncated Normal between the threshold and the higher truncating point. Similarly the travel time without congestion is truncated Normal between the lower truncating point and the threshold. The threshold itself is uniformly sampled between 2 and 3 standard deviations higher than the mean. We then sample the actual travel times from the conditional distributions given the congestion condition.

Table 1: Estimation Results (t-tests are against true values)

Parameter (True Value)	Cognitive Cost	No Information	Full Information
$\hat{\alpha}_{\text{Mean}}$ (-0.08)	-0.0816	-0.0167	-0.00417
Robust Std err	0.0016	0.000129	2.46E-05
t-test	-1	490.7	3082.5
$\hat{\alpha}_{\text{std}}$ (-0.03)	-0.0305	-0.0161	
Robust Std err	0.0005	0.0000942	
t-test	-1.031	147.6	
$\hat{\beta}_{\text{CognitiveCost}}$ (-0.2)	-0.227		
Robust Std err	0.0522		
t-test	-0.517		
$\hat{\beta}_{\text{Benefit}}$ (0.1)	0.111		
Robust Std err	0.0097		
t-test	1.131		
$\widehat{ASC}^{\text{path}}$ (0.5)	0.499		
Robust Std err	0.0420		
t-test	-0.024		
$\hat{\gamma}_{\text{Benefit}}$ (0.1)	0.102		
Robust Std err	0.0056		
t-test	0.355		
$\hat{\gamma}_{\text{YEARS}}$ (-0.2)	-0.208		
Robust Std err	0.0129		
t-test	-0.620		
$\hat{\gamma}_{\text{WINDOW}}$ (-0.2)	-0.207		
Robust Std err	0.0129		
t-test	-0.543		
Final log-likelihood	-28558	-33234	-40158
No. of Parameters	8	2	1
Adjusted $\rho^2$	0.518	0.440	0.323
Number of observed paths: 54000			
BIOGEME (Bierlaire, 2003) has been used for all model estimations			

The two variables representing network familiarity and arrival time flexibility are discrete and uniformly sampled from the set (0, 1, 2, 3).

For the estimation we use the latest version of Biogeme (biogeme.epfl.ch 2.0 Python, Bierlaire, 2003), which allows a flexible model specification for latent variables. The main purpose is to show that the true values can be retrieved for a cognitive-cost model. Two less general models are also estimated: one assuming that no travelers search for information and base their choices on unconditional travel time distributions, and the other assuming that travelers have full information and know exactly the realized path travel times before their trips. For these two models, only the path utility parameters are estimated, as all other parameters are related to search decisions which are not modeled explicitly in the two simplified models. Furthermore, the full-information model does not have the parameter for travel time standard deviations, since a traveler with full information always knows exactly what is going to happen and there is no travel time uncertainty at his/her decision time. Note that the full-information model is still a random utility model, since even though the traveler has full information, we as the modelers still might not fully understand his/her behavior (and thus might omit factors that affect the choice) and might not have perfect measurements of travel times, both of which contribute to the error terms in the utilities. The three models are estimated separately, and thus the potentially different scales of the models are implicitly accounted for.

Estimation results are reported in Table 1. The t-tests are against true values (shown in parenthesis next to the parameter) rather than zero and indicate that the true values of the path utility parameters and those related to latent



classes can be retrieved as all estimates are within around one standard error of their true values. We see that the standard errors of the path utility parameters are smaller than those of the latent class membership function parameters, including the cognitive cost and search benefit in the stop-and-go Logit. This is expected, as path choices are directly observed while latent class choices are not.

The no-information and full-information models also have statistically significant estimates for the path utility parameters. However they are significantly different from the true values. Most notable is the much smaller travel time coefficient in the full-information model. This is due to the omission of all the other explanatory variables in the true model, which results in a much larger variance of error terms of the random utility model, or equivalently, a smaller scale of the parameters. More intuitively, the erroneous full-information model cannot explain why travelers choose longer routes (true reason being that they do not have full information and cannot perceive true travel times) and has to attribute the dispersion of route shares to insensitivity to travel times.

The final log-likelihoods of the two simplified models are also worse than the true model. Prediction results based on the estimated model parameters are presented next to show the biases introduced by the no-information or full-information assumption, given that travelers behave according to the cognitive-cost model.

## 4.2. Prediction

The three estimated models are applied to a specific network setting and predictions of path shares and average travel times are compared to illustrate the potential biases introduced by over-simplifying assumptions of either no information or full information in a route choice model. Specifically we study how model differences change as a function of cognitive cost.

We set the mean and standard deviation of paths 1 and 2 travel times at 80 and 70 respectively to represent highly unreliable routes. The travel time on path 3 is fixed at 100, which could serve as a detour in case paths 1 and/or 2 get congested. YEARS and WINDOW are both set at 1, indicating 5 to 10 years commuting experience and a moderately flexible trip with an arrival time window of 10 to 20 minutes.

Predicted path shares are obtained by mixing the path choice probabilities and path travel time distributions in the cognitive-cost and full-information models through simulations, as the choice probabilities depend on the realized path travel times. It follows that path shares in the two models are also random variables and thus we present their expected values as well as standard deviations. The path shares predicted by the no-information model are fixed as only unconditional travel time distributions are utilized in the decision making, which are assumed stable over time. Thus standard deviations of path shares from a no-information model are zero.

Another measure of interest is the travel time averaged over individuals. As path shares are random in the cognitive-cost and full-information models, average travel times are also random. The no-information model predicts fixed path shares, however as the travel times are by themselves random, the resulting average travel times are also random. It follows that we need to present the expected values and standard deviations of average travel times for all three models.

The means and standard deviations of path shares and average travel times are plotted against the cognitive cost. Figures 2 through 4 show the impacts of  $\beta_{\text{CognitiveCost}}$  in the stop-and-go Logit represented as multiples of  $\beta_{\text{Benefit}}$ . As parameters in a random utility model include scale parameters, it makes more sense to talk about ratios of parameters than the absolute values. As discussed in Section 3.4, the ASC in the membership function for the path search class includes cognitive cost, yet we cannot separate it from other fixed factors that have entered the ASC. The scale parameters of the stop-and-go Logit and membership functions are also likely different. Therefore we adjust  $\text{ASC}^{\text{path}}$  by the same proportion of change in the stop-and-go Logit. For example, if  $\beta_{\text{CognitiveCost}}$  is set at 0, indicating a change of two times of  $\beta_{\text{Benefit}}$ , then  $\text{ASC}^{\text{path}}$  is adjusted also by two times of  $\gamma_{\text{Benefit}}$ .

Figure 2 presents the expected path shares on the three paths for each of the three models, where the solid line represents the cognitive-cost model, the dashed line the full-information model and the dotted line the no-information model. As expected, path shares are not functions of the cognitive-cost in the full- or no- information models, as it is not included in these two models. Due to the high variability of travel times on paths 1 and 2, the no-information model predicts a large share on the longer but safer route, path 3. Paths 1 and 2 have slightly different shares, even though they have exactly the same mean and standard deviation, because path 2 overlaps with path 3 to some degree and is penalized by the PS variable. The full-information model predicts higher shares on the two risky

routes, and lower share on the safe route. This is because with full information, the two originally risky routes become risk-free and since it does have a smaller mean travel time the shares will be higher.

The cognitive-cost model's prediction changes with the cognitive cost as expected. Specifically the shares on the risky routes decrease with the cognitive cost. Let us consider the following. The higher the cognitive cost, the less likely a traveler will conduct a search at all or search beyond the first path. When no search is conducted, we have the no-information situation and travelers are deterred by the risks on paths 1 and 2. A search decision is made by trading off the cognitive cost and the expected net benefit, defined as the difference between the two logsums in the stop-and-go Logit or the membership functions. Note that the expected net benefit of searching is always non-negative due to the fact that the search enables a traveler to be adaptive. If the search reveals a shorter travel time on the risky routes than his/her current choice when there is no information (or less information), then he/she can take it. If it happens to be higher, then he/she can still stick to the original choice. If a search is performed which indicates the expected net benefit is large enough, the traveler must encounter the situation where the revealed travel time is shorter and attracts him/her to the risky routes. This effectively moves traffic from the safe route to the risky routes. When the cognitive cost is smaller, more searches are likely and thus more travelers take the risky paths 1 and 2.

For this data we can see that the expected path shares of the cognitive-cost model, for most values of cognitive cost, lie between the path shares predicted by the two other models (less than the full-information model and greater than no-information model for paths 1 and 2 and the opposite for path 3). Note that however the no-information and full-information models are not exactly the extreme cases of the more general cognitive-cost model. Indeed, a zero cognitive cost does not necessarily make all travelers perform a search since the search model is probabilistic, and thus a zero-cognitive-cost model is not equivalent to the full-information model. In the DC model of Gabaix et al. (2006) the choice is assumed deterministic such that a search is performed whenever the net benefit is positive. In such a case, zero cognitive cost is equivalent to full information. On the other extreme, a large cognitive cost indeed drives all travelers not to search at all. However since the two simplifying models have biased estimates of the path utility parameters, even under the same information scenario path shares are different. We have conducted the same analysis with other travel time settings and the relationships between the three models vary depending on the travel time distributions. However a generally valid observation is that the shares on the risky routes decrease with the cognitive cost.

We also note that the effect of the cognitive cost is smaller on path 2 than path 1. Paths 1 and 2 have exactly the same mean and standard deviations, but path 1 is assumed to be the first in the search sequence. The benefit that can be provided by searching path 2 beyond path 1 is in general marginal and large enough to warrant a search only when path 1 is bad and path 2 is good. In our case the two travel times are positively correlated and thus the chance of such a situation is relatively small.

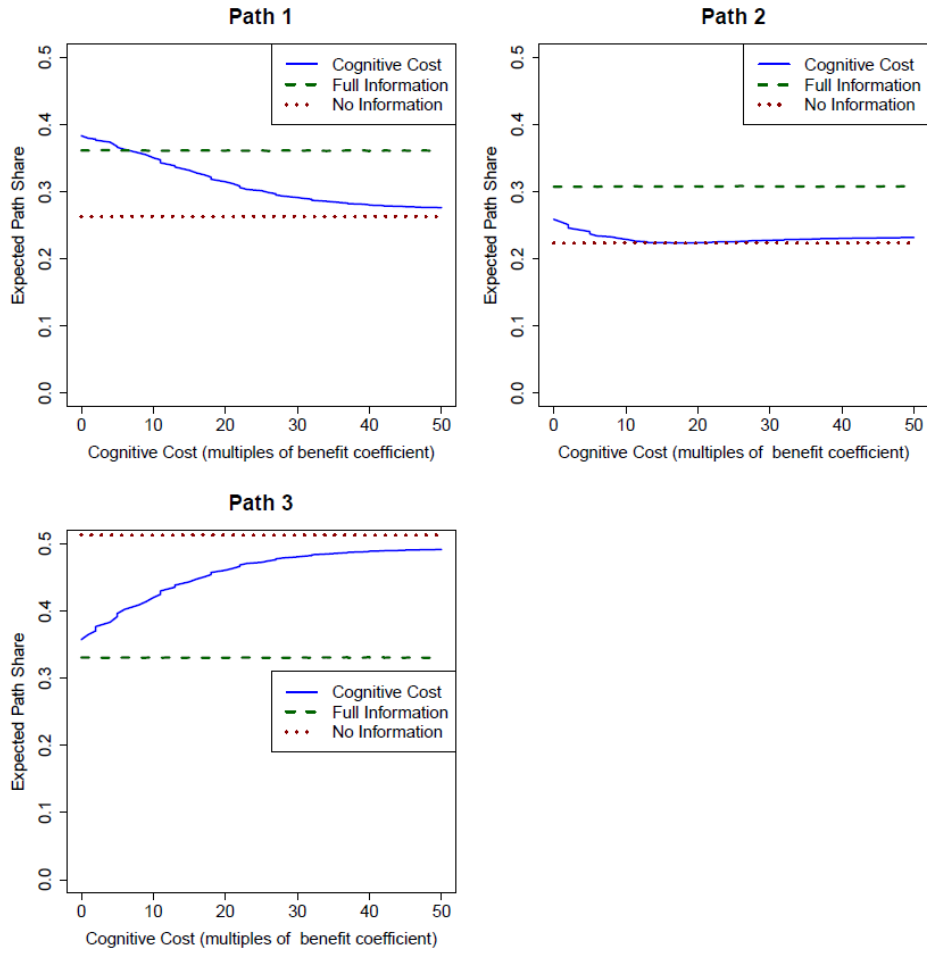


Figure 2: Cognitive Cost Impacts on Expected Path Shares

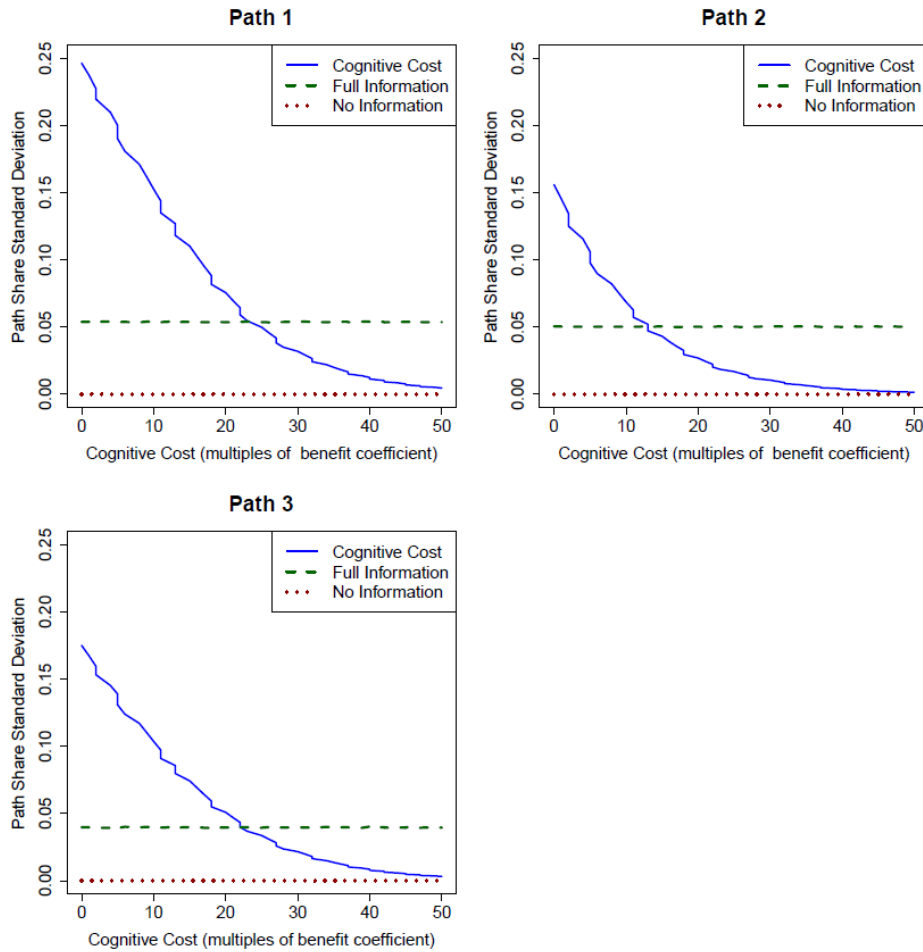


Figure 3: Cognitive Cost Impacts on Path Share Standard Deviations

Figure 3 shows the standard deviations of path shares. The no-information model predicts fixed shares so the standard deviation is zero. The full-information model has constant standard deviations because the cognitive cost is not in the model. The standard deviations from the cognitive-cost model are generally high compared to the full-information model and decrease sharply with the cognitive cost. Consider the case with small cognitive cost such that quite some travelers do the searches. On the one hand, under full information travelers' choices follow closely with the travel time distribution as they know the realizations of the travel times. With less than full information such as in the case predicted by the cognitive-cost model, there are still uncertainties even after the initial search operations. This could dampen the effect of travel time variability on path share variability, as travelers cannot be as responsive in the full-information case. Thus we should expect a lower standard deviation from the cognitive-cost model. On the other hand, the estimates of the full-information model parameters are smaller in scale than those of the cognitive-cost model, which makes it less sensitive to travel times and therefore the shares vary less across different travel time realizations. The second effect obviously dominates the first one in our case. The standard deviations approach zero as cognitive cost increases, since at some point no search is performed and the decisions are purely based on the fixed unconditional travel time distributions and thus are stable.

Figure 4 shows expected values and standard deviations of travel times averaged over individuals. The average travel time is the mix of two probabilistic quantities: the path travel times and the path shares. A higher search cost suggests a lower number of searches and thus lower shares on the fast but risky routes and higher shares on the safe but slow route. This results in an on-average slower but less variable travel time, as shown in both parts of the figure.

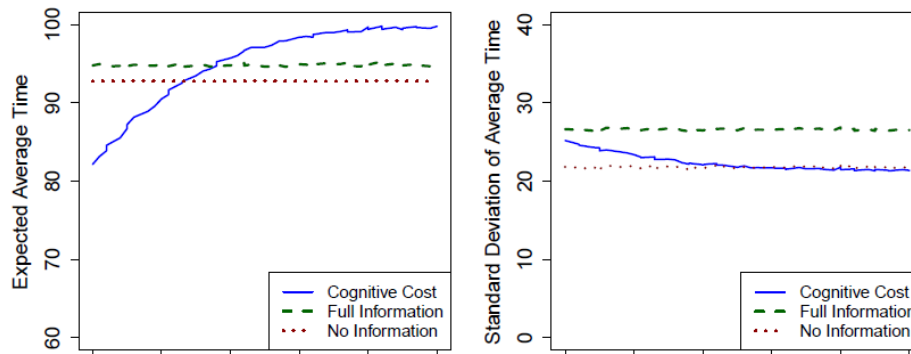


Figure 4: Cognitive Cost Impacts on Average Travel Times

Note however the standard deviation is not zero even with fairly fixed path shares at a high cognitive cost, since the underlying travel times are random. It however approaches the no-information case.

The large differences in expected travel times between the extreme cases of the cognitive-cost model and the other two simplifying models suggest that one cannot simply assume that a simplifying model is a limiting case of the more general one. These results indicate that even though searching could become very cheap given the fast development in telecommunication and computing technologies, it does not warrant the adoption of a full-information model since the availability of information is not equivalent to the actual acquisition of the information. This fact is reflected through our random utility models for class membership and the stop-and-go decisions.

## 5. Conclusions and Future Directions

In this paper we develop a route choice model that explicitly considers the cognitive cost in searching for real-time information to reduce the uncertainty of the travel times. A latent class model is proposed where the decision to search or not to search and the depth of the search are latent and only the final path choices are observed. The model is consistent with a general network topology and can potentially be estimated based on revealed preferences data. We use an illustrative example with three alternative routes to explain and analyze the model. A Logit class membership model is applied to two classes: no search and searching by path. Explanatory variables in the membership function include the net benefit of searching one path as well as the familiarity with the network and the arrival time flexibility of the trip. The net benefit of search is defined as the difference between the expected maximum utility before and after the search. A traveler who searches by path is assumed to further consider whether to continue the search on the second path. A stop-and-go Logit model is proposed for such decisions and considers the trade-off between the net benefit of searching one more path and the cognitive cost.

A synthetic data set is used for the purpose of validation and ease of illustration. The data are generated from the postulated cognitive-cost model, and estimation results show that the true values of the parameters can be recovered. Two other models with simplifying assumptions of no information and full information are also estimated with the same set of data, and have significantly biased path choice utility parameter estimates. Prediction results show that a smaller cognitive cost encourages information search on risky and fast routes and thus higher shares on those routes. As a result, the expected average travel time decreases and the variability increases. The no-information and full-information models are extreme cases of the more general cognitive-cost model in some cases, but not generally so. Thus, the increasing ease of information acquisition does not necessarily warrant a full-information model. Note that the results are derived from a particular setting in this paper, therefore caution should be taken in generalizing them to real networks.

We use a mean-standard-deviation model in this paper to model travelers' risk-averse behavior. More realistic models of decision under risk could be adopted in the future, for example, the cumulative prospect theory (Tversky and Kahneman, 1992) that takes into account the distorted perception of probabilities and the differences between gains and losses. Applications of the theory in a route choice context can be found in the authors' previous work (Gao et al., 2010). It is not used in the current paper since it adds unnecessary complexity without more insights into the cognitive-cost model.

The information in this paper is somewhat simplified, in the sense that once a path is searched its true travel time is revealed. In reality this is not necessarily the case as information might contain errors, especially in a highly congested and dynamic network context. Any information on travel times is essentially predictive and predictions can be inaccurate such that later pieces of information invalidate earlier ones. A model that takes into account the imperfection of information is an interesting topic for future research.

The logical next step is the validation of the model against empirical data. We plan to first collect stated preference (SP) data where we observe the information search as well as the final path choice. Our experience with the synthetic data generation suggests that much larger variability in the data is required to estimate a latent class model than a regular one. An SP setting allows for controlled data variability and could help validate the model before it is applied to RP data.

In this paper, we assume a fixed search sequence to model the case when there is a natural search order. However, there are situations where a natural search order is not available, e.g., a traveler has multiple sources of information (such as webcams and travel time predictions) and it is not clear which one s/he will consult with first. Therefore it will be desirable to extend the model to accommodate multiple search sequences for the application with RP data. This will however add another layer of latency to the model, and potentially require even more data.

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