Measuring and Modeling Activity and Travel Well-Being

by

Maya Abou Zeid

Bachelor of Engineering in Civil and Environmental Engineering
American University of Beirut, 2001

Master of Science in Transportation
Massachusetts Institute of Technology, 2003

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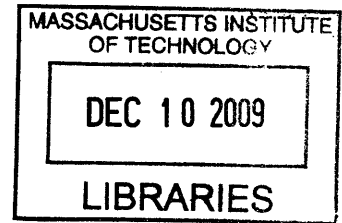
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Author ....
Department of Civil and Environmental Engineering
August 7, 2009

Certified by ....
Moshe E. Ben-Akiva
Edmund K. Turner Professor of Civil and Environmental Engineering
Thesis Supervisor

Accepted by ....
Daniele Veneziano
Chairman, Departmental Committee for Graduate Students

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Abstract

This thesis develops methods for the measurement of activity and travel well-being and models for linking well-being and behavior. The hypotheses underlying this research are that (1) activities are planned to maintain or enhance subjective well-being, and (2) given the activity choices, travel choices are likely to be motivated by a desire to maintain or enhance travel well-being. The aim is to enhance travel demand models, which over-emphasize the generalized cost of travel, to better capture travel benefits, and to contribute more broadly to measurement and modeling efforts in the subjective well-being field.

The thesis develops and tests a modeling framework that incorporates happiness measures as additional indicators of utility in discrete choice models based on random utility theory. The framework is applied to modeling both activity and travel choices and, in doing so, new well-being measurement methods are developed. Even though the applications focus on activities and travel, the framework is general and can be applied to modeling behavior in other domains.

Activity well-being is investigated both empirically and theoretically. The empirical analysis consists of the development of models of activity participation and well-being using data from a web-based cross-sectional survey of a sample of commuters. The models reveal significant correlations between well-being and behavior: higher propensity of activity participation is associated with greater activity happiness and greater satisfaction with travel to the activity. The theoretical analysis consists of the development of a framework and measures for the incorporation of well-being within activity-based models of travel demand.

The analysis of travel well-being is done in the context of the commute to work. First, using the web-based cross-sectional survey, we develop a structural equations model to model the causes and correlates of commute satisfaction. Second, we study travel well-being in a dynamic context. We postulate that due to the routine nature of commuting, people are unlikely to fully think about their travel happiness unless they need to reconsider their decisions. We conduct experiments in Switzerland and at MIT requiring habitual car drivers to commute temporarily by public transportation and measure their travel happiness and mode choice pre- and post-treatment. We find that the routine (pre-

treatment) and non-routine (post-treatment) measures of travel happiness are significantly different, as postulated. We then use the data from these experiments to estimate the proposed modeling framework, whereby the car and public transportation happiness measures are used as indicators of utility. We find that the combined choice-happiness model results in more efficient parameter estimates than a choice model alone, thus demonstrating the benefits of the extended framework that includes happiness.

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Title: Edmund K. Turner Professor of Civil and Environmental Engineering

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Chapter 1

Introduction

This thesis is concerned with the study of activity and travel well-being, defined as people's own evaluation of and feelings about their activities and travel experiences. The thesis addresses the measurement of activity and travel well-being, the modeling of its relationship to travel behavior, and the implications of the well-being approach for transportation planning. This chapter provides a motivation for this study and presents the thesis objectives, contributions, and organization.

1.1   Motivation

This research has been motivated by three main factors. First, at a general level, developments in the study of subjective well-being and its application to various life domains have called our attention to study this topic in the transportation field. Second and more specifically, the strong dependence of travel behavior models and project evaluation methods on time and cost factors, without systematic consideration of other factors affecting well-being, motivated us to consider a well-being based approach to travel demand modeling. Third, the fact that the demand for travel is derived from the demand for activities and that participation in activities is crucial for people's subjective well-being, provided another motivation for the study of well-being in the context of activities and travel.

1.1.1 Subjective Well-Being

The study of happiness or subjective well-being has been the subject of extensive research resulting in the emergence of fields such as hedonic psychology (Kahneman et al., 1999), positive psychology (Seligman, 2002), and happiness economics (Bruni and Porta, 2007; Frey and Stutzer, 2002). These fields have come to recognize the limitations of economic indicators as the sole measures for guiding public policy. Because "happiness is generally considered to be an ultimate goal in life" (Frey and Stutzer, 2002), social scientists and behavioral economists are now stressing the relevance of subjective well-being measures, which are concerned with people's evaluations of the quality of their lives, as additional indicators for informing or evaluating public policy

(Diener and Seligman, 2004; Dolan and White, 2007; Loewenstein and Ubel, 2008). To this end, a great number of surveys have been conducted to measure the well-being of citizens in many different countries (see, for example, DIW Berlin, German Institute for Economic Research, 2009; The ESRC United Kingdom Longitudinal Studies Centre, 2009; European Commission, 2009; National Opinion Research Center at the University of Chicago, 2009; World Values Survey, 2009).

In addition to their policy relevance, measures of well-being can potentially enhance behavioral models. In his lecture "The New Science of Pleasure", Daniel McFadden (2005) anticipates that "this modern behavioral revaluation of the consumer will lead to profound changes in the way economics is done." The concept of utility, on which many behavioral models are based, is not remote from the concept of happiness. Historically, Bentham (1789) equated utility with happiness and defined it as the experiences of pleasure and pain (i.e. in a hedonic sense). Later, neoclassical economists associated utility with the weight of outcomes in making decisions, where preferences can only be inferred from choices. With the recent upsurge in happiness research, the two concepts of happiness and utility have been brought close together once again; Kahneman et al. (1997) and Kahneman (2000) refer to Bentham's definition of utility as experienced utility and to the modern usage of utility as decision utility. The ability to measure subjective well-being directly will provide more information about the utility beyond what is indicated through observed choices. It will potentially lead to the development of richer and more efficient behavioral models.

1.1.2   Travel Behavior Models and Project Appraisal

Although the study of subjective well-being has been explored in various domains such as work, marriage, income, and health (Van Praag and Ferrer-i-Carbonell, 2004), the area of transportation has been less subject to this type of research. Travel behavior models have been for a long time grounded in the concept of the generalized cost of travel. That is, these models assume that people mostly base their travel choices on time and cost considerations. We postulate, however, that travel choices are more likely to be motivated by a desire to maintain or enhance travel well-being. In addition to time and cost, travelers value factors such as reliability, comfort, convenience, safety, etc. Thus, travel well-being is a broader concept that encompasses generalized cost.

Travel behavior models provide the basis for transportation project appraisal. Conventional cost-benefit analyses used in appraisal are mainly concerned with evaluating travel time savings to the end users and typically ignore the overall well-being of users and non-users. The conventional approach has two limitations. First, in addition to the tangible time and cost effects, a transportation project impacts the quality of the travel experience and the well-being of users. For example, Novaco et al. (1991) associate car commuting on congested roadways with "costs not only in terms of time and work but also with regard to physical and psychological well-being. These "externalities" of the marketplace are receiving increased attention as social costs in the transportation field". Second, non-users of a transportation alternative may simply benefit from its availability even if they don't use it. A transportation project therefore affects the

well-being of users and non-users. Ignoring the qualitative non-monetary impacts of travel and the impact on non-users may produce misleading assessments of the value of transportation projects.

1.1.3 Travel and Activities

Our study of travel well-being has also been motivated by the relationship between travel and activities. People travel in order to participate in activities, and this in turn provides a sense of well-being (Cantor and Sanderson, 1999). For example, using a Canadian time-use survey, Spinney et al. (2006) found significant correlation between the daily exposure to different types of out-of-home activities and quality of life for elderly non-working Canadians. Recent empirical evidence from time-use well-being surveys shows that happiness varies by socio-economic group and by type of activity and explores how people allocate their time to pleasant and unpleasant activities (Kahneman et al., 2004; Krueger, 2007).

Despite this evidence, well-being is not yet accounted for in activity-based models of travel demand. These models are an enhancement over trip-based models because they explicitly account for activities as the driver of travel, but they don't explain well the drivers of activities. As a result, activities are typically modeled in ad-hoc ways as a function of the generalized cost of travel and various mobility and lifestyle variables. We postulate, however, that activities are planned to maintain or enhance subjective well-being (Ben-Akiva, 2007, 2009a). Measuring activity and travel well-being and modeling it as a driver of activities will potentially lead to enhanced behavioral representations in these models.

1.2 Why Is Travel Well-Being Relevant?

In addition to the above motivating factors for our research, it is intrinsically useful to measure and account for travel well-being because it is related to a number of important consequences and uses.

First, travel well-being is closely linked to sustainability and governments have started to incorporate well-being into their public policies. For example, in Bogota, former mayor Enrique Peñalosa, through his "politics of happiness", stressed the importance of planning sustainable cities and created a new mass transit system, additional pedestrian streets and bikeways, and policies such as car-free days (Peñalosa, 2009; Project for Public Spaces, 2006). The Kingdom of Bhutan has introduced the concept of Gross National Happiness which holds priority over economic growth and is closely linked to the promotion of long-term sustainable development (Planning Commission, Royal Government of Bhutan). The importance of planning for sustainable transportation systems which promote travelers' well-being has also been recognized in the transportation and urban planning literature (O'Brien, 2005; O'Brien, 2003; Salvucci, 2005).

Second, travel is associated with psychological benefits. In addition to facilitating participation in activities which, as discussed above, is crucial for maintaining well-being, travel can have positive utility in itself. People sometimes value their travel as a means of self-expression, control, or escape (Ory and Mokhtarian, 2005). Thus, greater travel well-being fosters these psychological benefits.

Third, there can be spillover effects between travel well-being and well-being associated with the related activities. For example, commute well-being is associated with well-being at both ends of the commute: home and work. Moods at home in the evening, performance at work, absenteeism, and more generally job satisfaction may be related to commuting stress (Koslowsky et al., 1995; Novaco et al., 1990, 1991; Wener et al., 2005). Commuting stress may also impact driving capabilities and have adverse health impacts such as elevated blood pressure, increased heart rate, and chest pain (Novaco et al., 1979, 1990; Schaeffer et al., 1988; White and Rotton, 1998). Thus, greater travel well-being resulting from lower commuting stress is better for health and performance at work and other closely related domains.

Finally, knowing the affective states of drivers (such as stress, frustration, or fatigue), thanks to advances in affective computing and physiological measurement methods, will increasingly enable the design of vehicle systems that are responsive to those affective states. Such systems can act to alert drivers, prioritize information given, automate certain driving maneuvers, or manage workload (Reimer et al., 2009). For example, if a driver is stressed, non-critical in-vehicle systems such as radios or cell phones could be automatically managed to help the driver cope with his/her stress (Healey and Picard, 2005). Examples of these systems include the "Aware Vehicle" concept developed by the MIT AgeLab (Reimer et al., 2009) and the POD which is an "affective car" designed by Toyota in collaboration with Sony (Clothier, 2005).

1.3   Research Objectives

Given the above background, this research aims to understand and quantify the determinants of activity and travel well-being in order to enhance travel behavior models and to better capture travel benefits. Our investigation will not be limited to a qualitative analysis of the effects of well-being on behavior. Rather, the focus of this research is on the use of models that quantitatively represent the relationship between the two.

From the outset it is important to note a distinction that we adopt in our study of activity and travel well-being. The two concepts of activity and travel well-being are related; as mentioned above, people travel in order to participate in activities, and there are often interdependencies or spillovers between the psychological effects of travel and of activities. When people judge their satisfaction with their travel, they may confound it with their satisfaction with the corresponding activities. One context where travel well-being is more clearly defined as a separate concept is the commute to work. Commuting is habitual travel that is usually conducted in peak hours of the day and is more well-defined in people's minds. Therefore, our analysis of travel well-being will mainly focus

on commuting. We will also study activity well-being mostly from a conceptual standpoint but also support it with an empirical investigation. The conceptual developments that are presented early on in the thesis (Chapter 3) are applicable to the study of both activity and travel well-being. The analyses that follow (Chapters 4 to 7) will focus separately on commute well-being and on activity well-being.

This thesis has three main objectives:

- Develop and test activity and travel well-being measurement methods
- Model the relationship between activity and travel well-being and behavior
- Assess the implications of the well-being approach for transportation planning

1.3.1 Measurement

We develop and test methods for the measurement of travel well-being in the context of the commute to work. We first approach the measurement issue from a cross-sectional perspective, as is commonly done in studies of subjective well-being. We draw on the subjective well-being and commute stress literatures in developing self-reported measures of travel well-being, including both cognitive (satisfaction) and affective (enjoyment, stress, anxiety, etc.) components. We collect data using a web-based survey of a sample of commuters. Second, we measure travel well-being in a dynamic context. We postulate that due to the routine nature of commuting, people are unlikely to think about their travel well-being unless they need to reconsider their decisions. We design and conduct experiments that induce habitual car drivers to reconsider their mode choice decisions after a temporary switch to public transportation. We analyze the differences between their routine (cross-sectional) and non-routine (after temporary change in behavior) reports of commute satisfaction.

We also measure happiness with different types of activities and satisfaction with travel to those activities in a cross-sectional setting. We propose measures to capture the well-being at the level of activity patterns.

1.3.2 Modeling

We develop modeling frameworks for relating well-being and behavior within the context of random utility models, and propose the use of well-being measures as additional indicators of utility.

We illustrate the models empirically in the context of activities and travel. First, using the cross-sectional data, we estimate a structural equations model that relates commute well-being to a number of commute attributes and individual characteristics and other models that predict the propensity to participate in activities as a function of activity and travel well-being. We find significant correlations between well-being and behavior. Second, using the dynamic data, we estimate models of travel well-being and mode switching. We use the models to study the relevance of different travel well-being measures to modeling

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behavior. Third, we propose extensions to activity-based models by developing a modeling framework where measures of well-being at the level of activity patterns are used as indicators of the utility of the activity patterns.

1.3.3 Implications

We study the implications of the activity and travel well-being approach for transportation planning. First, we provide suggestions for the extension of household travel surveys to include activity and travel well-being measures. Second, we discuss the relevance of different travel well-being measures given the challenge posed by routine behavior. Third, we briefly discuss how findings from travel well-being research in general and from our own investigation in particular can be used to inform transportation policies.

1.4   Research Contributions

The study of activity and travel well-being is relatively recent. Apart from the vast commuting stress literature, there are very few studies that have touched upon the travel well-being area. The study of activity well-being and its relation to time use has been of interest to researchers but has mostly been approached qualitatively.

The contributions of this thesis lie mainly in measurement and modeling. First, we develop a new method for the measurement of travel well-being that accounts for the routine nature of travel by inducing people to rethink their decisions. This same principle may be applied to the measurement of subjective well-being in other domains characterized by routine behavior. We also suggest measures for capturing well-being at the level of activity patterns; these measures can easily be incorporated in travel-activity household surveys that are commonly conducted by metropolitan planning organizations in the U.S. and elsewhere.

Second, we develop and test a new modeling framework that enriches behavioral models by explicitly including well-being measures as indicators of utility. The framework is applied for modeling well-being in the context of both travel behavior (mode switching) and activity pattern generation. Standard approaches to modeling behavior have relied on observed choices as the only indicators of utility. By adding the well-being indicators, a gain in efficiency is achieved. Although the framework is demonstrated in a transportation context, it is general and can be applied to other contexts where random utility models are used to represent behavior.

The well-being approach to modeling activities and travel is expected to lead to enhancements in travel behavior models and project evaluation methods and to the design of policies that enhance people's well-being.

1.5   Thesis Organization

This thesis is organized as follows.

Chapter 2 provides background material to this study. It reviews random utility theory, including criticisms and enrichments of behavioral models based on random utility. It then discusses the relationship between happiness and utility and suggests the use of happiness data to further enrich random utility models by using happiness measures as indicators of utility. It reviews measurement methods, issues, and findings in the subjective well-being literature. It concludes by reviewing behavioral models based on random utility in the transportation field, their enrichments, and recent efforts to include well-being in these models.

Chapter 3 develops the activity and travel well-being idea conceptually from different angles: which aspects of activity and travel well-being should be measured, measurement methods, issues with these methods, and a framework for modeling well-being and behavior. This chapter provides the theoretical basis for the empirical investigations of commute well-being pursued in Chapters 4 to 6 and for the theoretical developments related to activity pattern well-being pursued in Chapter 7.

Chapter 4 studies cross-sectionally the measurement and modeling of travel well-being in the context of the commute to work, and the measurement and modeling of activity well-being. It describes a set of postulates about the causes and correlates of commute well-being. It then describes a web-based survey that was conducted to measure commute well-being. This is followed by the specification and estimation of a structural equations model that relates commute well-being to its hypothesized correlates. The chapter also investigates the relationship between well-being and behavior. In particular, models of activity participation as a function of activity happiness and travel satisfaction are developed using the cross-sectional survey data.

Chapter 5 studies dynamically the measurement of travel well-being (in the context of the commute to work) in a way that accounts for the routine nature of travel. It reviews experiments in the literature on travel behavior modification that have studied the effects of temporary changes in behavior on subsequent behavior and psychological constructs. Then it describes the design and implementation of two experiments that we conducted in Switzerland and at the Massachusetts Institute of Technology (MIT) to measure travel well-being under routine and non-routine conditions. The treatment (intervention) employed is a temporary "required" use of public transportation that disrupts the commuting routine of a sample of habitual car drivers. The chapter presents a descriptive analysis of these experiments, including the pre- and post-treatment travel well-being measures collected, mode choice, perceptions, attitudes, plans, and expectations about public transportation. It discusses similarities and differences between the Swiss and MIT findings.

Chapter 6 focuses on the modeling of travel well-being using the data collected from the experiments described in Chapter 5. A model based on the theoretical framework

presented in Chapter 3 is developed where the travel well-being measures are used as indicators of utility in addition to the standard mode choice measures. The model is estimated separately using the Swiss and MIT datasets and jointly combining the two. It demonstrates the benefits of the proposed framework and illustrates the implications of different well-being measures for modeling behavior.

Chapter 7 provides a theoretical analysis of well-being and activities. It reviews time allocation theories and empirical evidence on the relationship between well-being and activities. It then proposes enhancements to activity-based models drawing on well-being research. It reviews activity-based models, points to limitations in their specifications, and motivates well-being as a driver of activity patterns. This is followed by the development of a framework for modeling well-being and activities, based on the general framework of Chapter 3, and by suggested measures of activity pattern well-being.

Chapter 8 concludes the thesis. It summarizes the research objectives, approach, and findings, discusses the measurement and policy implications and the limitations of the research, and presents directions for future research.

Chapter 2

Literature Review

As discussed in Chapter 1, this thesis contributes to efforts aimed at enhancing the behavioral richness of models based on random utility theory. This chapter therefore contains related background material. The first part of the chapter (Sections 2.1-2.3) is a review of random utility theory, including its criticisms and recent efforts aiming at its enrichment. The second part (Sections 2.4-2.5) introduces the concept of happiness as a potential enrichment of behavioral models. It elaborates on the relationship between happiness and utility and describes methods and findings from happiness research. The third part (Section 2.6) reviews random utility theory and happiness research as they apply to travel demand models. Section 2.7 concludes.

2.1 Random Utility Theory

Utility theory is the cornerstone of the standard consumer model used in economics. In this model, a decision-maker is faced with the problem of choosing a consumption bundle subject to a given budget constraint. A bundle represents quantities of goods to purchase. Under conditions of completeness, transitivity, and continuity[1], which characterize rational behavior, a continuous utility function is associated with the consumption bundles. It maps the quantities x of goods in every consumption bundle to a real number $U(x)$. The utility can be thought of as a measure of the desirability of the bundle. It determines preference ordering among the bundles: if $U(x_1) > U(x_2)$, bundle 1 is preferred to 2.

The consumer chooses the bundle that maximizes his/her utility subject to a budget constraint. The demand function that maximizes utility is obtained by solving this optimization problem. It is a function of the prices of the goods and the consumer's income. When substituted back in the utility equation, it gives the indirect utility

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[1] Completeness means that an individual can always determine his/her preference between any two bundles / alternatives. Transitivity means that if an individual prefers alternative A to B, and B to C, then he/she also prefers A to C. Continuity means that if an individual prefers A to B, then he/she also prefers alternatives suitably "close to" A to alternative B.

function, i.e. the maximum utility as a function of the prices of the goods and the consumer's income. Utility is used in an ordinal sense. That is, the value of the utility is irrelevant. What matters is the ordering of the utilities of different alternatives. One can therefore apply any transformation to the utility function that preserves the preference ordering without changing the solution obtained in the utility maximization problem.

Utility theory as used in the standard consumer model is based on a number of assumptions: (1) goods are homogeneous, and so utility depends on quantities of goods as mentioned above, (2) goods are continuous, and (3) behavior is deterministic. For a more detailed exposition of microeconomic consumer theory, the reader is referred to microeconomic textbooks (such as Mas-Colell et al., 1995; Nicholson, 2004; Varian, 1992).

One of the important extensions of the original utility theory is random utility which has its origins in mathematical psychology (Luce, 1959; Marschak, 1960; Thurstone, 1927). Here the utility of an alternative is considered as a latent or unobserved variable consisting of the sum of a systematic part, which is a function of attributes of the alternative (which may also be interacted with characteristics of the decision-maker), and a random part or error term. The idea is that while consumers may know exactly the utility they derive from different alternatives, the analyst may not know this utility with certainty. Sources of randomness include unobserved variables, measurement errors, unobserved taste heterogeneity, and instrumental or proxy variables (Manski, 1977). Utility maximization is still used as the decision protocol, but now the choice is stochastic.

Random utility theory is the behavioral foundation of discrete choice methods which model choices among discrete alternatives (Ben-Akiva and Lerman, 1985; McFadden, 1984). The standard discrete choice framework is shown in Figure 2.1. The utility of every alternative is a function of attributes of the alternative and random factors. Utility is inferred from observed choices and is used to explain these choices. That is, the alternative that is chosen has the maximum utility among the alternatives in the choice set.
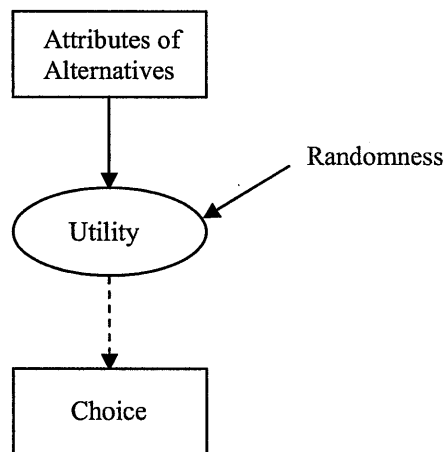
Figure 2.1. Standard discrete choice framework based on random utility theory.

As mentioned above, a central tenet of utility theory is the rationality assumption. Stated more simply, this is the assumption that decision-makers are rational agents with stable preferences who are able to predict the utilities from various outcomes and choose the outcome with maximum utility. McFadden (1999) distinguishes among three types of rationality: perception-rationality, preference-rationality, and process-rationality:

> *The standard model in economics is that consumers behave as if information is processed to form perceptions and beliefs using strict Bayesian statistical principles (perception-rationality), preferences are primitive, consistent, and immutable (preference-rationality), and the cognitive process is simply preference maximization, given market constraints (process-rationality).*

Moreover, utility theory assumes that behavior is individualistic, i.e. that it is based on self-interest.

2.2 Criticisms of Random Utility Theory

Choice models based on random utility theory have been criticized for their inadequate representation of behavior on several grounds. First, they do not sufficiently incorporate the psychological elements of the actual decision-making process. Second, the rationality assumption on which these models are built has been challenged by evidence for departures from rationality, collected from a large number of experiments conducted by social scientists and behavioral economists. Third, studies have also shown that behavior is often affected by social motives and is not purely individualistic as postulated by utility theory. We discuss each of these criticisms below. In discussing violations of rationality, we adopt the definition of rationality suggested by McFadden (1999). Our discussion of this topic is selective. For additional readings on violations of rationality, see for example, Ariely (2008).

2.2.1 Limited Representation of the Behavioral Process

Behavioral researchers have emphasized the role of psychological factors, including perceptions/beliefs, attitudes, affect, motives, and preferences in the decision-making process. Figure 2.2 presents an example of a framework showing the psychology of decision-making (McFadden, 1999). Although technically there is nothing in random utility theory that prevents modelers from accounting for such factors in the choice process, models based on random utility theory have in practice not sufficiently represented the actual workings of the decision-making process. They have mostly been specified as "black box" models that map observed inputs into observed choices through the utility function.
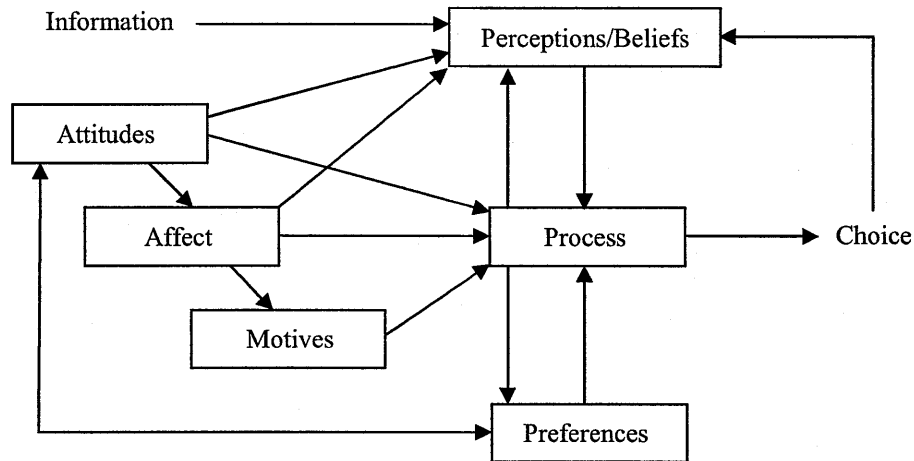
Figure 2.2. The decision process (McFadden, 1999).

2.2.2 Violations of Perception-Rationality

There is substantial evidence showing that people often make mistakes in their judgment of the probabilities of events, violating the principles of statistical sampling and Bayesian updating assumed by the standard economic model. A substantial amount of the work in the area of judgment under uncertainty has been done by cognitive psychologists Amos Tversky and Daniel Kahneman (see for example, Tversky and Kahneman, 1974). For other discussions, see Rabin (1998) and McFadden (1999).

People may use a number of heuristics to make probability judgments which, while useful at times, can lead to biases in judgment. Examples of these heuristics follow. The "availability heuristic" refers to the use of available or salient information to judge the likelihood of future events. "Representativeness" occurs when people overestimate unconditional probabilities because of high conditional probabilities in a way that violates Bayes' law. "Primacy/recency" effects occur when people attach more weight to initial or most recent events. The "law of small numbers" is a type of bias that occurs when people exaggerate the resemblance of a small sample to the population from which it is drawn. Other biases include belief perseverance (inattention to new information contradicting strongly held beliefs), confirmatory bias (misinterpretation of evidence as further support for initial beliefs), and a number of memory biases such as easy recall of salient information and of coincidences and reconstruction of imperfect memories.

These and a number of other "cognitive anomalies" in the judgment of probabilities are "systematic, persistent, pervasive, and large in magnitude" (McFadden, 1999).

2.2.3 Violations of Preference-Rationality

Standard preference theory assumes that preferences are stable and reference independent. However, numerous studies have shown that preferences are volatile, may be constructed as needed (see, for example, Slovic, 1991), and may be time-inconsistent and reference-dependent.

Preferences are affected by framing, context, anchoring, and method of elicitation. Framing refers to the way in which alternatives are presented. A number of experiments have found that framing the same problem in different ways leads to different choices. For example, in their classic "Asian disease" example, Tversky and Kahneman (1981) attribute this cognitive anomaly to asymmetry of perceptions for gains and losses.

Context refers to the setting in which a choice is offered, such as the set of options under consideration. Again, experiments have found that people tend to choose one alternative over another in a given choice context but may reverse their preferences when other alternatives are added to the choice set (Tversky and Simonson, 2000). Moreover, the context in which a choice is made may be different from the context of the actual experience, which may lead to misprediction of future preferences or utility. This occurs when certain comparative effects are salient at the time of the choice (e.g. attributes of various choice options) but not at the time of the experience. One example of this is the salience of variety-seeking when simultaneously choosing goods that will be consumed sequentially in the future (see, for example, Simonson, 1990).

Studies have also shown that people sometimes make decisions that may be affected by arbitrary anchors or reference points (Ariely et al., 2003). People may also exhibit "preference reversals" when the method of preference elicitation is changed, such as when evaluating pairs of goods jointly or separately (Hsee, 2000).

A large literature on intertemporal choices explores how preferences may be time-inconsistent. That is, short-term preferences, which are largely affected by a tendency for immediate gratification, may be inconsistent with long-term preferences. For a review of this literature, see Frederick et al. (2002).

Finally, preferences are often more sensitive to changes from reference points than to absolute levels. The reference point could be for instance the status quo level of wealth. Moreover, reference points change over time because of adaptation and possibly other reasons. Effects arising from reference dependence include loss aversion and diminishing sensitivities (Kahneman and Tversky, 1979). Loss aversion means that people are more averse to a given loss than they are attracted to an equal-size gain. Diminishing sensitivity is the property of being less sensitive to changes (e.g. in wealth) as one moves further away from the reference point. Such effects are not captured by standard reference-independent utility specifications.

2.2.4 Violations of Process-Rationality

People may choose decision protocols that are different from utility maximization due to limitations of human information processing and computational capabilities (McFadden, 1999). Examples of these protocols are dominance rules, satisfaction rules, lexicographic rules, or random choice (Slovic et al., 1977; Svenson, 1979). People could use heuristics or rules, for example, when the costs and benefits involved in a decision have varying timeframes, salience, or scale (Prelec, 1991). They also often follow exemplars in order to reduce the cognitive effort involved in making a choice. A large literature on social interactions explores how people's decisions may be affected by the behavior of others in their social networks (see, for example, Brock and Durlauf, 2001; Manski, 1993, 2000).

2.2.5 Preference for Non-Individualistic Outcomes

Random utility models assume that decision-makers maximize their self-interested individual utility functions without concern for other people's outcomes, motives, or beliefs. Yet, a large literature including many experiments (e.g. in game theory) explores how preferences may be affected by social forces such as altruism, reciprocity, attribution, fairness, etc., suggesting that "economists should move away from the presumption that people are *solely* self-interested" (Rabin, 1998).

2.3 Enrichment of Random Utility Theory

Given the shortcomings of the random utility model described above, a substantial amount of work has been done over the last few decades to enrich it. There have generally been two approaches for enrichment. The first is to modify or enhance certain assumptions or components of the standard model in a way that preserves its basic structure. The second is to depart from the random utility model and propose alternative theories. We describe below a number of these enrichment efforts.

2.3.1 Attitudes, Perceptions, and Other Latent Variables

Behavioral models based on random utility have recently started to incorporate several of the psychological constructs that affect decision-making. In discrete choice models, a framework that has been proposed for doing that is the Hybrid Choice Model (HCM) (Ben-Akiva et al., 2002a; Walker and Ben-Akiva, 2002). The HCM combines a choice model (based on random utility) with a latent variable model. The latent variable model adds behavioral richness as it can be used to model the formation of latent (unobserved) psychological constructs such as attitudes, perceptions, and plans and, through its linkage to the choice model, allows a representation of the effect of these constructs on preferences. The evolution of psychological constructs can also be accommodated within a dynamic version of the HCM which combines a Hidden Markov model with a discrete choice model (Ben-Akiva et al., 2006; Choudhury et al., 2007a, 2007b). A latent class

model may be added to this framework to reflect latent segmentation of the population, choice set formation, and decision protocols other than utility maximization (Gopinath, 1995).

To facilitate identification, the latent variables are usually related to indicators commonly obtained through surveys (such as perceptual and attitudinal ratings). Utility has the standard choice indicators (revealed or stated preferences).

2.3.2 Social Preferences

One way to model social preferences is to use "social utility" functions that include terms representing the dependence of an individual's utility on his/her outcomes and other people's outcomes (or difference between own and others' outcomes) (Fehr and Schmidt, 1999; Rabin, 1993). A number of experiments have been conducted by behavioral economists to estimate mathematical functions of social utility (Loewenstein et al., 1989; Messick and Sentis, 1985). These studies have provided further evidence that choices are not purely individualistic but may be motivated by various factors including self-interest, self-sacrifice, altruism, aggression, cooperation, and competition (MacCrimmon and Messick, 1976).

Models of social preferences have also been used to represent conformity or herd behavior, for example, by including the average behavior of others in an individual's utility function (Brock and Durlauf, 2001; Timmins and Murdock, 2007).

2.3.3 Time-Inconsistent Preferences

Intertemporal choice models that assume time-consistent preferences have been traditionally specified using discounted utility models with a constant discount rate so that the discount function is an exponential function of time. Alternatives to this model that can allow for time-inconsistent preferences have either modified the discount functions / enriched the utility function or have departed more radically from the discounted utility model. An example of the first approach is the use of hyperbolic discounting that is based on declining discount rates. An example of the second approach is multiple-self models, such as the planner-doer model that represents an individual self as a series of myopic doers focusing on immediate gratification and one planner who cares both about the present and future. For a review of these and alternative enhancements in the domain of intertemporal choices, see Frederick et al. (2002).

2.3.4 Non-Expected Utility Theories and Reason-Based Choice

A number of non-expected utility theories have been proposed as alternatives to expected utility theory (for a review, see Starmer, 2000). These theories can address some of the "cognitive anomalies" or biases in judgment identified by behavioral research. One of the most popular among them is prospect theory (Kahneman and Tversky, 1979). In this

theory, a probability weighting function that underweights large and overweights small probabilities is used to evaluate risky prospects. A value function replaces the usual utility function and evaluates outcomes relative to a reference point. The value function is concave in the domain of gains and convex and steeper in the domain of losses. The shape of the value function implies diminishing sensitivity (as one moves away from the reference point) and loss aversion.

An alternative class of decision models that is not value-based (i.e. does not associate a numerical value with every alternative) is reason-based models of choice (Shafir et al., 1993). Contrary to quantitative economic models that rely on value maximization, reason-based models identify reasons and arguments that influence the decision in question and explain the choice as a balance of these reasons. Reason-based models can account for the effects of framing, contexts, and elicitation methods on choice. For example, different frames can highlight different features of the options that induce different reasons for making the choice under consideration.

2.4 Happiness and Utility

Happiness research has flourished over the last two decades and may be seen as a promising direction within the broader behavioral movement in economics (Camerer and Loewenstein, 2003). Happiness data can be used to enrich behavioral models based on random utility theory. An understanding of the relationship between happiness and utility is crucial to this endeavor and is the subject of this section. Before that, however, we begin by reviewing definitions of happiness as the terms subjective well-being and happiness have been conceptualized in many different ways.

2.4.1 Definitions of Happiness

Early philosophical accounts equated happiness with eudemonia, in which happiness is judged by external objective criteria (such as virtue) and is associated with the character of one's life rather than pleasure or enjoyment (Diener, 1984; Diener et al., 2003). Recent studies of happiness, on the other hand, are concerned with happiness as a subjective state in which individuals judge their own happiness. There are several views of what happiness in this psychological sense is, including life satisfaction, hedonism, affective states, perceived desired satisfaction, and a hybrid of these accounts most commonly referred to as subjective well-being (Haybron, 2000). Andrews and Withey (1976) postulated that subjective well-being is determined by three separable components: life satisfaction, positive affect, and negative affect. Satisfaction with domains of life may be added as a fourth component (Diener et al., 2003).

Life satisfaction judgments are global cognitive evaluations of an individual's quality of life from his/her own perspective. Affect refers to the moods and emotions people experience through their daily lives. Affective and cognitive well-being are related, with the former used to varying degrees when judging life satisfaction. Domain satisfaction refers to the evaluation of one's satisfaction with specific domains of life, such as work,

health, marriage, income, etc., which are thought to affect global life satisfaction (although the reverse direction from global life satisfaction to domain satisfaction has also been discussed in the literature).

Within the subjective classifications of happiness, Lazarus and Lazarus (1996) distinguish between two meanings of the word happiness. The first is an estimate of well-being. For example, when people are asked how happy they are (as in standard well-being surveys), the answer they give is an evaluation of their overall subjective well-being and is not a specific emotion that is connected to a time and an event. The second meaning is happiness as an emotion, which is tied to an event and could vary from one moment to another as other events unfold.

In this thesis, we use the concept of happiness in a subjective or psychological sense. Moreover, we use the words happiness and subjective well-being interchangeably. We will be explicit when we refer to the cognitive (satisfaction) or affective component of subjective well-being.

2.4.2 Relationship Between Happiness and Utility

McFadden (2005) nicely summarizes the history of the study and measurement of well-being and its relationship to utility in classical and neoclassical economics and in the modern behavioral revaluation of the consumer. Some of the discussion in this section draws on McFadden's (2005) overview.

Classical Era

As briefly stated in Chapter 1, the relationship between happiness and utility goes back to the days of Jeremy Bentham (1789) who defined utility as the experiences of pleasure and pain. Utility was related to the process, experience, or sensation attached to actions rather than to their consequences. Utility, according to Bentham, would be determined by four dimensions of an experience: intensity, duration, certainty, and temporal distance. The influence of others' well-being on one's own well-being was recognized, and utilitarianism was further associated with the "greatest happiness principle": that is, the moral value of an action is determined by its contribution to the happiness summed across all people. There were other proponents of the Benthamite conceptualization of utility including James Mill, John Stuart Mill, and Francis Edgeworth who in 1881 called for a hedonimeter that can provide a measure of the intensity of pleasure and envisioned happiness as the integral of pleasure over the duration of an experience. Even though it was believed that utility or happiness was measurable, no attempt was made at the actual measurement of happiness in the classical era of consumer theory. Measurement was viewed as a task left to psychometricians.

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Neoclassical Era

Edgeworth's work marked the crossover from the classical to the neoclassical eras of consumer theory. Towards the end of the 19th century, economists started to distance themselves from psychological introspections of utility, conceptualizing it instead as a "black box whose inner workings were not their concern" (McFadden, 2005). In 1892, Irving Fisher tried to provide a quantitative definition of utility and maintained that it can be measured albeit not directly through psychological or physiological means but rather indirectly through people's behavior (Colander, 2007).

Although Fisher thought that "it is not [the economist's] province to build a theory of psychology", he believed that utility had to be measurable in order for it to be useful. In the neoclassical era that followed, economists abandoned the idea of the indirect measurement of utility with Lionel Robbins' argument in 1932 against using interpersonal comparisons of utility, and after the idea of recovering utility solely from demand functions was formalized by a number of economists as the theory of revealed preferences. Moreover, the emphasis in the conceptualization of utility moved from the process to the consequences of actions and conveniently ignored the effects of social forces such as reciprocity and altruism. Thus, to summarize, neoclassical economists associated utility with the weight of outcomes in making decisions, where preferences can only be inferred from choices.

Modern Behavioral Revaluation

In the modern behavioral revaluation of consumer theory, there has been a revived interest in the measurement of happiness. This movement has been aided by developments in several fields including hedonic and cognitive psychology, behavioral and experimental economics, happiness economics, neuroscience, and others.

Daniel Kahneman and his colleagues in particular have made significant contributions to the revival of discussions about the relationship between happiness and utility. In a key paper entitled "Back to Bentham? Explorations of Experienced Utility", Kahneman et al. (1997) and later Kahneman (2000) referred to Bentham's definition of utility as experienced utility and to the modern usage of utility by neoclassical economists as decision utility. They further made a distinction between three forms of experienced utility: remembered, moment, and predicted utility. Remembered utility is a retrospective global assessment of an experience. Moment utility is the real-time characterization of the affective/hedonic state of each moment of experience, and can under certain conditions be used to characterize the total "objective" utility of an experience. Predicted utility is the anticipated feeling of pleasure or pain associated with an outcome that will be experienced in the future.

Through a series of experiments, Kahneman and his colleagues (Kahneman et al., 1993; Redelmeier et al., 2003; Schreiber and Kahneman, 2000) demonstrated that remembered utility (of pain or pleasure) is determined by selected moments of the actual experience. In their experiments, those moments were the peak and end of the experience (peak-end

rule); the length of the experience did not affect its retrospective evaluation (duration neglect). They also found that people tended to repeat choices which they remembered as less unpleasant or more pleasant, that is remembered utility affects predicted utility which is part of decision utility. See also Wirtz et al. (2003) for further evidence. However, these choices often failed to maximize experienced moment-to-moment utility. That is, people were more likely to choose to repeat experiences which they remembered as less painful even though objectively (i.e. experienced moment by moment) these experiences were more painful. This line of evidence shows that decision utility might diverge from experienced moment-to-moment utility. Other experimental evidence (Loewenstein and Schkade, 1999; Wilson and Gilbert, 2003) has shown that affective predictions are often biased for a number of reasons, including misprediction of adaptation.

A number of economists have also discussed the relationship between happiness and utility or used happiness data in modeling efforts. Various researchers make different assumptions or use different definitions of happiness and utility. A few examples follow.

Di Tella and MacCulloch (2006) suggested that happiness data capture "something meaningful about true utility" because happiness ratings tend to be correlated with a number of variables that are associated with utility. They continued to say that "Ultimately, happiness research takes the view that happiness scores measure true internal utility with some noise, but that the signal-to-noise ratio in the available data is sufficiently high to make empirical research productive."

Kimball and Willis (2006) argued that happiness (which they defined as current affect) is different from utility; individuals have a preference for happiness, implying that happiness affects utility, but also happiness depends on utility through news about lifetime utility.

Frey et al. (2004a) introduced the concept of procedural utility which is concerned with utility derived from the process as opposed to the outcome, echoing the earlier conceptualizations of utility in the classical economic era. They defined procedural utility as "the hedonic well-being people gain from the quality of treatment in institutionalized processes as it contributes to a positive sense of self". Frey et al. (2004b), Benz and Stutzer (2003), and Van Praag and Ferrer-i-Carbonell (2004) have used reported life satisfaction data empirically as a proxy for utility.

Thesis Direction

In this thesis, we adopt the following conceptualization of happiness and utility. If happiness is broadly defined as overall satisfaction or general happiness considering all aspects of a situation or an experience, then it is plausible to assume that happiness is the same as utility and use measures of happiness as indicators of utility. If, however, happiness is more narrowly defined as satisfaction with particular aspects of the experience of interest, then happiness will just be part of the overall utility, and happiness measures can then be used as indicators of part of the utility.

Moreover, a distinction needs to be made among the different notions of utility described above, and happiness measures can then be used as indicators of utility accordingly. That is, different measures of happiness could reflect different notions of utility.

2.5 Subjective Well-Being Research

Researchers have tried to understand the nature, determinants, and consequences of subjective well-being. The relevance of the study of subjective well-being has been manifested in the emergence of new fields such as hedonic psychology, positive psychology, and happiness economics. A large number of national and international surveys have been conducted to measure it as mentioned in Chapter 1. And there are journals (such as the Journal of Happiness Studies) and databases (such as the World Database of Happiness) dedicated to this topic.

In this section, we review conceptual issues within the study of subjective well-being. First, we discuss why it is relevant to study well-being. Second, we review methods that have been used to measure it and associated measurement issues. Third, we discuss the main findings from this literature.

2.5.1 Why Is Subjective Well-Being Relevant?

In addition to the potential contribution of happiness data to the improvement of random utility models as discussed above, the study of subjective well-being is intrinsically relevant for several reasons. First, happiness is desirable for its own sake; the majority of people prefer to be happy rather than unhappy (Layard, 2003). Second, happiness has a "survival value", often fostering active living, social bonds, health, longevity, and success in several domains including work and marriage (Lyubomirsky et al., 2005; Veenhoven, 1988, 1991). Third, happiness measures are additional indicators of the quality of life in society which could supplement traditional economic and social-based indicators (Diener et al., 2003). A classic case that has been made in support of using happiness measures is the observation that during a period of time when income rose significantly in industrialized nations like the US and Japan, happiness ratings remained relatively flat (Easterlin, 1995; Oswald, 1997). Thus, to get a complete picture of society's well-being, it is important to consider what people say in addition to traditional income-based indicators. A better understanding of happiness will be useful for public decisions and policies that orient people towards happier lives.

2.5.2 Measurement

Several measures have been developed to asses the cognitive and affective components of subjective well-being. Cognitive evaluations require satisfaction ratings from respondents. Emotions are reflected in multiple channels and may be measured using both psychological and physiological means. We discuss in this section different measurement methods that have been used to capture subjective well-being.

Psychological Measures

Psychological measures of well-being are obtained via self-reports or observer ratings provided through questionnaires. They could be single-item or multiple-item measures. They are the most common type of well-being measures.

Self-Reports

A number of measures have been used with self-reports of happiness. Meaasures used for tapping emotional or affective well-being usually measure respondents' current or recent moods and emotions. Examples of these measures include the Affect Balance Scale (Bradburn, 1969), the Affectometer (Kammann and Flett, 1983), the Positive and Negative Affect Scale or PANAS (Watson et al., 1988), mood adjective lists (Diener, 1997), or memory measures (Diener, 2000) where respondents are asked to recall within a short period of time as many positive and negative events from their lives. For additional examples of these measures, see Diener (984). For example, the PANAS asks respondents to indicate to what extent they have felt in a certain way during a specified time period (right now, today, past few days, etc.). Using a 5-point scale ranging from "Very slightly or not at all" to "Extremely", respondents rate 10 feelings in the positive affect category (attentive, interested, alert, excited, enthusiastic, inspired, proud, determined, strong, active) and 10 feelings in the negative affect category (distressed, upset, hostile, irritable, scared, afraid, ashamed, guilty, nervous, jittery).

Life satisfaction measures are used to judge life satisfaction as a reflective evaluation as opposed to a report of current or recent emotions. For example, the World Values Survey asks "Taking all things together, would you say you are: very happy, rather happy, not very happy, or not at all happy?"[2] The Satisfaction with Life Scale or SWLS (Diener et al., 1985) asks respondents to rate on a 7-point scale their level of agreement with the following five statements: "In most ways my life is close to my ideal", "The conditions of my life are excellent", "I am satisfied with my life", "So far I have gotten the important things I want in life", and "If I could live my life over, I would change almost nothing".

An alternative to global and retrospective measures of subjective well-being is real-time measures. One such measure is obtained using the Experience Sampling Method (ESM) (Hektner et al., 2006). Respondents keep a handheld computer which prompts them at regular intervals of the day to answer questions related to the activities they are engaged in, their physical location, the people in their environment, and the extent of presence or absence of certain feelings such as anger, happiness, impatience, etc. The Day Reconstruction Method (Kahneman et al., 2004) is similar to the ESM in the sense that it is activity-based but is a retrospective measure of the previous day's activities. Respondents report the activities they conducted in the previous day along with the attributes of these activities and the degree to which various feelings were experienced during these activity episodes.

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[2] http://www.worldvaluessurvey.org/

Observer Ratings

The second type of psychological measure is observer ratings whereby observers that are related (e.g. family members or friends) or unrelated to the subject provide assessments of the subject's well-being. Observers are typically provided with emotion-relevant information about the subject before making the assessment and might also receive training. The advantages of this approach are that it is unobtrusive and provides an easy way to collect the data. However, its validity can be constrained by the available information at hand and by self-serving tendencies of observers who might be related to the subject (Larsen and Fredrickson, 1999).

Issues

Self-reported measures of well-being are relatively easy to collect. Yet, economists have been skeptical about the use of these measures because of a number of issues. The issues discussed below are measurement-related. In addition, there are other issues related to adaptation and aspirations which are discussed in the next section.

First, these measures have been used mostly globally or retrospectively, which may cause memory and aggregation (over several domains of life or over time) biases. For example, as discussed earlier, people may use a peak-end rule when they evaluate temporally extended episodes, whereby they tend to overweigh the peak and end moments of their emotional experience when judging it retrospectively. To overcome memory bias, real-time collection instruments have recently emerged as discussed before.

Second, the validity of these measures relies on the assumption that respondents are both able and willing to provide assessments of their subjective well-being (Larsen and Fredrickson, 1999). Distortions to true judgments may arise because of social desirability or acquiescence. However, research using self-reported measures has generally shown that they are temporally reliable and not greatly subject to distortions (Diener, 1984).

Third, judgments of subjective well-being may be affected by momentary mood and context. For example, Schwarz and Clore (1983) found that weather conditions on a given day and thinking about good or bad past experiences affect mood and consequently well-being judgments. The order of questions in a survey may also affect these judgments. Schwarz et al. (1991) asked respondents about their satisfaction with life and with marriage. The correlation between the answers to these questions differed depending on their order, highlighting the effect of salience of information on forming judgments.

Fourth, there is the issue of interpersonal comparability. That is, people may use the scale differently making it difficult to compare responses across people. Kahneman (2000) argues that this is not an "intractable problem" because of three observations. First, there is substantial agreement among people on the psychophysical processes that relate their subjective reports of their experiences to the actual intensity of the stimuli characterizing these experiences. Second, observers' ratings of other people's subjective experiences seem to agree with self-reports. Third, self-reports and physiological measures (such as measures of brain activity, discussed in the next section) are often highly correlated.

Moreover, interpersonal comparability becomes less of an issue when groups are compared (as opposed to comparing two individuals) because systematic differences in reporting biases become less probable (Di Tella and MacCulloch, 2006).

Physiological Measures

Although not as frequently used as psychological measures for well-being assessment, advances in physiological measurement technologies have recently provided alternative means for emotion assessment. Examples of these physiological measures include facial expressions, autonomic, and brain measures.

Facial expression recognition techniques classify emotions based on facial expressions. For example, coding systems such as the Facial Action Coding System (Ekman and Friesen, 1978) detect observable changes in facial features (such as those related to the eyebrows, mouth, etc.) to infer emotions (such as happiness, sadness, anger, etc.). Electromyography has also been used to measure electrical signal generated by facial muscle contraction. Facial measures are useful to the extent that they convey emotions rather than reflect biological processes. Their use, however, requires extensive data processing.

Another type of physiological measures is autonomic measures which rely on the notion that emotions affect the autonomic nervous system activity. They therefore measure electrodermal (e.g. skin conductance), respiratory, salivary cortisol, or cardiovascular (e.g. heart rate, blood pressure) activity and associate changes in these measurements with emotions (e.g. increased blood pressure or skin conductance may be associated with stress). Although they provide continuous measurement of emotion over an extended period, these methods can be intrusive and cannot be used by themselves to infer the presence of emotions.

Brain measures are another type of physiological measure that have gained attention recently especially in the domain of neuroeconomics (Camerer et al., 2005). These methods measure activity in the brain and correlate it to emotions. Greater activity in the left pre-frontal region has been associated with positive affect and approach tendencies while greater activity in the right pre-frontal region has been associated with negative emotions and avoidance tendencies. Examples of brain activity measurement technologies include Electroencephalography (EEG), Functional Magnetic Resonance Imaging (fMRI), and Positron Emission Tomography (PET) (Blood et al., 1999; Calhoun et al., 2001, 2002; Chanel et al., 2005; Coan and Allen, 2004; Kennedy et al., 1997; Lane at al., 1997). The advantages and disadvantages of this category of physiological measures are similar to those of the autonomic measures.

2.5.3 Causes and Correlates

One way of evaluating the validity of reported subjective well-being measures is to consider their correlation with individual characteristics and other non-reported well-

being measures (such as physiological measures) and how well they predict future outcomes.

So what are the causes and correlates of happiness? Many psychologists have tried to answer this question. Their findings indicate that demographic, socio-economic, life cycle, and lifestyle variables affect happiness. People also make comparisons that affect their happiness, and they adapt over time to their situations in ways that make the effects of events on their lives seem less intense. Self-reported happiness measures have also been found to be correlated with other types of measures and have been able to predict certain outcomes. In this section, we review the various causes and correlates of well-being.

Demographic and Personality Variables

Studies have shown that demographic variables account for 10-15% of the variance in happiness (Andrews and Withey, 1976; Diener, 1984). Age has a U-shaped impact on happiness, with a minimum occurring at a middle age; happiness increases slightly with age after that which might be because elderly people have lower aspirations and can thus be more easily satisfied (Campbell et al., 1976; Felton, 1987; Oswald, 1997), or because they are more religiously active (Argyle, 1999). Ethnic minorities are generally found to have lower happiness due to their lower incomes, education, and job status (Argyle, 1999). Happiness does not seem to vary with gender.

Personality has a strong influence on well-being. Several models (e.g. temperament, congruence, and goal models) have been posited to explain the relationship between personality and well-being; in general, extraversion has been shown to be related to pleasant affect while neuroticism is linked to unpleasant affect (Diener and Lucas, 1999).

Socio-Economic, Life Cycle, and Lifestyle Variables

Various socio-economic, life cycle, and lifestyle variables have been linked to happiness or satisfaction. We describe here the most significant of these variables.

The effect of income on life satisfaction has received notable attention (see, for example, Csikszentmihalyi, 1999 and Frank, 2004); increases in income are associated with increases in well-being at low income levels when basic needs are not met completely (Helliwell and Putnam, 2005). However, the relationship is almost flat at high income levels. Moreover, there is evidence that relative income matters more than absolute income in determining satisfaction with wages (Easterlin, 1974, 1995). Social class seems to have a greater impact on happiness in societies where there is greater inequality of income. This impact is through the effect of income and education on happiness as well as through a sheer social status effect (Argyle, 1999).

Unemployment results in unhappiness (see, for example, Frey and Stutzer, 1999 and Oswald, 1997) due to financial loss, decrease in self-esteem, and the lack of other benefits that work provides. Education is slightly positively correlated with happiness,

which might be attributed to the effect of education on income and occupation status which in turn affect happiness (Argyle, 1999). Competencies such as social skills and health have varying degrees of positive correlation with happiness.

Life events, leisure, and activities, such as relationships with friends, the basic pleasures of food, drink, and sex, and success experiences, are positively correlated with happiness (Scherer et al., 1986). People who are more religious are generally found to be happier which might be attributed to the effect of social support derived from religious activities and to good health (Layard, 2003). Finally, marriage has been shown to have a strong effect on happiness (Glenn and Weaver, 1979).

Comparison Processes

Comparison processes across various dimensions can have an impact on well-being. Three types of comparison processes have been discussed in the literature: comparison to self, comparison to others, and counterfactuals (Schwarz and Strack, 1999).

Comparison to self involves comparing one's present situation with one's previous situation or predicted future situation. Perceived improvements in one's situation (e.g. a higher income, better health, etc.) lead to increases in ratings of well-being but this is limited by changing aspiration levels and adaptation effects (see next section). Comparison to others (or social comparison) is the most discussed type of comparison and involves comparing one's own situation to that of a comparison group and making judgments of well-being based on whether one is faring better (downward comparison) or worse (upward comparison) than others (Wills, 1981). However, the effect of social comparison on well-being is inconclusive (Diener and Fujita, 1997). Finally, counterfactuals refer to comparisons of one's current situation with hypothetical situations that did not happen but could have happened and making well-being judgments accordingly.

Adaptation, Aspirations, and Treadmill Effects

In 1971, Brickman and Campbell introduced the concept of a hedonic treadmill which captures the effect of adaptation on well-being and is based on a set point level theory of happiness. They argued that people are doomed to a state of hedonic neutrality because the impact of major life events on well-being becomes less intense as time passes by. In a classic demonstration of this effect, Brickman et al. (1978) found that lottery winners were not significantly happier than a control group, and victims of major debilitating accidents were slightly less happy than a control group. The hedonic treadmill phenomenon is one reason economists become more wary of using happiness measures because people give answers that reflect their adaptation to life events so that different objective circumstances across people (e.g. good vs. bad health) may result in similar satisfaction ratings.

The hedonic treadmill hypothesis has been supported in some studies but debated in others. Some researchers have suggested that the extent to which it occurs varies over life

domains and individuals, and the hedonic set points need not be hedonically neutral (Diener et al., 2006; Dolan and White, 2007).

Kahneman (2000) advanced the notion of a satisfaction treadmill, which is based on the idea of changing aspiration levels (such as those that accompany an increase in income). While the satisfaction treadmill exhibits the same pattern of subjective well-being reports as that of the hedonic treadmill, the difference is that the latter is attributed to true habituation of affective experiences while the former is not.

Correlation with Other Measures and Outcomes

Finally, there is evidence for the existence of correlations between reported well-being measures and physiological / medical measures. For example, it has been found that people who report a tendency to experience positive emotions are less likely to catch a cold (Cohen et al., 2003) and those with higher stress and other negative emotions are slower to recover from illness or wounds (Kiecolt-Glaser et al., 1995, 2002). There is other evidence showing correlations between reported life satisfaction and brain activity (Urry et al., 2004).

2.6   Travel Demand Modeling

As this thesis is concerned with the measurement and modeling of activity and travel well-being, we now consider the application of the material discussed earlier to the area of travel demand modeling.

McFadden (2007) distinguishes among three levels of consumer travel behavior modeling. The first is based on physical analogies such as the gravity model used in trip distribution of aggregate four-step travel demand models. The second and most commonly used is the discrete choice model based on utility maximization. The third consists of using models that draw upon findings from behavioral studies. The choice of modeling approach may depend on the application at hand. For example, models based on physical analogies may be sufficient for long-term aggregate forecasting. Discrete choice models are needed to predict choices that are sensitive to policy scenarios (e.g. mode choice in the presence of congestion pricing) and can be enhanced with insights from behavioral theories.

In this section, we focus on random utility models. We review the application of these models in transportation, show examples of recent enhancements of these models, and conclude by discussing happiness research in transportation.

2.6.1 Random Utility Models of Travel Demand

Discrete choice models based on random utility theory are the most widely used methods for modeling travel demand. The early applications were mostly focused on mode choice

(Ben-Akiva and Lerman, 1985). Nowadays these methods form components of four-step models (such as mode and route choices) and activity-based models (activity pattern generation, destination, mode, time-of-travel, and route choices) and are used to model longer term decisions as well such as auto ownership and residential location.

Regarding the specification of these models, as discussed in more detail in Chapter 3, time and cost attributes have played a major role in the specification of the systematic utility. The ratio of their coefficients gives the value of travel time savings. The most common distribution assumed for the error term (random utility component) is the extreme value Type I distribution which results in the logit model. The logit model has been the workhorse of discrete choice methods in transportation applications due to its analytical tractability and the existence of commercial software programs for estimating it.

As with random utility models in general, those used in transportation applications have also been criticized for their simplistic behavioral representation (see, for example, Avineri, 2009; Gärling, 1998). As a consequence, these models have started to incorporate some of the findings from behavioral research. While some have departed from the random utility model, it is usually taken among modelers that the random utility model is a good starting point that can be enriched using findings from behavioral studies (see, for example, McFadden, 2008, 2009; Walker and Gaker, 2009). The next section gives an overview of these behavioral enhancements.

2.6.2 Enrichment of Travel Demand Models

We discuss enrichments to travel behavioral modeling in three areas: the incorporation of latent variables, social preferences, and prospect theory.

Attitudes, Perceptions, and Other Latent Variables

The Hybrid Choice model discussed earlier was originally developed and applied in a transportation context. Ben-Akiva et al. (2002b) demonstrated the applicability of the integrated choice and latent variable framework to several applications: mode choice incorporating the latent constructs of comfort and convenience, employees' adoption of telecommuting incorporating the latent constructs of benefits to lifestyle quality and associated costs, and use of traffic information systems accounting for the effect of overall satisfaction with the service. Psychometric data consisting of responses to attitudinal and perceptual survey questions are used as indicators of the latent variables. The integrated framework results in better behavioral representation, meaningful latent variables, and improvements in goodness of fit relative to models without latent variables. Other more recent applications that account for the effects of perceptions and attitudes on travel behavior include mode choice (Johansson et al., 2006), vehicle type choice (Choo and Mokhtarian, 2004), and airline itinerary choice (Theis et al., 2006).

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Latent class models have also been integrated with choice models in transportation applications. Ben-Akiva and Boccara (1995) allowed for different choice sets among commuters in modeling their choice of travel mode. Gopinath (1995) modeled different decision protocols in the context of travelers' intercity mode choice and different time and cost sensitivities in the context of shippers' choices between train and truck.

Social Preferences

Recognizing the importance of the social dimension in choice behavior, there has been a growing interest among transportation researchers in understanding the patterns of social interactions and their effect on travel decision-making. We describe below selected studies that either collected data on social interactions or modeled their effects on behavior.

Among the studies dealing with data collection aspects, Axhausen (2008) postulated that travel choices are determined not only by the generalized cost of travel, resources, attitudes, and lifestyle but also by an individual's social network. He proposed extensions to traditional travel diaries in order to capture the social content of activities, social network geographies, and mobility biographies. Carrasco et al. (2008) designed and conducted surveys and interviews to collect data on affective social networks (i.e. those classified as 'close' to an individual) and social activities, including interaction media, using an egocentric approach (i.e. network members are the contacts of a given individual called an ego). van den Berg et al. (2009) also conducted a social network egocentric survey and used the data to develop models that predict social network size, the social categories of an individual's contacts, geographical distance of the contacts, and contact frequency for several contact types / media.

Among the modeling efforts, the effect of social influence on travel choice behavior has been studied within the context of residential location choice (Páez and Scott, 2006), the decision to adopt telecommuting (Páez and Scott, 2007), and mode choice (Dugundji and Walker, 2005). In this literature, the most prevalent method of modeling the effect of others' actions on one's own actions is to incorporate others' previous actions as an additional explanatory variable in the utility of one's alternatives. Another method that has been used is to incorporate the interdependencies among decisions as correlations among the error components of the members of the social network.

Prospect Theory

A number of recent research efforts have started to explore some of the cognitive anomalies described earlier as they apply to travel behavior. In particular, transportation researchers have been interested in the application of prospect theory as illustrated below.

Hjorth and Fosgerau (2009) modeled loss aversion in the time and cost dimensions of travel. They conducted stated preferences experiments that presented respondents with a number of binary choice scenarios involving time and cost trade-offs. Using the attributes of a regular trip (reported by the respondents) as a reference point, they estimated

reference-dependent choice models that account for loss aversion as a function of individual characteristics and features of the choice experiments.

Senbil and Kitamura (2004) modeled commuter departure time choice using a prospect theory approach. They assumed the existence of multiple decision frames determined by various reference points including earliest permissible arrival time, preferred arrival time, and work start time. Using multi-day survey data where respondents stated their intentions for departure time changes on the following day, the authors estimated binary probit models and obtained value functions that are consistent with prospect theory.

Avineri (2006) discussed route choice under stochastic network conditions and studied network equilibrium based on cumulative prospect theory (CPT). He presented a numeric binary route choice example showing how CPT-based equilibrium might differ from equilibrium conditions based on expected utility maximization. He also illustrated the sensitivity of the results to the chosen reference point.

2.6.3 Happiness Research in Transportation

Subjective well-being has recently become a topic of interest within the transportation research community. Transportation researchers have measured travel stress, liking and other affective reactions, happiness and satisfaction. Modeling efforts linking travel well-being to behavior have been more limited, and to the best of our knowledge, non-existent for the case of activity well-being and behavior. We highlight below these measurement and modeling efforts and their main findings.

Commuting Stress

There is an extensive literature on measuring commuting stress and explaining its causes and consequences. These studies have shown that commuting stress is caused by various commute attributes, such as long travel or waiting time or distance, traffic congestion, unpredictability and the lack of perceived control, crowding, and other commuting conditions (Evans et al., 2002; Kluger, 1998; Koslowsky et al., 1995, 1996; Novaco et al., 1990; Schaeffer et al., 1988; Singer et al., 1978; Van Rooy, 2006; Wener et al., 2003). It could also be affected by individual factors, such as the flexibility of the work schedule (Lucas and Heady, 2002) and the use of en-route time to conduct activities as a coping strategy for reducing stress (Lyons and Urry, 2005). The effects of commuting stress on work performance and mood at home have also been investigated (Koslowsky et al., 1995; Novaco et al., 1990, 1991; Wener et al., 2005).

Both self-reported and physiological measures have been used to capture commuting stress. A host of self-reported measures have been used. For example, in Wener et al. (2003), respondents rated statements such as "Commuting to work takes effort" and "Overall commuting is stressful for me" using a Likert scale. In Singer et al. (1978), urine specimens were taken from a sample of train commuters and were analyzed for adrenaline and nonadrenaline excretion as "adrenaline levels tend to reflect changes in

the psychosocial environment, including crowding and controllability". Wener et al. (2003) measured salivary cortisol for a sample of train commuters. Elevation in cortisol levels is associated with stress. Healey and Picard (2005) recorded electrocardiogram, electromyogram, skin conductance, and respiration of a sample of drivers during real-world driving tasks. They found that skin conductivity and heart rate were most closely related to stress.

Travel Liking

Salomon and Mokhtarian (1998) and Mokhtarian and Salomon (2001) postulated that travel may have positive utility. That is, people may enjoy traveling for a number of reasons including adventure and variety seeking, independence, control, status, escape, etc. Ory and Mokhtarian (2005) measured liking or enjoyment of travel in a number of categories differentiated by mode, purpose, and distance. They asked the following question which had a 5-point response scale ranging from strongly dislike to strongly like:

How do you feel about traveling in each of the following categories? We are not asking how you feel about the activity at the destination, but about the travel required to get there. Even if you seldom or never travel in a certain category, you may still have a feeling about it.

They developed linear regression models to explain travel liking as a function of the following types of variables: objective mobility (distance, travel time, etc.), subjective mobility (subjective assessment of the amount of travel), personality, lifestyle, attitudes, excess travel (measures of frequency of unnecessary travel), mobility limitations, and socio-demographic variables. The key variables that were found to affect travel liking are attitudes, personality, and lifestyle.

Turcotte (2008) analyzed commute liking using data from the time-use General Social Survey. This survey asked respondents to rate their level of liking of different activities on a 5-point scale, where 1 means "dislike the activity a great deal" and 5 means "enjoy the activity a great deal". He found that those who bike enjoyed their commutes the most. Moreover, using ordinal regressions, he found that factors affecting commute liking were commute duration, distance, city (as an indication of congestion), job liking, age, and education level.

Other Affective Reactions

Affective measures other than stress and liking have been collected as well. Three examples of these measures are described.

In the Day Reconstruction Method developed by Kahneman et al. (2004), respondents are asked to report, for every activity (including commuting) they conducted on the preceding day, the extent to which they experienced certain feelings on a 6-point scale ranging from "Not at all" to "Very much". The feelings are: impatient for it to end,

happy, frustrated/annoyed, depressed/blue, competent/capable, hassled/pushed around, warm/friendly, angry/hostile, worried/anxious, enjoying myself, criticized/put down, and tired. Data based on this method have been used to evaluate how people allocate their time to different activities, how affect varies with activity types, and the proportion of time that people spend predominantly on the negative side of emotions. For example, Kahneman et al. (2004) and Kahneman and Krueger (2006) found that the morning commute was the activity with the least net affect (mean positive affect minus mean negative affect) for a sample of Texas female workers.

Van Rooy (2006) studied the effect of the commuting environment on affect. Respondents indicated the extent to which they experienced various emotions while commuting on a 7-point Likert scale ranging from "not at all feeling that way" to "extremely much feeling that way". The positive emotions were: happy, joyful, and pleased. The negative emotions were: depressed, frustrated, angry, anxious, stressed, overwhelmed, and confused.

Gatersleben and Uzzell (2007) studied affective appraisals of the daily commute for car drivers, public transportation users, and non-motorized commuters. Respondents rated on a 5-point scale the extent to which their commute is usually stressful, exciting, boring, relaxing, pleasant, and depressing. They also indicated the most pleasant and unpleasant aspects of their commutes. The results indicated that the degree of arousal is high for car commuting (reflecting stress) and not high enough for public transportation commuting (reflecting boredom). Non-motorized commuters rated the commute positively on both the arousal and pleasure dimensions, a result the authors interpret as non-motorized commuting being "an optimum form of travel from an affective experience".

Happiness and Satisfaction

In addition to the affective measures described above, other studies have examined well-being more globally as described next.

Satisfaction with Public Transportation

Public transportation agencies often collect data on customer satisfaction with their overall service and certain attributes of it, such as safety, courtesy of staff, cleanliness, frequency of service, availability of schedule information, etc. (Metropolitan Council, 2007; Sacramento Regional Transit, 2006).

Friman et al. (2001) and Friman and Gärling (2001) investigated factors affecting public transportation users' satisfaction with the service by conducting a large-scale mail survey and a stated preferences survey. In the mail survey, respondents rated their overall and attribute-specific satisfaction. They answered questions, such as the following, using a 9-point scale ranging from "very dissatisfied" to "very satisfied":

Are you in general satisfied with traveling by bus/streetcar?

Respondents also judged negative critical incidents (NCIs) based on whether they had experienced or heard that somebody else had experienced a similar incident and reported the frequency of the NCIs they experienced.

In the stated preferences survey, respondents rated their overall satisfaction and satisfaction with different attributes (treatment by employees, reliability of service, simplicity of information, and design) using a scale ranging from 10 (very dissatisfied) to 90 (very satisfied). They were then presented with NCI scenarios corresponding to the four attributes listed above and were asked how satisfied they would be with the public transportation service if these NCIs had occurred with different frequencies.

In both surveys, the authors reached very similar conclusions. They found that overall satisfaction is positively related to attribute-specific satisfaction, which is negatively related to the frequency of NCIs. Structural equation modeling using the maximum likelihood method and various statistical tests were used to reach these conclusions.

Pedersen et al. (2009) studied car users' affective forecasts of their satisfaction with public transportation and potential biases in these forecasts due to a focusing illusion (i.e. when people use salient attributes of the service, such as a critical incident, in making these forecasts). They measured current satisfaction with public transportation for a sample of car users ("How satisfied are you currently with...?"). They then presented them with scenarios involving negative, positive, neutral, or no public transportation incidents and asked them to predict their satisfaction with the service after such incidents ("How satisfied do you think you will be...?"). Respondents rated their satisfaction using an 11-point response scale ranging from "extremely dissatisfied" to "extremely satisfied". The authors found through statistical tests that negative incidents resulted in significantly lower predicted satisfaction compared to the other types of incidents, thus providing support to their hypothesis that car users may focus their attention on particular incidents when predicting their satisfaction with public transportation.

Other Studies

Ettema et al. (2009) presented a theoretical framework that represents the effects of travel well-being on subjective well-being through three sources. First, traveling is directly associated with affective reactions. Second, travel facilitates activity participation, which in turn affects well-being. Third, the way travel is organized determines the amount of time left for conducting activities and the amount of stress associated with these activities.

Duarte et al. (2008, 2009a, 2009b) studied travel happiness in relation to mode choice decisions. They assessed current happiness (or what they call experienced happiness) with work and leisure trips by asking the following questions using a response scale ranging from 0 (the most unhappy/unsatisfied) to 10 (the highest happy / satisfied).

How happy do you feel by using your current mode of transport to make a work related trip?

How happy do you feel by using your current mode of transport to make a leisure trip?

Additionally, they presented the respondents with stated preferences (SP) scenarios involving the choice between car and public transportation (metro). As part of the attributes of these modes, respondents were presented with cartoons depicting the travel environments. The cartoons were intended to act as proxies for low, medium, or high expected happiness associated with car and public transportation. This happiness measure can be thought of as an affective measure, as the cartoons do not contain information about travel time, cost, etc. The authors also collected other measures of expected happiness with the chosen alternative in these SP exercises, phrased as follows (10-point scale):

How happy would you feel with the chosen option?

The authors developed a modeling framework where the utility of a given mode (in the SP exercises) is a function of the experienced happiness (happiness with usual mode) and the expected happiness (using dummy variables for low, medium, and high levels of happiness based on the cartoons presented), in addition to other standard variables.

They found that the experienced happiness variable significantly improved the model, but was only significant for the car alternative. The cartoon variables reflecting expected happiness were more significant for the car than the metro alternative.

2.7   Conclusion

This chapter provided a context for the topic of this thesis. We started by reviewing the origins of random utility theory, described its criticisms, and provided an overview of recent efforts that have aimed at enriching it. We then presented happiness as another enrichment to random utility models and discussed the relationship between happiness and utility. We reviewed methods and findings from the subjective well-being literature. Finally, we showed the application of random utility models and their enrichments (including happiness research) in the area of travel demand modeling.

Quantitative methods used to analyze well-being data, both in transportation and in the general subjective well-being research, have focused on the use of statistical tests (e.g. a large number of studies analyzing commuting stress) and the development of models that explain happiness as a function of causes and correlates using regressions (see, for example, Frey et al., 2004b; Ory and Mokhtarian, 2005; Van Praag and Ferrer-i-Carbonell, 2004) and structural equation models (see, for example, Friman et al., 2001, and Friman and Gärling, 2001). Happiness has also been modeled within the framework of discrete choice models as an additional explanatory variable in the utility (Duarte et al., 2008). Yet, we have found no evidence for the use of happiness measures as indicators of utility in random utility models.

This thesis, therefore, contributes to these modeling efforts by explicitly incorporating happiness measures as indicators of utility within random utility models. Happiness in this sense is broadly defined as overall satisfaction considering all aspects of a situation or an experience, which makes it plausible to assume that happiness is the same as utility. If, however, happiness is more narrowly defined as satisfaction with particular aspects of the experience of interest, then as discussed in Section 2.4.2, happiness will just be part of the overall utility, and happiness measures can be used as indicators of part of the utility.

We propose a general modeling framework for using happiness measures as indicators of utility (or part of the utility) in a static and a dynamic context. In a static context, we show how the standard discrete choice model can be extended by using happiness measures as indicators of decision utility. In a dynamic framework, we further distinguish in the modeling framework among the notions of decision, moment, and remembered utility (reviewed in Section 2.4.2) and show how happiness measures can be used as indicators of each of these notions of utility. We then apply the framework to modeling both activity and travel choices and, in doing so, we propose new well-being measurement methods. Even though the applications focus on activities and travel, the framework is general and can be applied to modeling behavior in other domains.

Chapter 3

Conceptual Issues and Frameworks in Measuring and Modeling Activity and Travel Well-Being

So far in this thesis, we have provided a general motivation for the study of activity and travel well-being and reviewed a number of studies that have addressed this topic. We have also briefly discussed how measures of well-being can be used to enhance behavioral models based on random utility theory. In this chapter, we develop the activity and travel well-being idea conceptually. We start in Section 3.1 by discussing in more detail the concept of the generalized cost of travel and propose activity and travel well-being as a broader objective for activity and travel choices. Section 3.2 discusses how an activity and travel well-being approach to modeling travel behavior may be operationalized: which aspects of activity / travel well-being to measure, examples of measures, and measurement issues. Section 3.3 presents frameworks for modeling well-being and behavior that extend random utility models, using happiness measures as indicators of utility. Section 3.4 concludes.

3.1   From Generalized Cost of Travel to Well-Being

3.1.1 The Role of Time

Time is an important dimension of activities and travel. Time allocation to activities has been studied for a long time (see next section and Chapter 7) and empirically measured through time use surveys. Time also plays a central role in travel decisions including the choice of mode, time-of-travel, and route and is a key variable in models predicting these choices. And the valuation of travel time savings is central to cost-benefit analyses typically employed in transportation project appraisal.

Recognition of the relevance of the time dimension of travel can be traced back to Jules Dupuit (1844, 1849), a French inspector of bridges and highways. According to Bruzelius (1979), Dupuit "seemed to have been well aware of the role of time in transportation and the importance of considering the savings in travel time from investments in the transport sector when appraising these investments". He maintained that the utility of a new railroad can be captured via the toll which would convince passengers to switch from the slower alternative mode to the railroad. Later, at the beginning of the twentieth century, the Bureau of Public Roads and various state highway departments studied time savings in highway projects and developed manuals for estimating these savings. A number of European countries later followed a similar approach recommending or requiring that cost-benefit analyses be conducted for project appraisal.

3.1.2 Measuring the Value of Time

A theoretical approach for measuring the value of time savings for activities and travel is derived from time allocation models which extend the theory of consumer demand to handle the time dimension of consumption (activities and travel). Another approach that is specifically relevant for measuring the value of travel time savings and is more widely used in applied analysis estimates the value of travel time from demand models based on the generalized cost of travel. In both approaches, the value of time plays a central role, so we start by defining it. The marginal value of time is the consumer's willingness to pay to save a marginal unit of time from an activity or during a journey and at a given level of income (Bruzelius, 1979).

Time allocation models will be discussed in Chapter 7 in the context of activities and well-being. Suffice it to say here that the marginal value of time can be computed from these models as the ratio of the marginal utility of a reduction in the time required to conduct an activity or a journey to the marginal utility of income. Moreover, this value depends on the activity conducted (or good consumed) and could reflect for instance different values of time for different activities or for different travel conditions (traveling by car or bus, under crowded or uncrowded conditions, etc.).

The second approach for computing the value of travel time relies on the notion of the generalized cost of travel. For a trip using a given transportation alternative, such as a travel mode or route, the generalized cost is defined as the sum of the price paid and the monetary equivalent of the time spent by the traveler to complete the trip using the given alternative:

$$GC_i = p_i + a\, q_i \tag{3.1}$$

where GC_i is the generalized cost of alternative i, p_i is the price of alternative i, q_i is the travel time (or time requirement) of alternative i, and a is the value of time.

The concept of the generalized cost of travel has been used for a long time in travel demand models. The value of time is estimated from these models (such as mode or route choice) as the ratio of the time coefficient to the cost coefficient in the generalized cost

expression. It is then used in cost-benefit analysis in transportation planning to measure the value of time savings.

Bruzelius (1979) describes a number of strong conditions that need to be satisfied in order for the value of travel time savings computed in applied analysis to be equal to the value obtained from time allocation models and hence to be theoretically correct. The demand function and the marginal value of time should not be a function of income. The compensated marginal value of time should not be a function of the time required to conduct an activity and the price. Bruzelius (1979) shows that in order to generate consumer behavior that is consistent with these assumptions, a set of restrictions have to be imposed on the utility function. Moreover, the resulting demand is a function of only one parameter, the generalized cost of travel.

3.1.3 Qualitative Factors

The value of time computed from time allocation models or from models based on the generalized cost of travel accounts implicitly for qualitative factors that are related to the time dimension through the values of the taste parameters. The qualitative factors however are not represented explicitly and hence they are ignored in conventional evaluation practices, which could bias investment decisions aiming at improving the quality of the travel experience such as public transportation service quality improvements.

Travel decisions are often affected by the quality of available travel alternatives. Soft factors affecting the quality of travel include comfort, convenience, safety, reliability, etc. (Johansson et al., 2006). For example, people may prefer to use a longer but more reliable route, a slower but more enjoyable mode of transportation (such as walking or biking), or a more expensive but more comfortable service (such as first class train service) (Litman, 2008b). Moreover, as discussed in Chapter 2, in certain situations travel time could have minimal cost or positive utility. People may enjoy moderate amounts of daily travel, recreational/social and non-motorized travel, and even the commute if it is perceived as transition or private time (Mokhtarian, 2005). Travelers may also conduct activities while traveling (reading, working, etc.) which makes the travel experience seem more productive and less onerous (Lyons and Urry, 2005).

Empirical evidence has also shown that travel time costs are affected by qualitative aspects of travel. For example, they tend to be higher under unfavorable travel conditions (uncomfortable, unsafe, unreliable, stressful, etc.). Litman (2008a, 2008b) reviewed a number of studies that suggested different values of time to use under different travel conditions. For example, TransFund New Zealand uses a value of time for standing bus passengers that is twice the value for seated passengers, thus accounting for comfort, and Douglas Economics suggests values of waiting and walking times for public transportation users that depend on the level of crowding measured in passengers per square meter. A number of researchers have also discussed or measured values of reliability (Bates et al., 2001; Brownstone and Small, 2005; Lam and Small, 2001). These

values could be more relevant than values of travel time in the context of valuation of toll road projects for example.

3.1.4 Activity and Travel Well-Being: A Broader Objective

The above discussion indicates that qualitative factors matter for people's well-being. The generalized cost of travel is only part of well-being. Thus, in order to account for well-being, one needs to go beyond the measurement and modeling of generalized cost and try to measure subjective well-being more fully. Measuring and modeling subjective well-being is relevant because it allows better modeling of activity and travel choices. In particular, we postulate that:

- Activity patterns are planned to maintain or enhance subjective well-being
- Given the activity choices, travel choices are likely to be motivated by a broader goal than one that considers only time and cost. The broader goal is to maintain and enhance travel well-being.

Broadly defined, activity and travel well-being refers to people's satisfaction with their activities and travel experiences from their own perspectives. It may also include more specific affective reactions, such as enjoyment, relaxation, stress, anxiety, and other emotions that may be experienced during activities and travel.

It is recognized that activity and travel decisions are not made in isolation from other decisions in life. Consider travel for example. The decision on how much an individual wants to commute is related to decisions about housing and jobs. And in this broader context, enhancing travel well-being may not be the ultimate objective. In fact, some travel decisions may lower travel and even overall subjective well-being. Stutzer and Frey (2008) found evidence for a "commuting paradox" among a sample of German workers. They postulated that if people choose to live further from work and hence lower their travel well-being (e.g. because of a longer or more stressful commute), the decrease in their travel well-being should be compensated by an increase in well-being in other domains (e.g. due to housing or job benefits) so that their overall well-being does not decline (otherwise why make these choices). Their data showed however that the overall well-being of those commuters dropped due to the travel choices they made.

While consideration of overall well-being and the interplay between different domains is relevant, it is outside the scope of this thesis. We consider activity and travel choices that are conditioned upon other longer term choices in life (such as housing, jobs, etc.). In this sense, we believe that our study hypothesis that "the broader goal is to maintain and enhance travel well-being or well-being derived from activities" is justifiable.

The remainder of this chapter focuses on the development of the activity and travel well-being concept from a measurement and modeling perspective.

3.2   Activity and Travel Well-Being Measurement

3.2.1 Which Aspects of Activity and Travel Well-Being Are of Interest?

As mentioned before, activity and travel well-being includes both cognitive and affective components. The cognitive component is a satisfaction judgment of the conditions of one's activities and travel experiences. The affective component refers to the moods and emotions experienced during activities and travel.

Affective reactions are usually short-term feelings that are tied to specific events or experiences although they could also be defined on a more cumulative basis (e.g. affective reactions experienced during usual activity patterns or usual travel). Satisfaction judgments are longer term cognitions that are determined by the accumulation of experiences. Satisfaction judgments may also be influenced by affective reactions (Schwarz and Clore, 1983).

The specific aspects of activity or travel well-being that are of interest depend on the context of the study. As reviewed in Chapter 2, a number of studies for example have focused on investigating the causes of commuting stress and the consequences for driving capabilities and performance at work. In these studies, the measures of interest are mainly emotions and moods experienced during the commute or during the work activity (such as stress, anxiety, fatigue, etc.).

Other studies may examine well-being more globally. For example, public transportation agencies often collect data on customer satisfaction with their overall service and certain attributes of it, such as safety, courtesy of staff, cleanliness, frequency of service, availability of schedule information, etc. In addition, global satisfaction judgments can include cost considerations that are typically not accounted for by affective ratings. Satisfaction is also likely to be more relevant when predicting medium or long term travel choices, such as mode choice, or activity patterns.

3.2.2 Measurement Methods

As in the subjective well-being research, both reported and physiological measures can be used to capture activity and travel affective reactions. Activity and travel satisfaction can be measured through self-reports.

Self-Reported Measures

Satisfaction

Self-reported measures of travel satisfaction can be obtained retrospectively from surveys. For example, to assess satisfaction with the commute to work, one may ask:

Taking all things together, how satisfied (or how happy) are you with your commute to work?

These questions refer to the current (chosen) travel options (mode, route, etc.). One may also ask specifically about satisfaction with alternative travel options (e.g. satisfaction with a car commute, satisfaction with a public transportation commute). The phrase "Taking all things together" emphasizes that the judgment is global while leaving the judgment criteria up to the respondent. The response scale may range from very dissatisfied to very satisfied, or not too happy to very happy.

Similarly, one can measure satisfaction with certain types of activities by using questions such as:

Taking all things together, how satisfied (or how happy) are you with your social/recreational (or shopping) activities?

The measurement of satisfaction with activity patterns is discussed in Chapter 7.

Affect

Self-reported affective reactions related to activities and travel can be tapped by asking respondents to indicate the extent to which they feel in certain ways while conducting certain activities or during their travel. These measures can be obtained retrospectively or in real-time.

Consider the measurement of commuting stress. One example would be to present the respondent with statements about the stress of his/her commute and ask the respondent to rate his/her level of agreement with those statements, such as:

My commute makes me feel stressed out.

Or

Commuting is stressful for me.

Another example of rating the extent to which commuting stress is experienced would be to ask the respondent to use a scale of "Not at all" to "Very much" in rating how stressed out he/she feels during the commute. This same scale can be used to rate the presence or absence of emotions experienced during different types of activities as in the Day Reconstruction Method survey referred to in Chapter 2.

Physiological Measures

Physiological measures of activity and travel well-being are collected in real-time by using a physiological device attached to the subject. This involves taking measures of

skin conductance, respiration rate, heart rate, blood pressure, salivary cortisol, etc., and correlating them with affective reactions such as stress, arousal, and fatigue.

In the case of travel, physiological measures of well-being have mostly been collected in the context of human factors research (Healey and Picard, 2005; Mehler et al., 2009). In some cases, they have been collected in conjunction with the more traditional self-reported or behavioral measures of travel well-being[3]. In general, issues surrounding the use of physiological measurements in activity and travel well-being research are similar to those discussed in the context of overall well-being measurement (Chapter 2).

3.2.3 Issues with Self-Reported Measures

As in social indicators surveys in general and well-being surveys in particular, a number of issues arise when measuring activity and travel well-being through self-reported means.

Context Effects

Judgments of subjective well-being are sensitive to context effects (Schwarz and Strack, 1999). Similarly, we expect reports of activity and travel well-being to be influenced by context.

First, the information that the survey makes accessible and the order of questions may influence these judgments. For example, if questions on satisfaction with travel by different modes are included in the same questionnaire, contrast effects may arise as respondents compare their experiences with different modes and their perceptions of them.

Second, the prevalent mood at the time of judgment may affect the activity and travel satisfaction ratings. For example, if an individual is surveyed on a bad day (bad weather, bad day at work or at home, heavy congestion, incident, etc.), his/her satisfaction ratings may be lower than those given on an average day.

The order of questions and salience of certain conditions can be controlled by the researcher. As to mood effects, we expect these to balance out across respondents so as not to systematically bias these measurements.

Comparison Processes

Comparison processes might affect travel satisfaction judgments. When asked to evaluate satisfaction with the commute, people may compare the conditions of their current

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[3] An example of a behavioral measure is people's performance on a proof-reading task (e.g. ability to detect spelling and grammatical errors in text passages) as an indication of motivational performance and stress (see, for example, Wener et al., 2003, for the use of this measure in a study of commuting stress in the context of train travel).

commute to those of a previous commute or to other people's commutes and form their satisfaction judgments accordingly. For example, a bad past commute may render the current commute more pleasant or satisfactory. In Chapter 4, we explicitly incorporate social and intrapersonal comparisons into a model of commute well-being. Comparison processes may also affect activity satisfaction; for instance, work satisfaction may be affected by comparison to previous or other people's work conditions.

Social Desirability

This issue is more relevant for the measurement of travel well-being. As in any survey dealing with topics of a social nature, people may rate their travel well-being to influence a certain outcome. For example, in customer satisfaction surveys administered by public transportation agencies, respondents may intentionally give lower satisfaction ratings to highlight their concern with certain issues and drive planners' and policy makers' attention to those issues. To reduce potential biases due to social desirability, travel well-being surveys should be kept as objective as possible. For example, a survey measuring satisfaction with different modes of travel should not come across as favoring one mode over another.

Treadmill Effects

Travel is a routine. Consider commuting for example. The daily decision to choose travel mode and route is automatic. As with other routine things in life, people may have a set point or a baseline level of travel well-being under routine conditions. Changes in the travel environment (such as a new road, improved public transportation, congestion pricing) or in people's lives (such as residential relocation or job change) disrupt the commuting routine. During these times of change, travel well-being may move up or down from its set point as in the hedonic treadmill hypothesis. Therefore, measures of travel well-being might be different depending on when they are collected, and in particular under routine or non-routine situations. This issue is explored in detail in Chapter 5 through experiments that measure travel well-being before and after a temporary change in behavior.

Treadmill effects may also arise in the context of activities, especially those that are characterized by routine conditions, such as the daily work activity.

Activity Versus Travel Well-Being

As mentioned in Chapter 1, people may confound their feelings about travel with their feelings about the activity at the destination. This issue was discussed by Ory and Mokhtarian (2005) who suggested several techniques to try to separate the two concepts. This includes interactive probing, confirmation of responses, stated preferences surveys, and a "teleportation test" ("If you could instantaneously be teleported to a desired location, would you prefer doing that more than traveling there in the conventional

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way?'') (Mokhtarian and Salomon, 2001). The latter technique tries to capture the value derived from travel per se.

As discussed in Chapter 1, confounding feelings about travel with feelings about activities is however less likely to be an issue in the context of the commute to work which is more clearly defined in people's minds due to its repetitive nature. However, techniques that can help clarify the distinction between activity and travel well-being, such as those discussed by Ory and Mokhtarian (2005), are desirable.

3.3   Modeling Well-Being and Behavior

In this section, we first discuss the general enhancements to random utility models brought about by the use of happiness data. Then we present modeling frameworks that incorporate happiness measures within random utility models. The discussion and frameworks are general and may be applied to domains other than just activities and travel.

3.3.1 Potential Enhancements

Including well-being in random utility models entails the extension of these models in at least two ways: enriching the utility and measuring the utility better.

First, taking advantage of research on the causes and correlates of subjective well-being (reviewed in Chapter 2), one can develop richer utility specifications in choice models. In standard choice models, utility is specified as a function of attributes (e.g. time and cost in travel demand models) and individual characteristics. Recent efforts to enrich the standard random utility model have modeled the influences of "soft" variables on choice behavior, such as comfort, reliability, scenic travel, and more generally perceptions, attitudes, and decision protocols (see, for example, Ben-Akiva et al., 2002b; Choo and Mokhtarian, 2004; Johansson et al., 2006; Theis et al., 2006). These extended models have enhanced the behavioral realism of discrete choice methods based on random utility models.

Using happiness research, one can further enhance these models by specifying utility in a way that systematically accounts for the relevant causes and correlates of well-being. This includes the usual observed attributes and qualitative factors but also other latent variables that can be modeled using a latent variable model which relates them to utility (through structural equations) and to indicators (through measurement equations). For example, one can enrich utility specifications with variables that reflect interpersonal and intrapersonal comparisons. This requires traditional surveys to include questions on the choices of people in the respondent's reference group (for interpersonal comparisons) and on one's past or future expected choices (for intrapersonal comparisons).

Second, as discussed in Chapter 2, if we consider happiness broadly as overall satisfaction or general happiness considering all aspects of a situation or an experience,

then we can assume that happiness is the same as utility and use happiness measures as indicators of utility. Even if happiness is more narrowly defined as satisfaction with particular aspects of the experience of interest, the happiness measures can still provide information about the utility since happiness will just be part of the overall utility. Therefore, the modeling framework that we develop below will also be valid in that case. The use of the happiness indicators aids model identification and makes the parameters more efficient.

Moreover, we need to be explicit about the type of utility we are considering. As discussed in Chapter 2, there are several conceptions of utility. The standard notion of utility that is used in choice models is decision utility; it refers to the weight of outcomes in making a choice and is traditionally measured by the observed choice. Moment utility refers to the instantaneous (or moment-to-moment) experience of the choice made. Remembered utility refers to how the moment utility over extended temporal episodes is remembered. For the purpose of modeling behavior, decision utility is what matters; therefore, happiness measures that reflect decision utility should be used. In a dynamic context, this can be done by collecting happiness measures at the time of decision-making. In a static context, this is more challenging because happiness measures are collected after the choice has been made and so these measures will be imperfect indicators of decision utility. Moreover, in a dynamic context, it is possible to make a distinction among the different notions of utility, explicitly model their causal relationships, and use happiness measures that reflect these different utility concepts.

In the next section, we develop these ideas into a modeling framework that extends random utility models though the use of happiness measures. We consider both static and dynamic contexts. The framework is general and can be applied to modeling behavior in several domains.

3.3.2 Modeling Framework

We distinguish between two cases: static and dynamic. In the static framework, choice and happiness measures are observed at one point in time. In the dynamic framework, choice and happiness measures are available at multiple points in time. After presenting the model structures and formulations, we provide an example illustrating the different components of the framework and describe how the extended model (including happiness) can be compared to a standard model without happiness.

Static Framework

We develop the modeling framework and formulation in three steps: first considering only a standard choice model, then adding a latent variable model with indicators, and finally adding the happiness indicators.

Let X denote observed variables, X^* denote latent or unobserved variables, U denote utility, h denote happiness indicators, I denote indicators of the latent variables, and y

denote the choice ($y(i)=1$ if alternative i is chosen and 0 otherwise). All these quantities are vectors. The dimensionality of y is equal to the number of alternatives; one element of y is equal to 1 and the remaining elements are 0.

Standard Choice Model

Figure 3.1 shows a standard choice model framework where the utility is a function of observed variables and is measured by the choice. In this figure and other figures in the thesis, we represent observed variables in rectangles, latent (or unobserved) variables in ovals, structural relationships by solid arrows, and measurement relationships by dashed arrows.

Observed
Variables
X
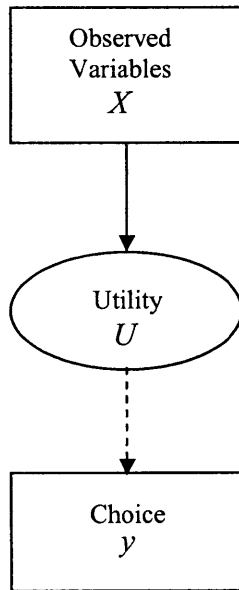
Utility
U

Choice
y

Figure 3.1. Static standard choice model framework.

Let $P(y|U)$ denote the choice probability given the utility. For example, if utility maximization is used as a decision protocol, this conditional probability can be expressed as follows:

$$P\big(y(i)=1|U\big)=\begin{cases}1 & \text{if } U(i)=\max_{j} U(j) \\ 0 & \text{otherwise}\end{cases}$$

(3.2)

The unconditional choice probability is obtained by integrating the conditional choice probability (3.2) over the density function of the utility as follows:

$$P(y|X)=\int_{U} P(y|U)f(U|X)\, dU$$

(3.3)

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where $f(U|X)$ denotes the density function of the utility conditional on explanatory variables X.

Choice and Latent Variable Model

Figure 3.2 shows a choice model integrated with a latent variable model, also known as the Hybrid Choice Model (HCM) (Ben-Akiva et al., 2002a; Walker and Ben-Akiva, 2002). The utility is now a function of both observed and latent variables. The error term of the utility can be viewed as part of these latent variables. The latent variables may also have indicators obtained from answers to survey questions.
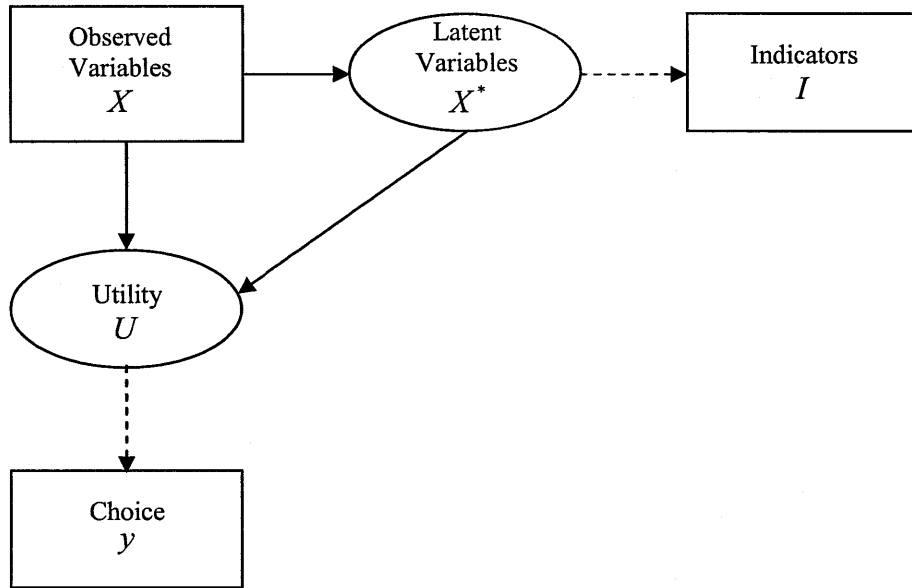
Figure 3.2. Static Hybrid Choice Model framework (Ben-Akiva et al., 2002a; Walker and Ben-Akiva, 2002)

Let the density function of the utility conditional on both the latent and observed variables be denoted as $f(U|X^*, X)$. Let $f(X^*|X)$ denote the density function of the latent variables X^* conditional on X. The unconditional choice probability is now obtained by integrating the conditional choice probability (3.2) over the density functions of the utility and the latent variables as follows:

$$P(y|X) = \int_{X^*} \int_U P(y|U) f(U|X^*, X) f(X^*|X) \, dU dX^* \tag{3.4}$$

We next introduce the indicators I of the latent variables into the formulation. Let $f(I|X^*)$ denote the conditional density function of the indicators of the latent variables. The likelihood of a given observation is the joint probability of the choice and the indicators. It can be expressed by integrating the product of the conditional choice probability and the conditional density functions of the indicators over the densities of the utility and the latent variables as follows:

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$$P(y, I | X) = \iint\limits_{X^* U} P(y|U) f(I|X^*) f(U|X^*, X) f(X^*|X) \, dU \, dX^* \tag{3.5}$$

Choice, Latent Variables, and Happiness

We next add to the HCM the happiness measures h as indicators of utility as shown in Figure 3.3.
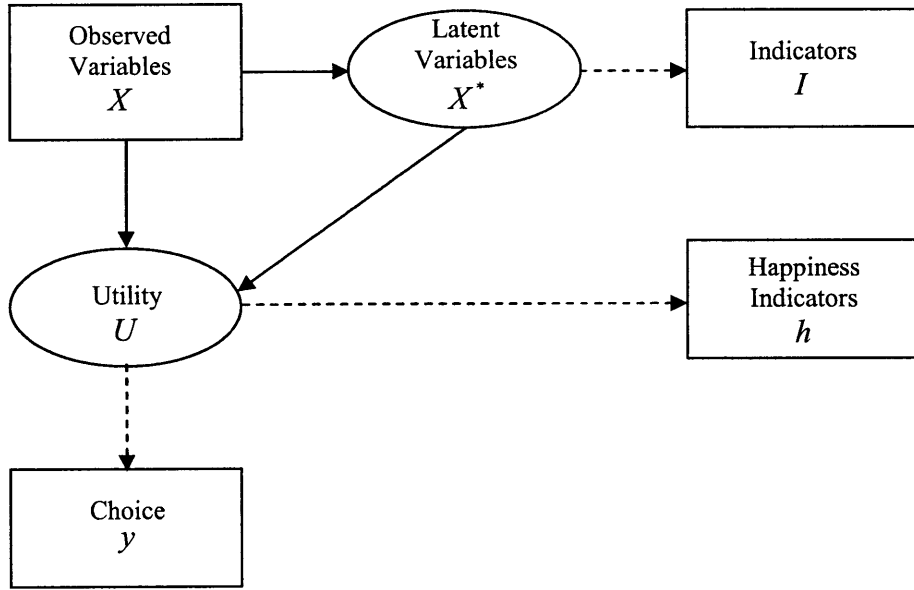
Figure 3.3. Static Hybrid Choice Model with happiness framework.

Let $f(h|U)$ denote the conditional density function of the happiness indicators. The likelihood of a given observation is the joint probability of the choice, the indicators of the latent variables, and the happiness indicators. It can be expressed by integrating the product of the conditional choice probability and the conditional density functions of the indicators over the densities of the utility and the latent variables as follows:

$$P(y, I, h | X) = \iint\limits_{X^* U} P(y|U) f(I|X^*) f(h|U) f(U|X^*, X) f(X^*|X) \, dU \, dX^* \tag{3.6}$$

This extended model can be estimated using maximum likelihood or simulated maximum likelihood depending on the dimensionality of the integral. It should be noted that the indicators (I and h) are typically used in model estimation but not in model application. They ease identification but do not influence behavior (Walker, 2001).

We discuss next two issues related to the use of happiness indicators in a static context. First, happiness measures are typically available for the chosen alternative only (i.e. people are asked how happy they are with their chosen alternative). To account for that,

the density function of the happiness indicator can be specified as conditional on both the utility and the choice, i.e. $f(h|U,y)$.

Second, the happiness measures are given after experiencing the outcomes of the choice, while the choice is made before the actual experience. This means that the happiness measures reflect remembered utility while the choice reflects decision utility. However, since we are modeling behavior in a static context, we only represent decision utility in the static framework recognizing that the happiness measures are imperfect indicators of decision utility. This issue can nevertheless be accounted for by obtaining measures of how different the experience was from expectations and using the happiness measures as indicators of decision utility only if the experience was as expected. If E denotes a measure of how different the experience was from expectations (e.g. $E = 1$ if the experience was as expected and 0 otherwise), the density function of the happiness indicators can be specified conditional on E, i.e. $f(h|U,y,E)$. Accounting for these two issues, the likelihood of a given observation can be modified as follows:

$$P(y,I,h|X,E) = \iint_{X^*U} P(y|U)f(I|X^*)f(h|U,y,E)f(U|X^*,X)f(X^*|X)\,dU\,dX^* \qquad (3.7)$$

We next turn to the formulation of the model in a dynamic context where choice and happiness measures are collected at multiple points in time.

Dynamic Framework

In a dynamic framework, one can distinguish among the different conceptions of utility discussed earlier and depict well-being as a temporal and iterative process (see, for example, Dolan and White, 2006). At any given point in time, people make choices based on decision utility from various courses of action available to them and choose the alternative with maximum utility. Decision utility is assumed to contain predicted utility (i.e. affective forecasts) as part of it. Decision utility depends on attributes of the alternatives (observed or latent) which may also be interacted with individual characteristics.

After people make a choice, they experience its outcomes. Every moment of experience is associated with certain affective feelings and its utility depends on the attributes of the choice made. This moment-to-moment experience is known as moment utility. What people remember of the experience is known as remembered utility, and may be determined by certain moments of the experience (such as the peak and the end) and some other factors. Thus, moment utility affects remembered utility.

Remembered utility in one time period affects decision utility in the next time period; experiences that are remembered as more pleasant or less painful than other experiences are more likely to be chosen again. There may also be inertia effects. That is, choices made in one time period are more likely to be repeated in the next time period.

A dynamic framework incorporating these relationships among different types of utility and inertia effects is shown in Figure 3.4 for one time period. Each of the three types of utility may have its own happiness indicators (the indicator of remembered utility at time t is obtained at time $t+1$). In addition, decision utility has choice indicators and, as in the static framework, latent variables may affect decision utility and may have their own indicators (In time periods when people are in a routine and behavior is habitual, the choice process need not be explicitly modeled, but happiness measures reflecting the routine situation may be available and can be modeled). Figure 3.5 shows the dynamic framework for the entire time horizon without the happiness indicators and indicators of the latent variables. Note that "moment utility" as represented in the framework refers to the entire moment-to-moment utility profile over the duration of an experience (but only certain moments of the experience may affect remembered utility). Thus, the index t accounts for the duration of the experience.
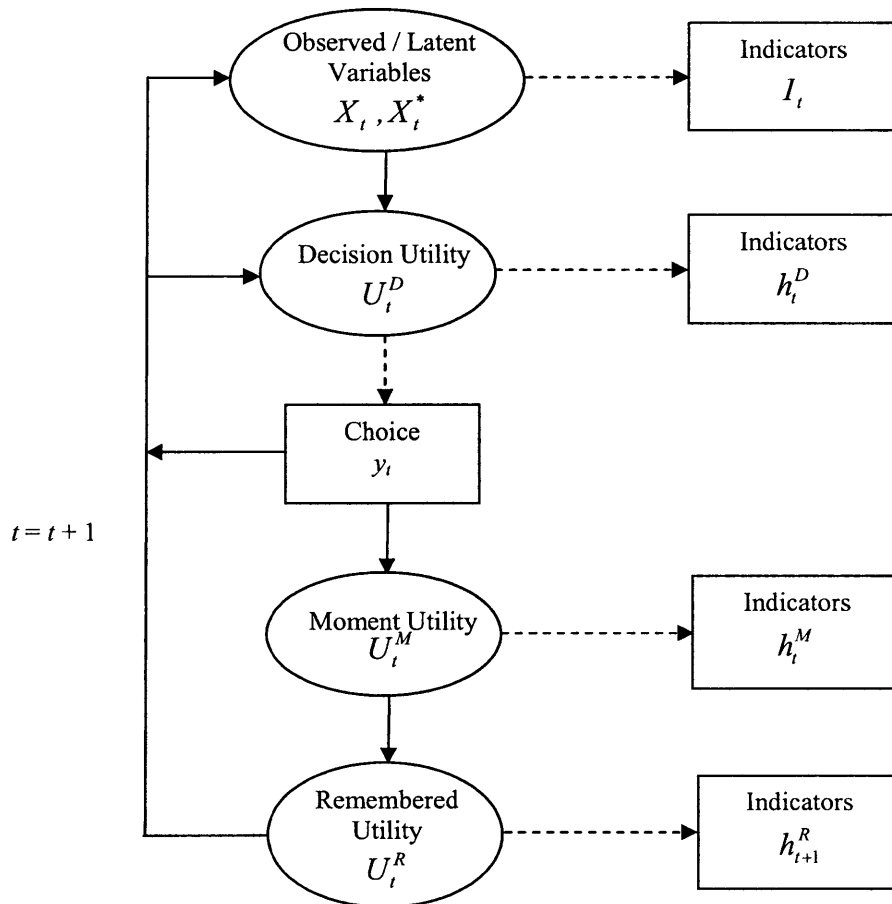
Figure 3.4. Dynamic framework for modeling happiness and behavior shown at one point in time.

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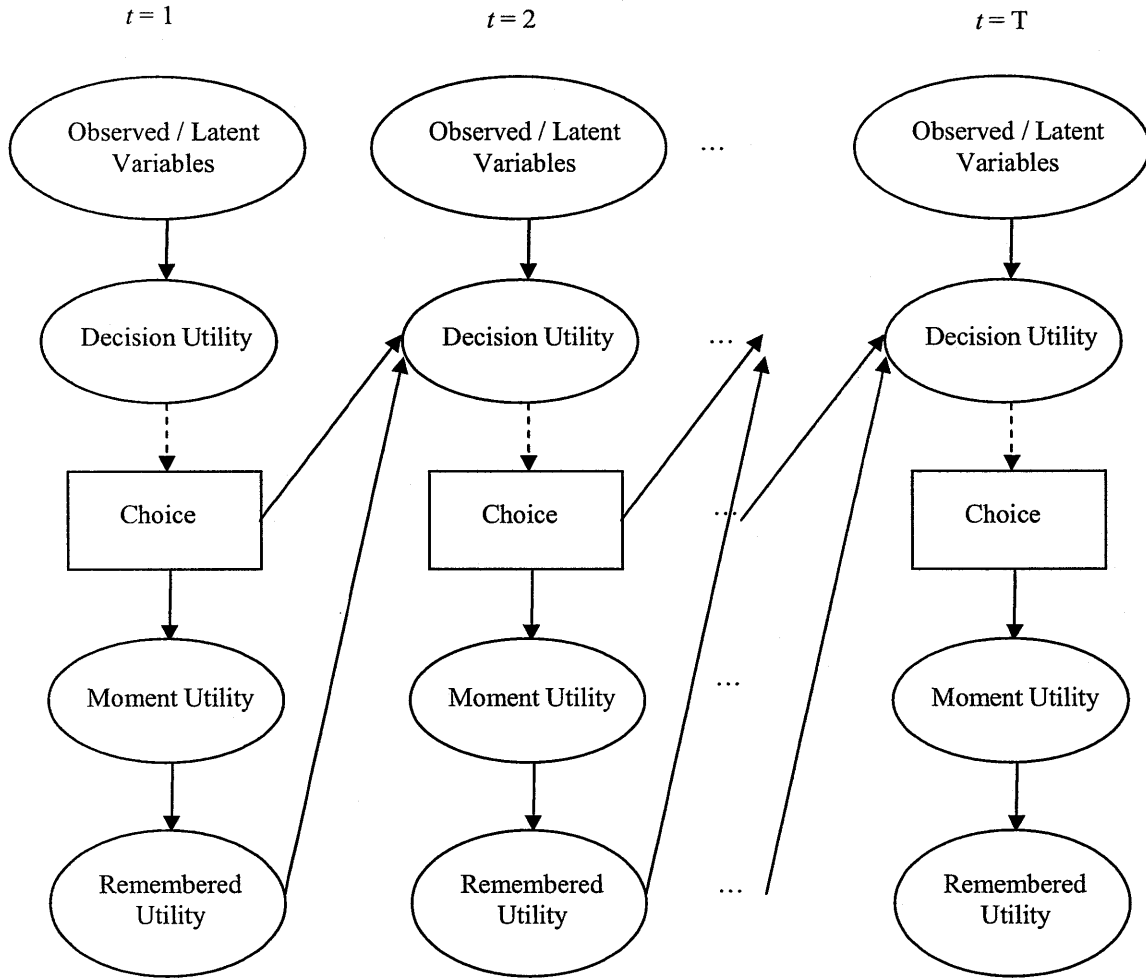
Figure 3.5. Dynamic framework for modeling happiness and behavior shown over time (happiness indicators and indicators of latent variables are omitted from the figure).

To formulate the model, we proceed incrementally starting with a standard choice model, then adding a latent variable model with indicators, and finally adding the different notions of utility and the happiness indicators.

The notation for the dynamic framework is similar to that for the static framework except that the variables now refer to sequences over time. That is, $X = (X_1, \ldots, X_T)$, $X^* = (X_1^*, \ldots, X_T^*)$, $y = (y_1, \ldots, y_T)$, and $I = (I_1, \ldots, I_T)$, where T is the number of time periods. $U^D = (U_1^D, \ldots, U_T^D)$ denotes decision utility and $U^R = (U_1^R, \ldots, U_T^R)$ denotes remembered utility. $h^D = (h_1^D, \ldots, h_T^D)$ and $h^R = (h_1^R, \ldots, h_T^R)$ denote happiness indicators measuring decision and remembered utility, respectively. In the formulation, we will not consider moment utility to keep the formulation tractable.

Standard Choice Model

Let $P\left(y_t \middle| U_t^D\right)$ denote the conditional choice probability at time t, as given in Equation (3.2). Let $f\left(U_t^D \middle| U_{t-1}^D, X_t, y_{t-1}\right)$ denote the density function of decision utility at time t conditional on decision utility and choice at time $t-1$ (to reflect inertia effects) and on the observed variables at time t. The joint probability of the choice and decision utility at time t conditional on decision utility and choice at time $t-1$ and on the observed variables at time t is given as:

$$P\left(y_t \middle| U_t^D\right) f\left(U_t^D \middle| U_{t-1}^D, X_t, y_{t-1}\right) \tag{3.8}$$

The probability of a sequence of choices and decision utilities is given as the product of the joint probability over time, as follows:

$$\prod_{t=1}^{T}\left(P\left(y_t \middle| U_t^D\right) f\left(U_t^D \middle| U_{t-1}^D, X_t, y_{t-1}\right)\right) \tag{3.9}$$

The unconditional probability of the sequence of choices can then be expressed by integrating Equation (3.9) over decision utility, as follows:

$$P(y|X) = \int_{U^D}\left(\prod_{t=1}^{T}\left(P\left(y_t \middle| U_t^D\right) f\left(U_t^D \middle| U_{t-1}^D, X_t, y_{t-1}\right)\right)\right) dU^D \tag{3.10}$$

It is assumed that the initial conditions (U_0^D and y_0) are known. If they are not known, they can be determined by methods that handle initial conditions problems (see, for example, Wooldridge, 2005).

Choice and Latent Variable Model

We now add the latent variables to the model. Let $f\left(U_t^D \middle| U_{t-1}^D, X_t^*, X_t, y_{t-1}\right)$ denote the density function of decision utility at time t conditional on decision utility and choice at time $t-1$ and latent and observed variables at time t. Let $f\left(X_t^* \middle| X_{t-1}^*, X_t\right)$ denote the density function of the latent variables at time t conditional on the latent variables at time $t-1$ and the observed variables at time t.

The probability of the sequence of choices is now given by integrating the product (over time) of the joint probability of the choice, decision utility, and latent variables over the decision utility and the latent variables as follows:

$$P(y|X) = \int_{X^*}\int_{U^D}\left(\prod_{t=1}^{T}\left(P\left(y_t \middle| U_t^D\right) f\left(U_t^D \middle| U_{t-1}^D, X_t^*, X_t, y_{t-1}\right) f\left(X_t^* \middle| X_{t-1}^*, X_t\right)\right)\right) dU^D \, dX^* \tag{3.11}$$

We next add the indicators of the latent variables to the model. Let $f\left(I_t \middle| X_t^*\right)$ denote the conditional density function of the indicators of the latent variables at time t. The probability of the sequence of choices and indicators of the latent variables is given as follows:

$$P(y,I|X) = \int_{X^* U^D} \int \left(\prod_{t=1}^{T} \left(\frac{P\left(y_t \middle| U_t^D\right) f\left(I_t \middle| X_t^*\right) f\left(U_t^D \middle| U_{t-1}^D, X_t^*, X_t, y_{t-1}\right)}{f\left(X_t^* \middle| X_{t-1}^*, X_t\right)} \right) \right) dU^D \, dX^* \qquad (3.12)$$

It is also assumed here that the initial conditions (U_0^D, X_0^*, and y_0) are known.

Choice, Latent Variables, Decision and Remembered Utility, and Happiness

We now distinguish between the notions of decision and remembered utility in the formulation. We do not consider moment utility in the formulation to keep the model tractable. Let $f\left(U_t^D \middle| U_{t-1}^R, X_t^*, X_t, y_{t-1}\right)$ denote the density function of decision utility at time t conditional on remembered utility at time $t-1$ (following the framework shown in Figures 3.4 and 3.5) as well as the latent variables and at time $t-1$ and the observed variables at time t. Let $f\left(U_t^R \middle| X_t^*, X_t, y_t\right)$ denote the density function of remembered utility at time t conditional on the latent variables, observed variables, and choice at time t.

The probability of the sequence of choices is given by integrating the product (over time) of the joint probability of the choice, decision utility, remembered utility, and latent variables as follows:

$$P(y|X) = \int_{X^* U^R U^D} \int \int \left(\prod_{t=1}^{T} \left(\frac{P\left(y_t \middle| U_t^D\right) f\left(U_t^D \middle| U_{t-1}^R, X_t^*, X_t, y_{t-1}\right)}{f\left(U_{t-1}^R \middle| X_{t-1}^*, X_{t-1}, y_{t-1}\right) f\left(X_t^* \middle| X_{t-1}^*, X_t\right)} \right) \right) dU^D \, dU^R \, dX^* \qquad (3.13)$$

Let $f\left(h_t^D \middle| U_t^D\right)$ denote the conditional density function of the happiness indicators of decision utility at time t, and let and $f\left(h_t^R \middle| U_{t-1}^R\right)$ denote the conditional density function of the happiness indicators of remembered utility at time $t-1$.

The probability of the sequence of choices, indicators of the latent variables, and happiness indicators of decision and remembered utility can be expressed as follows:

$$P\left(y, I, h^D, h^R \middle| X\right) = \int_{X^* U^R U^D} \int \int \left(\prod_{t=1}^{T} \left(\begin{array}{c} P\left(y_t \middle| U_t^D\right) f\left(I_t \middle| X_t^*\right) f\left(h_t^D \middle| U_t^D\right) f\left(h_t^R \middle| U_{t-1}^R\right) \\ f\left(U_t^D \middle| U_{t-1}^R, X_t^*, X_t, y_{t-1}\right) \\ f\left(U_{t-1}^R \middle| X_{t-1}^*, X_{t-1}, y_{t-1}\right) f\left(X_t^* \middle| X_{t-1}^*, X_t\right) \end{array} \right) \right) dU^D \, dU^R \, dX^*$$

$$(3.14)$$

It is assumed that the initial conditions (U_0^R, X_0^*, and y_0) are known.

Example

In the formulation of the static and dynamic frameworks, we only showed the likelihood function expressed as a function of general probability functions. In this section, we provide an example showing the equations of the structural and measurement models of the dynamic framework. We adopt linear specifications of the error terms to keep the models tractable, and we omit the model parameters in the equations below for ease of presentation.

Structural Model

The structural model consists of a specification of decision utility, remembered utility, and the latent variables as follows:

$$U^D = U^D\left(U^R, X^*, X, y\right) + \varepsilon^D \qquad (3.15)$$
$$U^R = U^R\left(X^*, X, y\right) + \varepsilon^R \qquad (3.16)$$
$$X^* = X^*\left(X\right) + \psi \qquad (3.17)$$

where ε^D, ε^R, and ψ are error terms. Given the structural equations and the error term distributions, the density function of each of the utilities and the latent variables can be derived. Consider, for example, the density function $f\left(X^*|X\right)$ of the latent variables. It can be derived as the product of the density function of ψ evaluated at the inverse transformation (of ψ as a function of X^*) and the absolute value of the determinant of the Jacobian of the transformation (Greene, 2002). Since X^* is a linear function of ψ in this example, the density function of X^* will be equal to the density function of ψ evaluated at the inverse transformation.

Measurement Model

The measurement model consists of a specification of the choice, happiness indicators, and latent variable indicators as follows:

$$y = y\left(U^D + \eta\right) \qquad (3.18)$$
$$h^D = h^D\left(U^D\right) + \omega^D \qquad (3.19)$$
$$h^R = h^R\left(U^R\right) + \omega^R \qquad (3.20)$$
$$I = I\left(X^*\right) + \upsilon \qquad (3.21)$$

where η, ω^D, ω^R, and υ are error terms.

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Equation (3.18) is the choice model which is usually based on utility maximization. The error term η added to the utility may represent optimization errors on the part of the decision-maker. The remaining indicators are typically specified as a linear function of the corresponding utilities or latent variables. As before, the density functions of the indicators depend on the distributions of the corresponding error terms. For example, if the error term η is Extreme Value distributed and the error term ε^D is normally distributed, then the choice model is an error component logit mixture.

Finally, note that the happiness measures and indicators of the latent variables are typically obtained using an ordinal response scale (e.g. 1 to 5). In this case, an ordinal regression framework should be used where the observed indicators h^D, h^R, and I are replaced in Equations (3.19) to (3.21) by underlying continuous latent response variables h^{*D}, h^{*R}, and I^*. The observed indicators and their latent response variables are then related to each other through a threshold model of the following form (shown for the indicators of the latent variables), where M is the number of categories of the indicator, and the τ's are thresholds with $\tau_0 = -\infty$ and $\tau_M = \infty$:

$$I = \begin{cases} 1 & \text{if } \tau_0 < I^* \le \tau_1 \\ 2 & \text{if } \tau_1 < I^* \le \tau_2 \\ \vdots \\ M & \text{if } \tau_{M-1} < I^* \le \tau_M \end{cases}$$

(3.22)

Standard Versus Extended Framework

It is anticipated that the extended framework that incorporates happiness data will lead to enhanced behavioral realism and greater efficiency.

Capturing the different types of utility and modeling their interrelationships draws on recent evidence from behavioral experiments and increases the behavioral richness of choice models. The modeling framework can also be used to establish the relevance of different types of happiness measures to choice behavior, which has implications for data collection (in terms of types and timing of measures) and for project evaluation.

The addition of happiness measurement equations to random utility models with choice indicators will potentially make these models more efficient. The gain in efficiency can be evaluated by comparing the variance-covariance matrices of the estimated parameters in the standard (without happiness) and extended (with happiness) models, or by comparing the variance of the systematic utility in both models. However, the estimated parameters of the choice model in the extended framework should be similar to those obtained in a choice model estimated without happiness data; both should be consistent. To test the consistency of these parameters, a Hausman specification test (Hausman, 1978) can be conducted. Under the null hypothesis, both sets of parameters are consistent, and those estimated in the extended model are more efficient. If the null

hypothesis is rejected, either the happiness data are invalid measures of the utility or alternative model specifications should be explored for the choice and/or happiness models.

The happiness equations are typically used in model estimation but not in application or prediction of behavior since the happiness measures do not have a causal influence on behavior. The benefits of the framework lie mainly in producing more robust models and more efficient estimates of quantities of interest that can be derived from these models, such as value of time and market shares. However, the happiness equations can also be used on their own to predict happiness levels if predictions of the corresponding utilities are available.

3.4   Conclusion

In this chapter, we argued that standard travel behavior models and project appraisal methods over-emphasize the role of travel time and cost in travel behavior and investment decisions. We referred to a number of recent studies that have started to factor in qualitative factors such as reliability and comfort. We motivated the concept of activity and travel well-being as a broader goal than generalized cost. We discussed activity and travel well-being measurement methods and issues, and proposed an extended general framework that models well-being and behavior by using happiness measures as indicators of utility, distinguishing among different conceptions of utility including decision, moment, and remembered utility.

The following four chapters of this thesis focus on operationalizing the activity and travel well-being concepts following the ideas and frameworks described in this chapter. Chapter 4 measures travel well-being in a cross-sectional or static setting in the context of the commute to work and models the causes and correlates of commute well-being. It also analyzes relationships between well-being and behavior in the context of activity participation. Chapters 5 and 6 are devoted to a dynamic measurement and analysis of travel well-being also in the context of the commute to work. Chapter 5 presents a dynamic measurement methods and descriptive statistics from an implementation of this method, while Chapter 6 estimates models of travel well-being and mode switching using the dynamic data. Chapter 7 presents theoretical developments relating well-being and activity patterns following the static modeling framework presented in this chapter.

Chapter 4

Cross-Sectional Measurement and Modeling of Activity and Travel Well-Being and Behavior

In this chapter, we analyze activity and travel well-being in a cross-sectional setting. This analysis has two main objectives: (1) to understand the causes and correlates of travel well-being, focusing on the commute to work, and (2) to find empirical evidence for the presence of correlations between well-being and behavior.

We measure activity and travel well-being through a web-based survey of a sample of commuters. We then develop models to explain the causes and correlates of commute well-being and the effect of travel satisfaction and activity happiness on activity participation.

This chapter is organized as follows. Section 4.1 presents our hypotheses regarding the causes and correlates of commute well-being and a framework for modeling it. We specifically focus on commute satisfaction as the well-being construct. Section 4.2 presents a framework for modeling the relationship between well-being and activity participation. Section 4.3 describes the survey that was conducted to measure commute and activity well-being and the sample that was obtained. Section 4.4 presents a descriptive analysis of the socio-economic and demographic characteristics of the sample and of the travel and activity well-being measures. Section 4.5 presents the formulation of the commute well-being model and estimation results. Section 4.6 presents the formulation of the activity participation models and estimation results. Section 4.7 concludes.

4.1   Commute Satisfaction

4.1.1 Causes and Correlates

We classify the determinants of commute satisfaction into three main categories: commute attributes, individual characteristics, and comparisons.

First, attributes of the commute such as travel time and cost affect commute satisfaction. Certain attributes such as costs are expected to affect the overall evaluation of the commute (i.e. satisfaction) directly, while other attributes may influence the actual experience (i.e. moods and emotions such as stress and enjoyment) which in turn affects overall satisfaction. For example, the degree to which the commute is perceived as stressful affects satisfaction with the commute. Travel stress is caused by long travel or waiting time or distance, traffic congestion, unpredictability and the lack of perceived control, crowding, and other commuting conditions (Evans et al., 2002; Kluger, 1998; Koslowsky et al., 1995, 1996; Novaco et al., 1990; Schaeffer et al., 1988; Singer et al., 1978; Van Rooy, 2006; Wener et al., 2003). It could also be moderated by individual factors, such as the flexibility of the work schedule (Lucas and Heady, 2002) and the use of en-route time to conduct activities as a coping strategy for reducing stress (Lyons and Urry, 2005). Enjoyment of the commute may also affect satisfaction with it. People may enjoy their commute for a number of reasons; they may consider their commute as their private time or as a useful transition between work and home (see, for example, Ory and Mokhtarian, 2005).

Second, individual characteristics such as personality and overall well-being may affect commute satisfaction. Personality has been shown to be a major determinant of overall well-being (DeNeve and Cooper, 1998; Diener and Lucas, 1999), and we hypothesize that it also plays a role in determining commute well-being. For example, individuals with high negative affectivity (e.g. those who get stressed out easily) are likely to get irritated by transportation stressors more quickly than others (Hennessy and Wiesenthal, 1997). Those who plan their activities and are generally on time may be more relaxed and satisfied with their commutes if they have arranged their commuting patterns so that they are less stressful (e.g. plan to arrive to work on time), but they may also be more sensitive to unfavorable traffic conditions that may change their plans or delay their arrival at work. Overall well-being is likely to affect commute well-being in the sense that people who are satisfied with life and its major domains would also tend to be satisfied with their commutes. The personality and overall well-being effects are related to the "top-down approach" to the study of subjective well-being (see, for example, Diener, 1984; Headey et al., 1991), in the sense that stable traits and overall perspective on life affect how people feel about specific life domains. While there might also be an effect from commute well-being on overall well-being (bottom-up approach), we do not study this effect in this research as we treat overall well-being as an exogenous variable.

Third, people conduct comparisons that affect their commute satisfaction. These include interpersonal (or social) and intrapersonal (or intraindividual) comparisons (Schwarz and

Strack, 1991, 1999). We term the happiness arising from these comparisons as "comparative happiness" which in turn affects overall commute satisfaction. Support for the effect of social comparisons on happiness comes from social comparison theories which postulate that people often conduct social comparisons for the purpose of explicit self-enhancement or self-evaluation (Buunk and Mussweiler, 2001; Taylor and Lobel, 2007) among other things; downward comparisons where one compares oneself to others who are not faring as well on the item of comparison may make one happier, while upward comparisons to others who are better off may make one less happy (Wills, 1981). In the context of travel, relevant dimensions of comparison could include travel time, auto availability, or mode of travel. People may also conduct intrapersonal comparisons whereby they compare their current situation to previous or anticipated situations. For example, if one's current commute is much shorter than one's previous commute, one may feel more satisfied with the current commute.

The subjective well-being literature also describes the presence of "interdomain transfer effects" where the psychological consequences of conditions in one life domain spill over to another domain. For example, commuting conditions and associated moods may affect job satisfaction, performance at work, residential satisfaction and moods at home (Koslowsky et al., 1995; Novaco et al., 1990, 1991; Wener et al., 2005). In particular, we expect that when people think about their job satisfaction, they factor in their commuting conditions.

4.1.2 Modeling Framework

A framework for modeling commute satisfaction following the causes and correlates described above is shown in Figure 4.1. Commute satisfaction is influenced by commute stress, commute enjoyment, organized personality, overall well-being, social comparative happiness (arising from social comparisons), and intrapersonal comparative happiness (arising from intrapersonal comparisons). Commute satisfaction affects work well-being, which is also influenced by organized personality, overall well-being, and quality of the work environment.

All variables shown in ovals in this framework are latent or unobserved. Commute satisfaction and work well-being are determined within the model system. The other latent variables may be endogenous or exogenous. Moreover, latent variables typically have indicators for identification purposes. These indicators, as well as the causes of the endogenous latent variables, are not shown in this figure for simplicity. They will be described in more detail in the empirical analysis in Section 4.5. The resulting model is a structural equations model consisting of structural and measurement relationships.

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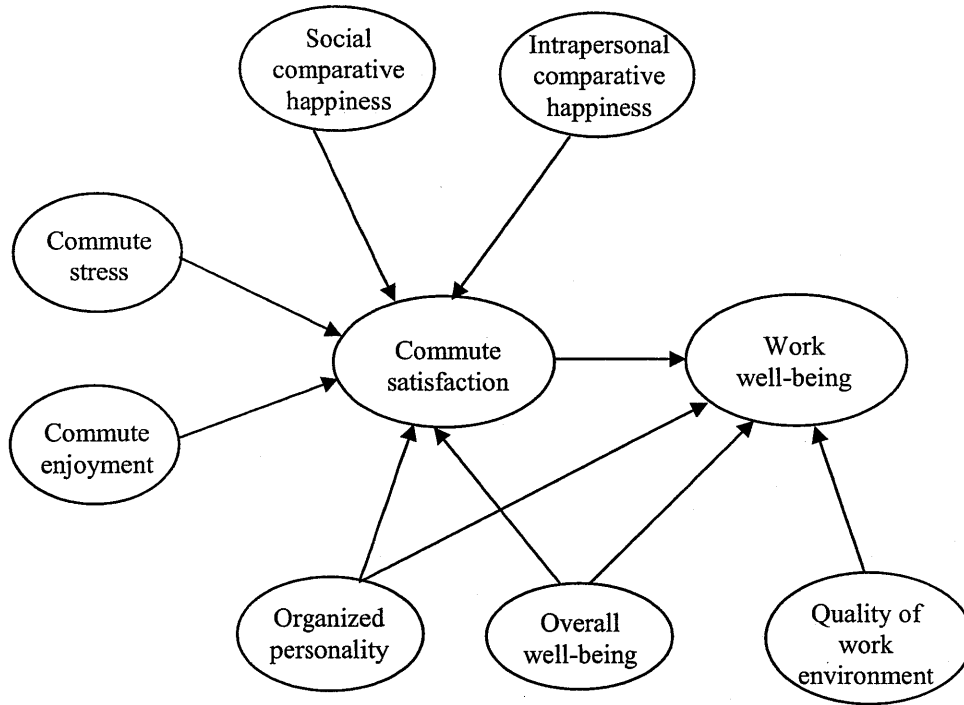
Figure 4.1. Commute satisfaction model framework (indicators of all latent variables and causes of variables other than commute satisfaction and work well-being are not shown in the figure).

4.2   Well-Being and Behavior: Activity Participation

We now present a framework for linking well-being and activity participation. The fundamental hypothesis is that people select actions that maintain or enhance their well-being. Consider, for example, the choice of how often to conduct a certain activity. We postulate that the greater the happiness derived from an activity and the greater the satisfaction with travel to the activity, the more frequently an activity is conducted. Other attributes may also affect activity frequency. A general framework linking well-being and behavior in the context of activity participation is shown in Figure 4.2.
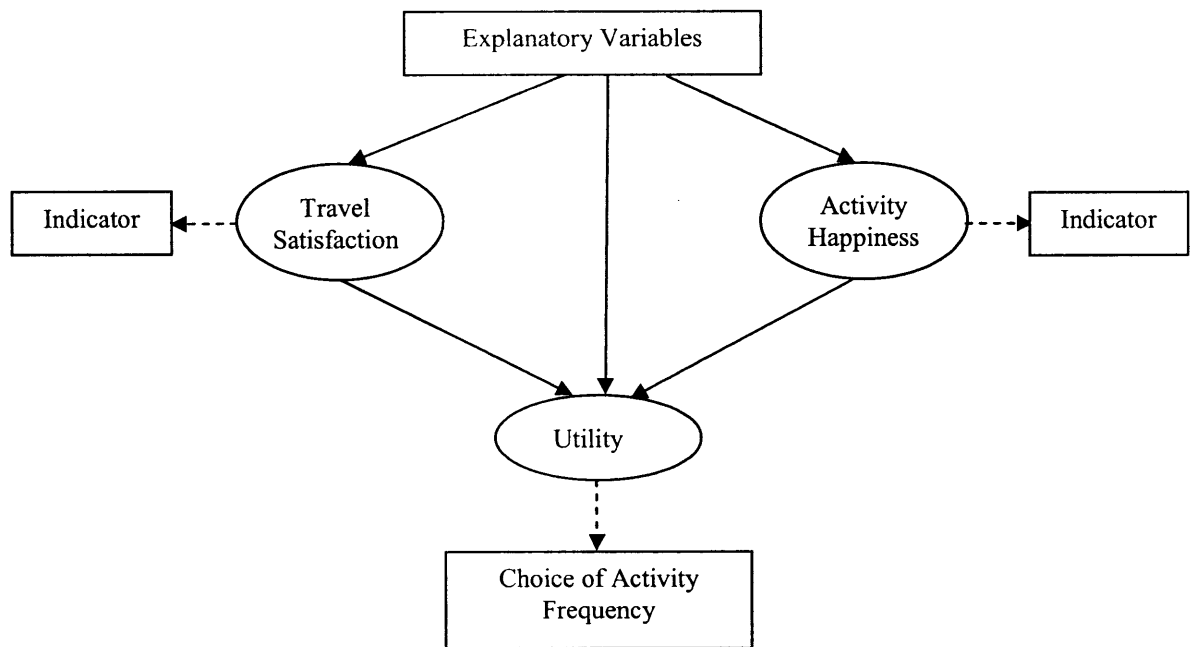
Figure 4.2. Well-being and activity participation model framework.

Travel satisfaction is a function of level of service variables such as mode and distance. This assumes that the location of the activity and the travel mode used to reach it are given. If the location and mode were not given, level of service would be replaced by an accessibility (or logsum) measure defined over all potential destinations or modes that can be used to conduct or reach the activity. Travel satisfaction may also be affected by individual and comparison variables and may have one or more indicators.

Activity happiness may be explained as a function of socioeconomic variables such as gender, age, income, and household size as well as attributes of the activity such as its location, the quality of its environment, etc. It may also have one or more indicators.

Travel satisfaction and activity happiness are part of the overall utility of different activity frequencies. The utility may also be affected by socio-economic variables. If we assume that an individual makes the choice of activity frequency considering all alternatives simultaneously, then we can specify a utility equation for every frequency alternative considered. However, considering the ordinal nature of the choice problem, a more reasonable model might be an ordered response model whereby an individual arrives at his/her current choice of activity frequency by making a sequence of decisions, first whether to conduct the activity or not, then, conditional on conducting the activity at least once, whether to conduct it once or more, and so on. The total number of binary choice models estimated in this case is equal to the number of alternatives minus one.

We will come back to the model specification in the empirical analysis in Section 4.6.

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4.3 Data

We conducted a cross-sectional web-based survey for measuring and modeling travel and activity well-being. While the focus of the survey was primarily on the commute to work, it also measured non-work travel and activity well-being and included a few hypothetical scenarios to assess the impact of well-being on willingness-to-pay for travel options. In Section 4.3.1, we describe the types of variables that were collected in this survey. In Section 4.3.2, we describe the study sample. Appendix A presents the well-being questions of this survey. The full questionnaire can be obtained from the author upon request.

4.3.1 Measures

Commute Satisfaction

One measure of commute satisfaction was collected. The question was phrased as follows:

Taking all things together, how satisfied would you say you are with your commute from home to work?

Respondents rated their satisfaction on a 5-point semantic scale labeled "Very dissatisfied" to "Very satisfied".

Commute Attributes, Stress, and Enjoyment

Commute attributes such as distance, average travel time, travel time variability, predictability, information, travel time use, and other mode-specific attributes (e.g. waiting time for public transportation, safety/type of terrain for non-motorized modes, etc.) were collected.

Measures of commute stress involved rating the following statements on a 5-point scale ranging from "Strongly disagree" to "Strongly agree":

My commute makes me feel stressed out.

My commute makes me feel anxious.

Measures of commute enjoyment also involved rating statements on a 5-point scale ranging from "Strongly disagree" to "Strongly agree", as follows:

I enjoy my commute.

I view my commute as a useful and needed transition between home and work.

My commute gives me valuable private time.

Non-Work Travel Attributes

Non-work travel attributes were also collected. For a number of activity types (shopping, personal business, eat out, social / recreational, organizational / volunteer / religious), respondents indicated how often they conduct these activities per week, the distance they travel to participate in these activities, and the mode they use.

Individual Characteristics

First, personality measures were collected. Respondents rated on a 5-point scale labeled "Strongly disagree" to "Strongly agree" the following statements about their planning, timeliness, and stress traits.

I usually plan my activities ahead.

I am usually on time to do my activities.

I get irritated and stressed out easily.

Second, measures of life and domain satisfaction were rated on a "Very dissatisfied" to "Very satisfied" 5-point scale ("How satisfied are you today with the following areas of your life?"). This included life overall, health, work, residence, free time, family life, and social life. Measures of activity happiness were rated on a "Very unhappy" to "Very happy" 5-point scale ("How happy do you feel when you conduct the following activities?"). The question covered the following types of activities: work, shopping, personal business (e.g. banking, errands, etc.), eating out, social / recreational (e.g. visiting friends, going to the movies, sports and hobbies, etc.), organizational / volunteer / religious, and at home activities. For each of these activity types, respondents also rated their satisfaction with their travel to the activity ("How satisfied are you with your travel to these activities?" 5-point scale ranging from "Very dissatisfied" to "Very satisfied).

Third, socio-economic and demographic characteristics were collected and included gender, age, education level, occupation status, job type, work schedule flexibility, marital status, household size, presence of kids, workers in the household, residence and work area types, and personal income.

Social and Intrapersonal Commute Comparison

Respondents were asked to consider a person in their metropolitan area whose commute was familiar to them. This person is called "comparison other" in what follows. Respondents were then asked about their relationship to the comparison other (e.g. friend,

colleague, neighbor, relative, family member, or other acquaintance). Then they answered three comparison questions.

First, they indicated the commute mode of the comparison other. Second, they rated the stress level of their commute relative to that of the comparison other (5-point scale ranging from much more stressful to much less stressful). This rating is a measure of their comparative happiness due to the social comparison. Third, they indicated how much time their commute takes relative to that of the comparison other (5-point scale ranging from much more time to much less time).

Respondents also compared the stress level of their current commute to that of a previous commute (5-point scale ranging from much more stressful to much less stressful). This rating is a measure of their comparative happiness due to the intrapersonal comparison.

4.3.2 Sample

A sample of commuters was recruited via emails sent by the author to friends, colleagues, and anonymous web users. The sample included respondents from different countries with the largest proportion coming from the United States. The survey was web-based but also included a few personal interviews. The survey covered the following modes of commuting to work: solo car driver, car driver with others in the car, car passenger, bus, subway/train, walk, and bike.

The data used in this chapter were collected between June and October 2007. The data were checked for inconsistencies of responses, and observations that were deemed unreliable were removed. After cleaning and accounting for missing values, the sample used in model estimation consists of 594 observations for the commute satisfaction model and 558-676 observations for the activity participation models.

4.4   Descriptive Statistics

This section presents a descriptive analysis of the socio-economic and demographic characteristics of the sample as well as their travel and activity well-being.

4.4.1 Socio-Economic and Demographic Characteristics

The majority of the sample was male (66%), young (58% less than 40 years old), and highly educated (56% with a graduate degree and 32% with an undergraduate degree). The average household size was 2.5 and 26% of respondents had kids in the household. Most commuters (89%) had partially or completely flexible work schedules. Of those who reported their job type, the majority (74%) worked in management / professional / technical jobs followed by education / research (17%) and self-employed (3%) jobs. The average annual pre-tax personal income was distributed almost evenly among various

categories, possibly due to the fact that different countries are included, with an average value of $69,000.

4.4.2 Commute Well-Being

The distribution of this sample by commute mode was as follows: 43% car, 25% public transportation, and 32% non-motorized commuters. Figures 4.3 to 4.11 show the distribution of a number of commute well-being measures by mode for this sample. For both cognitive and affective measures of commute well-being, the general pattern that emerges is that commuters are mostly on the happy side, with non-motorized commuters being the happiest, followed by public transportation commuters, and then car commuters. Most commuters view their commute as a useful and needed transition between home and work, and many of them think that it gives them valuable private time.
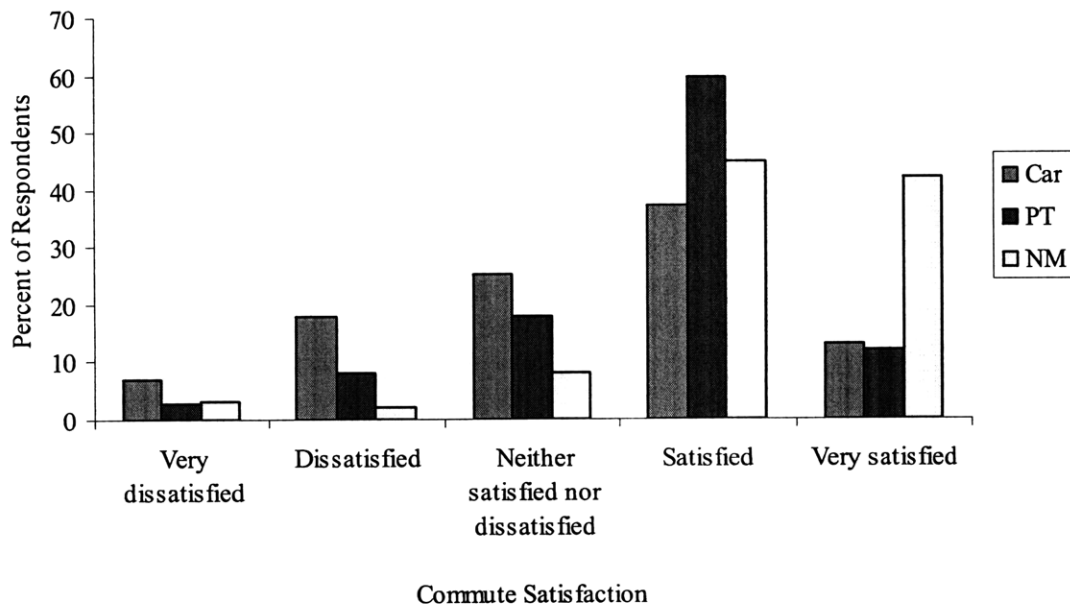
Figure 4.3. Distribution of commute satisfaction by mode (PT = public transportation; NM = non-motorized).
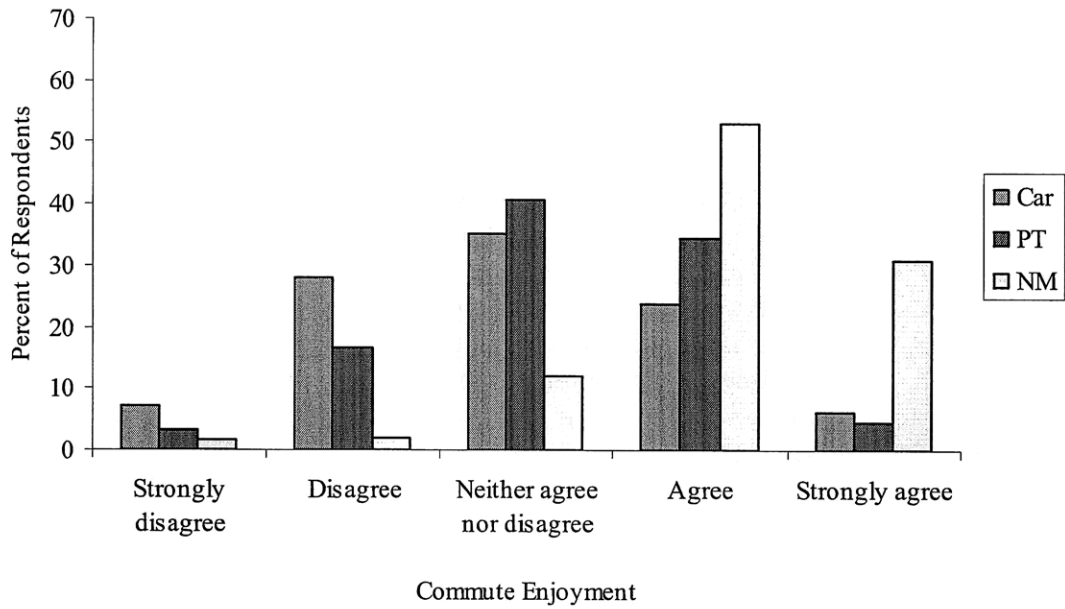
Figure 4.4. Distribution of commute enjoyment by mode (PT = public transportation; NM = non-motorized).
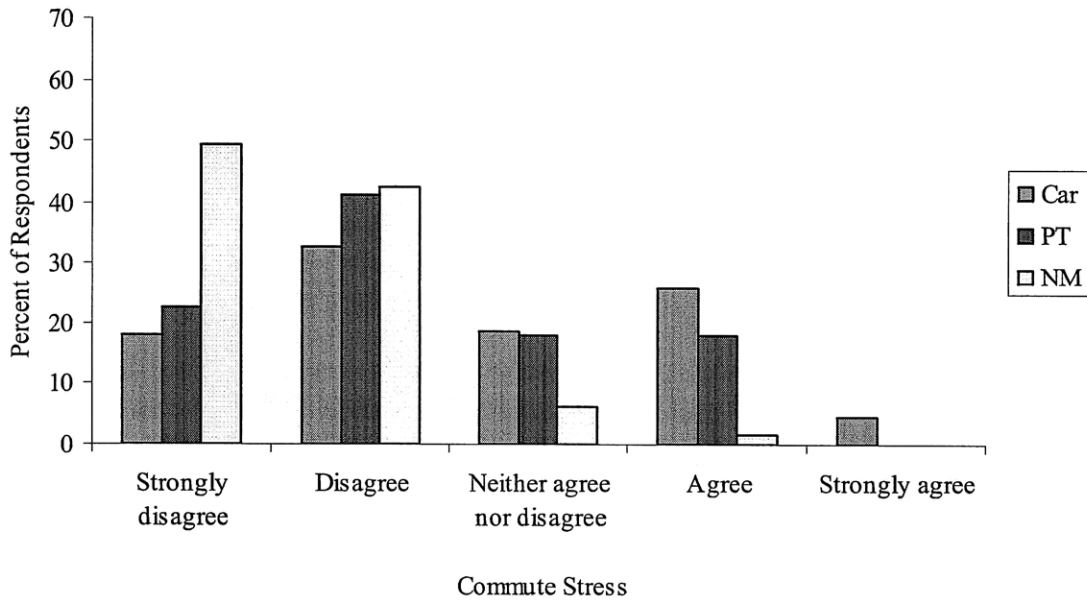
Figure 4.5. Distribution of commute stress by mode (PT = public transportation; NM = non-motorized).
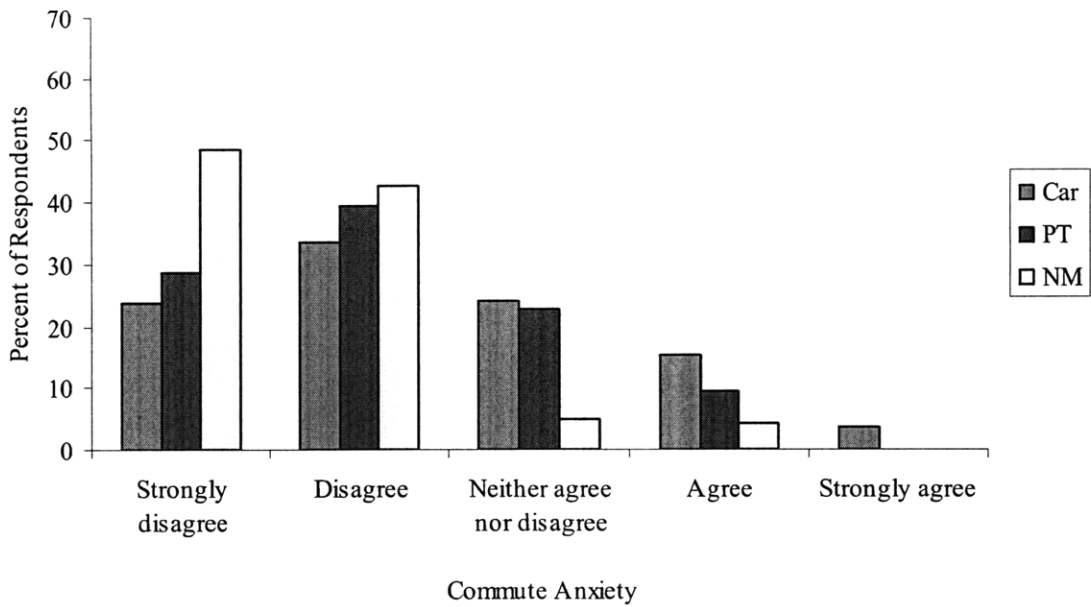
Figure 4.6. Distribution of commute anxiety by mode (PT = public transportation; NM = non-motorized).
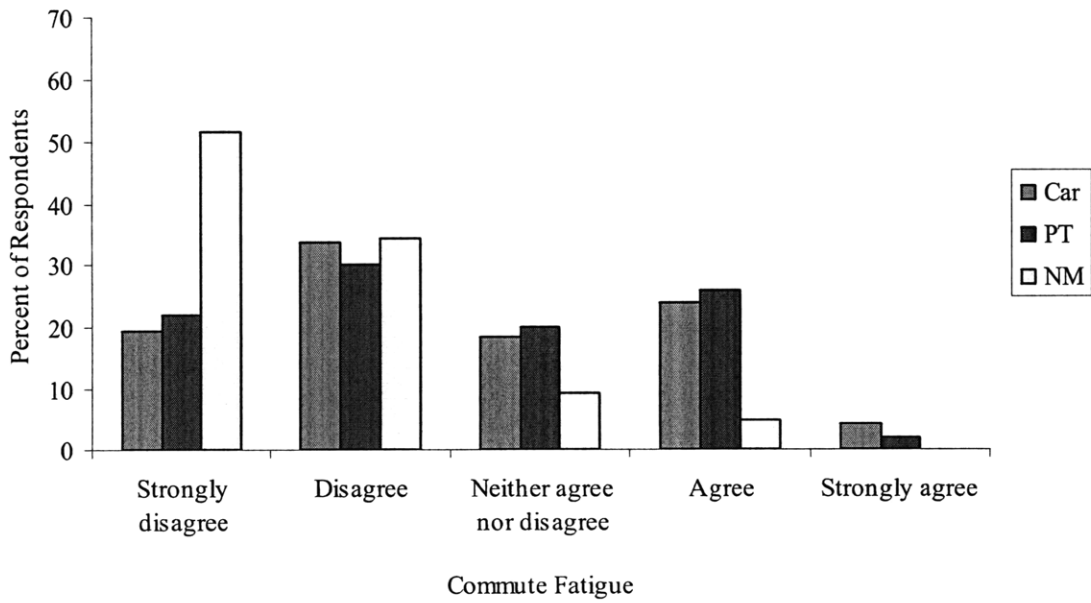
Figure 4.7. Distribution of commute fatigue by mode (PT = public transportation; NM = non-motorized).
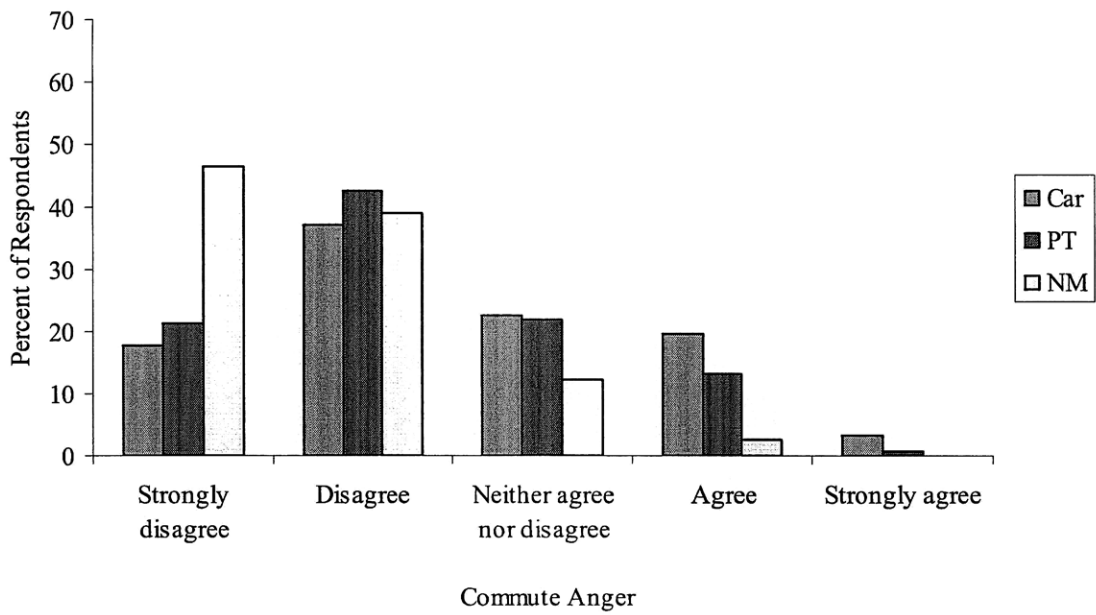
Commute Anger

Figure 4.8. Distribution of commute anger by mode (PT = public transportation; NM = non-motorized).

Commute Impatience
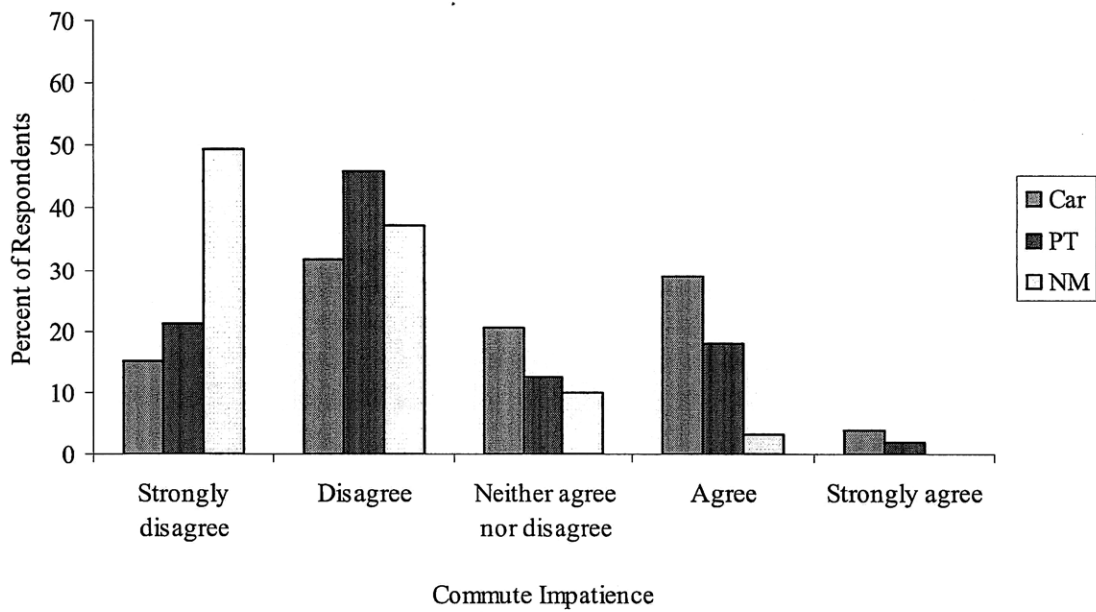
Figure 4.9. Distribution of commute impatience by mode (PT = public transportation; NM = non-motorized).

Commute as Buffer
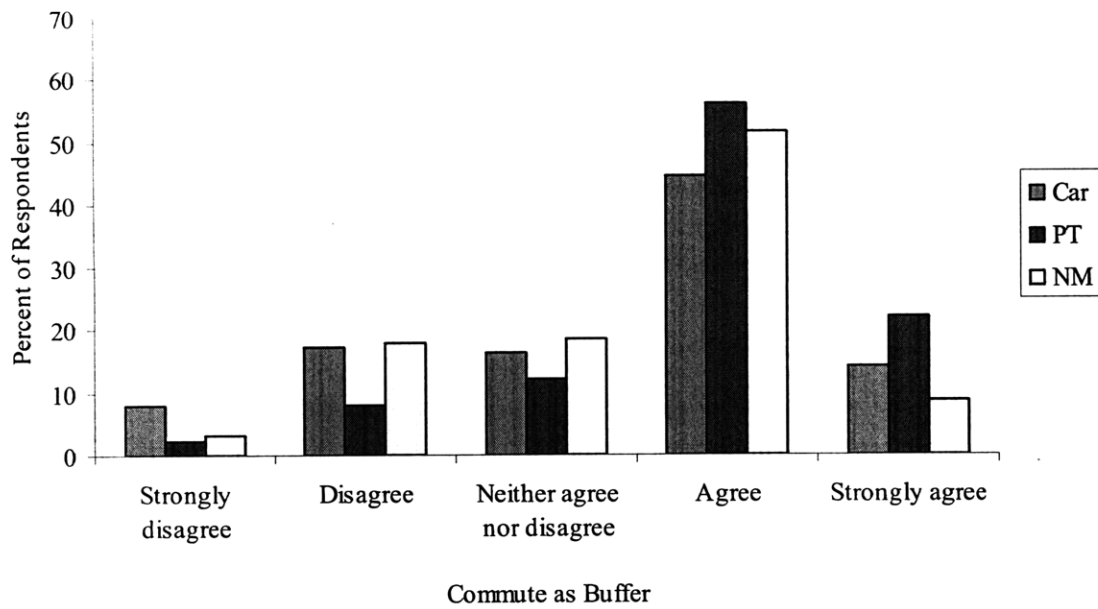
Figure 4.10. Distribution of commute perception, by mode, as a useful and needed transition between home and work (PT = public transportation; NM = non-motorized).

Commute as Private Time
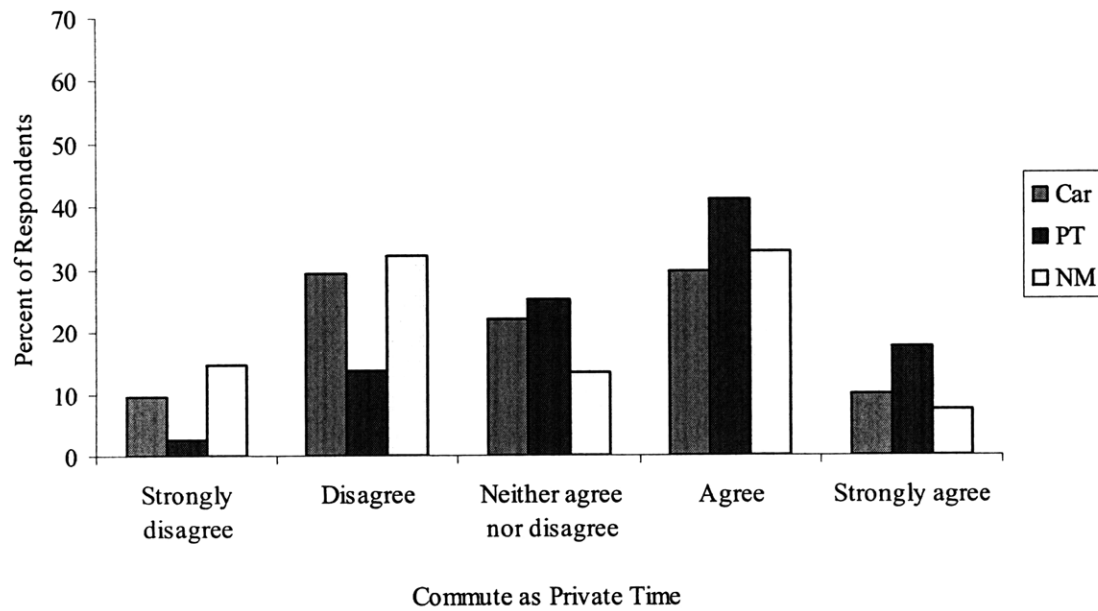
Figure 4.11. Distribution of commute perception, by mode, as providing valuable private time (PT = public transportation; NM = non-motorized).

4.4.3 Non-Work Travel Satisfaction

Table 4.1 shows the percentage of survey respondents by their self-reported level of satisfaction with travel to different activities. Overall, most respondents are satisfied with their travel to different types of activities. They are most satisfied with their travel to eat-out activities and least satisfied with their travel to organizational, volunteer, or religious activities. As discussed in Chapter 3, reports of travel satisfaction may be confounded with happiness or satisfaction with the activity.

Table 4.1. Non-work travel satisfaction.

Travel to Activity	% Dissatisfied	% Neither satisfied nor dissatisfied	% Satisfied
Eating out	4.8	23.1	72.2
Social and recreational	6.5	21.9	71.6
Personal business	10.0	26.2	63.9
Shopping	12.9	25.0	62.0
Organizational, volunteer, or religious	6.0	36.1	58.0

4.4.4 Activity Happiness

Table 4.2 shows the percentage of survey respondents by the self-reported happiness levels that they experience when they conduct different activities. The results indicate that people in this sample are happiest when they conduct social and recreational activities and least happy when they conduct personal business activities.

Table 4.2. Happiness by activity type.

Activity	% Unhappy	% Neither happy nor unhappy	% Happy
Social and recreational	0.6	4.4	95.0
Eating out	1.6	10.6	87.9
At home activities	3.9	17.3	78.8
Organizational, volunteer, or religious	3.2	26.9	69.9
Work	8.2	36.2	55.6
Shopping	15.7	45.1	39.2
Personal business	13.1	61.3	25.6

4.5 Commute Satisfaction Model

We formulate in Section 4.5.1 a model that explains commute satisfaction as a function of the variables described in Section 4.1.1. The model formulation follows the framework shown in Section 4.1.2. Then we show the estimation results in Section 4.5.2.

4.5.1 Formulation

We present a structural equations model formulation of commute satisfaction. For a review of structural equations models, the reader is referred to Bollen (1989) for the case of continuous indicators and to Muthén (1984) for the case of ordered categorical indicators.

The structural part of the model consists of five equations corresponding to latent variables that can be explained by variables available in the survey. As shown in Figure 4.1, commute satisfaction, expressed by Equation (4.1), is caused by commute stress, commute enjoyment, social comparative happiness, intrapersonal comparative happiness, organized personality, and overall well-being. Work well-being, expressed by Equation (4.2), is caused by commute satisfaction, quality of the work environment, organized personality, and overall well-being. Since quality of the work environment has no indicators in the survey, its effect on work well-being is set to 1. Commute stress, expressed by Equation (4.3), is hypothesized to be a function of average travel time by mode, time variability for motorized modes (defined as the difference between travel time on a good and a bad day), the occurrence of frequent congestion for travel by car or bus, and traveling beside traffic for non-motorized modes. Social comparative happiness, expressed by Equation (4.4), depends on travel time and mode comparisons; "Time less than other" is a dummy variable indicating that own commute time is less or much less than the comparison other's commute time, and the different mode combinations refer to "own" mode – "comparison other" mode, where PT denotes public transportation and NM denotes non-motorized. Finally, quality of the work environment, given by Equation (4.5), is a function of work time flexibility, job type (with dummy variables included for individuals working in education/research or who are self-employed), and income (with a dummy variable for missing income). The other latent variables in the model, namely commute enjoyment, intrapersonal comparative happiness, organized personality, and overall well-being, are treated as exogenous as they cannot be well explained by data available in the survey. The β's are unknown parameters to be estimated, and the ζ's are error terms.

$$
\begin{aligned}
\text{Commute satisfaction} = {} & \beta_1 * \text{Commute stress} + \beta_2 * \text{Commute enjoyment} \\
& + \beta_3 * \text{Social comparative happiness} \\
& + \beta_4 * \text{Intrapersonal comparative happiness} \\
& + \beta_5 * \text{Organized personality} + \beta_6 * \text{Overall well-being} + \zeta_1
\end{aligned} \tag{4.1}
$$

$$
\begin{aligned}
\text{Work well-being} = {} & \beta_7 * \text{Commute satisfaction} + 1 * \text{Quality of work environment} \\
& + \beta_8 * \text{Organized personality} + \beta_9 * \text{Overall well-being} + \zeta_2
\end{aligned} \tag{4.2}
$$

$$
\begin{aligned}
\text{Commute stress} = {} & (\beta_{10} * \text{Car} + \beta_{11} * \text{PT} + \beta_{12} * \text{NM}) * \text{Travel time} \\
& + \beta_{13} * \text{Time variability} + \beta_{14} * \text{Frequent congestion} \\
& + \beta_{15} * \text{NM travel beside traffic} + \zeta_3
\end{aligned} \tag{4.3}
$$

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Social comparative happiness $= \beta_{16}$ * Time less than other $+ \beta_{17}$ * Car-Car   (4.4)
$\qquad + \beta_{18}$ * Car-PT $+ \beta_{19}$ * Car-NM $+ \beta_{20}$ * PT-Car
$\qquad + \beta_{21}$ * PT-PT $+ \beta_{22}$ * PT-NM $+ \beta_{23}$ * NM-Car
$\qquad + \beta_{24}$ * NM-PT $+ \zeta_4$

Quality of work environment $= \beta_{25}$ * Flexible work schedule   (4.5)
$\qquad + \beta_{26}$ * Education/research
$\qquad + \beta_{27}$ * Self-employed $+ \beta_{28}$ * Income
$\qquad + \beta_{29}$ * Missing income $+ \zeta_5$

The measurement part of the model, given by Equations (4.6) – (4.20), consists of equations for eight latent variables: commute satisfaction, work well-being, commute stress, commute enjoyment, social comparative happiness, intrapersonal comparative happiness, organized personality, and overall well-being. Each of these variables has one or more ordered categorical indicators obtained from responses to questions with a 5-point semantic scale. Each indicator is associated with a continuous latent response variable that is assumed to underlie the observed categorical variable. The measurement equations relate the latent variables (of Figure 4.1) to the continuous latent response variables. The scale of every latent variable is set by fixing the factor loading for one of its continuous latent response variables to 1. If I denotes an observed indicator, we let I^* denote the corresponding continuous latent response variable. In some cases, a latent variable is set identically equal to its latent response variable for identification purposes. The λ's are unknown factor loadings to be estimated, and the η's are error terms.

Commute satisfaction* = 1 * Commute satisfaction   (4.6)

Work satisfaction* = 1 * Work well-being $+ \eta_2$ (4.7)
Work activity happiness* = λ_3 * Work well-being $+ \eta_3$ (4.8)

Commute stress* = 1 * Commute stress $+ \eta_4$ (4.9)
Commute anxiety* = λ_5 * Commute stress $+ \eta_5$ (4.10)

Commute enjoyment* = 1 * Commute enjoyment $+ \eta_6$ (4.11)
Buffer* = λ_7 * Commute enjoyment $+ \eta_7$ (4.12)
Privacy* = λ_8 * Commute enjoyment $+ \eta_8$ (4.13)

Stress less than other* = 1 * Social comparative happiness   (4.14)

Stress less than before* = 1 * Intrapersonal comparative happiness   (4.15)

Planner* = 1 * Organized personality $+ \eta_{11}$ (4.16)
On time* = λ_{12} * Organized personality $+ \eta_{12}$ (4.17)

Life satisfaction* = 1 * Overall well-being + η_{13} (4.18)

Residence satisfaction* = λ_{14} * Overall well-being + η_{14} (4.19)

Social life satisfaction* = λ_{15} * Overall well-being + η_{15} (4.20)

The last component of the model is the threshold model which relates the observed indicators I to their continuous latent response variables I^*. For each of the indicators, the threshold model is given as follows:

$$I = \begin{cases} 1 & \text{if } \tau_0 < I^* \leq \tau_1 \\ 2 & \text{if } \tau_1 < I^* \leq \tau_2 \\ \vdots \\ M & \text{if } \tau_{M-1} < I^* \leq \tau_M \end{cases} \qquad (4.21)$$

where M is the total number of categories of I and the τ parameters are thresholds or cutoff points for I^* that determine the probabilities of observing the different categories of I with $\tau_0 = -\infty$ and $\tau_M = \infty$. For example, the probability that I corresponds to category j can be computed as follows: $P(I = j) = P(\tau_{j-1} < I^* \leq \tau_j)$. If the latent response variables are normally distributed, the corresponding model is probit.

4.5.2 Estimation Results

Structural equation models with ordered categorical indicators can be estimated using custom software programs such as the Mplus software (Muthén and Muthén, 1998-2006) or the Integrated Choice and Latent Variable Model software (Bolduc, 2007) or can be programmed and estimated using statistical estimation software such as GAUSS (Aptech Systems, 1995). The model shown in Figure 4.1 was estimated using the Mplus software. The estimator used is a limited information robust (mean- and variance-adjusted χ^2 test statistic) method of Weighted Least Squares (WLSMV) (Muthén et al., 1997).

The estimation results shown in Table 4.3 correspond to the structural parameters of the model. The parameters corresponding to the commute satisfaction and work well-being equations are also shown in Figure 4.12.

The estimated structural parameters can be interpreted as follows. Supporting the hypotheses on the causes of commute satisfaction, stress decreases satisfaction and the effect is very significant. Longer travel time, higher variability, encountering congestion frequently, and walking or biking beside traffic[4] increase commuting stress. Greater

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[4] Walking or biking beside traffic is a dummy variable that takes a value of one if the response to the question "Do you walk / bike beside traffic on a highway for most of your trip?" is "yes", and is zero if the response is "no".

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commute enjoyment also increases commute satisfaction, and the effect is very significant.

Greater social comparative happiness increases overall commute satisfaction; the effect is significant but the impact on overall satisfaction is smaller than that of the commute stress and enjoyment variables. Social comparative happiness is mostly determined by travel time comparison; people whose commute is shorter than others' commutes view their situation in a more favorable way (downward comparisons) and feel happier or less stressed. With respect to mode comparisons, car commuters are happiest (in a comparative sense) if the comparison other also commutes by car and least happy if the comparison other commutes by non-motorized modes; non-motorized commuters are happiest if the comparison other commutes by car and least happy if the comparison other commutes by non-motorized modes. The effects for public transportation commuters are not significant. These findings could be interpreted as non-motorized travelers looking down on car commuters as an indication of personal views held by non-motorized travelers about the stress of driving which they don't experience, and the reverse can be said about car commuters. Greater intrapersonal comparative happiness resulting from comparing one's current commute to one's previous commute also increases current commute satisfaction.

People characterized by an organized personality trait, measured by planning and timeliness indicators, are likely to experience less commute satisfaction perhaps because they may be more sensitive to unfavorable traffic conditions that may change their plans or delay their arrival at work. The effect, however, is not significant. People who have high overall well-being are likely to exhibit this optimistic tendency as well in their evaluation of their commute but again the effect is not significant.

We also find a positive and significant effect of commute satisfaction on work well-being, supporting the spillover hypothesis between these two domains. In addition, people whose work schedules are partially or completely flexible and those with higher incomes, both important attributes defining the quality of the work environment, experience greater work well-being. Job type also affects satisfaction and happiness at work, with those working in education or research or who are self-employed happier than others. Although there are possibly more work environment related variables determining work well-being (see, for example, Warr, 1999), they were not included in the survey to keep it to a manageable length and maintain its primary focus on commute well-being. Work well-being is also positively and significantly affected by the organized personality trait and overall well-being.

The measurement and threshold model parameters, variances, and correlations are presented in Table B.1 in Appendix B.

Table 4.3. Structural model estimation results for commute satisfaction model (PT = public transportation, NM = non-motorized).

Parameter	Estimate	t-stat
Commute satisfaction		
Commute stress	-0.486	-13.53
Commute enjoyment	0.744	9.32
Social comparative happiness	0.108	2.81
Intrapersonal comparative happiness	0.0838	1.99
Organized personality	-0.0871	-1.17
Overall well-being	0.0590	1.09
Work well-being		
Commute satisfaction	0.0920	3.38
Quality of work environment	1.00	-
Organized personality	0.170	2.51
Overall well-being	0.484	9.76
Commute stress		
Average travel time (minutes)		
Car	0.0156	5.04
PT	0.00597	1.36
NM	0.00917	1.85
Travel time variability (minutes): car and PT	0.0112	3.53
Frequent congestion dummy: car and bus	0.745	5.42
NM travel beside traffic dummy: NM	0.302	1.39
Social comparative happiness		
Shorter time than others dummy	0.967	9.46
Car – car dummy	0.553	1.65
Car – PT dummy	0.514	1.40
Car – NM dummy	-0.356	-0.85
PT – car dummy	0.268	0.72
PT – PT dummy	0.119	0.31
PT – NM dummy	-0.309	-0.73
NM – car dummy	0.595	2.16
NM – PT dummy	0.505	1.67
NM – NM dummy	0.00 (base)	-
Quality of work environment		
Flexible work schedule dummy	0.168	1.22
Income (in thousands of US dollars)	0.00446	3.15
Missing income dummy	0.253	1.02
Education/research job type dummy	0.410	2.91
Self-employed job type dummy	0.447	1.68
Missing job type dummy	0.152	0.68
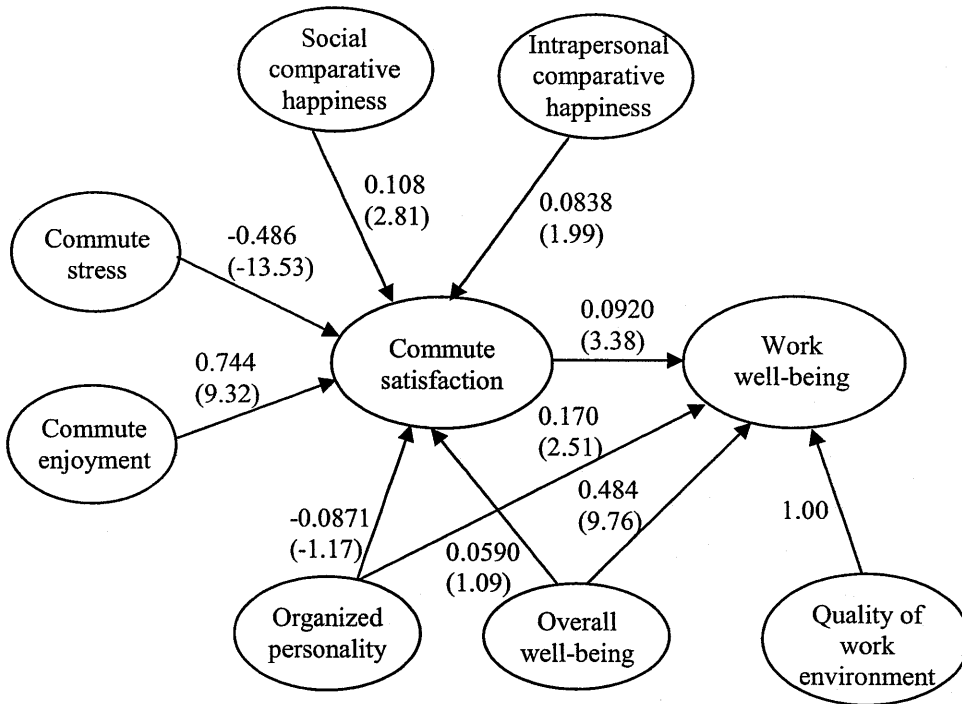
Figure 4.12. Structural parameters for commute satisfaction model (t-statistics are shown in parentheses).

4.6   Activity Participation Models

4.6.1 Formulation

Models of activity participation that include well-being were estimated following the framework of Figure 4.2 (shown also in Figure 4.13 with some more detail) and using the data collected in the web-based survey. Due to software limitations, utility was however replaced by an activity propensity latent variable with the activity frequency used as an indicator of this propensity factor. The resulting model is a structural equations model with latent variables. Moreover, since every latent variable (activity happiness, travel satisfaction, and propensity to engage in an activity) has only one observed indicator, each of these latent variables is set equal to the continuous latent response variable for identification purposes.
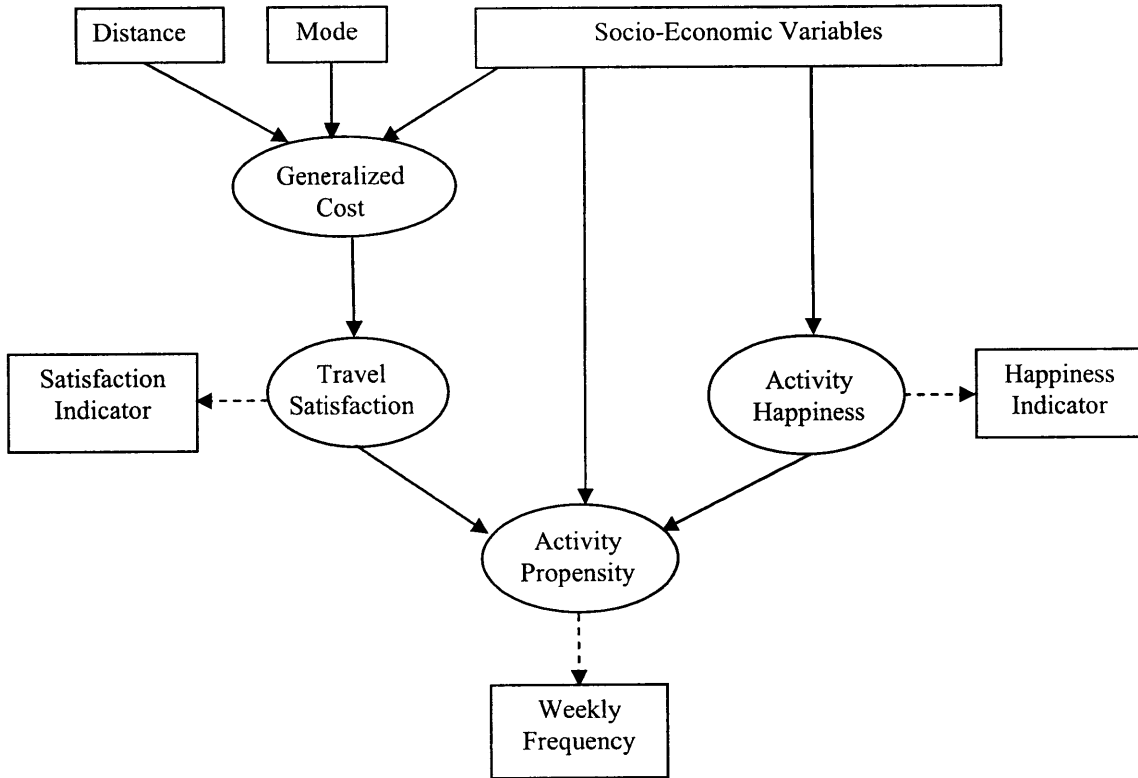
Figure 4.13. Activity propensity model.

Models were estimated for the following activity types: shopping, social / recreational, eat-out, organizational / volunteer / religious, and personal business. The shopping model was specified as follows, with the other models specified similarly.

Activity propensity = β_1 * travel satisfaction + β_2 * activity happiness
$\qquad +\beta_3$ * Age(0-30) + β_4 * Age(30-60) + β_5 * Age(60+) $\qquad$ (4.22)
$\qquad + \beta_6$ * 1-person household dummy + ζ_1

Travel satisfaction = β_7 * distance/income
$\qquad + \beta_8$ * distance*missing income dummy
$\qquad + \beta_9$ * missing distance dummy $\qquad$ (4.23)
$\qquad + \beta_{10}$ * missing income dummy
$\qquad + \beta_{11}$ * car dummy + β_{12} * public transportation dummy + ζ_2

Activity happiness = β_{13} * Age(0-30) +β_{14} * Age(30-60) + β_{15} * Age(60+)
$\qquad + \beta_{16}$ * male dummy + β_{17} * income $\qquad$ (4.24)
$\qquad + \beta_{18}$ * missing income dummy + ζ_3

The normalization of the measurement model implies a factor loading of 1 and an error variance of zero in each measurement equation. Since the indicators of travel satisfaction,

activity happiness, and activity propensity are ordered categorical, a threshold model is specified as in Equation (4.21).

4.6.2 Estimation Results

The models were estimated using the Mplus software (Muthén and Muthén, 1998-2006). The estimation results for the structural part of the shopping activity propensity model are shown in Table 4.4. Table B.2 in Appendix B shows the estimated thresholds for the shopping model, and Tables B.3 to B.6 show the results for other activity types. The factor loadings in the measurement equations are not shown as they are all normalized for identification purposes. We next interpret the shopping model results.

The propensity to participate in shopping activities is positively and significantly correlated with the happiness derived from shopping and the satisfaction with travel to shopping activities. This result provides evidence for the existence of relationships between well-being and behavior in the context of travel and activities; the greater the well-being derived from a given behavior, the more frequently people engage in that behavior.

The propensity to participate in shopping activities is also affected by socio-economic variables. Not all these variables are significant; however, they are retained in the models if the parameter estimates agree with apriori hypotheses. Age is specified as a piecewise linear variable with breakpoints at the ages of 30 and 60. The estimated coefficients of age imply that the propensity to shop increases till the age of 30, continues increasing till the age of 60 but at a slower rate, and then decreases afterwards. Individuals who live alone have a higher propensity to shop than those who live with others, possibly because of the sharing of shopping responsibilities in multi-person households.

Travel satisfaction is modeled as a function of level of service, which is determined by distance divided by income and mode of travel. The distance coefficient is negative and significant as expected. The car and public transportation dummy variables have negative coefficients, signifying that all else equal, traveling by non-motorized modes leads to greater travel satisfaction. Dummy variables for income with missing values and distance with missing values are also included.

Shopping activity happiness is modeled as a function of socioeconomic variables. Age is specified as a piecewise linear variable with breakpoints at the ages of 30 and 60. The estimated coefficients of age imply that shopping activity happiness is a decreasing function of age, with the greatest rate of decrease past the age of 60. Compared to females, males tend to dislike shopping. Higher income is associated with higher activity happiness as might be expected, but the effect is not significant.

The estimation results for other activity types (shown in Appendix B) can be interpreted similarly. We note that in all these models, the propensity to participate in activities was found to be positively correlated with the happiness derived from the activities and the satisfaction with travel to the activities.

Table 4.4. Structural model estimation results for shopping activity propensity.

Parameter	Estimate	t-stat
Propensity to shop		
Travel satisfaction	0.219	5.50
Activity happiness	0.220	5.18
Age (0-30)	0.0563	2.69
Age (30-60)	0.0243	3.86
Age(60+)	-0.0296	-1.14
1-person household dummy	0.167	1.48
Travel satisfaction		
Distance/income	-0.822	-2.20
Distance * missing income dummy	-0.0297	-0.74
Missing distance dummy	-0.584	-1.27
Missing income dummy	-0.0312	-0.098
Car dummy	-0.483	-4.22
Public transportation dummy	-0.255	-1.60
Activity happiness		
Age (0-30)	-0.00696	-0.37
Age (30-60)	-0.00568	-0.92
Age(60+)	-0.0389	-1.18
Male dummy	-0.668	-7.27
Income	0.000440	0.29
Missing income dummy	-0.401	-1.34

4.7   Conclusion

We conducted an exploratory analysis of activity and travel well-being in a cross-sectional setting. The objective was to determine the causes and correlates of commute satisfaction and to find evidence for relationships between well-being and behavior.

Using a web-based cross-sectional survey conducted with a convenience sample of commuters, we collected a number of travel well-being (satisfaction and emotions) and activity happiness measures. We then developed structural equations models of commute satisfaction and propensity to participate in activities.

We found that overall commute satisfaction is influenced by attributes of the commute, individual characteristics, and comparative happiness arising from social and intrapersonal comparisons. Attributes including average travel time, travel time variability, congestion, and walking or biking beside traffic were found to increase commute stress and consequently decrease commute satisfaction. Commute enjoyment (such as enjoyment and perceiving the commute as a buffer or private time) increases

satisfaction. Organized personality (planning and timeliness) decreases satisfaction, while overall well-being increases satisfaction. Greater social and intrapersonal comparative happiness increases commute satisfaction. Social comparative happiness was found to be influenced by travel time and mode comparisons of one's commute to other people's commute.

We also found significant correlations between well-being and behavior: greater travel satisfaction and activity happiness were associated with higher propensities of activity participation for different activity types. This supports the hypothesis that in the context of travel and activities choices are likely to be motivated by a desire to maintain or enhance well-being.

The commute well-being and activity participation models were estimated for illustration purposes using a convenience universal sample of highly-educated commuters. Using more representative samples may change the specific weights associated with the relationships represented in these models, but we do not expect the basic relationships in the model to change qualitatively.

The models were estimated in a cross-sectional setting which makes it difficult to determine directions of causality. Yet, the results obtained were mostly in accordance with the hypothesized relationships. Moreover, the measurement of travel well-being in a cross-sectional setting is useful for assessing travelers' satisfaction with their chosen alternatives at a given point in time. However, as we argue in the next chapter, the routine nature of travel and especially of commuting is likely to render the cross-sectional measurement of travel well-being less relevant for predicting behavior. We explore this measurement issue in the next chapter through data collection procedures conducted in a dynamic context.

In this chapter, we examined the relationship between well-being and activity participation for one activity at a time. In Chapter 7, we extend the scope to the case of an activity pattern. We present conceptual frameworks and models for incorporating well-being within activity-based travel demand models.

Chapter 5

Dynamic Measurement and Descriptive Analysis of Travel Well-Being and Behavior

In this chapter, we investigate the measurement of travel well-being in a way that accounts for the routine nature of travel. The main postulate is that in routine situations people don't fully engage in a cognitive process of evaluating their travel happiness. Only when people evaluate their options and reconsider their decisions will they carefully think of their travel happiness. This hypothesis is tested through an experiment requiring habitual car drivers to switch temporarily to public transportation and measuring their reported travel happiness before and after this intervention.

This chapter is organized as follows. Section 5.1 provides further background on the relationship between routine situations, decisions, and happiness. Section 5.2 briefly describes the experiment we use in this research to disrupt the commuting routine and summarizes mechanisms that have been used in the travel behavior modification literature for that purpose. Section 5.3 describes the design and implementation of the experiment we conducted in Switzerland and at the Massachusetts Institute of Technology (MIT) to temporarily change travel behavior and measure happiness. Sections 5.4 and 5.5 present descriptive findings from the Swiss and MIT experiments, respectively, and Section 5.6 analyzes their similarities and differences. Section 5.7 summarizes the main findings and the limitations of this study.

5.1   Happiness and Routine Situations

How do people evaluate their well-being? Schwarz and Strack (1991) argue that judgments of well-being are influenced by the available information and by the heuristics people use at the time of making these judgments. They present a model showing the influence of mood and comparison processes on well-being evaluations. Interpersonal or social (comparison to others) and intrapersonal (e.g. comparison to previous experiences)

comparison processes are especially relevant in evaluations of domain satisfaction where comparison information is more readily available.

Evaluation standards are, however, not clearly defined. As a result, it is not easy to evaluate well-being and "some people hardly ever think of it at all" (Lazarus and Lazarus, 1996). We postulate that this effect is more pronounced in domains involving routine behavior. Studies in the literature point to the potential cessation of affective responses under routine conditions and to dormant emotions when life is running smoothly (see, for example, Singer et al., 1978). Consider, for example, commuting, which is habitual in nature. Car commuters do not consider on a daily basis the choice of travel mode (Verplanken et al., 1994); rather, the choice is automatic. We postulate that in the absence of a deliberate decision-making process, travelers do not fully think about their travel happiness. When they are asked to judge their commute well-being, they may use salient attributes of their commute and certain comparison standards. Their judgments would reflect the remembered utility of their habitual commuting alternatives but not the utility that is relevant for decision-making since under routine conditions people don't fully consider the pros and cons of all commuting options available to them.

On the other hand, "all decisions involve predictions of future tastes or feelings" (cited in Loewenstein and Schkade, 1999; see also Kahneman et al., 1993). Decision-making triggers a reflective evaluation of well-being as people consider the pros and cons of different courses of action. Consider, for example, the choice of commuting mode following a residential relocation. The relocation is associated with reconsideration of the previous commute mode choice and other alternative modes based on the attributes of the new commuting environment (distance to work, public transportation accessibility, etc.), and it is during this window of change that people carefully evaluate their happiness with available travel alternatives.

In summary, we postulate that when people are asked about their commute satisfaction, the information they use and the processes they employ to arrive at an answer under routine conditions are different from those in operation after they have been "forced" to think about their options. Consequently, the two measures of travel happiness (routine vs. non-routine) are expected to be different and are expected to measure different things; the routine measure captures remembered utility while the non-routine measure captures decision utility. This hypothesis may be supported by research in the subjective well-being literature which found evidence for the existence of a "hedonic treadmill" (Brickman and Campbell, 1971; Brickman et al., 1978). According to this theory, people have a set point or a baseline level of happiness which they experience under routine conditions. Life events may temporarily move individuals up or down the hedonic scale, but adaptation brings them back to their happiness set points. The baseline (or routine) well-being reports may be relevant for assessing the well-being of society at any given point in time, but if the purpose is to predict behavior, well-being reports obtained after temporary life events or changes are likely to be more relevant.

In this chapter, we investigate the nature of this anticipated difference between travel well-being measures. In Chapter 6, we incorporate different measures of well-being as

indicators of different types of utility within a random utility modeling framework. And in Chapter 8 we discuss measurement implications.

5.2   Mechanism for Temporary Change in Behavior

One way to induce people to reconsider their decisions is to have them change their habitual travel behavior temporarily. The psychological interpretation is that once a habit is interrupted, the behavior becomes more deliberate and may then be more strongly influenced by reason-based factors such as intentions/attitudes, as postulated by the theory of planned behavior (Ajzen, 1985, 1991), or norms as postulated by the theory of norm activation (Schwartz, 1977; Schwartz and Howard, 1981). Deliberate behavior means reconsideration of travel choices and, as hypothesized earlier, careful evaluation of travel happiness. To test our research hypothesis, we conduct an experiment in a mode choice context requiring habitual car drivers to switch temporarily to public transportation for their commute to work in return for free public transportation tickets. We measure their travel happiness before and after the intervention. The details of the experiment are described in the next section. In this section, we review mechanisms that have been used in travel behavior modification studies for testing the effects of temporary interventions on attitudes and behavior.

Various types of mechanisms have been used to induce participants to disrupt a travel habit and try out a new behavior, including communication/deliberation, commitments, and incentives. The resulting changes in travel decisions and/or associations with psychological factors (such as attitudes, perceptions, habits, norms) influencing those decisions have been studied.

Communication/deliberation techniques provide information or advice related to changing the behavior in question or induce a deliberation process prior to conducting the behavior so as to interrupt its habitual nature. Fujii and Taniguchi (2006) reviewed a number of personalized communication programs in Japan which they termed as travel feedback programs. They found that these programs were generally effective in reducing emissions and car use and increasing public transportation use. In a mode choice study, Verplanken et al. (1998) induced a deliberation condition in a group of participants who were asked to think about the circumstances under which they were to execute their trips. It was found that the deliberation strengthened the relationship between intentions and car use but did not affect habits. Eriksson et al. (2008) also employed a deliberation condition whereby participants filled out a prospective travel diary and thought about options for car use reduction on the planned trips. It was found that after the intervention, the mode choice process became more deliberate as the correlation between car use and personal norms (i.e. moral motivation / obligation to reduce car use in order to help the environment) increased, and participants with both a strong car habit and a strong personal norm reduced their car use.

With commitment strategies, participants are asked to make certain types of commitments regarding the desired behavior for a certain period of time. For example,

Bachman and Katzev (1982) tested commitments involving the use of public transportation by participants with or without free tickets and found that these interventions increased public transportation ridership during and after the treatment periods compared to control conditions. Matthies et al. (2006) employed a combination of pro-environmental strategies, such as a phase of free public transportation tickets followed by a phase of pro-environmental behavioral commitments, and found that this sequence of interventions worked best in the long run and that pro-environmental norms had an influence on behavior when coupled with commitments. The observed effects were, however, small.

Various types of incentives have been offered in travel behavior modification studies to reduce car use and/or encourage switching to public transportation. Everett et al. (1974) showed that offering tokens on a bus, which can be exchangeable for certain types of merchandise or bus tickets, increased ridership substantially while the incentive was in effect but not after it was stopped. Foxx and Hake (1977) used monetary incentives to encourage reduction in average daily mileage and found that the incentives were effective while the incentive was in place, with the effect remaining to some extent after the treatment phase. This type of incentive is also offered in more recent studies of pay-as-you-drive leasing or insurance (see, for example, Abou-Zeid et al., 2008). Fujii et al. (2001) studied the effect of a temporary freeway closure on mode switching and perceptions and found that the temporary change was effective in increasing public transportation use substantially by drivers during the closure as well as correcting their misperceptions of travel time by public transportation. A follow-up survey (Fujii and Gärling, 2003) indicated that those who temporarily used public transportation during the closure continued to use it more frequently one year later than those who did not use it during the closure. Fujii and Kitamura (2003) offered an experimental group of students a one-month free bus ticket and observed an improvement in attitude, a stronger habit, and a higher frequency of public transportation use during the treatment. These changes were sustained to some extent one month after the treatment.

5.3   Experiment Design and Implementation

In this section, we describe the design of the experiment we conducted in Switzerland and at MIT to disrupt the commuting routine and measure travel happiness under non-routine situations and mode switching. In relation to the above literature, our experiment can be classified as combining a commitment strategy (willingness to commute temporarily by public transportation is used as a condition for participation) and an incentive (free public transportation pass). However, our study is different from the above mentioned studies in that the primary psychological factor of interest in our research is travel well-being and its relationship to behavior. Section 5.3.1 describes the design of the experiment, and Section 5.3.2 describes its implementation.

5.3.1 Design

The experiment consists of three phases: pre-treatment, treatment, and post-treatment, where treatment refers to the required use of public transportation for 2-3 days in a certain week by habitual car commuters.

In the pre-treatment phase, potential recruits are interviewed to determine their eligibility to participate and to collect their socio-economic and demographic characteristics. Eligibility conditions entail being a habitual car commuter and having public transportation available to the place of residence and work. Eligible individuals who agree to participate fill out a questionnaire about their happiness with the commute by car and perceptions and attitudes towards commuting by car and public transportation. They also fill out a daily travel pre-treatment diary intended to measure their baseline travel behavior.

In the treatment phase, participants are required to commute by public transportation for at least 2-3 days in a given week. As an incentive, they are given a free public transportation pass that is valid throughout the treatment period. This type of treatment therefore combines a commitment device with an incentive as discussed earlier. No other compensation is offered so as to avoid cognitive dissonance issues and to focus the participants' attention to the experiment instead of the compensation. Moreover, no information about public transportation routes or schedules is provided to the participants. Participants continue to fill out the daily travel diaries during the treatment period.

In the post-treatment phase, participants are no longer required to commute by public transportation. At the beginning of this phase, they fill out the same questionnaire they had filled out in the pre-treatment phase, with a few additional questions related to their public transportation experience (satisfaction, comparison to expectations, and attributes) and their current commute mode. The purpose of this questionnaire is to measure changes in participants' travel happiness, perceptions, attitudes, plans, and mode choice. For a certain period during this phase, participants continue to fill out the daily travel diaries. One or more follow-up surveys are conducted a few weeks or months later to collect data on their travel happiness and usage of public transportation.

The well-being questions used in the pre-treatment and post-treatment (right after the experiment) questionnaires are shown in Appendix C. The full questionnaires can be obtained from the author upon request.

5.3.2 Implementation

The experiment was conducted at three institutions/organizations in Switzerland (Geneva airport, Université de Lausanne (UNIL), and Ecole Polytechnique Fédérale de Lausanne (EPFL)) in the spring/summer of 2008 and at the Massachusetts Institute of Technology (MIT) in the fall of 2008. A pilot test was conducted in March and April 2008.

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Swiss Experiment

The Swiss experiment included 30 self-selected individuals who were recruited via emails sent in April 2008 to all employees of Geneva airport and to employees with parking permits at UNIL and EPFL. The emails provided a brief description of the study and the eligibility conditions. Telephone interviews were conducted in April with individuals who expressed interested in the study. Figure 5.1 shows the experiment schedule and the various questionnaires.

At the beginning of May (denoted t_0 in Figure 5.1), participants filled out Questionnaire 1 measuring their satisfaction with the commute by car and attitudes and perceptions towards commuting by car and public transportation. Then participants took part in the experiment for three consecutive weeks selected based on their availability between May and July, during which they filled out daily travel diaries (Questionnaire 2). The second week was the treatment period, when participants were required to commute for 2-3 days by public transportation. No control group was used since the number of volunteers for the study was small. Participants were given a free public transportation pass that was valid for 2-4 weeks starting from Week 2 (treatment period).

At the beginning of the third week (denoted t_1 in Figure 5.1), participants filled out Questionnaire 3, which contained the same questions as Questionnaire 1 with a few additional questions related to the public transportation experience (satisfaction, comparison to expectations, and attributes). Then, after the public transportation pass had expired and just before the parking permit[5] was about to expire (denoted t_2 in Figure 5.1), participants filled out Questionnaire 4, which was almost identical to Questionnaire 1. Finally, at the beginning of November (denoted t_3 in Figure 5.1), a brief follow-up survey (Questionnaire 5) was conducted to measure participants' current mode choice, usage of public transportation since the expiration of the free pass, and commute satisfaction. Instructions on filling out the various questionnaires and on the treatment were given to participants via email with periodic reminders. Questionnaires 1 to 4 were web-based, and Questionnaire 5 was administered via email. All questionnaires were in French, the local language used in Geneva and Lausanne.

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[5] Geneva airport participants had monthly parking permits, while UNIL and EPFL participants had annual or semi-annual permits.

Questionnaire 2: Daily travel diary

Questionnaire 1
Questionnaire 3
Questionnaire 4
Questionnaire 5

May-June
May-July

t_0
(May)

Week 1   Week 2   Week 3

t_1

t_2 Parking permit expiration

t_3
(November)

Pre-Treatment   Treatment   Post-Treatment
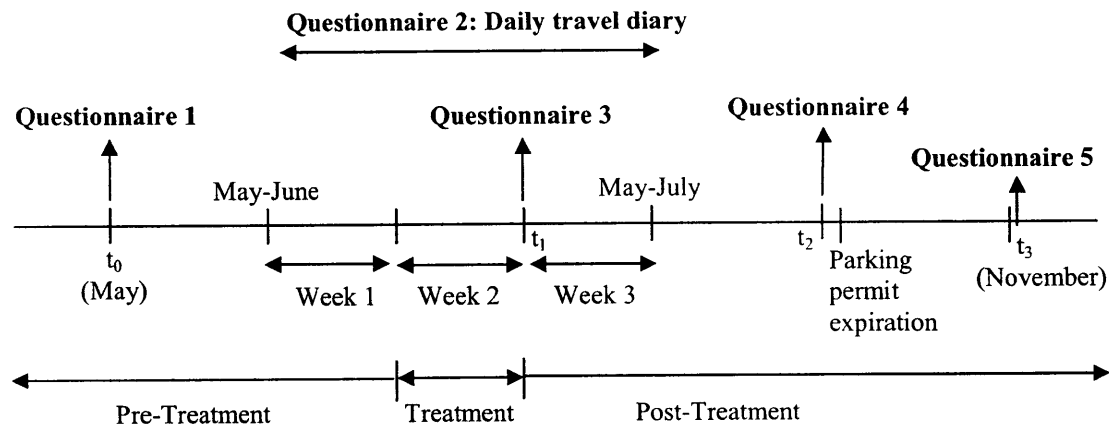
Figure 5.1. Swiss experiment schedule and questionnaires.

MIT Experiment

The MIT experiment included 93 self-selected individuals who were recruited as part of a MIT-wide free public transportation pass program that was implemented in September 2008. Employees with full-time parking permits were eligible for the free pass. Those that applied online for the pass were asked if they were willing to participate in a related research project, and interested participants were then contacted by email and telephone in August 2008. 93 eligible individuals were interviewed and received a free pass from MIT. Although they had all agreed to commute by public transportation as a condition of the study, only 74 out of these commuted by public transportation for at least 1-3 days in September; the remaining 19 individuals later declined to participate due to personal constraints or inadequacy of public transportation service and so did not commute by public transportation at all. Moreover, out of the 74 individuals who participated, 3 individuals did not fill out the post-treatment questionnaire, 1 individual changed her job location immediately post-treatment, and 3 individuals switched to occasional parking post-treatment (i.e. using free MIT-operated shuttles or carpooling). Therefore, the final sample used for reporting descriptive statistics and for model estimation consists of the 67 remaining participants. Figure 5.2 shows the experiment schedule and the various questionnaires.

In August (denoted t_0 in Figure 5.2), right after the telephone interview, participants filled out Questionnaire 1 measuring satisfaction, attitudes, and perceptions. Then participants took part in the experiment for three weeks in September and one week in October selected based on their availability, during which they filled out daily travel diaries (Questionnaire 2). In most cases, the second week was the treatment period (or if not possible, another week in September was chosen), when participants were required to commute for 2-3 days (1 day in a few cases) by public transportation. No control group was used since the number of volunteers for the study was small.

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At the beginning of October (denoted t_1 in Figure 5.2) and right after the free pass had expired, participants filled out Questionnaire 3, which contained the same questions as Questionnaire 1 with a few additional questions related to the public transportation experience (satisfaction, comparison to expectations, and attributes). In the middle of December (denoted t_2 in Figure 5.2), a brief follow-up survey (Questionnaire 4) was conducted to measure participants' current parking permit / public transportation pass choice, usage of public transportation since the expiration of the free pass, and satisfaction with the commute by car and public transportation. In the beginning of April 2009, another brief follow-up survey (Questionnaire 5) was conducted to measure participants' current parking permit / public transportation pass choice, satisfaction with the commute by car and public transportation, and any changes that might have affected their commuting patterns.

Instructions on filling out the various questionnaires and on the treatment were given to participants via email with periodic reminders. All questionnaires were in English. Questionnaires 1 to 3 were web-based, and Questionnaires 4 and 5 were administered via email. Data on the participants' parking permit choice and public transportation pass purchase for the months following the treatment were also available from the MIT parking office.
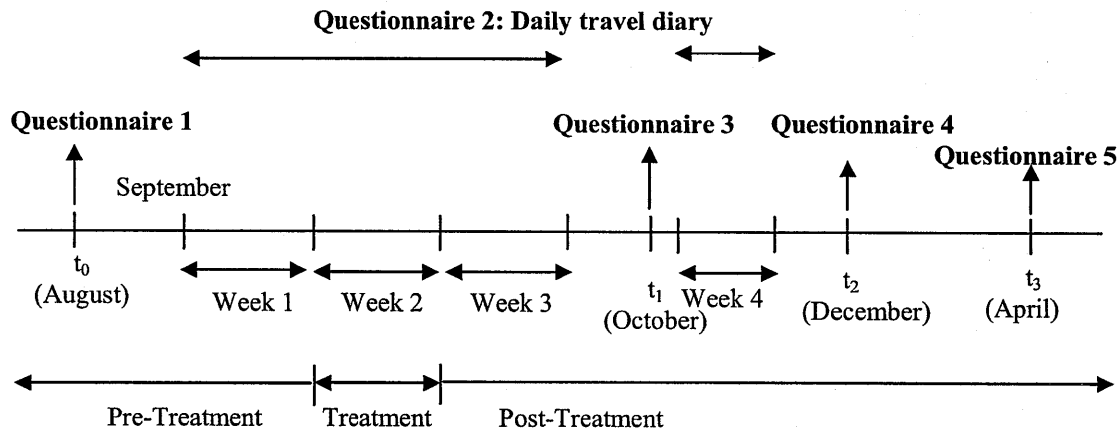
Figure 5.2. MIT experiment schedule and questionnaires.

5.4 Swiss Experiment Descriptive Analysis

This section presents a descriptive analysis of the Swiss experiment. This includes socio-economic and demographic characteristics, mode switching, commute satisfaction, mode choice intentions / plans, perceptions, attitudes, comparison of the public transportation experience to expectations, and self-selection bias.

5.4.1 Socio-Economic and Demographic Characteristics

About half of the participants were male. The majority of participants were between 30 and 60 years old, with an average age of 43 years. The average household size was 3.1. Most participants had 2 cars in the household, but there was a substantial number with 1 car only (average car ownership was 1.8).

None of the participants was accustomed to commuting by public transportation. Out of 30 participants, 7 participants have never commuted by public transportation to their current workplace; 9 participants have not used it in the year before the study; 10 participants have used it more than 3 months before the study; and 4 have used it a few weeks before the study.

5.4.2 Mode Switching

Since this experiment does not involve a control group, every participant's pre-treatment data are used as his/her control. Moreover, data were not available on aggregate trends in public transportation use to support a seasonality analysis.

After the public transportation trial, none of the participants cancelled his/her parking permit or switched entirely to public transportation. However, a number of participants commuted by public transportation a few times after the trial.

In the first week of the experiment, none of the participants commuted by public transportation. Following the intervention, 10 out of 30 participants commuted by public transportation at least once during the third week of the experiment (when the public transportation pass was still valid but participants were no longer required to use public transportation), and 12 out of 30 participants indicated that it is likely that they will commute by public transportation in the future.

Moreover, of the 25 participants who were contacted several months after the expiration of the public transportation pass, 5 participants indicated that after the expiration of the pass they commuted by public transportation at a higher rate than before the intervention. This suggests that the intervention was effective in inducing behavioral modification for a fraction of the participants or at least in having them consider public transportation as part of their choice set for the commute mode.

5.4.3 Commute Satisfaction

Car Satisfaction

Prior to the experiment, participants rated their satisfaction with their commute by car on a 5-point scale anchored by "Very dissatisfied" (rating of 1) to "Very satisfied" (rating of 5), as a response to the following question[6]:

"Taking all things together, how satisfied are you with your commute by car between your residence and EPFL/UNIL/Geneva airport?"

After trying public transportation, participants answered the same question about satisfaction with the commute by car. Figure 5.3 shows the distribution of responses to this question. Figure 5.4 shows the number of participants by the change in the rating of satisfaction with the commute by car (computed as post-treatment minus pre-treatment ratings), where the numbers on the horizontal axis indicate the magnitude of the change in satisfaction ratings. The distribution of satisfaction with the commute by car changed after the treatment with a number of participants mostly reporting higher satisfaction with their commute by car. Participants were also asked to directly rate the change in their happiness with the decision to commute by car, and most participants also reported higher satisfaction. These statistics support the hypothesis that the travel happiness measure collected in a cross-sectional setting is different from that collected after people evaluate their options.
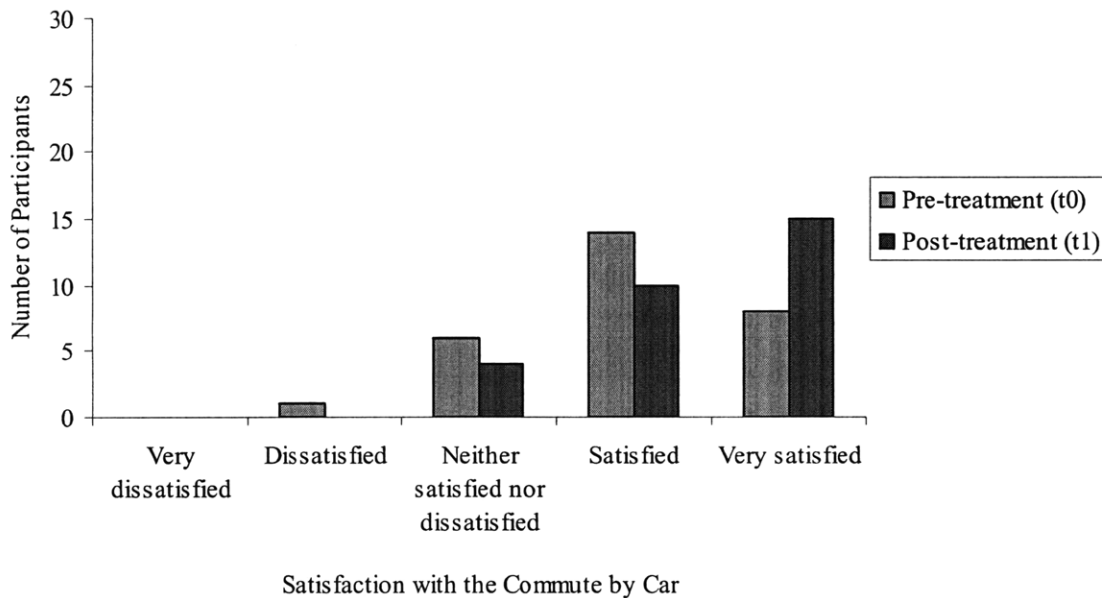
Figure 5.3. Distribution of Swiss participants' reported pre-treatment (t_0) and post-treatment (t_1) satisfaction with the commute by car (N = 29).

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[6] The question about satisfaction with the commute by car was the first question in the pre-treatment questionnaire and among the first questions in the post-treatment questionnaire.

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Post-Treatment (t1) - Pre-Treatment (t0) Satisfaction with the Commute by Car
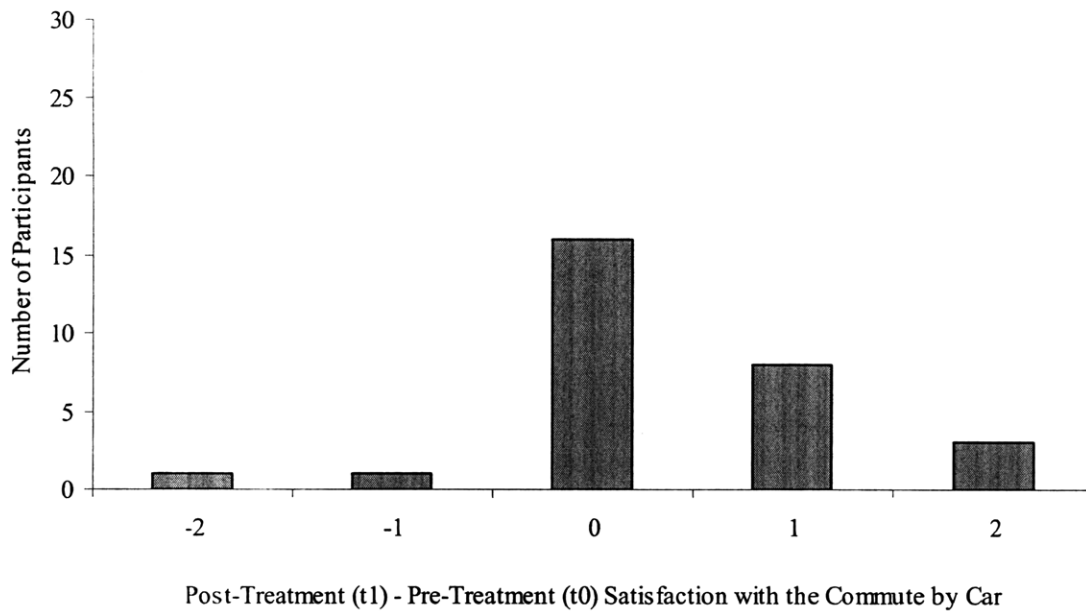
Figure 5.4. Distribution of Swiss participants' change in reported satisfaction with the commute by car (post-treatment (t_1) minus pre-treatment (t_0) ratings; N = 29).

Moreover, participants reported their satisfaction with their commute by car several months after the experiment. Figure 5.5 shows the distribution of responses at three points in time: pre-treatment (t_0), right after the treatment (t_1), and 4-5 months after the treatment (t_3)[7]. The sample used to plot Figure 5.5 is a subset of the sample used to plot Figures 5.3 and 5.4 since not all participants answered the follow-up questionnaire.

The self-reported satisfaction ratings follow a treadmill pattern indicating that the increase in satisfaction with the commute by car reported right after the experiment levels off a few months later as people go back to their commuting routines. It should be noted though that there is a subtle difference in the treadmill interpretation used in this study and that used in the subjective well-being literature. With the standard treadmill effect observed in the subjective well-being literature, people experience a new condition that remains with them over time (e.g. money won in a lottery, a disability, etc.). In this study, however, the public transportation condition does not remain with the participants over time (i.e. when they are back to the routine a few months after the treatment) unless they decide to switch completely to public transportation.

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[7] The happiness measure obtained right before the expiration of the parking permit (time t_2 in Figure 5.1) is not used in the analysis as the time elapsed between the treatment and the collection of this measure varies greatly among participants.
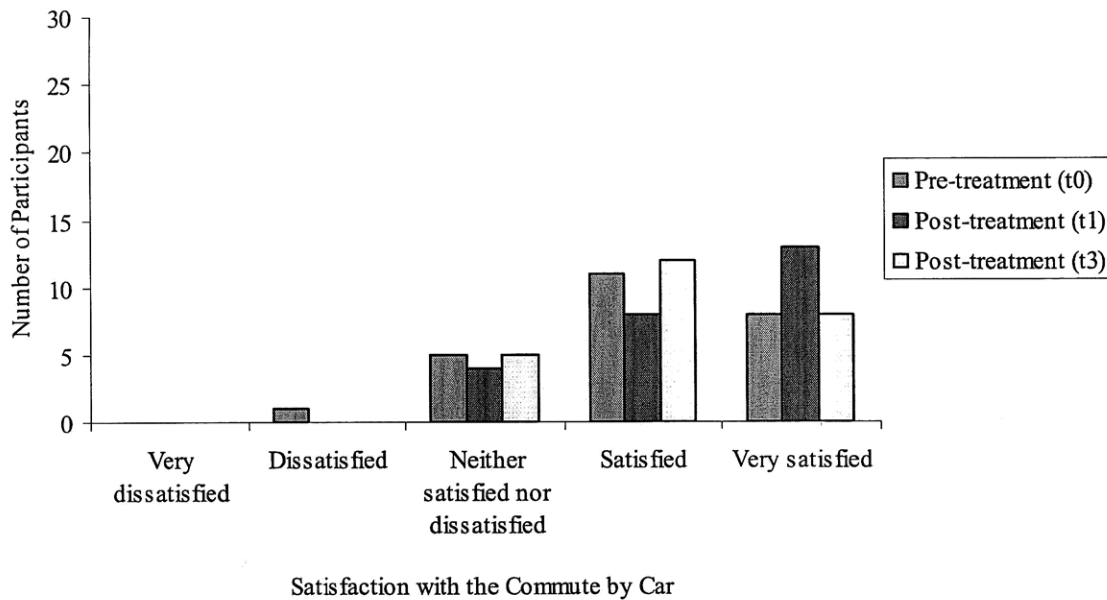
Figure 5.5. Distribution of Swiss participants' reported satisfaction with the commute by car at different time points (N = 25).

Statistical Significance Test

We test the statistical significance of the difference in car satisfaction ratings observed at different time points. Since the satisfaction ratings are ordinal (scale of 1 to 5) and are dependent over time (same individuals giving ratings), tests for matched pairs ordinal data are used (Agresti, 2007). These tests require a cross-tabulation of the number of participants by their answers to the first and second satisfaction questions that are compared. Two tests are used. The first one tests if the distribution of satisfaction ratings is different for the two measures (e.g. pre- and post-treatment). The second test compares the mean scores of satisfaction ratings. Details about these tests are provided in Appendix D. Below we show the results of these tests for the Swiss data.

Pre-Treatment (t_0) and Post-Treatment (t_1) Car Satisfaction

Table 5.1 shows the number of participants by their pre-treatment (t_0) and post-treatment (t_1) car satisfaction ratings, where t_1 is the time period right after the treatment.

For test 1, the test statistic is 1.90 which indicates that the distributions of the pre-treatment (t_0) and post-treatment (t_1) satisfaction ratings are significantly different at the 90% level of confidence (but not at the 95% level). For test 2, the test statistic is -2.2 which also indicates a significant difference between the means of these measures at the 90% level of confidence (and at the 95% level).

Table 5.1. Distribution of Swiss participants by pre- (t_0) and post-treatment (t_1) car satisfaction ratings.

| Pre-Treatment Car Satisfaction (t_0) | Post-Treatment Car Satisfaction (t_1) | | | | | |
	1 (Very dissatisfied)	2 (Dissatisfied)	3 (Neither satisfied nor dissatisfied)	4 (Satisfied)	5 (Very satisfied)	Total
1 (Very dissatisfied)	0	0	0	0	0	0
2 (Dissatisfied)	0	0	1	0	0	1
3 (Neither satisfied nor dissatisfied)	0	0	1	2	3	6
4 (Satisfied)	0	0	1	8	5	14
5 (Very satisfied)	0	0	1	0	7	8
Total	0	0	4	10	15	29

Pre-Treatment (t_0) and Post-Treatment (t_3) Car Satisfaction

Table 5.2 shows the number of participants by their pre-treatment (t_0) and post-treatment (t_3) car satisfaction ratings, where t_3 is the time period 4-5 months after the treatment.

Table 5.2. Distribution of Swiss participants by pre- (t_0) and post-treatment (t_3) car satisfaction ratings.

| Pre-Treatment Car Satisfaction (t_0) | Post-Treatment Car Satisfaction (t_3) | | | | | |
	1 (Very dissatisfied)	2 (Dissatisfied)	3 (Neither satisfied nor dissatisfied)	4 (Satisfied)	5 (Very satisfied)	Total
1 (Very dissatisfied)	0	0	0	0	0	0
2 (Dissatisfied)	0	0	1	0	0	1
3 (Neither satisfied nor dissatisfied)	0	0	2	3	0	5
4 (Satisfied)	0	0	2	7	2	11
5 (Very satisfied)	0	0	0	2	6	8
Total	0	0	5	12	8	25

For test 1, the test statistic is 0.63 which indicates that the distributions of the pre-treatment (t_0) and post-treatment (t_3) satisfaction ratings are not significantly different at the 90% level of confidence. For test 2, the test statistic is -0.63 which also indicates that the means of these measures are not significantly different at the 90% level of confidence.

Post-Treatment (t_1) and Post-Treatment (t_3) Car Satisfaction

Table 5.3 shows the number of participants by their post-treatment car satisfaction ratings measured at t_1 and t_3.

For test 1, the test statistic is -1.71 which indicates that the distributions of the post-treatment satisfaction ratings measured at t_1 and t_3 are significantly different at the 90% level of confidence (but not at the 95% level). For test 2, the test statistic is 1.73 which also indicates that the means of these measures are significantly different at the 90% level of confidence (but not at the 95% level).

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Table 5.3. Distribution of Swiss participants by post-treatment car satisfaction ratings measured at t_1 and t_3.

Post-Treatment Car Satisfaction (t_1)	Post-Treatment Car Satisfaction (t_3)					
	1 (Very dissatisfied)	2 (Dissatisfied)	3 (Neither satisfied nor dissatisfied)	4 (Satisfied)	5 (Very satisfied)	Total
1 (Very dissatisfied)	0	0	0	0	0	0
2 (Dissatisfied)	0	0	0	0	0	0
3 (Neither satisfied nor dissatisfied)	0	0	2	2	0	4
4 (Satisfied)	0	0	2	6	0	8
5 (Very satisfied)	0	0	1	4	8	13
Total	0	0	5	12	8	25

These three pairwise comparisons statistically support at the 90% level of confidence the treadmill pattern for the car satisfaction ratings: the pre-treatment ratings are significantly different from the immediate post-treatment ratings (t_1) but not from the post-treatment ratings measured a few months after the treatment (t_3) when participants are back to their commuting routines.

Public Transportation Satisfaction

Participants also rated their satisfaction with public transportation after trying it by answering the following question using a 5-point scale anchored by "Very dissatisfied" to "Very satisfied":

"Taking all things together, how satisfied were you with your commute by public transportation between your residence and EPFL/UNIL/Geneva airport during this study?"

Figure 5.6 shows the distribution of responses. The majority of participants were neither satisfied nor dissatisfied, but there were slightly more dissatisfied than satisfied commuters.
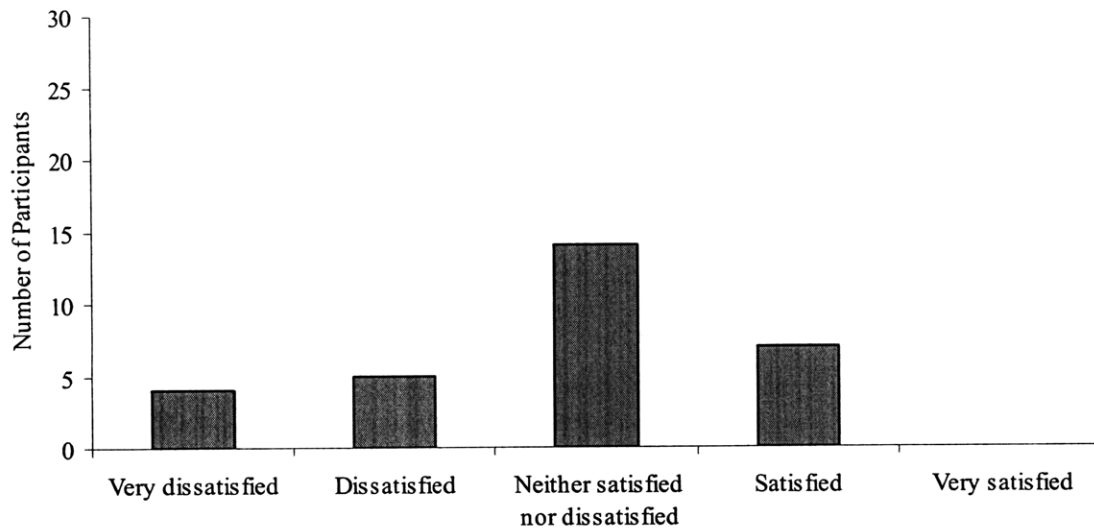
Post-Treatment Satisfaction with the Commute by Public Transportation

Figure 5.6. Distribution of Swiss participants' reported post-treatment satisfaction with the commute by public transportation (N = 30).

As to the correlation between satisfaction with public transportation and post-treatment usage of public transportation (in the third week of the experiment), Table 5.4 shows the average satisfaction (where 1 denotes "Very dissatisfied" and 5 denotes "Very satisfied") and the proportion of participants who were dissatisfied with their experience. This is shown separately for participants who used public transportation post-treatment and those who didn't. As expected, the average satisfaction is greater among participants who used public transportation post-treatment. Moreover, the proportion of dissatisfied participants is larger among those who didn't use public transportation post-treatment. These results are consistent with findings in the services marketing literature that relate customer satisfaction to retention and service usage (see, for example, Athanassopoulos, 2000; Rust and Zahorik, 1993; Soderlund, 1998).

Table 5.4. Distribution of Swiss participants' satisfaction with commuting by public transportation and post-treatment (in Week 3) usage of public transportation (PT) (N=30).

	Average PT satisfaction	Proportion dissatisfied
Didn't use PT post-treatment	2.5	0.40
Used PT post-treatment	3.4	0.10

5.4.4 Mode Choice Intentions / Plans

During the initial telephone interview, participants were asked about their intentions to commute by car and public transportation in the future, using a 5-point response scale

(definitely not, probably not, indifferent, probably yes, definitely yes). They were asked the same question post-treatment.

Table 5.5 shows a cross-tabulation of participants' pre- and post-treatment intentions towards commuting by car. Most participants maintained the same strong intentions of commuting by car in the future.

Table 5.5. Distribution of Swiss participants by pre- (t_0) and post-treatment (t_1) car commuting plans (N = 30).

Pre-Treatment Car Plan (t_0)	Post-Treatment Car Plan (t_1)					
	Definitely not	Probably not	Indifferent	Probably yes	Definitely yes	Total
Definitely not	0	0	0	0	0	0
Probably not	0	0	0	0	0	0
Indifferent	0	0	0	0	1	1
Probably yes	0	0	0	0	0	0
Definitely yes	0	0	0	5	24	29
Total	0	0	0	5	25	30

Table 5.6 shows a cross-tabulation of participants' pre- and post-treatment intentions towards commuting by public transportation. The majority of participants changed their plans stating post-treatment that they are more likely to commute by public transportation in the future compared to their pre-treatment plans. Yet, none of the participants switched completely to public transportation post-treatment. The post-treatment plan was however correlated to some extent with the number of times public transportation was used post-treatment, with a higher post-treatment stated likelihood of using public transportation associated with more frequent use.

Table 5.6. Distribution of Swiss participants by pre- (t_0) and post-treatment (t_1) public transportation commuting plans (N = 30).

Pre-Treatment PT Plan (t_0)	Post-Treatment Plan PT (t_1)					
	Definitely not	Probably not	Indifferent	Probably yes	Definitely yes	Total
Definitely not	1	6	2	1	0	10
Probably not	0	7	0	7	1	15
Indifferent	0	1	0	1	0	2
Probably yes	0	1	0	2	0	3
Definitely yes	0	0	0	0	0	0
Total	1	15	2	11	1	30

5.4.5 Perceptions

Participants rated their perceptions towards commuting by car and public transportation in the pre-treatment and post-treatment periods. They rated on a 5-point scale anchored by "Strongly disagree" to "Strongly agree" their level of agreement with statements (in the context of their commute) such as:

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Perception of reliability: *"I can count on the car (public transportation) to get me to work on time."*
Perception of cost: *"Using the car (public transportation) does not cost much."*
Perception of comfort: *"The car (public transportation) is comfortable."*

After the treatment, almost all participants had favorable perceptions of the reliability, flexibility, travel time, and comfort of the car. However, only 10% of them agreed that using the car does not cost much.

Regarding public transportation perceptions, the majority of participants had favorable perceptions of overall service, reliability, the ability to conduct activities en-route, and the convenience of public transportation to their residence and workplace. The majority however had unfavorable perceptions of the flexibility offered by public transportation and the travel time. More participants disagreed that public transportation does not cost much, while more participants agreed that public transportation is comfortable.

We also observe a change in the ratings of perceptions from the pre-treatment to the post-treatment period for both car and public transportation. For car, the change might for instance reflect a change in the frame of reference. For public transportation, the change might be due to prior misperceptions that were corrected once information was gained through direct experience. Table 5.7 shows the distribution of the change (in terms of number of participants) in participants' perceptual ratings of commuting by public transportation. For all aspects of service, there is a fraction of participants that changed their perceptual ratings. Although most participants provided higher perceptual ratings of the overall service and certain aspects of it (such as reliability), several others provided lower perceptual ratings especially of travel time.

Table 5.7. Distribution of the change in Swiss participants' perceptual ratings of commuting by public transportation (N = 30 for perceptions other than comfort; N = 29 for comfort).

Perception	Worse Perception	Same Perception	Better Perception
Overall service	8	9	13
Travel time	9	16	5
Reliability	6	12	12
Flexibility	5	20	5
Comfort	7	14	8
Cost	5	18	7

5.4.6 Attitudes

Participants also rated their attitudes towards commuting by public transportation in the pre-treatment and post-treatment periods. They rated on a 5-point scale anchored by "Strongly disagree" to "Strongly agree" their level of agreement with the following statements (in the context of their commute):

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Attitude towards walking: *"I wouldn't mind walking a few minutes to get to public transportation stations."*

Attitude towards transfers: *"I wouldn't mind having to make a transfer when using public transportation."*

Attitude towards travel time: *"I wouldn't mind spending more time in my commute using public transportation."*

Attitude towards contact with others: *"I wouldn't mind being around other people when using public transportation."*

Attitude towards cost: *"I am willing to use public transportation if the fare is much cheaper than the cost of using my car."*

After the treatment, the majority of participants stated that they wouldn't mind walking a few minutes to get to public transportation stations, having to make a transfer when using public transportation, and being around other people when using public transportation. More participants stated that they are willing to use public transportation if the fare is much cheaper than the cost of using their car, but more participants would mind spending more time in their commute using public transportation.

Again, we observe a change in the ratings of attitudes towards commuting by public transportation from the pre-treatment to the post-treatment period for about half the sample, with more change occurring in the positive direction (except for transfers). Table 5.8 shows the distribution of the change (in terms of number of participants) in participants' attitudinal ratings.

Table 5.8. Distribution of the change in Swiss participants' attitudinal ratings of commuting by public transportation (N = 30).

Attitude	Worse Attitude	Same Attitude	Better Attitude
Walking	6	17	7
Transfers	10	11	9
Travel time	6	11	13
Contact with others	3	17	10
Cost	6	16	8

5.4.7 Comparison to Expectations

After the treatment, participants rated how their public transportation experience compared to their prior expectations. The rating was done for overall service and for several attributes including reliability, travel time, convenience, and comfort. The rating scale used was a 5-point scale ranging from "much worse than expected" to "much better than expected". Table 5.9 shows the distribution of participants by their ratings of every service attribute. Except for travel time, there were more participants who had a better than expected experience than those who had a worse than expected experience.

Table 5.9. Distribution of Swiss participants by their ratings of how their public transportation experience compared to expectations.

Service Attribute	Worse than expected	Same as expected	Better than expected
Overall service	5	18	7
Reliability	4	15	11
Time	15	11	4
Convenience	6	16	8
Comfort	2	17	11

Disconfirmation (i.e. the comparison of actual experience to prior expectations) is also related to customer satisfaction (Oliver, 1977, 1980). Experiences that turn out to be better than expected increase satisfaction, and those that are worse than expected decrease satisfaction. This relationship is supported by the Swiss data. Table 5.10 shows for every service attribute the average satisfaction level (with 1 denoting "Very dissatisfied" and 5 denoting "Very satisfied") with commuting by public transportation among those who said the experience was worse than expected, same as expected, or better than expected. For every service attribute, those who found the experience better than expected were more satisfied with it, while those who found it worse than expected had lower satisfaction.

Table 5.10. Average satisfaction levels with public transportation by service attribute and disconfirmation level for Swiss participants.

Service Attribute	Worse than expected	Same as expected	Better than expected
Overall service	1.6	2.7	3.9
Reliability	2.0	2.7	3.2
Time	2.3	3.2	3.5
Convenience	2.0	2.8	3.4
Comfort	2.0	2.6	3.2

5.4.8 Self-Selection Bias

In this study, self-selection bias may be an issue. It may be hypothesized that people who are more predisposed to consider using public transportation (for example, because of unfavorable commuting conditions by car or because of their attitudes towards different modes) and who may have thought about mode switching anyway would be more willing than others to participate in this study. The correlation between the decision to participate and mode switching may occur through observable or unobservable variables. In this section, we examine whether self-selection with respect to observable variables was prominent in the study. However, note that self-selection purely through observable variables does not lead to bias in the mode switching model as this model can be conditioned on these observable variables (Vella, 1998). In Appendix F, we test for the presence of self-selection bias occurring through the correlation of unobservable variables between the processes affecting the decision to participate and mode switching.

First, we note that none of the participants dropped out of the study after it had started. To evaluate the differences between participants and non-participants, a survey was conducted with non-participant employees of Geneva airport, UNIL, and EPFL between June and August 2008. The survey contained questions related to the eligibility to participate, travel patterns by car and public transportation, and demographic and socio-economic characteristics. In the case of UNIL and EPFL, telephone interviews were conducted with employees randomly chosen from the university directories. In the case of Geneva airport and also for UNIL, survey forms were distributed at parking lots to employees arriving by car, who were given stamped envelopes and asked to mail back the forms.

A total of 90 non-participants filled out the survey or answered the telephone interview. But only 46 of them were eligible to participate in the study[8]. Using this sample of eligible non-participants and the data from the 30 participants, we conducted multiple statistical tests on various characteristics and attributes to see if any are significantly different between the two samples.

The characteristics compared were gender, age, education level, living arrangement, household size, and income. Income was statistically significantly different, with participants having a higher income than non-participants. The distribution of living arrangement was also significantly different, with a greater percentage of couples with kids in the participant sample.

The travel attributes compared were distance between home and work, travel time by car, travel time by public transportation, and number of transfers by public transportation. Distance and travel time by public transportation were not significantly different between participants and non-participants. However, participants had a significantly larger average travel time by car (27.5 vs. 20.7 minutes) and a significantly smaller average number of transfers by public transportation (1.1 vs. 1.9 transfers). This may suggest that participants may have been more inclined to switch to public transportation than non-participants although the magnitude of the difference in the travel attributes is not substantial.

There are some caveats to this analysis. First, this analysis should have been ideally done for every study site separately (Geneva airport, UNIL, and EPFL). But this was not possible due to the very small number of participants at UNIL and EPFL. Second, the non-participant sample is not totally random. About 50% of non-participants who got survey forms at parking lots did not fill out the survey. Third, in the comparison of public transportation attributes, we used the actual data reported in the travel diaries for participants. The estimates of these attributes by non-participants may have been biased due to their infrequent use of public transportation.

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[8] Eligibility criteria were defined based on how many times people drive alone to work per week, the last time they commuted by public transportation, and time elapsed since they have been living at the same residence and working at the same place.

In summary, participants and non-participants did not differ significantly on most socio-economic characteristics and on certain travel attributes. Yet, the possibility that participants may have been more inclined to participate because of more favorable travel conditions by public transportation conditions or less favorable travel conditions by car than those of non-participants suggests that it would be desirable in the future to collect additional data that could explain better the decision to participate. This could include travel well-being, perceptions and attitudes towards car and public transportation, and general willingness to consider changing commute mode. Such data would be collected from both participants and non-participants.

5.5 MIT Experiment Descriptive Analysis

This section presents a descriptive analysis of the MIT experiment. This includes socio-economic and demographic characteristics, mode switching, commute satisfaction, mode choice intentions / plans, perceptions, attitudes, comparison of the public transportation experience to expectations, self-selection bias, and seasonality.

5.5.1 Socio-Economic and Demographic Characteristics

About one third of the participants were male. The majority of participants were between 40 and 60 years old, with an average age of 47 years. The average household size was 2.8. Most participants had 2 cars in the household, but there was a substantial number with 1 car only (average car ownership was 1.9).

None of the participants was accustomed to commuting by public transportation (not more than once per month, on average). Out of 67 participants, 8 participants had never commuted by public transportation to MIT; 15 participants had used it but at least one year before the study; 17 participants had used it more than 3 months before the study; and 27 had used it within 3 months of the study.

5.5.2 Mode Switching

After the public transportation trial (i.e. in October), 19 out of 67 participants (i.e. 28%) cancelled their full-time parking permits and switched to public transportation: out of these 19, 4 participants purchased public transportation passes, and 15 participants purchased public transportation passes plus occasional parking permits. One month after the trial (i.e. in November), one more participant cancelled his full-time parking permit and purchased a public transportation pass and an occasional parking permit.

While it was not possible in this study to randomize participants into a treatment and a control group, a measure of seasonality in public transportation use is available by computing changes in public transportation pass purchases for those MIT employees who did not apply for a free pass from MIT (or applied but did not use it) even though they were eligible for it. This analysis is described in Section 5.5.9.

5.5.3 Commute Satisfaction

Car Satisfaction

Prior to the experiment, participants rated their satisfaction with the commute by car on a 5-point scale anchored by "Very dissatisfied" (rating of 1) to "Very satisfied" (rating of 5), as a response to the following question:

"Taking all things together, how satisfied are you with your commute by car between your residence and MIT?"

After trying public transportation, participants answered the same question (worded as "level of satisfaction with a car commute" since some participants switched to public transportation after the treatment). Figure 5.7 shows the distribution of responses to this question. Figure 5.8 shows the number of participants by the change in the rating of satisfaction with the commute by car (computed as post-treatment minus pre-treatment ratings), where the numbers on the horizontal axis indicate the magnitude of the change in satisfaction ratings. The distribution of satisfaction with the commute by car changed after the treatment. Even though Figure 5.7 does not show a substantial difference between the two distributions, Figure 5.8 indicates that about half of the participants changed their satisfaction ratings with most of the change reflecting an increase in satisfaction with the commute by car. Again, this supports the hypothesis that the travel happiness measure collected in a cross-sectional setting is different from that collected after people carefully evaluate their options.

Satisfaction with the Commute by Car
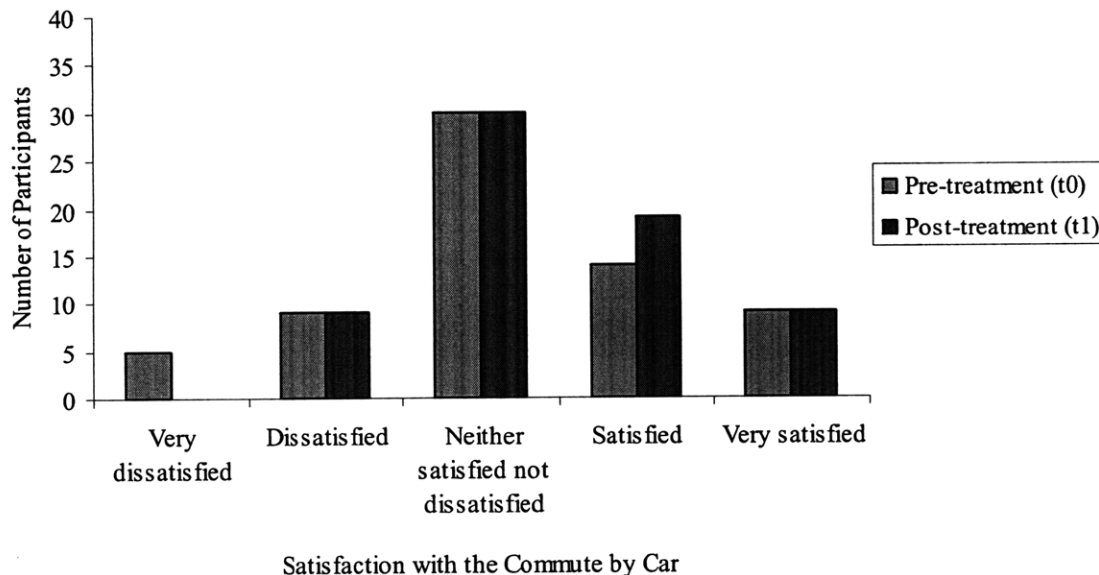
Figure 5.7. Distribution of MIT participants' reported pre-treatment (t_0) and post-treatment (t_1) satisfaction with the commute by car (N = 67).

Post-Treatment (t1) - Pre-Treatment (t0) Satisfaction with the Commute by Car
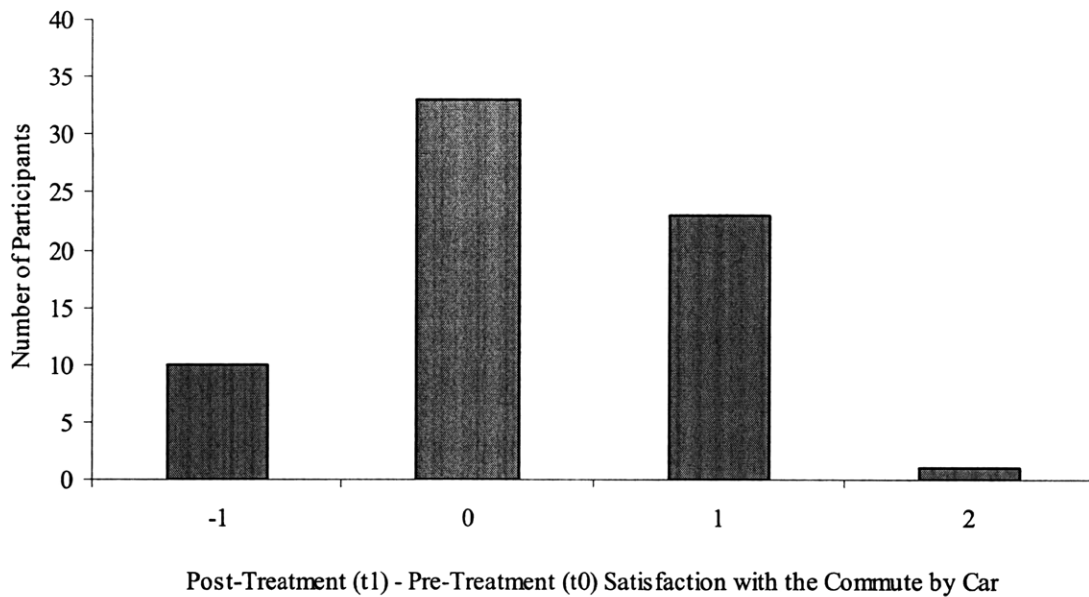
Figure 5.8. Distribution of MIT participants' change in reported satisfaction with the commute by car (post-treatment (t_1) minus pre-treatment (t_0) ratings; N = 67).

Moreover, participants reported their satisfaction with a commute by car and public transportation about two months (t_2) and six months (t_3) after the experiment. Figure 5.9 shows the distribution of responses at three points in time: pre-treatment (t_0), right after the treatment (t_1), and six months after the treatment (t_3). The sample used to plot Figure 5.9 is a subset of the sample used to plot Figures 5.7 and 5.8 since not all participants answered the follow-up questionnaire.

Unlike the Swiss case, the self-reported satisfaction ratings do not follow a treadmill pattern. The reported satisfaction with car keeps increasing six months after the experiment. A similar pattern is observed if we compare the t_0, t_1, and t_2 satisfaction ratings or if we just analyze participants who kept commuting by car post-treatment. If we instead analyze satisfaction with the commute by the chosen mode, then the difference between the t_1 and t_3 ratings is not substantial, but the t_0 and t_3 ratings continue to be substantially different.

Satisfaction with the Commute by Car
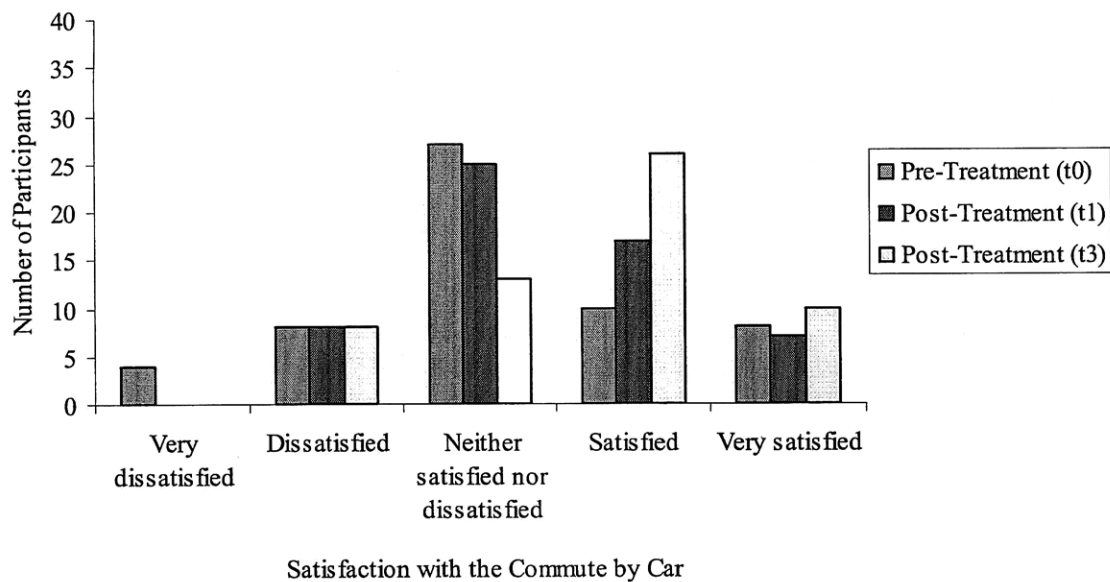
Figure 5.9. Distribution of MIT participants' reported satisfaction with the commute by car at different time points (N = 57).

Statistical Significance Test

We conduct the same two statistical tests of the difference in car satisfaction ratings observed at different time points as in the Swiss case.

Pre-Treatment (t_0) and Post-Treatment (t_1) Car Satisfaction

Table 5.11 shows the number of participants by their pre-treatment (t_0) and post-treatment (t_1) car satisfaction ratings, where t_1 is the time period right after the treatment.

Table 5.11. Distribution of MIT participants by pre- (t_0) and post-treatment (t_1) car satisfaction ratings.

Pre-Treatment Car Satisfaction (t_0)	Post-Treatment Car Satisfaction (t_1)					
	1 (Very dissatisfied)	2 (Dissatisfied)	3 (Neither satisfied nor dissatisfied)	4 (Satisfied)	5 (Very satisfied)	Total
1 (Very dissatisfied)	0	5	0	0	0	5
2 (Dissatisfied)	0	2	7	0	0	9
3 (Neither satisfied nor dissatisfied)	0	2	18	9	1	30
4 (Satisfied)	0	0	5	7	2	14
5 (Very satisfied)	0	0	0	3	6	9
Total	0	9	30	19	9	67

For test 1, the test statistic is 2.42 which indicates that the distributions of the pre-treatment (t_0) and post-treatment (t_1) satisfaction ratings are significantly different at the 95% level of confidence. For test 2, the test statistic is -2.47 which also indicates a significant difference between the means of these measures at the 95% level of confidence.

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Pre-Treatment (t_0) and Post-Treatment (t_3) Car Satisfaction

Table 5.12 shows the number of participants by their pre-treatment (t_0) and post-treatment (t_3) car satisfaction ratings, where t_3 is the time period 6 months after the treatment.

Table 5.12. Distribution of MIT participants by pre- (t_0) and post-treatment (t_3) car satisfaction ratings.

Pre-Treatment Car Satisfaction (t_0)	Post-Treatment Car Satisfaction (t_3)					
	1 (Very dissatisfied)	2 (Dissatisfied)	3 (Neither satisfied nor dissatisfied)	4 (Satisfied)	5 (Very satisfied)	Total
1 (Very dissatisfied)	0	2	0	2	0	4
2 (Dissatisfied)	0	3	4	1	0	8
3 (Neither satisfied nor dissatisfied)	0	3	6	14	4	27
4 (Satisfied)	0	0	3	5	2	10
5 (Very satisfied)	0	0	0	4	4	8
Total	0	8	13	26	10	57

For test 1, the test statistic is 3.55 which indicates that the distributions of the pre-treatment (t_0) and post-treatment (t_3) satisfaction ratings are significantly different at the 95% level of confidence. For test 2, the test statistic is -3.35 which also indicates that the means of these measures are significantly different at the 95% level of confidence.

Post-Treatment (t_1) and Post-Treatment (t_3) Car Satisfaction

Table 5.13 shows the number of participants by their post-treatment car satisfaction ratings measured at t_1 and t_3.

Table 5.13. Distribution of participants by post-treatment car satisfaction ratings measured at t_1 and t_3.

Post-Treatment Car Satisfaction (t_1)	Post-Treatment Car Satisfaction (t_3)					
	1 (Very dissatisfied)	2 (Dissatisfied)	3 (Neither satisfied nor dissatisfied)	4 (Satisfied)	5 (Very satisfied)	Total
1 (Very dissatisfied)	0	0	0	0	0	0
2 (Dissatisfied)	0	5	1	2	0	8
3 (Neither satisfied nor dissatisfied)	0	2	11	10	2	25
4 (Satisfied)	0	1	1	12	3	17
5 (Very satisfied)	0	0	0	2	5	7
Total	0	8	13	26	10	57

For test 1, the test statistic is 2.31 which indicates that the distributions of the post-treatment satisfaction ratings measured at t_1 and t_3 are significantly different at the 95% level of confidence. For test 2, the test statistic is -2.40 which also indicates that the means of these measures are significantly different at the 95% level of confidence.

These three pairwise comparisons again indicate that a treadmill effect is not observed in the MIT data.

Public Transportation Satisfaction

Participants also rated their satisfaction with public transportation after trying it by answering the following question using a 5-point scale anchored by "Very dissatisfied" to "Very satisfied":

"Taking all things together, what is your level of satisfaction with a public transportation commute between your residence and MIT?"

Figure 5.10 shows the distribution of responses. The participants were almost equally divided across the satisfied (including very satisfied), dissatisfied (including very dissatisfied), and neither satisfied nor dissatisfied categories.
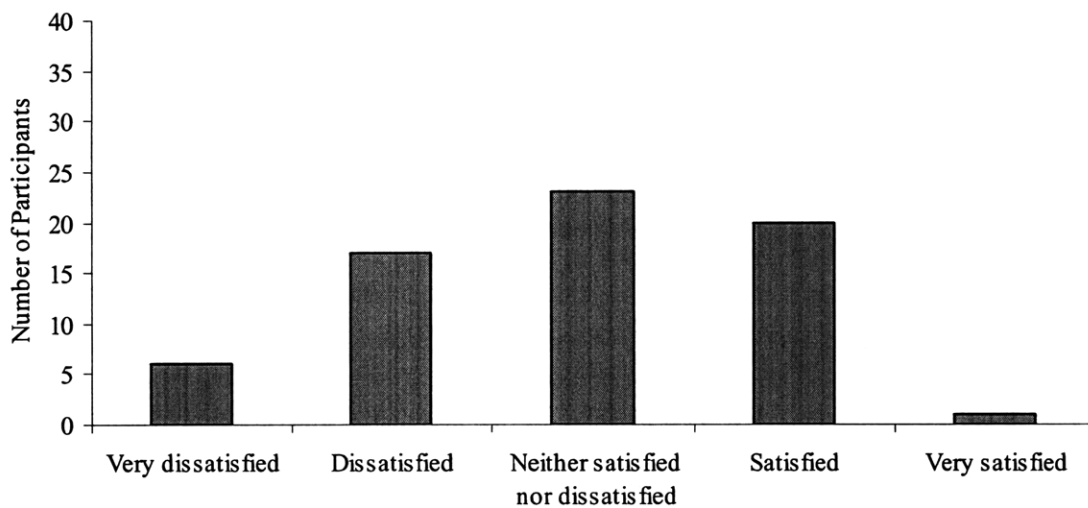
Post-Treatment Satisfaction with the Commute by Public Transportation

Figure 5.10. Distribution of MIT participants' post-treatment satisfaction with their commute by public transportation (N=67).

Table 5.14 shows the correlation between mode choice and satisfaction. Average satisfaction (where 1 denotes "very dissatisfied" and 5 denotes "very satisfied") and the proportion of participants who were dissatisfied with their public transportation experience are shown for those who switched or didn't switch to public transportation post-treatment. As expected, compared to those who switched to public transportation, those who didn't switch had a lower average satisfaction and a larger proportion of them were dissatisfied with commuting by public transportation.

Table 5.14. Distribution of MIT participants' satisfaction with commuting by public transportation and post-treatment switching to public transportation (PT) (N=67).

	Average PT satisfaction	Proportion dissatisfied
Didn't switch to PT post-treatment	2.6	0.49
Switched to PT post-treatment	3.7	0

5.5.4 Mode Choice Intentions/Plans

Participants stated their intentions for choice of commuting mode in the future. The question and response scale differed between the pre- and post-treatment periods, so the analysis is presented separately for each of these periods.

In the pre-treatment period, participants were asked how likely they would be to commute regularly by car and public transportation in the future. A 5-point response scale was used with the following categories: definitely not, probably not, indifferent, probably yes, definitely yes.

Tables 5.15 and 5.16 show the pre-treatment car plan and public transportation plan (measured in August), respectively, versus the mode choice that was made post-treatment (in November). The pre-treatment plans are to some extent consistent with the choices (except for 13 participants who intended to commute by car but switched to public transportation; 12 participants who intended to commute by public transportation but stayed with the car option; and 3 participants who didn't intend to commute by public transportation but switched to public transportation). However, these numbers may be a bit misleading since several participants indicated that it is likely that they will commute by both car and public transportation. Moreover, the question referred to commuting in the "future", so it was interpreted in different ways.

Table 5.15. Distribution of MIT participants by their pre-treatment car plan vs. post-treatment mode choice.

Pre-Treatment Car Plan	Post-Treatment Mode Choice			
	Car (Full-time parking permit)	PT (PT pass only)	PT (PT pass + occasional parking permit)	Total
Definitely not	0	0	0	0
Probably not	0	2	1	3
Indifferent	7	1	3	11
Probably yes	23	0	10	33
Definitely yes	17	1	2	20
Total	47	4	16	67

Table 5.16. Distribution of MIT participants by their pre-treatment PT plan vs. post-treatment mode choice.

	Post-Treatment Mode Choice			
Pre-Treatment PT Plan	Car (Full-time parking permit)	PT (PT pass only)	PT (PT pass + occasional parking permit)	Total
Definitely not	3	0	0	3
Probably not	16	0	3	19
Indifferent	16	1	5	22
Probably yes	11	2	7	20
Definitely yes	1	1	1	3
Total	47	4	16	67

In the post-treatment period, participants were asked how often they will commute by car and public transportation in the next academic year (2008-2009)[9]. A 6-point response scale was used with the following categories: never or less than once a month, once a month, 2-3 times per month, once a week, 2-3 times per week, 4 or more times per week.

Tables 5.17 and 5.18 show the post-treatment car plan and public transportation plan (measured in October), respectively, versus the choice that was made post-treatment (in November). The commuting pattern plans are consistent with the parking permit / public transportation pass choice. The greater consistency for the post-treatment plans may be attributed to the fact that these plans are measured after the treatment (and thus are better thought through), are closer in time to the mode choices, and are less abstract than the pre-treatment plans (both in terms of response scale and time horizon). The reader is referred to Ben-Akiva (2009b) where a modeling framework is developed to relate these plans to subsequent mode choices.

Table 5.17. Distribution of MIT participants by their post-treatment car plan vs. post-treatment mode choice.

	Post-Treatment Mode Choice			
Post-Treatment Car Plan	Car (Full-time parking permit)	PT (PT pass only)	PT (PT pass + occasional parking permit)	Total
Never or less than once a month	0	2	1	3
Once a month	0	0	1	1
2-3 times per month	0	2	6	8
Once a week	0	0	7	7
2-3 times per week	4	0	1	5
4 or more times per week	43	0	0	43
Total	47	4	16	67

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[9] The question was changed from the pre-treatment period due to the difficulties some participants encountered in answering that question.

Table 5.18. Distribution of MIT participants by their post-treatment PT plan vs. post-treatment mode choice.

Post-Treatment PT Plan	Car (Full-time parking permit)	PT (PT pass only)	PT (PT pass + occasional parking permit)	Total
Never or less than once a month	19	0	0	19
Once a month	11	0	0	11
2-3 times per month	13	0	0	13
Once a week	3	0	0	3
2-3 times per week	1	0	6	7
4 or more times per week	0	4	10	14
Total	47	4	16	67

5.5.5 Perceptions

The perceptions questions were the same as in the Swiss study. After the treatment, participants that switched to public transportation (switchers), as one would expect, were more negative in their perceptions of travel by car than those who didn't switch (non-switchers). The majority of switchers and non-switchers had favorable perceptions of the reliability, flexibility, and comfort of the car. While the majority of non-switchers believed that the car gets them to work quickly, more switchers disagreed with this statement than agreed. The majority of switchers disagreed with the statement that the car does not cost much, whereas less than half of the non-switchers disagreed with this statement.

The majority of switchers thought that the overall public transportation service is good, offers the opportunity to conduct activities en-route, is conveniently located to their residence and MIT, and does not cost much. Nearly half of them thought that the service is reliable. The majority, however, believed that public transportation does not offer them the flexibility they need, and nearly half thought that public transportation is not quick. They were mostly neutral about their perception of comfort.

Non-switchers were less positive in most instances about public transportation than those who switched. The majority of non-switchers believed that public transportation is unreliable, inflexible, and slow. Nearly half thought that they cannot get other things done while commuting by public transportation and that it is uncomfortable. The majority, however, thought that public transportation was conveniently located to their residence and MIT. They were mostly neutral about how good the overall service is and about costs.

As in the Swiss case, we observe a change in the ratings of perceptions from the pre-treatment to the post-treatment period for both car and public transportation. Table 5.19 shows the distribution of the change (in terms of number of participants) in participants'

perceptual ratings of commuting by public transportation. For all aspects of service, there is a fraction of participants that changed their perceptual ratings, and more participants changed towards better perceptions than towards worse perceptions (except for flexibility).

Table 5.19. Distribution of the change in MIT participants' perceptual ratings of commuting by public transportation (N =67).

Perception	Worse Perception	Same Perception	Better Perception
Overall service	13	30	24
Travel time	14	34	19
Reliability	19	26	22
Flexibility	19	34	14
Comfort	14	36	17
Cost	17	22	28

5.5.6 Attitudes

The attitudinal questions were the same as in the Swiss study. After the treatment, the majority of switchers and non-switchers stated that they wouldn't mind walking a few minutes to get to public transport stations but would mind spending more time in their commute using public transportation; many wouldn't mind making a transfer or being around other people when using public transportation. Most switchers are willing to use public transportation if the fare is much cheaper than the cost of using their car, while many non-switchers are not willing to switch to public transportation even if the fare is much cheaper than the cost of using their car.

There is also a change in the ratings of attitudes towards commuting by public transportation from the pre-treatment to the post-treatment period, as shown in Table 5.20. For all attitudinal aspects measured, there is a greater number of participants changing their attitudes towards commuting by public transportation negatively than positively.

Table 5.20. Distribution of the change in MIT participants' attitudinal ratings of commuting by public transportation (N = 67).

Attitude	Worse Attitude	Same Attitude	Better Attitude
Walking	21	37	9
Transfers	21	29	17
Travel time	29	31	7
Contact with others	21	34	12
Cost	35	24	8

5.5.7 Comparison to Expectations

As in the Swiss experiment, MIT participants compared their public transportation experience to their prior expectations. Table 5.21 shows this comparison. Except for

travel time and comfort, there were more participants who had a better than expected experience than those who had a worse than expected experience.

Table 5.21. Distribution of MIT participants by their ratings of how their public transportation experience compared to expectations.

Service Attribute	Worse than expected	Same as expected	Better than expected
Overall service	10	36	21
Reliability	12	37	18
Time	25	28	14
Convenience	15	34	18
Comfort	16	43	8

Table 5.22 shows for every service attribute the average satisfaction level (with 1 denoting very dissatisfied and 5 denoting very satisfied) with commuting by public transportation among those who said the experience was worse than expected, same as expected, or better than expected. As in the Swiss experiment, satisfaction with commuting by public transportation increases the more the service exceeds expectations.

Table 5.22. Average satisfaction levels with commuting by public transportation by service attribute and disconfirmation level for MIT participants.

Service Attribute	Worse than expected	Same as expected	Better than expected
Overall service	2.2	2.7	3.6
Reliability	2.4	2.7	3.7
Time	2.4	2.9	3.8
Convenience	2.3	2.9	3.4
Comfort	2.9	2.9	3.0

5.5.8 Self-Selection Bias

As in the Swiss experiment, to assess self-selection bias, a survey was conducted with non-participant MIT employees between January and July 2009. The pool of non-participants consisted of all MIT employees who did not participate in this study regardless of whether they obtained a free public transportation pass from MIT in September 2008. The survey contained questions related to the eligibility to participate, travel patterns by car and public transportation, and demographic and socio-economic characteristics. It was conducted by calling or emailing MIT employees chosen randomly from the database of employees who were eligible for the pass (were emailed about it) but chose not to participate in this study (regardless of whether they got the free pass), or by distributing surveys to MIT employees at MIT parking lots.

A total of 96 non-participants filled out the survey or answered the telephone interview. But only 58 of them were eligible to participate in the study[10]. In addition, 19 individuals

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[10] Eligibility criteria were defined based on how many times people drive to work per week and their monthly frequency of commuting by public transportation.

who agreed to participate in the study ended up dropping out of it without using public transportation. We add the drop-out sample to the non-participant sample to obtain a total of 77 non-participants. Using this sample of eligible non-participants and the data from 73 participants[11], we conducted multiple statistical tests on various characteristics and attributes to see if any are significantly different between the two samples.

The characteristics compared were gender, age, education level, household size, living arrangement, and income. None of them was significantly different between participants and non-participants.

The travel attributes compared were distance between home and work, travel time by car, travel time by public transportation, and number of transfers by public transportation. Distance, travel time by car, and travel time by public transportation were not significantly different between participants and non-participants. However, participants had a significantly smaller average number of transfers by public transportation (0.95 vs. 1.7 transfers; at the 95% level of confidence) when the actual number of transfers was used for the participant sample. But when the pre-treatment stated (or anticipated) number of transfers was used for the participant sample, the average number of transfers in the participant sample (2.2) was significantly larger than the average number of transfers in the non-participant sample (1.7). The difference between the anticipated and the actual number of transfers for the participants may be due to a number of factors, such as misperceptions before the treatment, slightly different wording of the question, etc. Thus, the comparison of number of transfers is inconclusive. Moreover, the same caveats that were mentioned in the Swiss analysis of sample selection apply here as well.

The issue of sample selection will be further considered through modeling in Appendix F.

5.5.9 Seasonality Analysis

To capture seasonality effects in mode switching behavior, we analyzed the sample of MIT employees who were eligible for the free public transportation pass but did not use the pass. This sample consists of those full-time parkers who were informed by the MIT parking office about the free pass but chose not apply for it, or who applied for it but ended up not using it for their commute in September. The size of this sample is 2470 MIT employees.

The seasonality effect was estimated as the percentage of this sample that switched to public transportation in the months following the free pass program (particularly in November). 10 out of these 2470 MIT employees (or 0.4%) purchased public transportation passes from the MIT parking office in November. Thus, the seasonality effect is negligible.

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[11] In this analysis, we included 6 additional participants who commuted by public transportation during the study but switched to carpooling or free shuttle after the study, did not fill out the final study questionnaire, or changed their job location right after the experiment ended.

5.6 Comparison of Swiss and MIT Results

In this section, we discuss the similarities and differences between the findings from the Swiss and MIT experiments and suggest possible interpretations for these findings. We focus on mode switching and commute satisfaction.

5.6.1 Mode Switching

Compared to the Swiss experiment in which none of the participants cancelled his/her parking permit post-treatment, almost one third of MIT participants gave up the car as their primary mode of commuting. The difference between the mode switching patterns can be attributed to individual characteristics, travel attributes, and contextual aspects.

First, average values of individual characteristics such as age, household size, and car ownership were similar for the two samples. Differences occurred with respect to income, gender, and work schedule. Average annual income was slightly higher for the Swiss sample, there was a higher percentage of males in the Swiss sample, and 17% of the Swiss sample consisted of individuals whose work schedules (for a certain number of days per week) fall outside the hours of operation of public transportation. None of the MIT participants had this constraint. It can also be observed by comparing the pre-treatment levels of satisfaction with the commute by car (Figures 5.3 and 5.7) that the proportion of participants dissatisfied with their commute to work by car was higher in the MIT sample than the Swiss sample. Thus, the MIT participants might have been more predisposed to switch to public transportation than the Swiss participants.

Second, there were differences in the travel attributes between the two samples. The structure of the parking fee and public transportation subsidy was different across the various study sites. The monthly parking fee ranged from 50 to 80 Swiss Francs per month at Geneva airport and was 12.5 Francs at EPFL, 13.5 Francs at UNIL, and $65.5 at MIT. EPFL and UNIL didn't offer public transportation subsidies, while Geneva airport offered a subsidy of up to 32% of the annual cost of a public transportation pass, and MIT offered a subsidy of 50% of the monthly cost of a public transportation pass. Fuel prices were also higher at the time the MIT experiment was conducted. Thus, from a cost perspective, conditions seemed to have been more favorable for mode switching at MIT than at the Swiss sites particularly at EPFL and UNIL. Even considering time-cost trade-offs, almost all EPFL and UNIL participants had longer travel times by public transportation than by car and no cost benefits from public transportation. Finally, parking permits are granted at Geneva airport only to those employees who live in areas that are not well served by public transportation or to those whose work schedules fall outside the hours of operation of public transportation. Thus, commuting by public transportation was particularly less convenient to Geneva airport participants.

Third, contextual differences between the two experiments might have also played a role in the observed mode switching patterns. The Swiss study was conducted as a stand-alone research project and did not aim at influencing participants' decisions or opinions.

Employees of each of the Swiss sites were emailed about a research project conducted by students at MIT and EPFL. The email contained a brief description of the study objectives (as a study about travel patterns and the use of different modes of transportation, without mentioning happiness), eligibility conditions (including willingness to commute by public transportation for 2-3 days), and procedure. The study announcement and subsequent telephone and email contact with the participants did not come across as favoring switching to public transportation. Thus, the resulting mode choices observed post-treatment are not likely to have been influenced by factors related to communication with participants and framing of the study.

The MIT experiment, on the other hand, was conducted as part of a larger free public transportation pass program designed by MIT to encourage drivers to switch to public transportation, conserve energy, and help the environment. MIT employees with full-time parking permits received emails announcing the free pass program and encouraging them to try it (and during the month of the free pass program received emails encouraging them to switch to public transportation). Those who applied online for the pass checked off a box indicating whether they are willing to participate in a related doctoral research project, and those who were willing to were then contacted by us via email. Our contact with those who were interested in our research project was then as objective as in the Swiss case: we simply described the objectives, eligibility conditions, and procedure without showing any signs of endorsing switching to public transportation. Thus, while our study approach was objective, the wider context of the MIT experiment and its greater visibility may have made those who participated more predisposed to switch to public transportation or to consider using it occasionally.

5.6.2 Commute Satisfaction

In both the Swiss and MIT experiments, participants reported significantly different levels of satisfaction with the commute by car post-treatment compared to pre-treatment. Thus, both experiments support the hypothesis that the routine and non-routine measures of travel well-being are different because under non-routine conditions people think more fully about their options and their well-being in relation to their decisions. Moreover, the reported post-treatment level of satisfaction was mostly higher than the pre-treatment level.

However, several months after the experiment, when participants were asked again to report their satisfaction with the commute by car, different patterns emerged in the Swiss and MIT studies. Swiss participants reported satisfaction levels that were closer to the pre-treatment levels than to the post-treatment levels (i.e. a treadmill effect), while MIT participants' levels of satisfaction several months after the treatment continued to be significantly higher than the pre-treatment levels.

Various mechanisms may explain this pattern. First, it may be the case that the observed satisfaction ratings reflect a persistent effect of the treatment on MIT participants' commute well-being. That is, participants perceive a real increase in commute well-being and do not go back to their pre-treatment levels of commute well-being. There has been

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research in the subjective well-being literature supporting the idea that people don't always go back to their set point levels of happiness after certain life events, contrary to the hedonic treadmill hypothesis (see, for example, Diener et al., 2006). Seasonal effects, including the drop in the price of fuel and the increase in park-and-ride fees at public transportation stations in Massachusetts between times t_0/t_1 (pre-treatment and immediate post-treatment) and t_3, may be in favor of this effect. Second, the increase in car satisfaction at time t_3 for MIT participants might be due to an anchoring effect. At both times t_1 and t_3, MIT participants rated their satisfaction with both a car commute and a public transportation commute, while Swiss participants rated their satisfaction with their commute at time t_3 without reference to a particular mode. The salience of the public transportation satisfaction rating in the MIT case might have served as an anchor for the car satisfaction rating. In fact, there was a high correlation between the differences of car and public transportation satisfaction ratings at times t_1 and t_3 for MIT participants.

5.7   Conclusion

5.7.1 Summary

We postulated that under routine situations such as commuting, people don't fully evaluate their travel well-being since their decisions are driven by automatic processes. Careful evaluation of travel well-being occurs when people think about their options and reconsider their decisions. Thus, measures of travel well-being obtained under routine and non-routine situations are likely to be different. For the purpose of predicting behavior, happiness measures obtained under non-routine conditions are likely to be more relevant because they measure decision utility, while routine measures reflect remembered utility.

To test this hypothesis, we conducted experiments in Switzerland and at MIT requiring a temporary change in behavior. Participants who habitually commuted by car were required to commute temporarily by public transportation and were given free public transportation passes as an incentive. Their satisfaction with their commute, perceptions, attitudes, plans, and mode choice were measured pre- and post-treatment. The following findings emerged:

- None of the Swiss participants switched completely to public transportation although some continued to use it occasionally. In the MIT case, 20 out of 67 participants switched to public transportation post-treatment. This suggests that the intervention was effective in inducing a number of participants to change their behavior or at least to consider public transportation in their choice sets.

- In both the Swiss and MIT experiments, participants reported significantly different pre- and post-treatment satisfaction levels with the commute by car, thus supporting our study hypothesis. Through follow-up surveys conducted a few months post-treatment, a treadmill effect was observed in the car satisfaction ratings of Swiss participants but not of MIT participants.

- The majority of Swiss participants were neither satisfied nor dissatisfied with their public transportation experiences. MIT participants were equally divided across the dissatisfied, neutral, and satisfied categories. Satisfaction with public transportation was positively correlated with post-treatment usage, as expected. Satisfaction was also greater when the public transportation experience exceeded expectations.

- Participants' post-treatment commuting pattern plans, measured as intended frequency of commuting by car and public transportation, were generally consistent with their post-treatment mode choice decisions.

- A number of Swiss and MIT participants changed their perceptual and attitudinal ratings towards commuting by car and public transportation, which might reflect a change in the frame of reference and/or correction of previously held misperceptions of public transportation.

5.7.2 Limitations and Extensions

This study provided preliminary support to the hypothesis about well-being measures obtained under routine and non-routine conditions. Yet, it has a number of limitations that could be accounted for in future extensions. First, the number of participants was very small. It would be desirable to replicate the findings of this study using larger scale experiments. Second, it was not possible to have a control group in this study. Future data collection efforts should try to randomize individuals willing to participate into a treatment and a control group. Third, comparisons of participants and non-participants were done for a few socio-economic and demographic characteristics and travel attributes. Comparisons of travel well-being, perceptions, and attitudes should be included in future similar studies. Fourth, a number of factors were kept fixed in the experimental design and could be varied in future designs including employment location and geographic coverage, time of the year (to account for seasonality effects), length of the treatment (longer treatment periods could give participants the chance to experiment further and to adjust to the use of public transportation), and type of the treatment (switching to modes other than public transportation or to travel at different times of day, or relying on naturalistic interventions including changes in personal circumstances or transportation system conditions that "force" people to reconsider their travel options and their well-being).

5.7.3 Next Chapter

In this chapter, we studied the nature of the difference between travel well-being measures collected under routine and non-routine situations. In the next chapter, we will incorporate these measures of well-being in a random utility dynamic modeling framework that relates travel well-being to behavior.

Chapter 6

Dynamic Analysis of Travel Well-Being: Behavioral Models

In this chapter, we apply a simplified version of the dynamic modeling framework developed in Chapter 3 using the dynamic experiments described in Chapter 5. The framework consists of a standard mode choice model combined with a happiness model where happiness measures are used as indicators of utility. The routine (pre-treatment) and non-routine (post-treatment) periods in the experiment provide a natural context for representing the relationships between remembered and decision utilities. The pre- and post-treatment happiness measures provide indicators of these utilities.

Although the dynamic framework is applied in a specific context involving mode choice where the car is the pre-treatment habitual mode, the framework is applicable to other travel decision-making contexts (e.g. route or time-of-travel choice), regardless of whether they involve habitual behavior or not, as long as the choice and / or happiness judgments are observed in multiple time periods. Choices made under non-routine conditions are of greater interest, since as discussed in Chapter 5, choices are driven by automatic processes if they are habitual.

This chapter is organized as follows. Section 6.1 presents the model framework and formulation. Section 6.2 shows the estimation results for the Swiss data, MIT data, and the combined Swiss-MIT data. Section 6.3 compares the MIT model to a standard model estimated without happiness data. Section 6.4 concludes.

6.1   Modeling Framework

Figure 6.1 shows the dynamic modeling framework applied to the mode choice experiments. We distinguish between two periods: pre-treatment and post-treatment. In the pre-treatment period, since participants commute habitually by car and are not making new decisions, they have a remembered utility from the car. This utility is

reflected by the pre-treatment car happiness measure. In the post-treatment period, the participants decide whether they will switch to public transportation or keep commuting by car. The utility concept that is relevant at this decision-making period is decision utility of car and public transportation. These utilities are reflected by the post-treatment car and public transportation happiness measures, respectively, and by the choice. Participants select the mode that maximizes their utility.

Remembered and decision utility are affected by explanatory variables. The remembered utility of car is correlated with the decision utility of car and of public transportation, and the decision utilities of car and public transportation are also correlated. The correlations among the three happiness measures are captured through the correlations among the utilities. Note that although the model framework does not explicitly represent a causal relationship from remembered to decision utility (as in the dynamic framework of Chapter 3) but rather shows a correlation structure, the correlation relationship can be viewed as a special case of the causal structure.
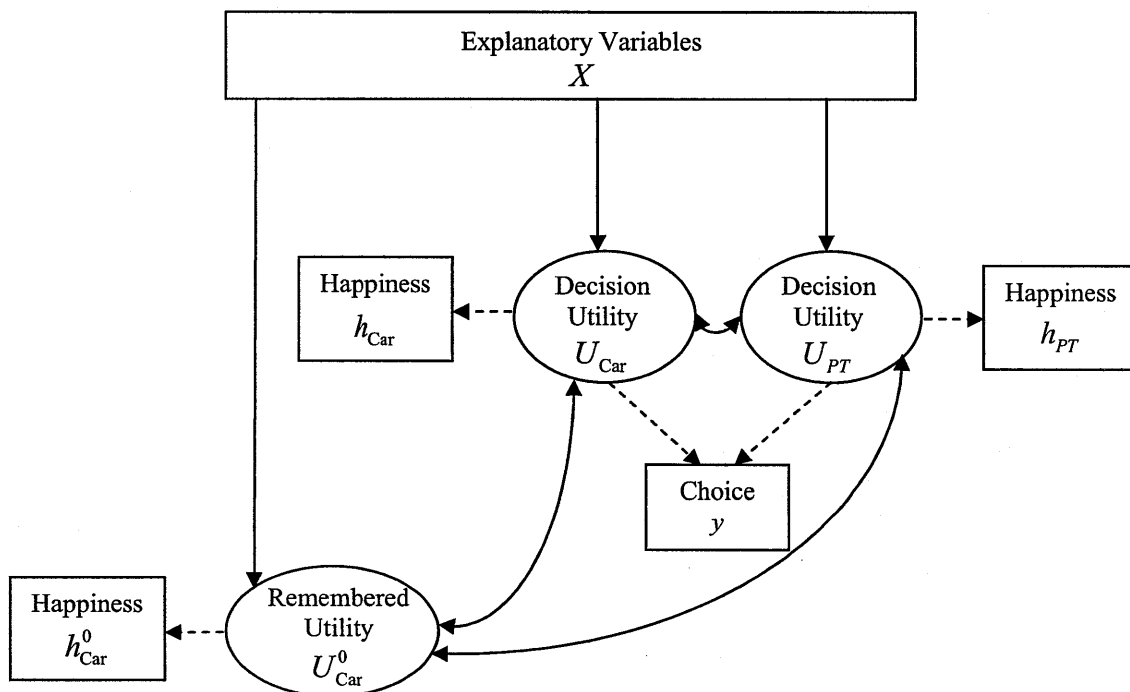
Figure 6.1. Modeling framework.

6.1.1 Structural Model

The structural model is a specification of the utility equations of car and public transportation. For car, we specify pre-treatment (remembered) and post-treatment (decision) utilities. For public transportation, we specify only a post-treatment (decision) utility equation as public transportation becomes relevant to the participants only after

they try it and decide if they want to switch to it. These utilities are given by Equations (6.1) – (6.3).

$$U_{\text{Car}}^0 = V_{\text{Car}}^0 + \varepsilon_{\text{Car}}^0 = \beta_0 + \beta_1 * \text{Time}_{\text{Car}} + \beta_2 * \text{Cost}_{\text{Car}}/\text{income} + \varepsilon_{\text{Car}}^0 \qquad (6.1)$$

$$U_{\text{Car}} = V_{\text{Car}} + \varepsilon_{\text{Car}} = \beta_3 + \beta_1 * \text{Time}_{\text{Car}} + \beta_2 * \text{Cost}_{\text{Car}}/\text{income} + \varepsilon_{\text{Car}} \qquad (6.2)$$

$$U_{\text{PT}} = V_{\text{PT}} + \varepsilon_{\text{PT}} = \beta_1 * \text{Time}_{\text{PT}} + \beta_2 * \text{Cost}_{\text{PT}}/\text{income} + \varepsilon_{\text{PT}} \qquad (6.3)$$

where U_{Car}^0 is the pre-treatment car utility, U_{Car} is the post-treatment car utility, and U_{PT} is the post-treatment public transportation utility; V_{Car}^0, V_{Car}, and V_{PT} are the corresponding systematic utilities which are specified as a function of time and cost divided by income. Even though the utility may be affected by soft variables such as comfort, convenience, and reliability as discussed in Chapter 3, these variables are not included for two reasons. First, we wanted to keep the model simple given the small number of observations. Second, we only had one indicator of each of these soft variables, which would require imposing several restrictions in the corresponding measurement equations for identification purposes.

We assume that the coefficients of time and cost are stable over time and are generic over alternatives. We specify two different car constants in the pre-treatment and post-treatment utilities since the error terms in these equations are different. $\varepsilon_{\text{Car}}^0$, ε_{Car}, and ε_{PT} are error terms distributed as multivariate normal with zero means, unit variances, and non-zero covariances (or correlations since the variances are one), as follows:

$$\begin{bmatrix} \varepsilon_{\text{Car}}^0 \\ \varepsilon_{\text{Car}} \\ \varepsilon_{\text{PT}} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_c & \rho_b \\ \rho_c & 1 & \rho_a \\ \rho_b & \rho_a & 1 \end{bmatrix} \right)$$

where ρ_c is the correlation between the pre-treatment and post-treatment car utilities; ρ_a is the correlation between the post-treatment car and public transportation utilities; and ρ_b is the correlation between the pre-treatment car utility and post-treatment public transportation utility. Let ΔU denote the difference between the post-treatment car and public transportation utilities.

$$\Delta U = U_{\text{Car}} - U_{\text{PT}} \qquad (6.4)$$

6.1.2 Measurement Model

The measurement model consists of a specification of the mode choice and happiness indicators. The choice between car and public transportation is assumed to be based on post-treatment utility maximization (since the choice is made post-treatment), as follows:

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$$y = \begin{cases} 1 \ \text{(Car)} & \text{if } \varDelta U + \eta \geq 0 \\ 0 \ \text{(PT)} & \text{otherwise} \end{cases} \tag{6.5}$$

where η is a Logistic error with a location of 0 and a scale parameter of $1 \left(\eta \sim \text{Logistic}(0,1)\right)$. η can be thought of as representing optimization errors on the part of the decision-maker. Since the total utility difference contains a normal error term ($\varepsilon_{\text{Car}} - \varepsilon_{\text{PT}}$) and a logistic error term, the choice model is an error component logit mixture.

We have three happiness measures: pre-treatment car happiness, post-treatment car happiness, and post-treatment public transportation happiness. These measures are ordinal with a 5-point scale (with 1 denoting very dissatisfied, and 5 denoting very satisfied). Therefore, for each of these observed ordinal measures, there is an underlying continuous latent response variable that is an indicator of the corresponding utility, as follows:

$$h_{\text{Car}}^{*0} = \lambda_1 U_{\text{Car}}^0 + \upsilon_1 \tag{6.6}$$

$$h_{\text{Car}}^* = \lambda_2 U_{\text{Car}} + \upsilon_2 \tag{6.7}$$

$$h_{\text{PT}}^* = \lambda_3 U_{\text{PT}} + \upsilon_3 \tag{6.8}$$

where h_{Car}^{*0}, h_{Car}^*, and h_{PT}^* are the continuous latent response variables corresponding to the measures of pre-treatment car happiness, post-treatment car happiness, and post-treatment public transportation happiness, respectively. λ_1, λ_2, and λ_3 are scaling parameters. υ_1, υ_2, and υ_3 are Logistic error terms with a location of 0 and a scale parameter of $1 \left(\upsilon_1, \upsilon_2, \upsilon_3 \sim \text{Logistic}(0,1)\right)$.

Through this formulation, the correlation between the happiness measures is captured through the correlation between the error terms in the corresponding utility equations. For example, the correlation between the measures of pre-treatment and post-treatment car satisfaction is captured through the correlation between $\varepsilon_{\text{Car}}^0$ and ε_{Car}, and similarly for the correlations between the other two pairs of happiness measures.

The observed happiness measures are related to the continuous latent response variables through a threshold model as follows:

$$h_{\text{Car}}^0 = \begin{cases} 1 & \text{if } -\infty < h_{\text{Car}}^{*\,0} \leq \tau_1 \\ 2 & \text{if } \tau_1 < h_{\text{Car}}^{*\,0} \leq \tau_2 \\ 3 & \text{if } \tau_2 < h_{\text{Car}}^{*\,0} \leq \tau_3 \\ 4 & \text{if } \tau_3 < h_{\text{Car}}^{*\,0} \leq \tau_4 \\ 5 & \text{if } \tau_4 < h_{\text{Car}}^{*\,0} < \infty \end{cases} \tag{6.9}$$

$$h_{\text{Car}} = \begin{cases} 1 & \text{if } -\infty < h_{\text{Car}}^* \leq \tau_1 \\ 2 & \text{if } \tau_1 < h_{\text{Car}}^* \leq \tau_2 \\ 3 & \text{if } \tau_2 < h_{\text{Car}}^* \leq \tau_3 \\ 4 & \text{if } \tau_3 < h_{\text{Car}}^* \leq \tau_4 \\ 5 & \text{if } \tau_4 < h_{\text{Car}}^* < \infty \end{cases}$$ (6.10)

$$h_{\text{PT}} = \begin{cases} 1 & \text{if } -\infty < h_{\text{PT}}^* \leq \tau_1 \\ 2 & \text{if } \tau_1 < h_{\text{PT}}^* \leq \tau_2 \\ 3 & \text{if } \tau_2 < h_{\text{PT}}^* \leq \tau_3 \\ 4 & \text{if } \tau_3 < h_{\text{PT}}^* \leq \tau_4 \\ 5 & \text{if } \tau_4 < h_{\text{PT}}^* < \infty \end{cases}$$ (6.11)

where h_{Car}^0, h_{Car}, and h_{PT} are the observed measures of pre-treatment car happiness, post-treatment car happiness, and post-treatment public transportation happiness, respectively. τ_1, τ_2, τ_3, and τ_4 are threshold parameters. The thresholds are assumed to be the same for the three happiness measures as it is assumed that people use the same happiness scale in answering these questions.

6.1.3 Likelihood Function

The maximum likelihood method is used for model estimation. The likelihood of a given observation is the probability of observing the choice and the three happiness indicators. Conditional on $\varepsilon_{\text{Car}}^0$, ε_{Car}, and ε_{PT}, the probabilities of the choice and each of the happiness indicators are independent. The likelihood for observation n is computed by integrating the product of these conditional probabilities over the joint density of $\varepsilon_{\text{Car}}^0$, ε_{Car}, and ε_{PT}, as follows:

$$P_n = \int_{\varepsilon_{\text{PT}}} \int_{\varepsilon_{\text{Car}}} \int_{\varepsilon_{\text{Car}}^0} \begin{pmatrix} \Lambda_1\left(y|\varepsilon_{\text{Car}},\varepsilon_{\text{PT}}\right)P_2\left(h_{\text{Car}}^0|\varepsilon_{\text{Car}}^0\right)P_3\left(h_{\text{Car}}|\varepsilon_{\text{Car}}\right)P_4\left(h_{\text{PT}}|\varepsilon_{\text{PT}}\right) \\ f_5\left(\varepsilon_{\text{Car}}^0,\varepsilon_{\text{Car}},\varepsilon_{\text{PT}}\right)d\varepsilon_{\text{Car}}^0\ d\varepsilon_{\text{Car}}d\varepsilon_{\text{PT}} \end{pmatrix}$$ (6.12)

where $\Lambda_1\left(y|\varepsilon_{\text{Car}},\varepsilon_{\text{PT}}\right)$ is the choice probability, $P_2\left(h_{\text{Car}}^0|\varepsilon_{\text{Car}}^0\right)$ is the probability of the pre-treatment car happiness measure, $P_3\left(h_{\text{Car}}|\varepsilon_{\text{Car}}\right)$ is the probability of the post-treatment car happiness measure, and $P_4\left(h_{\text{PT}}|\varepsilon_{\text{PT}}\right)$ is the probability of the post-treatment public

transportation happiness measure – all conditional on ε_{Car}^0, ε_{Car}, and ε_{PT} which have a joint density function denoted as $f_5\left(\varepsilon_{Car}^0, \varepsilon_{Car}, \varepsilon_{PT}\right)$.

$A_1\left(y|\varepsilon_{Car}, \varepsilon_{PT}\right)$ is a logit model given by the following equation:

$$A_1\left(y|\varepsilon_{Car}, \varepsilon_{PT}\right) = \left(\frac{1}{1+e^{-\Delta U}}\right)^y \left(\frac{e^{-\Delta U}}{1+e^{-\Delta U}}\right)^{(1-y)} \tag{6.13}$$

$P_2\left(h_{Car}^0|\varepsilon_{Car}^0\right)$, $P_3\left(h_{Car}|\varepsilon_{Car}\right)$, and $P_4\left(h_{PT}|\varepsilon_{PT}\right)$ are given by differences of logistic probability functions, as shown in Equations (6.14) – (6.28):

$$P_2\left(h_{Car}^0 = 1|\varepsilon_{Car}^0\right) = \frac{1}{1+e^{-\tau_1+\lambda_1 U_{Car}^0}} \tag{6.14}$$

$$P_2\left(h_{Car}^0 = 2|\varepsilon_{Car}^0\right) = \frac{1}{1+e^{-\tau_2+\lambda_1 U_{Car}^0}} - \frac{1}{1+e^{-\tau_1+\lambda_1 U_{Car}^0}} \tag{6.15}$$

$$P_2\left(h_{Car}^0 = 3|\varepsilon_{Car}^0\right) = \frac{1}{1+e^{-\tau_3+\lambda_1 U_{Car}^0}} - \frac{1}{1+e^{-\tau_2+\lambda_1 U_{Car}^0}} \tag{6.16}$$

$$P_2\left(h_{Car}^0 = 4|\varepsilon_{Car}^0\right) = \frac{1}{1+e^{-\tau_4+\lambda_1 U_{Car}^0}} - \frac{1}{1+e^{-\tau_3+\lambda_1 U_{Car}^0}} \tag{6.17}$$

$$P_2\left(h_{Car}^0 = 5|\varepsilon_{Car}^0\right) = 1 - \frac{1}{1+e^{-\tau_4+\lambda_1 U_{Car}^0}} \tag{6.18}$$

$$P_3\left(h_{Car} = 1|\varepsilon_{Car}\right) = \frac{1}{1+e^{-\tau_1+\lambda_2 U_{Car}}} \tag{6.19}$$

$$P_3\left(h_{Car} = 2|\varepsilon_{Car}\right) = \frac{1}{1+e^{-\tau_2+\lambda_2 U_{Car}}} - \frac{1}{1+e^{-\tau_1+\lambda_2 U_{Car}}} \tag{6.20}$$

$$P_3\left(h_{Car} = 3|\varepsilon_{Car}\right) = \frac{1}{1+e^{-\tau_3+\lambda_2 U_{Car}}} - \frac{1}{1+e^{-\tau_2+\lambda_2 U_{Car}}} \tag{6.21}$$

$$P_3\left(h_{Car} = 4|\varepsilon_{Car}\right) = \frac{1}{1+e^{-\tau_4+\lambda_2 U_{Car}}} - \frac{1}{1+e^{-\tau_3+\lambda_2 U_{Car}}} \tag{6.22}$$

$$P_3\left(h_{Car} = 5|\varepsilon_{Car}\right) = 1 - \frac{1}{1+e^{-\tau_4+\lambda_2 U_{Car}}} \tag{6.23}$$

$$P_4\left(h_{PT} = 1|\varepsilon_{PT}\right) = \frac{1}{1+e^{-\tau_1+\lambda_3 U_{PT}}} \tag{6.24}$$

$$P_4\left(h_{PT} = 2|\varepsilon_{PT}\right) = \frac{1}{1+e^{-\tau_2+\lambda_3 U_{PT}}} - \frac{1}{1+e^{-\tau_1+\lambda_3 U_{PT}}} \tag{6.25}$$

$$P_4\left(h_{PT} = 3|\varepsilon_{PT}\right) = \frac{1}{1+e^{-\tau_3+\lambda_3 U_{PT}}} - \frac{1}{1+e^{-\tau_2+\lambda_3 U_{PT}}} \tag{6.26}$$

$$P_4\left(h_{\mathrm{PT}}=4\middle|\varepsilon_{\mathrm{PT}}\right)=\frac{1}{1+e^{-\tau_4+\lambda_3 U_{\mathrm{PT}}}}-\frac{1}{1+e^{-\tau_3+\lambda_3 U_{\mathrm{PT}}}} \tag{6.27}$$

$$P_4\left(h_{\mathrm{PT}}=5\middle|\varepsilon_{\mathrm{PT}}\right)=1-\frac{1}{1+e^{-\tau_4+\lambda_3 U_{\mathrm{PT}}}} \tag{6.28}$$

$f_5\left(\varepsilon_{\mathrm{Car}}^0,\varepsilon_{\mathrm{Car}},\varepsilon_{\mathrm{PT}}\right)$ is a multivariate normal density function given by:

$$f_5\left(\varepsilon_{\mathrm{Car}}^0,\varepsilon_{\mathrm{Car}},\varepsilon_{\mathrm{PT}}\right)=\frac{1}{(2\pi)^{3/2}|\Sigma|^{1/2}}exp\left(-\frac{1}{2}\begin{bmatrix}\varepsilon_{\mathrm{Car}}^0 & \varepsilon_{\mathrm{Car}} & \varepsilon_{\mathrm{PT}}\end{bmatrix}\Sigma^{-1}\begin{bmatrix}\varepsilon_{\mathrm{Car}}^0\\\varepsilon_{\mathrm{Car}}\\\varepsilon_{\mathrm{PT}}\end{bmatrix}\right) \tag{6.29}$$

where Σ is the variance-covariance matrix of $\varepsilon_{\mathrm{Car}}^0$, $\varepsilon_{\mathrm{Car}}$, and $\varepsilon_{\mathrm{PT}}$, $|\Sigma|$ denotes the determinant of Σ, and Σ^{-1} is the inverse of Σ. Since Σ is given by:

$$\Sigma=\begin{bmatrix}1 & \rho_c & \rho_b\\\rho_c & 1 & \rho_a\\\rho_b & \rho_a & 1\end{bmatrix} \tag{6.30},$$

$|\Sigma|$ and Σ^{-1} are given by Equations (6.31) and (6.32), respectively.

$$|\Sigma|=1-\rho_a^2-\rho_c^2-\rho_b^2+2\rho_a\rho_c\rho_b \tag{6.31}$$

$$\Sigma^{-1}=\frac{1}{|\Sigma|}\begin{bmatrix}1-\rho_a^2 & \rho_a\rho_b-\rho_c & \rho_a\rho_c-\rho_b\\\rho_a\rho_b-\rho_c & 1-\rho_b^2 & \rho_b\rho_c-\rho_a\\\rho_a\rho_c-\rho_b & \rho_b\rho_c-\rho_a & 1-\rho_c^2\end{bmatrix} \tag{6.32}$$

Given the structure of the variance-covariance matrix (with unit variances), it can be shown using the Cholesky decomposition that in order to guarantee a positive definite variance-covariance matrix, the following three constraints should be imposed on the correlations:

$$-1\le\rho_c\le1 \tag{6.33}$$

$$-1\le\rho_b\le1 \tag{6.34}$$

$$\rho_a=\gamma\sqrt{1-\rho_c^2}+\rho_b\rho_c, 0\le\rho_b^2+\gamma^2\le1 \tag{6.35}$$

where γ is a parameter to be estimated.

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6.2   Model Estimation

In this section, we show the estimation results corresponding to the above model framework for the Swiss data (Section 6.2.1), the MIT data (Section 6.2.2), and the combined Swiss and MIT data (Section 6.2.3). The models were programmed in Gauss (Aptech Systems, 1995) and estimated using the maximum likelihood approach with multiple imputations for income. The results shown below are based on 5 imputed datasets for each of the models. The details of the income imputation procedure are shown in Appendix E. Numerical integration was used to estimate the integrals in the likelihood function.

Moreover, we tested for the presence of sample selection bias using a simplified version of the above model. In particular, we postulated that the decision to participate in the experiment may be correlated with the mode switching decision. That is, people who decide to participate may have already thought about switching to public transportation anyway or may be more inclined in general to switch. Using data on participants and non-participants, we estimated sample selection models and tested for the presence of sample selection bias and found no evidence for it. The details of these models and tests are given in Appendix F.

6.2.1 Swiss Data

For the Swiss experiments, we model commute mode choice on a given day in relation to commute satisfaction, using mode choice data from the travel diaries recorded in the week following the treatment. We cannot model usual mode choice (i.e. retain full-time parking permit or cancel it) since none of the participants gave up his/her parking permit and switched completely to public transportation. Since multiple mode choice observations are available for every participant, we account for correlation among mode choice observations of the same participant by making the error terms ε_{Car} and ε_{PT} individual-specific. For any given individual, conditional on ε_{Car} and ε_{PT}, the probability of a sequence of mode choices is the product of the probabilities of mode choices made on different home-to-work trips on several days. The likelihood of a given observation is modified as follows:

$$P_n = \int\limits_{\varepsilon_{\text{PT}}} \int\limits_{\varepsilon_{\text{Car}}} \int\limits_{\varepsilon_{\text{Car}}^0} \left(\begin{array}{c} \left(\prod\limits_{t=1}^{T_n} A_{1t}\left(y_t \middle| \varepsilon_{\text{Car}}, \varepsilon_{\text{PT}}\right) \right) P_2\left(h_{\text{Car}}^0 \middle| \varepsilon_{\text{Car}}^0\right) P_3\left(h_{\text{Car}} \middle| \varepsilon_{\text{Car}}\right) P_4\left(h_{\text{PT}} \middle| \varepsilon_{\text{PT}}\right) \\ f_5\left(\varepsilon_{\text{Car}}^0, \varepsilon_{\text{Car}}, \varepsilon_{\text{PT}}\right) d\varepsilon_{\text{Car}}^0 \, d\varepsilon_{\text{Car}} d\varepsilon_{\text{PT}} \end{array} \right) \tag{6.36}$$

where T_n is the number of mode choice observations for individual n and y_t is the mode choice for observation t.

With respect to the framework presented in Section 6.1, the travel time variable used in the utility equations is door-to-door home-to-work commute time in hours as stated by

the participants in the travel diaries. For any given day for which mode choice is observed and modeled, the travel time used is the average of home-to-work travel time on all previous days recorded in the diaries. Distance (measured in kilometers and obtained from the travel diaries) is used as a proxy for car commuting fuel costs since parking subscription costs have already been paid for by the participants. No cost variable is included in the systematic utility of public transportation since the data come from a post-treatment week when participants still had a valid free public transportation pass. The income variable is monthly personal pre-tax income measured in hundreds of Swiss Francs.

When the model was estimated, the correlation parameter ρ_a between the post-treatment car and public transportation utilities approached -1 (corner solution). Therefore, we set this correlation to -1 (which means that the error term ε_{PT} is equal to -1 times ε_{Car}) and estimated only one correlation parameter between the pre-treatment and post-treatment car utilities. Table 6.1 shows the parameter estimates, standard errors, and t-statistics for the resulting model. Figure 6.2 shows the model structure and parameter estimates (except for the thresholds) with t-statistics in parentheses.

A number of parameters have counterintuitive signs and are mostly insignificant, including the distance/income variable, the correlation parameter ρ_c, and the scaling parameter λ_2. A number of other specifications were tried but did not resolve these issues which might be attributed to the small sample size of 28.

It was not possible to test the consistency of the parameters estimated in this model in comparison to a mode choice only model using a Hausman specification test (Hausman, 1978). The difference between the variance-covariance matrices of the two estimators (with and without happiness) was not positive-definite. The details are given in Appendix G.

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Table 6.1. Swiss model estimation results (N = 28).

Parameter	Estimate	Std Error	t-stat
Structural Model			
Car constant (pre-treatment)	0.624	1.71	0.36
Car constant (post-treatment)	-0.217	0.942	-0.23
Time (hours)	-3.97	1.57	-2.52
Distance$_{Car}$/income (km/100 Swiss Francs per month)	0.433	2.09	0.21
ρ_c	-0.130	0.809	-0.16
$\rho_b = -\rho_c$	0.130	-	-
ρ_a	-1.00 (fixed)	-	-
Measurement Model			
Pre-Treatment Car Happiness			
λ_1	0.594	0.519	1.14
Post-Treatment Car Happiness			
λ_2	-0.106	0.310	-0.34
Post-Treatment PT Happiness			
λ_3	0.770	0.404	1.91
Thresholds			
τ_1	-5.58	1.18	-4.72
τ_2	-4.38	1.00	-4.37
τ_3	-1.74	0.696	-2.50
τ_4	0.333	0.660	0.50
Log-Likelihood	-138.0		

Figure 6.2. Swiss model structure and parameter estimates (the car constants and the thresholds are not shown in the figure; t-statistics are shown in parentheses).

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6.2.2 MIT Data

For the MIT experiment, we model usual commute mode choice (car or public transportation) in relation to commute satisfaction. Participants who cancel their full-time parking permit and purchase a public transportation pass after the experiment are assumed to use public transportation as their usual commute mode. Those who keep their full-time parking permits are assumed to use the car as their usual commute mode. Note that participants cannot keep both a full-time parking permit and a subsidized public transportation pass purchased from MIT. But if they purchase a subsidized public transportation pass, they can purchase additionally an occasional parking permit that allows them to park at MIT at most 8 times a month.

With respect to the framework presented in Section 6.1, the travel time variable used in the utility equations is the natural logarithm of door-to-door time in minutes. It is obtained from the diaries as in the Swiss case. Costs are defined as monthly commuting costs. Car cost includes parking, fuel, and tolls (if any). Public transportation costs include public transportation pass cost plus additional costs related to using the car as an access mode or occasionally. If the public transportation commute involves using the car as an access mode to public transportation stations, we add park-and-ride parking fees, fuel, and tolls (if any). Moreover, occasional parking costs at MIT (fees, fuel, and tolls if any, based on expected car usage) are added to public transportation costs for all participants who kept the car as their usual commute mode after the experiment or participants who switched to public transportation with occasional parking permit. The decision to purchase an occasional parking permit is not modeled in this thesis in order to keep the model tractable given the small sample size. The income variable is annual personal pre-tax income measured in thousands of dollars.

When the model formulated in Section 6.1 was estimated, the correlation parameter ρ_c between the pre- and post-treatment car satisfaction ratings approached 1 (corner solution). In fact, the correlation between these ratings in the data was high at 0.75. Therefore, we set this correlation to 1 (which means that the error terms ε_{Car}^0 and ε_{Car} are identical, and so are the utilities U_{Car}^0 and U_{Car}) and estimated only one correlation parameter between car and public transportation utilities.

When the model was re-estimated, the cost coefficient was positive, insignificant, and of a much smaller order of magnitude than the cost coefficient estimated in a mode choice only model. We then postulated that the cost coefficient may have different impacts on mode choice and on happiness ratings. In particular, people may take the cost as given when judging their satisfaction with modes but not when deciding on which mode to choose. This can also be interpreted as satisfaction ratings reflecting the actual affective experience (time, comfort, convenience, etc.) that does not include monetary aspects.

Indeed, when cost was included as a separate explanatory variable in the happiness equations (in addition to the utility), its coefficient was such that it almost annulled the effect of the cost component of the utility on happiness. That is, if the happiness

equations are rewritten as in Equations (6.6') – (6.8'), we find that $\lambda_2 \text{Cost}_{\text{Car}}/\text{income} + \gamma * \text{Cost}_{\text{Car}}/\text{income}$ is almost zero (The same car utility is used in the pre-treatment and post-treatment equations below since ρ_c was set to 1).

$$h_{\text{Car}}^{*0} = \lambda_1 U_{\text{Car}} + \gamma * \text{Cost}_{\text{Car}}/\text{income} + \upsilon_1 \qquad (6.6')$$

$$h_{\text{Car}}^{*} = \lambda_2 U_{\text{Car}} + \gamma * \text{Cost}_{\text{Car}}/\text{income} + \upsilon_2 \qquad (6.7')$$

$$h_{\text{PT}}^{*} = \lambda_3 U_{\text{PT}} + \gamma * \text{Cost}_{\text{PT}}/\text{income} + \upsilon_3 \qquad (6.8')$$

Therefore, we re-estimated the model with cost only affecting mode choice but not happiness ratings; that is, the utility that is used in the happiness equations is netted out of the cost variable. More specifically, the happiness equations are modified as follows:

$$h_{\text{Car}}^{*0} = \lambda_1 \left(\beta_0 + \beta_1 * \text{Time}_{\text{Car}} + \varepsilon_{\text{Car}} \right) + \upsilon_1 \qquad (6.6'')$$

$$h_{\text{Car}}^{*} = \lambda_2 \left(\beta_0 + \beta_1 * \text{Time}_{\text{Car}} + \varepsilon_{\text{Car}} \right) + \upsilon_2 \qquad (6.7'')$$

$$h_{\text{PT}}^{*} = \lambda_3 \left(\beta_1 * \text{Time}_{\text{PT}} + \varepsilon_{\text{PT}} \right) + \upsilon_3 \qquad (6.8'')$$

Table 6.2 shows the parameter estimates, standard errors, and t-statistics for this specification. Figure 6.3 shows the model structure and parameter estimates (except for the thresholds) with t-statistics in parentheses. A Hausman test applied to this model indicated that the parameter estimates of this model are consistent at the 90% level of confidence. The details are given in Appendix G.

The structural model coefficients indicate that if everything else is the same the car is preferred to public transportation for this sample of habitual car commuters. Both the time and cost coefficients are negative and significant. The value of time depends on the income level and on the travel time (since a logarithmic specification of travel time is used). For example, at an annual personal income of $100,000 and a travel time of 15 minutes, the model implies a willingness to pay of $174 per month to save one hour of travel time on every commuting trip from home to work.

The correlation ρ_a (and ρ_b) between the car and public transportation utilities (and hence satisfaction ratings) is negative, as expected, but insignificant. As to the scale parameters λ_1, λ_2, and λ_3, they are all positive as expected.

Table 6.2. MIT model estimation results (N = 67).

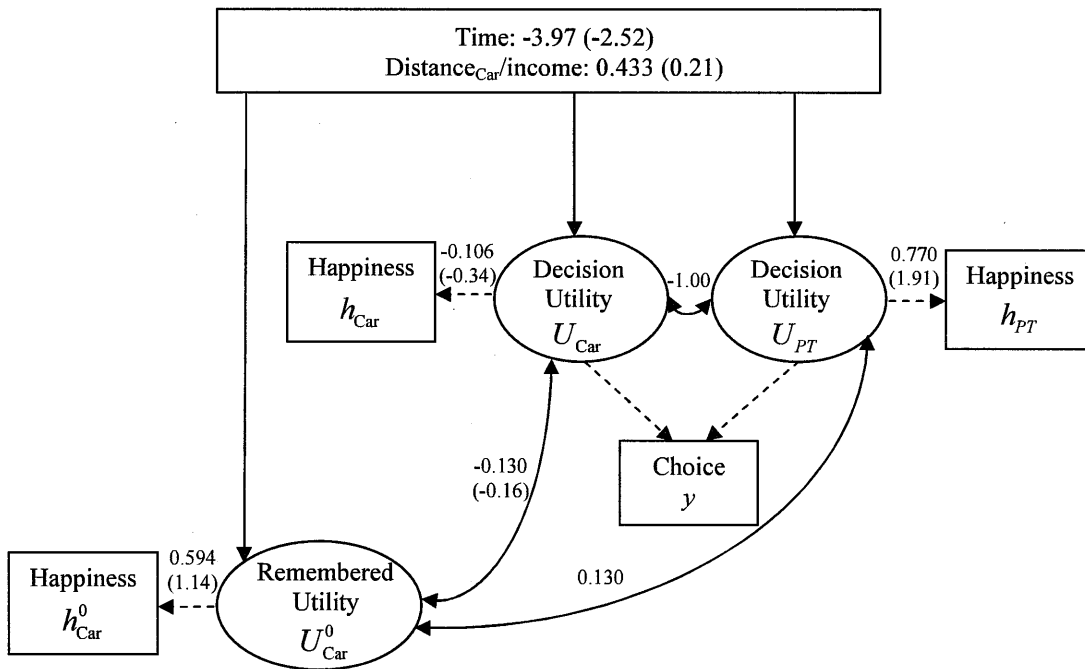| Parameter	Estimate	Std Error	t-stat
Structural Model			
Car constant	0.799	0.313	2.55
ln Time (minutes)	-0.568	0.211	-2.70
Cost/income ($ per month/$1000 per year)	-1.31	0.679	-1.93
ρ_c	1.00 (fixed)	-	-
$\rho_b = \rho_a$	-0.0644	0.155	-0.41
Measurement Model			
Pre-Treatment Car Happiness			
λ_1	4.34	0.903	4.81
Post-Treatment Car Happiness			
λ_2	3.55	0.724	4.91
Post-Treatment PT Happiness			
λ_3	3.00	0.697	4.30
Thresholds			
τ_1	-12.7	3.09	-4.10
τ_2	-9.04	2.83	-3.19
τ_3	-4.55	2.64	-1.72
τ_4	-0.356	2.58	-0.14
Log-Likelihood	-275.1		
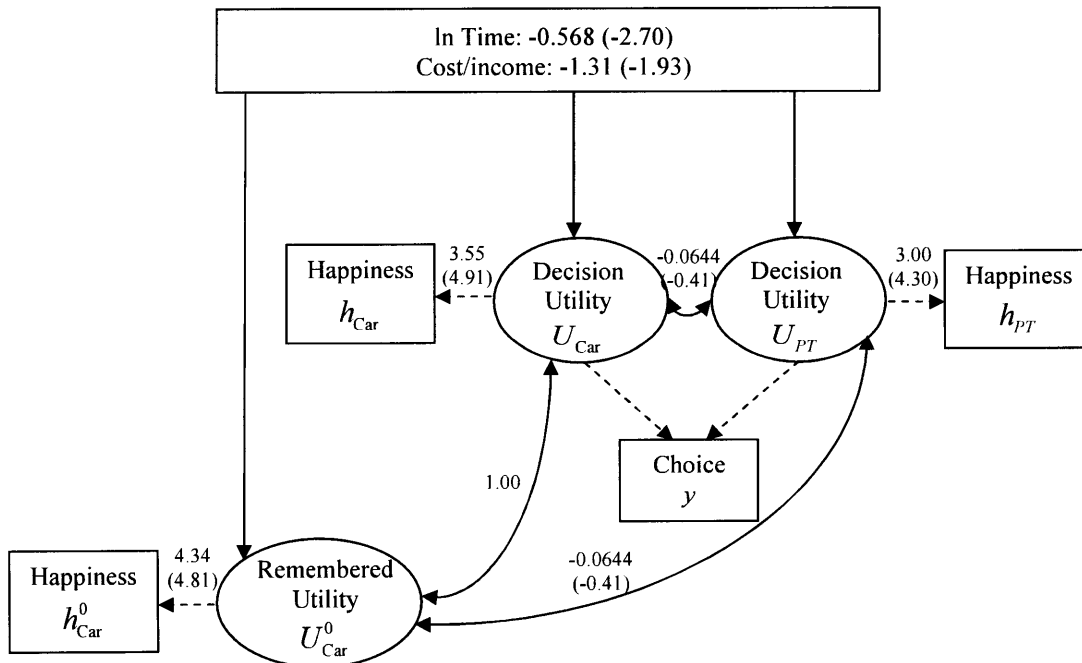
Figure 6.3. MIT model structure and parameter estimates (the car constant and the thresholds are not shown in the figure; t-statistics are shown in parentheses).

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6.2.3 Combined Swiss-MIT Data

In this section, we show the results of a model estimated using the combined Swiss and MIT data. The model follows the same structure described in Section 6.1. We allow the coefficients of the variables in the utility equations to vary; i.e. each dataset has its own car constants, time and cost coefficients, and correlation parameters.

When a general variance-covariance matrix was allowed for each of the Swiss and MIT data (with three correlation parameters for each), the correlation between the pre-treatment and post-treatment car utilities in the MIT data approached 1 as in the model presented in Section 6.2.2. Therefore, we fixed this correlation at 1 for the MIT data and estimated only one correlation between the car and public transportation utilities; for the Swiss data, we were able to estimate all three correlation parameters.

The common coefficients between the two datasets are the coefficients of the happiness model: the scale parameters multiplying the utilities and the threshold parameters. We do not include a cost or distance effect in the happiness equations, as in the MIT model estimated in Section 6.2.2 (If we add a distance effect in the happiness equations of the Swiss data, we find that it is statistically insignificant). The estimation results for the combined model specification are shown in Table 6.3. Figures 6.4 and 6.5 show the model structure and parameter estimates (except for the thresholds) with t-statistics in parentheses for the Swiss and MIT parts of the model, respectively.

Comparing the coefficients of the combined Swiss-MIT model to those of the MIT model, we note that the coefficients of the structural model are similar between the two. The λ parameters and the thresholds are more different as these are constrained to be the same for the Swiss and MIT data. At an annual personal income of $100,000 and a travel time of 15 minutes, the model implies a willingness to pay of $132 per month to save one hour of travel time on every commuting trip from home to work.

Comparison of the combined Swiss-MIT model to the Swiss model cannot be performed as the Swiss model was estimated with a different correlation structure (i.e. with the correlation between the post-treatment car and public transportation utilities fixed at -1). However, note that the signs of the parameters of the Swiss part of the combined model are now intuitive although not all parameters are statistically significant. Assuming a gas mileage range of 20-30 miles/gallon (8.5-12.7 km/liter) and a gas price of $6.36/gallon (or 1.9 Swiss Francs/liter), the implied value of time for commuting trips is 16-24 Swiss Francs/hour at a monthly personal income of 7500 Swiss Francs.

Hausman tests applied to compare the car constant, time, and cost/income (or distance/income) variables obtained in the combined Swiss-MIT model (with happiness) and those obtained in mode choice only models (estimated separately using Swiss and MIT data) indicated that these coefficients are consistent at the 90% level of confidence. See Appendix G for further details.

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Table 6.3. Combined Swiss-MIT model estimation results (N = 67 + 28 = 95).

Parameter	Estimate	Std Error	t-stat
Structural Model			
Car constant (MIT)	0.851	0.317	2.68
Car constant (Swiss, pre-treatment)	0.854	0.320	2.67
Car constant (Swiss, post-treatment)	1.46	0.429	3.39
ln Time (minutes) (MIT)	-0.440	0.123	-3.59
Time (hours) (Swiss)	-1.67	0.487	-3.43
Cost/income ($ per month/$1000 per year) (MIT)	-1.33	0.690	-1.93
$Distance_{Car}$/income (km/100 Swiss Francs per month) (Swiss)	-1.17	1.33	-0.88
ρ_c (MIT)	1.00 (fixed)	-	-
$\rho_b = \rho_a$ (MIT)	-0.110	0.168	-0.66
ρ_c (Swiss)	0.819	0.320	2.56
ρ_b (Swiss)	-0.107	0.353	-0.30
ρ_a (Swiss)	-0.592	0.435	-1.36

Measurement Model			
Pre-Treatment Car Happiness			
λ_1	3.15	0.712	4.43
Post-Treatment Car Happiness			
λ_2	2.38	0.564	4.21
Post-Treatment PT Happiness			
λ_3	2.07	0.593	3.48
Thresholds			
τ_1	-7.86	1.48	-5.33
τ_2	-5.25	1.17	-4.48
τ_3	-1.64	0.896	-1.83
τ_4	1.67	0.936	1.79
Log-Likelihood	-423.5		
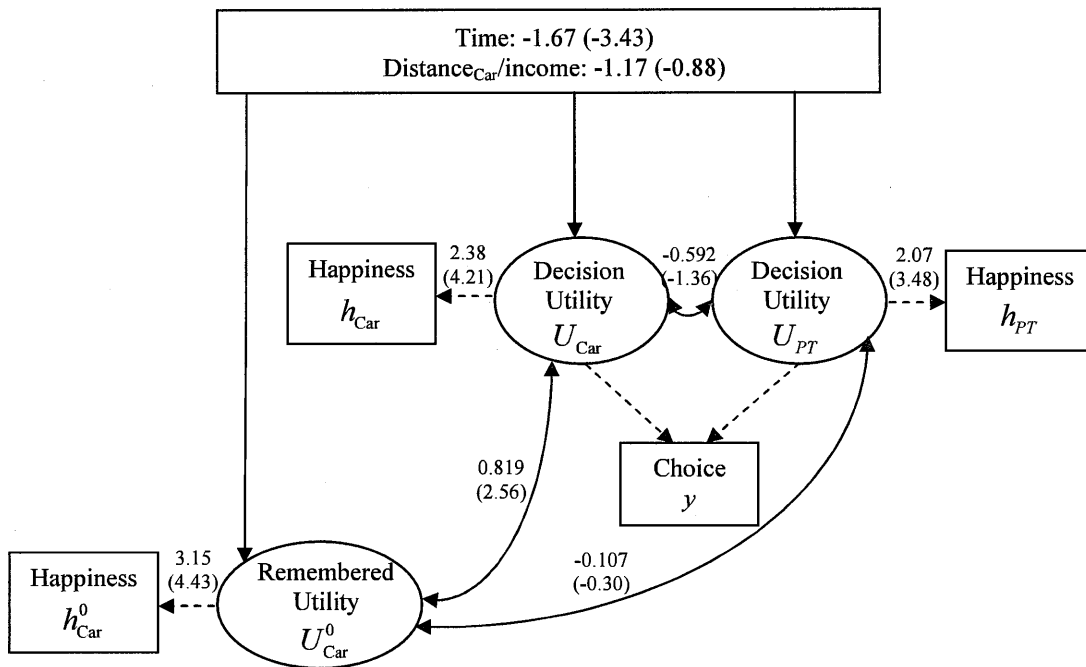
Figure 6.4. Swiss-MIT model structure and parameter estimates for the Swiss part of the model (the car constants and the thresholds are not shown in the figure; t-statistics are shown in parentheses).
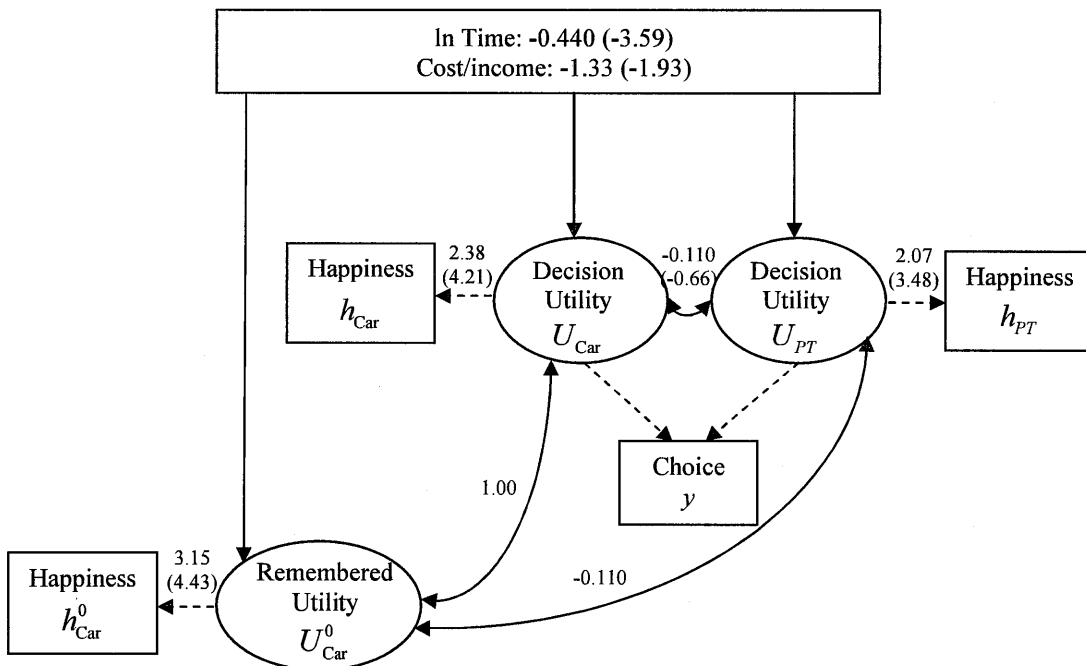
Figure 6.5. Swiss-MIT model structure and parameter estimates for the MIT part of the model (the car constant and the thresholds are not shown in the figure; t-statistics are shown in parentheses).

6.3   Model Performance

In this section, we compare the extended model including choice and happiness submodels to a standard choice only model (without happiness) using four criteria: goodness-of-fit, efficiency, consistency, and forecasting. We focus this analysis on the MIT model since the Swiss model on its own produced counterintuitive parameter estimates.

We show two specifications of the standard model: the first one is a logit model, and the second one is an error component logit mixture model that includes (in addition to the logit error) error terms in the utility equations of car and public transportation that are bivariate normally distributed with zero means, unit variances, and a correlation parameter fixed at the value of the correlation parameter obtained in the extended model. Essentially, the second specification of the standard model sets the standard model at the same scale as the extended model (which includes these bivariate normally distributed error terms previously denoted as ε_{Car} and ε_{PT}).

Table 6.4 shows the parameter estimates and standard errors of the common structural parameters of the extended (as in Table 6.2) and logit standard model. Table 6.5 shows the parameter estimates and standard errors of the common structural parameters of the extended (as in Table 6.2) and error component logit mixture standard model.

In both Tables 6.4 and 6.5, we note that the parameter estimates are different between the extended and standard models but are relatively of a close order of magnitude. The standard errors of the estimates in the standard model are greater than those in the extended model.

Table 6.4. MIT extended and logit standard model estimation results (N = 67).

Parameter	Extended model (Choice + Happiness)		Standard model (Choice only - logit)	
	Estimate	Std Error	Estimate	Std Error
Car constant	0.799	0.313	1.24	0.735
ln Time (minutes)	-0.568	0.211	-0.648	1.24
Cost/income ($ per month/$1000 per year)	-1.31	0.679	-2.03	0.803

Table 6.5. MIT extended and error component logit mixture standard model estimation results (standard model is estimated at a correlation parameter of -0.0644) (N = 67).

Parameter	Extended model (Choice + Happiness)		Standard model (Choice only - error component logit mixture)	
	Estimate	Std Error	Estimate	Std Error
Car constant	0.799	0.313	1.63	0.969
ln Time (minutes)	-0.568	0.211	-0.918	1.68
Cost/income ($ per month/$1000 per year)	-1.31	0.679	-2.66	1.03

We use the logit standard model (i.e. the results shown in Table 6.4) for comparison of goodness-of-fit, efficiency, and forecasting since a logit model is what is typically used in practice to estimate and apply a binary mode choice model. Additionally, we use the error component logit mixture standard model (i.e. the results shown in Table 6.5) for comparison of efficiency and consistency since the error component logit mixture standard model has the same scale as the extended model.

6.3.1 Goodness-of-Fit

Table 6.6 shows the choice log-likelihood for each of the extended and standard models.

Table 6.6. Choice log-likelihood of the extended and standard MIT models.

	Extended model (Choice + Happiness)	Standard model (Choice only - logit)
Choice log-likelihood	-35.4	-32.6

The choice log-likelihood of the extended model is smaller than that of the standard model, indicating that the standard model fits the choice data better. This is to be expected since the standard model optimizes the likelihood over the choice only, while the extended model optimizes the likelihood over both the choice and happiness measures.

6.3.2 Efficiency

Efficiency is a measure of the accuracy of parameter estimators. A more efficient estimator has a smaller variance. We compare the efficiency of the parameter estimators of the extended and standard models using a number of criteria: positive-definiteness of the difference of the variance-covariance matrices, the variance of the systematic utility, the trace and the determinant of the variance-covariance matrices. $\hat{\beta}_{Extended}$ and $\hat{\beta}_{Standard}$ denote the parameter estimators of the extended and standard models, respectively. Tables 6.7 and 6.8 show these measures of efficiency using the logit standard model and the error component logit mixture standard model, respectively.

All criteria used for comparison, except for the difference of the variance-covariance matrices when the logit standard model is used, indicate that the extended model parameters are more efficient than the standard model parameters. The variance of the systematic utility of car and public transportation, computed as the average variance across the sample, is substantially smaller in the extended model than in the standard model. Finally, both the trace (sum of the variances of the estimated parameters) and the determinant of the variance-covariance matrix of the parameter estimates in the extended model are smaller than the corresponding measures in the standard model.

Table 6.7. Efficiency of the extended and standard MIT models (using logit for standard model).

	Extended model (Choice + Happiness)	Standard model (Choice only - logit)
$\text{Var}\left(\hat{\beta}_{\text{Standard}}\right)-\text{Var}\left(\hat{\beta}_{\text{Extended}}\right)$	Not positive definite (one Eigen value is negative)	
$\overline{\text{Var}}\left(\hat{V}_{\text{Car}}\right)$	3.69	31.1
$\overline{\text{Var}}\left(\hat{V}_{\text{PT}}\right)$	3.61	30.7
$\text{Trace}\left(\text{Var}\left(\hat{\beta}\right)\right)$	0.604	2.73
$\left|\text{Var}\left(\hat{\beta}\right)\right|$	0.00128	0.0924

Table 6.8. Efficiency of the extended and standard MIT models (using error component logit mixture for standard model).

	Extended model (Choice + Happiness)	Standard model (Choice only - error component logit mixture)
$\text{Var}\left(\hat{\beta}_{\text{Standard}}\right)-\text{Var}\left(\hat{\beta}_{\text{Extended}}\right)$	Positive definite	
$\overline{\text{Var}}\left(\hat{V}_{\text{Car}}\right)$	3.69	56.8
$\overline{\text{Var}}\left(\hat{V}_{\text{PT}}\right)$	3.61	55.9
$\text{Trace}\left(\text{Var}\left(\hat{\beta}\right)\right)$	0.604	4.83
$\left|\text{Var}\left(\hat{\beta}\right)\right|$	0.00128	0.494

6.3.3 Consistency

The consistency (or asymptotic unbiasedness) of the estimators of the extended and standard models is tested using a Hausman specification test (Hausman, 1978). The Hausman test is used when two estimators are available and one is more efficient than the other. Under the null hypothesis, both estimators are consistent.

For our models, the underlying assumption is that both the extended and the standard model coefficients are consistent but the happiness indicators make the coefficients of the extended model more efficient than those of the standard model. For this test, the error component logit mixture standard model is used since it has the same scale as the extended model. The details of this test as applied to these models are given in Appendix G. We failed to reject the null hypothesis of consistent parameter estimates at the 90% level of confidence.

6.3.4 Forecasting

Finally, we compare the forecasts given by the extended and logit standard models. We consider a scenario where MIT provides free public transportation passes to employees. We compute the change in the public transportation market share predicted by each of the two models.

The change in the public transportation market share, the standard error of the change, and its confidence interval are determined by Monte Carlo simulation using 5000 pseudo-random draws from the multivariate normal distribution of the parameter estimators (car constant, time coefficient, and cost/income coefficient). The mean and the variance-covariance matrix of this distribution are given by the parameter estimates shown in Table 6.4 and their variance-covariance matrix, respectively. Table 6.9 shows the forecasting results for the extended and the standard models.

Table 6.9. Forecasting results for the extended and standard MIT models.

	Extended model (Choice + Happiness)	Standard model (Choice only - logit)
Difference in PT market share (in %)	$D_1 = 18.0\%$	$D_2 = 29.2\%$
Standard error of the difference	7.1%	7.8%
95% confidence interval of the difference	4.1% - 31.9%	13.9% - 44.4%

The estimates of the change in the public transportation market share are substantially different between the extended and the standard models ($D_1 = 18.0\%$ versus $D_2 = 29.2\%$). The standard error of the change is smaller in the extended model, as would be expected given that the parameters of the extended model are more efficient.

It is not straightforward to calculate the standard error of the difference in the change in public transportation market share (i.e. the standard error of $D_2 - D_1$) to test if it is statistically significant since we don't know the correlation between D_1 and D_2. We suspect that the difference between D_1 and D_2 is attributed to the difference in efficiency between the extended and standard models. The fact that the confidence intervals of D_1 and D_2 overlap also indicates that the variances of the error terms in these models are large relative to the variances of the systematic utilities due to the small sample sizes. We anticipate that with better specified models utilizing larger sample sizes, the variance of the parameter estimators will have a larger effect than the variance of the error terms on the accuracy of the model forecasts. In this sense, we anticipate that the gain in accuracy in market shares predicted by the extended model will be more pronounced with larger sample sizes.

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6.4   Conclusion

In this chapter, we operationalized the dynamic framework proposed in this thesis for the enhancement of random utility models by using happiness measures as indicators of utility in addition to the standard choice indicators. Using dynamic data from the Swiss and MIT mode choice experiments described in Chapter 5, we added three happiness equations to the mode choice model: a pre-treatment car happiness indicator measuring pre-treatment car utility (or remembered utility), a post-treatment car happiness indicator measuring post-treatment car utility (or decision utility), and a post-treatment public transportation happiness indicator measuring post-treatment public transportation utility (or decision utility). We accounted for the correlations between the happiness ratings through explicitly modeling the correlations between preferences (or utilities). The utilities were specified as a function of travel time and travel cost (or distance) divided by income.

We estimated the model framework using the Swiss and MIT datasets separately and jointly. The Swiss model resulted in generally insignificant parameter estimates and some counterintuitive signs, possibly owing to the small sample size. The MIT model results were more intuitive: the signs of the coefficients of variables in the utilities were correct, and the utilities were positively associated with the happiness ratings, which supports the validity of using these measures as indicators of utility. One finding that emerged in the MIT data is that the happiness ratings seemed to measure the non-monetary components of the utility. That is, people seemed to rate their satisfaction as if the costs were given. This finding has measurement implications as will be discussed in Chapter 8. The combined Swiss-MIT model produced similar conclusions as those reached in the MIT analysis and the signs of the coefficients pertaining to the Swiss data became intuitive.

We compared the extended MIT model (choice and happiness model) to a standard mode choice only model (without happiness) using four criteria. First, the goodness-of-fit of the extended model was worse than that of the standard model as indicated by a comparison of the choice log-likelihood of both models. Second, the extended model had more efficient parameter estimates than the standard model. Third, both the extended and standard models had consistent parameter estimates as indicated by a Hausman specification test. Fourth, the forecasts produced by both models were substantially different but had large standard errors which might be attributed to the small sample size.

Two conclusions may be drawn from the empirical illustration of the dynamic framework. First, it is useful to distinguish between different conceptions of utility (remembered and decision utility in this case) and to use appropriate measures of each. Second, these preliminary results indicate that the extended model which includes happiness produces consistent parameter estimates which are more efficient than those of a choice only model, thus demonstrating the benefits of the framework that includes happiness.

As mentioned in Chapter 3, the usefulness of the happiness indicators lies mainly in producing more accurate parameter estimates. They are typically not used in model

application because they don't influence behavior. As such, the quantities of interest that can be derived from the extended model are the same as those obtained in a standard model (value of time, market shares, etc.). However, one can still use the happiness measurement equations to predict satisfaction levels if predictions of utility are available.

Two extensions to the empirical model may be considered. First, the thresholds used in the ordinal happiness regressions were assumed to be constant over participants and over time owing to the small sample size. With larger datasets, the thresholds can be modeled as random parameters (with or without a behavioral model, specifying the thresholds as a function of socio-economic variables for example). Other parameters in the model can also be modeled as random with larger datasets.

Second, the happiness model was developed at an absolute level rather than at a difference level. That is, every happiness measure was used as an indicator of the corresponding utility. One can alternatively model differences between happiness measures (e.g. difference between car and public transportation satisfaction ratings) as indicators of the differences between the corresponding utilities. This would allow testing the idea that people give relative than rather absolute satisfaction judgments.

Chapter 7

Well-Being and Activity-Based Models

In Chapter 4, we introduced a framework that relates activity participation to activity happiness and travel satisfaction. The overriding hypothesis was that activities are planned to maintain and enhance subjective well-being (Ben-Akiva, 2007, 2009a). We estimated models that supported this hypothesis; greater activity happiness and greater travel satisfaction were significantly associated with higher propensity of activity participation. These models considered one activity at a time. In this chapter, we extend the framework to model well-being at the level of an activity pattern (i.e. group of activities) and show how it can be incorporated within activity-based models of travel demand. The proposed framework is an application of the static framework that was developed in Chapter 3 to relate happiness measures to behavior in a static context.

The chapter is organized as follows. Section 7.1 discusses the theoretical basis behind the relationship between activities and well-being and presents empirical evidence supporting this relationship. Section 7.2 reviews activity-based models of travel demand and their specification in practice. Section 7.3 presents a framework for introducing well-being within activity pattern models of the activity-schedule approach and shows examples of well-being measures. Section 7.4 concludes.

7.1   The Relationship Between Happiness and Activities

The idea that happiness or utility varies by activity type can be derived from time allocation theories. As Jara-Díaz et al. (2008) put it, "time assignment theories can make a contribution to a better understanding of individual well-being within the ever evolving work and social environments, as they have since long established theoretical relations among the different values of time... After all, understanding time allocation is just as understanding life itself."

In addition to theoretical studies on time allocation, a number of empirical studies have directly measured happiness by activity type. In this section, we review time allocation models and empirical evidence on happiness and activities.

7.1.1 Time Allocation Models

Time allocation models extend the standard model of consumer demand by explicitly accounting for the time used in consumption. In these models, utility is a function of the time allocated to various goods/commodities/activities in addition to their quantities. This formulation reflects the idea that time itself produces utility or disutility which may vary by good/activity type (e.g. time spent working versus shopping, or time spent traveling in a car versus bus). In addition to the monetary budget constraint, two constraints are added: a time budget constraint reflecting the limited amount of time available for consumption, and time allocation constraints specifying the minimum amount of time (or time requirement) that should be allocated for every activity. The demand that maximizes utility is a function of the prices of goods, the wage rate, the time requirements, and non-labor income. A number of time allocation models that follow this basic structure are available in the literature. One example that closely follows DeSerpa's model (1971) is the model proposed by Bruzelius (1979) and is formulated as follows:

$$\text{Max} \quad U\left(x_1, \ldots, x_J, l, t_1, \ldots, t_J, t_w\right) \tag{7.1}$$

Subject to:

$$\sum_j p_j x_j - w t_w - I \leq 0 \tag{7.2}$$

$$l + \sum_j t_j + t_w - T = 0 \tag{7.3}$$

$$q_j x_j - t_j \leq 0 \qquad j = 1, \ldots, J_1 \tag{7.4}$$

$$q_j x_j - t_j = 0 \qquad j = J_1 + 1, \ldots, J \tag{7.5}$$

where U is the utility, x_j is the quantity demanded of good j, p_j is the price of one unit of j, t_j is the time spent consuming good j, t_w is time spent at work, l is leisure time, w is the wage rate, I is non-labor income, T is the total time budget available, and q_j is the time requirement for good j. Equation (7.2) is the monetary budget constraint. Equation (7.3) is the time budget constraint. Equations (7.4) and (7.5) are the time allocation constraints for unconstrained and constrained goods/activities, respectively, where J_1 is the number of goods that may be allocated more than the minimum required consumption time, and J is the total number of goods.

The marginal value of time saved from the consumption of a good/activity is the ratio of the marginal utility of a reduction in the time requirement to the marginal utility of income. For a given good/activity, this value can be computed as the ratio of the Lagrange multiplier $\left(\gamma_j\right)$ of a time allocation constraint to the Lagrange multiplier (λ) of the monetary budget constraint. Moreover, it can be shown that the marginal value of time saved is related to the value of time as a resource and the value of time assigned to consuming a good/activity as follows:

$$\frac{\gamma_j}{\lambda} = \frac{\mu}{\lambda} - \frac{\partial U/\partial t_j}{\lambda} \tag{7.6}$$

where μ is the Lagrange multiplier of the time budget constraint. $\frac{\mu}{\lambda}$ is the value of time as a resource, and $\frac{\partial U/\partial t_j}{\lambda}$ is the value of time assigned to the consumption of good/activity j and is also known as the value of time as a commodity.

Equation (7.6) implies that the marginal value of time saved depends on the activity conducted or good consumed. The more an activity is enjoyed (i.e. the larger is $\frac{\partial U/\partial t_j}{\lambda}$), the smaller is the value of time savings for this activity. In a travel context, this could reflect for instance different values of time assigned for traveling by car or bus, under crowded or uncrowded conditions, etc.

Jara-Díaz et al. (2008) proposed a similar framework that explicitly separates goods from activities and also includes constraints relating the amounts of goods consumed to pre-specified minimum amounts. Using a Cobb-Douglas utility specification, they derived expressions for optimal time allocation to work and other activities and consumption of goods. They empirically estimated values of work and leisure time using observed data for Swiss, German, and Chilean samples.

For reviews of other time allocation models, see Bruzelius (1979) and Jara-Díaz et al. (2008) and the references therein. For examples of discrete-continuous formulations of activity choice and time allocation, see Kitamura et al. (1996b) and other recent developments described in Bhat (2009) and Kapur and Bhat (2007).

7.1.2 Empirical Evidence

Recently, there has been great interest in studying empirically how happiness varies by activity type and in relating it to the amount of time people spend on different activities. The empirical models of well-being and activity participation that we estimated in Chapter 4 are part of this effort.

Earlier studies used the Experience Sampling Method for capturing emotions in real-time (see, for example, Hektner et al., 2006). More recent studies have used the Day Reconstruction Method (Kahneman et al., 2004), which captures emotions and time use for activities conducted on the previous day. Evidence from this line of research shows that happiness varies significantly by activity type and socio-economic group. Findings from selected studies are described below.

Kahneman et al. (2004) and Kahneman and Krueger (2006) used the Day Reconstruction Method with a convenience sample of employed women from Texas. They found that net affect, defined as the average positive affect minus the average negative affect

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experienced in a given activity episode, was largest for intimate relations and then for socializing after work. Net affect was smallest for the morning commute and then for working.

Krueger (2007) conducted the Princeton Affect and Time Survey which involves a reconstruction of the activities conducted on the day preceding the survey. For every activity, respondents indicated the activity duration and assessed their subjective experiences. Using this survey, Krueger (2007) found that people in his sample were happiest when they conducted engaging leisure and spiritual activities, and were least happy when they conducted unpleasant personal maintenance activities. Using a 2005 time-use survey, he found that people spent about 17% of their day on average doing the former activity and 4% of their day doing the latter activity. Thus, having direct measurements of happiness by activity type is useful for analyzing trends in time allocation in relation to happiness derived from different activities.

Using the 2005 time-use General Social Survey which asked respondents to report their level of liking of different activities, Turcotte (2008) found that Canadian respondents in this sample liked most having supper at home or at a restaurant and liked least cleaning the house and doing grocery shopping.

7.1.3 Chapter Objective

The evidence reviewed above indicates that happiness varies by activity type. Thus, to predict activity choices and subsequently travel choices, it is important to account for well-being when modeling activities and travel. This involves both measurement tools that can capture well-being at the level of an activity pattern (group of activities conducted in a day for example) and methods for modeling activity pattern choices and well-being.

In the remainder of this chapter, we therefore discuss how well-being can be measured at the level of an activity pattern and used to enhance the specification of activity patterns in activity-based models of travel demand. Before presenting our proposed framework and measures, we present a brief review of activity-based models in the next section.

7.2   Activity-Based Models

7.2.1 Overview

Basics of Activity-Based Travel Theory

Activity-based approaches to travel demand modeling are based on the idea that the demand for travel is derived from the demand for activities. These approaches explicitly model activities, trip chaining, and the interdependence among tours. They account for temporal and spatial constraints that limit activity schedule choice. The models usually

have a fine temporal resolution and are consequently better able (compared to four-step travel demand models) to represent complex responses to transportation policies such as congestion pricing.

Classes of Activity-Based Models

Three classes of activity-based approaches characterized by the above features can be distinguished. The first class is based on Markov models that represent the scheduling decision as a sequence of transitions (signifying trips) between states (signifying activities). The second class is rule-based models that use rules to eliminate alternatives and apply utility maximization for modeling the choice among a small number of alternatives. The third class is based on multi-dimensional choice models that employ deterministic choice set generation rules and focus on the representation of utility-based multi-dimensional probabilistic choice. For a review of the features and limitations of each of the three classes of activity-based models, the reader is referred to Bowman (1998). In this chapter, we will focus on the review and development of the third class as it is grounded in consumer theory and based on utility maximization.

Two main approaches that fall within the class of multi-dimensional choice models are the activity-travel simulator (Kitamura et al., 1996a) and the activity-schedule approach (Ben-Akiva et al., 1996). The activity-travel simulator approach is based on sequential scheduling of activities and travel. It decomposes the activity-travel decision into the following dimensions: activity type choice, destination choice, mode choice conditional on destination, and activity duration choice. It generates activities using a detailed representation of spatial and temporal constraints within time-space prisms (Hagerstrand, 1970). The activity-schedule approach is based on simultaneous scheduling of activities and travel. It decomposes the activity-travel decision into two sets of models: an activity pattern model and tour models and also accounts for spatial and temporal constraints but at a less detailed level than the activity-travel simulator. For a discussion of the two approaches, see, for example, Ben-Akiva (2009a). In the remainder of the chapter, we focus on the review and extension of the activity-schedule approach.

Activity-Schedule Approach

Figure 7.1 shows the structure of the activity-schedule approach. The activity pattern model (upper level) sets a schedule for the day; it determines the number, purposes, priorities, and structure of travel and activities. It replaces the trip generation step of four-step models. The tour models (middle and lower levels) determine the destinations, timing, and access modes for activities on the primary and secondary tours. The tour models are conditional on the activity pattern. The choice of activity pattern is in turn sensitive to travel and activity conditions through expected utility arising from the tour models. Discrete choice models based on random utility theory are used for the different components of the model system.

The first applications of the activity-schedule approach were the work done by John Bowman in his master's and doctoral theses (Bowman, 1995; Bowman, 1998; Bowman

and Ben-Akiva, 2001). He empirically demonstrated the approach to Boston, Massachusetts, and to Portland, Oregon. Since then, a number of metropolitan planning organizations in the U.S. and elsewhere have adopted the activity-schedule approach to travel demand modeling. Examples of operational model systems using this approach in the U.S. include the models developed for Columbus, Lake Tahoe, New York, Portland, Sacramento, and San Francisco County. Other model systems currently under development include models for Atlanta, Denver, Jerusalem, Ohio, Oregon, San Francisco Bay Area, Seattle, and Tel-Aviv (see, for example, Bradley et al., 2008 and Rossi et al., 2009).

Activity Pattern

Primary activity/tour type,
Number/purpose of secondary tours

Primary Tours

Timing, destination, and mode

Secondary Tours

Timing, destination, and mode
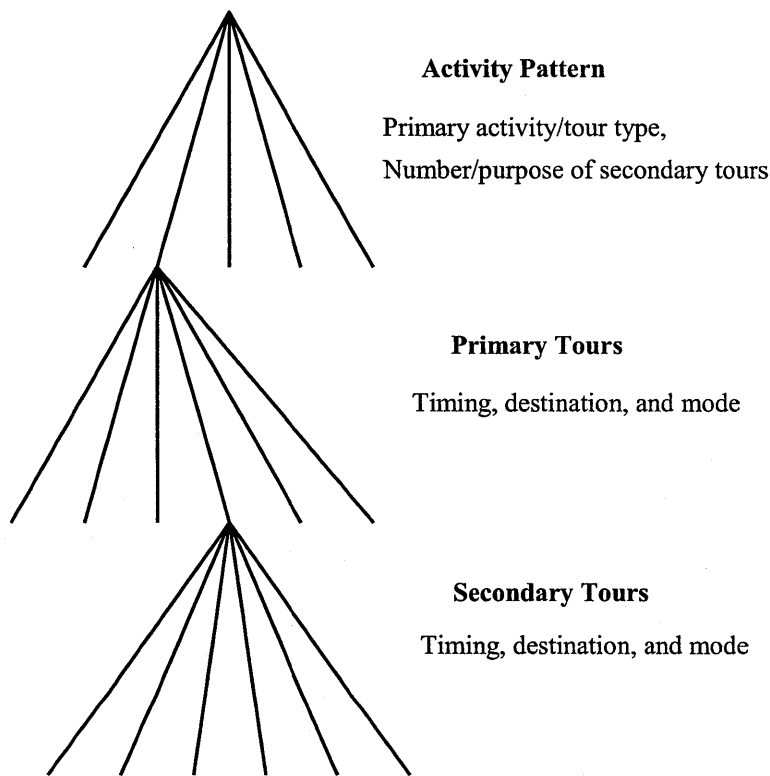
Figure 7.1. Activity-schedule approach (Ben-Akiva et al., 1996; Bowman and Ben-Akiva, 2001)

7.2.2 Formulation of Activity Pattern Models in the Activity-Schedule Approach

We show next the formulation of activity pattern models in the activity-schedule approach. Bowman (1998) specified the systematic utility of a pattern p as consisting of three components: a component $\tilde{V}_p$ for the overall pattern p to capture activity synergy and related time and energy limitations, a component V_a related to every activity a in the

pattern, and a component V_t related to the expected maximum utility of each tour t in pattern p. The systematic utility is therefore given as follows:

$$V_p = \tilde{V}_p + \sum_{a \in A_p} V_a + \sum_{t \in T_p} V_t \qquad (7.7)$$

where A_p denotes the set of activities in pattern p, and T_p denotes the set of tours in pattern p.

The component $\tilde{V}_p$ reflects activity placement options (e.g. which secondary activities occur on which tours, position with respect to the primary activity, and presence of multiple secondary stop placements on primary tours) and inter-tour effects (combination of tour purposes used in the pattern). It depends on lifestyle and mobility variables in addition to attributes of the pattern. The utility component V_a is also a function of lifestyle and mobility variables and is defined for both primary and secondary activities. Finally, the component V_t depends on variables – including the generalized cost of travel – that affect the time of day, mode, and destination attributes of the tours.

In practice, the specification of activity-based models in operational model systems (reviewed in the previous section) strikes a different balance between behavioral realism and complexity (Shiftan and Ben-Akiva, 2008). For example, some models introduce joint decision making through household interactions which is more behaviorally realistic but makes the model more complex. The number of activity purposes and person types and the level of temporal disaggregation also vary among these models.

Perhaps the most striking differences are related to the specification of the activity pattern model. Different model types, including logit and nested logit, have been used. Choice sets of different sizes have been used. For example, the San Francisco County model has 49 alternatives for the pattern choice, while the Portland model has 570 alternatives. The utility functions, formulated as in Equation (7.7), usually combine in ad-hoc ways variables related to mobility, lifestyle, socio-economics, and accessibility.

The main point to be made here is that activity pattern models as they are currently used in practice do not account in a systematic way for the main drivers of activities. As we have argued above, activity patterns are chosen to maintain or enhance well-being. Therefore, including well-being in these models will allow for better behavioral representation of the drivers of activities. One can go even further by explicitly accounting for how various patterns satisfy people's needs differently and relating need satisfaction to well-being. This will not be pursued here, but the reader is referred to Arentze and Timmermans (2009) and Ettema et al. (2009) for discussions about need satisfaction and activities.

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7.3 Well-Being at the Activity Pattern Level

In this section, we discuss how well-being can be incorporated in the specification of activity pattern models in the activity-schedule approach. We also discuss measurement needs.

7.3.1 Modeling Framework

We consider two cases. First, we consider the case where well-being measures are available at the activity pattern level. We show how the standard model formulation is extended by adding measurement equations for the utility of the pattern. Second, we consider the case where in addition to the availability of well-being measures at the activity pattern level, explanatory variables and indicators related to the utility of different components (activities and travel) of the pattern are available. We show how the pattern utility specification is re-formulated.

Well-Being Measures Available at the Activity Pattern Level

We consider the availability of one or more well-being measures at the level of the activity pattern. If the well-being measure is broad enough to consider all aspects of the pattern, then it can be used as an indicator of the pattern utility. The advantage of having this measure is that it provides more information about the utility beyond what is provided by the choice and makes the estimation more efficient.

Since an individual faces a very large number of activity patterns to choose from, it is impractical to collect well-being measures for every activity pattern in the choice set. Therefore, we consider the case where well-being measures are available only for the chosen activity patterns.

Moreover, as noted in Chapter 3, utility is used in discrete choice models in a predictive sense. That is, people make choices based on decision utility (before they actually experience the outcomes). In a static context though, well-being measures reflect remembered utility (after people experience the outcomes) and are therefore imperfect indicators of decision utility. To account for this issue, we consider the availability of a measure of how different the chosen pattern was from prior expectations, and use the well-being measure as an additional indicator of the decision utility of a pattern only if the pattern happened as expected.

Notation

Let U_p denote the total utility of pattern p. y_p is a choice indicator (dummy variable equal to 1 if the chosen pattern is p and equal to 0 otherwise), h_p is a well-being measure associated with pattern p, and E_p is a measure of how different pattern p was

from prior expectations (e.g. $E_p = 1$ if p happened as expected and is 0 otherwise). h_p and E_p are collected for the chosen pattern only.

Formulation

The structural part of the activity pattern model is a specification of activity pattern utility. U_p is specified in the usual way as a function of attributes of the pattern, characteristics of the individual, and an error term (e.g. with the systematic utility specified as in Equation 7.7).

The measurement model consists of the choice and happiness equations specified for every pattern p as follows:

$$y_p = \begin{cases} 1 & \text{if } U_p \geq U_{p'} \quad \forall p' \\ 0 & \text{otherwise} \end{cases} \tag{7.8}$$

$$h_p = h_p(U_p, y_p, E_p) \tag{7.9}$$

Well-Being Measures Available for Individual Components of the Activity Pattern

In addition to the availability of the measures discussed above, we consider the availability of well-being measures for the different components of the activity pattern, such as all activities and travel. Equation (7.7) specifying the systematic utility of an activity pattern can now be re-formulated so that the total utility of a pattern is a function of the utility from all activities and tours on the pattern. Activity utility is a function of the attributes of the activity and characteristics of the individual. Tour utility is a function of the attributes of destinations, modes, and times-of-travel that are available for the tour. The measures of well-being for the overall pattern, for every activity, and for every tour are indicators of the pattern utility, activity utility, and tour utility, respectively.

Notation

Let U_p denote the total utility of pattern p. Let U_{ap} and U_{tp} denote the utility of activity a and tour t, respectively, in pattern p. X_{ap} is the set of attributes of activity a in pattern p, and X_{tp} is the set of attributes of tour t in pattern p. Denote by A_p the number of activities composing pattern p and T_p the number of tours in pattern p. E_p is a measure of how different pattern p was from prior expectations (e.g. $E_p = 1$ if p happened as expected and is 0 otherwise). E_{ap} and E_{tp} are defined similarly for activities and tours, respectively.

Formulation

For an activity pattern p, the structural model is given by Equations (7.10) – (7.12) which specify the utilities of the overall pattern, the activities in the pattern, and the tours in the pattern.

$$U_p = U_p\left(U_{ap}, U_{tp}, X_p; a = 1, \ldots, A_p; t = 1, \ldots, T_p\right) \tag{7.10}$$

$$U_{ap} = U_{ap}\left(X_{ap}\right), \ a = 1, \ldots, A_p \tag{7.11}$$

$$U_{tp} = U_{tp}\left(X_{tp}\right), \ t = 1, \ldots, T_p \tag{7.12}$$

Although we do not specify the exact functional forms, we note that these functions should be flexible enough to allow for complementarities and substitutions across activity types and to represent effects such as satiation and variety-seeking.

The measurement model is given by Equations (7.13) – (7.16). Equation (7.13) is the choice equation, and Equations (7.14) – (7.16) are the happiness equations for the overall pattern, the activities in the pattern, and the tours in the pattern.

$$y_p = \begin{cases} 1 & \text{if } U_p \geq U_{p'} \quad \forall p' \\ 0 & \text{otherwise} \end{cases} \tag{7.13}$$

$$h_p = h_p\left(U_p, y_p, E_p\right) \tag{7.14}$$

$$h_{ap} = h_{ap}\left(U_{ap}, y_p, E_p, E_{ap}\right) \tag{7.15}$$

$$h_{tp} = h_{tp}\left(U_{tp}, y_p, E_p, E_{tp}\right) \tag{7.16}$$

7.3.2 Measurement

At the activity pattern level, a well-being measure that can be used as an indicator of the utility of the pattern should be general enough to capture all aspects of the pattern, including activities and travel. An example of such a measure (h_p in the previous section) is a broad satisfaction question as follows:

Thinking about yesterday, how satisfied were you overall with the way you traveled, the places you went to (including staying at home), and the things you did at these places?

Respondents would answer using an ordinal scale ranging from "Very dissatisfied" to "Very satisfied".

Another question that is specific to the measurement of mood, adapted from the Day Reconstruction Method (Kahneman et al., 2004), is the following.

Thinking overall about how you felt and what your mood was like yesterday, would you say you were most of the time in a bad mood, a little low or irritable, in a mildly pleasant mood, or in a very good mood?

The degree to which the activity pattern happened as expected (E_p in the previous section) can be measured by a question such as:

In most ways, did yesterday's activities (including travel) happen as you had expected?

Respondents could answer on a Yes/No scale or using an ordinal scale expressing their level of agreement with the statement.

The utility of various activities and tours can be measured by satisfaction questions such as:

Taking all things together, how satisfied were you with this activity / tour?

Respondents would answer using an ordinal scale ranging from "Very dissatisfied" to "Very satisfied".

Affective measures of activity and tour happiness can also be obtained by asking respondents to rate the extent to which they experienced certain emotions during the corresponding activity and travel episodes.

7.4   Conclusion

Activity-based modeling has become a widely used approach for modeling travel demand. These models are based on the assumption that the demand for travel is derived from the demand for activities. The purpose of this chapter was to present a framework for incorporating well-being within activity pattern models, starting from the hypothesis that activities are planned to maintain and enhance subjective well-being.

We started by presenting theoretical developments based on time allocation theories and empirical evidence to support the relationship between happiness and activities. Then we provided an overview of the theory of activity-based models and major classes of these models. We focused on one particular method called the activity-schedule approach (Ben-Akiva et al., 1996) which structures the day into an overarching activity pattern and then determines the timing, destination, and modes of tours and trips composing the pattern. We showed how activity pattern models have been specified in ad-hoc ways in practice. We then presented a framework showing how the specification of activity pattern models can be improved by using well-being measures as additional indicators of the utility of the pattern and/or its component activities and travel. We also provided examples of these measures. The proposed framework is an application of the static framework that was developed in Chapter 3 to relate happiness measures to behavior in a static context.

As activity-based models continue to be increasingly adopted by metropolitan planning organizations in the U.S. and elsewhere, the incorporation of well-being measures into

surveys supporting the development of these models will lead to more systematic and behaviorally realistic specifications of these models.

Chapter 8

Conclusion

This chapter concludes the thesis. Section 8.1 summarizes the thesis topic, approach, and main findings. The following sections consider the implications of the activity and travel well-being approach for transportation planning and policy. Section 8.2 discusses implications related to the measurement of subjective well-being given the challenge posed by routine behavior. Section 8.3 discusses transportation policy implications of the well-being approach drawing on findings from the cross-sectional and dynamic analyses conducted in this thesis. Section 8.4 presents directions for future research. Section 8.5 concludes.

8.1   Summary

8.1.1 Motivation, Objectives, and Contributions

The topic of this thesis was motivated by a number of factors including: (i) increasing interest and recent developments in the study of subjective well-being, (ii) limitations in travel behavior models and project appraisal methods that include the time and cost components of travel but often exclude factors related to its quality, and (iii) the interplay between travel and activities which are fundamentally related to subjective well-being.

The guiding philosophy in the development of this thesis was that measures of subjective well-being can be used to enhance behavioral models based on random utility theory. The thesis was concerned with demonstrating this idea in the context of activities and travel and, in doing so, developing methods for activity and travel well-being measurement that can be used for this purpose.

The main contributions of this thesis thus lie in the measurement and modeling of activity and travel well-being. In terms of measurement, we developed a measurement method that can capture well-being under routine versus non-routine conditions and other measures that capture the overall well-being derived from activity patterns. In terms of modeling, we developed a general framework for incorporating happiness measures as indicators of utility within random utility models and demonstrated the framework empirically.

8.1.2 Random Utility and Happiness

We reviewed the origins of random utility theory and presented its criticisms and recent efforts at its enrichment drawing on findings from behavioral research. We then discussed the relationship between happiness and utility and reviewed the distinction among different notions of utility: moment utility (real-time experience), remembered utility (retrospective evaluation), and decision utility (pertinent to decision-making). We argued that happiness broadly defined as satisfaction with all aspects of an experience can be interpreted as utility and measures of happiness or well-being can be used as indicators of utility, but a distinction needs to be made among the different notions of utility. This led us to review relevant findings in the subjective well-being literature and to show how well-being and other behavioral enhancements have started to materialize in travel behavior models.

8.1.3 Conceptual and Modeling Frameworks

We presented conceptual developments to illustrate how an activity and travel well-being approach can be operationalized including measurement methods and related issues. We developed static and dynamic modeling frameworks that represent behavior and well-being, focusing on decision utility as the utility concept that is relevant for modeling behavior. In the static framework shown in Figure 8.1, we incorporated happiness measures which reflect remembered utility as "imperfect" indicators of decision utility. In the dynamic framework shown in Figure 8.2, we further distinguished among the different notions of utility, representing their causal relationships and measuring each of these utilities by appropriate happiness indicators. These frameworks were applied to travel and activities (see next), but they are general and can be applied to modeling behavior in other domains.
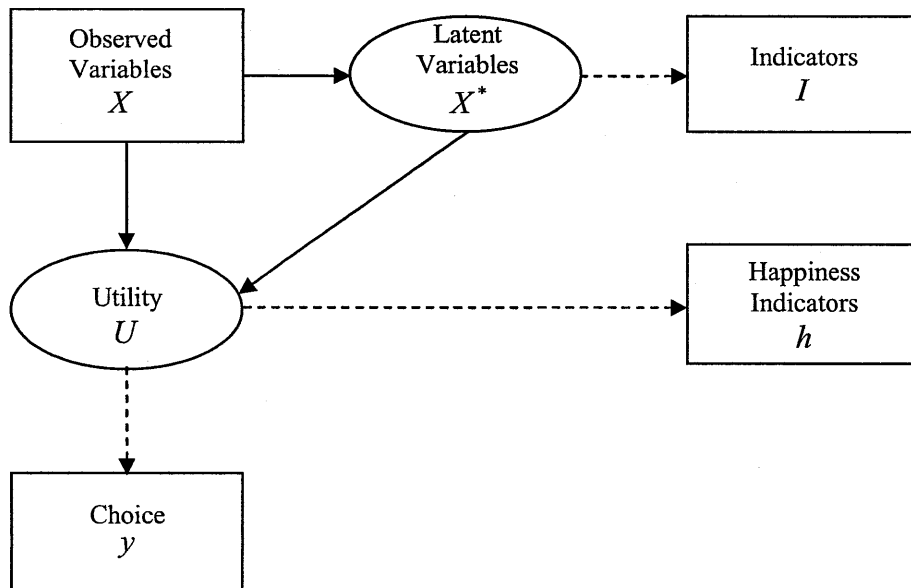
Figure 8.1. Static Hybrid Choice Model with happiness framework.

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Observed / Latent
Variables
X_t , X_t^*

Indicators
I_t

Decision Utility
U_t^D

Indicators
h_t^D

Choice
y_t

$t = t + 1$

Moment Utility
U_t^M

Indicators
h_t^M

Remembered
Utility
U_t^R

Indicators
h_{t+1}^R
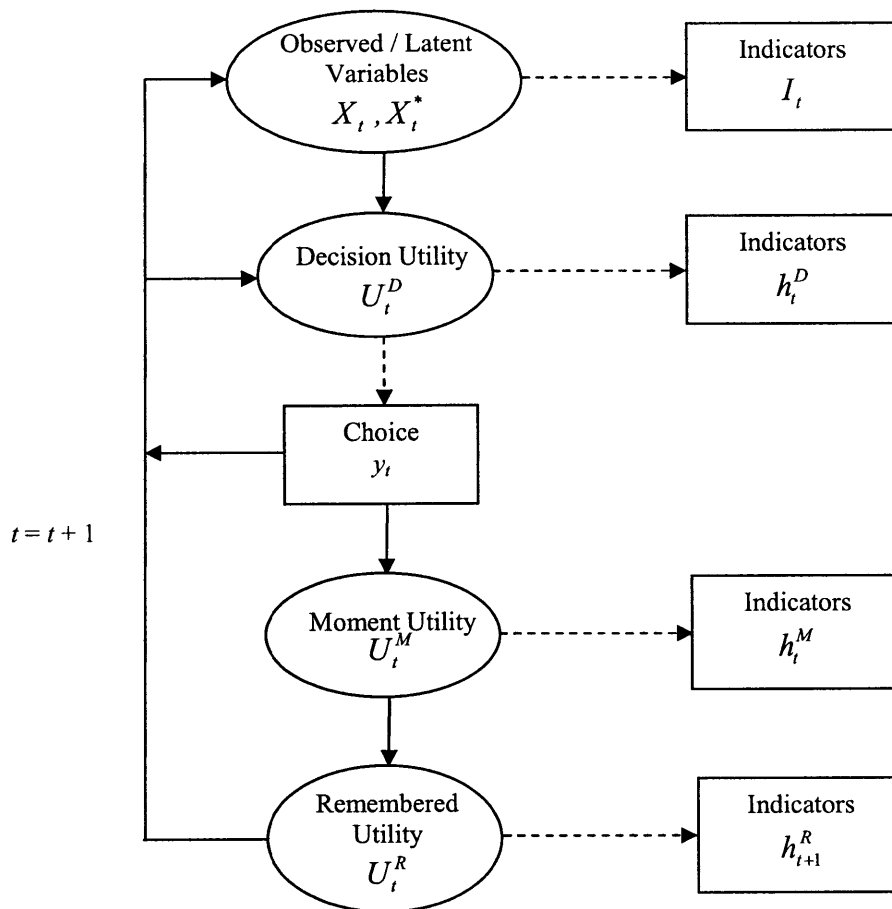
Figure 8.2. Dynamic framework for modeling happiness and behavior shown at one point in time.

8.1.4 Applications

Cross-Sectional Analysis of Travel and Activity Well-Being

We analyzed travel and activity well-being in a cross-sectional or static context. Using a web-based survey, we measured travel and activity well-being of a convenience sample of commuters that use car, public transportation, or non-motorized modes for their commute to work. We developed a model of commute satisfaction and found that commute satisfaction is related to (i) affective factors such as commute enjoyment and stress that are determined by commute attributes, including travel time, travel time variability, congestion, and walking/biking beside traffic (ii) individual characteristics such as personality and overall well-being, and (iii) comparison to others' commutes and to past commuting experiences. We also found significant correlations between well-being and behavior. Using the same survey, we developed models of activity participation as a function of activity happiness and travel satisfaction. We found for

different types of activities that higher propensity of activity participation was positively and significantly related to activity happiness and travel satisfaction.

Dynamic Analysis of Travel Well-Being

We measured and modeled travel well-being in a dynamic context. We postulated that due to the routine nature of travel, people are unlikely to fully think about their travel happiness unless they need to reconsider their options and decisions. We anticipated that the measures of travel well-being collected under routine conditions (such as in a cross-sectional survey) will be different from those collected under non-routine conditions when people are making new decisions; the pre-treatment measure reflects remembered utility while the post-treatment measure reflects decision utility. To test this hypothesis, we conducted experiments in Switzerland and at MIT that aimed at getting travelers temporarily out of their commuting routines, thus inducing them to reconsider their decisions and think about their travel happiness. In particular, participants who habitually commuted by car agreed to commute temporarily by public transportation and were given free public transportation passes as an incentive. We measured their travel happiness, mode choice, perceptions, and attitudes before (routine) and after (non-routine) this intervention (or treatment). In both the Swiss and MIT experiments, participants reported significantly different levels of satisfaction with their commute by car pre- and post-treatment (with an overall trend of higher levels of car satisfaction post-treatment), supporting the study hypothesis. In the Swiss case, none of the participants switched completely to public transportation but some continued to use it occasionally post-treatment. At MIT, about 30% of participants switched to commuting by public transportation post-treatment.

We used the data collected in these dynamic contexts to illustrate the dynamic modeling framework linking travel well-being and behavior. The framework consisted of a mode choice model combined with three happiness equations expressing pre-treatment car satisfaction, post-treatment car satisfaction, and post-treatment public transportation satisfaction ratings as a function of pre-treatment car remembered utility, post-treatment car decision utility, and post-treatment public transportation decision utility, respectively.

In the Swiss case, we modeled mode choice on a given day using travel diary data collected in a post-treatment week. In the MIT case, we modeled usual mode choice (i.e. the post-treatment decision to keep a full-time parking permit or cancel it). The estimation results for the Swiss data produced some counterintuitive coefficients, possibly owing to the small sample size of 28 participants. The MIT results, using a larger sample of 67 participants, were intuitive and showed that (i) utility is positively correlated with level of satisfaction thus showing the validity of happiness measures as indicators of utility, (ii) participants' satisfaction ratings were determined by non-monetary aspects of the commute experience, and (iii) the extended model with happiness fit the choice data worse than a model without happiness, but the extended model coefficients were consistent with those obtained in a mode choice only model yet more efficient, thus demonstrating the benefits of the extended framework. A model

estimated using the combined Swiss and MIT data produced similar conclusions to those reached using the MIT data alone.

Activity Patterns

After the empirical demonstrations, we presented theoretical developments related to the measurement and modeling of activity well-being at the level of activity patterns as an application of the static modeling framework of well-being and behavior. We postulated that activities are planned to maintain or enhance subjective well-being. Measuring well-being at the level of activity patterns can then potentially lead to the enhancement of activity-based models of travel demand. We reviewed activity-based models and argued that activity pattern models have been specified in ad-hoc ways in practice as a function of accessibility, mobility, and lifestyle variables. We presented modeling frameworks that include measures of activity pattern well-being as indicators of the utilities of those patterns, and provided examples of these measures that can be incorporated in activity-travel household surveys.

8.1.5 Benefits of the Well-Being Approach

This thesis has demonstrated that a well-being based approach to modeling activities and travel has the potential to enhance these models compared to an approach that does not account for well-being.

The empirical analysis of activity and travel well-being showed that (1) well-being matters for activity choices. Accounting for well-being will result in a better prediction of activity choices and consequently travel behavior, and (2) random utility models with happiness measures used as indicators of utility are more efficient than models that do not include happiness measures.

The theoretical framework, supported by the dynamic empirical analysis, also points to the usefulness of distinguishing among different notions of utility and capturing each of them through appropriate happiness measures. This has implications for the measurement of well-being as described in Section 8.2.

Finally, although not studied in this thesis, the analysis of activity and travel well-being has implications for policy design and project appraisal. The policy implications of the analyses conducted in this thesis are briefly discussed in Section 8.3.

8.2   Measurement Implications

We postulated that routine and non-routine measures of subjective well-being are different because they are based on different considerations and reflect different notions of utility. Under non-routine conditions, people may reconsider their decisions and think more fully about their happiness than under routine conditions where decisions are

automatic. Non-routine happiness measures reflect decision utility while routine happiness measures reflect remembered utility. The experiments conducted in Switzerland and at MIT in the context of commuting to work supported this hypothesis.

However, for most of the time, people are not making new decisions. For example, in the context of travel, decisions on car and public transportation pass ownership and commute mode are generally medium to long term decisions, and so travelers are likely to be in a routine most of the time. The question then is how to assess people's well-being at any given point in time when the majority is in a routine.

Drawing on the dynamic framework that distinguishes among different notions of utility and the empirical findings from the Swiss and MIT experiments, one can argue that different happiness measures capture different things. So the happiness measure to use depends on the measurement objective.

If the measurement objective is to assess quality of life generally, measures of remembered utility captured under routine conditions may be used. For example, in the context of travel, the standard travel satisfaction question that asks people how satisfied they are overall with their travel will be useful even under routine conditions. As we saw in Chapter 4, this cross-sectional measure of well-being was correlated with a number of factors that are generally expected to affect satisfaction, such as travel time, travel time variability, and congestion.

If the measurement objective is to provide real-time policy interventions, measures of moment utility captured through self-reported or physiological means will be useful. For example, in the context of driving, real-time physiological measures that indicate drivers' states of stress are useful for providing real-time solutions to drivers that can help them manage their workload and stress. Physiological measurements will become easier to capture with advances in vehicle systems equipped with cameras and stress monitors, but will remain more difficult to collect regularly for non-auto travel.

If the measurement objective is to assess well-being so as to model behavior, measures of decision utility captured after people have carefully thought through all the available options may be used. A natural way to obtain such measures of well-being is to follow people through periods of change associated with new decisions they need to make, such as residential relocation or job changes, and conduct well-being surveys during such periods. However, this may be difficult to achieve in practice on a large-scale basis. Certain major changes in the system of interest could provide an opportunity for reconsideration of decisions for a large segment of the population. Well-being can then be measured at these moments in time. For example, in the context of travel, Gray (1991) reported that due to the closing of the San Francisco - Oakland Bay Bridge in 1989 after an earthquake, "it became necessary for the 80,000 workday morning peak-period drivers that had been using the bridge to reassess their travel." The majority used the San Francisco Bay Area Rapid Transit System (BART) during the disruption, and a large fraction continued to use it several months later.

Other interventions that do not require naturalistic changes in people's lives or in the system of interest can be used to obtain measures of decision utility. The dynamic Swiss and MIT experiments requiring a temporary switch to public transportation in return for free public transportation tickets is an example of such interventions. Another example that does not require a temporary change in behavior is to induce people to think more carefully about their well-being by means of the survey design. For example, they can be presented with hypothetical scenarios involving choices among various alternatives in a way that "requires" them to think about the pros and cons of various options. Or, in the context of travel, they can be asked to record mobility biographies (Axhausen, 2008) with details about previous major mobility-related decisions they had made, also potentially invoking a recall of various alternatives they had faced when making previous travel choices. The travel satisfaction question can then be asked after using such techniques to measure people's satisfaction with alternatives they are currently facing. These manipulations through the survey design to obtain measures of decision utility may be worth testing in future research. However, one caveat of using hypothetical scenarios in surveys to obtain measures of decision utility is that if people are asked about their satisfaction with various alternatives, they may mispredict how happy they will be with options they have little or no experience with as well as the extent of their adaptation to these options (see, for example, Loewenstein and Angner, 2002, for a discussion of the issue of misprediction of adaptation in the public health domain in the context of allocating resources to medical interventions).

8.3   Policy Implications

Happiness researchers have been advocating the use of happiness measures to inform policy. Diener and Seligman (2004) argue that well-being measures should be used alongside economic indicators to inform policies at many levels, such as those at the workplace and those related to mental disorders. They go on to propose creating a national well-being index that can systematically monitor people's well-being. Dolan and White (2007) cite a number of areas where subjective well-being measures can be used to inform policy, such as in the valuation of costs and benefits that are hard to quantify (e.g. noise and pollution) and in setting policy defaults.

Measures of activity well-being can be used to inform policies that aim at making people's experiences more enjoyable. For example, measures of work activity happiness can be used to inform policies that improve people's affective states and consequently their productivity at the workplace. Measures of travel well-being can also be used to inform transportation and urban design policies. A recent article in the Boston Globe (Bennett, 2009) discusses how happiness data can be used to influence where people live:

> The trade-off between house size and commute length is familiar to every suburbanite, but as Cornell economist Robert Frank has pointed out, the two things affect our mood in different ways. While we quickly adapt to a bigger house and start taking it for granted, research suggests that a long, trafficky commute is something we never adjust to, and that even grows more onerous with

time. Work like this could give added heft to arguments for policy measures like higher gas taxes, and for zoning laws that concentrate housing and cut down on traffic and commuting distances - arguments that now tend to be cast chiefly in environmental terms, but which also might push people toward decisions that make them happier in the long term.

This and other potential policies benefit from research that quantifies the effects of various factors on activity and travel well-being. Both the cross-sectional and dynamic analyses conducted in this thesis have implications for the design of policies that aim at enhancing travel well-being.

8.3.1 Implications of the Cross-Sectional Analysis

In the cross-sectional analysis, a number of commute attributes were significantly correlated with commute stress and satisfaction. Policies could try to affect these attributes (or the perception of these attributes) so as to enhance people's well-being. For example, it was found that travel time variability is a significant cause of commuting stress. As travelers would benefit from lower anxiety, it would be desirable to have Intelligent Transportation Systems in place that can reduce travelers' uncertainty and stress by providing real-time information about traffic conditions.

Another finding was that commute satisfaction affects work well-being, as has been found in other studies examining the spillover effects between these two domains. Organizations can play an active role in providing conditions that make the commute more pleasant or less onerous to their employees. This could include policies such as telecommuting and flexible working hours (e.g. to reduce commuting in rush hours) and organizing carpooling arrangements for those whose commutes are very stressful.

8.3.2 Implications of the Dynamic Analysis

We discuss two implications of the dynamic analysis. The first one relates the availability of travel options to well-being, and the second looks into the relevance of satisfaction and other psychological factors for mode switching.

The Value of Having Travel Options

Regardless of the outcome of the dynamic experiments described in this thesis (i.e. mode switching decision), we believe that the mere experience of the non-habitual mode increases people's travel well-being as it makes them more aware of the options they have. If they decide to continue commuting by car, then they are probably more convinced of the choice they had made earlier yet more aware that they have public transportation available to them if they decide to use it occasionally. Several comments from MIT participants who didn't switch to public transportation support this observation explicitly or implicitly (An example of a quote from an MIT participant who didn't switch to public transportation is the following: *"The September free pass was a great*

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way to get me to start thinking about using public transportation more. I may not change my ways overnight, but am thinking more about using the bus.").

If, on the other hand, people decide to switch to public transportation for their commute, then they have probably done so because they think it is better for them (An example of a quote from an MIT participant who switched to public transportation is the following: "*My commute to MIT used to drive me crazy every single day. Now that I take the train, my mood has gotten better, I have time to think, read or engage in other activities I didn't have time for before; I'm on time to pick up my daughter in the afternoon and I'm saving big money in gas.*").

Data from the experiments also support this observation. When asked how their happiness about the decision to commute by car has changed post-treatment, two thirds of Swiss participants stated post-treatment that they became happier about their decision to use the car for commuting. Only 2 out of 30 participants stated that they became less happy. In the MIT experiment, around 45% of participants stated after the treatment that they became happier with their commute (regardless of whether they switched to public transportation) compared to the pre-treatment period. Only 3 out of 67 participants stated that they became less happy.

The policy implication is that providing travelers with easier access to unfamiliar options (for example, through monetary incentives such as free tickets or through information) may enhance their well-being in two ways: by making them aware of other options in their choice set that could be used occasionally and by helping them reconfirm earlier decisions they had made. There are some caveats though. Factors such as hedonic adaptation and potential regret may reduce the intensity of increases in well-being in the longer term. Moreover, research on subjective well-being has shown that sometimes not having options makes people happier as it allows them to enjoy the choice they have made instead of constantly being reminded that they could choose otherwise (Gilbert, 2006). These factors were not explored in this thesis except for a brief analysis of treadmill effects which showed different patterns in the Swiss and MIT experiments. In the Swiss experiment, we found evidence for a treadmill effect through the follow-up conducted with the participants several months post-treatment, whereby participants' reported happiness with the commute by car several months post-treatment was close to the pre-treatment reported happiness (although it cannot be determined whether this pattern reveals a true change in experienced well-being or a change in comparison standards). In the MIT experiment, we did not find evidence for a treadmill effect; reported happiness with the commute by car kept increasing several months post-treatment.

Satisfaction, Psychological Factors, and Mode Switching

As reviewed in Chapter 5, studies aiming at behavioral modification through the provision of information or incentives or the formation of commitments have generally been successful to a certain extent in influencing behavior and/or influencing perceptions and attitudes. The experiments conducted in this thesis contribute to the findings in the

behavioral modification literature. A number of participants undergoing the treatment switched to public transportation post-treatment, continued to use it occasionally, and/or changed their perceptions and attitudes towards it.

Moreover, we found evidence for some key findings on satisfaction in the marketing literature. First, satisfaction was correlated with behavior. Participants who switched to public transportation or who were more likely to use it in the future were on average more satisfied with their public transportation experience than those who didn't switch. Second, satisfaction with the public transportation experience was affected by how different the experience was from prior expectations. Participants who had better than expected experiences were more greatly satisfied with public transportation than those who had worse than expected experiences.

These findings on the interplay between psychological factors (including satisfaction) and behavior are relevant for organizations and public transportation agencies trying to induce behavioral modification from car to public transportation. For example, public transportation agencies seeking to attract non-users should try to improve those aspects of service that have the greatest influence on satisfaction, including both monetary and qualitative factors. A large literature on public transportation service quality and market segmentation has discussed the relevance of "soft" attributes (such as comfort, convenience, safety, etc.) as well as attitudinal and perceptual factors in influencing satisfaction with service and subsequent mode choice decisions (see, for example, Proussaloglou et al., 2001; TCRP Report Number 47, 1999; Zhou et al., 2004). Litman (2008a) argues that attracting car commuters towards alternative modes of travel will require improving the quality of those modes. He refers to studies indicating that a portion of car commuters will switch to public transportation if it is comfortable and convenient.

We conclude this section by summarizing suggestions given by the participants (as qualitative comments) as a way of decreasing the reliance on the car for commuting. These are not solutions endorsed by us but rather a reflection of the issues involved from the perspectives of the participants. Swiss participants were amenable to using public transportation more if certain aspects of the service were improved. In addition, they proposed alternatives such as carpooling arrangements, telecommuting, and policies encouraging drivers to use more energy efficient cars. MIT participants suggested solutions that MIT could adopt to make the switch from car to public transportation or other environmental-friendly means more attractive. Among these ideas are a four-day work week, having more central pick-up locations where employees could take a shuttle to the Institute, identifying parking areas that are safe and approved for leaving cars to encourage carpooling, pairing up drivers who commute from the same area, basing the cost of parking on individual salaries and on distance from work, and having a more flexible mobility offer that encourages people to drive less without necessarily being considered full-time users of public transportation. The latter idea comes from a perception of the MIT mobility offer as too rigid: employees are either allowed to have a full-time parking permit or get a subsidized public transportation pass (with or without occasional parking permit that allows parking for up to 8 days per month). An

intermediate mobility offer which allows a more varied multimodal mix and could charge on a per-use basis can work better for certain commuters (see, for example, the mobility pass concept described in Block-Schachter, 2009).

8.4   Future Research Directions

This thesis has developed new methods for measuring activity and travel well-being and a new approach for modeling well-being within random utility models. To a large extent, the methods are exploratory and the findings are preliminary and would benefit from deeper inquiry into a number of measurement and modeling issues, and will eventually be valuable for project appraisal methods that account for well-being.

8.4.1 Measurement

A number of extensions can be considered to enhance the measurement of travel well-being.

First, the sample sizes used in the dynamic analysis in this thesis were very small. Larger scale experiments are needed to validate the differences between the routine and non-routine measures of well-being found in our small scale experiments. Larger experiments will also be useful for allowing more robust designs that include both treatment and control groups, which was not possible with the small samples that volunteered for our study.

Second, different measures of travel well-being should be explored and other response scales should be experimented with (for instance, 7-point and 11-point scales as in some other subjective well-being surveys). Our dynamic analysis focused for the most part on the measurement of satisfaction using a single measure. Multiple measures will ease the identification of models estimated with these datasets. Related to this is the fact that these happiness measurements were obtained for a given fixed treatment. Some factors that were fixed in the treatment can be varied in future research as discussed in Chapter 5 (such as treatment period length, type of treatment, time of the year, etc.).

Third, as revealed in the models estimated using the MIT data, participants' satisfaction ratings appeared to measure their affective non-monetary experiences. The satisfaction questions asked post-treatment were *"Taking all things together, what is your level of satisfaction with a car (or public transportation) commute between your residence and MIT?"* The finding that participants didn't seem to factor in costs when they answered this satisfaction question suggests that potentially other measures that induce people to think about the costs of their travel should be tested in future research.

Fourth, as previously mentioned, naturalistic interventions such as changes in personal circumstances and transportation conditions can be tested as alternative and perhaps more realistic ways of measuring travel happiness in a dynamic context.

Regarding activity well-being, the validity of the measures proposed for capturing well-being at the activity pattern level should be tested empirically in activity-travel household surveys.

8.4.2 Modeling

A number of extensions will also be useful to support the modeling frameworks developed in this thesis.

First, the model specifications used in the dynamic analysis were limited by the nature of the data collected and the sample size to a consideration of only the effects of time and cost on the utilities of different modes. Larger scale experiments and a larger number of indicators will provide an opportunity for modeling the effects of "soft" factors such as comfort, reliability, and convenience on well-being and behavior. With larger scale experiments, one can also try to measure and account for pro-social and altruistic attitudes and their effects on mode switching and happiness. Another limitation of the small sample size is that the thresholds, which set the happiness scale of the model, and other model parameters were fixed over individuals. Larger sample sizes will allow modeling these parameters as randomly distributed.

Second, although we qualitatively discussed potential reasons for the differences between happiness ratings under routine and non-routine conditions and incorporated them as indicators of remembered and decision utility, we did not explicitly model behavioral processes driving the differences among various happiness measures. This is an interesting extension of this work and may involve testing hypotheses such as the hedonic treadmill or the satisfaction treadmill (and scale norming). It would require collecting additional measures of travel well-being and behavior at multiple time points after the treatment.

Finally, when measuring well-being in a cross-sectional context, one of the issues that arises (as discussed earlier) is that the happiness judgment, given after the choice had been made, is an indicator of remembered utility while the choice is an indicator of decision utility. The happiness measure is thus an imperfect indicator of decision utility in a cross-sectional context. We have suggested a method for addressing this issue by collecting measures of how different the experience was from expectations, but this should be tested empirically.

8.4.3 Project Appraisal and Policy

One of the motivating factors for this research was limitations in the quantification of benefits in transportation project appraisal methods. Benefits are usually quantified as the travel time savings multiplied by the value of time if demand is assumed to remain constant. If demand is assumed to change (e.g. due to induced travel), consumer surplus is approximated by calculating the change in the area under the demand curve (versus generalized cost) using a linear approximation (Meyer and Miller, 1984). Benefits from

improvements in qualitative travel attributes are usually not accounted for. Moreover, project appraisal methods generally do not account for the well-being of non-users who may simply benefit from the availability of transportation options brought along by transportation projects even if they don't use them. Addressing these limitations in project appraisal was beyond the scope of this thesis but is an exciting direction for future research.

The quantification of benefits may be better informed through the use of happiness research. First, utility-based measures of consumer surplus (such as the use of the logsum variable as a measure of accessibility) can also be used to evaluate benefits (Ben-Akiva and Lerman, 1985). The use of happiness measures as indicators of utility results in better estimation of the utility and consequently in more reliable measures of the benefits of transportation projects (compared to the standard evaluation of benefits as described above). Second, direct measures of benefits could be obtained by asking people about their happiness with various transportation alternatives (including the project under consideration). Happiness with various attributes of these alternatives could be measured through stated preferences surveys.

Accounting for qualitative factors will require incorporating these factors in demand models and then estimating the willingness to pay for changes in these factors, along with the willingness to pay for travel time savings. This will require a deeper understanding and quantification of factors determining the quality of travel, particularly with advances in information and communication technologies that are reshaping our travel experiences (e.g. use of in-vehicle time to conduct activities).

Finally, non-users' preferences and well-being can also be measured through stated preferences surveys for instance. Accounting for the well-being of non-users will require an understanding of how their preferences for transportation investments compare to those of users and how both should be weighted in the quantification of benefits (see, for example, Loewenstein and Angner, 2002, for a discussion of differences between the preferences of patients and healthy people for the allocation of resources in the public health domain).

8.5   Conclusion

Drawing on subjective well-being research, this thesis has contributed to efforts aiming at increasing the behavioral richness of random utility models with applications to activities and travel. We have outlined the measurement and policy implications of this research and directions for future research on well-being covering the aspects of measurement, modeling, and project appraisal. We anticipate that the methods developed in this research will also be appealing in non-transportation contexts, particularly in the services sector.

We have illustrated the potential benefits of the well-being approach to modeling behavior, but how much of a difference the approach will practically make will need to

be further investigated with larger datasets than those used in this research and with potentially other applications.

Appendix A

Well-Being Questions in the Cross-Sectional Survey

This appendix contains the well-being questions that were used in the cross-sectional activity and travel well-being survey. Section A.1 presents the commute well-being questions. Section A.2 presents the activity happiness and travel satisfaction questions. Section A.3 presents the life and domain satisfaction questions. The full questionnaire can be obtained from the author upon request.

A.1 Commute Well-Being Questions

Taking all things together, how satisfied would you say you are with your commute from home to work?

Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
☐	☐	☐	☐	☐

Please indicate your level agreement with the following statements regarding how you feel about your commute.

I enjoy my commute.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
☐	☐	☐	☐	☐

My commute makes me feel:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Stressed out	☐	☐	☐	☐	☐
Anxious	☐	☐	☐	☐	☐
Tired / drowsy	☐	☐	☐	☐	☐
Angry / frustrated	☐	☐	☐	☐	☐
Impatient / intolerant	☐	☐	☐	☐	☐

I view my commute as a useful and needed transition between home and work.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
☐	☐	☐	☐	☐

My commute gives me valuable private time.

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
☐	☐	☐	☐	☐

Please think about a person in your metropolitan area and whose commute you are familiar with. This person could be your friend, colleague, neighbor, family member, etc.

On average, compared to this person's commute, your commute is:
- ☐ Much more stressful
- ☐ Somewhat more stressful
- ☐ As good/bad as his/her commute
- ☐ Somewhat less stressful
- ☐ Much less stressful
- ☐ Don't know

Please think about the commute you had previously (from a different residential location, to a different job, by a different mode of transportation or route, etc.). This previous commute can be for work or school as long as you were at least 18 years old. Skip this question if you didn't have a previous commute.

Compared to your previous commute, your current commute is:

- ☐ Much more stressful
- ☐ Somewhat more stressful
- ☐ As good/bad as your previous commute
- ☐ Somewhat less stressful
- ☐ Much less stressful
- ☐ Don't know

A.2 Activity Happiness and Travel Satisfaction Questions

How happy do you feel when you conduct the following activities?

	Very unhappy	Unhappy	Neither happy nor unhappy	Happy	Very happy
Work	☐	☐	☐	☐	☐
Shopping	☐	☐	☐	☐	☐
Personal business (e.g. banking, errands, etc.)	☐	☐	☐	☐	☐
Eating out	☐	☐	☐	☐	☐
Social and recreational (e.g. visiting friends, going to the movies, sports and hobbies, etc.)	☐	☐	☐	☐	☐
Organizational, volunteer, or religious	☐	☐	☐	☐	☐
At home activities	☐	☐	☐	☐	☐

How satisfied are you with your _travel_ to these activities?

	Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
Shopping	☐	☐	☐	☐	☐
Personal business (e.g. banking, errands, etc.)	☐	☐	☐	☐	☐
Eating out	☐	☐	☐	☐	☐
Social and recreational (e.g. visiting friends, going to the movies, sports and hobbies, etc.)	☐	☐	☐	☐	☐
Organizational, volunteer, or religious	☐	☐	☐	☐	☐

A.3 Life and Domain Satisfaction Questions

How satisfied are you today with the following areas of your life?

	Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
Your life overall	☐	☐	☐	☐	☐
Your health	☐	☐	☐	☐	☐
Your work	☐	☐	☐	☐	☐
Your residence	☐	☐	☐	☐	☐
Your free time	☐	☐	☐	☐	☐
Your family life	☐	☐	☐	☐	☐
Your social life	☐	☐	☐	☐	☐

Appendix B

Additional Estimation Results Related to the Cross-Sectional Activity and Travel Well-Being Survey

This appendix presents additional estimation results related to the models presented in Chapter 4. Section B.1 presents results related to the commute satisfaction model, and Section B.2 presents results related to the activity participation models.

B.1 Commute Satisfaction Model

Table B.1 shows the measurement and threshold model parameters, variances, residual variances, and correlations for the commute satisfaction model described in Chapter 4.

Regarding the measurement equations, every latent variable's scale is fixed by setting the factor loading for one of its indicators to 1. As expected, we find that work well-being loads positively on work satisfaction and happiness at work. Commute stress loads positively on the stress and anxiety indicators. Commute enjoyment loads positively on the enjoyment, buffer, and privacy indicators. The organized personality factor loads positively on the planning and timeliness indicators; overall well-being loads positively on life, residence, and social life satisfaction.

Each of the categorical indicators has five categories (ranging from "Strongly disagree" to "Strongly agree" or from "Very dissatisfied" to "Very satisfied"), and therefore four thresholds are estimated for every indicator. Most of the thresholds are significant. The thresholds can be interpreted as scales for the corresponding latent response variables. Their values are different for different latent response variables, but are relatively close for similar latent response variables (see, for example, the thresholds for the planner and on time equations, and those for work satisfaction, life satisfaction, residence satisfaction, and social life satisfaction).

The values of the variances and residual variances can be interpreted in terms of the fit of the structural and measurement equations. The estimation software Mplus reports R-

squared measures for these equations defined as the ratio of estimated explained variance to estimated total variance. All equations had a reasonable fit (smallest R-squared = 0.241 for the Buffer measurement equation, and largest R-squared = 0.966 for the Commute Stress measurement equation).

There is a positive and significant correlation between commute enjoyment and each of organized personality, overall well-being, and intrapersonal comparative happiness. Moreover, organized personality and overall well-being are positively correlated as might be expected. The correlations of intrapersonal comparative happiness with organized personality and overall well-being are insignificant.

Table B.1. Measurement and threshold model, variances, residual variances, and correlations estimation results for the commute satisfaction model.

Parameter	Estimate	t-stat
Measurement Equations		
Commute satisfaction		
Commute satisfaction	1.00	-
Work well-being		
Work satisfaction	1.00	-
Work activity happiness	0.811	14.59
Commute stress		
Commute stress	1.00	-
Commute anxiety	0.824	19.04
Commute enjoyment		
Commute enjoyment	1.00	-
Buffer	0.617	11.70
Privacy	0.707	12.61
Social comparative happiness		
Less stress than other	1.00	-
Intrapersonal comparative happiness		
Less stress than before	1.00	-
Organized personality		
Planner	1.00	-
On time	1.25	6.37
Overall well-being		
Life satisfaction	1.00	-
Residence satisfaction	0.637	12.32
Social life satisfaction	0.672	13.22

Table B.1 (cont.). Measurement and threshold model, variances, residual variances, and correlations estimation results for the commute satisfaction model.

Parameter	Estimate	t-stat
Thresholds		
Commute satisfaction		
τ_{11}	-3.12	-10.92
τ_{12}	-2.39	-8.60
τ_{13}	-1.66	-6.03
τ_{14}	-0.182	-0.67
Work satisfaction		
τ_{21}	-1.69	-5.57
τ_{22}	-0.791	-2.80
τ_{23}	-0.0368	-0.13
τ_{24}	1.38	4.91
Work activity happiness		
τ_{31}	-2.34	-7.43
τ_{32}	-1.59	-5.40
τ_{33}	-0.247	-0.86
τ_{34}	1.45	4.96
Commute stress		
τ_{41}	0.178	0.57
τ_{42}	1.42	4.42
τ_{43}	2.00	6.21
τ_{44}	3.45	9.53
Commute anxiety		
τ_{51}	0.0471	0.16
τ_{52}	1.21	3.94
τ_{53}	1.97	6.39
τ_{54}	3.11	9.10
Commute enjoyment		
τ_{61}	-3.48	-10.76
τ_{62}	-2.37	-7.73
τ_{63}	-1.32	-4.44
τ_{64}	0.0696	0.24
Buffer		
τ_{71}	-2.15	-7.20
τ_{72}	-1.32	-4.67
τ_{73}	-0.826	-2.95
τ_{74}	0.647	2.34
Privacy		
τ_{81}	-1.67	-5.86
τ_{82}	-0.676	-2.37
τ_{83}	-0.107	-0.38
τ_{84}	1.04	3.66

Table B.1 (cont.). Measurement and threshold model, variances, residual variances, and correlations estimation results for the commute satisfaction model.

Parameter	Estimate	t-stat
Thresholds (cont.)		
Less stress than other		
τ_{91}	-1.07	-3.25
τ_{92}	-0.307	-0.96
τ_{93}	0.625	1.98
τ_{94}	1.36	4.21
Less stress than before		
$\tau_{10\text{-}1}$	-1.68	-5.29
$\tau_{10\text{-}2}$	-0.899	-2.90
$\tau_{10\text{-}3}$	-0.302	-0.99
$\tau_{10\text{-}4}$	0.256	0.84
Planner		
$\tau_{11\text{-}1}$	-2.18	-6.19
$\tau_{11\text{-}2}$	-1.05	-3.41
$\tau_{11\text{-}3}$	-0.417	-1.38
$\tau_{11\text{-}4}$	1.27	4.15
On time		
$\tau_{12\text{-}1}$	-2.19	-5.67
$\tau_{12\text{-}2}$	-1.15	-3.63
$\tau_{12\text{-}3}$	-0.579	-1.85
$\tau_{12\text{-}4}$	1.06	3.35
Life satisfaction		
$\tau_{13\text{-}1}$	-2.27	-6.70
$\tau_{13\text{-}2}$	-1.44	-4.96
$\tau_{13\text{-}3}$	-0.738	-2.54
$\tau_{13\text{-}4}$	1.08	3.74
Residence satisfaction		
$\tau_{14\text{-}1}$	-1.72	-4.62
$\tau_{14\text{-}2}$	-0.980	-2.97
$\tau_{14\text{-}3}$	-0.341	-1.06
$\tau_{14\text{-}4}$	1.19	3.68
Social life satisfaction		
$\tau_{15\text{-}1}$	-1.75	-5.77
$\tau_{15\text{-}2}$	-0.697	-2.46
$\tau_{15\text{-}3}$	-0.0190	-0.07
$\tau_{15\text{-}4}$	1.39	4.92

Table B.1 (cont.). Measurement and threshold model, variances, residual variances, and correlations estimation results for the commute satisfaction model.

Parameter	Estimate	t-stat
Variances		
Commute enjoyment	0.633	11.35
Intrapersonal comparative happiness	1.00	-
Organized personality	0.445	5.94
Overall well-being	0.864	13.32
Residual Variances		
Commute stress	0.950	18.69
Social comparative happiness	1.00	-
Work well-being	0.639	9.09
Correlations		
Organized personality with commute enjoyment	0.180	5.43
Organized personality with overall well-being	0.184	5.06
Organized personality with intrapersonal comparative happiness	0.0383	1.08
Overall well-being with commute enjoyment	0.202	5.66
Overall well-being with intrapersonal comparative happiness	-0.0148	-0.34
Commute enjoyment with intrapersonal comparative happiness	0.219	5.80

B.2   Activity Participation Models

Table B.2 shows the thresholds for the shopping activity participation model. The thresholds can be interpreted as scales for the corresponding latent response variables. Their values are different for different latent response variables (frequency versus happiness/satisfaction), but are relatively close for the travel satisfaction and activity happiness measures which indicates that people use the travel satisfaction and activity happiness scales similarly. Most of the thresholds are significant.

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Table B.2. Estimated thresholds for shopping activity propensity.

Parameter	Estimate	t-stat
Thresholds		
Activity frequency		
τ_{11}	0.460	0.83
τ_{12}	2.37	4.21
τ_{13}	3.28	5.70
Travel satisfaction		
τ_{21}	-3.11	-5.45
τ_{22}	-2.05	-3.86
τ_{23}	-1.22	-2.30
τ_{24}	0.521	0.98
Activity happiness		
τ_{31}	-2.48	-4.90
τ_{32}	-1.61	-3.17
τ_{33}	-0.222	-0.44
τ_{34}	1.06	2.10

Tables B.3 to B.6 show models of the propensity to participate in social / recreational, eat-out, organizational / volunteer / religious, and personal business activities, respectively. The estimated parameters can be interpreted similarly to the results reported for the shopping model in Chapter 4. Note that in all these models, the propensity to participate in activities was positively and significantly correlated with the happiness derived from the activities and the satisfaction with travel to the activities.

Table B.3. Structural and measurement model estimation results for social / recreational activity propensity.

Parameter	Estimate	t-stat
Structural Equations		
Propensity to do social / recreational activities		
Travel satisfaction	0.175	4.03
Activity happiness	0.256	5.36
Age (0-30)	-0.0641	-3.27
Age (30-60)	-0.00522	-0.84
Age(60+)	0.0430	1.16
Education job dummy	0.0650	0.53
Self-employed dummy	0.143	0.57
Missing job type dummy	0.0686	0.36
Income	0.00108	0.68
Missing income dummy	-0.0169	-0.06
Kids in household dummy	-0.308	-3.02
Missing number of kids dummy	-0.0485	-0.17
Travel satisfaction		
Distance/income	-0.237	-1.24
Distance * missing income dummy	-0.0305	-1.12
Missing distance dummy	-0.533	-1.35
Missing income dummy	0.308	0.79
Car dummy	-0.361	-3.00
Public transportation dummy	-0.494	-3.10
Activity happiness		
Age (0-30)	-0.0387	-1.70
Age (30-60)	-0.0141	-2.04
Age(60+)	-0.0171	-0.51
Male dummy	-0.217	-2.01
Income	0.00400	2.32
Missing income dummy	0.322	0.84

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Table B.3 (cont.) Structural and measurement model estimation results for social / recreational activity propensity.

Parameter	Estimate	t-stat
Thresholds		
Activity frequency		
τ_{11}	-3.54	-6.33
τ_{12}	-1.97	-3.61
τ_{13}	-1.02	-1.87
τ_{14}	0.0300	0.05
Travel satisfaction		
τ_{21}	-3.20	-5.58
τ_{22}	-2.40	-4.28
τ_{23}	-1.41	-2.56
τ_{24}	0.492	0.89
Activity happiness		
τ_{31}	-2.99	-4.80
τ_{32}	-1.38	-2.23

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Table B.4. Structural and measurement model estimation results for eat-out activity propensity.

Parameter	Estimate	t-stat
Structural Equations		
Propensity to eat-out		
Travel satisfaction	0.155	3.67
Activity happiness	0.141	3.44
Age (0-30)	-0.0755	-3.71
Age (30-60)	-0.00736	-1.12
Age(60+)	-0.00647	-0.14
Income	0.00594	3.91
Missing income dummy	-0.0872	-0.24
Kids in household dummy	-0.379	-3.14
Missing number of kids dummy	-0.127	-0.55
Flexible work schedule dummy	0.133	0.97
Travel satisfaction		
Distance/income	-0.555	-1.77
Distance * missing income dummy	-0.0227	-0.51
Missing distance dummy	-0.559	-1.48
Missing income dummy	0.131	0.32
Car dummy	-0.524	-4.07
Public transportation dummy	-0.546	-3.45
Activity happiness		
Age (0-30)	0.00512	0.24
Age (30-60)	-0.00791	-1.12
Age(60+)	0.0356	0.92
Male dummy	-0.0666	-0.68
Flexible work schedule dummy	0.346	2.35
Thresholds		
Activity frequency		
τ_{11}	-2.37	-4.31
τ_{12}	-0.955	-1.75
τ_{13}	-0.222	-0.41
τ_{14}	0.458	0.81
Travel satisfaction		
τ_{21}	-2.36	-3.93
τ_{22}	-1.22	-2.08
τ_{23}	0.747	1.26
Activity happiness		
τ_{31}	-2.10	-3.60
τ_{32}	-0.968	-1.72
τ_{33}	0.783	1.39

Table B.5. Structural and measurement model estimation results for organizational / volunteer / religious activity propensity.

Parameter	Estimate	t-stat
Structural Equations		
Propensity to do organizational / volunteer / religious activities		
Travel satisfaction	0.251	5.62
Activity happiness	0.583	15.61
Age (0-30)	-0.0128	-0.56
Age (30-60)	0.00955	1.35
Age(60+)	0.0248	0.89
Kids in household dummy	0.135	1.04
Missing number of kids dummy	0.369	0.65
Travel satisfaction		
Distance/income	-0.510	-2.31
Distance * missing income dummy	-0.0648	-1.34
Missing distance dummy	-0.522	-2.93
Missing income dummy	0.286	0.65
Car dummy	-0.350	-2.88
Public transportation dummy	-0.468	-2.28
Missing mode dummy	-0.580	-1.94
Activity happiness		
Age (0-30)	-0.0518	-2.35
Age (30-60)	0.0105	1.48
Age(60+)	0.0173	0.52
Male dummy	-0.331	-3.02
1-person household dummy	0.233	1.76

Table B.5 (cont.) Structural and measurement model estimation results for organizational / volunteer / religious activity propensity.

Parameter	Estimate	t-stat
Thresholds		
Activity frequency		
τ_{11}	-1.28	-1.85
τ_{12}	0.191	0.28
τ_{13}	1.03	1.48
τ_{14}	1.29	1.70
Travel satisfaction		
τ_{21}	-3.21	-4.40
τ_{22}	-2.39	-3.61
τ_{23}	-0.958	-1.47
τ_{24}	0.809	1.23
Activity happiness		
τ_{31}	-4.22	-6.44
τ_{32}	-3.63	-5.89
τ_{33}	-2.22	-3.72
τ_{34}	-0.765	-1.28

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Table B.6. Structural and measurement model estimation results for personal business activity propensity.

Parameter	Estimate	t-stat
Structural Equations		
Propensity to do personal business activities		
Travel satisfaction	0.101	2.32
Activity happiness	0.253	6.67
Age (0-30)	0.0435	2.14
Age (30-60)	0.00790	1.20
Age(60+)	0.0293	0.90
Flexible work schedule dummy	0.177	1.33
1-person household dummy	-0.045	-0.39
Travel satisfaction		
Distance/income	-0.863	-2.81
Distance * missing income dummy	-0.07	-0.92
Missing distance dummy	-0.497	-1.40
Missing income dummy	0.425	1.11
Car dummy	-0.346	-3.34
Public transportation dummy	-0.431	-2.68
Activity happiness		
Age (0-30)	-0.0554	-2.84
Age (30-60)	0.0125	1.80
Age(60+)	-0.0313	-0.61
Male dummy	-0.150	-1.56
Flexible work schedule dummy	0.146	1.22

Table B.6 (cont.) Structural and measurement model estimation results for personal business activity propensity.

Parameter	Estimate	t-stat
Thresholds		
Activity frequency		
τ_{11}	0.372	0.67
τ_{12}	2.26	4.05
τ_{13}	3.01	5.41
τ_{14}	3.48	6.26
Travel satisfaction		
τ_{21}	-3.39	-5.61
τ_{22}	-2.37	-4.21
τ_{23}	-1.43	-2.58
τ_{24}	0.364	0.65
Activity happiness		
τ_{31}	-3.51	-6.32
τ_{32}	-2.57	-4.76
τ_{33}	-0.764	-1.44
τ_{34}	0.582	1.09

Appendix C

Well-Being Questions in the Dynamic Surveys

This appendix contains the well-being questions that were used in the dynamic surveys conducted in Switzerland and at MIT. Section C.1 presents the questions used in the Swiss study (translated here to English). Section C.2 presents the questions used in the MIT study. The full questionnaires can be obtained from the author upon request.

C.1   Questions in the Swiss Study

Pre-Treatment Questions

Taking all things together, how satisfied are you with your commute by car between your residence and EPFL/UNIL/Geneva airport?

1 (very dissatisfied)	2	3	4	5 (very satisfied)
☐	☐	☐	☐	☐

Post-Treatment Questions

Taking all things together, how satisfied are you with your commute by car between your residence and EPFL/UNIL/Geneva airport?

1 (very dissatisfied)	2	3	4	5 (very satisfied)
☐	☐	☐	☐	☐

After your experience during this study, how do you feel about your decision to use the car for commuting to work?

1 (Less happy)	2	3	4	5 (Happier)
☐	☐	☐	☐	☐

Taking all things together, how satisfied were you with your commute by public transport between your residence and EPFL/UNIL/Geneva airport during this study?

1 (very dissatisfied)	2	3	4	5 (very satisfied)
☐	☐	☐	☐	☐

C.2 Questions in the MIT Study

Pre-Treatment Questions

Taking all things together, how satisfied are you with your commute by car between your residence and MIT?

1 (very dissatisfied)	2	3	4	5 (very satisfied)
☐	☐	☐	☐	☐

Post-Treatment Questions

Compared to the period before the study, how do you currently feel about your commute to MIT?

1 (Less happy)	2	3	4	5 (Happier)
☐	☐	☐	☐	☐

Now that you have experienced both the car and public transportation for your commute to MIT, in the following pages we would like to ask you about your evaluation of these two alternative means of transportation in the context of your commute to MIT.

Taking all things together, what is your level of satisfaction with a <u>car</u> commute between your residence and MIT?

1 (very dissatisfied)	2	3	4	5 (very satisfied)
☐	☐	☐	☐	☐

Taking all things together, what is your level of satisfaction with a <u>public transportation</u> commute between your residence and MIT?

1 (very dissatisfied)	2	3	4	5 (very satisfied)
☐	☐	☐	☐	☐

Appendix D

Statistical Tests for Matched Pairs Ordinal Data

This appendix describes the tests that were used for assessing the statistical significance of the difference between the measures of travel happiness. These tests, described in Agresti (2007), are appropriate for comparing matched pairs ordinal data as is the case in our dynamic commuter sample. The first test compares the distributions of the two measures being compared, and the second test compares their mean scores.

D.1 Test 1

Let Y_{n1} denote the response of individual n for question 1 (e.g. pre-treatment happiness) and Y_{n2} denote the response of individual n for question 2 (e.g. post-treatment happiness). Each question has J categories, with indices denoted as j and k.

A test of whether the responses to questions 1 and 2 are significantly different uses a cumulative ordinal logit model for each of question 1 and question 2 as follows:

$$\text{logit}[P(Y_{n1} \le j)] = \alpha_{nj} + \beta, \ \text{logit}[P(Y_{n2} \le j)] = \alpha_{nj} \tag{D.1}$$

(or equivalently, $P(Y_{n1} \le j) = \dfrac{e^{\alpha_{nj}+\beta}}{1+e^{\alpha_{nj}+\beta}}$ and $P(Y_{n2} \le j) = \dfrac{e^{\alpha_{nj}}}{1+e^{\alpha_{nj}}}$) $\tag{D.2}$

The parameter β captures differences in the distributions of responses between the two questions. The null hypothesis is that $\beta = 0$ (i.e. that the two distributions are not different). An estimate of β is given by the following equation:

$$\hat{\beta} = \ln\left(\frac{\sum_{k<j}\sum_{j}(j-k)N_{kj}}{\sum_{k>j}\sum_{j}(k-j)N_{kj}}\right) \tag{D.3}$$

where N_{kj} denotes the number of individuals that chose category k for question 1 and category j for question 2. The standard error of $\hat{\beta}$ is given by the following equation:

$$SE(\hat{\beta}) = \sqrt{\frac{\sum_{k<j}\sum_j (j-k)^2 N_{kj}}{\left[\sum_{k<j}\sum_j (j-k) N_{kj}\right]^2} + \frac{\sum_{k>j}\sum_j (k-j)^2 N_{kj}}{\left[\sum_{k>j}\sum_j (k-j) N_{kj}\right]^2}} \tag{D.4}$$

The test statistic $\dfrac{\hat{\beta}}{SE(\hat{\beta})}$ has an approximate standard normal distribution.

D.2 Test 2

This test compares the means of the responses to questions 1 and 2. Let the score (e.g. satisfaction rating) for category k be denoted as u_k. Let $\bar{x} = \sum_k u_k p_k$ denote the average response for question 1 (e.g. pre-treatment happiness), where p_k denotes the proportion of responses in category k. Similarly, $\bar{z} = \sum_j u_j p_j$ denotes the average response for question 2 (e.g. post-treatment happiness). Suppose the corresponding population means are denoted as μ_x and μ_z, respectively.

Under the null hypothesis, the two means are equal ($\mu_x - \mu_z = 0$) and an estimate of the standard error of $(\bar{x} - \bar{z})$ is given by the following equation:

$$SE(\bar{x} - \bar{z}) = \sqrt{\frac{1}{N}\left[\sum_k \sum_j (u_k - u_j)^2 p_{kj}\right]} \tag{D.5}$$

where p_{kj} denotes the proportion of individuals who chose category k for question 1 and category j for question 2, and N is the total number of individuals.

The test statistic $\dfrac{\bar{x} - \bar{z}}{SE(\bar{x} - \bar{z})}$ has an approximate standard normal distribution.

Appendix E

Income Imputation

In this appendix, we describe the models that were estimated for the purpose of income imputation.

E.1 Swiss Data

In the Swiss experiment, respondents who answered the initial telephone interview were asked about their personal before-tax monthly income. Five response categories were used: Less than 2500 Swiss Francs, Between 2500 and 5000 Francs, Between 5000 and 7500 Francs, More than 7500 Francs, and No response.

36 individuals interviewed reported their income. This sample was used to develop a model of personal before-tax monthly income as a function of socio-economic and demographic characteristics. The model was then used to predict the income category of three participants who did not answer the income question.

Since the response categories are ordinal, an ordinal logit model is specified as follows:

$$\text{Income}^* = \beta_1 \text{ Male} + \beta_2 \text{ Undergraduate education} + \beta_3 \text{ Graduate education} \\ + \beta_4 \text{ Age(0--40)} + \beta_5 \text{ Age(40+)} + \varepsilon \tag{E.1}$$

where Income^* is a continuous latent response variable; Male is a dummy variable equal to 1 if the respondent is male and 0 otherwise; Undergraduate education and Graduate education are dummy variables for these categories of education, respectively, with the base selected as high school or less or technical or vocational school; Age(0--40) and Age(40+) are ranges of a piecewise linear function of age, defined as follows: Age(0--40) = min (Age, 40), and Age(40+) = max (0, Age − 40); and ε is an error term distributed Logistic(0, $\pi^2/3$). It was expected that higher levels of education and experience (age) are associated with higher incomes. A male dummy variable was included to test the effect of gender on income.

The observed income category is related to its latent response through a threshold model. A full set of thresholds is estimated and thus an intercept term is not included in the

Income* model. In the data, none of the respondents had an income less than 2500 Francs. Therefore, the following threshold model is used.

$$\text{Income} = \begin{cases} 2500 - 5000 \text{ Francs} & \text{if } -\infty < \text{Income}^* \leq \tau_1 \\ 5000 - 7500 \text{ Francs} & \text{if } \tau_1 < \text{Income}^* \leq \tau_2 \\ \text{More than } 7500 \text{ Francs} & \text{if } \tau_2 < \text{Income}^* < \infty \end{cases} \qquad (E.2)$$

where τ_1 and τ_2 are threshold parameters to be estimated.

The estimation results are shown in Table E.1.

Table E.1. Income imputation model for the Swiss data.

Parameter	Estimate	Std Error	t-stat
Male	1.18	0.781	1.51
Undergraduate education	0.501	0.916	0.55
Graduate education	0.661	1.02	0.65
Age(0–40)	0.127	0.116	1.10
Age(40+)	0.0148	0.0651	0.23
Thresholds			
τ_1	3.56	4.18	0.85
τ_2	5.43	4.25	1.28

As expected, income tends to be higher for males (perhaps because males tend to occupy positions that are better paid), for those with undergraduate and graduate degrees, and for those with greater experience as indicated by age.

For each of the three participants who did not report their income, this model was used to calculate the probabilities of being in any of the three income categories. Each of these three participants was then assigned to an income category through Monte Carlo simulation. This process was repeated five times to generate five datasets for the estimation of the models described Chapter 6.

E.2   MIT Data

In the MIT experiment, respondents who answered the initial telephone interview were asked about their personal before-tax annual income. Six response categories were used: Less than $35,000, Between $35,000 and $50,000, Between $50,000 and $75,000, Between $75,000 and $100,000, More than $100,000, and No response.

86 individuals interviewed reported their income. This sample was used to develop a model of personal before-tax annual income as a function of socio-economic and demographic characteristics. The model was then used to predict the income catgeory of 12 participants who did not answer the income question.

As in the Swiss case, an ordinal logit model is specified as follows:

Income* = β_1 High school / technical / vocational education

$\quad\quad$ + β_2 Admin non-leader + β_3 Admin leader $\hspace{4cm}$ (E.3)

$\quad\quad$ + β_4 Academic non-leader + β_5 Academic leader + ε

where Income* is a continuous latent response variable and High school / technical / vocational education is a dummy variable for this category of education with the base selected as undergraduate or graduate education. The other four explanatory variables are dummy variables for occupation type (administrative versus academic, inferred based on MIT's classification of employees) and leadership status (such as manager, director, etc.). Admin non-leader, for example, is a dummy variable equal to 1 for an administrative employee who is not in a leadership position and 0 otherwise. The other dummy variables can be interpreted similarly. The base category used is support staff. ε is an error term distributed Logistic(0, $\pi^2/3$).

It was expected that higher levels of education and leadership status would be associated with higher incomes. Employees in academic and administrative positions would earn more than support staff.

The observed income category is related to its latent response through a threshold model as follows:

$$\text{Income} = \begin{cases} \text{Less than \$35,000} & \text{if } -\infty < \text{Income}^* \leq \tau_1 \\ \$35,000 - \$50,000 & \text{if } \tau_1 < \text{Income}^* \leq \tau_2 \\ \$50,000 - \$75,000 & \text{if } \tau_2 < \text{Income}^* \leq \tau_3 \\ \$75,000 - \$100,000 & \text{if } \tau_3 < \text{Income}^* \leq \tau_4 \\ \text{More than \$100,000} & \text{if } \tau_4 < \text{Income}^* < \infty \end{cases} \hspace{2cm} (E.4)$$

where τ_1, τ_2, τ_3, and τ_4 are threshold parameters to be estimated.

The estimation results are shown in Table E.2.

Table E.2. Income imputation model for the MIT data.

Parameter	Estimate	Std Error	t-stat
High school / technical / vocational education	-0.921	0.595	-1.55
Admin non-leader	2.62	0.689	3.80
Admin leader	3.71	0.736	5.04
Academic non-leader	2.35	0.770	3.05
Academic leader	4.96	1.05	4.71
Thresholds			
τ_1	-2.44	0.780	-3.13
τ_2	0.484	0.522	0.93
τ_3	2.42	0.627	3.86
τ_4	3.94	0.675	5.83

As expected, income tends to be lower for employees with high school / technical / vocational education than for those with undergraduate or graduate education. Employees in both administrative and academic positions earn more than support staff, and those with leadership positions tend to have higher incomes than those without leadership positions.

The procedure for applying the model to the 12 participants who did not report their income was the same one used in the Swiss case.

Appendix F

Testing for Sample Selection Bias

In this appendix, we describe the tests we conducted to check if there is sample selection bias in the Swiss and MIT models. For a review of sample selection tests for discrete choice models, the reader is referred to Dubin and Rivers (1989), Vella (1992), and Eklöf and Karlsson (1999).

The form of sample selection that we test for is whether the decision to participate in the experiment is correlated (through unobservable variables) with the mode switching decision. Intuitively, people who decide to participate may have already thought about switching to public transportation anyway or may be more inclined in general to switch.

We conducted two tests. The first one is an omitted variable test proposed by Vella (1992) which assumes a bivariate normality distribution of the error term in the participation decision and the error term in the mode switching decision. The second test is also an omitted variable test derived from the test proposed by McFadden (1987) for logit models. We describe each of these tests and show their application to the Swiss and MIT data. We observe the participation decision for a choice-based sample of participants and non-participants and the mode switching decision for the participant sample.

F.1   Vella's (1992) Omitted Variable Test

F.1.1 Formulation

The mode choice model is given by Equations (F.1) – (F.5). All terms are as defined in Chapter 6.

$$U_{\text{Car}} = V_{\text{Car}} + \varepsilon_{\text{Car}} \tag{F.1}$$

$$U_{\text{PT}} = V_{\text{PT}} + \varepsilon_{\text{PT}} \tag{F.2}$$

$$\text{Let } \varepsilon_1 = \varepsilon_{\text{Car}} - \varepsilon_{\text{PT}} \tag{F.3}$$

$$\Delta U = U_{\text{Car}} - U_{\text{PT}} = V_{\text{Car}} - V_{\text{PT}} + \varepsilon_1 \tag{F.4}$$

$$y = \begin{cases} 1 \text{ (Car)} & \text{if } \Delta U \geq 0 \\ 0 \text{ (PT)} & \text{otherwise} \end{cases} \tag{F.5}$$

The participation (or selection model) is given by Equations (F.6) – (F.10).

$$U_{\text{Participate}} = V_{\text{Participate}} + \varepsilon_{\text{Participate}} \tag{F.6}$$

$$U_{\text{Non-participate}} = V_{\text{Non-participate}} + \varepsilon_{\text{Non-participate}} \tag{F.7}$$

Let $\varepsilon_2 = \varepsilon_{\text{Participate}} - \varepsilon_{\text{Non-Participate}}$ \hfill (F.8)

$$d^* = U_{\text{Participate}} - U_{\text{Non-Participate}} = V_{\text{Participate}} - V_{\text{Non-Participate}} + \varepsilon_2 \tag{F.9}$$

$$d = \begin{cases} 1 \text{ (Participate)} & \text{if } d^* \geq 0 \\ 0 \text{ (Non-Participate)} & \text{otherwise} \end{cases} \tag{F.10}$$

where $U_{\text{Participate}}$ is the utility of participation consisting of a systematic utility, $V_{\text{Participate}}$, and an error term, $\varepsilon_{\text{Participate}}$. $U_{\text{Non-Participate}}$, $V_{\text{Non-Participate}}$, and $\varepsilon_{\text{Non-Participate}}$ are the corresponding terms for the non-participation alternative. The decision to participate, d, is based on whether the utility difference, d^*, is positive or negative.

The error terms, ε_1 and ε_2, in the mode switching and participation equations are assumed to be bivariate normally distributed with zero means, unit variances, and correlation parameter ρ:

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \tag{F.11}$$

Using the bivariate normality assumption, we rewrite Equation (F.4) as follows:
$$\Delta U = V_{\text{Car}} - V_{\text{PT}} + \rho\,\varepsilon_2 + \eta \tag{F.12}$$
where η is a white noise error term.

Conditioning (F.12) on the observed value of d, we get:
$$\Delta U = V_{\text{Car}} - V_{\text{PT}} + \rho\,e_2 + \eta \tag{F.13}$$
where e_2 is the "generalized residual" obtained from the univariate probit participation model (Equations F.6 – F.10).

For a univariate probit model, the generalized residuals e_2 are given by:

$$e_2 = \frac{\varphi(\beta'X)}{\Phi(\beta'X)(1 - \Phi(\beta'X))}\left[d - \Phi(\beta'X)\right] \tag{F.14}$$

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where ϕ denotes the standard normal probability density function, Φ denotes the standard normal cumulative distribution function, and $\beta'X = V_{\text{Participate}} - V_{\text{Non-Participate}}$.

Under the null hypothesis of no sample selection bias, $\rho = 0$ (and $\eta = \varepsilon_1$) and the parameter estimates from the univariate probit mode choice model (F.13) are consistent (although they are inconsistent under the alternative hypothesis).

A test of sample selection bias is therefore a t-test of the null hypothesis that $\rho = 0$.

The steps to conduct this test are as follows:
1. Estimate the univariate probit selection model (Equations F.6 − F.10) using the full sample of participants and non-participants.
2. Calculate the generalized errors e_2 for the participants. Since for participants, $d = 1$, the generalized errors reduce to: $e_2 = \dfrac{\phi(\beta'X)}{\Phi(\beta'X)}$.
3. Substitute $\hat{e}_2$ for e_2 in Equation (F.13) and estimate a univariate probit mode choice model with this extra term in it, using the sample of participants. Do a statistical test of the coefficient of e_2 (i.e. ρ).

F.1.2 Application to Swiss Data

We specify the utility of car as a function of time and distance divided by income (as a proxy for cost divided by income) and the utility of public transportation as a function of time as follows:

$$U_{\text{Car}} = \beta_0 + \beta_1 * \text{Time}_{\text{Car}} + \beta_2 * \text{Distance}_{\text{Car}}/\text{income} + \varepsilon_{\text{Car}} \qquad (F.15)$$

$$U_{\text{PT}} = \beta_1 * \text{Time}_{\text{PT}} + \varepsilon_{\text{PT}} \qquad (F.16)$$

The utility equations of the participation model are specified as in Equations (F.17) and (F.18). The non-participation alternative is set as the base. We select a model that maximizes the adjusted rho squared, where the utility of participation is specified as function of car travel time, anticipated travel time by public transportation, transfers by public transportation, distance between home and work, presence of kids in the household, and income.

$$U_{\text{Participate}} = \beta_3 * \text{Time}_{\text{Car}} + \beta_4 * \text{Time}_{\text{PT}} + \beta_5 * \text{Distance}_{\text{Car}} + \beta_6 * \text{Transfers}_{\text{PT}}$$
$$+ \beta_7 * \text{Kids} + \beta_8 * \text{Income} + \varepsilon_{\text{Participate}} \qquad (F.17)$$

$$U_{\text{Non-participate}} = 0 + \varepsilon_{\text{Non-participate}} \qquad (F.18)$$

Since the non-participant data are collected through a choice-based sampling scheme and the selection model is probit, we estimate the model using the Weighted Exogenous

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Sample Maximum Likelihood (WESML) method with the log-likelihood function expressed as follows:

$$\sum_{n=1}^{N}\sum_{i}\frac{W_i}{H_i}\ln P(i|X_n,\beta)$$ (F.19)

where H_i is alternative i's share in the sample, and W_i is alternative i's share in the population.

For our sample of 27 participants (out of 30 participants, 3 didn't report their income) and 35 non-participants (after removing observations with missing values for some variables):

$$H_{\text{Participate}} = \frac{27}{27+35} = 0.435$$ (F.20)

$$H_{\text{Non-Participate}} = 1 - 0.435 = 0.565$$ (F.21)

The population of employees having a full-time parking permit at Geneva airport, UNIL, and EPFL consists of about 6778 individuals. Assuming that this is the full eligible population, we have:

$$W_{\text{Participate}} = \frac{30}{6778} = 0.004$$ (F.22)

$$W_{\text{Non-Participate}} = 1 - 0.004 = 0.996$$ (F.23)

The estimation results of the participation model are shown in Table F.1.

Table F.1. Decision to participate (selection) probit model for Swiss data (N = 62: 27 participants and 35 non-participants).

Parameter	Estimate	Std Error	t-stat
Participation constant	-4.08	3.30	-1.23
Car time (hours)	5.73	12.2	0.47
Anticipated PT time (hours)	-0.769	3.49	-0.22
Car distance (km)	-0.0379	0.132	-0.29
PT transfers	-0.232	1.19	-0.19
Kids dummy	0.201	1.93	0.10
Income (1000 Swiss Francs per month)	0.149	0.346	0.43

The mode switching model, including the generalized residual as in Equation (F.13), is shown in Table F.2. We also include an error component that does not vary over a given individual to represent the panel nature of the mode choice data (multiple observations were available from every participant). σ_{panel} in the table below is the standard deviation of this error component.

Table F.2. Mode switching model for Swiss data with correlation parameter (N = 25).

Parameter	Estimate	Std Error	t-stat
Car constant	-0.0947	2.61	-0.04
Generalized residual (Correlation ρ)	-0.0655	1.09	-0.06
Time (hours)	-4.10	4.07	-1.01
Distance$_{Car}$/income (km/100 Swiss Francs per month)	-0.690	4.76	-0.14
σ_{panel}	2.44	0.981	2.49

The coefficient of the generalized residual, i.e. the correlation parameter, is not significantly different from zero. Therefore, we cannot reject the null hypothesis of no sample selection bias at the 95% level of confidence.

F.1.3 Application to MIT Data

We specify the utility of car and public transportation in the mode switching model as a function of ln(time) and cost as follows:

$$U_{Car} = \beta_0 + \beta_1 * \ln(\text{Time}_{Car}) + \beta_2 * \text{Cost}_{Car}/\text{income} + \varepsilon_{Car} \qquad (F.24)$$

$$U_{PT} = \beta_1 * \ln(\text{Time}_{PT}) + \beta_2 * \text{Cost}_{PT}/\text{income} + \varepsilon_{PT} \qquad (F.25)$$

The utility equations of the participation decision are specified as in Equations (F.26) and (F.27) with the non-participation alternative fixed as the base. We select a model that maximizes the adjusted rho squared, where the utility of participation is specified as function of car travel time, anticipated travel time by public transportation, transfers by public transportation, gender, presence of kids in the household, household size, and age.

$$U_{Participate} = \beta_3 * \text{Time}_{Car} + \beta_4 * \text{Time}_{PT} + \beta_5 * \text{Transfers}_{PT} + \beta_6 * \text{Male}$$
$$+ \beta_7 * \text{Kids} + \beta_8 * \text{Household Size} + \beta_9 * \text{Age} + \varepsilon_{Participate} \qquad (F.26)$$

$$U_{Non\text{-}participate} = 0 + \varepsilon_{Non\text{-}participate} \qquad (F.27)$$

As in the Swiss case, we estimate the participation model using WESML since the non-participant data are collected through a choice-based sampling scheme and the selection model is probit. The total eligible MIT population consists of 3151 individuals, of whom 73 agreed to participate and did not drop out of the study. The non-participant sample with no missing data on any of the variables above includes 65 individuals consisting of a sample of those who didn't participate and those who agreed to participate but later dropped out of the study without undergoing the treatment. The sample and population shares are as follows:

$$H_{Participate} = \frac{73}{73 + 65} = 0.529 \qquad (F.28)$$

$$H_{Non\text{-}Participate} = 1 - 0.529 = 0.471 \qquad (F.29)$$

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$$W_{\text{Participate}} = \frac{73}{3151} = 0.023 \tag{F.30}$$

$$W_{\text{Non-Participate}} = 1 - 0.023 = 0.977 \tag{F.31}$$

The estimation results of the participation model are shown in Table F.3.

Table F.3. Decision to participate (selection) Probit model for MIT data (N = 138: 73 participants and 65 non-participants; non-participants include drop-outs who were not subjected to the treatment).

Parameter	Estimate	Std Error	t-stat
Participation constant	-1.86	1.59	-1.16
Car Time (hours)	1.34	1.01	1.33
Anticipated PT Time (hours)	-0.238	0.719	-0.33
PT Transfers	-0.870	0.528	-1.65
Male dummy	0.229	0.608	0.38
Kids dummy	0.619	0.92	0.67
Household Size	-0.285	0.372	-0.77
Age	0.0147	0.028	0.53

The mode switching model, including the generalized residual as in Equation (F.13), is shown in Table F.4.

Table F.4. Mode switching model for MIT data with correlation parameter (N = 67).

Parameter	Estimate	Std Error	t-stat
Car constant	-0.0448	0.699	-0.06
Generalized residual (Correlation ρ)	0.508	0.385	1.32
ln Time (minutes)	0.0993	0.838	0.12
Cost/income ($ per month/$1000 per year)	-1.24	0.479	-2.58

The coefficient of the generalized residual, i.e. the correlation parameter, is not significantly different from zero. Therefore, we cannot reject the null hypothesis of no sample selection bias at the 95% level of confidence.

F.2 McFadden's (1987) Omitted Variable Test

F.2.1 Formulation

The test described in this section is based on McFadden's (1987) omitted variable test applied to logit models. As in the previous test, the mode choice model is given by Equations (F.1) – (F.5), and the selection model is given by Equations (F.6) – (F.10). The essential idea of this test is to test whether a variable related to the selection process should enter the utility equations of the mode choice model. In particular, we assume this

variable is the expected value of the decision to participate, i.e. $E(d|X)$, which is estimated as follows:

$$\hat{E}(d|X) = 1 * \hat{P}_{\text{Participate}} + 0 * \hat{P}_{\text{Not-Participate}} = \hat{P}_{\text{Participate}} \tag{F.32}$$

To test if this variable should be included in the mode choice mode, the test proceeds as follows.

1. Estimate a logit sample selection model (Equations F.6 – F.10) using the full sample of participants and non-participants, and calculate $\hat{E}(d|X)$ for every participant.

2. Estimate a logit mode choice model (Equations F.1 – F.5) using the sample of participants, and calculate the fitted probabilities $\hat{P}_{\text{Car}}$ and $\hat{P}_{\text{PT}}$.

3. Calculate for every observation in the participant sample the auxiliary variables:

$$z_j = \begin{cases} 0 - \bar{z} & \text{if } j = \text{Car} \\ \hat{E}(d|X) - \bar{z} & \text{if } j = \text{PT} \end{cases} \tag{F.33}$$

$$\text{where } \bar{z} = 0 * \hat{P}_{\text{Car}} + \hat{E}(d|X)* \hat{P}_{\text{PT}} = \hat{E}(d|X)* \hat{P}_{\text{PT}} \tag{F.34}$$

4. Re-estimate a logit mode choice model as in Step 2 and adding z_{Car} and z_{PT} to the utility equations of car and public transportation, respectively, with a generic coefficient β_z.

Under the null hypothesis of no sample selection bias, the coefficient β_z in the mode choice model is zero.

F.2.2 Application to Swiss Data

We specify the systematic utilities of the mode choice model and the selection model as in Section F.1.2. Since the non-participant data are collected through a choice-based sampling scheme and the selection model is logit, we estimate the model using logit and correct the alternative specific constants using Exogenous Sample Maximum Likelihood (ESML), where:

ASC Participate (Corrected) = ASC Participate − ln($H_{\text{Participate}}$ / $W_{\text{Participate}}$)   (F.35)

where $H_{\text{Participate}}$ is the share of participants in the sample, and $W_{\text{Participate}}$ is the share of participants in the population.

The estimation results of the selection model (logit) including the correction of the constant are shown in Table F.5.

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Table F.5. Decision to participate (selection) logit model for Swiss data (N = 62: 27 participants and 35 non-participants).

Parameter	Estimate	Std Error	t-stat
Participation constant	-4.58	1.57	-2.92
Car Time (hours)	13.9	5.11	2.73
Anticipated PT Time (hours)	-1.49	1.28	-1.17
Car Distance (km)	-0.0911	0.0494	-1.85
PT Transfers	-0.708	0.466	-1.52
Kids dummy	1.11	0.735	1.51
Income (1000 Swiss Francs per month)	0.397	0.152	2.61

The estimation results of the mode choice model including the z variable (calculated based on the selection model and a mode choice mode with time and distance/income variables and an agent effect) are shown in Table F.6.

Table F.6. Mode switching model for Swiss data with z variable (N = 25).

Parameter	Estimate	Std Error	t-stat
Car constant	-0.999	3.14	-0.32
z	-4.06	11.6	-0.35
Time (hours)	-7.88	6.95	-1.13
Distance$_{Car}$/income (km/100 Swiss Francs per month)	-1.77	8.36	-0.21
σ_{panel}	4.30	1.76	2.45

The coefficient of the z variable is not significantly different from zero. Therefore, we cannot reject the null hypothesis of no sample selection bias at the 95% level of confidence.

F.2.2 Application to MIT Data

We specify the systematic utilities of the mode choice model and the selection model as in Section F.1.3. As in the Swiss case, we estimate the selection model using logit and correct the alternative specific constants using ESML. The estimation results of the selection model (logit) including the correction of the constant are shown in Table F.7.

Table F.7. Decision to participate (selection) logit model for MIT data (N = 138: 73 participants and 65 non-participants; non-participants include drop-outs who were not subjected to the treatment).

Parameter	Estimate	Std Error	t-stat
Participation constant	-1.82	1.47	-1.24
Car time (hours)	2.2	0.752	2.93
Anticipated PT time (hours)	-0.645	0.605	-1.07
PT transfers	-1.68	0.328	-5.13
Male	0.186	0.452	0.41
Kids	1.02	0.738	1.38
Household size	-0.492	0.305	-1.62
Age	0.0196	0.0231	0.85

The estimation results of the mode choice model including the z variable (calculated based on the selection model and a mode choice mode with ln(time) and cost/income variables) are shown in Table F.8.

Table F.8. Mode switching model for MIT data with z variable (N = 67).

Parameter	Estimate	Std Error	t-stat
Car constant	1.53	0.968	1.58
z	1.34	2.81	0.48
ln Time (minutes)	-0.425	1.31	-0.32
Cost/income ($ per month/$1000 per year)	-2.05	0.806	-2.54

The coefficient of the z variable is not significantly different from zero. Therefore, we cannot reject the null hypothesis of no sample selection bias at the 95% level of confidence.

Appendix G

Hausman Specification Tests

This appendix describes a number of Hausman specification tests (1978) that we conducted to test the validity of the extended model, consisting of mode choice and happiness models, by comparing it against a mode choice only model. The Hausman test compares two sets of coefficients obtained from different models. Under the null hypothesis, both sets of coefficients are consistent but one of them is more efficient than the other. Under the alternative hypothesis, one or both sets of coefficients are inconsistent. Let $\hat{\beta}_E$ denote the vector of efficient parameter estimates and $\hat{\beta}_I$ denote the vector of inefficient parameter estimates. Let $V(\hat{\beta}_E)$ and $V(\hat{\beta}_I)$ denote the variance-covariance matrices of $\hat{\beta}_E$ and $\hat{\beta}_I$, respectively. Let $\hat{q} = \hat{\beta}_I - \hat{\beta}_E$, and let $V(\hat{q})$ denote the variance-covariance matrix of $\hat{q}$.

The null hypothesis is $q = 0$. Under the null hypothesis, $V(\hat{q}) = V(\hat{\beta}_I) - V(\hat{\beta}_E)$, and the Hausman statistic:

$H = \hat{q}' V^{-1}(\hat{q}) \hat{q}$ is chi-squared distributed with degrees of freedom equal to the number of parameters in $\hat{\beta}_E$ or $\hat{\beta}_I$. If H is smaller than the critical value of the chi-squared distribution, then we fail to reject the null hypothesis.

Applying this test to the models of this thesis, $\hat{\beta}_I$ is the vector of coefficients estimated from a mode choice only model (standard model), and $\hat{\beta}_E$ is the vector of corresponding coefficients estimated from an extended model consisting of a mode choice model and a happiness model. The underlying assumption is that both sets of coefficients are consistent but the happiness indicators make the coefficients of the extended model more efficient than those of the standard model. The coefficients in each of $\hat{\beta}_I$ and $\hat{\beta}_E$ are the car constant, the time coefficient, and the cost / income (or distance / income) coefficient. In the extended model a correlation parameter between the post-treatment car and public transportation utilities is also estimated, but this correlation cannot be estimated in the standard model. So in order to do the Hausman test, we set the two models (standard and extended) at the same scale by fixing the correlation coefficient in the standard model to

the value estimated in the extended model (i.e. the standard model is an error component logit mixture as described in Chapter 6).

Section G.1 shows the extended (with happiness) and standard (without happiness) models using the Swiss data; it was not possible to conduct a Hausman test for this model. Sections G.2 and G.3 show the Hausman tests that were done for the MIT and combined Swiss-MIT models, respectively.

G.1   Swiss Model

Since the correlation between the post-treatment car and public transportation utilities was fixed at -1 in the extended model (Section 6.2.1), we fix it at -1 in the mode choice only model and obtain the estimation results shown in Table G.1. The mode choice model also has a counterintuitive positive distance coefficient, but none of the coefficients is statistically significant.

Table G.1. Swiss extended and standard model estimation results (standard model is estimated at a correlation parameter of -1) (N = 28).

Parameter	Extended model (Choice + Happiness)		Standard model (Choice only)	
	Estimate	Std Error	Estimate	Std Error
Car constant	-0.217	0.942	0.292	1.34
Time (hours)	-3.97	1.57	-2.80	3.02
Distance$_{Car}$/income (km/100 Swiss Francs per month)	0.433	2.09	1.13	3.44

The difference between the variance-covariance matrices of the two estimators is given by:

$$V(\hat{\beta}_I) - V(\hat{\beta}_E) = \begin{bmatrix} 1.81 & 2.88 & -0.466 \\ 2.88 & 9.12 & 5.67 \\ -0.466 & 5.67 & 11.8 \end{bmatrix} - \begin{bmatrix} 0.887 & 0.875 & -0.906 \\ 0.875 & 2.47 & 0.647 \\ -0.906 & 0.647 & 4.36 \end{bmatrix}$$

$$= \begin{bmatrix} 0.919 & 2.01 & 0.440 \\ 2.01 & 6.65 & 5.02 \\ 0.440 & 5.02 & 7.46 \end{bmatrix}$$

This matrix is not positive-definite. It has one negative and two positive Eigen values. Therefore, the Hausman test cannot be conducted for the Swiss model.

G.2   MIT Model

Since the correlation between the post-treatment car and public transportation utilities was estimated at -0.0644 in the extended model (Section 6.2.2), we fix it at -0.0644 in the mode choice only model and obtain the estimation results shown in Table G.2.

Table G.2. MIT extended and standard model estimation results (standard model is estimated at a correlation parameter of -0.0644) (N = 67).

Parameter	Extended model (Choice + Happiness)		Standard model (Choice only)	
	Estimate	Std Error	Estimate	Std Error
Car constant	0.799	0.313	1.63	0.969
ln Time (minutes)	-0.568	0.211	-0.918	1.68
Cost/income ($ per month/$1000 per year)	-1.31	0.679	-2.66	1.03

Therefore, $\hat{q} = \begin{bmatrix} 0.831 & -0.349 & -1.35 \end{bmatrix}'$. Under the null hypothesis, the variance-covariance matrix of $\hat{q}$ is equal to:

$$V(\hat{q}) = \begin{bmatrix} 0.939 & 1.37 & -0.349 \\ 1.37 & 2.83 & -0.00788 \\ -0.349 & -0.00788 & 1.06 \end{bmatrix} - \begin{bmatrix} 0.0979 & -0.0324 & -0.0748 \\ -0.0324 & 0.0444 & 0.0474 \\ -0.0748 & 0.0474 & 0.461 \end{bmatrix}$$

$$= \begin{bmatrix} 0.841 & 1.40 & -0.274 \\ 1.40 & 2.79 & -0.0553 \\ -0.274 & -0.0553 & 0.599 \end{bmatrix}$$

and the Hausman test statistic is equal to 8.90 which is smaller than the critical value of 11.35 (at 3 degrees of freedom) at the 90% level of confidence. Therefore, we fail to reject the null hypothesis of consistent parameter estimates. Note that we reject the null hypothesis however at a 95% level of confidence.

G.3 Combined Swiss-MIT Model

We now do two sets of Hausman tests comparing the coefficients of the combined Swiss-MIT model (with happiness) to the coefficients obtained in a mode choice only model using each of the Swiss and MIT data (separately).

G.3.1 Testing Against Swiss Model

The mode choice model is now estimated using the Swiss data with the correlation parameter set to the value of -0.592 obtained in the combined Swiss-MIT model. Table G.3 shows the estimated coefficients and their standard errors in the combined Swiss-MIT model (extended model) and in the mode choice only model (standard model) estimated using the Swiss data.

Table G.3. Estimated parameters of variables in the Swiss utility equations in the combined Swiss-MIT model and in the mode choice only model of the Swiss data.

Parameter	Extended model (Choice + Happiness) (Swiss-MIT data) (N = 95)		Standard model (Choice only) (Swiss Data) (N = 28)	
	Estimate	Std Error	Estimate	Std Error
Car constant	1.46	0.429	0.316	1.23
Time (hours)	-1.67	0.487	-2.59	2.77
Distance$_{Car}$/income (km/100 Swiss Francs per month)	-1.17	1.33	1.01	3.15

Therefore, $\hat{q} = \begin{bmatrix} -1.14 & -0.913 & 2.17 \end{bmatrix}'$. Under the null hypothesis, the variance-covariance matrix of $\hat{q}$ is equal to:

$$V(\hat{q}) = \begin{bmatrix} 1.34 & 2.45 & -0.153 \\ 2.45 & 7.45 & 4.48 \\ -0.153 & 4.48 & 8.14 \end{bmatrix}, \text{ and the Hausman test statistic is equal to } 1.49$$

which is smaller than the critical value of 7.82 (at 3 degrees of freedom) at the 95% level of confidence. Therefore, we fail to reject the null hypothesis of consistent parameter estimates.

G.3.2 Testing Against MIT Model

The mode choice model is now estimated using MIT data with the correlation parameter set to the value of -0.110 obtained in the combined Swiss-MIT model. Table G.4 shows the estimated coefficients and their standard errors in the combined Swiss-MIT model (extended model) and in the mode choice only model (standard model) estimated using MIT data.

Table G.4. Estimated parameters of variables in the MIT utility equations in the combined Swiss-MIT model and in the mode choice only model of the MIT data.

Parameter	Extended model (Choice + Happiness) (Swiss-MIT data) (N = 95)		Standard model (Choice only) (MIT Data) (N = 67)	
	Estimate	Std Error	Estimate	Std Error
Car constant	0.851	0.317	1.64	0.978
ln Time (minutes)	-0.440	0.123	-0.927	1.70
Cost/income ($ per month/$1000 per year)	-1.33	0.690	-2.68	1.04

Therefore, $\hat{q} = \begin{bmatrix} 0.793 & -0.487 & -1.35 \end{bmatrix}'$. Under the null hypothesis, the variance-covariance matrix of $\hat{q}$ is equal to:

$$V(\hat{q}) = \begin{bmatrix} 0.855 & 1.42 & -0.278 \\ 1.42 & 2.87 & -0.0351 \\ -0.278 & -0.0351 & 0.601 \end{bmatrix}$$, and the Hausman test statistic is equal to 8.15

which is smaller than the critical value of 11.35 (at 3 degrees of freedom) at the 90% level of confidence. Therefore, we fail to reject the null hypothesis of consistent parameter estimates.

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