Modelling learning and dynamic route and parking choice behaviour under uncertainty

Modelling Learning and Dynamic Route and Parking Choice Behaviour under Uncertainty

PROEFSCHRIFT

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Elaine Cristina Schneider de Carvalho
December 2019

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Introduction

1.1 Background and Motivation

The transportation system plays an essential role in the development and growth of cities and nations. It allows people to move along the network in order to satisfy needs and perform activities, and goods to flow from origins to destinations. However, despite these vital functions for society and the economy, the transportation system also generates negative effects, such as environmental pressure, accidents, and congestion.

Technically, congestion arises when service speeds are lower than free-flow speeds, not necessarily implying queues, but certainly variability in travel times and delays, the latter generally being defined as the difference between actual travel times and travel times under uncongested or other acceptable conditions (Kockelman, 2004).

The simultaneous use of the network by individual agents who make decisions (regarding departure times, transport modes, routes etc.) at their own discretion, in combination with weather conditions, accidents and other events which are to a certain extent unpredictable, assign a random component to congestion. Therefore, travellers are faced with varying travel times and need to make decisions under an uncertain state of the system – more specifically to drivers, under uncertain travel times of network links and occupancy levels of parking areas.

Decision making under uncertainty is, therefore, part of travellers' daily lives. The relevance of investigating the impacts of network variability on travel behaviour has therefore resulted in a plethora of different research topics such as individuals' coping strategies, perception of uncertainty, attitudes towards risk, and the role of advanced traveller information systems (e.g. Bates *et al.*, 2001; Noland & Polak, 2002; Bonsall, 2004; Han, 2006; Tseng *et al.*, 2009; Carrion & Levinson, 2012; Ramos *et al.*, 2014; Rasouli & Timmermans, 2014; Ben-Elia & Avineri, 2015; Van Essen *et al.*, 2018; Fosgerau & Jiang, 2019), with emphasis on travel time variability and its directly associated decision dimensions, such as route and departure time choice.

However, the majority of models in travel behaviour research developed so far assumes that the network's attributes are invariant over time, besides being completely and perfectly known by the users. Yet, among the models which incorporate uncertainty, most comprise one-shot decisions with clearly formulated payoffs, causing choices to be made on general contentions (Rasouli & Timmermans, 2014).

In reality, however, travellers learn from their own experience, i.e. by the repeated process of making choices and realizing their outcomes. The distribution of uncertain attributes may be learned as experience is accumulated, and used to anticipate future states of the world, allowing travellers to adapt their behaviour in reinforcing positive or desirable outcomes, and avoiding negative or less preferred ones.

In fact, models of travel behaviour under uncertainty can be improved and become behaviourally more realistic when (a) extended to dynamic contexts by integrating the outcomes of past experiences to the choice mechanisms of future decisions, and when (b) explicitly incorporating the learning process of uncertain network attributes that takes place in repeated choice situations. Such improvements may impact a range of topics (as endorsed for instance by Chen & Mahmassani, 2004; Jotisankasa & Polak, 2006; De Maio *et al.*, 2013; Khademi *et al.*, 2016), from traffic management and operations, to the assessment of effects of new transport policies, including the appraisal of responses to infrastructure interventions, and the deployment of intelligent transportation systems.

Nevertheless, models which encompass the features mentioned in the previous paragraph are scarce in the scientific literature, and their empirical validation occurs even more rarely. This research aims at developing and empirically validating a dynamic travel behaviour model which incorporates both the response to uncertainty and the learning mechanism, bridging a gap in the scientific body of knowledge, and at the same time aspiring to positively influence the state-of-practice of transport planning.

1.2 Research Objectives

Following the motivations exposed in the previous section, the objectives of this research are defined as:

1. ***Developing and empirically validating a model of learning and dynamic route and parking choice behaviour under uncertainty of travel and parking times,***
2. ***Investigating the suitability of Bayesian belief updating for representing drivers' learning mechanism, given a multitude of possible starting points of calibration, and***

3. ***Investigating the implications, for the mechanisms of learning and choice under uncertainty, of providing information on the fastest foregone alternative.***

The incorporation of an additional uncertain facet (i.e. *parking time*) and its associated decision dimension (i.e. *parking choice*) to the typical context of *travel time uncertainty and route choice* makes the model more sensible since, in real life, it is likely that drivers encounter numerous sources of uncertainty while traveling. Moreover, because parking the car is an essential part of the trip, *parking time* and *parking choice* are reasonable choices as additional uncertain facets and decision dimensions.

Bayesian belief updating is a behaviourally intuitive approach to represent learning that, despite allowing direct application of the model (i.e. not requiring empirical estimation), has not yet been extensively explored to model travellers' learning of uncertain network attributes. The approach allows treating travel and parking time as continuous random variables, and to represent drivers' initial beliefs and the trust they assign to them[1], respectively as the *starting values* and associated *measures of reliability* for the descriptive parameters of the random variables' distributions. Unlike other models, Bayesian belief updating enables to keep track of the evolution of the *measures of reliability* while learning takes place, as well as to indirectly[2] test a variety of *starting values* and associated starting *measures of reliability*[3] for the descriptive parameters, which plays a critical role for the empirical estimation of travel choice models.

In dynamic and uncertain contexts it is natural and expected that the chosen courses of action are eventually outperformed by foregone alternatives. Therefore, testing the impacts on learning and dynamic choice behaviour of the provision of information on faster foregone options is also part of the scope of this research.

[1] Also referred to, in this dissertation, as drivers' *degree of trust*.

[2] By means of using the method's outputs as inputs for choice model estimation with empirical data.

[3] In other words, a variety of starting points of calibration.

1.2.1 Conceptual framework

To enable the development of the proposed model, the research objectives were extended into a conceptual framework, which includes the definition of a few necessary boundary conditions and assumptions, as shown in the paragraphs below.

The framework represents the daily choice of route and parking area by private automobile drivers who commute to work and are not (yet) familiar neither with the network of routes connecting their home to their work location, nor with the parking lots in the surroundings of their destination. For every route and parking area available, respectively the time spent driving (i.e. travel time) and the time spent looking for a free spot to park (i.e. parking time) vary day-by-day, following probability distributions which are unknown to drivers.

The two main components of the framework are: the *Learning Model*, representing drivers' learning of the probability distributions of travel and parking times, which takes place as they accumulate experience by repeatedly using the routes and parking areas; and the *Choice Model*, which represents the choice mechanism of drivers, encompassing the analysis and comparison of the available alternatives in the light of their preferences and their beliefs about the alternatives' attributes, resulting in the choice of a favourite. Moreover, the *Choice Model* reveals the adjustment of drivers' behaviour as a result of learning and habit development.

The two components are interdependent, characterizing the dynamics of the model, as shown in Figure 1.1. After every decision, drivers receive the realizations of travel and parking times for the chosen alternative, and perhaps also for the foregone option which happened to had been the fastest that day[4]. These realizations are then incorporated into the drivers' learning process (which has as starting point some external prior information they detain about the distri-

[4]In case the chosen alternative had not been the fastest.

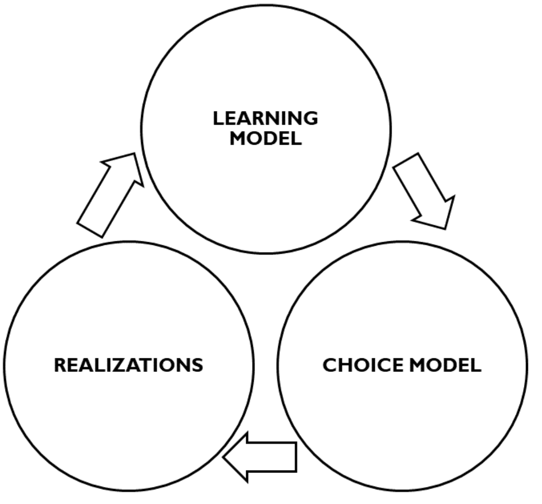

Figure 1.1: *Model dynamics.*

butions[5]), resulting in the update of their subjective probability distributions[6] of travel and parking times for the corresponding routes and parking areas – which should start resembling, as drivers acquire more experience, the shape of the distributions from which the realizations have been withdrawn. The subjective distributions can be seen as drivers' "mental representation" of the possible future states of the world for a given route or parking area, and together with the history of previous choices, are used as input for the analysis and comparison of alternatives, which leads to next day's decision.

The framework assumes that drivers learn the probability distributions of travel and parking times from their own experience (i.e. from the travel and parking times of the alternatives they choose), as well as from an external source of information that provides the realizations of travel and parking times of the fastest non-chosen alternatives[7]. Drivers are, nevertheless, assumed to have some

[5] Reflecting the fact that drivers will try to obtain some minimum amount of information before traveling to work for the first time.

[6] In this dissertation, drivers' subjective probability distributions are also referred to as learned distributions, beliefs or knowledge.

[7] For the days when the chosen alternative was not the fastest.

prior belief about the distributions of travel and parking times for the routes and parking areas available, before they experience them for the first time. Apart from these, drivers do not receive or acquire any other information about travel and parking times.

1.3 Dissertation Outline

The structure of this dissertation, which reflects the methodology employed to accomplish the research objectives stated in the previous section, is described next.

Chapter 2 reviews the scientific literature on two components of dynamic models of travel behaviour: learning of uncertain attributes, and choice under uncertainty. Emphasis is given to models which uncertain attribute is travel time.

The dynamic stated choice experiment, designed to collect empirical data necessary to validate the model, is the focus of **Chapter 3**. A high level overview of the survey structure is provided first, followed by the description and discussion of the core part of the experiment: the context of the choice, the choice set and the different experiment profiles. Operational (but rather important) aspects of the experiment are also discussed: the selection of the density functions of travel and parking times (and ways of representing their realizations to respondents), and the selection of the initial information about travel and parking times to be given to respondents, together with their representation as density functions to be used in the Bayesian belief updating model.

Chapter 4 brings an overview of the data obtained after a sample of subjects participated in the dynamic experiment. The criteria for selecting the sample, as well as for verifying the quality of the data collected, are discussed. The statistics of the sample's demographic and driving-habit variables are described, followed by an exploration of the shares of the choice options.

The *Learning Model*, which has as main inputs the realizations of travel and parking times faced by those individuals who completed the experiment, is the object of **Chapter 5**. The model's theoretical background and mathematical formulation are described and discussed, as well as relevant operational aspects and the output of its application to the collected data.

The focus of **Chapter 6** is the *Choice Model*, which needs, in order to be estimated, the outputs produced by the *Learning Model* (subjective distributions of travel and parking times), and the choices made by the subjects who participated in the dynamic experiment. A first level exploration of the use of different databases generated by the *Learning Model* (using a range of LTs) for discrete choice model estimation is provided in the beginning of the chapter. Next, the econometric specification of the dynamic choice model, followed by the interpretation of its results are on focus. Comments are also provided regarding the other possible specifications of the model.

Chapter 7 introduces a different perspective on learning, by exploring subjects' stated perceptions of the uncertain travel and parking times they faced in the experiment, which were collected during the dynamic experiment. First, an overview of the data collected and a discussion of the criteria adopted to clean the data are provided. Next, the statistics of the stated perceptions are explored, followed by their evolution with time and experience, and their correlations with the experiment design attributes. The chapter also includes a comparison of the stated perceptions with outcomes generated by the Bayesian approach, and explores the application of stated perceptions for choice model estimation.

This dissertation is finalized in **Chapter 8** with a summary of the research findings and contributions, and suggestions for future exploration of the topic.

2

Literature Review

2.1 Introduction

This chapter reviews the scientific literature on two components of dynamic models of travel behaviour: learning and choice[1]. The first section (Section 2.2) focuses on the most widely used mechanisms to represent travellers' learning of the uncertain attributes of the network: weighed average approaches, adaptive expectation approaches and Bayesian approaches. In the sequence, Section 2.3 is dedicated to the main theories (and derived models) of choice used in travel

[1]The later component is also refereed to, in dynamic contexts, as behavioural adaptation model.

behaviour research in contexts of uncertainty and risk: Utility Theory, Prospect Theory and Regret Theory. Emphasis is given to models which uncertain attribute is travel time[2].

2.2 Learning of Uncertain Attributes

The majority of the experience-based learning models in the literature concerns the update of travellers' beliefs of the average value of the uncertain attribute, and only a few (which will be highlighted in the text) also include the update of the beliefs of the attribute's measure of spread. Besides, some models are adapted to incorporate information from external sources as well, such as outcomes of foregone options and predictive information provided by advanced traveller information systems.

Most of the models in this review[3], although varying in their ability to represent the limitations of human information-processing, such as selective perception of information and limited memory (Hogarth, 1987), fall within the classification proposed by Jotisankasa & Polak (2005): *weighted average* approaches, *adaptive expectation* approaches and *Bayesian* approaches. These classes differ in their core updating mechanism, reflecting different assumptions of how travellers learn.

The following three subsections are dedicated to models of these three categories, while the fourth subsection is dedicated to other approaches.

2.2.1 Weighted average approaches

Weighted average approaches represent the update of travellers' belief of the average value of the attribute, for a certain time period, as a weighted average of the outcomes experienced in previous time periods. Models within this category

[2]No dynamic models were found in the literature with *parking time* as the uncertain attribute. Nevertheless, literature about static models of parking location choice under risky searching times and parking availability exist, e.g. Chaniotakis & Pel (2015), Van der Waerden (2012).

[3]Which also includes applications within the broader context of transport network analysis.

may differ in their assumptions regarding the composition and role of the weights, and the memory length of travellers.

For instance, Cascetta (1989) assumed, in his empirical study, uniform weights for the previous outcomes experienced, implying that they are kept in memory with the same strength. On the other hand, in the models proposed by Wei *et al.* (2014), Guevara *et al.* (2017a, 2017b) and Tang *et al.* (2017), the weights are affected by the recency of the experiences and therefore follow declining functions, representing a memory decay effect. This was also done by Ettema *et al.* (2003, 2004, 2005), which assumed travellers segment travel times in mental classes and perform the update of beliefs within each class, including the update of the perceived variance (measure of spread) of travel times. Besides, Ettema *et al.* (2003, 2005) also incorporated, in the formulation of the weights, the representativeness of each experienced outcome, which is a function of the difference between the outcome and the expectation the traveller had before making the decision.

Regarding the memory length, the model of Horowitz (1984) assumes unlimited memory, while in the approach of Cascetta (1989), decision makers store in memory only a limited number of outcomes. In Ettema *et al.* (2003, 2005), previous experiences are incorporated to the belief updating mechanism as long as their memory strength (a function of the recency and representativeness of the experiences) exceeds a certain threshold value.

Nakayama *et al.* (1999) also assumed travellers divide the range of travel times in intervals, however assigning weights to each interval, allowing to represent different attitudes towards risk among travellers. Nakayama *et al.* (2001), who assumed travellers update their beliefs as a weighted average of the mean experienced travel time and the difference between the maximum and the minimum experienced outcomes, also allowed the representation of different attitudes towards risk – for instance, a higher weight to the difference between the maximum and the minimum (i.e. the amplitude of experienced travel times) would correspond to a risk averse attitude.

2.2.2 Adaptive expectation approaches

In adaptive expectation approaches, the decision maker's belief is a weighted average of the previously updated belief and the last outcome experienced. Examples are Ben-Akiva *et al.* (1991), Iida *et al.* (1992), Koutsopoulos & Xu (1993), Vaughn *et al.* (1993), Emmerink *et al.* (1995), Van der Mede & Van Berkum (1993), Bogers *et al.* (2007), Tian *et al.* (2010) and De Maio *et al.* (2013) – having Van der Mede & Van Berkum (1993) and De Maio *et al.* (2013) used the logic of adaptive expectation to update also the belief of the variance of travel times.

In comparison to weighted average approaches, adaptive expectation models are computationally simpler, the empirical analysis of their parameters happening more often. Again, differently from weighted average approaches, where previous outcomes are explicitly present in the equation used to update beliefs, in adaptive expectation approaches the previously updated beliefs indirectly carry the influence of outcomes experienced in the past. Therefore, as the outcome becomes older, its influence necessarily fades in the updating process. This is in line with the fact that, in dynamic contexts, more recent experiences might provide more reliable information.

The magnitude of the weights in this category of models is able to represent the strength of the last experience relative to the strength of habit, the latter represented by the weight of the previously updated belief. Related to the role of habit in travellers' beliefs, Jotisankasa & Polak (2006) added a mechanism to trigger the belief updating mechanism, which occurs if the discrepancy between the previous belief and the experienced outcome exceeds some threshold value (either in the direction of over or underestimation).

Recently, Zhang *et al.* (2018) extended the adaptive expectation framework by modelling the belief update of travel times as a weighted average of travellers' previous belief, their last experience and the choices made by their social network in the previous time period.

2.2.3 Bayesian approaches

Overview and benefits

Approaches based on the law of conditional probabilities (first published by Thomas Bayes in 1763) treat travellers' beliefs of the networks' attributes as random variables, which probability density functions are updated from a prior to a posterior state as travellers gain experience or external information about the attributes.

Both the belief of the expected value (average) and the measure of spread (variance) of the attributes can be treated as random variables, and a variety of density functions can be adopted, each implying a diverse level of complexity for deriving the updating equations and operationalizing the approach (Fink, 1997).

Recurrent in travellers' learning models is the use of the Normal distribution to represent the belief of the expected value of travel times. In this case, the posterior (updated) belief of the expected travel time is a weighted average of the prior belief and the mean of the outcomes experienced since the last update (showing some resemblance with the adaptive expectation approach), with the weights reflecting their associated perceived reliability. The evolution of the perceived reliability of the updated belief is an interesting feature of the Bayesian approach: in the case of the Normal distribution, its standard deviation decreases (i.e. the reliability of the updated belief increases) as learning takes place, approaching zero as the learning process is complete.

An advantage of the Bayesian approach, in opposition to the weighted average and adaptive expectation approaches, is that it does not require empirical estimation of the weights, allowing for direct application of the model. On the other hand, Bayesian models need as starting point for their application, the parameter values of the prior distributions. Despite the debate whether people take into account or neglect prior information[4] while performing judgements (Bar-Hillel, 1980; Birnbaum, 1983), the definition of such priors plays a critical role for empirical estimation of travel choice models in dynamic contexts. Nevertheless, the topic seems not to have received yet enough attention in the scientific literature on travel behaviour research.

Criticism

Initially proposed as a normative theory for likelihood calculation, discussion exists whether and to what extent Bayesian statistics is consistent with human prediction (Kahneman & Tversky, 1973; Tversky & Kahneman, 1974; Edwards, 1982; El-Gamal & Grether, 1995).

Gigerenzer & Hoffrage (1995) for instance, argued that humans have evolved cognitive algorithms that can perform statistical inferences. These algorithms, however, would not be tuned to probabilities or percentages as input format, but rather to the natural format of frequencies (as actually experienced in a series of events).

Sanborn & Chater (2016) also argued that the human brain is poorly adapted to calculate probabilities of all states-of-the-world simultaneously. Instead, a Bayesian sampling approach (i.e. an algorithm that produces samples of the states-of-the-world) would be better suitable for representing human learning.

Despite this debate, Bayesian statistics has been used as a descriptive method of human learning in a diversity of areas of knowledge, from psychology to neurosciences (Edwards *et al.*, 1963; Tenenbaum *et al.*, 2006; Mathys *et al.*, 2011; Payzan-LeNestour & Bossaerts, 2011), and there is evidence that its outcomes make sense behaviourally (Gopnik *et al.*, 2004; Xu & Tenenbaum, 2007).

[4] Also referred to as *base rate* in the specialized literature.

Applications in dynamic models of travel behaviour

The exploration of the possibilities and limitations of Bayesian updating to model learning of uncertain network attributes is not yet very extensive in the travel behaviour literature.

The use of Bayesian statistics to update the belief of time, in dynamic models of travel behaviour[5], has been explored in fewer studies, in comparison to the weighted average and adaptive expectation approaches. The existent studies differ in the probability density function chosen to represent beliefs, in the frequency and moment of update, whether external information (besides experience-based) is also included in the update, whether the variance of the attribute is also updated (or only the expected value) and, finally, whether the studies were empirically validated.

The belief of mean travel time is assumed to be normally distributed in the studies of Jha *et al.* (1998), Chen & Mahmassani (2004), Chorus *et al.* (2008a), De Carvalho *et al.* (2015a, 2015b, 2016a, 2016b) and Ma & Di Pace (2017), while Zheng *et al.* (2018) used a Gamma distribution to represent the belief of waiting time. When accounting for correlation in travel times of different routes, Chorus *et al.* (2008a) adopted a multivariate Normal distribution for perceived mean travel times.

Regarding the update of the perceived variance of travel times, Chorus *et al.* (2008a) assumed an inverted Gamma distribution for the univariate case (also done by De Carvalho *et al.*, 2015a, 2015b, 2016a, 2016b), and an inverted Wishart to represent the covariance matrix of the travel times of two routes.

Basic frameworks assume that the update of perceived travel times happens every day, after the travellers acknowledge the outcomes of their choices. The study of Jha *et al.* (1998) extended this framework by assuming that the update of drivers' beliefs happens every day, before and after route choice: when trav-

[5]Although applications of the Bayesian approach for belief updating exist as well in non-feedback based dynamic models, e.g. Chorus *et al.*, 2006; Chorus *et al.*, 2009; Parvaneh *et al.*, 2012.

ellers receive pre-trip information, and after they realize the outcomes of their decision. The same extension was later adopted by Ma & Di Pace (2017). Chen & Mahmassani (2004), on the other hand, proposed (three different) heuristic rules to trigger and terminate the updating mechanism, arguing there is a cost associated to belief update, and therefore not necessarily drivers will engage in the mechanism after every experience. Instead, updating will occur when the salience of the outcomes reaches a certain threshold.

With exception of Ma & Di Pace (2017), who validated the model with empirical data (collected by means of a stated choice experiment), the studies mentioned are limited to simulation efforts. Jha *et al.* (1998) applied the learning model to a dynamic traffic simulator, in a hypothetical network of 50 notes and 158 links. Chen & Mahmassani (2004) embedded the learning model inside a microscopic (agent-based) simulation framework to study the collective effects of route choice on day-to-day evolution of traffic flows. Chorus *et al.* (2008a) conducted numerical simulations of a single traveller choosing between two routes connecting a single origin-destination pair – the same case of De Carvalho *et al.* (2015a, 2015b, 2016a, 2016b), who however used three routes. In their investigation of taxi drivers' dynamic passenger-finding behaviour, Zheng *et al.* 2018 conducted simulations in a real road network.

With exception of Chorus *et al.* (2008a), the models mentioned above (which deal with the update of beliefs of travel times), are associated to choice models that either derive from Utility Theory (Jha *et al.*, 1998; Chen & Mahmassani, 2004; Ma & Di Pace, 2017; Zheng *et al.*, 2018) or Regret Theory (De Carvalho *et al.*, 2015a, 2015b, 2016a, 2016b).

Although not related to travel time learning, the studies of Arentze & Timmermans (2004, 2005a, 2005b) used Bayesian methods to model cognitive learning of location attributes in a context of mental map representation and dynamic activity-travel behaviour under conditions of uncertainty. The proposed models were tested via numerical simulations in a hypothetical area.

2.2.4 Other approaches

Besides the models in the categories listed above, the *reinforcement learning* approach is also applied in dynamic models of travel choice behaviour (e.g. Arentze & Timmermans, 2003; Avineri & Prashker, 2005; Ben-Elia *et al.*, 2013b). It can be considered an *implicit* learning model: instead of having a belief updating mechanism (associated to a choice mechanism), travellers are supposed to have a propensity to choose each alternative. This propensity is updated as a weighted average function of travellers' initial propensity for the alternative (i.e. before their first choice) and the average payoff (or reward) obtained from choosing the alternative in the previous time periods. Therefore, good outcomes increase the probability that an alternative is chosen again, the opposite happening when unfavourable outcomes are experienced.

It is also worth to mention the studies of Mahmassani & Chang (1986), Arentze & Wielens (2014), Wielens & Arentze (2014) and Khademi *et al.* (2016). Mahmassani & Chang (1986) proposed a myopic model where the updated belief depends only on the last experienced outcome and its associated schedule delay (early or late). Arentze & Wielens (2014) proposed a model of likelihood judgment of uncertain events which takes into consideration the influence of emotions and saliency of events on beliefs (which was also done by Wielens & Arentze, 2014), as well as the human bias of overestimation of low frequencies and underestimation of high frequencies. Finally, Khademi *et al.* (2016) applied a combined artificial neural network and fuzzy logic approach to model learning.

2.3 Models to Represent Travel Choice Behaviour

The dominant theories of choice used in travel behaviour research in contexts of uncertainty and risk[6] are Utility Theory, Prospect Theory and Regret Theory,

[6]Conceptually, the difference between decision making under risk and under uncertainty lays in the fact that in risky contexts the individual is aware of the probabilities of each state of the world, while in uncertain contexts these probabilities are unknown to the individual, and thus

being the first cited theory the most widely used. The fundamentals of each of them, as well as their application to dynamic contexts are exposed in the following subsections. It is relevant to remark that some of the models discussed are not associated to an explicit belief-based learning model (as those introduced in the previous section), but rather treat learning implicitly via reinforcement (Erev & Barron, 2005).

2.3.1 Utility Theory (UT)

According to Utility Theory, the attractiveness of an alternative can be measured by an objective function of its attributes. The idea that decision makers always choose the alternative with the maximum utility, is used in deterministic models of choice (also referred to as *greedy rule* models) and can be applied to dynamic contexts as well – see, for instance, Nakayama *et al.* (1999), who assumed travellers always chose the route with the minimum perceived travel time. The downside of such approach, however, is that it might lead decision makers to constantly choose the same alternative (which might be sub-optimal) and prevent them to explore other options.

The first formal theory to address decision under risk and uncertainty, Expected Utility Theory (EUT), is derived from UT and was developed by Von Neumann & Morgenstern (1947). It assumes that individuals have a belief of the distribution of probabilities of a certain variable of interest and account for risk and uncertainty by weighting each possible state of the variable by its probability of occurring, choosing the option with the highest expected utility. EUT is, nevertheless, also a deterministic approach, and assumes that decision makers have a rational behaviour, which obeys the axioms of completeness, transitivity, continuity and independence. However, empirical evidences reported violations of these axioms, as demonstrated by the Allais' paradox (Allais, 1953) and the Ellsberg's paradox (Ellsberg, 1961). De Palma *et al.* (2008) enumerate two types

liable to subjective judgment.

of responses provided in the literature for these violations: (a) non-expected utility theories (such as Prospect Theory and Regret Theory, discussed in the following subsections), and (b) non-deterministic approaches to choice under risk and uncertainty, originating probabilistic choice models.

The application of non-deterministic approaches to UT and EUT gave rise to the consolidated Random Utility Maximization (RUM) model. In RUM models, a random term is added to the deterministic utility, representing decision makers' perception errors, or insufficient information about the options' attributes, or even limitations in the observation, specification or measurements from the side of the modeller. The choice of the density function and the correlation structure of the random terms gives rise to different econometric (discrete choice) models, such as the probit, logit, nested logit and mixed logit.

In dynamic contexts, mainly for route and departure time choice (or switching), commonly used stochastic models are the logit (e.g. Van der Mede & Van Berkum, 1993), nested logit (e.g. Jha *et al.*, 1998) and mixed logit – accounting also for random parameters and error components, besides panel effects (e.g. Jotisankasa & Polak, 2006; Bogers *et al.*, 2007; Ben-Elia & Shiftan, 2010; Ben-Elia *et al.*, 2013a; Tanaka *et al.*, 2014; Guevara *et al.*, 2017a; Tang *et al.*, 2017). Ettema *et al.* (2003, 2004, 2005) used the logit framework together with expected utility, integrating the utility of a certain departure time over its perceived distribution of travel times, while Srinivasan & Mahmassani (2003) applied a kernel logit.

In order to capture the effect of habit on repetitive decisions, Ben-Elia & Shiftan (2010) and Bogers *et al.* (2007) included, in the specification of utility, the number of times the alternative was chosen before. This is aligned with the fact that, when decisions have to be made repetitively, the deliberate effort done in the first choices ('preference-based' choices) is not necessarily required as travellers become experienced, giving space to 'script-based' choices – see Gärling *et al.* (2001), Fujii & Gaäling (2003) and Gärling & Axhausen (2003) for a discussion of the development of habit and script-based choices in the context of travel behaviour.

Utility theory can also be used in combination with a satisfying approach[7], which is based on the concept of bounded rationality, according to which decision makers maintain their previous choices as long as their outcomes do not exceed some threshold values (or fall outside indifference bands). If the outcome of the previous choice does not lie within these boundaries, travellers will adjust their decisions through some mechanism. Examples of combined use of the satisfying approach and utility theory are Emmerink *et al.* (1995), Jou & Mahmassani (1998) and Chen & Mahmassani (2004).

2.3.2 Prospect Theory (PT)

Prospect Theory was proposed by Kahneman & Tversky (1979) and its main differences relative to the EUT are: (a) the use of a non-linear weighting function to transform objective probabilities into subjective ones – allowing for the representation of distorted probabilities, such as over weighted small probabilities and under weighted large probabilities, reflecting the decision makers' attitude towards risk; and (b) the employment of a non-linear value function to measure the subjective value of an outcome, which is reframed as a gain or a loss measured against a reference point – allowing for the representation of loss aversion and of decreases in the marginal values of gains and losses with their magnitude.

An extension to PT, Cumulative Prospect Theory (CPT), was developed by the same authors (Tversky & Kahneman, 1992), by including rank-dependent probabilities and accommodating different probability weighting functions for gains and losses.

Despite discussions whether the assumptions of PT do or do not hold for feedback-based decisions involving learning and information acquisition (Barron & Erev, 2003; Avineri & Prashker, 2005; Li & Hensher, 2011), recently Yang *et*

[7]Although satisfying approaches can also be used alone in dynamic contexts, such as done by Mahmassani & Jou (2000).

al. (2017) and Zhang *et al.* (2018) applied CPT to dynamic contexts of travel choice, adopting dynamic reference points.

2.3.3 Regret Theory (RT)

Regret Theory was first proposed by Bell (1982) and Loomes & Sugden (1982), and later extended to the stochastic framework by Chorus *et al.* (2008b) and Chorus (2010) – who derived the Random Regret Minimization (RRM) model. RT is built upon the notion that individuals are willing to avoid feeling regret after they choose an uncertain prospect and acknowledge its outcome – regret arising if they perceive any non-chosen alternative as having higher payoff than the chosen one. Therefore, decision making requires not only the subjective anticipation of the future possible states of the alternatives but also (and in contrast with EUT), comparisons of each alternative with every competitor across all possible states of the world in order to anticipate the attractiveness of the alternative in question. Therefore, the reference point in RT depends on the composition of the choice set and the distribution of attribute values across choice alternatives.

Even when future regrets are anticipated previously, if the payoff of the chosen alternative is outperformed by the realized outcome of a foregone option (or by one of the possible outcomes subjectively anticipated for a foregone option), the emotion of regret arises. The psychological process of comparing the outcome obtained with other possible outcomes of the decision (had other courses of action been taken), is known as counterfactual thinking (Zeelenberg *et al.*, 1998).

Zeelenberg & Pieters (2007) list some regulation strategies decision makers engage in order to attenuate the regrets they experienced. For instance, reappraising the (better performing) foregone alternative, by generating counterfactuals that focus on worse decision outcomes for the foregone option (McCloy & Byrne, 2002), by derogating the outcome of the unchosen alternative or simply by refraining from using it as a comparison standard. Another strategy mentioned by the authors is psychological repair work, such as identifying silver linings by convincing oneself of how much one had learned from the (regretted) decision (Gilovich & Medvec, 1995).

In line with regret regulation strategies, Chorus (2014) proposed a formal model of the acquisition of ex-post travel information concerning non-chosen alternatives, where decision makers have to balance between the wish not to be confronted with the regret associated to a decision already made, and the wish to learn from the own mistakes and minimize regret in future decisions.

Regret models are also applied to contexts of feedback-based repetitive decisions, more specifically route choices – e.g. Fonzone *et al.* (2012), Ben-Elia *et al.* (2013b) and De Carvalho *et al.* (2015a, 2015b, 2016a, 2016b). Besides incorporating post-trip experiential feedbacks, the model of Ben-Elia *et al.* (2013b) also took into account the influence of receiving pre-trip descriptional information on route performance. Fonzone *et al.* (2012) and De Carvalho *et al.* (2015a, 2016a, 2016b) extended their regret-based models by adding the concept of disappointment to route choice. Models based on the notion of disappointment were developed by Bell (1985) and Loomes & Sugden (1986), and consist in comparing the outcome of an uncertain prospect with the prior expectation the decision maker had for that prospect, disappointment arising when the outcome obtained happens to be worse than the prior expectation. As it happens to the emotion of regret, disappointment is also related to counterfactual thinking. While the former emotion is related to behaviour focused counterfactuals, in which the decision-makers' own actions are changed, disappointment is related to situation-focused counterfactuals, in which aspects of the situation are changed (Zeelenberg *et al.*, 1998).

3

Dynamic Stated Choice Experiment

3.1 Introduction

This chapter presents and discusses the design of the dynamic stated route and parking choice experiment, aimed at collecting data to empirically validate the proposed model. The design of the experiment had as starting point the conceptual framework presented in Subsection 1.2.1.

The next section describes the structure of the survey, followed in Section 3.3 by the core part of the experiment: the context of the choice, the choice set and the different experiment profiles. The following two sections focus on operational (but rather important) aspects of the experiment: the choice of the density functions of travel and parking times, as well as ways of presenting their realizations to respondents (in Section 3.4), and the choice of the initial information about travel and parking times, besides their representation as density functions to be used in the Bayesian belief updating model (in Section 3.5). Finally, Section 3.6 brings a summary of the chapter.

3.2 Survey Structure

The data collection was web-based, built on the platform *Bergenquete 2.2*, an online survey hosting solution developed by and for the Design and Decision Support Systems Group (DDSS) of the Department of Built Environment at TU/e. The experiment was preceded by a sequence of demographic and driving-habits related questions that should be answered by the subjects: age, gender, nationality, level of education, occupation, income, family and living status, time in possession of driver's license, driving frequency to work or the study location, and trip duration (composed by the time spent driving and the time spent looking for parking).

In the core part of the experiment, subjects were required to make 50 consecutive choices of route and parking area, and after each decision they would acknowledge its realizations. Embedded in the sequence of 50 choices, there were three screens where subjects should indicate their perceptions about the average, minimum and maximum travel and parking times of the options they had already tried in the experiment[1]. The first screen appeared after the 10^{th} choice, while the second and the third appeared respectively after the 30^{th} and the 50^{th} choices. The questions, which were not compulsory (i.e. subjects had the option of not answering if they preferred so), were phrased as: *"When you drove via Route X: How long, on average, did you spend driving? What were the minimum and the*

[1] Investigation of stated (or reported) perceptions has also been done by Peer *et al.* (2014), Vreeswijk *et al.* (2014) Khavas & Hellinga (2018) and Tenenboim & Shiftan (2018).

maximum time you spent driving?". And for parking times, they were: *"When you parked in Neighbourhood Y: How long, on average, did you spend looking for a spot? What were the minimum and the maximum time you spent looking for a spot?"*. To include these screens within the experiment was an attempt to gain additional understanding of how subjects learn the uncertain travel and parking times, compare their stated perceptions with the outcomes of the *Learning Model* and eventually improve the results of the *Choice Model*.

Previous to the design of the experiment, a numerical simulation effort took place, in order to operationalize the conceptual framework and explore its sensitivity to changes in specifications and inputs. Despite the useful insights generated during this step, its results impacted the research in an indirect manner only: by contributing to the improvement of the model formulation and the design of the experiment. Therefore, they are not part of the arguments that build up this dissertation's conclusions and were omitted from this book. Nevertheless, they can be partly found in De Carvalho *et al.* (2015a; 2015b; 2016a; 2016b).

3.3 Context, Choice Set and Experiment Profiles

Subjects were asked to envisage they had just moved to a new city and would start a new job. Every morning at the same time, starting from the first day of work, they would go by car from home to the work location, and would need to decide which route to take and where to park the car. They were made aware that travel and parking times varied day-by-day.

The four choice options were presented as combinations of route and parking area, requiring subjects to make two decisions simultaneously:

- Route A (RA) and Parking Area A1 (PA1)
- Route A (RA) and Parking Area A2 (PA2)
- Route B (RB) and Parking Area B1 (PB1)
- Route B (RB) and Parking Area B2 (PB2)

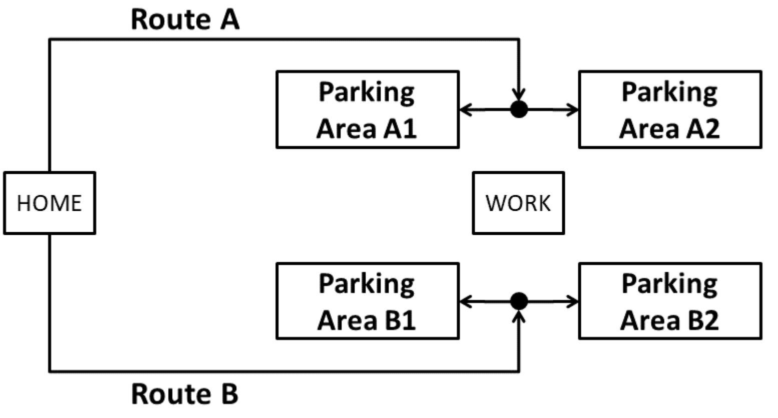

Figure 3.1: *Schematic map.*

The first and second alternatives share the same route. The same happens to the third and fourth alternatives. This is because RA gives access to both PA1 and PA2 (but not to PB1 or PB2), and RB instead is connected with PB1 and PB2 (but not with PA1 or PA2)[2].

A schematic map as the one in Figure 3.1 was displayed to subjects. The four parking areas (presented as neighbourhoods in which streets it was possible to park) were symmetrically placed around the work location, to give the impression that walking distances between each of them and the final destination were equivalent.

Because at the start of the experiment subjects did not have any experience with the choice options, before their first trip (i.e. their first choice) they were given information regarding probable travel and parking times of all routes and

[2]Despite this composition of the choice set exposes subjects to six different PDFs of travel and parking times (which can be challenging from a learning perspective), it allows enough information gain from the choices made by subjects. Because there are two attributes in the model (travel time and parking time), at least two routes and two parking areas are required in the choice set. However, even if both routes would be connected to both parking areas (generating four alternatives), the information gain would still be poor, given that only two out of the six possible comparisons among alternatives ($C_{4,2}$) would require subjects to trade-off between both attributes. For the chosen composition, on the other hand, four out of six comparisons rely on both attributes.

parking areas. Still, they were instructed to try the options themselves in order to find out how long each of them could take in reality.

In half of the experiment profiles, subjects were informed that travel times (for both routes) were on average 30 minutes and changes in traffic levels could make the trip 5 minutes shorter or longer. In the other half, subjects were also told the trip would take (for both routes) on average 30 minutes, but changes in traffic could add or subtract 10 minutes (instead of 5) to the travel time.

In all profiles subjects were informed that it could take between 0 and 7 minutes to find a spot to park in PA1 and PB1 (the parking areas at the left side of the work location in Figure 3.1), while in PA2 and PB2 (the parking areas at the right side of the work location in Figure 3.1) it would take between 3 and 4 minutes.

Subjects were asked to make 50 repeated decisions, each simulating a new commuting day. After every choice, they were informed of the corresponding travel and parking times. For some experiment profiles, information was provided also about the travel and parking times of the non-chosen options which happened to had been the fastest that day, i.e. with the lowest total time (the sum of travel and parking time)[3,4] – in case the fastest had not been the alternative chosen by the respondent.

Despite no preferred arrival time or penalty for arriving late was imposed, subjects were expected to avoid options which, based on their beliefs for the travel and parking time distributions, would very likely lead to the longest trips. In line with this assumption, subjects were reminded that arriving earlier at work meant having more free time left at the end of the day.

The travel and parking times of each route and parking area are random variables following lognormal probability density functions (PDFs)[5]. Because

[3]It could be that more than one foregone alternative reached the lowest total time in a specific day, in which case the realizations of them all were displayed after the choice.

[4]Another strategy would have been to display the realizations of foregone alternatives which both travel and parking time were smaller than those of the chosen option. This strategy, however, would reduce the amount of feedback on non-chosen options given to subjects, risking to compromise the analysis of its impacts on decision making.

[5]Lognormal PDFs have the left tail bounded at zero, which is particularly convenient for the

Table 3.1: *PDFs of travel and parking times.*

Random variable	LN(μ,σ)	(α,λ)
TT.NARR	LN(3.43, 0.02)	(31.0, 0.60)
TT.WIDE	LN(3.37, 0.12)	(29.3, 3.63)
PTB.NARR	LN(0.90, 0.14)	(2.49, 0.36)
PTB.WIDE	LN(0.32, 0.87)	(2.00, 2.12)
PTW.NARR	LN(1.50, 0.09)	(4.48, 0.40)
PTW.WIDE	LN(1.32, 0.31)	(3.95, 1.26)

there are two routes and four parking areas, in total there are six different random variables, which distribution parameters are shown in Table 3.1 (that also brings, in the third column, the mean α and the standard deviation λ in the lognormal scale). The criteria used to choose these PDFs is described in Section 3.4.

TT.NARR stands for "Travel Time Narrow", in reference to its low standard deviation (σ) when compared to *TT.WIDE* which, on its turn, stands for "Travel Time Wide". For all experiment profiles, the outcomes of RA came from *TT.NARR*, while those of RB came from *TT.WIDE*.

PTB.NARR and *PTB.WIDE* mean, respectively, "Parking Time Best Narrow" and "Parking Time Best Wide", while *PTW.NARR* and *PTW. WIDE* mean, respectively, "Parking Time Worst Narrow" and "Parking Time Worst Wide". "Narrow" and "wide" are, here again, a reference to the relative magnitudes of the standard deviations (σ), while "best" and "worst" refer to the relative magnitudes of the averages (μ) – in the sense that the lower the average of the PDF, the better it is.

In half of the experiment profiles, the outcomes of PA1 and PA2 came respectively from *PTB.WIDE* and *PTB.NARR*, while those of PB1 and PB2 came from *PTW.WIDE* and *PTW.NARR*, respectively. In the remaining profiles, the

distributions of parking times.

assignment scheme was inverted: *PTW.WIDE* was assigned to PA1, *PTW.NARR* to PA2, *PTB.WIDE* to PB1 and finally *PTB.NARR* to PB2.

To each PDF in Table 3.1 corresponds a vector of either travel or parking times, from where were extracted the outcomes displayed to subjects after their decisions. Two different methods of extraction were employed: *sequence of the vector*, with the outcomes displayed to respondents in the same sequence they appeared in the vectors (without skipping any position of the vector); and *outcome of the day*, with the outcomes displayed being the ones which positions in the vector corresponded to the day the choice was made (i.e. the outcome in position n was displayed if the choice was made in day n). The mechanism of each of these strategies is explained in more detail in Appendix C.

The motivation for testing these two different strategies has its origins in the results of numerical simulations, which showed that the use of the strategy *sequence of the vector* produced more stable results[6] across repeated runs of the same simulated scenario, in comparison to the strategy *outcome of the day*[7]. Although the latter strategy is more realistic than the former, and despite the behaviour of the simulated agents being very simplified in comparison to that of drivers (in such a way that the same stability revealed by the simulations should not necessarily be expected in the collected data), both strategies were adopted with the intention of testing whether there would be significant differences in results between the groups of subjects exposed to one or another strategy.

The four attributes (and their levels) which differentiated the experiment profiles are summarized below:

[6] Average utilities, average choice probabilities and shares of choice options.

[7] This is explained by the fact that, for the first strategy, the outcomes of a vector are experienced by the simulated agents in the same order. It means that all agents who experienced realizations of a certain PDF the same number of times will have exactly the same subjective distribution (resulting from the Bayesian belief updating), which is a main input for the simulated decision making. Such homogeneity in the outputs of the learning mechanism cannot be reproduced when the strategy *outcome of the day* is used.

1. Display of outcomes of the fastest foregone option:
   - *yes*
   - *no*
2. Strategy to extract outcomes from the vectors:
   - *sequence of the vector*
   - *outcome of the day*
3. Initial information regarding travel times:
   - *30+/-5 minutes*
   - *30+/-10 minutes*
4. Assignment scheme of PDFs to parking areas:
   - *best PDFs for PA1 and PA2, worst PDFs for PB1 and PB2*
   - *best PDFs for PB1 and PB2, worst PDFs for PA1and PA2*

All possible combinations of the attributes above generated 16 different profiles. However, only 12 could be used, because the strategy *sequence of the vector* is in practice incompatible with displaying the outcomes of foregone options (further explanations can be found in Appendix C. The rationale underlying the

Table 3.2: *Experiment profiles.*

Exper. profile	Outcome foregone	Strategy extract	Info. RA, RB	Info. PA1, PB1	Info. PA2, PB2	PDFs
1	Yes	Out.Day	30±05	[0,7]	[3,4]	Profiles 1 to 6: RA: *TT.NARR* PA1: *PTB.WIDE* PA2: *PTB.NARR* RB: *TT.WIDE* PB1: *PTW.WIDE* PB2: *PTW.NARR*
2	Yes	Out.Day	30±10	[0,7]	[3,4]	
3	No	Seq.Vector	30±05	[0,7]	[3,4]	
4	No	Seq.Vector	30±10	[0,7]	[3,4]	
5	No	Out.Day	30±05	[0,7]	[3,4]	
6	No	Out.Day	30±10	[0,7]	[3,4]	
7	Yes	Out.Day	30±05	[0,7]	[3,4]	Profiles 7 to 12: RA: *TT.NARR* PA1: *PTW.WIDE* PA2: *PTW.NARR* RB: *TT.WIDE* PB1: *PTB.WIDE* PB2: *PTB.NARR*
8	Yes	Out.Day	30±10	[0,7]	[3,4]	
9	No	Seq.Vector	30±05	[0,7]	[3,4]	
10	No	Seq.Vector	30±10	[0,7]	[3,4]	
11	No	Out.Day	30±05	[0,7]	[3,4]	
12	No	Out.Day	30±10	[0,7]	[3,4]	

third attribute of the list above is described in Section 3.5. Table 3.2 offers an overview of the profiles used in the experiment.

The screenshots of the experiment (written in Dutch) and the corresponding text translated to English can be found respectively in Appendices A and B.

3.4 PDFs of Travel and Parking Times

3.4.1 Criteria to choose PDFs

Besides producing travel and parking times which were coherent with the reality in Dutch cities, the PDFs presented in Table 3.1 (which curves are depicted in Figures 3.2 and 3.3), should allow competition among the choice options. There should be competition between the routes, between the parking areas connected to the same route (i.e. PA1 versus PA2 and PB1 versus PB2) and, ideally, also between parking areas connected to different routes (i.e. PA1 or PA2 versus PB1 or PB2).

The first two requisites mentioned above (i.e. competition between routes and between parking areas connected to the same route) were achieved by choosing PDFs which shapes are, as can be seen in Figures 3.2 and 3.3, easy enough to differentiate – so that trade-offs are clear and random choices are prevented. In fact, the distributions of *TT.NARR*, *PTB.NARR* and *PTW.NARR* have higher averages and smaller variances, whereas their competitors (respectively *TT.WIDE*, *PTB.WIDE* and *PTW.WIDE*) have lower averages and higher variances. Hence, the routes and parking areas associated with the first group of PDFs had the advantage of being more reliable in the sense that their travel and parking times varied within a narrow range of possible outcomes. The advantage of the routes and parking areas associated with the second group of PDFs, on their turn, was that they were on average faster. The averages of any two competing PDFs, nonetheless, are close enough to each other to allow some overlap between the curves, avoiding one of them to be dominant over the other.

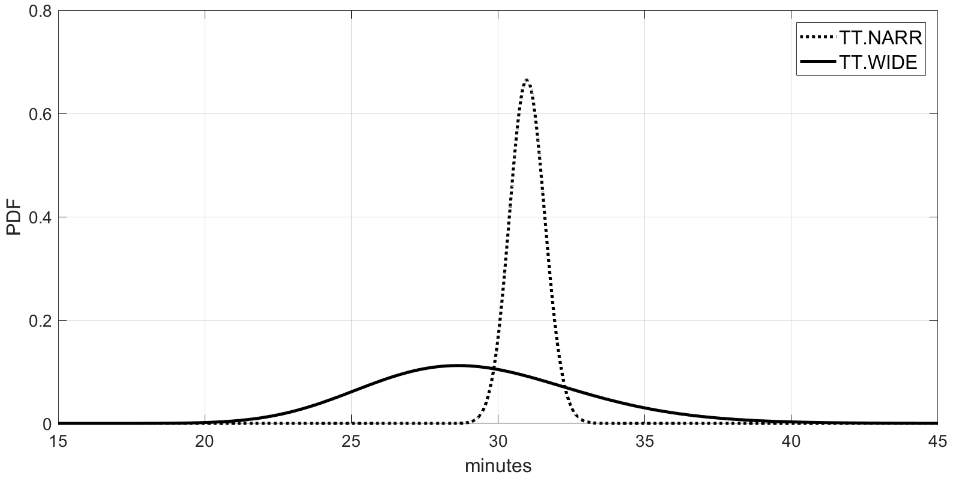

Figure 3.2: *PDFs of travel times.*

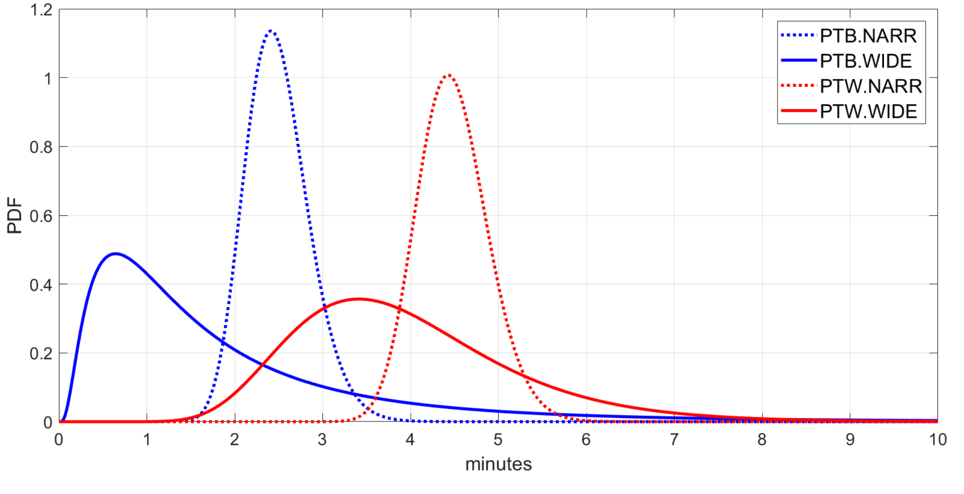

Figure 3.3: *PDFs of parking times.*

However, the competition between any two parking areas not connected to the same route was not possible to be accomplished. Indeed, *PTB.WIDE* and *PTB.NARR* are both clearly superior to any of the other two distributions.

Related to the above is the fact that, from the six possible pairs which can be created out of the PDFs shown in Figure 3.3, only two competing pairs can be created: *PTB.WIDE* & *PTB.NARR* and *PTW.WIDE* & *PTW.NARR* (all other combinations result in one dominated or nearly dominated PDF). It was in order to explore the consequences of linking *TT.WIDE* and *TT.NARR* to each of these pairs, that two different schemes were used to assign the PDFs of parking times to the parking areas (as shown in the last column of Table 3.2). In half of the experiment profiles, the best PDFs for parking times were combined with *TT.NARR*, while in the other half they were combined with *TT.WIDE*.

3.4.2 Criteria to create vectors of outcomes

For each of the six distributions was created a vector of length 50, which frequencies of the (rounded to integer) outcomes were in accordance with the original PDFs (those in Table 3.1 and in Figures 3.2 and 3.3), so that vectors were a truthful enough representation of the distributions. The length of the vectors was equal to 50 because this was the maximum number of choices a subject could make in the experiment. There was no correlation between any two vectors, as demonstrated in Appendix D (where the vectors per see are also shown).

The composition (elements and their frequencies) of each vector can be seen in Tables 3.3 and 3.4, and give a more realistic impression of what subjects encountered during the experiment.

Because outcomes were rounded and vectors limited to 50 elements, the average and standard deviation of the vectors were not the same as those of the original PDFs, as can be seen by comparing the last two lines of Tables 3.3 and 3.4 with the third column of Table 3.1. Such a deviation, however, did not affect the relative positions of advantage and disadvantage of the PDFs: the outcomes of *TT.NARR*, *PTB.NARR* and *PTW.NARR* were concentrated around the mean, whereas their competing vectors (*TT.WIDE*, *PTB.WIDE* and *PTW.WIDE*, respectively) had lower averages. Table 3.5 shows, for the three pairs of competing vectors, the number of days a vector was faster than its competitor, and also how faster on

Table 3.3: *Frequencies of travel times in the vectors of outcomes.*

Travel time (minutes)	Freq. of outcomes for *TT.NARR*	Freq. of outcomes for *TT.WIDE*
22	-	1
23	-	1
24	-	2
25	-	3
26	-	4
27	-	5
28	-	5
29	-	6
30	10	5
31	30	5
32	10	4
33	-	3
34	-	2
35	-	2
36	-	1
37	-	1
average	31.00	29.28
std.dev.	0.64	3.45

average the competitor was during the remaining days[8]. Such analysis is done by comparing the elements occupying the same position in two different vectors, i.e. the first position of *TT.NARR* with the first position of *TT.WIDE*, the second position of *TT.NARR* with the second position of *TT.WIDE*, and so on.

For the experiment profiles which used the strategy *outcome of the day*, it is useful to have an overview of the total times (the sum of the vectors of travel and parking times) of each choice alternative, because the rules defining which foregone option to display were based on comparisons of total times. Tables 3.6 and 3.7 show the relative position of advantage and disadvantage of the four choice

[8]There were also days when both competing vectors had the same travel or parking time: 2 days for *TT.NARR* and *TT.WIDE*, 8 days in the case of *PTB.NARR* and *PTB.WIDE*, and finally 13 days for *PTW.NARR* and *PTW.WIDE*.

Table 3.4: *Frequencies of parking times in the vectors of outcomes.*

Parking time (minutes)	Freq. of outcomes for *PTB.NARR*	Freq. of outcomes for *PTB.WIDE*	Freq. of outcomes for *PTW.NARR*	Freq. of outcomes for *PTW.WIDE*
0	-	6	-	-
1	-	22	-	-
2	28	11	-	5
3	22	5	-	16
4	-	3	27	15
5	-	1	23	9
6	-	1	-	4
7	-	1	-	1
average	2.44	1.78	4.46	3.88
std.dev.	0.50	1.50	0.5	1.19

Table 3.5: *Competition between pairs of vectors.*

Vector of outcomes	Days with fastest outcome (out of 50)	How faster competing vector was on average (for the remaining days)
TT.NARR	14	3.56 min
TT.WIDE	34	2.50 min
PTB.NARR	9	1.55 min
PTB.WIDE	33	2.00 min
PTW.NARR	9	1.46 min
PTW.WIDE	28	1.33 min

options, regarding their potential of being outperformed by the others.

From Table 3.7, it is worth noticing the advantage of RBPB1 and the disadvantage of RAPA2 in profiles 7 to 12. For profiles 1 to 6 (Table 3.6), there is no such extreme difference among the alternatives.

Table 3.6: *Competition among options (profiles 1 to 6).*

Choice option	Days with fastest outcome (out of 50)	How faster other options were on average (for the remaining days)
RAPA1	26	6.25 min
RAPA2	9	4.80 min
RBPB1	20	5.70 min
RBPB2	8	5.43 min

Table 3.7: *Competition among options (profiles 7 to 12).*

Choice option	Days with fastest outcome (out of 50)	How faster other options were on average (for the remaining days)
RAPA1	10	10.00 min
RAPA2	2	9.81 min
RBPB1	36	3.36 min
RBPB2	14	2.33 min

3.5 Initial Information and Initial Guesses

3.5.1 Criteria to choose initial information

As introduced earlier in Section 3.3, the initial information regarding travel times had two levels: *30 +/- 5 minutes* and *30 +/- 10 minutes.* The range of variation of the first level (25 to 35 minutes) is in-between the ranges of the vectors *TT.NARR* (used for RA) and *TT.WIDE* (used for RB), which were respectively 30 to 32 minutes and 22 to 37 minutes. The range of variation of the second level (20 to 40 minutes), on the other hand, is wider than the ranges of both vectors. A third level, with a range narrower than that of both vectors, would not be possible to implement since the variance of *TT.NARR* was already very low – i.e. a third level would imply providing information about a fixed travel time (i.e. with no variability).

The initial information regarding parking times was different for the parking areas at the left side (PA1 and PB1) and the right side (PA2 and PB2) of the work location, but unique across all experiment profiles (as shown in Table 3.2). The use of other levels was not possible due to practical limitations regarding the number of new profiles to be created and the required sample for each of them. Since only one level was used, the information was chosen to resemble the range of variation of the vectors associated to the respective parking areas, providing a starting point for choosing and learning which was close to what subjects would experience. Indeed, PA1 and PB1 used the vectors of outcomes *PTB.WIDE* and *PTW.WIDE*, which ranges were (respectively) 0 to 7 minutes and 2 to 7 minutes, being the corresponding initial information "0 to 7 minutes"; while PA2 and PB2 used the vectors of outcomes *PTB.NARR* and *PTW.NARR*, which ranges were respectively equal to 2 to 3 minutes and 4 to 5 minutes, being the associated initial information "3 to 4 minutes".

3.5.2 Bayesian representation of initial information

The initial information provided to subjects needed a representation in the Bayesian model, so that the learned (subjective) distributions of travel and parking times had a starting point (or an initial guess) for their update. With this intent, lognormal distributions were found that approximately reproduced the ranges of variation of the information provided – and also the averages, for the information on travel times. These distributions are depicted in Figures 3.4 and 3.5 (together with the curves of the six PDFs), and have their descriptive parameters shown in Table 3.8, including their average α and standard deviation λ in the lognormal scale[9].

[9]For each information, other (slightly different) distributions produced approximately the same ranges of variation and averages as the distributions in Table 3.8. However, differences in the evolution of the learned PDFs as a result of using these slightly different distributions were found to be negligible.

Table 3.8: *Bayesian representation of initial information.*

Information	LN(μ,σ)	(α,λ)
30+/-5 minutes	LN(3.40, 0.07)	(30.05, 2.21)
30+/-10 minutes	LN(3.37, 0.18)	(29.53, 5.24)
0 to 7 minutes	LN(0.72, 0.62)	(2.50, 1.72)
3 to 4 minutes	LN(1.25, 0.10)	(3.51, 0.35)

Despite the Bayesian methods employed in this research being capable of complex representations of the starting point of learning (as will be described in Chapter 5), it is fair to say that the way people understand information regarding the variability of time is more simplified when compared to the spectrum of possible representations and requirements of the Bayesian model. The latter requires, for instance, to input the degree of reliability of the initial information provided – an equivalent of the confidence the subject has on the initial information. However, communicating such feature to respondents is challenging and (to the extent of the attempts made during the design of this experiment) would require more elaborated and longer instructions. Hence, in order to make these instructions easy enough to understand and remember, the initial information about travel and parking times was made simple and straightforward, (a) by not mentioning the degree of reliability of the initial information provided[10]; (b) by the way variability was communicated – with ranges of variation and, for travel times, also with averages; and (c) by the fact that each subject was given only three pieces of initial information – one regarding travel times and other two regarding parking times (one for the parking areas at the left side of the work location, and another for the areas at the right side).

In line with the above, there was a distortion between the lognormal distributions used to represent the initial information, and the message communicated to respondents – and this is a limitation this research could not overcome. The

[10]An issue that had to be handled later, while developing the *Learning Model* in Chapter 5 and using its outputs for choice model estimation in Chapter 6.

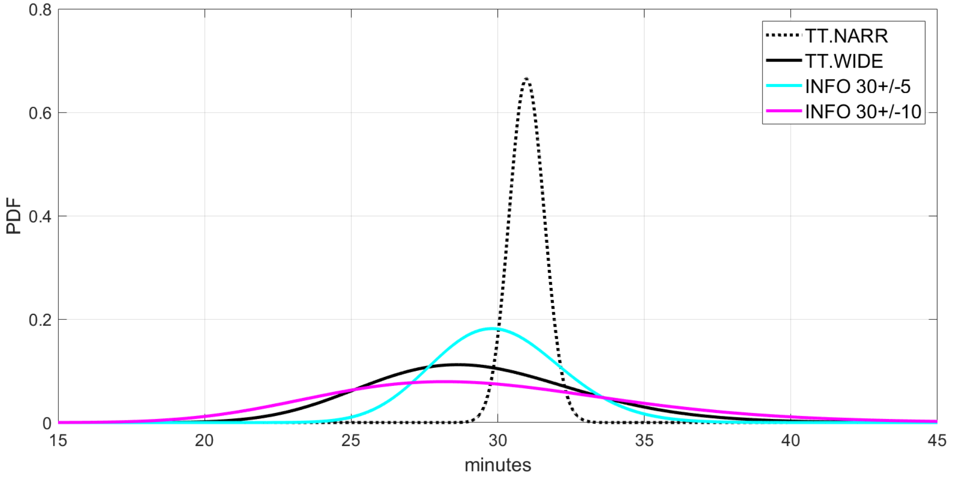

Figure 3.4: *PDFs of travel times and initial guesses.*

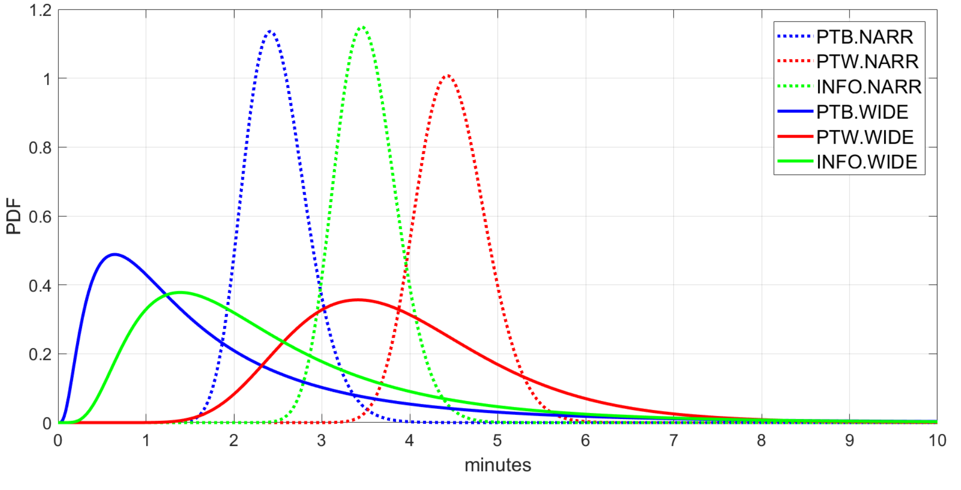

Figure 3.5: *PDFs of parking times and initial guesses.*

curves depicted in Figure 3.4, for instance, are not symmetric around 30 minutes as the initial information suggested. For the parking times, the distortion is more severe, given that the information provided implies uniform distributions and no average parking time was mentioned.

3.6 Summary

This chapter described and discussed the design of the (web-based) dynamic stated choice experiment, which aimed at collecting empirical data for model validation. The design extended the conceptual framework and successfully complied with the research objectives presented in Section 1.2.

The core part of the experiment required subjects to make 50 consecutive choices of route and parking area, each decision followed by the display of its outcomes. The choice set was composed of four combinations of route and parking area (i.e. two routes, each giving access to two different parking lots). The uncertain travel and parking times followed Lognormal distributions, summing up six different PDFs, which were chosen in order to guarantee the necessary trade-offs among the alternatives, i.e. assuring competition between routes and between parking areas connected to the same route. The relative frequencies of travel and parking times in these PDFs were reproduced in the vectors of outcomes (the sequences of either travel or parking times from which elements were extracted and displayed to subjects after each of their choices), maintaining the relative positions of advantage and disadvantage among the alternatives.

Composed of 12 experiment profiles, the design controlled for the effect of presenting the outcomes of the fastest foregone option, the assignment scheme of PDFs to parking areas, besides varying the initial information provided for travel times. To each piece of initial information provided to subjects, a corresponding distribution of probabilities was chosen to represent the start of the learning mechanism (i.e. the Bayesian belief updating).

The design also included insights gathered during the simulation efforts (by varying the strategy to extract outcomes from the vectors), and added questions to capture subjects' stated perceptions of the average, minimum and maximum travel and parking times of the routes and parking areas they had tried in the experiment.

4

Sample Description and Data Overview

4.1 Introduction

This chapter brings an overview of the data obtained after a sample of subjects participated in the dynamic experiment described in Chapter 3. The criteria for selecting the sample, as well as for verifying the quality of the data, are the object of the following section. Next, Section 4.3 describes the statistics of the sample's demographic and driving-habit variables, Section 4.4 explores the shares of the choice options, and finally Section 4.5 brings a summary of the chapter's findings.

In the entire chapter, all statistically significant results have a confidence interval of at least 95%.

4.2 Sample Selection and Data Quality

In order to collect the empirical data, it was desirable that subjects had some level of real-life engagement and experience in trip contexts similar to that of the dynamic experiment described in Chapter 3. With this motivation, the recruitment of subjects was restricted to individuals who (a) either worked or studied, (b) had driver's license and (c) the habit of driving to work or the study location. To maximize the number of individuals meeting these requisites and living in the same geographic area, they were recruited in the Dutch city of Rotterdam, within a radius of 20 kilometres from the city's central train station.

A survey agency was hired to recruit the sample with the desired characteristics. Individuals received the link to the online experiment via e-mail sent by the agency. Out of 822 subjects who started the experiment, 654 (79.56%) managed to complete it. The data was collected during the months of April and May of 2017.

After a quality check of the responses obtained, 54 individuals were excluded from the sample. Most of them (43 subjects) selected the same alternative in all 50 consecutive decisions of the experiment, meaning they did not explore at all the choice options and their variability of travel and parking times, not offering any data for choice model estimation. The remaining 11 subjects were excluded because they took more than 60 minutes to answer the 50 consecutive choices[1], which was the main part of the experiment. The longer one takes to complete the experiment, the higher the risk of losing track of the choices made and the outcomes experienced, compromising the reliability of the answers given. The final sample size was then equal to 600 subjects.

[1]Including two screens to capture perceptions placed after 10 and 30 choices.

4.3 Demographics and Driving Routines

The sample was mainly composed by Dutch subjects (98.67% against 1.33% from other nationalities), and had almost equal proportions of men (51.67%) and women (48.33%).

On average, individuals were 39.44 years old and had driver's license already for a period of 19.27 years, as can be seen in Table 4.1, which shows the statistics of the distributions of *age* and *time with driver's license* in the sample. As expected, both variables are statistically significantly correlated, with Pearson coefficient equal to 0.963. The high correlation becomes clear when comparing the statistics for *age* and *time with driver's license*: apart from the standard deviation (which is very similar for both), all other statistics (mean, minimum, maximum and the percentiles) are approximately "20 years distant" from each other.

Regarding the *family and living status*, more than half of the subjects (52.83%)

Table 4.1: *Distribution of age and time with driver's license.*

Statistic	Age (years)	Time with driver's license (years)
Mean	39.44	19.27
Std.Dev.	12.26	12.04
Minimum	18	0
Maximum	73	54
10^{th} *centile*	24	4
20^{th} *centile*	27	8
30^{th} *centile*	31	11
40^{th} *centile*	35	14
50^{th} *centile*	38	17.5
60^{th} *centile*	43	22
70^{th} *centile*	47	26
80^{th} *centile*	52	31
90^{th} *centile*	56	37

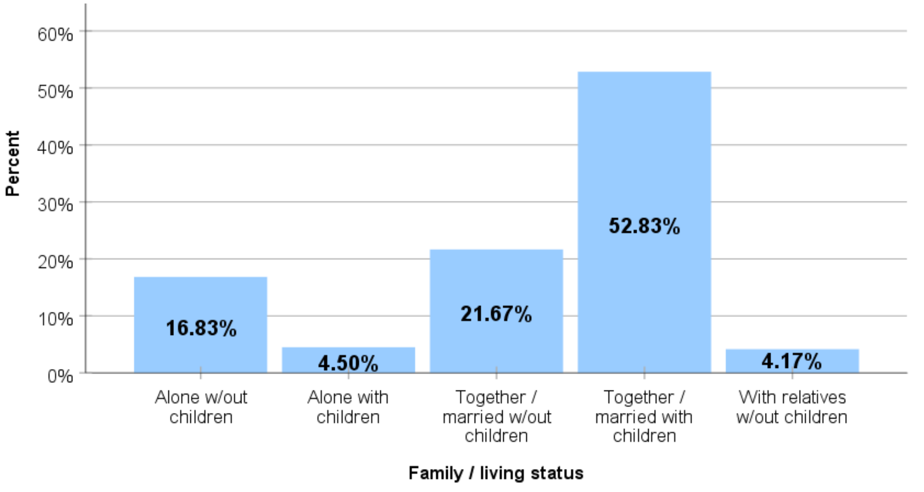

Figure 4.1: *Distribution of family and living status.*

declared to live with the partner and at least one child. The other two categories with higher concentration of respondents were living with partner but without children (21.67%), and living alone without partner and without children (16.83%), as can be seen in Figure 4.1.

The *education level* of subjects is shown in Figure 4.2. More than half of the sample (52.50%) had either higher or university education, and the minority (5.17%) had less than the secondary level.

The majority of subjects were concentrated in the intermediate ranges of *net individual income* (54.50% in the categories from 1251 to 2500 euros per month), with the percentages lessening for higher and lower income levels – as shown in Figure 4.3.

Almost the entire sample (95.00%) declared work (instead of study) as the *occupation*, being 67.17% from the total full-time workers (with work load higher than 32 hours per week), and 27.83% part time workers (with maximum load of 32 weekly hours). This finding is compatible (having in mind a daily work load of 8 hours) with the fact that the distribution of *frequency of driving to work or study* reached its peak (40.67%) at 5 days per week (as shown in Figure 4.4).

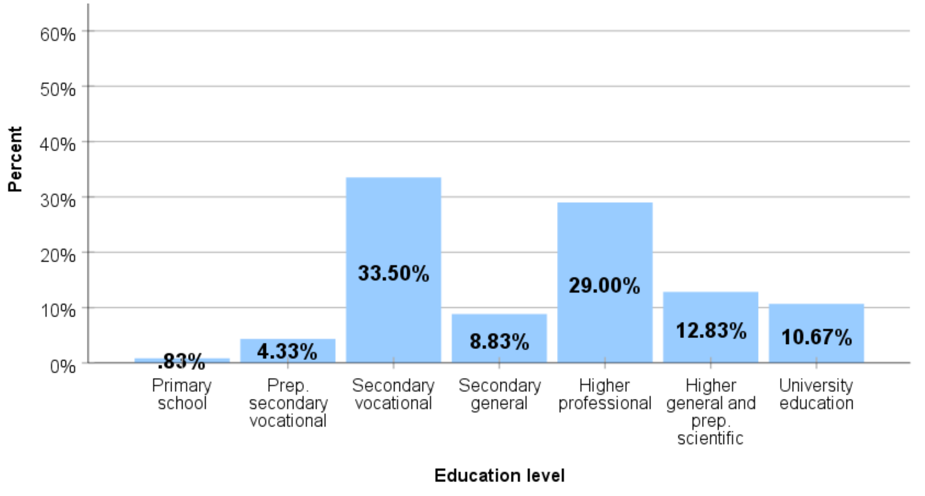

Figure 4.2: *Distribution of education level.*

Concerning the duration of the trip to work or the study location, the averages declared by subjects were: 27.17 minutes as *driving time* and 5.81 minutes as *parking search time* (according to Table 4.2). Although some records seem unlikely to be part of daily life (such as 140 minutes driving and 67 minutes searching for

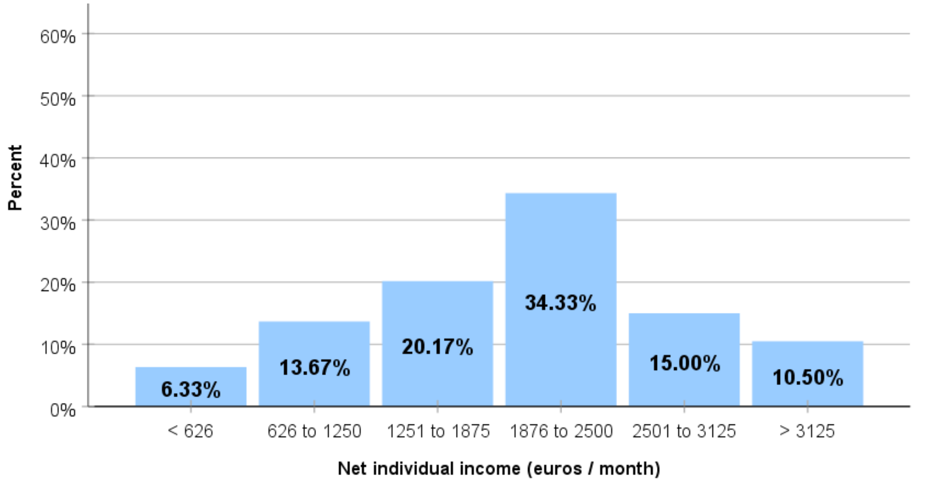

Figure 4.3: *Distribution of net individual income.*

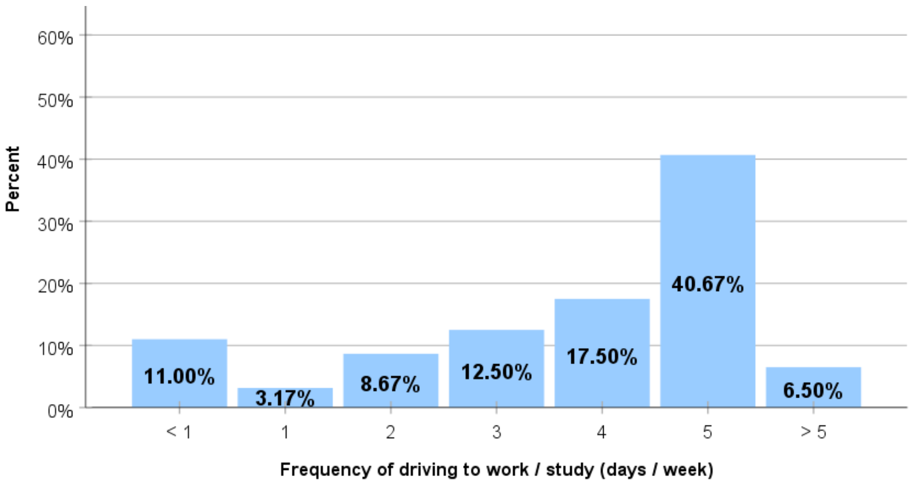

Figure 4.4: *Distribution of driving frequency to work or study.*

parking), they were maintained in the database. Most of the sample (90%), nevertheless, declared driving duration lower than or equal to 45 minutes, and parking search duration of maximum 15 minutes (with the 80^{th} percentile for the latter variable equal to 5 minutes). These variables are statistically significantly correlated with Pearson coefficient equal to 0.175.

The accuracy of these variables, however, is questionable, since each subject might have had a different understanding of the boundary between the driving part and the parking search part of the trip – i.e. the moment in which driving to reach the destination ends, and searching for parking starts. No definitions on that were provided in the instructions of the experiment.

The sum of the driving and parking search times gives the *total duration* of the trip, which average was 32.98 minutes as shown by Table 4.2. Although the maximum declared total trip time was 146 minutes, 90% of the subjects declared a total duration not higher than 60 minutes, which seems to be a more credible value for the variable. Regarding the proportion of the total duration consumed by parking search (shown in the fifth column of Table 4.2), the average in the sample was 14.91%. Despite the maximum for this variable being 75%, indicating

Table 4.2: *Distribution of trip duration.*

Statistic	Driving time (minutes)	Parking search time (minutes)	Total duration (minutes)	Park.search/ total dur. (%)
Mean	27.17	5.81	32.98	14.91
Std.Dev.	16.95	9.92	21.09	16.51
Minimum	1	0	2	0.00
Maximum	140	67	146	75.00
10^{th} *centile*	10	0	11	0.00
20^{th} *centile*	15	1	17	2.78
30^{th} *centile*	18	1	21	4.76
40^{th} *centile*	20	1	23	6.25
50^{th} *centile*	25	2	30	9.09
60^{th} *centile*	30	3	32	11.76
70^{th} *centile*	30	5	40	14.29
80^{th} *centile*	40	5	46	25.00
90^{th} *centile*	45	15	60	50.00

that searching for parking might take longer than driving, its 90^{th} percentile equals 50%.

The relations of the demographic and driving-habit variables with the experiment profiles and experiment design attributes[2] were also investigated, and no statistically significant results were found, i.e. there was no concentration of subjects with whatever demographic or driving-habit characteristic in any profile or group of profiles sharing the same design attribute. This finding is coherent with the fact that subjects were randomly assigned to the experiment profiles.

Although not a demographic or driving-habit variable, it is worth to mention some findings regarding the time to complete the experiment[3]. The average for the sample was 10.22 minutes, with minimum of 2 minutes and maximum of 59,

[2] As introduced in Section 3.3: display of outcomes of the fastest foregone option; strategy to extract outcomes from the vectors; initial information regarding travel times; and assignment scheme of PDFs to parking areas.

[3] From the 1^{st} to the 50^{th} consecutive choice, including two screens to capture perceptions placed after 10 and 30 choices.

being the 10^{th} and 90^{th} percentiles equal to 5 and 16 minutes, respectively. It was found that subjects assigned to profiles which displayed the outcomes of foregone options took statistically significantly longer to answer than those assigned to the other profiles: 11.22 against 9.72 minutes. Besides, subjects with higher or university education were statistically significantly faster than those with lower levels of education: 9.20 against 11.36 minutes.

4.4 Shares of Choice Options

The average final shares[4] of the choice options, per experiment profile, are presented in Table 4.3, which also displays (in parenthesis below the shares) the total number of times the alternatives were chosen by the respondents assigned to the corresponding profile. In profile 1, for instance, in total 2550 choices were made (51 respondents x 50 choices per respondent), from which 1137 corresponded to RAPA1, 463 to RAPA2 and so on.

The relations between the shares and the experiment profiles were tested, and the statistically significant results are discussed in this section. The tests were done separate for the group of profiles 1 to 6, and for the group of profiles 7 to 12, because the assignment of PDFs of parking times was different for these two groups (as shown in Table 3.2). For both groups of profiles, the only experiment design attribute which significantly affected shares was the display of feedback on foregone options. The shares of all alternatives were sensitive to the presence of this type of feedback, apart from the shares of RBPB2 in profiles 1 to 6.

The impact of the feedback on foregone options is shown in Table 4.4, which presents the average shares per alternative, grouped per profiles with and without feedback on foregone options. Except for profiles 3 to 6, the highest shares corresponded to the alternatives with the lowest average total times[5], which were

[4] After 50 consecutive choices.

[5] Calculated by summing the means of the corresponding PDFs for travel and parking times, which can be done using Tables 3.3 and 3.4 in combination.

Table 4.3: *Shares of choice options per experiment profile.*

Profile	Sample size	RA PA1	RA PA2	RB PB1	RB PB2	Total
1	51	44.59% (1137)	18.16% (463)	22.00% (561)	15.25% (389)	100% (2550)
2	52	35.12% (913)	16.38% (426)	28.15% (732)	20.35% (529)	100% (2600)
3	52	30.54% (794)	33.54% (872)	16.65% (433)	19.27% (501)	100% (2600)
4	50	26.08% (652)	33.96% (849)	22.12% (553)	17.84% (446)	100% (2500)
5	48	31.21% (749)	33.58% (806)	19.58% (470)	15.63% (375)	100% (2400)
6	48	27.38% (657)	30.25% (726)	21.29% (511)	21.08% (506)	100% (2400)
7	46	12.00% (276)	16.96% (390)	53.39% (1228)	17.65% (406)	100% (2300)
8	52	15.42% (401)	11.65% (303)	48.96% (1273)	23.96% (623)	100% (2600)
9	54	23.81% (643)	19.00% (513)	32.81% (886)	24.37% (658)	100% (2700)
10	48	21.67% (520)	20.75% (498)	33.63% (807)	23.96% (575)	100% (2400)
11	49	19.8% (485)	20.57% (504)	28.24% (692)	31.39% (769)	100% (2450)
12	50	21.60% (540)	20.56% (514)	31.84% (796)	26.00% (650)	100% (2500)

(as expected) also the alternatives that more often could have had the fastest outcomes (as can be seen in Tables 3.6 and 3.7).

Table 4.4 shows that, for profiles 1 and 2, the highest shares corresponded to

Table 4.4: *Shares of choice options according to display of feedback.*

Profile	Feedback on foregone	RA PA1	RA PA2	RB PB1	RB PB2
1, 2	yes	39.80%	17.26%	25.10%	17.84%
3, 4, 5, 6	no	28.80%	32.86%	19.86%	18.48%
7, 8	yes	13.82%	14.14%	51.04%	21.00%
9, 10, 11, 12	no	21.78%	20.18%	31.66%	26.38%

alternatives RAPA1 (39.80%) and RBPB1 (25.10%), which average total times were respectively 32.78 and 33.16 minutes (versus 33.44 and 33.74 minutes for RAPA2 and RBPB2), and number of days with the fastest outcome was respectively 26 and 20 (against 9 and 8 days for RAPA2 and RBPB2).

For profiles 7 to 12 the logic is the same, with the highest shares corresponding to RBPB1 and RBPB2, which average total times were respectively 31.06 and 31.72 minutes (against 34.88 minutes for RAPA1 and 35.46 for RAPA2), and quantity of days with the fastest outcome respectively equal to 36 and 14 (versus 10 for RAPA1 and 2 for RAPA2).

Still for the group of profiles 7 to 12, it is relevant to mention that the share for RBPB1 increased substantially to 51.04% in profiles 7 and 8 (in comparison to profiles 9 to 12), while those of all other alternatives dropped. It is possible that, with more information available, the advantage of RBPB1 became more evident: its associated PDFs allowed it to have the lowest outcomes (of both travel and parking times) which could possibly be attained in the entire experiment design, making this option the fastest very often[6].

Profiles 3 to 6, in contrast with the others, presented a different hierarchy of shares, with the favourite being RAPA2 (32.86%), followed by RAPA1 (28.80%). RAPA2 did not have the lowest average total time, neither the highest number of days with the fastest outcome (as it is the case of RAPA1). It is, however, the only

[6]Such advantage might be related as well to the fact that no other share, in the entire experiment, was higher than that of RBPB1 in profiles 7 and 8.

reliable option (i.e. very little variability of travel or parking times) in the choice set. In profiles 1 to 6, the relative advantages and disadvantages of the choice options were less evident (in comparison to profiles 7 to 12, as demonstrated by Tables 3.6 and 3.7), especially when there was no supply of extra information from other alternatives, which was the case of profiles 3 to 6. In such circumstance, the reliability of travel and parking times seems to have gained importance in decision making.

Complementing the previous tables, Figures 4.5 to 4.8 show the evolution of the average shares during the 50 consecutive choices, following the same grouping of profiles used in Table 4.4. Interestingly, the hierarchy of the shares at the start of the experiment is the same for all graphs (RAPA1 with the highest share, followed by RAPA2, then by RBPB1 and finally by RBPB2 with the lowest share), suggesting the position each option occupied in the choice menu displayed to respondents (as can be seen in Figure 2) might have impacted their first decisions.

The graphs also show that, for the profiles where feedback on foregone options was displayed, the preferences of respondents were more evident. Related to this finding, is the fact that the average number of times subjects changed the chosen alternative from one day to the next (i.e. the average number of switches) was found to be significantly lower for those profiles with feedback on foregone options: 19.56 switches versus 24.50 for the profiles without such feedback. This suggests that, the more information was gained from the same decision[7], the more knowledge subjects built, and the less exploration (of the available options) they needed to do.

Specifically to investigate the effects of the experiment design attribute *strategy to extract* (as introduced in Section 3.3) on the shares, Levene's test for homogeneity of variances was used. The test was performed separately for profiles 3 to 6, and 9 to 12[8]. Although simulations showed increased variability of the shares associated to the use of the strategy *outcome of the day*, Levene's test resulted

[7]By receiving, besides the outcomes of the chosen option, also those of the foregone.

[8]Profiles where feedback on foregone options was displayed were not considered for the test.

in no statistically significantly different variances of the shares due to this design attribute. This finding suggests that, after the sequence of 50 choices, subjects were not sensitive to the sequence in which they received the outcomes from the same PDF.

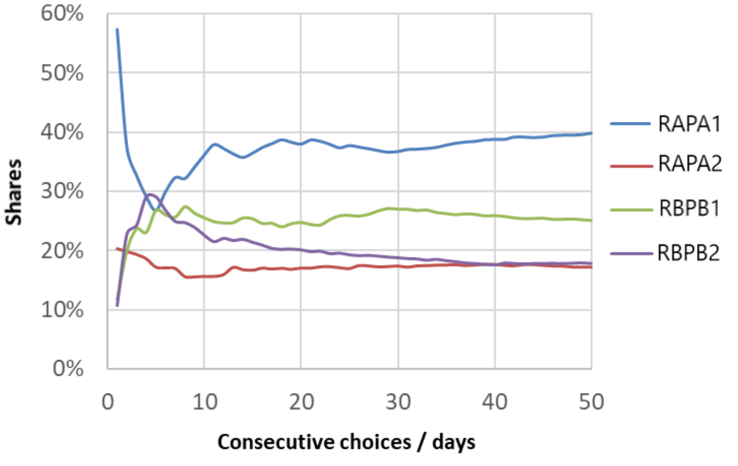

Figure 4.5: *Evolution of shares for profiles 1 and 2.*

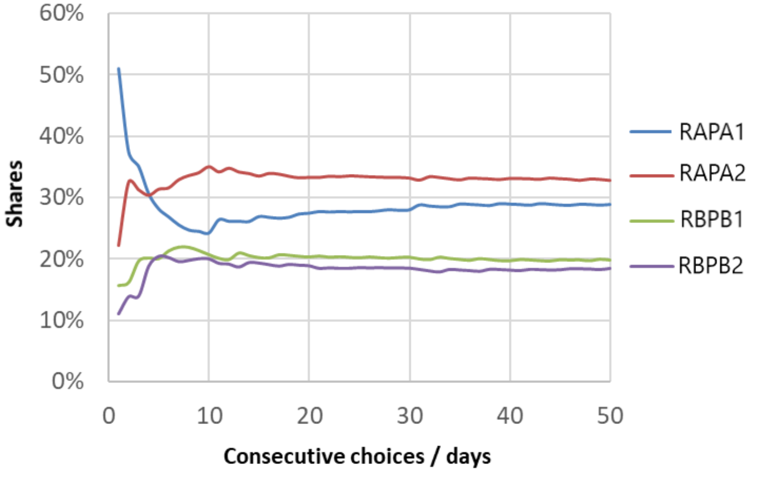

Figure 4.6: *Evolution of shares for profiles 3 to 6.*

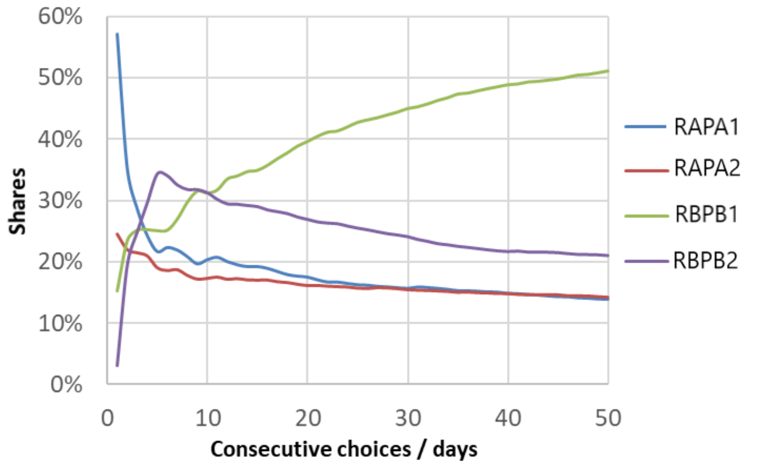

Figure 4.7: *Evolution of shares for profiles 7 and 8.*

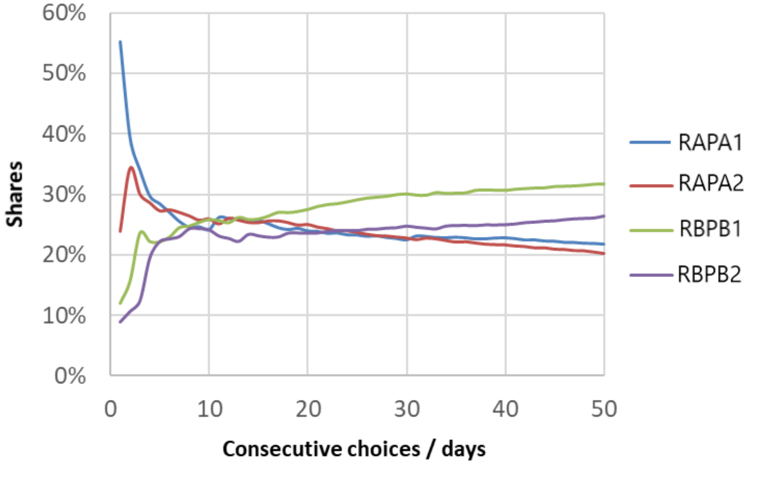

Figure 4.8: *Evolution of shares for profiles 9 to 12.*

4.5 Summary

This chapter brought an overview of the collected data. Subjects who had real-life engagement and experience in trip contexts similar to that of the dynamic experiment were recruited in the Dutch city of Rotterdam. After excluding non-valid answers, the final sample size was equal to 600 subjects, who were predominantly Dutch (98.67%), on average 39.44 years old, with driver's license for 19.27 years on average, and 51.67% were men.

The highest shares among the choice alternatives corresponded to those with the lowest average total times, regardless of the variability of their outcomes. Except for profiles 3 to 6, where the most reliable option was chosen (i.e. that with the smallest range of variation for the total time), followed by the one with the lowest average total time. Due to the assignment scheme of PDFs of parking times used in these profiles, the relative advantages and disadvantages of the choice options were less evident (in comparison to profiles where another assignment scheme was adopted), which was accentuated by the lack of feedback on foregone options. In such circumstances, the reliability of travel and parking times seems to have become relevant for decision making, exceeding the importance of lower average total times.

The only experiment design attribute which affected shares with statistical significance was found to be the display of feedback on foregone options, increasing the shares of the option with the lowest average total time. This attribute also affected the average number of times subjects changed the chosen alternative from one day to the next. The average number of switches was found to be statistically significantly lower in those profiles where feedback on foregone options was provided: 19.56 versus 24.50 for the other profiles. This result suggests that, the more information gained from the same decision, the more knowledge subjects built, and the less exploration they needed to do.

Regarding the experiment design attribute strategy to extract (outcomes from vectors), its influence on the shares was also tested. Although simulations showed increased variability of the shares associated to the use of the strategy *outcome of the day*, no statistically significant differences in the variances of the shares were found in the collected data, demonstrating that subjects (differently from simulated agents) were not sensitive to the sequence in which they received a certain PDF's outcomes.

5

Learning Model

5.1 Introduction

The first component of the proposed model (introduced in Section 1.2) is the object of this chapter. The *Learning Model* has as main inputs the realizations of travel and parking times faced by those individuals who completed the experiment, while its outputs are the mathematical representation of the subjective probability distributions for travel and parking times. The parameters of these subjective distributions (such as mean and standard deviation) are attributes of the choice options feeding the estimation of the *Choice Model* in Chapter 6.

The theoretical background and mathematical formulation of the *Learning Model* are the focus of Section 5.2, while the relevant operational aspects of its application[1] to the collected data are described and discussed in Section 5.3. The outputs of the *Learning Model* are analysed in Section 5.4. Final considerations regarding the applicability of the *Learning Model* are exposed in Section 5.5, and a summary of the chapter's findings is provided in Section 5.6.

5.2 Theoretical Background

As introduced in Chapter 3, travel and parking times were represented in the model as lognormally distributed independent[2] random variables. Let us define the driver's subjective knowledge about one of these random variables as $LN(\mu, \sigma^2)$, where μ is the mean and σ^2 is the variance of the normal distribution associated to the lognormal[3]. In simple terms, the knowledge update process consists of recalculating μ and σ^2 every time the driver acknowledges new observations from the random variable.

The relation between prior and posterior knowledge is established by the Bayes Theorem:

$$f(\mu, \sigma^2 \mid X) = \frac{g(X \mid \mu, \sigma^2) \cdot h(\mu, \sigma^2)}{k(X)} \tag{5.1}$$

Where:

X is a sample of observations the driver acknowledged.

$f(\mu, \sigma^2 \mid X)$ is the posterior joint distribution of the parameters μ and σ^2 conditional on the sample X – i.e. after the driver acknowledges the sample.

$g(X \mid \mu, \sigma^2)$ is the likelihood that the sample X was generated by the parameters μ and σ^2.

$h(\mu, \sigma^2)$ is the prior joint distribution of μ and σ^2 – i.e. before the driver experienced the sample X.

[1] Which was performed in the software Matlab.

[2] Given that there was no correlation between any two PDFs of travel and/or parking times.

[3] If $A \sim LN(\mu, \sigma^2)$ then $B = ln(A) \sim N(\mu, \sigma^2)$.

$k(X)$ represents the marginal density of the observed sample.

Equation 5.1, however, is not analytically tractable. Therefore, μ and σ^2 have to be updated separately, conditional on the knowledge of each other: the posterior distribution of μ (equation 5.2) depends not only on the sample X, but also on σ^2 (as if the variance σ^2 was known by the driver). Similarly, the posterior distribution of σ^2 (equation 5.3) depends on both X and μ (as if the latter was known by the driver).

$$f(\mu \mid X, \sigma^2) = \frac{g(X \mid \mu, \sigma^2) \cdot h(\mu)}{k(X)} \tag{5.2}$$

$$f(\sigma^2 \mid X, \mu) = \frac{g(X \mid \mu, \sigma^2) \cdot h(\sigma^2)}{k(X)} \tag{5.3}$$

To further develop the equations above, it is necessary to make assumptions about the type of probability density functions μ and σ^2 follow. Therefore, a normal distribution was assigned to μ with mean μ_{mean} and variance μ_{var}: $\mu \sim N(\mu_{mean}, \mu_{var})$; and an inverted gamma distribution was assigned to σ^2 with scale σ^2_{scale} and degrees of freedom σ^2_{df}: $\sigma^2 \sim IG(\sigma^2_{scale}, \sigma^2_{df})$ [4].

Both the normal and the inverted gamma distributions have the advantage of being natural conjugates (i.e. prior and posterior follow the same type of distribution), besides relying on a small number of parameters (two parameters each) which interpretations are enough intuitive. The inverted gamma distribution, specifically, by having no support for negative values, is extremely convenient to represent the driver's knowledge of the variance σ^2.

The hyper-parameters μ_{var} and σ^2_{df} define how spread or concentrated are the distributions of μ and σ^2. The higher the value of μ_{var} and the lower the value of σ^2_{df}, the more diffuse the distributions of μ and σ^2 become. Therefore, μ_{var} and σ^2_{df} are a representation of the degree of trust the driver attributes to his own

[4] As done, for instance, in Train (2009) and Chorus *et al.* (2008a) for μ and σ^2, and in Chen & Mahmassani (2004) for μ.

beliefs[5] about μ and σ^2: the lower the trust, the more diffuse the distributions are. Accordingly, as the driver acquires experience (by gathering a sample X), μ_{var} decreases and σ^2_{df} increases, and the distributions of μ and σ^2 become more concentrated, representing the driver now is more sure about the own beliefs.

Once the types of distributions for μ and σ^2 have been defined, equations 5.2 and 5.3 can be developed and yield the formulas for the update of the hyper-parameters (the mathematical proof can be found in Train, 2009):

$$\mu'_{mean} = \frac{(N/\sigma^2) \cdot \bar{X} + (1/\mu_{var}) \cdot \mu_{mean}}{(N/\sigma^2) + (1/\mu_{var})} \tag{5.4}$$

$$\mu'_{var} = \frac{1}{(N/\sigma^2) + (1/\mu_{var})} \tag{5.5}$$

$$\sigma^{2'}_{scale} = \frac{N \cdot \bar{S} + \sigma^2_{scale} \cdot \sigma^2_{df}}{N + \sigma^2_{df}} \tag{5.6}$$

$$\sigma^{2'}_{df} = N + \sigma^2_{df} \tag{5.7}$$

Where:

μ'_{mean}, μ'_{var}, $\sigma^{2'}_{scale}$ and $\sigma^{2'}_{df}$ are the posterior (updated) values of the hyper-parameters, after the driver experiences sample X – while μ_{mean}, μ_{var}, σ^2_{scale} and σ^2_{df} are their prior values.

σ^2 is the (supposedly) known variance of the random variable the driver wishes to learn.

N is the size of sample X.

$\bar{X} = (1/N) \cdot \sum_{n=1}^{N} ln(y_n)$ is the average of sample X.

$\bar{S} = (1/N) \cdot \sum_{n=1}^{N} (ln(y_n) - \mu)^2$ is the variance of sample X around the known mean μ.

[5] As introduced in Section 1.2.

μ is the (supposedly) known mean of the random variable the driver wishes to learn.

Obs.: $Y = \{y_1, y_2, ..., y_N\}$ *is the set of outcomes measured in the lognormal scale, while* $X = ln(Y) = \{ln(y_1), ln(y_2), ..., ln(y_N)\}$ *is the set of outcomes measured in the normal scale.*

Equations 5.4 to 5.7 show that the posteriors of μ and σ^2 are weighted averages of their priors and of the sample mean $\bar{X}$ and variance $\bar{S}$. Therefore, as the sample rises in size, the experienced sample becomes more relevant, the opposite happening to the priors.

In equations 5.4 and 5.5 σ^2 is treated as known by the driver, as well as μ (indirectly) in equation 5.6. In reality, however, the driver wishes to learn both and hence none of the parameters is known while updating the distribution of the other. Ways of tackling this issue are discussed in the next section.

5.3 Application

The application to this research of the knowledge update mechanism described in the previous section follows the steps below, for all random variables (i.e. for the two PDFs of travel times and the four PDFs of parking times) and all 600 subjects who completed the survey:

1. To calculate the subjective distributions the driver will rely on when choosing an alternative for his first trip – i.e. for decision making on *day 1*:

   (a) Take the lognormal distributions which correspond to the initial information about travel and parking times provided in the experiment, shown in Table 3.8 of Chapter 3. Consider the numbers in this table as the expected values of the parameters $\mu \sim N(\mu_{mean}, \mu_{var})$ and $\sigma^2 \sim IG(\sigma^2_{scale}, \sigma^2_{df})$ that the driver wishes to learn. For instance, the lognormal distribution corresponding to the information *30+/-5 minutes* is $LN(3.34, 0.07)$, hence: $E(\mu) = 3.34$ and $E(\sigma^2) = (0.07)^2$.

(b) Choose starting values for μ_{mean} and μ_{var} (named respectively μ_{mean}^{start} and μ_{var}^{start}) that are able to generate a normal PDF with expected value equal to $E(\mu)$ – which implies making $\mu_{mean}^{start} = E(\mu)$.

(c) Choose starting values for σ^2_{scale} and σ^2_{df} (named respectively $\sigma^{2^{start}}_{scale}$ and $\sigma^{2^{start}}_{df}$) that are able to generate an inverted gamma PDF with expected value equal to $E(\sigma^2)$.

2. For the daily update of the subjective distributions the driver will use for decision making from *day 2* onward:

   (a) Calculate μ'_{mean} and μ'_{var} with equations 5.4 and 5.5, using μ_{mean} and μ_{var} updated in the previous day (which, for decision making on *day 2* will be μ_{var}^{start} and $\sigma^{2^{start}}_{df}$), and $\bar{X}$ and N corresponding to the observations acknowledged after the decision of the previous day. Replace the supposedly known parameter σ^2 by the expected value of the distribution of σ^2 updated in the previous day (which, for decision making on *day 2* will be $E(\sigma^2)$ as defined in step 1a).

   (b) Calculate $\sigma^{2'}_{scale}$ and $\sigma^{2'}_{df}$ with equations 5.6 and 5.7, using σ^2_{scale} and σ^2_{df} updated in the previous day (which, for decision making on *day 2* will be $\sigma^{2^{start}}_{scale}$ and $\sigma^{2^{start}}_{df}$), and $\bar{S}$ and N corresponding to the observations acknowledged after the decision of the previous day. To calculate $\bar{S}$, replace the supposedly known value of μ by the expected value of the distribution of μ updated in the previous day (which, for decision making on *day 2* will be $E(\mu)$ as defined in step 1a).

For the decision on *day 1*, drivers rely only on the initial information they received about the distributions and on their degree of trust in such information, represented by the initial values of the hyper-parameters μ_{var} and σ^2_{df} (defined in steps 1b and 1c, respectively). Hence, the initial values of these hyper-parameters need to be set at the start of the model's application. The criteria to define what are good initial values is discussed in Chapter 6.

After the first decision, drivers start updating their knowledge using the travel and parking times they experience out of their decisions, including outcomes from the chosen alternative and also from foregone options. Steps 2a and 2b are repeated before every new decision (i.e. every new day in the experiment). When, for a specific random variable (PDF), no new outcome is acknowledged from one day to the next, N equals zero and the updated values of the four hyper-parameters in equations 5.4 to 5.7 equal their values from the day before (i.e. no update happens). When new outcomes are acknowledged, however, the number of new observations per day per random variable (PDF) to be aggregated to the learning mechanism is always equal to one ($N = 1$), i.e. the subjective distributions are updated one experience at a time.

In this application, the supposedly known parameters μ (indirectly used in equation 5.6) and σ^2 (used in equations 5.4 and 5.5) are replaced by the expected values of the distributions of μ and σ^2 updated in the previous day. Another possible solution is to use the Gibbs sampling approach (as explained in Train (2009) and done by Chorus *et al.*, 2008a), which consists of using a draw from the most recently updated distribution of σ^2 to update the distribution of μ (using equations 5.4 and 5.5), and in the sequence use a draw from the last updated distribution of μ to update the distribution of σ^2 (using equations 5.6 and 5.7), in an iterative manner[6]. This approach, however, has the disadvantage of bringing randomness to the outputs of the *Learning Model*, an undesirable feature for the estimation of the *Choice Model*. An exploration of the consequences of randomness in the belief updating mechanism can be found in De Carvalho *et al.* (2016a, 2016b). The solution adopted in this application, on the other hand, besides not bringing randomness to the outputs, requires less computation time because it does not depend on the iterative sampling. Moreover, the expected values of μ and σ^2 can be seen as the drivers' most likely impressions about these parameters and hence, used for the update of each other's distribution.

[6]According to Train (2009), iterating through numerous cycles of draws eventually provides draws from the joint posterior.

Finally, for every subject, PDF and day, two subjective distributions are available: $\mu \sim N(\mu_{mean}, \mu_{var})$ and $\sigma^2 \sim IG(\sigma^2_{scale}, \sigma^2_{df})$. The learned mean α and variance λ^2 of travel and parking times (in the lognormal scale) which enter the estimation of the discrete choice models (in Chapter 6) are derived from the expected values of the distributions of μ and σ^2 (the equivalence between the expected value α and spread λ^2 of a lognormally distributed random variable $Y \sim LN(\mu, \sigma^2)$ and this variable's parameters μ and σ^2 can be found in Norstad, 2011):

$$\alpha = e^{E(\mu)+E(\sigma^2)/2} \tag{5.8}$$

$$\lambda^2 = e^{2\cdot E(\mu)+E(\sigma^2)} \cdot (e^{E(\sigma^2)} - 1) \tag{5.9}$$

5.4 Results and Discussion

For every subject in the sample the learned lognormal distributions of travel and parking times (six in total) were calculated, from day 1 to day 50 (i.e. before the first decision, and after every one of the 50 decisions), using the sequences of outcomes they received after their choices, including the outcomes of non-chosen options for those subjects allocated to profiles where outcomes of the fastest foregone alternative were displayed.

The prior for μ_{var} was set to be proportional to the initial value of μ_{mean}: $\overset{start}{\mu_{var}} = (\overset{start}{b} \cdot \overset{start}{\mu_{mean}})^2$, hence assuming a different value for each initial information provided. Making $\overset{start}{\mu_{var}}$ proportional to $\overset{start}{\mu_{mean}}$ allowed (the representation of) respondents' degree of trust to be equivalent across the different initial information they were exposed to. The prior for σ^2_{df} (i.e. $\sigma^{2^{start}}_{df}$), on the other hand, because it can be interpreted as the number of experiences the respondent had from a certain random variable, can be defined independently and was set to be the same for all initial information.

The definition of the starting values of the hyper-parameters μ_{var} and σ^2_{df} impacted the results of the discrete choice models estimated from the empirical data collected. A range of values for each of these hyper-parameters was tested in this research, and each pair (b^{start}, $\sigma^{2^{start}}_{df}$), called from now on a *level of trust (LT)*, yielded a different database (composed of the parameters and hyper-parameters calculated: μ_{mean}, μ_{var}, σ^2_{scale}, σ^2_{df}, α and λ^2) which was used for choice model estimation. For each LT, 300 (50 days x 6 PDFs) subjective distributions were calculated per individual, summing up 180000 for the whole sample (300 x 600 individuals).

An arbitrary pair ($b^{start} = 0.30, \sigma^{2^{start}}_{df} = 15$) within the range tested is used to exemplify the evolution of the learned parameters. The averages of α and λ (and not λ^2) across the sample, per day of the experiment are shown in Figures 5.1 to 5.8, for the chosen LT[7]. The graphs also show the value of the mean and the standard deviation of the elements in the vectors of outcomes, as a reference to compare the evolution of the learned parameters. From a Bayesian belief updating perspective, learning happens as the curves of the parameters α and λ approach this reference. The speed and evolution (smoothness) of this process depends on the combination of some factors: distance of the initial guesses from the real parameters, level of trust (LT) adopted for the initial guesses, variability of the data, number of experiences and type of parameter. Detailed explanations follow in the next paragraphs.

Regarding the *distance of the initial guesses from the real parameters (references)*, or how much the prior information coincides with the real distribution, everything else being equal, the closer the initial guess is from the real parameter values, the faster the learning occurs. This can be seen, for example, in the evolution of α and λ for *TT.NARR*. When the initial guess is *30+/-5 minutes* (Figure 5.1), the learned parameters are closer to the reference at day 50, in

[7] α and λ (instead of the hyper-parameters μ_{mean}, μ_{var}, σ^2_{scale} and σ^2_{df}) were chosen to interpret the outputs of the learning mechanism because, being in the lognormal scale, they are easier to be understood. De Carvalho *et al.* (2015b) explore the evolution of the hyper-parameters during the learning process.

comparison to what happens when the initial guess is *30+/-10 minutes* (Figure 5.2).

The *LT adopted for the initial guesses*, or the extent to which drivers consider the prior information reliable, also affects the evolution of the learned parameters. The higher the trust, the less the learned parameters deviate from the initial value. Accordingly, the lower the trust, the more the learned parameters suffer the influence of the outcomes experienced and deviate from the initial values in the direction of the real ones. Hence, high trust might be acceptable to PDFs which difference between the initial and the real parameters is small, however when the initial guesses are far from the real parameters, low trust might be more beneficial. Figure 5.10 exemplifies this: the parameter α of *PTW.WIDE* (averaged across the sample) approaches the average of the vector faster when a lower LT is adopted[8] in comparison to the LT used as reference in this section – after 50 days, α equals 3.66 in the first case, versus 3.35 in the second (being the average of the vector of outcomes equal to 3.88); and takes longer to approach the reference line when a higher LT is adopted[9] in comparison to the LT used as reference in this section – at the end of 50 days, the parameter α is 2.71 when the higher LT is adopted.

Regarding the *variability of the data*, data with lower variance tend to have a smoother curve and converge faster to the real parameter values, while that with higher variance tend to have a curve with more "ups and downs", especially when the number of outcomes is still small. This can be seen by comparing the left side of Figures 5.1 and 5.3: the learning curve for α is smoother for the PDF with lower variance (i.e. *TT.NARR*).

When it comes to the *number of experiences*, the more outcomes experienced per unit of time (which is measured in days in the experiment), the faster the learning happens. Hence, the curves for subjects who received feedback on fore-

[8] $b^{start} = 0.50$ and $\sigma_{df}^{2\,start} = 5$.
[9] $b^{start} = 0.10$ and $\sigma_{df}^{2\,start} = 25$.

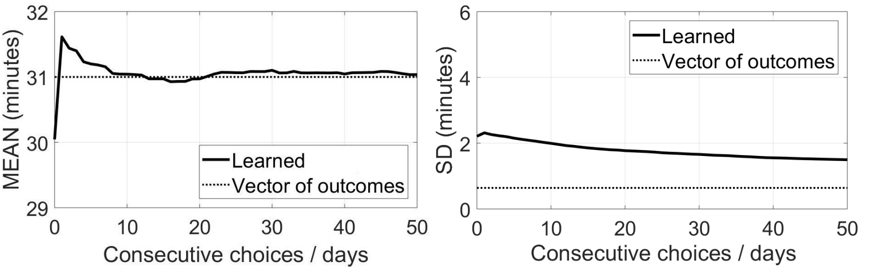

Figure 5.1: *Evolution of α (left) and λ (right) for TT.NARR (30+/-5).*

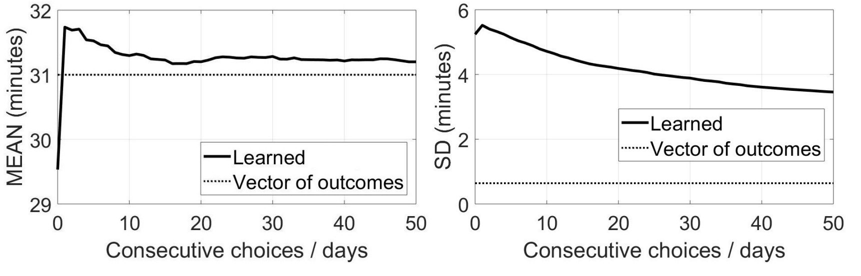

Figure 5.2: *Evolution of α (left) and λ (right) for TT.NARR (30+/-10).*

gone options converged faster (on average) than those of respondents who did not receive such extra information. This can be seen in Figure 5.9, which shows the (average) evolution of λ for *PTW.WIDE* for the sub-samples with and without feedback on foregone. The curve for the sub-sample with feedback converges faster towards the real parameter value, for the same LT.

Finally, the *type of parameter* being update also matters: α is easier to learn than λ, given that the definition of variance depends on the mean.

For *PTB.WIDE* and *PTW.WIDE*, the curve of λ seems not to approach (or to do it very slowly) the reference line of the standard deviation of the vector of outcomes. The explanation is threefold: these PDFs have higher variance and thus are more difficult to be learned (in comparison, for instance, with *PTB.NARR* and *PTW.NARR*); the starting point of the evolution of λ is, in both cases, more distant from the reference line than, for instance, the other two PDFs of parking times (a consequence of the starting point of the update, derived from

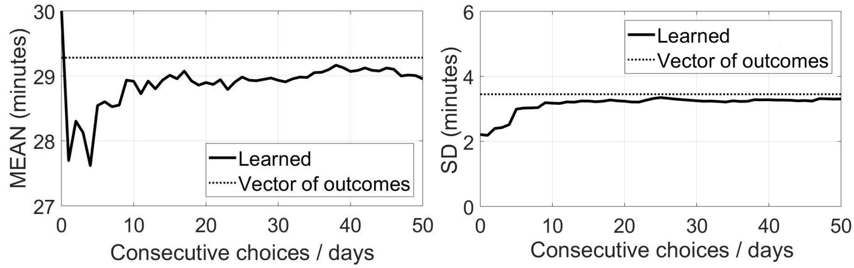

Figure 5.3: *Evolution of* α *(left) and* λ *(right) for TT.WIDE (30+/-5).*

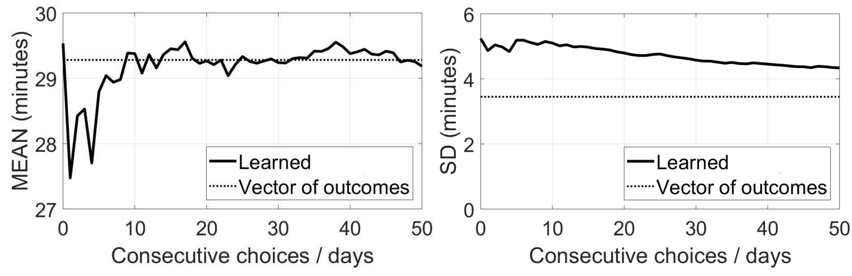

Figure 5.4: *Evolution of* α *(left) and* λ *(right) for TT.WIDE (30+/-10).*

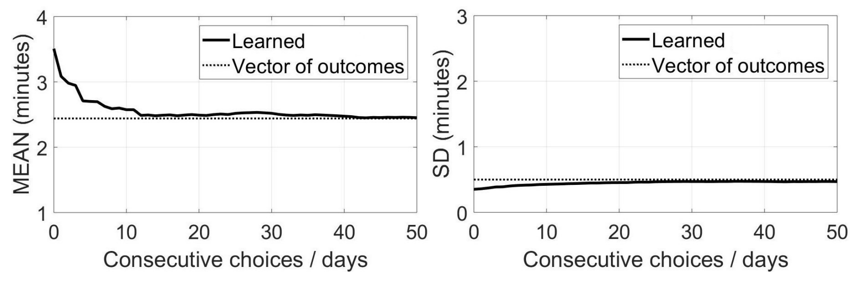

Figure 5.5: *Evolution of* α *(left) and* λ *(right) for PTB.NARR.*

the initial information provided to subjects in the experiment); and finally, the average number of outcomes experienced from these PDFs tends to be smaller than, for instance, the number experienced for *TT.WIDE*, which also has high variance but, being one out of two PDFs for travel times, will tend to have higher average shares than any of the four PDFs for parking times. Maintaining the same LT, the curves of λ for *PTB.WIDE* and *PTW.WIDE* would reach the reference

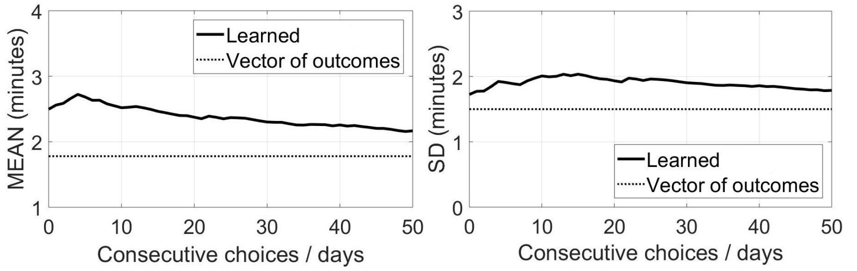

Figure 5.6: *Evolution of α (left) and λ (right) for PTB.WIDE.*

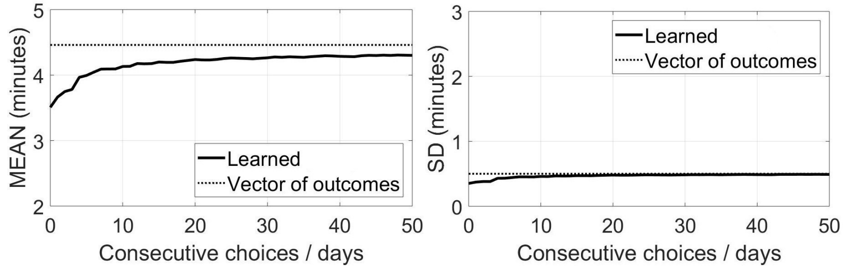

Figure 5.7: *Evolution of α (left) and λ (right) for PTW.NARR.*

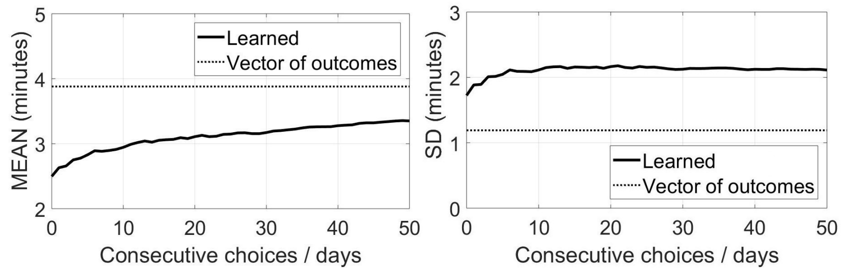

Figure 5.8: *Evolution of α (left) and λ (right) for PTW.WIDE.*

line as more outcomes would be incorporated to the learning mechanism (i.e. acknowledged by the driver).

The initial and final values of α and λ depicted in the graphs are also shown in Tables 5.1 and 5.2, together with the averages of the hyper-parameters across the sample. The values of the mean and standard deviation of the elements in the vectors of outcomes are also shown (in parenthesis, below the values of α and

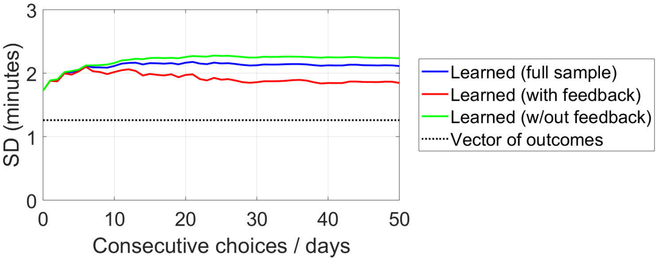

Figure 5.9: *Evolution of λ for PTW.WIDE according to display of feedback.*

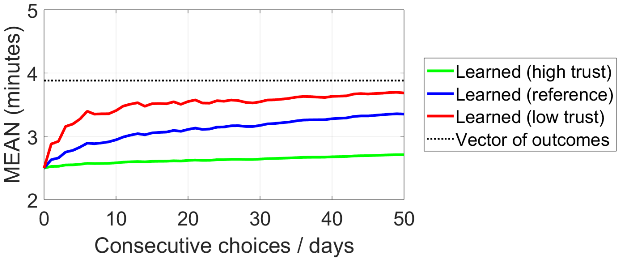

Figure 5.10: *Evolution of α for PTW.WIDE depending on LT.*

λ). As expected, μ_{var} evolves towards zero and σ^2_{df} increases as new outcomes are acknowledged and learning happens.

In both tables, α, λ and the hyper-parameters have the same starting values for those PDFs associated to the same initial information: *TT.NARR* and *TT.WIDE*, *PTB.NARR* and *PTW.NARR*, and finally *PTB.WIDE* and *PTW.WIDE*.

Table 5.1: *Learned parameters and hyper-parameters for travel times.*

Parameter	Day	*TT.NARR* 30+/-5	*TT.NARR* 30+/-10	*TT.WIDE* 30+/-5	*TT.WIDE* 30+/-10
Average of α	0	30.05	29.53	30.05	29.53
	50	31.04	31.20	28.95	29.18
	vector	(31.00)	(31.00)	(29.28)	(29.28)
Average of λ	0	2.21	5.24	2.21	5.24
	50	1.50	3.46	3.30	4.34
	vector	(0.64)	(0.64)	(3.45)	(3.45)
Average of $E(\mu)$	0	3.40	3.37	3.40	3.37
	50	3.43	3.43	3.36	3.36
Average of μ_{mean}	0	3.40	3.37	3.40	3.37
	50	3.43	3.43	3.36	3.36
Average of μ_{var}	0	1.040	1.022	1.040	1.022
	50	0.011	0.008	0.014	0.015
Average of $E(\sigma^2)$	0	0.005	0.031	0.005	0.031
	50	0.002	0.012	0.013	0.022
Average of σ^2_{scale}	0	0.005	0.027	0.005	0.027
	50	0.002	0.011	0.012	0.021
Average of σ^2_{df}	0	15.00	15.00	15.00	15.00
	50	43.05	41.65	43.89	45.77

Table 5.2: *Learned parameters and hyper-parameters for parking times.*

Parameter	Day	*PTB. NARR*	*PTB. WIDE*	*PTW. NARR*	*PTW. WIDE*
Average of α	0	3.51	2.50	3.51	2.50
	50	2.45	2.17	4.30	3.35
	vector	(2.44)	(1.78)	(4.46)	(3.88)
Average of λ	0	0.35	1.72	0.35	1.72
	50	0.47	1.79	0.49	2.11
	vector	(0.50)	(1.50)	(0.50)	(1.19)
Average of $E(\mu)$	0	1.25	0.72	1.25	0.72
	50	0.87	0.51	1.45	1.04
Average of μ_{mean}	0	1.25	0.72	1.25	0.72
	50	0.87	0.51	1.45	1.04
Average of μ_{var}	0	0.141	0.047	0.141	0.047
	50	0.006	0.019	0.010	0.021
Average of $E(\sigma^2)$	0	0.010	0.390	0.010	0.390
	50	0.037	0.481	0.013	0.334
Average of σ^2_{scale}	0	0.009	0.338	0.009	0.338
	50	0.034	0.451	0.012	0.307
Average of σ^2_{df}	0	15.00	15.00	15.00	15.00
	50	30.11	37.57	25.42	28.56

5.5 Considerations

The suitability and performance of the databases produced using the Bayesian approach was tested via the estimation of discrete choice models, presented in Chapter 6.

Nevertheless, the evolution of the parameters as presented and discussed in this chapter is a representation of learning using Bayesian statistics. The fact that the learned curves approach the reference value of a parameter does not necessarily mean that learning is also happening for the subjects in the sample. Neither the use of a specific LT that converges faster necessarily means that it produces a database which will allow the estimation of discrete choice models with higher explanation power. It is worth keeping in mind that, in reality, although the current chapter and the following use the same LT to all subjects, different people might have different degrees of trust in the initial information received, and the "most suitable" LT for a certain person might be different from those tested in this research. Still, it might be that the evolution of the learning process (i.e. the value each learned parameter assumes in time) is different in reality than it is depicted by the Bayesian process. Chapter 7 discusses the topic.

Last but not least, all the analysis of this chapter (and of the following ones) were performed replacing the zero parking time (which occurs for *PTB.WIDE*) with 0.5 minutes (30 seconds). This was necessary because absolute zero is not a value supported by the lognormal distribution.

5.6 Summary

This chapter presented the theoretical background and mathematical formulation of the *Learning Model*, as well as relevant operational aspects of its application to the collected data and the analysis of its outputs.

Drivers' knowledge about travel and parking times was represented as log-normally distributed random variables, which were updated following the Bayes

Theorem. The mean of each of these lognormal distributions was represented by a normal PDF, and the variance by an inverted gamma PDF. Both the normal and the inverted gamma distributions have the advantage of being natural conjugates and relying on a small number of parameters which interpretations are enough intuitive. Since joint estimation of the mean and variance of the random variables is not possible, the estimation was conditional on the knowledge of each other. The supposedly known parameters μ and σ^2 were replaced by the expected values of the distributions of μ and σ^2 updated in the previous day.

For every subject in the sample the learned lognormal distributions of travel and parking times (six in total) were calculated, from day 1 to day 50. The main inputs for calculation were the realizations of travel and parking times faced by subjects, and the prior distributions matching the initial information they received in the instructions of the experiment. These priors were composed of *starting values* for the parameters, directly derived from the initial information provided, and associated initial *measures of reliability*, or levels of trust (LTs). A range of LTs was created, each yielding a different database of subjective distributions to be used for choice model estimation.

An arbitrary LT within this range was used to exemplify the evolution of the learned parameters. The speed and evolution (smoothness) of this process depends on the combination of some factors: distance of the initial guesses from the real parameters, LT adopted for the initial guesses, variability of the data, number of experiences and type of parameter.

6

Choice Model

6.1 Introduction

The *Choice Model*, which is the second component of the proposed model introduced in Section 1.2, is the object of the present chapter. The main inputs for its estimation are the choices provided by the subjects who answered the dynamic experiment, and the subjective distributions of travel and parking times resulting from the *Learning Model* (object of Chapter 5).

A first level exploration of the use of different databases generated by the *Learning Model* (using a range of levels of trust, i.e. LTs) for discrete choice model estimation is done in Section 6.2. The specification of the dynamic choice model, followed by the interpretation of its results are the focus of Sections 6.3 and 6.4, respectively. Additional comments regarding the final and other possible specifications of the model are discussed in Section 6.5. Finally, a summary of the chapter is provided in Section 6.6.

6.2 Exploration

The use of different levels of trust (LTs) for the Bayesian belief updating generates, as already discussed, different databases to be used for choice model estimation. The process of estimating the best possible model[1], therefore, depends on exploring simultaneously a range of model specifications and a range of databases.

It was found that some LTs produce databases that lead to acceptable results for some model specifications, but generate poor outputs when the specifications become more sophisticated, such as non-intuitive signs for the coefficients (e.g. positive sign for the marginal utility of travel time) and flat log-likelihoods.

As an attempt to cope with such puzzle during the model estimation process, a range of 25 LTs – i.e. 25 pairs (μ_{var}^{start}, $\sigma_{df}^{2^{start}}$), was explored for discrete choice model estimation. Five values per hyper-parameter (that when combined produced 25 pairs) were chosen to allow the degree of trust in the initial information to vary within reasonable and realistic limits from high to low. The hyper-parameter μ_{var}^{start} was defined equal to $(b^{start} \cdot \mu_{mean}^{start})^2$ with $b^{start} = (0.01, 0.20, 0.40, 0.60, 0.80)$ – hence, assuming different values for different initial information provided to respondents. The hyper-parameter $\sigma_{df}^{2^{start}}$, on the other hand, did not vary with the initial information provided, and was defined to assume one of the following values: 5, 25, 45, 65 or 85.

Therefore, the degree of trust in the initial information regarding the mean travel or parking time was defined to vary from very high (when $b^{start} = 0.01$)

[1] Restricted, in the context of this chapter, to the use of the outputs of the Bayesian model of learning.

to very low (when $b^{start} = 0.80$). The same happened for the trust in the information regarding the spread (or variance) of the distributions: 85 degrees of freedom represent high trust (mathematically equivalent to having experienced 85 outcomes from the distribution), while 5 represent low trust (accordingly, as if the driver had experienced only 5 outcomes from the distribution).

At first, the 25 databases were tested with the basic random utility maximizing (RUM) specification below:

$$U_{n,t,i} = \phi \cdot (QT)_{n,t,i} + \theta \cdot (TT)_{n,t,i} + \gamma \cdot (PT)_{n,t,i} + \varepsilon_{n,t,i} \tag{6.1}$$

where $U_{n,t,i}$ is the utility of alternative i for individual n at moment (or choice situation) t, and $\varepsilon_{n,t,i}$ is a (generalized extreme value type one[2] distributed) error term which is independently and identically distributed over individuals, time and alternatives. ϕ, θ and γ are respectively the coefficients (to be estimated) representing the weights of the variables $(QT)_{n,t,i}$, $(TT)_{n,t,i}$ and $(PT)_{n,t,i}$ in respondents' decision making. These three variables are the most fundamental attributes of the choice alternatives, and represent respectively the number of times option i had already been chosen by individual n before decision at moment t; the expected value of the learned (subjective) PDF of travel times regarding alternative i for individual n before decision making at moment t; and the expected value of the learned (subjective) PDF of parking times for alternative i and individual n before decision making at time t. $(TT)_{n,t,i}$ and $(PT)_{n,t,i}$ are the same as the variable α from equation 5.8 of Chapter 5.

The 25 databases were used to estimate the above model via log-likelihood maximization[3]. The results are shown in Table 6.1, with all coefficients significant at 99% level of confidence.

For all 25 estimations, the signs of the coefficients were in accordance with the expectations: the marginal utility of past experienced outcomes was positive,

[2] I.e. Gumbel.
[3] The software NLOGIT was used for all model estimations in this chapter.

Table 6.1: *Basic RUM model estimation using different databases.*

			b, $\mu_{var}^{start} = (b \cdot \mu_{mean}^{start})^2$				
			1%	20%	40%	60%	80%
$\sigma_{df}^{2^{start}}$	85	ϕ	0.127	0.124	0.123	0.123	0.122
		θ	-0.082	-0.054	-0.055	-0.054	-0.054
		γ	-0.108	-0.156	-0.152	-0.143	-0.136
		LL	-33971	-33829	-33791	-33781	-33773
		$\bar{\rho}^2$	0.1831	0.1865	0.1874	0.1877	0.1879
	65	ϕ	0.127	0.125	0.123	0.123	0.122
		θ	-0.083	-0.054	-0.055	-0.054	-0.054
		γ	-0.105	-0.156	-0.152	-0.142	-0.136
		LL	-33972	-33831	-33792	-33781	-33774
		$\bar{\rho}^2$	0.1831	0.1865	0.1874	0.1877	0.1878
	45	ϕ	0.128	0.125	0.123	0.123	0.122
		θ	-0.083	-0.054	-0.055	-0.054	-0.054
		γ	-0.100	-0.156	-0.152	-0.143	-0.136
		LL	-33975	-33834	-33794	-33782	-33776
		$\bar{\rho}^2$	0.1830	0.1864	0.1874	0.1876	0.1878
	25	ϕ	0.128	0.125	0.124	0.123	0.123
		θ	-0.085	-0.054	-0.054	-0.054	-0.054
		γ	-0.089	-0.154	-0.152	-0.143	-0.137
		LL	-33980	-33840	-33798	-33786	-33779
		$\bar{\rho}^2$	0.1829	0.1862	0.1872	0.1875	0.1877
	05	ϕ	0.128	0.126	0.125	0.124	0.124
		θ	-0.084	-0.050	-0.051	-0.051	-0.051
		γ	-0.039	-0.140	-0.145	-0.137	-0.130
		LL	-33995	-33874	-33831	-33819	-33813
		$\bar{\rho}^2$	0.1825	0.1854	0.1865	0.1868	0.1869

$LL(null) = -41588.831$
$K = 3$
The goodness-of-fit measure $\bar{\rho}^2$ is calculated as: $1 - [(LL - K)/LL(null)]$

suggesting the effect of habit on decision making, while the marginal utilities for travel and parking times were negative, indicating that longer trips and parking search periods make choice alternatives less attractive.

In Table 6.1, the lower the degree of trust in the initial information regarding the mean travel or parking time (i.e. the closer b^{start} is to 0.80), and the higher the trust in the information regarding the variance of travel or parking times (i.e. the closer $\sigma_{df}^{2^{start}}$ is to 85), the better the model's goodness-of-fit. Accordingly, the databases for which the models had the best and the worst performances were, respectively, the one generated with $b^{start} = 0.80$ and $\sigma_{df}^{2^{start}} = 85$, and the one generated with $b^{start} = 0.01$ and $\sigma_{df}^{2^{start}} = 05$. Besides, changing b^{start} had a stronger impact in the log-likelihoods than changing $\sigma_{df}^{2^{start}}$ (at least for the LTs tested), and this might be due to the fact that the specified model relied only on the learned means α, instead of also depending on the learned standard deviations λ.

For most PDFs, the evolution of α in time (averaged across the sample) for a specific value of b^{start}, is practically the same regardless of the value of $\sigma_{df}^{2^{start}}$. But such is not the case for PDFs with very high variance (i.e. *TT.WIDE*) or very high skewness (i.e. *PTB.WIDE*): lower values for $\sigma_{df}^{2^{start}}$ lead the learned parameter for the standard deviation λ to move further from both (a) the starting point of learning (derived from the initial information provided in the experiment) and (b) the real variance of the experienced outcomes, before it starts approaching the latter, indirectly impacting the learning of the mean α by postponing its convergence with the average of the experienced outcomes. On the other hand, higher values for $\sigma_{df}^{2^{start}}$ lead the learned standard deviation λ to converge more smoothly towards the experienced variability. This is exemplified in Figures 6.1 and 6.2, which show the evolution of the learned mean α and the learned standard deviation λ for *PTB.WIDE*[4], averaged across the sample, for two LTs: $b^{start} = 0.80$ and $\sigma_{df}^{2^{start}} = 85$ (green curve) and $b^{start} = 0.80$ and $\sigma_{df}^{2^{start}} = 05$ (orange curve).

These findings suggest that, for the specification of utility in equation 6.1, and

[4]Which vector of outcomes has mean equal to 1.78 and standard deviation of 1.50.

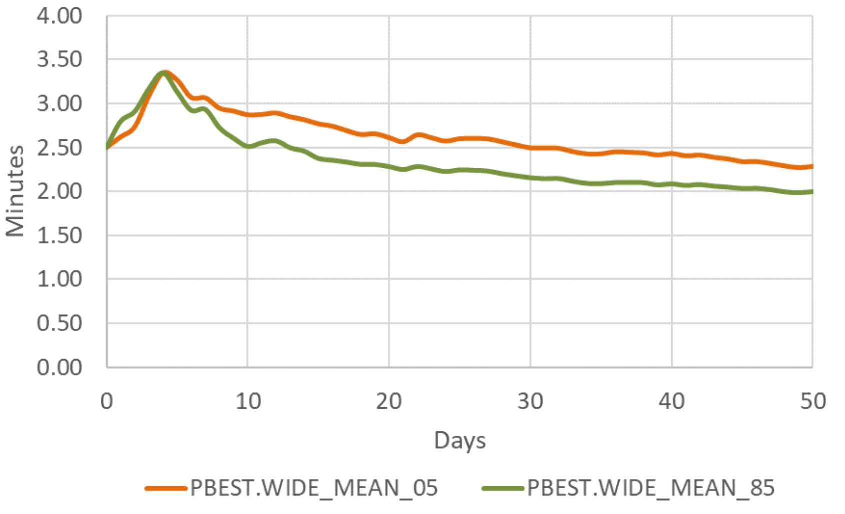

Figure 6.1: *Evolution of α for PTB.WIDE.*

taking into account the algorithm adopted for the Bayesian learning (presented in Section 5.3 of Chapter 5), as well as the way the initial information was translated into probability distributions (described in Section 3.5 of Chapter 3), LTs which allowed the mean α to converge faster were a better representation of respondents' learning outputs. Nevertheless, at least for the results in Table 6.1, this does not mean necessarily that subjects strongly trusted the initial information regarding the variability of travel and parking times.

Later exploration of the 25 databases with other model specifications, including for instance random taste variation and the influence of demographic variables on preferences, showed the same trend, with the best performing models being those with b^{start} equal to either 0.60 or 0.80, and $\sigma_{df}^{2^{start}}$ between 25 and 85. Nevertheless, the database leading to the best performing model varied (within this range) depending on how utility was specified. This might be an indication that there is no unique LT which is suitable for all subjects in the sample, otherwise the database created with this unique LT should always lead to the model with the highest goodness-of-fit no matter the specification of utility used.

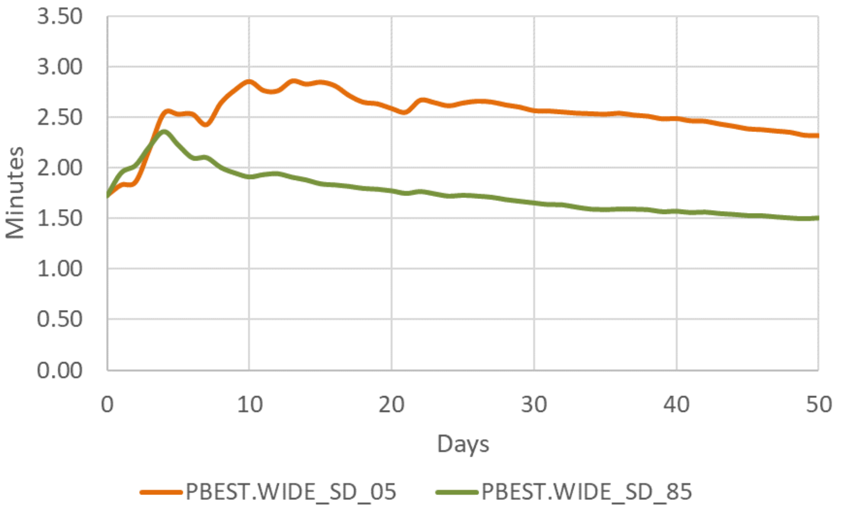

Figure 6.2: *Evolution of λ for PTB.WIDE.*

6.3 Model Specification

The exploration of different utility specifications and databases converged to the final model, the specification of which, is described here (and estimation results are presented in the following subsection): a random utility maximizing model accounting for random (unobserved) and systematic (observed) taste variation, correlations within the sequence of choices of the same individual (also referred to as *panel effect*), and correlations among unobserved variables shared by the choice options (also referred to as *error components*). The utility function of choice alternative i for subject n on day t was specified as:

$$\begin{aligned} U_{n,t,i} = {} & \Omega_{pos_1} \cdot (pos_1)_i + \Omega_{pos_2} \cdot (pos_2)_i + \Omega_{pos_3} \cdot (pos_3)_i + \\ & \Delta_{tt.na} \cdot (tt.na)_i + \Delta_{tt.wi} \cdot (tt.wi)_i + \\ & \Delta_{pt.na} \cdot (pt.na)_i + \Delta_{pt.wi} \cdot (pt.wi)_i + \\ & \Phi_{QT} \cdot (QT)_{n,t,i} + \Theta_{TT} \cdot (TT)_{n,t,i} + \Gamma_{PT} \cdot (PT)_{n,t,i} + \varepsilon_{n,t,i} \end{aligned} \quad (6.2)$$

where the error term $\varepsilon_{n,t,i}$ is independently and identically extreme value type one (Gumbel) distributed over individuals, time and alternatives, and the other coefficients are described in the following subsections.

6.3.1 Position in the choice menu

The coefficients Ω_{pos_1}, Ω_{pos_2} and Ω_{pos_3} are normally distributed random coefficients that vary across individuals, but are constant within the sequence of decisions of the same subject – capturing therefore the panel effect. Their means and standard deviations (to be estimated) are: $\Omega_{pos_1} \sim N(\beta_{pos_1}, \omega_{pos_1})$, $\Omega_{pos_2} \sim N(\beta_{pos_2}, \omega_{pos_2})$ and $\Omega_{pos_3} \sim N(\beta_{pos_3}, \omega_{pos_3})$.

They multiply the dummy variables pos_1, pos_2 and pos_3, which equal one if the alternative was (respectively) the first, second or third to be displayed in the choice menu of the experiment, and zero if it was the fourth (as can be seen in Figure 5).

These coefficients intend to capture any possible influence the position in the menu might have had. Figures 4.5 to 4.8 in Chapter 4 suggest that, at least for the first decisions subjects made, the position plays a role. The coefficients are not intended, however, to label the alternatives, since the experiment was unlabelled and (most importantly) the assignment scheme of PDFs of parking times changed across the profiles (e.g. alternative RAPA1 was associated to *PTB.WIDE* in profile 1, and to *PTW.WIDE* in profile 7).

6.3.2 Error components

In equation 6.2, *tt.na*, *tt.wi*, *pt.na* and *pt.wi* are dummy variables which identify, respectively: the choice alternatives which used *TT.NARR* as the PDF for travel times (RAPA1 and RAPA2); the alternatives with travel times following *TT.WIDE* (RBPB1 and RBPB2); the options which PDFs for parking times had small variances, i.e. were either *PTB.NARR* or *PTW.NARR* (RAPA2 and

RBPB2); and finally the options which PDFs for parking times had high variances, i.e. were either *PTB.WIDE* or *PTW.WIDE* (RAPA1 and RBPB1).

The corresponding coefficients ($\Delta_{tt.na}$, $\Delta_{tt.wi}$, $\Delta_{pt.na}$ and $\Delta_{pt.wi}$) are random and vary across individuals and time. They were specified to be normally distributed with zero means and standard deviations to be estimated: $\Delta_{tt.na} \sim N(0, \delta_{tt.na})$, $\Delta_{tt.wi} \sim N(0, \delta_{tt.wi})$, $\Delta_{pt.na} \sim N(0, \delta_{pt.na})$, and $\Delta_{pt.wi} \sim N(0, \delta_{pt.wi})$.

This portion of the utility function aims at testing the correlation among unobserved attributes shared by groups of choice alternatives, i.e. those alternatives connected to Route A (or Route B), and those located either on the right or the left side of the work location.

6.3.3 Dynamic taste variation

The variables QT, TT and PT have already being introduced in the previous section. In this specification, however, their coefficients follow bounded triangular density functions[5]. The random coefficient Φ_{QT} has mean equal to ϕ_{mean} and limit of the triangular equal to ϕ_{lim}, hence assuming values within the interval $[\phi_{mean} - \phi_{lim}, \phi_{mean} + \phi_{lim}]$. The random coefficient Θ_{TT}, on its turn, has mean equal to θ_{mean} and limit θ_{lim}, while Γ_{PT} has mean γ_{mean} and limit γ_{lim}.

The terms $\Phi_{QT} \cdot (QT)_{n,t,i}$, $\Theta_{TT} \cdot (TT)_{n,t,i}$ and $\Gamma_{PT} \cdot (PT)_{n,t,i}$ (in equation 6.2) each create a different environment for the evolution of the preferences in the model, as shown by equations 6.3 to 6.5, which depict the systematic heterogeneity

[5]The use of bounded triangular distributions produced superior results than the use of other (restricted or unrestricted) distributions, such as normal or uniform.

in the means of the random coefficients Φ_{QT}, Θ_{TT} and Γ_{PT}, respectively.

$$\begin{aligned}\phi_{mean} = {} & \phi_{cte} + \phi_{lic} \cdot (\text{lic})_n + \phi_{gen} \cdot (\text{gen})_n + \phi_{edu.b} \cdot (\text{edu.b})_n + \\ & \phi_{edu.m} \cdot (\text{edu.m})_n + \phi_{inc.l} \cdot (\text{inc.l})_n + \phi_{inc.m} \cdot (\text{inc.m})_n + \\ & \phi_{full} \cdot (\text{full})_n + \phi_{part} \cdot (\text{part})_n + \phi_{frq.l} \cdot (\text{frq.l})_n + \\ & \phi_{frq.m} \cdot (\text{frq.m})_n + \phi_{dur.d} \cdot (\text{dur.d})_n + \phi_{dur.p} \cdot (\text{dur.p})_n\end{aligned} \tag{6.3}$$

$$\begin{aligned}\theta_{mean} = {} & \theta_{cte} + \theta_{lic} \cdot (\text{lic})_n + \theta_{gen} \cdot (\text{gen})_n + \theta_{edu.b} \cdot (\text{edu.b})_n + \\ & \theta_{edu.m} \cdot (\text{edu.m})_n + \theta_{inc.l} \cdot (\text{inc.l})_n + \theta_{inc.m} \cdot (\text{inc.m})_n + \\ & \theta_{full} \cdot (\text{full})_n + \theta_{part} \cdot (\text{part})_n + \theta_{frq.l} \cdot (\text{frq.l})_n + \\ & \theta_{frq.m} \cdot (\text{frq.m})_n + \theta_{dur.d} \cdot (\text{dur.d})_n + \theta_{dur.p} \cdot (\text{dur.p})_n + \\ & \theta_{info} \cdot (\text{info})_n + \theta_{fbck} \cdot (\text{fbck})_n + \theta_{qt} \cdot (QT)_{n,t,i} + \\ & \theta_{var.tt} \cdot (\mu_{var.tt})_{n,t,i} + \theta_{var.pt} \cdot (\mu_{var.pt})_{n,t,i}\end{aligned} \tag{6.4}$$

$$\begin{aligned}\gamma_{mean} = {} & \gamma_{cte} + \gamma_{lic} \cdot (\text{lic})_n + \gamma_{gen} \cdot (\text{gen})_n + \gamma_{edu.b} \cdot (\text{edu.b})_n + \\ & \gamma_{edu.m} \cdot (\text{edu.m})_n + \gamma_{inc.l} \cdot (\text{inc.l})_n + \gamma_{inc.m} \cdot (\text{inc.m})_n + \\ & \gamma_{full} \cdot (\text{full})_n + \gamma_{part} \cdot (\text{part})_n + \gamma_{frq.l} \cdot (\text{frq.l})_n + \\ & \gamma_{frq.m} \cdot (\text{frq.m})_n + \gamma_{dur.d} \cdot (\text{dur.d})_n + \gamma_{dur.p} \cdot (\text{dur.p})_n + \\ & \gamma_{info} \cdot (\text{info})_n + \gamma_{fbck} \cdot (\text{fbck})_n + \gamma_{qt} \cdot (QT)_{n,t,i} + \\ & \gamma_{var.tt} \cdot (\mu_{var.tt})_{n,t,i} + \gamma_{var.pt} \cdot (\mu_{var.pt})_{n,t,i}\end{aligned} \tag{6.5}$$

The limits of the triangular distributions, ϕ_{lim}, θ_{lim} and γ_{lim}, are specified to be equal to the absolute values of ϕ_{cte}, θ_{cte} and γ_{cte} (respectively).

The random coefficient Φ_{QT} is related to the strength of habit in decision making, as it changes utility by the simple fact that a new outcome is experienced.

Its average, ϕ_{mean}, systematically varies across the sample, assuming different values depending on the demographic characteristics and the real-life driving routines of each individual – it is, however, invariant across choice alternatives and time[6].

The random coefficients Θ_{TT} and Γ_{PT}, on the other hand, explain the weight of expected travel and parking times on decision making. Their averages, θ_{mean} and γ_{mean}, besides depending on demographic characteristics and real-life driving routines of each individual (as it happens for ϕ_{mean}), also rely on experiment design attributes, and evolve as drivers accumulate experience (by depending on QT) and learn the distributions of travel and parking times (by varying with $\mu_{var.tt}$ and $\mu_{var.pt}$). Hence, θ_{mean} and γ_{mean} systematically vary across individuals, alternatives and time.

The variables in equations 6.3 to 6.5 are described below.

(a) Demographic variables: time in possession of drivers' license (lic), measured in years; gender (gen), which equals 1 for man and -1 for woman; level of education, effect coded with three levels: basic (edu.b=1, edu.m=0), medium (edu.b=0, edu.m=1), and higher/university level (edu.b=-1, edu.m=-1); net individual monthly income, effect coded variable also with three levels: low[7] (inc.l=1, inc.m=0), medium (inc.l=0, inc.m=1) and high (inc.l=-1, inc.m=-1); occupation, effect codded with three levels: full time worker[8] (full=1, part=0), part time worker (full=0, part=1), and student (full=-1, part=-1).

(b) Real-life driving routines: frequency of driving to work/study, effect coded variable with three levels: low [9] (frq.l=1, frq.m=0), medium (frq.l=0, frq.m=1) and high frequency (frq.l=-1, frq.m=-1); driving time to work/study (dur.d), measured in minutes; parking search time (dur.p), also measured in minutes.

[6] Instead, it is the product $[\Phi_{QT} \cdot QT]$ that varies with time.

[7] Low income: less than 1251 euros/month; medium income: between 1251 and 2500 euros/month; high income: more than 2500 euros/month.

[8] Full time worker: more than 32 hours/week; part time worker: up to 32 hours/week.

[9] Low frequency: less than 2 days/week; medium frequency: 2 or 3 days/week; high frequency: more than 3 days/week.

(c) Experiment design attributes: initial information provided regarding travel times (info), effect codded with two levels: 1 for *30+/-5 minutes*, and -1 for *30+/-10 minutes*; display of feedback on foregone options (fbck), effect coded with two levels: 1 for yes and -1 for no.

(d) Accumulated experience: number of times subject n chose alternative i before the decision on day t (QT). This variable is a proxy of the value of the hyper-parameter σ^2_{df} at the moment of the new choice, thus also representing the evolution of the learning process.

(e) Status of learning: variance of individual n's subjective distribution for the average travel and parking time of alternative i before decision making on day t, respectively $\mu_{var.tt}$ and $\mu_{var.pt}$ – as defined in Section 5.3[10].

The remaining two experiment design attributes, *strategy to extract* and *scheme of assignment of PDFs of parking times*, were not included in the specification. In fact, the former cannot be tested in the desegregated level, since the strategy *outcome of the day* implies the use of multiple levels (i.e. multiple sequences of outcomes) for the attribute – as many levels as subjects in the experiment. The effects of the design attribute *strategy to extract* were then tested in the aggregated level (i.e. on the shares of the choice options) in Section 4.4.

With regards to the design attribute *scheme of assignment of PDFs of parking times*, testing its impact on decision making could be done by creating dummy (or effect coded) variables indicating (a) whether an alternative was associated to one or another pair of PDFs for parking times (i.e. either with *PTB.WIDE* and *PTB.NARR*, or with *PTW.WIDE* and *PTW.NARR*), and whether (b) an alternative was associated to *TT.WIDE* or *TT.NARR*. This solution, however, would be equivalent to labelling the alternatives, and hence was not included in the final utility specification. It is expected that subjects are able to differentiate

[10] For ease of interpretation of the corresponding coefficients, $\mu_{var.tt}$ and $\mu_{var.pt}$ were standardized for each decision maker and PDF, thus always being equal to one before the first outcome is experienced, and converging towards zero as experience is accumulated.

the alternatives using the knowledge they acquire during the experiment about the distributions of travel and parking times, and hence a utility specification relying on the parameters of the subjective PDFs was preferred over specifications that depend on creating labels.

The variables QT, $\mu_{var.tt}$ and $\mu_{var.pt}$ are updated as respondents make choices, "granting" the dynamic character of the preferences for travel and parking times.

6.4 Results and Interpretation

The specification exposed in the previous subsection was estimated via simulated maximum likelihood using 1000 halton draws for the simulated probabilities[11].

The estimation was replicated using the databases generated with b^{start} equal to 0.60 and 0.80, and $\sigma_{df}^{2^{start}}$ equal to 25, 45, 65 and 85 (summing up eight databases in total)[12].

All databases resulted in successfully estimated models, with the coefficients ϕ_{cte}, θ_{cte} and γ_{cte} significant at 99% level of confidence and with the expected signs, although differences in signs and significance for other coefficients were observed (besides the obvious differences in magnitudes, the case for all coefficients).

Within the eight replications of the model, the database which lead to the best fit (highest log-likelihood) was, differently from what happened to the specification in equation 6.1 (see Section 6.2), the one generated with $b^{start} = 0.60$ and $\sigma_{df}^{2^{start}} = 65$. The results are shown in Table 6.2.

Most estimated coefficients in Table 6.2 are significant at 95% level of confidence, including the limits of the triangular distributions, ϕ_{lim}, θ_{lim} and γ_{lim}, confirming the hypothesis that the coefficients Φ_{QT}, Θ_{TT} and Γ_{PT} are in fact random.

[11] And performing the estimation in the software NLOGIT.

[12] As observed in the previous section, these databases lead to the models with the best goodness-of-fit, across a variety of specifications.

Table 6.2: *Estimated coefficients and model fit for final model.*

Coef.	Value	p-value	Coef.	Value	p-value	Coef.	Value	p-value
β_{pos_1}	1.3668	.00	β_{pos_2}	1.7202	.00	β_{pos_3}	.0564	.21
ω_{pos_1}	.8598	.00	ω_{pos_2}	1.0819	.00	ω_{pos_3}	.7454	.00
ϕ_{cte}	.3102	.00	θ_{cte}	-.9277	.00	γ_{cte}	-1.8487	.00
ϕ_{lim}	.3102	.00	θ_{lim}	.9277	.00	γ_{lim}	1.8487	.00
ϕ_{lic}	-.0031	.00	θ_{lic}	.0063	.00	γ_{lic}	.0208	.00
ϕ_{gen}	-.0049	.20	θ_{gen}	.0002	.99	γ_{gen}	-.0436	.15
$\phi_{edu.b}$	.0390	.00	$\theta_{edu.b}$	-.1200	.03	$\gamma_{edu.b}$	-.8389	.00
$\phi_{edu.m}$	-.0108	.04	$\theta_{edu.m}$	-.0013	.97	$\gamma_{edu.m}$	.2773	.00
$\phi_{inc.l}$	-.0156	.08	$\theta_{inc.l}$	.1952	.00	$\gamma_{inc.l}$	.3151	.00
$\phi_{inc.m}$	-.0498	.00	$\theta_{inc.m}$	-.0352	.19	$\gamma_{inc.m}$	.0319	.46
ϕ_{full}	-.0746	.00	θ_{full}	.2072	.00	γ_{full}	.3006	.00
ϕ_{part}	-.0186	.02	θ_{part}	.1414	.00	γ_{part}	-.0675	.24
$\phi_{frq.l}$	-.0400	.00	$\theta_{frq.l}$	.0783	.06	$\gamma_{frq.l}$	.3074	.00
$\phi_{frq.m}$	-.0087	.13	$\theta_{frq.m}$	-.0473	.14	$\gamma_{frq.m}$	-.1937	.00
$\phi_{dur.d}$	-.0028	.00	$\theta_{dur.d}$	-.0015	.21	$\gamma_{dur.d}$	.0043	.01
$\phi_{dur.p}$	-.0010	.00	$\theta_{dur.p}$	.0091	.00	$\gamma_{dur.p}$	.0191	.00
			θ_{qt}	-.0325	.00	γ_{qt}	-.0219	.00
$\delta_{tt.na}$	.1457	.92	$\theta_{var.tt}$	-.6907	.00	$\gamma_{var.tt}$	-.6292	.00
$\delta_{tt.wi}$	.1725	.92	$\theta_{var.pt}$	.3622	.00	$\gamma_{var.pt}$	.4893	.00
$\delta_{pt.na}$	.1370	.92	θ_{info}	.0010	.96	γ_{info}	-.0039	.87
$\delta_{pt.wi}$	1.3422	.49	θ_{fbck}	-.0967	.00	γ_{fbck}	-.0684	.01

$LL(final) = -30860.081$	χ^2 [59 d.f.] = 21457.500, p-value = 0.00
$LL(null) = -41588.831$	Halton sequences, 1000 draws
$K = 59$, $\bar{\rho}^2 = 0.2566$	600 groups, 50 obs./group, 30000 obs. in total

The coefficients measuring the influence of alternatives' position in the choice menu[13] (Ω_{pos_1}, Ω_{pos_2} and Ω_{pos_3}), have their means and standard deviations statistically significant (apart from β_{pos_3}). The fact that the magnitude of β_{pos_2} is higher than that of β_{pos_1}, summed to the fact that the three standard deviations (ω_{pos_1}, ω_{pos_2} and ω_{pos_3}) are high in comparison to the means (β_{pos_1}, β_{pos_2} and

[13]Which was the same for the entire experiment, i.e. RAPA1 occupying the first position, followed by RAPA2, then by RBPB1 and finally by RBPB2, as shown in Appendix A.

β_{pos_3}), suggest that these coefficients are capturing not only the influence of the position of the alternative in the menu, but also reflect other preferences (heterogeneous among subjects) that were not represented by the other terms in the specification of utility. It might also be that, even though the experiment was unlabelled, because choice alternatives have very specific characteristics, respondents might have (after learning these characteristics) subjectively attributed labels (to the choice alternatives), and in this sense the coefficients Ω_{pos_1}, Ω_{pos_2} and Ω_{pos_3} would reflect subjects' preferences for these labels – further interpretations in this direction, however, need to take into account that the association scheme of PDFs to choice alternatives varied across the experiment profiles.

The estimated standard deviations of the error components ($\delta_{tt.na}$, $\delta_{tt.wi}$, $\delta_{pt.na}$ and $\delta_{pt.wi}$) are all not statistically significant, revealing no correlation among unobserved characteristics of the choice alternatives.

The model's final $\bar{\rho}^2$, which is calculated using the null log-likelihood as reference, and adjusted to control for the number of coefficients, equals 0.2566. Log-likelihood ratio tests showed the specification used is superior than other specifications tried with the same database, including those without the error components, without the random coefficients indicating the influence of the choice alternative's position in the menu, and those not accounting for heterogeneity in the mean of the random coefficients.

An alternative database for belief updates was generated using the weighted average approach (as described in Subsection 2.2.1), assuming uniform weights for the outcomes experienced and unlimited memory. A model was estimated using this database and the same specification described in Section 6.3 – although not accounting for the influence of the status of the learning process, i.e. without including the hyper-parameters $\mu_{var.tt}$ and $\mu_{var.pt}$ and the corresponding coefficients in equations 6.4 and 6.5. Results of a log-likelihood ratio test suggested that this model is inferior to the one in Table 6.2.

6.4.1 Effect of habit

A thorough analysis of the results confirms that, the more experiences individuals have with a certain alternative, the more prone they are to choose it again: the value of ϕ_{mean} calculated (using equation 6.3) for all 600 subjects in the sample is on average 0.1066.

This coefficient has a tendency to increase, becoming stronger the effect of habit on decision making, (a) the lower the education level, (b) the higher the income, (c) for students (rather than for workers), (d) and the higher the frequency of driving to work or the study location. On the other hand, the impact of habit on decision decreases (e) the more driving experience the subject has (measured in years possessing a license) and (f) the longer are the subject's real-life driving and parking search times.

Taking the value of ϕ_{mean} calculated to each of the 600 respondents, together with the estimated value for ϕ_{lim}, the cumulative probability of $\Phi_{_{QT}}$ being negative, i.e. Prob($\Phi_{_{QT}} < 0$) was computed, and its average across the sample equals 24.77%. Because the calculation of ϕ_{mean} depends only on the characteristics of the individuals, which are static across the experiment, the probability of $\Phi_{_{QT}}$ being negative is constant during all 50 days.

6.4.2 Preferences for travel and parking times

When it comes to the marginal utilities of travel and parking times, calculating θ_{mean} and γ_{mean} across the full sample (using equations 6.4 and 6.5) yields, respectively, averages of -0.6658 and -0.7801. These results are in line with the presumption that, the higher the expected travel and parking times, the less willing the driver is to choose the corresponding alternative.

Similar to what was done for $\Phi_{_{QT}}$, the probabilities of $\Theta_{_{TT}}$ and $\Gamma_{_{PT}}$ being positive were calculated. Taking the values of θ_{mean} and γ_{mean} for every respondent, choice alternative and day, and using the values of θ_{lim} and γ_{lim},

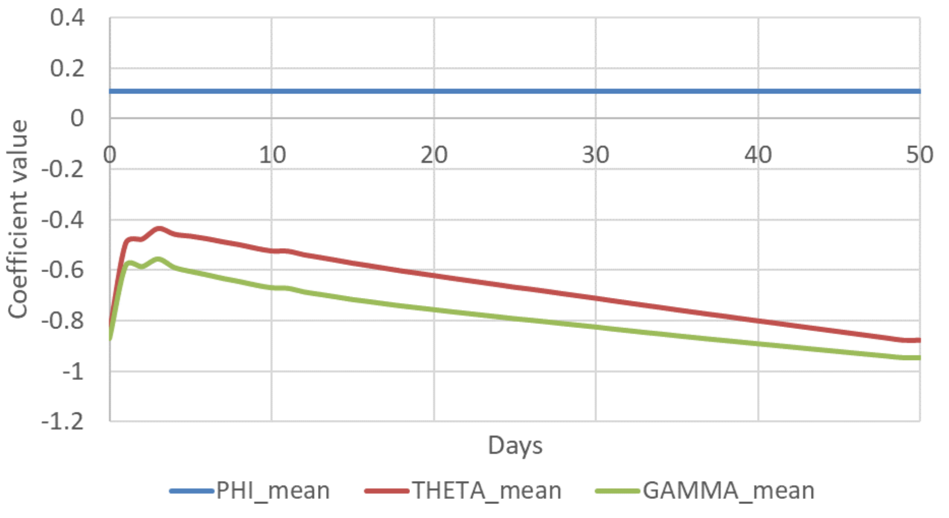

Figure 6.3: *Evolution of* ϕ_{mean}*,* θ_{mean} *and* γ_{mean}*.*

yielded the following averages across the sample: $\text{Prob}(\Theta_{TT} > 0) = 10.15\%$ and $\text{Prob}(\Gamma_{PT} > 0) = 20.43\%$.

Differently to what occurs with Φ_{QT}, the probabilities of Θ_{TT} and Γ_{PT} being positive decrease as time passes, due to the impact of experience (QT) in decreasing both θ_{mean} and γ_{mean}. At day 50, the average across the sample of $\text{Prob}(\Theta_{TT} > 0)$ equals 5.71%, while the average of $\text{Prob}(\Gamma_{PT} > 0)$ equals 16.05%.

Figures 6.3 and 6.4 depict, respectively, the evolution in time of the averages across the sample for θ_{mean} and γ_{mean} (and also show the average for ϕ_{mean}, which is constant), and the evolution of the averages across the sample of $\text{Prob}(\Theta_{TT} > 0)$, $\text{Prob}(\Gamma_{PT} > 0)$ and $\text{Prob}(\Phi_{QT} < 0)$ – the latter being constant.

A thorough analysis of the elements which compose θ_{mean} and γ_{mean} follows.

Evolution with experience and learning

Subjects in the sample seem to become more intolerant towards travel and parking times (i.e. Θ_{TT} and Γ_{PT} decrease) the more experience with the alternative they have (i.e. the higher QT becomes), as if the more consolidated their habits, the

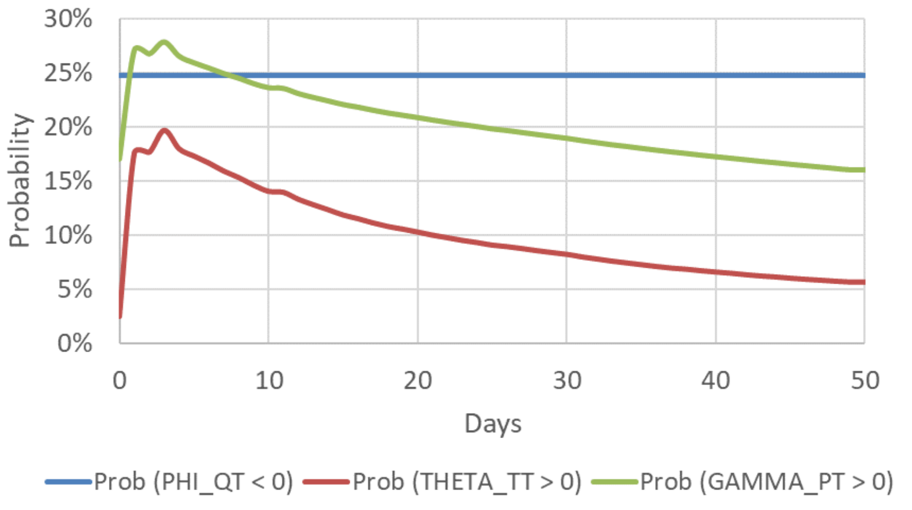

Figure 6.4: *Evolution of probabilities of* $\Phi_{QT} < 0$, $\Theta_{TT} > 0$ *and* $\Gamma_{PT} > 0$.

more critic about their choices subjects would become. This is shown by the negative signs of θ_{qt} and γ_{qt}.

The estimated values for $\theta_{var.tt}$, $\theta_{var.pt}$, $\gamma_{var.tt}$ and $\gamma_{var.pt}$ indicate that the impact of the status of the learning process for the distributions of travel times is in the opposite direction of the effect of the status of the learning process for the distributions of parking times. The more individuals have learned about the distribution of travel times for a specific alternative, the more tolerant they become towards both its travel and parking times. As learning takes place and (the normalized value of) $\mu_{var.tt}$ converges from one to zero, the (negative) influence of $\theta_{var.tt}$ and $\gamma_{var.tt}$ respectively on θ_{mean} and γ_{mean} fades away. On the other hand, the more individuals have learned about the distribution of parking times for a specific alternative, the more intolerant they become towards both its travel and parking times. As learning happens and the normalized value of $\mu_{var.pt}$ approaches zero, the (positive) impact of $\theta_{var.pt}$ on θ_{mean} and of $\gamma_{var.pt}$ on γ_{mean} disappears. In all cases, the faster learning happens, the faster the effects fade.

These apparently contradictory influences, when combined, lead θ_{mean} and

γ_{mean} to decrease when both the distributions of travel and parking times are still unknown, since $\theta_{var.tt} \cdot \mu_{var.tt} + \theta_{var.pt} \cdot \mu_{var.pt} = -0.3285$, and $\gamma_{var.tt} \cdot \mu_{var.tt} + \gamma_{var.pt} \cdot \mu_{var.pt} = -0.1399$, with $\mu_{var.tt}$ and $\mu_{var.pt}$ equal to one. On the other hand, when both distributions have been learned, the values of θ_{mean} and γ_{mean} increase, given that $\mu_{var.tt}$ and $\mu_{var.pt}$ are equal to zero, therefore $\theta_{var.tt} \cdot \mu_{var.tt} + \theta_{var.pt} \cdot \mu_{var.pt} = 0$ and $\gamma_{var.tt} \cdot \mu_{var.tt} + \gamma_{var.pt} \cdot \mu_{var.pt} = 0$.

A possible interpretation for the findings above is that, not knowing the distributions of travel and parking times increases the burden of deciding and hence makes the marginal utilities of travel and parking times smaller (i.e. more negative).

Influence of experiment design attributes

From the estimated values for θ_{fbck} and γ_{fbck} in Table 6.2, it can be interpreted that individuals who were exposed to the outcomes of faster foregone options assign lower marginal utilities for travel and parking times. These results suggest that, the more informed decision makers are, the more critic they become about their new choices. This is in accordance with the effects of $[\theta_{qt} \cdot QT]$ on θ_{mean} and of $[\gamma_{qt} \cdot QT]$ on γ_{mean}, as subjects who were faced with the outcomes of foregone options on average acknowledge a higher number of outcomes per decision made, meaning that their variable QT grows faster.

When it comes to the effects of the initial information regarding travel times, the estimated values for θ_{info} and γ_{info} show that receiving either the information *30+/-5 minutes* or *30+/-10 minutes* has no significant influence on the marginal utilities of travel and parking times.

Influence of demographic variables

The analysis of the effect of demographic variables on θ_{mean} shows that individuals become more tolerant towards travel times: (a) the higher their education level, (b) the lower their income (as it is expected that people with higher wages are more sensitive to travel times), (c) for workers rather than for students, (d) the lower the frequency of driving to work or the study location, (e) the more experienced drivers respondents are, and (f) the higher their usual parking search times in real life.

Regarding the impact of demographic characteristics on γ_{mean}, it was found, similarly to travel times, that subjects are more tolerant towards parking times: (a) the higher their education level, (b) the lower their income (the same reasoning applies: people with higher income might be more sensitive to parking times), (c) for full time workers, (d) the lower the frequency of driving to work or study, (e) the more experienced drivers respondents are (here again, the hypothesis is that more experience is related to less sensitivity), and (f) the higher their usual travel and parking search times in real life. However, the impacts of these variables on γ_{mean} tend to be stronger in magnitude than they are for θ_{mean}.

If the impacts of the demographic and real-life driving variables on θ_{mean} and γ_{mean} are compared to their impacts on ϕ_{mean}, an interesting pattern emerges: the more tolerant subjects are towards travel and parking times, the lower ϕ_{mean} becomes, and the more intolerant towards travel and parking times, the higher ϕ_{mean} becomes – as if more tolerant individuals would take longer to develop habits, maybe because they are more willing to explore the available options. Being more prone to explore the available options might be associated with being less negatively impacted when experiencing (especially high) travel and parking times. Another possible explanation is that more sensitive drivers are more critical in their decision making process, hence realizing their preferences and developing habits faster. This relation seems to hold for all demographic and real-life driving variables in the estimated model, and is in accordance with the fact that (as observed earlier during the interpretation of the results) an increase in the variable QT causes simultaneously the strengthening of the effect of habit and an increase in the intolerance towards travel and parking times (given that their marginal utilities decrease).

6.5 Additional Comments

6.5.1 The twofold role of accumulated experience

The accumulated experience, represented by the variable QT, has a double role in the evolution of utilities. On one hand it strengthens habit, and on the other it makes individuals more intolerant towards expected travel and parking times. These effects, however, compensate each other in the composition of utility: Φ_{QT}, which is time invariant, multiplies a variable which is constantly growing with experience (i.e. QT), while Θ_{TT} and Γ_{PT}, which continuously decrease as experience is accumulated (i.e. as QT grows), multiply variables that, once learned, become constants (i.e. TT and PT).

Some of the models specified previously for this dissertation, were built upon the expectation that accumulated experience would play an indirect role in the choice model, via its incorporation exclusively in the learning model. The hypothesis was that the updated learned distributions of travel and parking times would suffice for drivers' decision making, and habit would arise as the parameters of the subjective distributions would be learned (i.e. when μ_{var} approached zero, and σ^2_{df} was high enough) and the utilities of the choice alternatives would become constant. This expectation, however, was proven wrong as specifications of utility without the explicit incorporation of the variable QT persistently resulted in inferior models.

6.5.2 Feedback on foregone options and ex-post regret

Specifications for the utility function which included the differences in realized attributes (i.e. travel and parking times) between the chosen alternative and the fastest foregone option were also created. The objective was to test the effects of ex-post regrets on future decisions.

Results revealed that these differences in attributes increased (instead of decreased) the utility of the outperformed option, since their coefficients (marginal utilities) had a positive sign. This finding was common to all specifications tested for ex-post regret, for instance by adding to the utility function of subject n evaluating alternative i before decision making on day t the term: $-max\{0, \eta \cdot [(TT^{real}_{n,t-1,j} + PT^{real}_{n,t-1,j}) - (TT^{real}_{n,t-1,i} + PT^{real}_{n,t-1,i})]\}$ to account for ex-post regret relative to the differences in total times, or the terms: $-max\{0, \eta_{TT} \cdot (TT^{real}_{n,t-1,j} - TT^{real}_{n,t-1,i})\} - max\{0, \eta_{PT} \cdot (PT^{real}_{n,t-1,j} - PT^{real}_{n,t-1,i})\}$, to account for ex-post regret relative to travel and parking times separately – where j was the fastest foregone alternative on day $t-1$ when alternative i was chosen, TT^{real} and PT^{real} are the realizations of travel and parking times (of either alternative i or j acknowledged by subject n after decision on day $t-1$), and η, η_{TT} and η_{PT} are the coefficients to be estimated. Equivalent specifications for ex-post rejoice were also tested[14], and the differences in attributes leading to rejoice also increased the utility of the chosen option (i.e. had coefficients with positive signs).

Instead of revealing a negative impact of experienced regret (which would penalize the choice alternative by reducing its utility), the estimated coefficients (such as η, η_{TT} and η_{PT}) seem to confirm the subject's previous choice and preference for a specific alternative.

A behavioural interpretation for the apparent absence of ex-post regret is that, for dynamic contexts, learning requires experimenting the options available and risking to get non-optimal outcomes. In this sense, regret avoidance plays against learning. Another possible interpretation is that, after learning the distributions of the uncertain attributes, subjects who develop a preference for risky alternatives are aware of the pros and cons their choices might bring (such as the chosen option eventually being outperformed), the cons not being enough to weaken their preferences.

[14] Since the foregone alternative displayed was the one with the lowest total time, meaning that it was possible that either the travel or the parking time of the chosen option would have been smaller than those of the foregone.

6.5.3 Variance of the learned PDFs

The attribute λ^2, which represents the learned variance of the subjective distributions (see equation 5.9 in Chapter 5), was not included in the final model specification because, differently from the expected travel and parking times (i.e. TT and PT), analysing the effects of the variance on decision making is not straightforward.

Including the learned variances in the specification of utility (either directly or interacting with the learned means of the subjective distributions) is not a good strategy, since the design of the experiment does not offer enough variation of combinations of means and variances for the PDFs. For instance, in all experiment profiles, the route with the smallest average has the highest variance (Route B), and the one with the highest average has the smallest variance (Route A), as depicted in Table 3.1.

An appropriate way to evaluate the impact of the learned variances on decision making is under the perspective of anticipated regrets. The development of such models, however, requires to incorporate covariates to the specification of regrets (in order to explore systematic heterogeneity in choice behaviour) and to use either the $max(max)$[15] or the $sum(max)$[16] formulations for anticipated regrets – since the logarithm formulation[17] is not suitable when the differences in attributes are small in magnitude as it happens in this research, as it might compute regret when in fact it did not exist. This effort, however, is outside the scope of this research.

6.5.4 The iterative process towards the (final) choice model

As mentioned earlier in this chapter, the path that led to the results in Table 6.2 required the simultaneous exploration of the databases generated with different levels of trust (LTs), and a diversity of specifications for utility. More specifically,

[15] As introduced in the travel behaviour literature by Chorus *et. al* (2008b).
[16] As done for instance by Rasouli & Timmermans (2019).
[17] Proposed by Chorus (2010).

the process was iterative: departing from a basic specification (such as the one in equation 6.1), estimation was replicated for the 25 databases. Results were then analysed and a new specification was created, and again estimated with the 25 databases. This process went on until strong enough evidences were found to either rule out specifications or databases which consistently led to the poorest model fits or to non-intuitive marginal utilities for the most fundamental variables (QT, TT and PT). The iterative process then continued using a smaller number of databases, and perfecting the specification – quite often via testing covariates or increasing the complexity of the error structure, increasing as well the time required for estimation.

The iterations stopped when consistency of sign and statistical significance for the estimated coefficients was achieved across different combinations of specifications and databases (assuring, obviously, that results were interpretable). The final choice model (i.e. the one which results are in Table 6.2) was then chosen via comparison of log-likelihoods across the same specification estimated with different databases, and log-likelihood ratio tests across different specifications estimated with the same database.

This strategy was especially valuable when no strong previous expectations existed for the sign or statistical significance of certain coefficients.

6.6 Summary

This chapter explored the development and results of the *Choice Model*, which main inputs for estimation are the choices provided by the subjects who answered the dynamic experiment, and the subjective distributions of travel and parking times resulting from the *Learning Model* (object of Chapter 5).

Estimating the best possible model depends on exploring simultaneously a range of model specifications and a range of databases (each generated by the use of a different LT), in an iterative manner. The combination of database and specification of the final model, and the process that lead to it, are among the most important contributions of this dissertation.

It was found that some LTs produce databases that lead to acceptable results for some model specifications, but generate poor outputs when the specifications become more sophisticated, such as non-intuitive signs for the coefficients (e.g. positive sign for the marginal utility of travel time) and flat log-likelihoods.

Nevertheless, in general for specifications relying on the mean of the subjective distributions (but not including their variances), it was found that LTs which allowed the learned mean to converge faster to the average of the experienced outcomes[18] generated databases which increased models' goodness-of-fit. This result suggests that these databases were a better representation of subjects' learning outputs. However, the exact LT leading to the best performing model varied depending on how utility was specified. Such finding may be an indication that there is no unique LT suitable for all subjects in the sample, otherwise its database should always lead to the highest goodness-of-fit no matter the specification of utility.

The final choice model was specified as a mixed logit utility maximizing model accounting for random and systematic taste variation, correlations within the sequence of choices of the same individual (i.e. *panel effect*), and correlations among unobserved variables shared by the choice options (i.e. *error components*). The main attributes of the model were QT – the accumulated experience with the alternative, TT – the mean of the subjective distribution of travel times, and PT – the mean of the subjective distribution of parking times. Their coefficients were specified to follow bounded triangular density functions, which means varied systematically across the sample as a function of demographic characteristics and real-life driving routines of respondents, experiment design attributes, accumulated experience with the alternatives, and status of the learning process, making dynamic the marginal utilities of the model – with exception of the marginal

[18] I.e. the mean of the distribution from where the experiences were drawn

utility of QT which is constant for each subject, but nevertheless multiplies an attribute (QT) which grows as the subject accumulates experience.

The interpretation of the results of the final model (which $\bar{\rho}^2$ was equal to 0.257) produced interesting findings. One of them is the influence of the status of the learning process on the marginal utilities of travel and parking times: the burden of deciding increases and makes the marginal utilities of travel and parking times smaller (i.e. more negative) the less the learning process has evolved (i.e. the closer to the start it is).

Accumulated experience was found to have a twofold role in the evolution of utilities: on one hand it strengthens habit, and on the other it makes individuals more intolerant towards travel and parking times. These effects, however, compensate each other in the composition of utility.

Another relevant finding was that the same demographic characteristics and real-life driving routines leading to higher (i.e. less negative) marginal utilities for travel and parking times also lead to lower (i.e. less positive) marginal utilities for the accumulated experience. As if higher tolerance towards travel and parking times was associated to a weaker effect of habit – and the other way around: as if lower tolerance towards travel and parking times was associated to a stronger effect of habit. More tolerant individuals might be more prone to explore the alternatives, taking longer to develop habits, while more intolerant individuals might be more critical in their decision making process, hence developing their preferences and developing habits faster.

Regarding the experiment design attributes, results revealed that individuals who were exposed to the outcomes of foregone options had lower (i.e. more negative) marginal utilities for travel and parking times. These findings suggest that, the better informed decision makers are, the more critic they become about their new choices. Varying the initial information provided for travel times, however, had no significant influence on the marginal utilities of travel and parking times.

Finally, the effect of ex-post regret was also tested in the specification of utility. Instead of revealing a negative impact which would penalize the alternative by reducing its utility, the estimated coefficients were statistically significant with positive signs, reinforcing the subject's previous choice. This finding suggests that avoidance of ex-post regret does not play a role in decision making under uncertainty in dynamic contexts.

7

Stated Perceptions of Travel Times and Parking Times

7.1 Introduction

As introduced in Section 3.2, during the dynamic experiment subjects were asked to complete three screens with questions regarding their impressions about the travel and parking times of the alternatives they had already tried. The objective was to gain additional understanding of how subjects learn the uncertain travel and parking times, compare their stated perceptions with the outcomes of the

Learning Model and eventually improve the results of the *Choice Model*.

Next section provides an overview of the data collected, besides discussing the criteria used for cleaning the data. The following sections explore the statistics of the stated perceptions (Section 7.3), their evolution with time and experience (Section 7.4), and how they are impacted by the experiment design attributes (Section 7.5). A comparison with outcomes generated by the Bayesian approach is the object of Section 7.6, while Section 7.7 explores the application of stated perceptions for choice model estimation. Finally, Section 7.8 brings a summary of the chapter's findings.

In the entire chapter, all statistically significant results have a confidence interval of at least 95%.

7.2 Overview and Data Quality

The first screen was displayed after the first 10 consecutive choices, the second after 30 choices, and the final screen was displayed at the end of the experiment (i.e. after all 50 choices). In each screen, there were three questions per route and parking area: perceived minimum (*perc.min*), perceived average (*perc.avg*) and perceived maximum (*perc.max*), summing up 18 questions per screen and 54 per subject. Thus, the possible total number of data points was 32400 (600 x 54) for the whole sample. The questions were not compulsory, but still 26290 answers (81.14% from the total) were obtained, from which 24204 (74.70% from the total) were considered valid – i.e. answers between 10 and 50 minutes travel times, and between 0 and 15 minutes parking times[1].

The valid answers were (when necessary) rearranged so that *perc.min* $\leq$ *perc.avg* $\leq$ *perc.max*, instead of being removed from the data base in case their relative

[1]Both ranges of acceptable answers are wide in comparison to the outcomes that subjects could possibly have experienced and also in comparison to the initial information provided to them. Experienced travel times range from 22 to 37 minutes, and parking times from 0 to 7 minutes. Regarding the initial information provided for travel times, the widest range possible is 20 to 40 minutes (used for the even-numbered experiment profiles), and for parking times it is 0 to 7 minutes (used for the parking areas located at the left side of the work place).

magnitudes were incoherent. This rearrangement was done to every combination of subject, PDF[2] and screen.

Determining whether extreme or apparently incoherent answers (such as perceived travel times higher than the maximum of the vector of outcomes for the corresponding PDF) reflect lack of engagement, or whether they are subjects' true impressions is a difficult task. The filtering and rearrangement of data mentioned in the two previous paragraphs intended to exclude as few entries as possible from the data base of stated perceptions.

All the analyses which follow in this chapter refer to the 24204 rearranged valid answers, and are based on the stated perceptions *perc.min*, *perc.avg* and *perc.max*, as well as on the differences between the perceived travel and parking times and the outcomes subjects received during the experiment (as results of their decisions). For every combination of subject, PDF and screen the average (*exp.avg*), minimum (*exp.min*) and maximum (*exp.max*) experienced travel or parking times (including the outcomes of foregone alternatives) were computed. Accordingly, for every combination of subject, PDF and screen, the differences were calculated as: $dif.min = per.min - exp.min$, $dif.avg = per.avg - exp.avg$ and $dif.max = per.max - exp.max$. In this way, positive differences indicate that subjects overestimated the experienced travel and parking times, while negative differences mean they underestimated them. Furthermore, the closer to zero the differences are, the more realistic the perceptions.

Because perceptions should (at least in theory) vary according to the experienced outcomes, more emphasis is given to the analysis of the differences between perceptions and experiences, rather than to the analysis of perceptions per see.

For every combination of perception type (i.e. *perc.min*, *perc.avg* or *perc.max*), PDF and screen, the number of valid answers lies between 409 and 529, indicating that no combination is poorly represented in the sample of stated perceptions.

[2] *TT.NARR* and *TT.WIDE*, the PDFs of travel times associated to the routes; and *PTB.NARR*, *PTB.WIDE*, *PTW.NARR* and *PTW.WIDE*, the PDFs of parking times associated to the parking areas.

The average number of answers per subject was 40.34 (out of 54), and 50% of the subjects gave between 47 and 54 answers. It was found that the quantity of answers provided is statistically significantly higher among subjects who were not faced with the outcomes of faster foregone options: 41.34 answers against 38.35 for those who were.

Before proceeding to the following sections, two remarks should be made. First, the findings reported in this chapter might be, at least to some extent, an artefact originated from the nature of the (computer based) experiment. Hence, not necessarily subjects' perceptions in real life would have the same characteristics as those they stated during the experiment. Second, since the analysis of the stated perceptions was not within the core objectives of this research, the collected sample of stated perceptions was intended to be small and the related questions were not compulsory, to not overwhelm respondents or deviate them from the most important part of the experiment. Any further investigations on the topic would require a more complete and bigger sample, and most likely some deepening in the literature related to the psychology of time perception.

7.3 Similarity of Perceived Distributions

The statistics of the distributions of *dif.min*, *dif.avg* and *dif.max* for the six PDFs are exposed in Tables 7.1 to 7.3. The statistics were calculated in the aggregated level, i.e. using all the data available for the combination of perception type and PDF regardless of which screen they came from. Figures 7.1 to 7.6, on the other hand, show the evolution of the mean stated perceptions versus the mean experienced outcomes (both averaged across the sample), for three moments of the experiment: after 10, 30 and all 50 consecutive choices.

The first conclusion that can be drawn from these tables and graphs is that the PDFs with smaller variances (i.e. *TT.NARR*, *PTB.NARR* and *PTW.NARR*) are perceived wider (i.e. with a larger range of variation of travel/parking times) than

Table 7.1: *Distribution of dif.min/avg/max for TT.NARR and TT.WIDE.*

	TT.NARR			TT.WIDE		
Statistic	*dif.min*	*dif.avg*	*dif.max*	*dif.min*	*dif.avg*	*dif.max*
Mean	-2.28	-0.80	1.50	2.13	0.02	-2.77
Std.Dev.	4.56	4.46	4.32	4.59	4.35	4.56
Minimum	-21.00	-21.25	-21.00	-18.00	-19.95	-25.00
Maximum	15.00	19.33	19.00	28.00	21.25	19.00
10^{th} *centile*	-7.00	-4.01	-2.00	-1.00	-3.69	-7.00
20^{th} *centile*	-5.00	-1.78	-1.00	0.00	-1.95	-6.00
30^{th} *centile*	-3.00	-1.00	0.00	0.00	-1.23	-5.00
40^{th} *centile*	-2.00	-0.84	1.00	1.00	-0.40	-4.00
50^{th} *centile*	-1.00	-0.71	1.00	2.00	0.13	-3.00
60^{th} *centile*	0.00	0.00	2.00	3.00	0.67	-2.00
70^{th} *centile*	0.00	0.20	3.00	4.00	1.22	-1.00
80^{th} *centile*	0.00	1.06	4.00	5.00	2.15	0.00
90^{th} *centile*	1.00	2.26	6.00	6.00	3.77	1.00

they are in reality. This is shown, for instance in the negative mean of *dif.min* and the positive mean of *dif.max* for *TT.NARR*. In contrast, the PDFs with higher variances (i.e. *TT.WIDE*, *PTB.WIDE* and *PTW.WIDE*) are perceived narrower. An example is *PTW.WIDE*, which has negative means for *dif.min* and *dif.max*, but being the latter bigger in absolute value than the former, results in a perceived distribution narrower than it is in reality.

Another conclusion is that the gaps among perceived averages of different PDFs are smaller than the experienced gaps. These distortions show that the distributions (of either travel or parking times) are more similar to each other in the perception of subjects than they are in reality. An example are the positive means of *dif.avg* for *PTB.NARR* and *PTB.WIDE*, and the negative means of *dif.avg* for *PTW.NARR* and *PTW.WIDE*.

The means of *dif.min*, *dif.avg* and *dif.max* are an indication of how much perceptions move away from reality, making the PDF seem on average either more attractive or less in the eyes of subjects. Two good examples are the perceived distributions for *PTB.NARR* and *PTW.WIDE*, shown respectively in

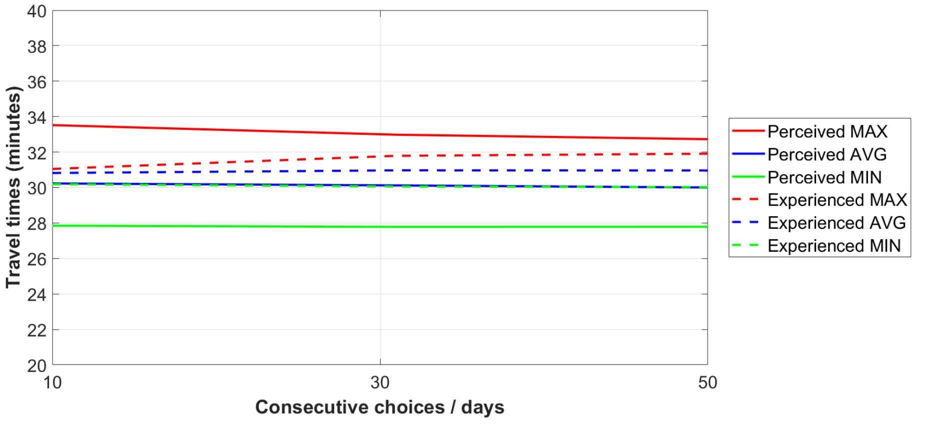

Figure 7.1: *Evolution of perc.avg and exp.avg for TT.NARR.*

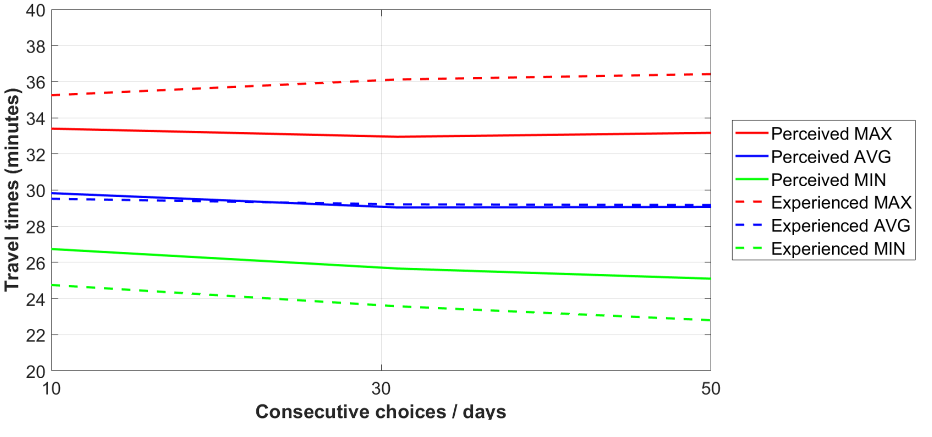

Figure 7.2: *Evolution of perc.avg and exp.avg for TT.WIDE.*

Figures 7.3 and 7.6. In the first case, the means of the three perception types are overestimated relative to experience (as can be seen in Table 7.2), leading subjects to have on average a false pessimistic impression of the PDF. The opposite happens to *PTW.WIDE*: the means of all perception types are underestimated (according to Table 7.3), also creating an erroneous (but optimistic) impression of the PDF.

Table 7.2: *Distribution of dif.min/avg/max for PTB.NARR and PTB.WIDE.*

Statistic	PTB.NARR *dif.min*	PTB.NARR *dif.avg*	PTB.NARR *dif.max*	PTB.WIDE *dif.min*	PTB.WIDE *dif.avg*	PTB.WIDE *dif.max*
Mean	0.25	0.89	1.51	0.75	0.65	-0.66
Std.Dev.	2.09	2.13	2.49	2.10	2.27	2.76
Minimum	-3.00	-3.00	-3.00	-3.25	-4.75	-6.50
Maximum	13.00	12.58	12.00	14.50	13.83	11.50
10^{th} *centile*	-1.50	-0.88	-1.00	-1.00	-1.50	-4.00
20^{th} *centile*	-1.00	-0.58	-0.50	0.00	-0.82	-3.00
30^{th} *centile*	-1.00	-0.17	0.50	0.00	-0.43	-2.00
40^{th} *centile*	0.00	0.31	0.50	0.00	0.06	-2.00
50^{th} *centile*	0.00	0.41	1.50	0.00	0.34	-1.00
60^{th} *centile*	0.00	0.60	1.50	0.50	0.63	0.00
70^{th} *centile*	1.00	1.39	2.00	0.50	1.22	0.00
80^{th} *centile*	1.00	2.17	3.40	1.50	1.68	1.00
90^{th} *centile*	2.40	3.17	4.00	2.50	2.75	3.00

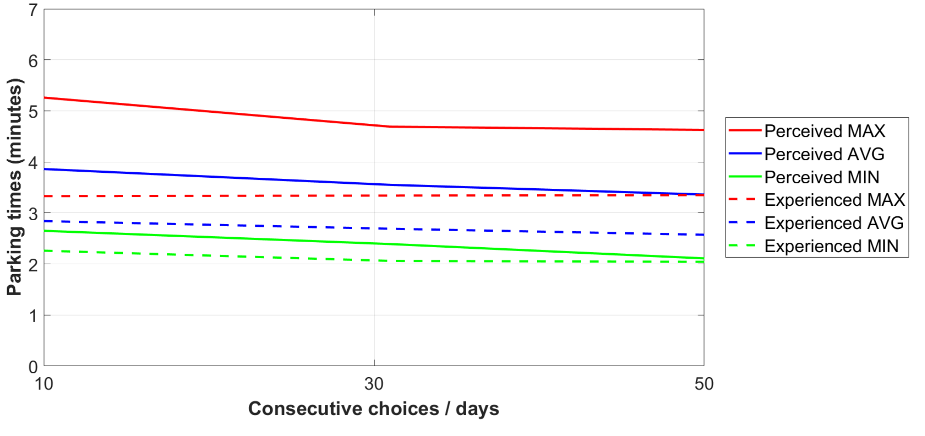

Figure 7.3: *Evolution of perc.avg and exp.avg for PTB.NARR.*

A common finding for perceived travel and parking times is that subjects (although not fully differentiating the PDFs) were on average able to identify the real ranking order for *perc.min* and also for *perc.avg* – i.e. the perceived minimum for the different PDFs follows the same order of magnitude as the experienced minimum (the same is valid for the perceived and experienced averages), as

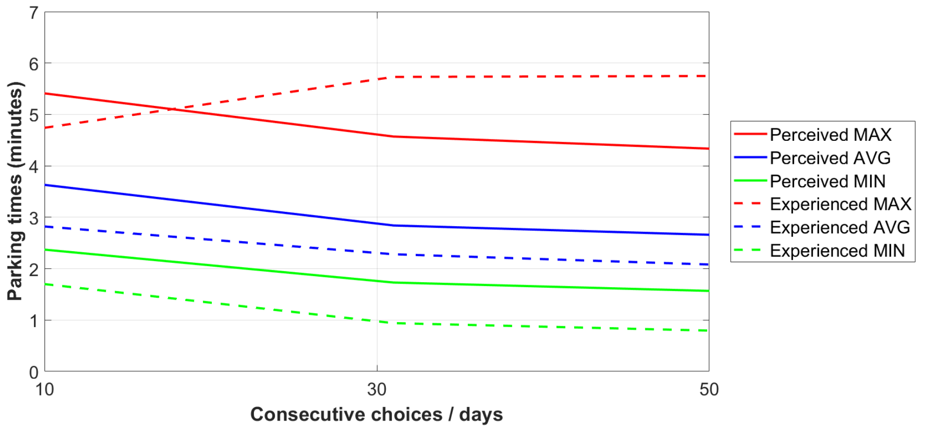

Figure 7.4: *Evolution of perc.avg and exp.avg for PTB.WIDE.*

Table 7.3: *Distribution of dif.min/avg/max for PTW.NARR and PTW.WIDE.*

	PTW.NARR			*PTW.WIDE*		
Statistic	*dif.min*	*dif.avg*	*dif.max*	*dif.min*	*dif.avg*	*dif.max*
Mean	-0.87	-0.19	0.50	-0.12	-0.34	-0.70
Std.Dev.	2.13	2.18	2.51	2.01	2.18	2.68
Minimum	-3.25	-4.13	-4.50	-4.25	-4.75	-6.50
Maximum	11.50	10.75	11.00	13.00	11.68	11.50
10^{th} *centile*	-3.00	-2.82	-3.00	-2.00	-2.76	-4.00
20^{th} *centile*	-2.50	-1.58	-1.00	-1.50	-1.90	-3.00
30^{th} *centile*	-1.75	-1.25	-0.50	-1.00	-1.42	-2.00
40^{th} *centile*	-1.50	-0.75	0.00	-1.00	-0.95	-1.00
50^{th} *centile*	-1.50	-0.35	0.00	0.00	-0.50	-1.00
60^{th} *centile*	-0.75	-0.15	1.00	0.00	-0.10	0.00
70^{th} *centile*	-0.50	0.51	1.00	0.00	0.25	0.00
80^{th} *centile*	0.50	0.83	2.00	1.00	0.81	1.00
90^{th} *centile*	1.50	2.25	3.00	2.00	1.82	2.25

demonstrated in Table 7.4.

When it comes to the ranking order for *perc.max*, for travel times the perceived order is the same as the experienced one, but such is not the case for parking times, which ranking order for *perc.max* resembles that of *perc.min* (or *exp.min*)

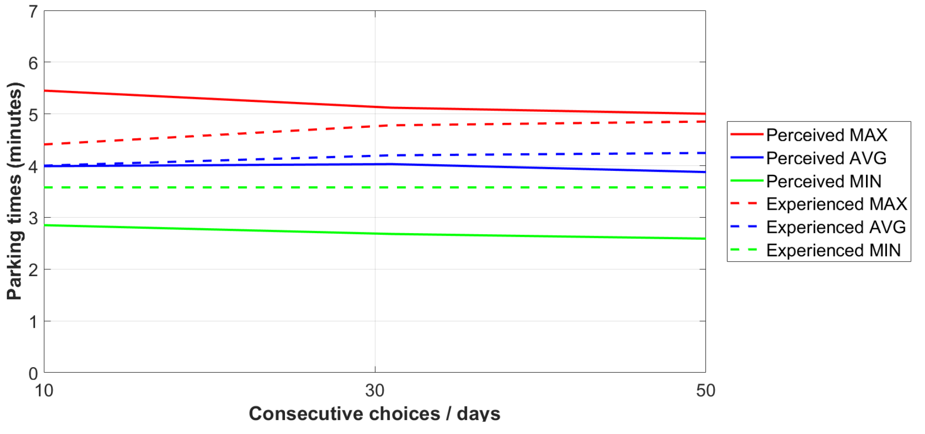

Figure 7.5: *Evolution of perc.avg and exp.avg for PTW.NARR.*

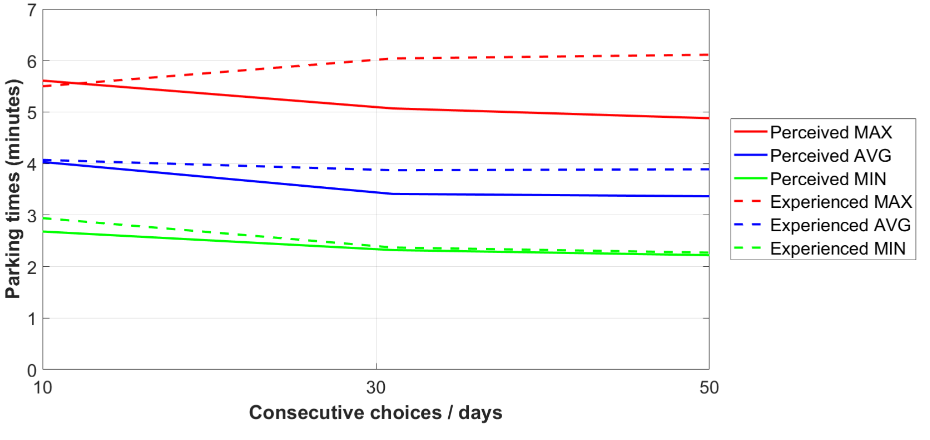

Figure 7.6: *Evolution of perc.avg and exp.avg for PTW.WIDE.*

and *perc.avg* (or *exp.avg*).

The analysis of the ranking orders suggests subjects have difficulty to understand the upper boundaries of the distributions, to a much higher extent than the lower boundaries or the averages. Curiously, *perc.max* for parking times is recognized by subjects as following a similar ranking order as that of *perc.min* and *perc.avg*, as if a PDF with a lower minimum and a lower average should also

Table 7.4: *Means of perc.min/avg/max and exp.min/avg/max across the sample.*

PDF	Mean of *perc.min*	Mean of *exp.min*	Mean of *perc.avg*	Mean of *exp.avg*	Mean of *perc.max*	Mean of *exp.max*
TT.WIDE	25.81 (9.04%)	23.67	$29.32^{(b)}$ (0.07%)	$29.30^{(b)}$	$33.18^{(d)}$ (-7.71%)	35.95
TT.NARR	27.81 (-7.58%)	30.09	30.12 (-2.59%)	30.92	$33.08^{(d)}$ (4.75%)	31.58
PTB.WIDE	1.88 (66.37%)	1.13	3.04 (27.73)	2.38	$4.75^{(e)}$ (-12.36%)	5.42
PTB.NARR	$2.37^{(a)}$ (11.79%)	2.12	$3.58^{(c)}$ (32.59%)	2.70	$4.85^{(e)}$ (45.21%)	3.34
PTW.WIDE	$2.41^{(a)}$ (-4.74%)	2.53	$3.60^{(c)}$ (-8.86%)	3.95	$5.19^{(f)}$ (-11.73%)	5.88
PTW.NARR	2.70 (-24.58%)	3.58	3.96 (-4.58%)	4.15	$5.19^{(f)}$ (10.90%)	4.68

Obs.1: entrances with the same superscript are not statistically significantly different from each other.
Obs.2: percentages below the means of *perc.min*, *perc.avg* and *perc.max* represent how much they are above or below the means of *exp.min*, *exp.avg* and *exp.max*, respectively.

have a lower maximum (the same reasoning can be applied to higher minimum, average and maximum). This implies some difficulty in capturing the skewness of distributions[3].

7.4 Evolution with Time and Experience

When evaluating the evolution in time of *dif.min*, *dif.avg* and *dif.max*, it was found that perceptions are more optimistic in the end of the experiment than in the beginning (i.e. when comparing results from the last and the first screens)[4],

[3] Although the perceptions in Figures 7.4 and 7.6 reveal some understanding of the skewness for *PTB.WIDE* and *PTW.WIDE*, respectively.

[4] Which is confirmed by the negative and statistically significant correlation between the number of outcomes experienced from a certain PDF, and the differences *dif.min*, *dif.avg* and *dif.max*, measured across all screens and subjects. The Pearson correlation coefficient equals -0.064, meaning that the more experience subjects have, the smaller the differences are, indicating perceptions become less pessimistic.

indicating that subjects see the PDFs as more attractive after 50 choices. The following statistically significant differences were found: (i) the mean of *dif.max* for *TT.NARR* drops from 2.46 in the first screen to 0.78 minutes in the third; (ii) for *TT.WIDE*, the mean of *dif.max* equals -1.85 in the first screen, versus -3.26 minutes in the last; (iii) the mean of *dif.min* for *PTB.NARR* drops from 0.40 in the first screen to 0.04 minutes in the end of the experiment, while the mean of *dif.max* moves from 1.92 to 1.27 minutes; (iv) the mean of *dif.max* for *PTB.WIDE* moves from 0.67 in the first screen to -1.44 minutes in the third; (v) for *PTW.NARR*, the mean of *dif.avg* changes from -0.01 in the first screen to -0.39 minutes after 50 choices, and the mean of *dif.max* decreases from 1.04 to 0.12 minutes; (vi) for *PTW.WIDE*, the mean of *dif.avg* in the first screen equals -0.04, changing to -0.53 minutes in the last, whereas the mean of *dif.max* changes from 0.12 to -1.26 minutes.

The results above indicate that time leads subjects to more optimistic, but not necessarily more realistic perceptions. For instance, the PDFs of higher variances have *perc.max* either close to realistic (the case of *PTB.WIDE* and *PTW.WIDE*) or underestimated (the case of *TT.WIDE*) in the first screen, and when it decreases in the third screen, it becomes (even) further from reality. On the other hand, for the three PDFs of lower variances (*TT.NARR*, *PTB.NARR* and *PTW.NARR*), since *perc.max* is overestimated in the first screen, its decrease in the third screen brings perceptions for these PDFs closer to reality.

These findings were confirmed when the full sample (i.e. all 24204 observations obtained) of differences between stated perceptions and experienced outcomes was compared to the number of times PDFs were chosen. A small, although statistically significant correlation was found, with Person coefficient of -0.067, indicating that perceptions became more optimistic as experiences were accumulated (at least at the aggregated level).

7.5 Influence of Experiment Design

Regarding the influence of experiment design attributes[5] on the differences between perceptions and experience, statistically significant impacts were found for the assignment scheme of PDFs to routes and parking areas[6], the presence of feedback on faster foregone options, and the initial information provided for travel times. The influence of these attributes, however, was found for some of the PDFs (not for all of them), and was asymmetric for travel and parking times. Still, the paragraphs below bring an attempt to interpret the results found.

Regarding the assignment scheme of PDFs to routes and parking areas, when a route is connected to the parking areas with the best PDFs (i.e. *PTB.NARR* and *PTB.WIDE*), its travel times are perceived as more optimistic. A possible explanation for this finding is that the lower average parking times of these PDFs influenced the perceptions of travel times, making them more optimistic. The following statistically significant differences were found: (i) the mean of *dif.max* for *TT.NARR* is smaller when the route is combined with the best parking areas: 1.05 versus 2.01 minutes otherwise; (ii) for *TT.WIDE*, the mean of *dif.min* is smaller in profiles 7 to 12: 1.81 versus 2.49 minutes for the other profiles, the same happening to the mean of *dif.avg*: -0.48 versus 0.56 minutes otherwise.

For parking times, the assignment schemes have a different impact. When a parking area is combined with *TT.NARR*, its parking times are perceived as more realistic. A possible explanation for this result is that *TT.NARR* is more easily predictable than *TT.WIDE* (although, judging by the findings described in Section 7.3, subjects on average do not clearly distinguish these distributions' variances), not requiring much effort from subjects in terms of attention and memory, and hence allowing them to focus on the outcomes of parking times

[5] As introduced in Section 3.3 of Chapter 3: display of outcomes of faster foregone options; strategy to extract outcomes from the vectors; initial information regarding travel times; and assignment scheme of PDFs to routes and parking areas.

[6] In profiles 1 to 6, *TT.NARR* is combined with *PTB.NARR* and *PTB.WIDE*, while *TT.WIDE* is combined with *PTW.NARR* and *PTW.WIDE*. In profiles 7 to 12, the combination is inverted: *TT.NARR* is combined with *PTW.NARR* and *PTW.WIDE*, whereas *TT.WIDE* is combined with *PTB.NARR* and *PTB.WIDE*.

displayed after choices. The following statistically significant differences were found: (i) when *PTB.NARR* is combined with *TT.NARR* the mean of *dif.max* is 1.34 minutes (versus 1.67 when it is combined with *TT.WIDE*); (ii) when *PTW.NARR* is connected with *TT.NARR*, its mean for *dif.min* equals -0.66 minutes (against -1.09 minutes otherwise), the same happening to the mean of *dif.avg*: -0.02 versus -0.35 minutes; (iii) *PTW.WIDE*, when combined with *TT.NARR*, has the mean for *dif.avg* equal to -0.15 minutes (versus -0.54 minutes otherwise), which is also the case for the mean of *dif.max*: -0.41 versus -0.98 minutes when combined with *TT.WIDE*.

When it comes to the presence of feedback on faster foregone options, it was found that subjects who are not faced with such feedback provide more realistic perceptions for travel times. A possible explanation for this result might be that the lower amount of information to be "processed" by subjects in the experiment profiles without such feedback allows them to dedicate more attention to the outcomes received (with none or low risk of confounding the outcomes of both PDFs). The statistically significant relations found are: (i) the mean of *dif.min* for *TT.NARR* is higher when there is no such feedback: -1.91 versus -3.07 minutes when there is; (ii) the mean of *dif.avg* for *TT.NARR* is also higher in the absence of feedback on foregone options: -0.61 versus -1.19 minutes otherwise; (iii) for *TT.WIDE*, the mean of *dif.max* is higher among subjects who only received the outcomes of the options they chose: -2.37 versus -3.54 minutes for the other subjects.

For parking times, however, the impact of the absence of feedback on non-chosen alternatives is diverse. Subjects to whom only the outcomes of chosen options were displayed stated more optimistic perceived parking times. A hypothesis to explain such results is the fact that, being confronted with outcomes of faster forgone options might raise feelings of regret (although the impact of regret was not captured in the estimated choice models), and therefore influence the perceptions. And, if this hypothesis stands, it could be that, in the context of the experiment, the effect of regret is stronger for parking rather than for travel times. The statistically significant relations found are: (i) for *PTB.NARR* the mean of *dif.max* is smaller when there is no such feedback: 1.42 versus 1.73 minutes when there is; (ii) for *PTB.WIDE* the mean of *dif.min* is also smaller in the absence of feedback on non-chosen alternatives: 0.51 against 1.23 otherwise, the same happening to the means of *dif.avg* (0.36 versus 1.24 minutes) and *dif.max* (-0.79 versus -0.39); (iii) also for *PTW.WIDE*, the means of *dif.min*, *dif.avg* and *dif.max* become smaller when feedbacks on foregone options are not provided. They are, respectively: -0.25, -0.48 and -0.87 minutes against (respectively), 0.16, -0.03 and -0.31 minutes when the outcomes of faster foregone options are presented.

With regards to the initial information provided for travel times, no influence was found for the perceptions of *TT.NARR*, but perceptions for *TT.WIDE* become more optimistic when the information is 30+/-5 (in comparison to when it is 30+/-10 minutes). It might be that the more optimistic initial guess influenced perceptions in the same direction. The statistically significant results found are: (i) the mean of *dif.avg* for *TT.WIDE* is lower when the initial information is 30+/-5 minutes: -0.29 minutes against 0.32 for those profiles using the initial information 30+/-10 minutes; (ii) the mean of *dif.max* for *TT.WIDE* is lower for subjects assigned to profiles using 30+/-5 minutes as the initial information: -3.12 minutes against -2.43 otherwise.

A possible explanation for the absence of such influence in the perceptions of *TT.NARR*, is that, being this PDF easier to learn, any initial information which differs too much from the experienced outcomes might be understood as false and ignored.

7.6 Comparison with Bayesian Learning

The Bayesian approach as it is used in this research (see Chapter 5), despite having some flexibility, is not able to produce learned PDFs which are compatible with the stated perceptions presented in the previous sections. A non-exhaustive list of reasons follows.

The evolution in time of the perceived maximum of PDFs of wide variance (*TT.WIDE*, *PTB.WIDE* and *PTW.WIDE*) cannot be represented by the Bayesian approach. Perceptions become further from reality with time, while the accumulation of experiences leads the subjective distributions updated via the Bayesian approach to converge towards experience.

The shift of perceptions of travel times into becoming more realistic in the absence of feedbacks on foregone options cannot be represented either. The presence of feedback means more outcomes experienced, which leads the subjective distributions updated via the Bayesian approach to evolve towards experience faster than they would in the absence of such feedback.

Besides, the perceived ranges of variation of *PTB.NARR* and *PTW.NARR* can never be reached if the initial guess and starting point of the Bayesian updating are those corresponding to the initial information provided in the experiment. A PDF of larger variance as the starting point, together with a very strong trust in the initial guess (that would prevent the subjective PDFs from converging to the real shapes of *PTB.NARR* and *PTW.NARR*) would need to be used in order to reproduce the perceived ranges of variation. An analogous reasoning can be applied to *PTB.WIDE* and *PTW.WIDE* and their narrow perceived ranges of variation.

Attempts were made to compare the stated perceptions with the outputs of different databases produced with the Bayesian approach (i.e. databases generated with different LTs). Such a desegregated analysis was possible to perform for the perceived averages of travel and parking times (i.e. *perc.avg*), but not for the perceptions of minimum (*perc.min*) and maximum (i.e. *perc.max*). While stated perceived averages and Bayesian learned averages can be directly compared, perceived minimum and maximum are not straightforwardly comparable to the tails of the learned distributions. Apart from this difficulty, the comparison of the perceived averages with learned means from different databases (i.e. different LTs) revealed heterogeneity across the PDFs for the same subject. In other words, for the same individual, the learned mean which most approaches the stated perception for a certain PDF might "belong" to a different database than the learned mean which is closer to the stated perception of another PDF. For these reasons, desegregated comparisons were not pursued further and remain a topic for future research.

7.7 Use of Perceptions for Choice Modelling

The previous sections have shown that perceived travel and parking times deviate from the experienced outcomes and cannot be represented by the Bayesian approach adopted in this research. These findings raise two questions:

1. whether or not the decisions made by subjects were based on the impressions they stated – which can be tested by estimating discrete choice models that use the perceptions as attributes of the choice alternatives;
2. how the discrete choice models mentioned above compare to those estimated using the Bayesian learned parameters.

Utility maximizing MNL models were estimated[7] with the same specification of the utility function used in Section 6.2. The perceived mean (*perc.avg*) of travel and parking times captured in the first, second and third screens were used as attributes for the decisions of days 11, 31 and 50[8], respectively. The sample is restricted to observations (i.e. decisions) for which the perceived averages of all six PDFs were provided, resulting in a total of 1022 entries: 355 in the first screen, 333 in the second and 334 in the third. Estimation results are shown in columns two through six of Table 7.5, respectively using the sample of decisions made on day 11, then on days 11 and 31 together, on all three days (11, 31 and

[7]The software NLOGIT was used for all model estimations in this chapter.

[8]It is assumed that the perceptions given after the 50^{th} choice are likely to be similar to the impressions immediately before this choice.

Table 7.5: *Basic RUM model estimation using stated perceptions and Bayesian databases.*

	Stated Perceptions					LT 80% & 85				
	day 11	days 11,31	days 11,31, 50	days 31,50	day 50	day 11	days 11,31	days 11,31, 50	days 31,50	day 50
ϕ	.281	.147	.112	.099	.089	.289	.153	.111	.098	.086
θ	.011[a]	.014[a]	-.009[a]	-.009[a]	-.050[b]	.425	.367	.199	.068[b]	-.208
γ	-.130	-.152	-.136	-.138	-.083[b]	-.176	-.111	-.119	-.096	-.169
Sample	355	688	1022	667	334	355	688	1022	667	334
LL	-429	-827	-1199	-749	-362	-400	-791	-1185	-752	-356

[a] p-value $\geq$ .57.

[b] .10 $\leq$ p-value $\leq$ .16.

50) together, on days 31 and 50 together, and finally only on day 50. Because subject's perceptions evolve during the experiment, sub-samples were created to investigate the estimated choice model in the first half (columns two and three of Table 7.5) and in the second half (columns five and six of Table 7.5) of the experiment.

Columns seven through eleven correspond to the same specification, however estimated using the Bayesian learned parameters as attributes of the alternatives (the expected value of the learned distributions, i.e. α as defined in Equation 5.8, generated with the LT (80%, 85)[9]. The samples used are the same as those in columns two to six.

The models estimated with the stated perceived travel and parking times produced coefficients for parking time (γ) and for the amount of times the alternative was chosen before (ϕ) which have the expected signs and are statistically significant[10]. Despite θ (the coefficient for travel time) not being significant for any

[9] This LT was chosen as a reference for comparison because it lead to the better performing model in Sections 6.2.

[10] With exception of γ for the sub-sample of day 50, which p-value is a bit higher than for the other sub-samples.

sample size, its sign changes from positive to negative (which is the expected sign) when the samples corresponding to the second half of the experiment (columns five and six in Table 7.5) are used instead of the samples corresponding to the first half (columns two and three). This result indicates that stated perceptions become a better representation of subjects' expectations (which they use for decision making) with time and experience and, together with the estimated coefficients ϕ and γ, suggest that the perceptions stated by subjects are related to their decisions in a consistent manner[11].

Regarding the models estimated with the Bayesian learned parameters, ϕ and γ have the expected sings and are statistically significant for all sub-samples. The coefficient for travel times (θ), however, is statistically significant (with exception of the sub-sample of days 31 and 50) with counter intuitive sign (positive sign) for most sub-samples. This coefficient's sign is negative only for the sub-sample of day 50. These results suggest that the Bayesian learning algorithm perfects its outputs with time (i.e. the more realizations are incorporated to the updating mechanism), a similar trend as the one for the stated perceptions (mentioned in the paragraph above).

Further comparisons of models estimated using stated perceptions with those estimated with Bayesian learned parameters require more sophisticated specifications – for instance by including demographic characteristics and experiment design attributes as explanatory variables, or testing for random coefficients. To accomplish so, however, a sample of stated perceptions bigger than the one available is required, remaining the topic open for future investigations. Moreover, adjustments of the Bayesian learning algorithm (in the direction of producing databases that better resemble subjects' real beliefs) may also be required.

[11]It is possible to argue, however, that such a result is expected given that subjects made their choices immediately after (in the case of the first and second screens) or before (in the case of the third screen) filling in their impressions about travel and parking times, and it would be illogical, from the part of the subjects, to choose an option for which the impressions were not among the most positive.

7.8 Summary

This chapter investigated the stated perceptions of respondents regarding the average, minimum and maximum travel and parking times of the alternatives they experienced during the experiment. In total 24204 valid stated perceptions were collected (74.70% from the total number of stated perceptions that could have been obtained).

It was found that the PDFs with smaller variances were perceived wider (i.e. with a larger range of variation) than they were in reality, while the PDFs with higher variances, were perceived narrower. Additionally, the gaps among perceived averages of different PDFs were smaller than the experienced gaps. As a consequence, the distributions (of either travel or parking times) were more similar to each other in the perception of the subjects than they were in reality.

With regards to the evolution of the stated perceptions with time and experience, it was found that they were more optimistic (but not necessarily more realistic) in the end of the experiment than in the beginning, indicating that subjects see the PDFs as more attractive after the 50 choices.

When it comes to the influence of experiment design attributes, results showed that subjects who were not faced with feedbacks on foregone options stated more realistic perceptions for travel times, and more optimistic perceptions for parking times, and subjects who were informed travel times took 30+/-5 minutes (instead of 30+/-10 minutes) stated more optimistic perceptions for Route B (which PDF is *TT.WIDE*) – no impacts were found on the stated perceptions for Route A.

It was also found that travel times were perceived as more optimistic when the route was connected to the parking areas with the best PDFs (i.e. the PDFs of parking times with the lowest averages), while parking times were perceived as more realistic when the parking areas were connected to Route A (which PDF is *TT.NARR*).

It was found that the Bayesian model, despite its flexibility, is not able to produce subjective distributions with the characteristics of the perceptions stated by the subjects. Still, direct comparison of the perceived averages of travel and parking times with the outputs of different databases (generated with different LTs) was done. Results revealed that, for a considerable number of subjects, there was not a unique database which outputs were matching all the perceptions stated. In other words, for the same subject, different databases would be the best match to different perceptions (i.e. to perceptions concerning different PDFs).

Estimation of linear-in-parameters logit utility maximizing models indicated that the stated perceptions are related to subjects' decisions in a consistent manner. Results also suggested that both the stated perceptions and the subjective distributions produced with the Bayesian belief updating become a better representation of subjects' beliefs with time and experience.

8

Conclusions

8.1 Summary and Contributions

Models of travel behaviour under uncertainty which simultaneously: incorporate travellers' response to uncertainty in dynamic contexts, include an explicit mechanism to represent travellers' learning of the uncertain attributes of the network, and were validated with empirical data, are scarce in the scientific body of knowledge.

This research aimed at bridging this gap by (i) developing and empirically validating a model of learning and dynamic route and parking choice behaviour under uncertainty of travel and parking times, (ii) investigating the suitability of Bayesian belief updating for representing drivers' learning mechanism (given a multitude of possible starting points of calibration), and (iii) investigating the implications, for the mechanisms of learning and choice under uncertainty, of providing information on the fastest foregone alternative.

The research objectives were extended into a conceptual framework representing the daily choices of route and parking area by private automobile drivers who commute to work and are not familiar neither with the network of routes connecting their home to their work location, nor with the parking lots available at their destination. Travel and parking search times vary day-by-day following probability density functions which are also initially unknown to drivers.

After every decision, drivers receive the realizations of travel and parking times corresponding to their choice, which are incorporated into their learning mechanism, resulting in the update of their beliefs of travel and parking times – such mechanism is represented by the *Learning Model*. Drivers' updated beliefs, together with the history of their previous decisions, are then used as input for next day's choice of route and parking area. The analysis and comparison of the available alternatives in light of drivers' preferences, beliefs and habits, resulting in the choice of a favourite, is represented by the *Choice Model*.

Chapter 3 described and discussed the design of the (web-based) dynamic stated choice experiment, which extended the conceptual framework aiming at collecting empirical data for model validation.

The core part of the experiment required subjects to make 50 consecutive choices of route and parking area, each decision followed by the display of its outcomes. The choice set was composed of four combinations of route and parking area (i.e. two routes, each giving access to two different parking lots). The uncertain travel and parking times followed Lognormal distributions, summing up six different PDFs, which were chosen in order to guarantee the necessary trade-offs among the alternatives, i.e. assuring competition between routes and between parking areas connected to the same route. The relative frequencies of travel and parking times in these PDFs were reproduced in the vectors of outcomes (the sequences of either travel or parking times from which elements were extracted and displayed to subjects after each of their choices), maintaining the relative positions of advantage and disadvantage among the alternatives.

Composed of 12 experiment profiles, the design controlled for the effect of presenting the outcomes of the fastest foregone option, the assignment scheme of PDFs to parking areas, besides varying the initial information provided for travel times. To each piece of initial information provided to subjects, a corresponding distribution of probabilities was chosen to represent the start of the learning mechanism (i.e. the Bayesian belief updating).

The design also included insights gathered during the simulation efforts (by varying the strategy to extract outcomes from the vectors), and added questions to capture subjects' stated perceptions of the average, minimum and maximum travel and parking times of the routes and parking areas they had tried in the experiment.

In **Chapter 4**, an overview of the collected data was provided. The final sample size was equal to 600 subjects, who were predominantly Dutch (98.67%), on average 39.44 years old, with driver's license for 19.27 years on average, and 51.67% were men.

The highest shares among the choice alternatives corresponded to those with the lowest average total times, regardless of the variability of their outcomes. Except for profiles 3 to 6, where the most reliable option was chosen (i.e. that with the smallest range of variation for the total time), followed by the one with the lowest average total time. Due to the assignment scheme of PDFs of parking times used in these profiles[1], the relative advantages and disadvantages of the choice options were less evident (in comparison to profiles where another assignment

[1]In profiles 1 to 6, the PDFs of parking times with the lowest averages, i.e. *PTB.NARR* and *PTB.WIDE*, were connected to Route A (which PDF of travel times was *TT.NARR*), while the PDFs of parking times with the highest averages, i.e. *PTW.NARR* and *PTW.WIDE*, were connected to Route B (which PDF of travel times was *TT.WIDE*).

scheme was adopted[2]), which was accentuated by the lack of feedback on foregone options. In such circumstances, the reliability of travel and parking times seems to have become relevant for decision making, exceeding the importance of lower average total times.

The only experiment design attribute which affected shares with statistical significance was found to be the display of feedback on foregone options, increasing the shares of the option with the lowest average total time. This attribute also affected the average number of times subjects changed the chosen alternative from one day to the next. The average number of switches was found to be statistically significantly lower in those profiles where feedback on foregone options was provided: 19.56 versus 24.50 for the other profiles. This result suggests that, the more information gained from the same decision, the more knowledge subjects built, and the less exploration they needed to do.

Regarding the experiment design attribute strategy to extract (outcomes from vectors), its influence on the shares was also tested. Although simulations showed increased variability of the shares associated to the use of the strategy *outcome of the day*, no statistically significant differences in the variances of the shares were found in the collected data, demonstrating that subjects (differently from simulated agents) were not sensitive to the sequence in which they received a certain PDF's outcomes.

Chapter 5 presented the theoretical background and mathematical formulation of the *Learning Model*, as well as relevant operational aspects of its application to the collected data and the analysis of its outputs.

Drivers' knowledge about travel and parking times was represented as lognormally distributed random variables, which were updated following the Bayes Theorem. The mean of each of these lognormal distributions was represented by a

[2]In profiles 7 to 12, the PDFs of parking times with the highest averages, i.e. *PTW.NARR* and *PTW.WIDE*, were connected to Route A (which PDF of travel times was *TT.NARR*), while the PDFs of parking times with the lowest averages, i.e. *PTB.NARR* and *PTB.WIDE*, were connected to Route B (which PDF of travel times was *TT.WIDE*). In this assignment scheme the contrast among the choice options is stronger, as can be seen in Table 3.7 – in opposition to the contrast among options in profiles 1 to 6, shown in Table 3.6.

normal PDF, and the variance by an inverted gamma PDF. Both the normal and the inverted gamma distributions have the advantage of being natural conjugates and relying on a small number of parameters which interpretations are enough intuitive. Since joint estimation of the mean and variance of the random variables is not possible, the estimation was conditional on the knowledge of each other. The supposedly known parameters μ and σ^2 were replaced by the expected values of the distributions of μ and σ^2 updated in the previous day.

For every subject in the sample the learned lognormal distributions of travel and parking times (six in total) were calculated, from day 1 to day 50. The main inputs for calculation were the realizations of travel and parking times faced by subjects, and the prior distributions matching the initial information they received in the instructions of the experiment. These priors were composed of *starting values* for the parameters, directly derived from the initial information provided, and associated initial *measures of reliability*, or levels of trust (LTs). A range of LTs was created, each yielding a different database of subjective distributions to be used for choice model estimation.

An arbitrary LT within this range was used to exemplify the evolution of the learned parameters. The speed and evolution (smoothness) of this process depends on the combination of some factors: distance of the initial guesses from the real parameters, LT adopted for the initial guesses, variability of the data, number of experiences and type of parameter (i.e. whether the belief of the distribution's mean μ or of its the variance σ^2 is being updated).

The *Choice Model* was the object of **Chapter 6**, which described and discussed its development and results.

Estimating the best possible model depends on exploring simultaneously a range of model specifications and a range of databases (each generated by the use of a different LT), in an iterative manner. The combination of database and specification of the final model, and the process that lead to it, are among the most important contributions of this dissertation.

It was found that some LTs produce databases that lead to acceptable results for some model specifications, but generate poor outputs when the specifications become more sophisticated, such as non-intuitive signs for the coefficients (e.g. positive sign for the marginal utility of travel time) and flat log-likelihoods.

Nevertheless, in general for specifications relying on the mean of the subjective distributions (but not including their variances), it was found that LTs which allowed the learned mean to converge faster to the average of the experienced outcomes[3] generated databases which increased models' goodness-of-fit. This result suggests that these databases were a better representation of subjects' learning outputs. However, the exact LT leading to the best performing model varied depending on how utility was specified. Such finding may be an indication that there is no unique LT suitable for all subjects in the sample, otherwise its database should always lead to the highest goodness-of-fit no matter the specification of utility.

The final choice model was specified as a mixed logit utility maximizing model accounting for random and systematic taste variation, correlations within the sequence of choices of the same individual (i.e. *panel effect*), and correlations among unobserved variables shared by the choice options (i.e. *error components*). The main attributes of the model were QT – the accumulated experience with the alternative, TT – the mean of the subjective distribution of travel times, and PT – the mean of the subjective distribution of parking times. Their coefficients were specified to follow bounded triangular density functions, which means varied systematically across the sample as a function of demographic characteristics and real-life driving routines of respondents, experiment design attributes, accumulated experience with the alternatives, and status of learning, making dynamic the marginal utilities of the model – with exception of the marginal utility of QT which is constant for each subject, but nevertheless multiplies an attribute (QT) which grows as the subject accumulates experience.

[3] I.e. the mean of the distribution from where the experiences were drawn

The interpretation of the results of the final model (which $\bar{\rho}^2$ was equal to 0.257) produced interesting findings. One of them is the influence of the status of the learning process on the marginal utilities of travel and parking times: the burden of deciding increases and makes the marginal utilities of travel and parking times smaller (i.e. more negative) the less the learning process has evolved (i.e. the closer to the start it is).

Accumulated experience was found to have a twofold role in the evolution of utilities: on one hand it strengthens habit, and on the other it makes individuals more intolerant towards travel and parking times. These effects, however, compensate each other in the composition of utility.

Another relevant finding was that the same demographic characteristics and real-life driving routines leading to higher (i.e. less negative) marginal utilities for travel and parking times also lead to lower (i.e. less positive) marginal utilities for the accumulated experience. As if higher tolerance towards travel and parking times was associated to a weaker effect of habit – and the other way around: as if lower tolerance towards travel and parking times was associated to a stronger effect of habit. More tolerant individuals might be more prone to explore the alternatives, taking longer to develop habits, while more intolerant individuals might be more critical in their decision making process, hence developing their preferences and developing habits faster.

Regarding the experiment design attributes, results revealed that individuals who were exposed to the outcomes of foregone options had lower (i.e. more negative) marginal utilities for travel and parking times. These findings suggest that, the better informed decision makers are, the more critic they become about their new choices. Varying the initial information provided for travel times, however, had no significant influence on the marginal utilities of travel and parking times.

Finally, the effect of ex-post regret was also tested in the specification of utility. Instead of revealing a negative impact which would penalize the alternative by reducing its utility, the estimated coefficients were statistically significant with positive signs, reinforcing the subject's previous choice. This finding suggests that avoidance of ex-post regret does not play a role in decision making under uncertainty in dynamic contexts. A behavioural interpretation for this result is that, in dynamic contexts, learning requires experimenting and risking to get non-optimal outcomes. In this sense, regret avoidance plays against learning. Another possible interpretation is that, after learning the distributions of the uncertain attributes, subjects who develop a preference for risky alternatives are aware of the pros and cons their choices might bring (such as the chosen option eventually being outperformed), the cons not being enough to weaken their preferences.

Chapter 7 investigated the stated perceptions of respondents regarding the average, minimum and maximum travel and parking times of the alternatives they experienced during the experiment. In total 24204 valid stated perceptions were collected (74.70% from the maximum number that could have been obtained).

It was found that the PDFs with smaller variances were perceived wider (i.e. with a larger range of variation) than they were in reality, while the PDFs with higher variances, were perceived narrower. Additionally, the gaps among perceived averages of different PDFs were smaller than the experienced gaps. As a consequence, the distributions (of either travel or parking times) were more similar to each other in the perception of the subjects than they were in reality.

With regards to the evolution of the stated perceptions (of the average, minimum and maximum travel and parking times) with time and experience, it was found that they were more optimistic (but not necessarily more realistic) in the end of the experiment than in the beginning, indicating that subjects see the PDFs as more attractive after the 50 choices. This trend was present for all six PDFs.

When it comes to the influence of experiment design attributes, results showed that subjects who were not faced with feedbacks on foregone options stated more realistic perceptions for travel times, and more optimistic perceptions for parking times, and subjects who were informed travel times took 30+/-5 minutes (instead of 30+/-10 minutes) stated more optimistic perceptions for Route B (which PDF is *TT.WIDE*) – no impacts were found on the stated perceptions for Route A.

It was also found that travel times were perceived as more optimistic when the route was connected to the parking areas with the best PDFs (i.e. the PDFs of parking times with the lowest averages), while parking times were perceived as more realistic when the parking areas were connected to Route A (which PDF is *TT.NARR*).

It was found that the Bayesian model, despite its flexibility, is not able to produce subjective distributions with the characteristics of the perceptions stated by the subjects. Still, direct comparison of the perceived averages of travel and parking times with the outputs of different databases (generated with different LTs) was done. Results revealed that, for a considerable number of subjects, there was not a unique database which outputs were matching all the perceptions stated. In other words, for the same subject, different databases would be the best match to different perceptions (i.e. to perceptions concerning different PDFs).

Estimation of linear-in-parameters logit utility maximizing models indicated that the stated perceptions are related to subjects' decisions in a consistent manner. Results also suggested that both the stated perceptions and the subjective distributions produced with the Bayesian belief updating become a better representation of subjects' beliefs with time and experience.

8.2 Directions for Future Research

In the pursuit to accomplish this research's objectives, new questions were raised and limitations were faced. Fortunately, these will become fuel to put forward new research efforts. This section is dedicated to directions of future research derived from this dissertation.

A very promising field for exploration is the use of "dedicated" databases per subject, which may improve the explanation power of the choice models. The most suitable (or most likely to be suitable) LT for a certain subject might be found with the combined aide of individual characteristics (such as demographic, or even related to personality traits) and stated perceptions – for which a more comprehensive sample of stated perceptions than the one used in the present research is necessary. Treating the reliability of the initial information provided to subjects as an experiment attribute (which levels can be manipulated across the experiment profiles), is another possible path of exploration.

Regarding the Bayesian learning model, there is room for improvement by, for instance, testing the suitability of mechanisms for triggering and stopping the updating process, adapting the approach to incorporate other information sources (such as ATIS) or to use more flexible (in shape) probability density functions – which may not necessarily be continuous. The latter could help preventing distortions between the message given to subjects and the representation, in the learning model, of the information provided.

The choice model can also be improved by testing specifications which reframe the alternatives into a switching (and switching to what) versus not switching perspective. Another avenue to be followed is the estimation of regret minimization models, in which the variances of the subjective distributions could be used for anticipation of regrets, taking into account the full density of beliefs.

Finally, despite this dissertation's important step in empirically validating the model, the transferability and external validity of the results can be enhanced further by employing new methods for data collection such as augmented reality laboratories, and naturally also by the use of declared choice data.

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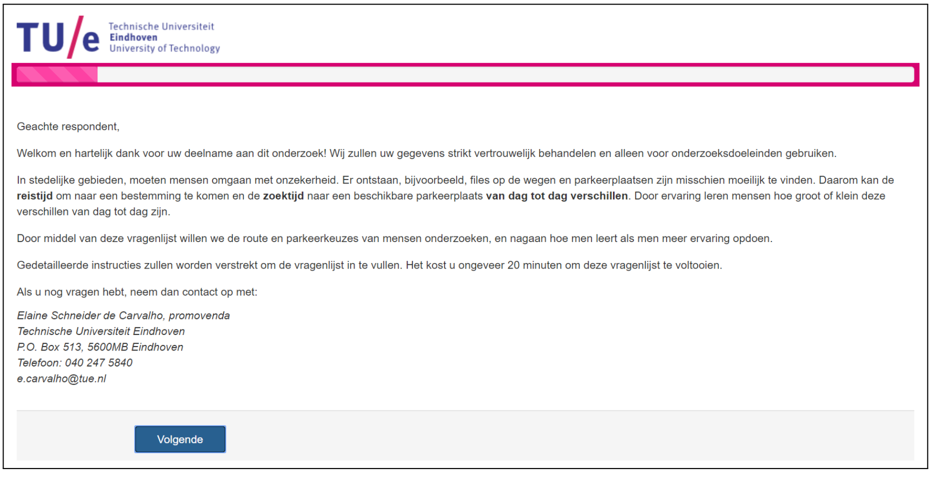
Appendix A: screens of the experiment


Technische Universiteit
Eindhoven
University of Technology

Geachte respondent,

Welkom en hartelijk dank voor uw deelname aan dit onderzoek! Wij zullen uw gegevens strikt vertrouwelijk behandelen en alleen voor onderzoeksdoeleinden gebruiken.

In stedelijke gebieden, moeten mensen omgaan met onzekerheid. Er ontstaan, bijvoorbeeld, files op de wegen en parkeerplaatsen zijn misschien moeilijk te vinden. Daarom kan de **reistijd** om naar een bestemming te komen en de **zoektijd** naar een beschikbare parkeerplaats **van dag tot dag verschillen**. Door ervaring leren mensen hoe groot of klein deze verschillen van dag tot dag zijn.

Door middel van deze vragenlijst willen we de route en parkeerkeuzes van mensen onderzoeken, en nagaan hoe men leert als men meer ervaring opdoen.

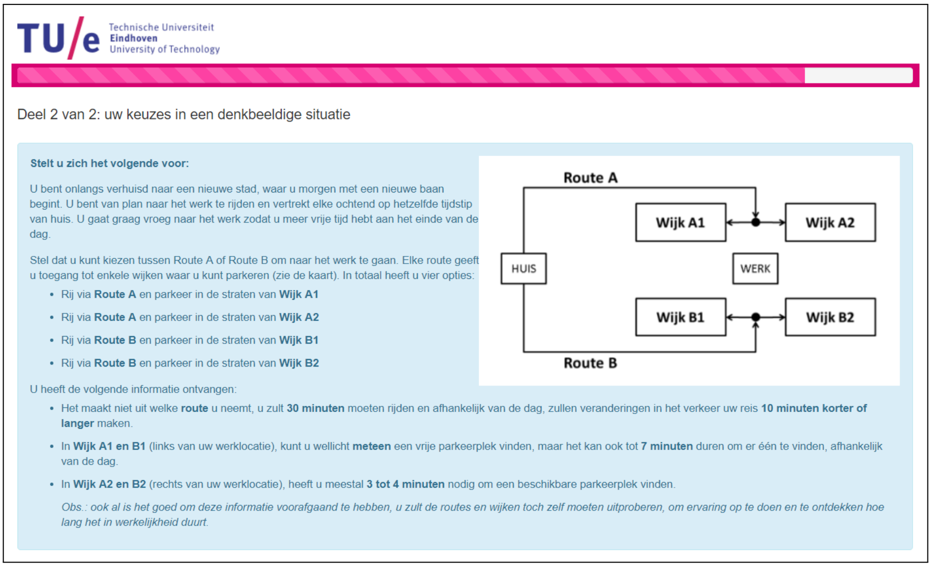
Gedetailleerde instructies zullen worden verstrekt om de vragenlijst in te vullen. Het kost u ongeveer 20 minuten om deze vragenlijst te voltooien.

Als u nog vragen hebt, neem dan contact op met:

Elaine Schneider de Carvalho, promovenda
Technische Universiteit Eindhoven
P.O. Box 513, 5600MB Eindhoven
Telefoon: 040 247 5840
e.carvalho@tue.nl

Volgende

Figure 1: *Introduction to the online experiment.*



TU/e Technische Universiteit Eindhoven University of Technology

Deel 2 van 2: uw keuzes in een denkbeeldige situatie

Stelt u zich het volgende voor:

U bent onlangs verhuisd naar een nieuwe stad, waar u morgen met een nieuwe baan begint. U bent van plan naar het werk te rijden en vertrekt elke ochtend op hetzelfde tijdstip van huis. U gaat graag vroeg naar het werk zodat u meer vrije tijd hebt aan het einde van de dag.

Stel dat u kunt kiezen tussen Route A of Route B om naar het werk te gaan. Elke route geeft u toegang tot enkele wijken waar u kunt parkeren (zie de kaart). In totaal heeft u vier opties:

- Rij via **Route A** en parkeer in de straten van **Wijk A1**
- Rij via **Route A** en parkeer in de straten van **Wijk A2**
- Rij via **Route B** en parkeer in de straten van **Wijk B1**
- Rij via **Route B** en parkeer in de straten van **Wijk B2**

U heeft de volgende informatie ontvangen:

- Het maakt niet uit welke **route** u neemt, u zult **30 minuten** moeten rijden en afhankelijk van de dag, zullen veranderingen in het verkeer uw reis **10 minuten korter of langer** maken.
- In **Wijk A1 en B1** (links van uw werklocatie), kunt u wellicht **meteen** een vrije parkeerplek vinden, maar het kan ook tot **7 minuten** duren om er één te vinden, afhankelijk van de dag.
- In **Wijk A2 en B2** (rechts van uw werklocatie), heeft u meestal **3 tot 4 minuten** nodig om een beschikbare parkeerplek vinden.

Obs.: ook al is het goed om deze informatie voorafgaand te hebben, u zult de routes en wijken toch zelf moeten uitproberen, om ervaring op te doen en te ontdekken hoe lang het in werkelijkheid duurt.

Figure 2: *Instructions before sequence of 50 choices.*

Met dit scenario in het achterhoofd, willen we u in de volgende schermen graag laten kiezen uit **één van de vier opties** om naar het werk te gaan, vanaf dag 1 (dit is de eerste dag van uw nieuwe baan) tot dag 50. Na elke gemaakte keuze, ontvangt u de **resultaten (reistijd en tijd besteed aan het zoeken naar een parkeerplek)** voor de optie die u hebt gekozen.

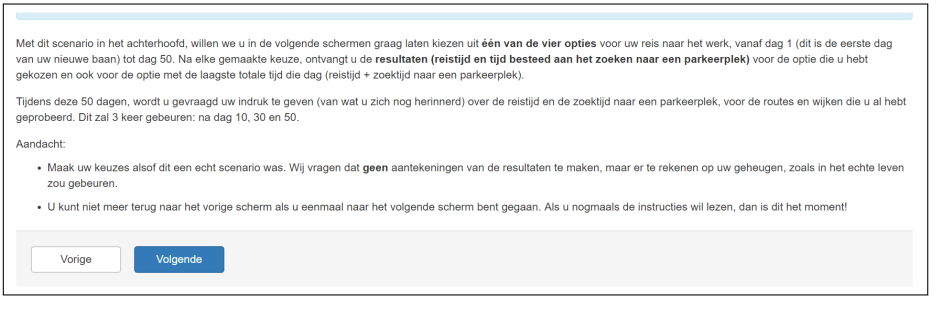
Tijdens deze 50 dagen, wordt u gevraagd uw indruk te geven (van wat u zich nog herinnerd) over de reistijd en de zoektijd naar een parkeerplek, voor de routes en wijken die u al hebt geprobeerd. Dit zal 3 keer gebeuren: na dag 10, 30 en 50.

Aandacht:

- Maak uw keuzes alsof dit een echt scenario was. Wij vragen dat **geen** aantekeningen van de resultaten te maken, maar er te rekenen op uw geheugen, zoals in het echte leven zou gebeuren.
- U kunt niet meer terug naar het vorige scherm als u eenmaal naar het volgende scherm bent gegaan. Als u nogmaals de instructies wil lezen, dan is dit het moment!

Vorige | Volgende

Figure 3: *Instructions (cont.) for profiles without feedback on foregone options.*



Met dit scenario in het achterhoofd, willen we u in de volgende schermen graag laten kiezen uit **één van de vier opties** voor uw reis naar het werk, vanaf dag 1 (dit is de eerste dag van uw nieuwe baan) tot dag 50. Na elke gemaakte keuze, ontvangt u de **resultaten (reistijd en tijd besteed aan het zoeken naar een parkeerplek)** voor de optie die u hebt gekozen en ook voor de optie met de laagste totale tijd die dag (reistijd + zoektijd naar een parkeerplek).

Tijdens deze 50 dagen, wordt u gevraagd uw indruk te geven (van wat u zich nog herinnerd) over de reistijd en de zoektijd naar een parkeerplek, voor de routes en wijken die u al hebt geprobeerd. Dit zal 3 keer gebeuren: na dag 10, 30 en 50.

Aandacht:

- Maak uw keuzes alsof dit een echt scenario was. Wij vragen dat **geen** aantekeningen van de resultaten te maken, maar er te rekenen op uw geheugen, zoals in het echte leven zou gebeuren.
- U kunt niet meer terug naar het vorige scherm als u eenmaal naar het volgende scherm bent gegaan. Als u nogmaals de instructies wil lezen, dan is dit het moment!

Vorige | Volgende

Figure 4: *Instructions (cont.) for profiles with feedback on foregone options.*

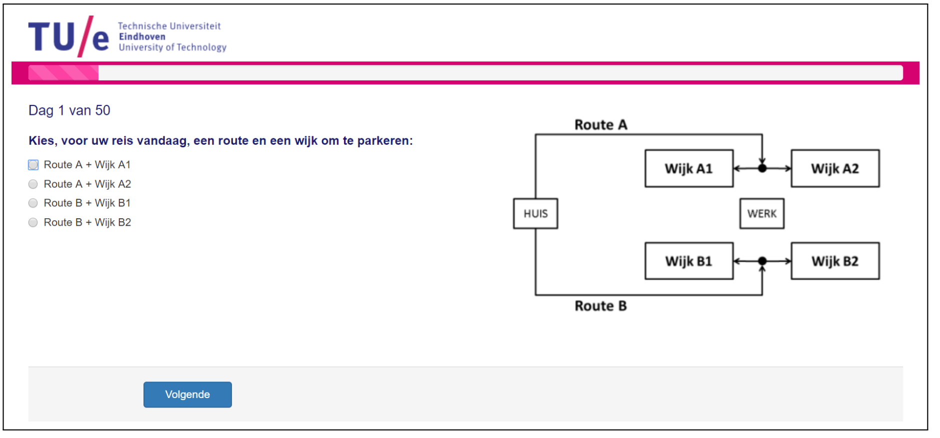


Figure 5: *Display of the choice menu.*

Figure 6: *Display of outcomes for profiles without feedback on foregone options.*

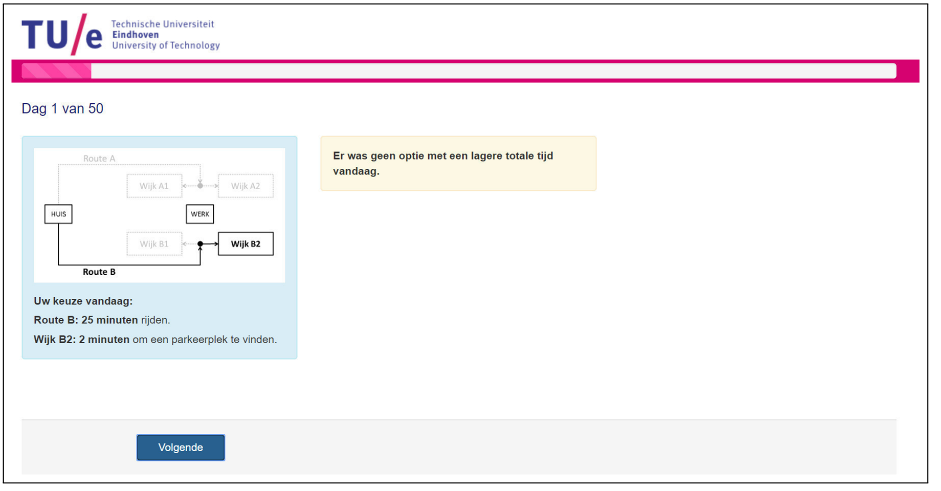


Figure 7: *Display of outcomes for profiles with feedback on foregone options (chosen is the fastest).*

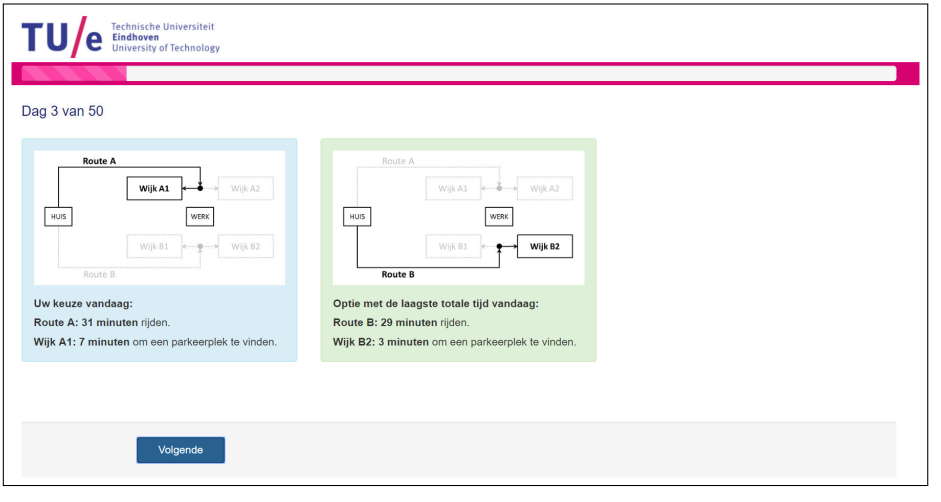


Figure 8: *Display of outcomes for profiles with feedback on foregone options (one foregone is the fastest).*

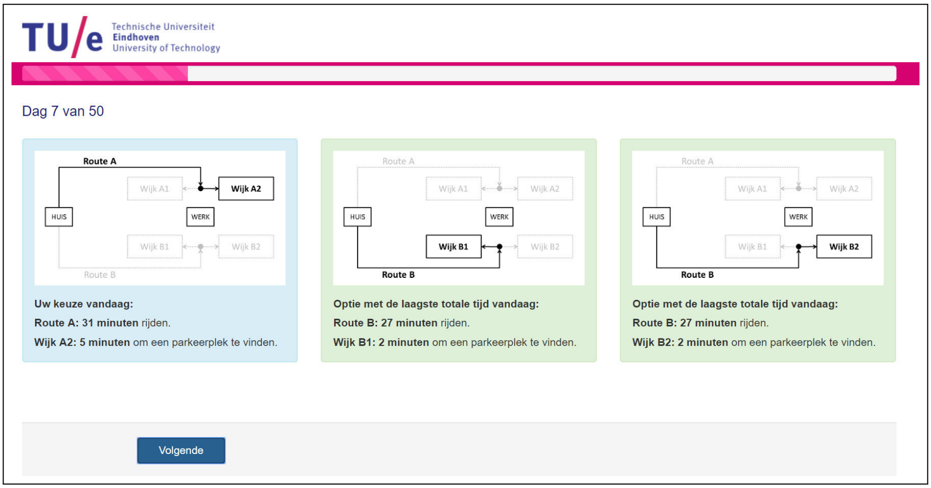


Figure 9: *Display of outcomes for profiles with feedback on foregone options (two foregone are the fastest).*

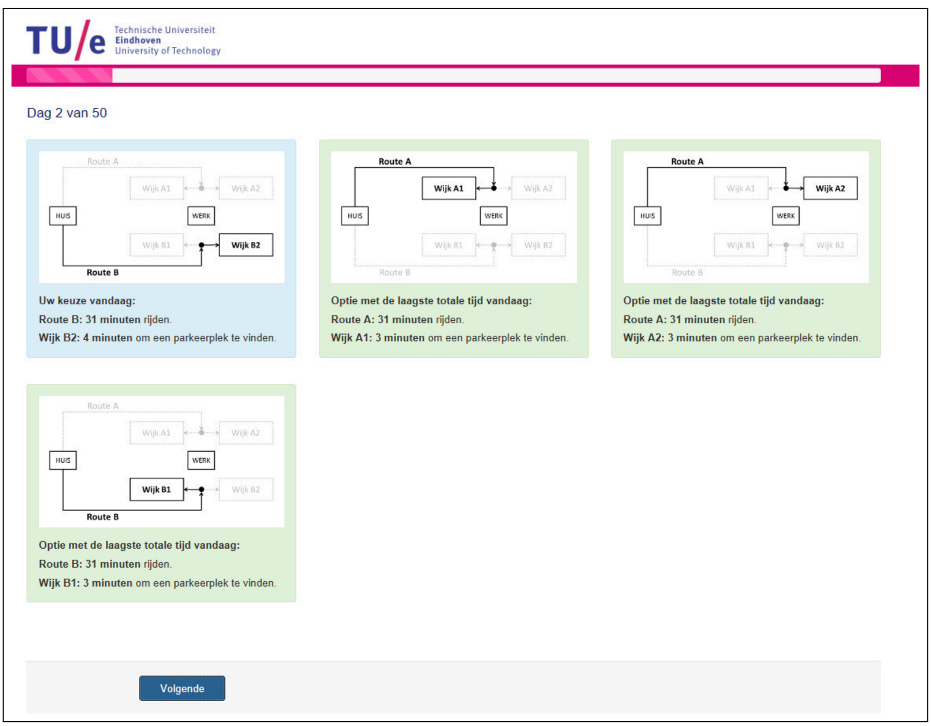


Figure 10: *Display of outcomes for profiles with feedback on foregone options (all three foregone are the fastest).*

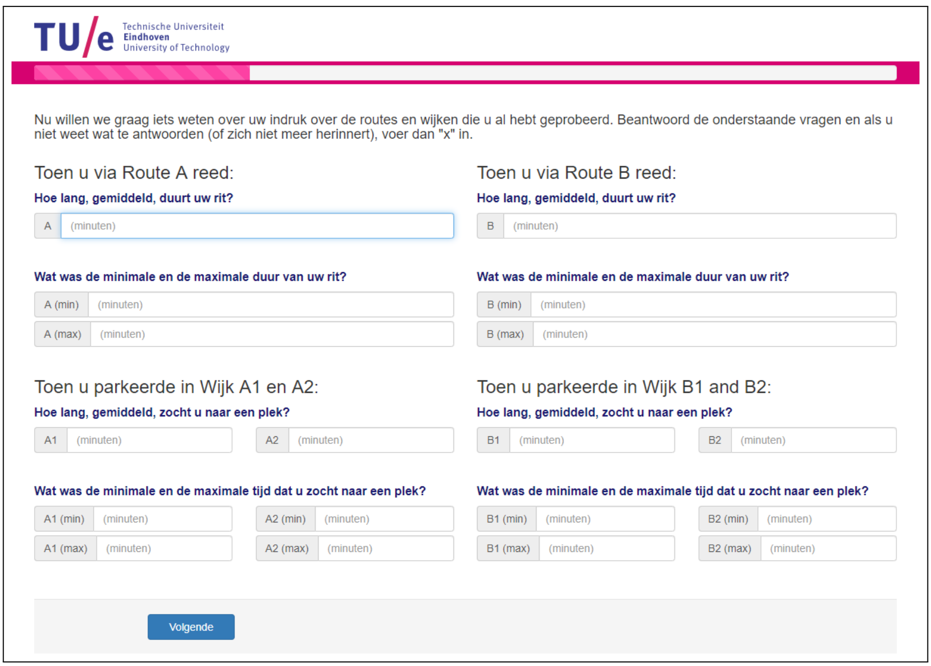


Figure 11: *Questions about perceived travel and parking times.*

Appendix B: translation of the screens

Translation of text in Figure 1:

Dear respondent,

Welcome and thank you for your participation in this survey!

We will keep your information strictly confidential and only use it for this investigation.

In urban areas, drivers must deal with some uncertainty. For instance, roads might be congested and parking spots might be hard to find. Because of that, the time spent driving to go somewhere, and the time spent looking for a place to park might vary day-by-day. As drivers gain experience, they learn how big or small these day-by-day variations are.

Through this questionnaire, we wish to investigate drivers' choices of route and parking, as they gain experience with routes and neighbourhoods which are new for them.

Detailed instructions will be provided to fill in the questionnaire. You will need approximately 20 minutes to complete it.

If you have any questions, please contact: *[Researcher's contact details]*

Translation of text in Figure 2:

Please envisage the following:

You recently moved to a new city, where you will start a new job tomorrow. You plan to drive to work, leaving your house every morning at the same time. You prefer to arrive early at work, to have more free time left at the end of the day.

You can drive to work via Route A or via Route B, and each route gives access to different neighbourhoods where you can park (please see the map). In total, you have four options:

- Drive via Route A and park at the streets of Neighbourhood A1
- Drive via Route A and park at the streets of Neighbourhood A2
- Drive via Route B and park at the streets of Neighbourhood B1
- Drive via Route B and park at the streets of Neighbourhood B2

You received the following information:

- No matter what route you take, you will spend 30 minutes driving and, depending on the day, changes in traffic can make your trip up to 10 minutes shorter or longer.
- In Neighbourhoods A1 and B1 (on the left side of your work location), depending on the day, you may immediately find a free spot to park, or you may have to spend up to 7 minutes searching.
- In Neighbourhoods A2 and B2 (on the right side of your work location), most of the times it takes 3 to 4 minutes to find a free spot to park.

  Obs.: although it is good to have this information to start with, you need to try the routes and neighbourhoods yourself, in order to gain experience and discover how long it takes in reality.

Translation of text in Figures 3 and 4:

Having this scenario in mind, in the next screens we would like you to choose one of the four options for you trip to work, from day 1 (which is your first day at the new job) to day 50. After every choice you make, you will receive the results (time spent driving and time spent looking for a spot to park) for the option you chose, ***and also for the option with the lowest total time (time driving + time looking for a spot to park) that day***[4].

During these 50 days, you will be asked to give your impressions (from what you remember) of the time spent driving and the time spent looking for a spot to park, for the routes and neighbourhoods you have already tried. This will happen 3 times: after days 10, 30 and 50.

Attention:

[4]This piece of text in ***bold and italics*** is exclusive for Figure 4.

- Please make your choices as if this scenario was real. We ask you not to make notes of the results, but to pay attention to them and count on your memory, as would happen in real life.
- You will not be able to come back to this screen after you advance to the next. If you wish to read the instructions again, this is the moment!

Translation of text in Figure 11:

Now we would like to know your impressions about the routes and neighbourhoods you have already tried. Please answer the questions below, and if you don't know what to answer (or don't remember), please type "x".

When you drove via Route A / B:

- How long, on average, did you spend driving?
- What were the minimum and the maximum time you spent driving?

When you parked in Neighbourhoods A1 and A2 / B1 and B2:

- How long, on average, did you spend looking for a spot?
- What were the minimum and the maximum time you spent looking for a spot?

Appendix C: extracting outcomes from vectors

Difference between strategies

When the strategy *sequence of the vector* is used, the outcomes are displayed in the same sequence they appear in the vector. For instance, if a subject chooses Route A on days 1, 3 and 5, the travel times in the vector *TT.NARR* which are in the first, second and third positions will be displayed (and hence will be "consumed" and no longer be available for display to the same subject). With this strategy, the outcomes of a vector are experienced by all subjects in the same order. It means that all subjects who experienced a certain PDF the same number of times (and were exposed to the same initial information about the distributions) will have exactly the same subjective distribution (resulting from the Bayesian updating).

The strategy *outcome of the day* determines that the outcome to be displayed is the one in the position of the vector corresponding to the day the choice is being made. Then, when the subject chooses Route A on days 1, 3 and 5, the travel times from the vector *TT.NARR* to be displayed are the first, the third and the fifth (and all positions up to and including position five will be "consumed" and no longer be available for display to the same subject). With this strategy, all subjects who make the same choice on day n will be faced with the same outcomes for travel and parking times, i.e. those corresponding to the state of the world in the day they made the choice.

This strategy is similar to shuffling the original vector and presenting different versions of it to each subject, in such a way that different subjects, even after choosing the same route or parking area the same amount of times during the experiment, might not experience the very same set of outcomes (and this is more extreme the higher the standard deviation of the PDF in question, because the elements of the vector are more diverse). As a consequence, their resulting subjective PDFs will not be the same.

Experiment profiles with feedback on foregone options

The strategy *sequence of the vector* cannot be used for the experiment profiles where the outcomes of the fastest foregone option is displayed. The reason for so is a practical one. Let us give an illustrative simple example, with only two generic choice options: *Route 1* and *Route 2*. Let us now take the first four positions of the vector of outcomes for *Route 1*: (32, 30, 31, 30, ...), and the equivalent positions of the vector for *Route 2*: (37, 31, 27, 29,...). Suppose that *Route 1* is chosen on the first day. Because *Route 2* has a worse outcome (37 minutes, in comparison to 32), there will be no feedback on the foregone option and the first position of the vector for *Route 2* will not be "consumed" and continue in a queue waiting to be displayed. Additionally, subjects will understand they made the best choice, and might maintain it for the next day (choosing *Route 1* again). If that is the case, because the next "non consumed" outcome of *Route 1* (which equals 30 minutes) is again better than the first non consumed and non displayed outcome of *Route 2* (which equals 37 minutes), again there will be no feedback on the foregone option, and the cycle goes on, creating a very unfavourable environment for the choice of *Route 2*, which might end up not being chosen at all.

Appendix D: vectors of outcomes

	TT. WIDE	*PTB. NARR*	*PTB. WIDE*	*PTW. NARR*	*PTW. WIDE*
TT. NARR	0.10 (0.48)	0.00 (1.00)	0.06 (0.66)	0.06 (0.66)	-0.11 (0.46)
TT. WIDE	-	-0.03 (0.86)	-0.11 (0.45)	-0.02 (0.91)	-0.07 (0.65)
PTB. NARR	-	-	0.00 (0.98)	-0.01 (0.95)	-0.05 (0.75)
PTB. WIDE	-	-	-	-0.05 (0.72)	-0.03 (0.86)
PTW. NARR	-	-	-	-	0.13 (0.38)

Obs.: p-values are in parenthesis.

Table 1: *Pearson coefficients of correlation among vectors of outcomes.*

Position	*TT. NARR*	*TT. WIDE*	*PTB. NARR*	*PTB. WIDE*	*PTW. NARR*	*PTW. WIDE*
1	32	25	2	4	4	6
2	31	31	3	3	4	3
3	31	29	3	5	4	7
4	30	24	2	7	5	3
5	31	37	3	1	4	4
6	31	31	3	1	5	6
7	31	27	2	2	5	2
8	30	29	2	0	4	3
9	31	35	3	0	4	3
10	31	29	2	0	5	5
11	31	26	3	2	4	5
12	31	33	2	3	5	4
13	30	26	3	0	4	3
14	31	33	2	1	4	2
15	31	30	3	0	5	5
16	30	28	3	1	4	3
17	31	32	2	1	4	3
18	31	24	3	1	5	4
19	32	27	3	2	5	2
20	31	30	2	1	5	6
21	32	27	2	1	4	5
22	32	31	3	6	4	2
23	32	23	3	1	5	3
24	31	34	2	1	5	6
25	31	34	3	4	5	3

Table 2: *Vectors of outcomes (positions 1 to 25).*

Position	*TT. NARR*	*TT. WIDE*	*PTB. NARR*	*PTB. WIDE*	*PTW. NARR*	*PTW. WIDE*
26	31	27	3	2	4	4
27	32	28	3	2	4	3
28	31	30	3	1	4	2
29	31	30	2	1	5	3
30	32	27	2	1	5	4
31	30	29	2	2	5	5
32	31	32	2	2	4	4
33	32	30	2	1	5	4
34	30	29	3	1	4	5
35	31	35	2	2	4	4
36	31	29	3	3	5	4
37	31	32	2	2	5	3
38	31	36	2	2	5	3
39	31	26	2	1	4	3
40	30	25	2	4	4	5
41	32	31	2	1	4	4
42	31	32	2	3	4	4
43	31	26	2	1	5	5
44	31	28	3	1	5	4
45	32	33	2	1	4	3
46	31	28	3	2	5	4
47	30	22	2	1	4	4
48	30	31	3	0	5	5
49	30	28	2	1	4	4
50	31	25	2	3	4	3

Table 3: *Vectors of outcomes (positions 26 to 50).*

Summary

Modelling Learning and Dynamic Route and Parking Choice Behaviour under Uncertainty

Models of travel behaviour under uncertainty which simultaneously: incorporate travellers' response to uncertainty in dynamic contexts, include an explicit mechanism to represent travellers' learning of the uncertain attributes of the network, and were validated with empirical data, are scarce in the scientific body of knowledge.

This research aimed at bridging this gap by (i) developing and empirically validating a model of learning and dynamic route and parking choice behaviour under uncertainty of travel and parking times, (ii) investigating the suitability of Bayesian belief updating for representing drivers' learning mechanism (given a multitude of possible starting points of calibration), and (iii) investigating the implications, for the mechanisms of learning and choice under uncertainty, of providing information on the fastest foregone alternative.

The research objectives were extended into a conceptual framework representing the daily choices of route and parking area by drivers commuting to work and faced with travel and parking search times which vary day-by-day, following probability density functions which are initially unknown to drivers. After acknowledging the realizations of every decision, drivers update their beliefs of travel and parking times, a mechanism represented by the *Learning Model*. Drivers' beliefs, together with their preferences and habits, are then used as input for next day's decision making, which is represented by the *Choice Model*.

The conceptual framework was translated into a dynamic stated choice experiment, designed to collect empirical data for model validation. Every subject from the sample (of 600 individuals in total) made 50 consecutive choices from a set of four options, each a combination of route and parking area which uncertain travel and parking times followed Lognormal distributions. The design controlled for the effect of presenting the outcomes of the fastest foregone option, the assignment scheme of PDFs to choice options, the sequence in which outcomes were displayed to respondents[5], besides varying the initial information provided regarding travel times. Additionally, a set of questions was included to capture subjects' stated perceptions of the average, minimum and maximum travel and parking times they had tried in the experiment.

After the data collection, the learned lognormal distributions (i.e. their means and variances) of travel and parking times were calculated following the Bayes Theorem, for every subject, from day 1 to day 50. The means of these learned distributions were represented by normal probability density functions, while their variances by inverted gamma densities. The main inputs for calculation were the realizations of travel and parking times faced by subjects, and the prior distributions matching the initial information (regarding travel and parking times) they received in the instructions of the experiment – being these priors composed of *starting values* for the parameters directly derived from the initial information, and their associated initial *measures of reliability*, or levels of trust (LTs). A range of levels of trust was created, each yielding a different database of subjective distributions to be used for choice model estimation.

Estimating the best possible *Choice Model* depended on exploring simultaneously a range of model specifications and a range of databases (each generated by the use of a different level of trust), in an iterative manner. The combination of database and specification of the final model, and the process that lead to it, are among the most important contributions of this dissertation.

[5]Which is referred to, in the text of this dissertation, as *strategy to extract* the outcomes from the vectors of outcomes.

In general, for specifications relying on the mean of the subjective distributions (but not including their variance), the adoption of levels of trust which allow the learned mean to converge faster to the average of the experienced outcomes[6], increased models' goodness-of-fit. However, the exact level of trust leading to the best performing model varied depending on how utility was specified, and such finding may be an indication that there is no unique level of trust suitable for all subjects in the sample.

The final choice model was specified as a mixed logit utility maximizing model accounting for random and systematic taste variation, correlations within the sequence of choices of the same individual, and correlations among unobserved variables shared by the choice options. The main attributes of the model were the *accumulated experience* with the alternative, the *mean of the subjective distribution of travel times*, and the *mean of the subjective distribution of parking times*. Their coefficients were specified to follow bounded triangular density functions, which means varied systematically across the sample as a function of demographic characteristics and real-life driving routines, experiment design attributes, accumulated experience with the alternatives, and status of learning.

The results of the model estimation showed that subjects were more intolerant to travel and parking times (i.e. their marginal utilities decreased, becoming more negative): in the beginning of the learning process, when they were exposed to the outcomes of foregone options, and the more they accumulated experience with the choice options. Accumulated experience, nevertheless, was found to have a twofold role in the evolution of utilities: despite making subjects more intolerant to travel and parking times, it strengthened the effect of habit on decision making (increasing its marginal utility, which became more positive).

Another relevant finding was that the same demographic characteristics and real-life driving routines leading to lower (i.e. more negative) marginal utilities for travel and parking times, also lead to higher (i.e. more positive) marginal

[6]I.e. the mean of the distribution from where the experiences were drawn.

utilities for the accumulated experience.

Including the ex-post regret as an attribute in the specification of utilities resulted in statistically significant coefficients which increased (instead of decreased) the utilities of the outperformed alternatives, suggesting that avoidance of ex-post regret does not play a role in decision making under uncertainty in dynamic contexts.

The investigation of the stated perceptions revealed that the distributions (of either travel or parking times) were more similar to each other in the perception of subjects than they were in reality, besides becoming more optimistic when more experience was accumulated.

Experiment design attributes also affected stated perceptions, either making them more optimistic or realistic. Perceptions of parking times were more optimistic in the absence of feedback on foregone options, while those of travel times were more optimistic when the initial information provided had a lower range of variation[7], or when the route was associated to the PDFs of parking times with lower averages. On the other hand, perceptions of parking times were more realistic when the parking area was associated to the PDF of travel times with the lowest variance, whereas those of travel times were more realistic when there was not feedback on foregone options.

A comparison of the stated perceptions with the databases generated by the *Learning Model* showed that, despite the flexibility of the Bayesian approach, it is not able to produce distributions with the characteristics of the perceptions stated by the subjects. Nevertheless, the use of the stated perceptions to estimate linear-in-parameters logit utility maximizing models indicated that they were related to subjects' decisions in a consistent manner. Besides, as it happened to the databases generated by the Bayesian approach, stated perceptions also became a better representation of subjects' beliefs with time and experience.

[7] I.e. when it was equal to 30+/-5 minutes, instead of 30+/-10 minutes.

Curriculum Vitae

Elaine obtained a Master of Sciences degree in Transportation Planning and Operations in 2013, from the Department of Transportation Engineering of the Polytechnic School of the University of Sao Paulo. During her studies, she was a teaching assistant for the undergraduate course on Urban Public Transportation at the same university, besides working as a consultant for urban transport projects in the metropolis of Sao Paulo and Rio de Janeiro.

The academic and consultancy experiences in this period motivated her to continue her professional development towards transportation planning and, more specifically, travel behaviour under uncertainty. After defending her Master dissertation, Elaine moved to the Netherlands and joined the Urban Planning and Transportation Group of the Department of Built Environment at TU/e, and started working on her PhD project. Her research interests include dynamic travel choice behaviour, behaviour under uncertainty, learning models and regret-based models.

Previous to her career in transportation, Elaine completed a Bachelor degree in Industrial Mechanical Engineering in 2003 at the Federal University of Santa Catarina, and worked for some years in industry as a Quality Assurance Engineer.

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