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Structural Equation Modeling of Relative Desired Travel Amounts

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Structural Equation Modeling of Relative Desired Travel Amounts

by

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DISSERTATION

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ABSTRACT

The "derived demand" perspective on daily travel, which has become axiomatic in the transportation field, holds that travel is derived from the demand to participate in spatially-separated activities. The act of traveling itself is not considered to offer any positive utility, and minimizing travel time is a primary goal of all travelers in all situations. This dissertation continues a recent effort to challenge this paradigm by directly modeling the interrelationships among travel amounts, perceptions, affections (or liking), and desires, and, in doing so, asking: why do some individuals want to travel more, and others less? By modeling quantities such as travel affection and desire, I am, importantly, first acknowledging the existence of these measures and, second, formally quantifying their relative impact on daily travel amounts and each other.

Five short-distance (one-way trips less than 100 miles) and five long-distance categories of travel are examined, specifically: short-distance overall, commute, work/school-related, entertainment/ social/recreation, and personal vehicle; long-distance overall, work/school-related, entertainment/ social/recreation, personal vehicle, and airplane. The models are estimated using data collected in 1998 from more than 1,300 commuting workers in the San Francisco Bay Area. Cross-model analysis reveals three robust relationships, namely: (1) myriad measures of actual travel amounts work together to affect qualitative perceptions of those amounts (e.g. "a little" or "a lot"); (2) those perceptions are consistently important in shaping desires to reduce or increase one's travel; and (3) affections for travel have a positive influence on those desires. The second finding suggests that two individuals who travel the same objective amount may not have the same desire to reduce their travel: how much each individual perceives his or her travel to be is important. The third point argues that the degree to which travel is enjoyed is a key determinant in shaping desires to reduce travel: the more travel is enjoyed, the less the desire to reduce it. Each of the ten models is estimated with the following four estimation techniques: maximum likelihood,

asymptotic distribution free, bootstrapping, and the M*plus* approach. A cross-model econometric comparison by estimation technique and sample size is included.

The implications of the work are largely theoretical, but the ideas presented can lead to very practical suggestions. For instance, those promoting travel demand management strategies, such as telecommuting, should pay attention to the travel perceptions of their target audience. Even though someone may be objectively traveling a lot, if the individual does not perceive those amounts to be high, he may not embrace a policy aimed at reducing his travel. And the same can be said for those who enjoy travel: those who see value in travel, perhaps because it provides a buffer between the work and home realms of daily life, will logically be less motivated to reduce their travel amounts. The survey respondents exhibit a considerable degree of liking for travel of all kinds studied, and this work unequivocally demonstrates the importance of travel liking to travel behavior.

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1. INTRODUCTION

Many seek to understand travel from different perspectives. Government officials strive to predict travel patterns in an effort to guide investment, accommodate growth, and improve the operating conditions of existing infrastructure, as well as to balance social goals such as energy conservation and economic development. Environmentalists want to know how travel impacts climate, open space, and air quality, as well as to understand how individuals connect these issues to travel. Psychologists and health care specialists explore how travel influences emotion and mental as well as physical well being. Authors of fiction often see travel as synonymous with adventure and excitement, and as a metaphor for self-exploration.

In many ways, travel behavior researchers incorporate each of these interests, while maintaining a primary interest in improving our basic understanding of, and ability to forecast, travel demand. Demand models, which are used to predict future travel patterns, utilize statistical modeling techniques in a way that, ideally, captures behavior. As such, the research in this field follows two major tracks: improving statistical modeling procedures and exploring human behavior. These two tracks are sometimes explored jointly and sometimes independently.

The work described in this dissertation aims to better understand human travel behavior. Though policy implications do arise from the work, direct applications to demand modeling practice are not the immediate goal. I seek a more basic understanding of the mechanisms at work that motivate and modify daily and other types of travel, for both work and leisure.

At its core, this dissertation aspires to answer a simple question: why do some individuals want to travel more, and others less? In the context of the daily commute, an initial reaction may be that such a question is almost ridiculous, and certainly not of concern to researchers, as the daily commute is stereotypically loathed by all. As such, the conventional answer is that no one would want to travel more; we all seek to travel less. Such thinking is consistent with travel demand models, which assume that minimizing travel time is a key objective of every trip, and with traditional economic thinking, which says that travel is a "derived demand" – derived from a desire to engage in an activity at a different location. But recent research is beginning to question this assumption. Salomon and Mokhtarian (1998) point out myriad reasons why travel in general and the commute in particular may be enjoyed, including its ability to provide a buffer between the work and home realms of daily life. Redmond and Mokhtarian (2001a), analyzing essentially the same sample of San Francisco Bay Area residents that I use here, found that the average ideal one-way commute time was near 15 minutes. Importantly, the ideal commute time was not zero minutes, which suggests that some desire travel, even to and from work. Here, I look more closely into who these individuals are and speculate as to what is motivating a desire for more or less travel.

Choo, *et al.* (2005) took a straightforward approach to answering the question of who wants to travel more or less. The authors used single-equation ordered response models on the same data set as the current study to estimate the impact of variables in a variety of categories, including socio-demographics, attitudes, and personality, on Relative Desired Mobility – the nomenclature given to the measure of wanting to travel more or less than current amounts. To fully understand the limitations of the work of Choo, *et al.*, I must discuss the body of work from which their research emerged.

The Choo, *et al.* (2005) paper grew out of a research program that has produced numerous journal articles and reports (e.g., Redmond and Mokhtarian, 2001b; Mokhtarian, *et al.*, 2001; Ory, *et al.*, 2004; Ory, *et al.*, forthcoming; Collantes and Mokhtarian, 2002; Ory and Mokhtarian, 2005). Drawing on the prior research of Ramon (1981), this body of work identified four key travel measures of interest, namely: Objective Mobility (how much I actually travel), Subjective Mobility (how much I think I travel), Travel Liking (how much I enjoy travel), and Relative Desired Mobility (how much more or less, as compared to current amounts, travel is desired). A mail out/mail back survey was used to collect the data for travel in a variety of categories, such as commuting and long-distance airplane travel.

Variables in the Objective Mobility category are referred to as (actual) travel *amounts* throughout this dissertation, and include reported measures of travel time, distance, and frequency. Variables in the Subjective Mobility (referred to as travel *perceptions* or sometimes *perceived amounts*), Travel Liking (*affections*), and Relative Desired Mobility (*desires*) categories are all measured on five-point scales for each type of travel (see *4.1 Key Endogenous Variables*). Explaining the variability of the Relative Desired Mobility measures is considered the end goal in the modeling because these variables are most likely to influence future behavior as they quantify desires that are not currently met.

As discussed in Ory, *et al.* (forthcoming), the term Objective Mobility is somewhat artful in that the variables in this category are not truly "objective" (i.e. they are collected by asking respondents directly, not by independently recording travel amounts). The category name is chosen to represent the contrast between the quantitative measures of distance and frequency that *could* be objectively assessed if resources permitted, and the qualitative measures captured by the Subjective Mobility variables. Ory, *et al.* (forthcoming) argue that because the literature has found very high correlations between actual and cognitive/reported distances (see, e.g., Canter and Tagg, 1975), the Objective Mobility measures serve as appropriate proxies for actual travel amounts. I take the same position here.

In the work by Mokhtarian, *et al.* (2001), Ory, *et al.* (2004), Collantes and Mokhtarian (2002), Ory and Mokhtarian (2005), and Choo, *et al.* (2005), each of the four key individual constructs was modeled, across numerous travel categories, using other variables in the dataset as well as, in some cases, the other remaining key variables. In each, single-equation models, such as linear regression or ordered probit, were used to determine the factors that shaped each construct.

While this work has produced many intriguing ideas and useful results, a key limitation is its lack of control for endogeneity. Consider, for example, the relationship between Subjective Mobility (SM) and Travel Liking (TL). One could ask: do I like my travel in part because I am doing it an amount that is about "right" for me (SM→TL)? Or are my subjective evaluations of how much I am doing it influenced in part by how much I like it (TL→SM)? Acknowledging that both directions of causality are plausible, the single-equation models of Subjective Mobility used Travel Liking as a covariate (Collantes and Mokhtarian, 2007) and the models of Travel Liking used Subjective Mobility as a covariate (Ory and Mokhtarian, 2005). In a single-equation model, the estimated coefficient represents a composite of the effect of each variable on the other; the true magnitude of each coefficient is not known. In the extreme, if the effect in one direction is negative (SM→TL) and in the other direction (TL→SM) is positive, the two impacts could cancel and a single-equation model might show *no* significant relationship, thereby obscuring what in fact are two interesting and important relationships.

In this dissertation, the endogeneity issue is addressed directly by using structural equation models (SEM), rather than single-equation models, to simultaneously represent each of the four key constructs and their relationships to each other. Thus, this work improves upon each of the previously estimated single-equation models. Structural models have the ability to estimate bidirectional effects, as well as to model direct and indirect effects (see *3.2 Methodology*). The goal of the modeling is to sort out, by travel category, the relationships between Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility. Because I see Relative Desired Mobility as an end, and most important, measure (see Chapter 3), the focus will be on how all these other measures combine to influence Relative Desired Mobility: after identifying all the causal directions, what drives Relative Desired Mobility?

An initial hypothesized conceptual model of the interrelationships among the four key constructs, as well as the other variable categories present in the dataset, is presented in Figure 1.1, and is discussed fully in *3.1 Conceptual Model*. Boxes in the diagram, both labeled and unlabeled, represent *categories* of observed variables (the size of the box is not relevant). Meaning, the generically named "Objective Mobility" box represents a host of travel category-specific variables, such as commute distance and annual frequency of airplane travel. The large, labeled circles represent latent variables; small, unlabeled circles represent error terms. The latent variables representing Attitudes, Personality, and Lifestyle are manifested in the responses to various indicator variables (unlabeled boxes) from the survey instrument (see *3.2.2.4 Latent Variables*).

The model in Figure 1.1 is only a first cut, which is tailored to particular specifications, and modified in keeping with empirical evidence and econometric limitations (such as identifiability; see *3.2.2.2 Model Identification*). In Chapters 5, 6, and 7, ten travel category-specific models similar in form to the conceptual model are presented. Because the boxes in Figure 1.1 represent categories of variables (rather than a single measure), the direction of causality shown does not always hold. For example, the figure shows Mobility Constraints influencing Socio-demographics, e.g. an individual who is limited in his ability to drive (for physical or psychological reasons) would probably not own multiple vehicles. But auto availability is also considered a Mobility Constraint and is logically influenced by Socio-demographic variables such as income and household size.

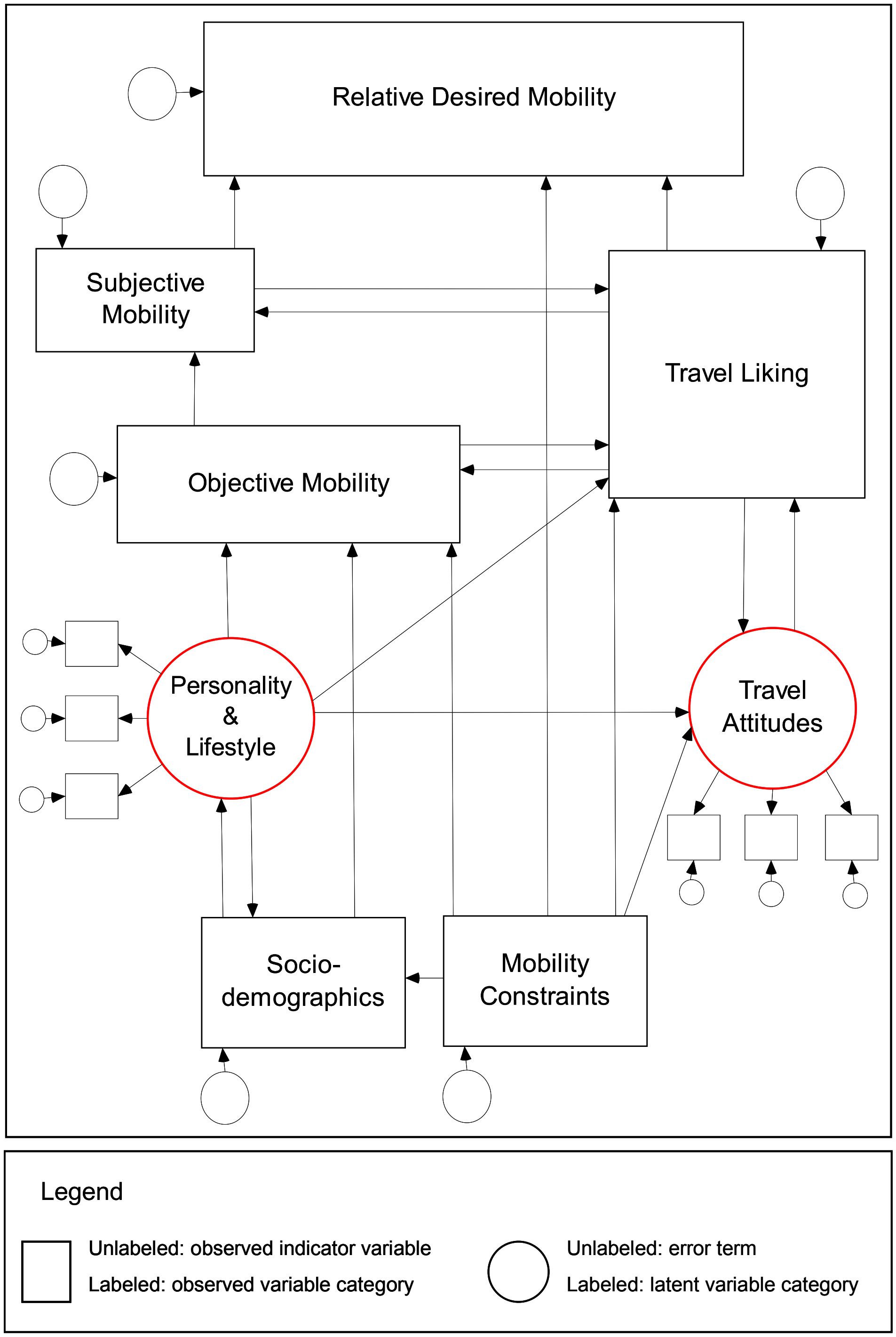


Figure 1.1: Hypothesized Conceptual Model

The work outlined in this dissertation will answer a variety of interesting questions about travel behavior, such as:

- Does affection for travel increase travel amounts? Or, do travel amounts determine affection for travel? Or, do both directions of causality hold? If so, what are the relative magnitudes of the opposing directions?

- The effect of Subjective Mobility on Travel Liking may be negative (the more I travel, the less I like it) while the converse effect may be positive (the more I like travel, the more I think I do it). Can these two counteracting effects be separately identified? Which is stronger?

- How are specific travel attitudes impacted by a general Travel Liking and vice-versa? Which direction of causality is strongest?

- The conceptual diagram shows Subjective Mobility impacting Relative Desired Mobility, both directly and indirectly through Travel Liking. Although both effects are expected to be negative, which one is stronger?

- Does the Subjective Mobility construct proposed here actually "filter" the Objective Mobility construct to form Relative Desired Mobility? Or is a direct impact of Objective Mobility on Relative Desired Mobility a stronger effect?

The contribution of this dissertation is multi-faceted. First, it expands and further clarifies the idea of a positive utility for travel. As mentioned previously, demand models uniformly assume that travel time is a cost to be minimized. More reliably determining the influences on wanting to travel more will give more credence to the concept of a positive utility for travel. Second, the work incorporates travel-related attitudes, personality, and lifestyle variables into models of travel behavior. Typical demand models ignore the impact of attitudes; this work further demonstrates the relative importance of attitudes in predicting travel behavior. Although previous studies have also addressed this issue, the structural model underpinning the proposed research is, to my knowledge, the most elaborate conceptualization to date of the role of attitudes (and other "soft" variables such as personality and lifestyle) in influencing travel behavior. Third, joint models of Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility tell a comprehensive and interesting story about travel behavior and the empirical results represent, in some respects, the most sophisticated insight achieved to date. Finally, I take advantage of the numerous models estimated and the sizable sample, to perform an empirical analysis of the robustness of the results to variations in estimation approach, sample size, and degree of non-normality – a useful and distinctive real-world complement to the numerous simulation studies of these issues.

The organization of the dissertation is as follows. Chapter 2 discusses literature in two key areas, namely the emerging interest in a so-called positive utility of travel and modeling techniques used in systems having multiple endogenous variables. Chapter 3 examines the conceptual model and outlines the methodology. Chapter 4 describes the data. Chapter 5 presents the results for the commute travel model, Chapter 6 the results for the other short-distance travel models and Chapter 7 the results for the long-distance travel models. Chapter 8 presents an econometric analysis of the different estimation techniques used for the models presented in Chapters 5 – 7. The concluding chapter summarizes the work, presents limitations and contributions of the study, and suggests directions for future research.

2. LITERATURE REVIEW

Literature relevant to this dissertation falls into two general areas: the positive utility for travel and multiple equation modeling techniques. The first section of this chapter focuses on the concept of positive utility for travel, from perspectives of both travel behavior and psychology. The second section discusses modeling techniques, specifically applications in the transportation field that relate behavior and attitudes.

2.1 Positive Utility of Travel

Traditional economic thinking considers travel to be a derived demand – derived from a desire to participate in spatially-separated activities. Travel demand models, which grew from basic economic theory, uniformly assume that travel time is a cost to be minimized. When considering the choice between travel modes (i.e. drive alone, transit, walk, etc.), whichever choice offers the quickest trip, all else equal, is considered preferable. Of course, models of mode choice contain myriad other variables that explicitly account for variables such as travel cost, and implicitly account, via constants, for at least the average net effects of unmeasured variables, such as convenience.

Though commentary on a so-called positive utility for travel is nascent, a number of transportation scholars have commented on the intrinsic benefits of travel for some time. Mokhtarian, *et al.* (2001) gives a thorough summary of such literature, including a quote from Israeli geographer Shalom Reichman (1976) suggesting that transportation may fulfill basic human needs in itself. Such ideas were expanded upon by Salomon and Mokhtarian (1998), who present a list of reasons why individuals may enjoy travel for its own sake. The list includes: adventure-seeking, variety-seeking, independence, control, status, buffer (between work and home), exposure to the environment, scenery and other amenities, and synergy. Ory and Mokhtarian (2005) empirically validate many of these reasons (using the same dataset as the current study) and add escape, curiosity, conquest, physical exercise, and the therapeutic value of movement/travel to those proposed by Salomon and Mokhtarian (1998).

Mokhtarian and Salomon (2001) suggest that an affinity for travel comprises three components, namely: the activities conducted at the destination; activities that can be conducted while traveling; and the activity of travel itself. The authors note that while these three elements may be empirically confounded, they are conceptually distinguishable, and go on to discuss each of the three in some detail.

Hess, *et al.* (2005) frames the positive utility of travel discussion in terms of model estimation. Specifically, using data taken from more than 4,000 users of a rail service between Montreal and Toronto in 1989, the researchers discuss the reasonableness of non-zero probabilities for positive coefficients, using mixed logit models, on travel time savings. Larson and Lew (2005) also present an econometric argument in a study of the leisure travel of approximately 200 fishermen in Willow Creek, Alaska. The authors' model reveals that the value of ancillary travel time (travel ancillary to the activity of fishing) could be either positive or negative. For about two-thirds of their sample, the travel time was valued positively, and for about one-third of the sample, the positive value of travel time was required in order for the total net utility of the trip to be positive (i.e. the positive utility of the fishing act alone was outweighed by the costs).

Analyses of the joy of travel extend beyond the work of transportation researchers. The environmental psychologist Steg (2005) empirically investigated what motivates automobile travel, in the context of trying to better guide environmental policy. In two separate studies performed in The Netherlands, one surveying 185 drivers in Groningen and Rotterdam in 1997 (response rate of 26%) and another in 1999 of 113 peak period commuters in Rotterdam (response rate of 52%), she found that instrumental motives (such as speed and convenience) play a secondary role to symbolic and affective motives (i.e. driving appeals to sensations of control, power, and status). Anable and Gaterslaben (2005) took on a similar investigation and found that for work travel, individuals appreciate instrumental aspects, and for leisure travel, instrumental and affective factors are important. The study of work travel used a sample of 265 respondents gathered from the University of Surrey (academics, staff, and graduate students) and local councils; the leisure study was performed at two National Trust attractions near Manchester using a short self-completion survey that gathered 679 returned questionnaires (response rate of 46%). In addition to these direct investigations of motivations, many others have commented on the "love affair" of travelers with their automobiles (see, e.g., Wachs and Crawford, 1992; Marsh and Collett, 1986; Sachs, 1992).

This dissertation continues this line of inquiry by offering a more sophisticated examination of the relationship between enjoyment of travel, actual travel amounts, and desired travel amounts. The work will directly improve the efforts of Choo, *et al.* (2005) and Ory and Mokhtarian (2005) by accounting for the endogeneity effects they initially set aside.

2.2 Analytical Methods

As discussed in Chapter 1, this work is, at its core, a pure investigation of travel behavior, and a relatively novel investigation at that. The work does not address well-established behavioral relationships with a new modeling technique. As such, finding analogous studies for comparing analytical techniques is somewhat difficult. The approach taken here will be to review studies in travel behavior that address the problem of having multiple endogenous variables. The goal is to determine the best possible approach to analyzing the conceptual model. The literature review is segmented by modeling technique: single-equation models, simultaneous equations, and structural equation models.

2.2.1 Single-Equation Models

Research into behavioral aspects of travel have long used single-equation models, such as ordinary least-squares regression and ordered probit. As mentioned in Chapter 1, the basis for the work presented here is the single-equation models of Objective Mobility (Mokhtarian, *et al.*, 2001; Ory, *et al.*, 2004), Subjective Mobility (Collantes and Mokhtarian, 2002; Collantes and Mokhtarian, 2007; Ory, *et al.*, forthcoming), Travel Liking (Ory and Mokhtarian, 2005), and Relative Desired Mobility (Choo, *et al.*, 2005).

A primary shortcoming of the aforementioned efforts is a lack of control for endogeneity. Single-equation models assume a single direction of effect and don't allow for two-way effects. The inadequacy of single-equation models in this context is a key motivation for this dissertation.

2.2.2 Simultaneous Equation Models

Simultaneous equations are a more specific form of structural equations (see *3.2 Methodology* for more details). As such, this sub-section and the following one on structural models could be discussed together. However, there are studies which do take the more limiting simultaneous equations approach, one of which is discussed here.

Tardiff (1976) uses simultaneous equations to investigate the relationship between attitudes and behavior. His focus was on determining if attitudes caused behavior, or vice versa; he investigated the modal choice of a relatively inadequate sample (not enough bus users were present to properly estimate a conventional mode choice model) of residents of West Los Angeles. His results, though limited, suggested that behavior is more likely to cause attitudes, than vice versa. In the present context, an analogous finding would be that Objective Mobility has a stronger impact on Travel Liking than the converse.

2.2.3 Structural Equation Models

The use of structural equation modeling (SEM) in the field of travel behavior has grown tremendously in recent years. In an introduction to the technique and review of existing literature, Golob (2003) pointed out that the total number of published travel behavior SEM studies doubled from the years 2000 to 2003. In this sub-section, a handful of SEM applications are reviewed and discussed. The goal is to highlight applications that are similar to those proposed in the conceptual model – meaning, the focus is on applications involving the complex relationships between attitudes and behavior.

In an early application, Dobson, *et al.* (1978) directly investigate the interrelationships of travel behavior and attitudes, namely the attitudes toward and use of the bus by 800 workers in downtown Los Angeles who lived within two miles of a radial freeway (connecting to downtown). The authors used two-stage structural equation modeling to show that affect, which was influenced by perceptions, had an influence on behavior, and vice versa. In the absence of affect, behavior influenced attitudes/perceptions, but not the converse.

Golob (2001), similar to Tardiff (1976), also found stronger links of behavior to attitudes than vice versa, in his study of congestion pricing and attitudes in the San Diego area. Using panel data of approximately 800 individuals, Golob modeled the relationship between attitudes towards high occupancy toll facilities (e.g. are they “fair”?) and the demand for carpooling and toll-road usage, and found that behavior shapes attitudes, rather than the reverse.

In another study of road pricing, Jakobsson, *et al.* (2000) examined 524 Swedish car users’ willingness to accept pricing. The authors confirmed a model structure in which income and the expectation of others’ car use reduction influenced the intention of car use reduction, which in turn influenced perceptions of fairness and infringement on freedom, which had a final impact on the acceptance of road pricing. Interestingly, environmental concerns did not impact the level of acceptance of road pricing.

Golob and Hensher (1998) investigated the relationship between environmental attitudes, with a focus specifically on greenhouse gas emissions, and travel behavior. Approximately 1,500 surveys taken in six Australian cities were used for the analysis, which, consistent with other studies, finds that mode choice influences attitudes. The authors also outline the type of person likely to have a strong environmental commitment (female, highly educated, wealthy), but also observe that females are more likely than men to view the car as a status symbol, which leads to more solo driving.

Garling, *et al.* (2001) extend the study of attitudes further into the realm of psychology by examining the role of habits and past behavior in conjunction with the interaction of attitudes and behavior. The authors, by questioning a small (approximately 50) number of students, found that positive attitudes towards driving can lead to driving more often, which, in turn, strengthens the habit of driving; they argue that such initial attitude-based choices can lead to script-based (or habit-based) choices.

While myriad other transportation studies using structural equation modeling to relate travel behavior to attitudes could be cited, the above summary indicates the prevalence and usefulness of such examinations.

2.3 Summary of Literature

The literature indicates that structural equation modeling is an adequate and appropriate tool for modeling the interactions between traveler behavior and attitudes. It also highlights the relatively specific nature of the work done to date, most of which has focused on the choice of mode or the relationship between attitudes and a specific aspect of the transportation system (e.g. high-occupancy toll lanes, bus transit, etc.). The work presented here not only continues the use of SEM, but also takes a more holistic view of travel by investigating both generic (e.g. overall short-distance) and specific (e.g. short-distance personal vehicle) travel types. Further, its consideration of attitudes extends well beyond the isolated variables used by the cited studies. Here, general measures of Attitudes, Personality, and Lifestyle are considered alongside specific measures of travel affect (Travel Liking) and perceived (cognitive) travel amounts (Subjective Mobility), along with revealed behavior (Objective Mobility), to predict a measure of desire (Relative Desired Mobility).

3. CONCEPTUAL MODEL AND METHODOLOGY

This chapter first discusses, in detail, the conceptual model introduced in Chapter 1. Following, a technical discussion of structural equation modeling, the selected technique, is presented.

3.1 Conceptual Model

The conceptual model is based on previous single-equation modeling efforts and the author's thoughts on travel behavior; it is shown in Figure 1.1. The model contains four key endogenous variable categories, namely Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility; four other variable categories (Attitudes, Personality and Lifestyle, Socio-demographics, and Mobility Constraints). Recall however that each category comprises a number of individual variables (also see Chapter 4), some of which may be classified differently than the category as a whole. For example, Socio-demographic variables such as gender and age can be considered exogenous, while a variable like income might be a function of age, education, employment, and Personality/Lifestyle. The remainder of this chapter discusses the hypothesized relationships shown in the figure. The focus of the discussion is on the four key endogenous variables; the relationships pertaining to each key variable category are discussed in separate sub-sections below.

3.1.1 Objective Mobility

Modeling Objective Mobility is a key aspect of traditional travel demand modeling. The first step in the widely-known "four-step model" is trip generation, which uses employment and socio-demographic data to estimate the number of trips made for different purposes in a typical day. Myriad other works have investigated the impact of various measures on daily travel distance and time.

Ory, *et al.* (2004) used the same dataset as the current study to estimate a variety of single-equation Objective Mobility models, including one-way commute distance, one-way commute time, weekly commute miles, and weekly commute minutes. Redmond and Mokhtarian (2001b) modeled other Objective Mobility measures, including weekly short-distance travel for all purposes in all modes, for work specifically, for work/school-related, for entertainment, in a personal vehicle, by non-motorized modes; and long-distance travel for all purposes in all modes, for work specifically, for entertainment, in a personal vehicle, and in an airplane. These models suggest that Objective Mobility is primarily a function of Mobility Constraints, Socio-demographics, Travel Liking, Attitudes, Personality, and Lifestyle.

As discussed in the references cited above, each of these relationships is highly plausible. How much we travel each day is probably a function of our ability to travel (Mobility Constraints), our wealth, activity patterns, employment status, and family structure (Socio-demographics), how much we enjoy the endeavor (Travel Liking), and our individual characteristics (Attitudes, Personality, and Lifestyle).

The conceptual model shown in Figure 1.1 reflects these findings. All of these effects are hypothesized to impact Objective Mobility directly, save Attitudes, which operates through the Travel Liking variables. Again, this discussion highlights the weakness of the approach of Ory, *et al.* (2004) and Redmond and Mokhtarian (2001b). In the single-equation models, impacts of the Attitudes variables on Objective Mobility may be direct or indirect. A multiple-equation approach has the potential to clarify this relationship.

3.1.2 Subjective Mobility

The Subjective Mobility variables are qualitative assessments of travel categories, e.g. for commuting, in a personal vehicle. Looking at travel in this general way, as opposed to isolated trips, is a unique aspect of the current research program. A report by Collantes and Mokhtarian (2002) presents the single-equation models of Subjective Mobility. This work follows the same pattern as the Objective Mobility model estimation by Redmond and Mokhtarian (2001b), as models in the following travel categories are estimated: short-distance overall, commute, work/school-related, entertainment, personal vehicle; long-distance overall, work/school, entertainment, personal vehicle, and airplane. Along with the report, papers by Collantes and Mokhtarian (2007) and Ory, *et al.* (forthcoming) discuss the results of the modeling in the context of the travel behavior and psychology literature, respectively.

The above references suggest that Subjective Mobility is a function of Objective Mobility, Travel Liking, Attitudes, Lifestyle, Personality, Mobility Constraints, and Socio-demographics. The conceptual model presented in Figure 1.1 assumes that the majority of these impacts are indirect, operating through the Objective Mobility and Travel Liking variables, with only these two groups of variables directly impacting Subjective Mobility. Such a model assumes that individuals' characteristics (Socio-demographics, Mobility Constraints, Personality, Attitudes, and Lifestyle) determine how much they actually travel in a given category; the perception of this travel amount is then magnified or diminished by the enjoyment of the type of travel, which together shape the qualitative assessment of travel amount. While this is probably an over-simplification of the relationships, it serves as a reasonable hypothesis.

3.1.3 Travel Liking

Single-equation models of Travel Liking can be found in Ory and Mokhtarian (2005), with complete estimates available in Ory and Mokhtarian (2004). The presence and importance of the Travel Liking variables to both the Objective and Subjective Mobility models validates the need for a direct investigation of the Travel Liking variables. In the work cited, Travel Liking was shown to be a function of Objective Mobility, Subjective Mobility, Attitudes, Personality, Lifestyle, Mobility Constraints, and Socio-demographics.

The conceptual model suggests that the Objective Mobility, Subjective Mobility, Attitudes, Personality, Lifestyle, and Mobility Constraint variables directly impact Travel Liking, as well as Travel Liking impacting Attitudes (such a relationship is not determinable in a single-equation model). Socio-demographics operate through Objective Mobility. The complexity of this relationship highlights the need for multiple-equation models capable of estimating direct and indirect effects. For example, the amount a person actually travels (Objective Mobility) certainly influences how much he enjoys traveling, but this influence may be largely indirect, shown through his qualitative travel assessments (Subjective Mobility), which may also influence the enjoyment of travel. Ascertaining the strength and direction of these effects is the end goal of this dissertation.

The complexity of the relationship between Travel Liking and the other key variables in the dataset warrants segmenting the sample into those with positive Travel Liking in a given category and those with negative responses (see *5.3 Travel Liking Market Segmentation*). Such an approach acknowledges that those with differing orientations may experience the relationships posed in the conceptual model in totally different ways. For example, consider the relationship between Travel Liking and commute distance for two individuals, one who enjoys travel and one who does not, who both travel 50 miles one way to work each day. For the individual who enjoys commuting, this longer-than average trip may have been a conscious decision; the commute being a welcome time to revel in his solitude. For the other individual, the long commute may be causing her dislike of travel. For the first individual, Travel Liking is positively impacting Objective Mobility. For the second, Objective Mobility is negatively impacting Travel Liking. The fundamental difference in the orientation of those holding these divergent opinions warrants segmenting the sample into those who enjoy travel, and those who do not.

3.1.4 Relative Desired Mobility

As mentioned previously, Relative Desired Mobility is seen as the end goal of the modeling because this measure, as opposed to Objective Mobility and Subjective Mobility, is most likely to influence future behavior as it measures desires that are not currently met. As such, it was precluded from influencing the other endogenous variables in the single-equation models under the assumption that the opposing direction of causality is more likely. The conceptual model echoes this position: no variables are impacted by Relative Desired Mobility. It should be noted, however, that it is conceivable for Relative Desired Mobility to affect Subjective Mobility. As discussed in Ory, *et al.* (forthcoming), a sense of surfeit or deprivation may stretch or shrink one's assessment of Subjective Mobility (see *5.4 Expanded Model Estimation Results*).

Choo *et al.* (2005) estimated single-equation models of Relative Desired Mobility and found that all the variable categories in the dataset impacted the measures. The single-equation models assumed a direct relationship in each case, whereas the conceptual model assumes only Travel Liking, Mobility Constraints and Subjective Mobility directly impact Relative Desired Mobility. The other variables operate through Objective Mobility (which then operates through Subjective Mobility) and Travel Liking.

3.1.5 Other variables

Beyond the four key endogenous variables, there are a few other interesting relationships hypothesized in the conceptual model. Each of these is discussed in this sub-section.

The Attitudes variable group is impacted by the Personality, Lifestyle, Mobility Constraints, and Travel Liking variables in the conceptual model. The idea here is that Attitudes, e.g. favoring environmentally-friendly solutions to transportation problems, are a function of underlying Personality traits, life stage (Lifestyle), enjoyment of travel (Travel Liking), and the ability to travel by different modes (Mobility Constraints). None of the previous work in the research program investigated the factors influencing Attitudes.

As stated above, the Personality and Lifestyle variables influence Attitudes. It is further hypothesized that Socio-demographics have the potential to influence Personality and Lifestyle variables, and vice versa. As an example, variables such as income and number of children may determine the type of Lifestyle (e.g. family/community-oriented) one pursues. Conversely, one may first choose a Lifestyle and then make choices regarding income and number of children accordingly. Both directions are plausible.

Socio-demographics are also hypothesized to be influenced by Mobility Constraints. Consider, as an example, an individual who is limited in his ability to walk. Such a limitation could certainly influence the number of vehicles he owns.

3.2 Methodology

In this section, the approach to estimating the conceptual model discussed previously is presented. The literature review of *2.2 Analytical Methods* indicates that structural equation modeling (SEM) is a useful technique for analyzing the relationships present in the conceptual model. Structural equation modeling offers several improvements over single-equation approaches, such as ordinary least-squares regression and ordered probit. These advantages include the ability to reveal bidirectional causal relationships, and to separately estimate direct (e.g. X impacts Y) and indirect (e.g. X impacts Y which impacts Z) relationships (as well as determine the combined effects) (for a discussion of the use of SEM in practice, see Tomarken and Waller, 2005).

It is important to note that structural equation modeling is a more general form of simultaneous equation modeling. Simultaneous equations are structural equations that assume no measurement error, which, as with ordinary-least squares regression, when present can lead to correlations between regressors and error terms. The estimation of these two types of equations often differs. Simultaneous equations are typically estimated by finding the parameter estimates that maximize the likelihood of obtaining the sample observations. Structural equations are generally estimated using covariance structural analysis (i.e. finding the parameter estimates that minimize the difference between the observed sample covariance matrix and the theoretical covariance matrix implied by the model) (Greene, 2000).

The remainder of this section discusses the general form of the structural equation model, followed by a presentation of the modeling procedure, including estimation approaches.

3.2.1 Model Structure

Throughout this sub-section, the matrix notation of Jöreskog, *et al.* (1999) is used. A general form of a structural equation model can be written as:

$$\eta = \alpha + B\eta + \Gamma\xi + \varsigma,$$

where η is a vector (N_η x 1) holding (N_η) endogenous variables, ξ is a (N_ξ x 1) column vector holding (N_ξ) exogenous variables, α is a column vector (N_η x 1) of intercept terms, B is a matrix (N_η x N_η) of coefficients describing the direct effects of the η-variables on the other η-variables, Γ is a matrix (N_ξ x N_η) of coefficients describing the direct effects of the ξ-variables on the η-variables, and ζ is a (N_η x 1) column vector of error terms (the notation for each observation is suppressed for the sake of clarity).

In the general case where the endogenous or exogenous variables may be latent, neither η nor ξ is observed. Rather, each is assumed to produce, or be manifested through, one or more observed endogenous variables (y) and exogenous variables (x), respectively, as follows:

$$y = \tau_y + \Lambda_y \eta + \varepsilon,$$

$$x = \tau_x + \Lambda_x \xi + \delta,$$

where the error terms ε and δ are assumed to be uncorrelated with η and ξ, Λ_y and Λ_x represent coefficients, and τ_y and τ_x represent intercepts.

Let the mean vector of ξ be κ, covariance matrix of ξ be Φ and the covariance matrix of ζ be Ψ. For the x and y equations, let Θ_ε and Θ_δ be the covariance matrices of ε, δ, respectively, and $\Theta_{\delta\varepsilon}$ the covariance matrix of the error terms. With these definitions, the mean vector of z = (y′, x′)′ is:

$$\mu = \begin{pmatrix} \tau_y + \Lambda_y B^*(\alpha + \Gamma\kappa) \\ \tau_x + \Lambda_x \kappa \end{pmatrix};$$

the covariance matrix of z becomes:

$$\Sigma(\theta) = \begin{bmatrix} \Lambda_y B^*(\Gamma\Phi\Gamma' + \Psi)B^{*'}\Lambda_y' + \Theta_\varepsilon & \Lambda_y B^*\Gamma\Phi\Lambda_x' + \Theta_{\delta\varepsilon}' \\ \Lambda_x \Phi\Gamma' B^{*'}\Lambda_y' + \Theta_{\delta\varepsilon} & \Lambda_x \Phi \Lambda_x' + \Theta_\delta \end{bmatrix},$$

where $B^* = (I - B)^{-1}$, and θ is a generic vector representing all the unknown parameters of the system. The restrictions imposed by specifying the structural equations allows for the estimation of each of these unknown parameters. A structural equation model is estimated by fitting the unknown parameters κ, α, τ_x, τ_y, B, Γ, Φ, Ψ, Λ_x, Λ_y, Θ_δ, Θ_ε, and $\Theta_{\delta\varepsilon}$ such that the difference between the model-implied population variance-covariance matrix and the sample variance-covariance matrix (an unbiased estimator of the population matrix) is minimized (Jöreskog and Sörbom, 1999; Jöreskog, *et al.*, 1999; Mueller, 1996).

3.2.2 Modeling Procedure

When developing a structural equation model, one must specify the model, check that the proposed structure is identified, estimate the model, and then assess the model's fit. The diagram in Figure 3.1 (adapted from Choo, 2005) outlines the procedure and highlights where feedback loops are necessary. Each of these procedural steps is discussed in this sub-section, along with a discussion of modeling latent variables.

3.2.2.1 Model Specification

Construction of an initial model specification, i.e. specifying the set of equations to be estimated, is guided by the conceptual model presented previously and the single-equation models already developed for the Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility key endogenous variables. After specifying an initial model, a certain amount of exploratory modeling work is performed, largely based on the estimation results, which leads to modifications of the initial conceptual model. Numerous model specifications were estimated and analyzed for each of the final models presented in Chapters 5, 6, and 7. Details of this approach, which are best illustrated via an example, are discussed in *5.1 Model Exploration and Specification*.

3.2.2.2 Model Identification

The issue of identification is important in both structural equation and simultaneous equation modeling. The issue of identification is explained most clearly through a simple example. Consider the equation x+y=9. Here, multiple values of the variables x and y can give rise to the same solution of 9. This equation is underidentified. While more complicated in the case of structural equation models, the concept is the same. Structural models can be transformed into a so-called reduced form, in which each endogenous variable is solved for as a function only of exogenous variables. When different sets of structural parameter values lead to the same set of reduced form parameters, the model is considered underidentified, or not identified (Kennedy, 1998). Such a model cannot be estimated.

A model can be exactly (or just) identified (e.g., the simple algebraic system of x+y=9 and x-y=3) or overidentified (e.g., x+y=9, x-y=3, and 2x=12) (Kmenta, 1997). As in the algebraic examples, the parameters in a structural model that is exactly or overidentified can be estimated.

The identifiability of a system can be determined before entering estimation. So-called "recursive" models (those that do not contain feedback loops) are always identified, assuming the number of parameters does not exceed the number of nonredundant covariances. Aside from the expanded model of *5.4 Expanded Model Estimation Results*, all of the models presented in this dissertation are recursive and thus, identification issues are not much of a concern.

For "non-recursive" models, two methods, namely checking order and rank conditions, are used for determining identifiability. Checking the order condition of the system involves counting the number of included and excluded exogenous variables and predetermined (fixed) variables in each equation. Specifically, the number of restrictions must be greater than or equal to N_η-1, where N_η is the number of endogenous variables. The rank condition is tested by calculating the rank of a sub-matrix of the reduced form (which consists of certain predetermined variables on the right-hand side of the model), which uses restrictions on the parameters of each equation (see, e.g. Greene, 2000); the rank of this matrix must be equal to N_η-1. These methods can be used together to test model specifications.

If the model is not identified, its specification needs to be modified, generally either by applying some restrictions (e.g. constraining some parameters to equal zero, or to be proportional to others), or by adding some exogenous variables to the system (Kennedy, 1998). The quest for identifiability often necessitates the imposition of restrictions that are undesirable from a conceptual standpoint (in essence assuming relationships that should in fact be statistically tested). The only way around this is to have an ample supply of relevant exogenous variables, which can be difficult in some applications. However, identifiability can and should be checked for the conceptual model, before the data collection stage.

3.2.2.3 Model Estimation

By far the most popular SEM estimation approach is maximum likelihood. To estimate the parameters, a scalar fitting function is defined as the difference between the sample-estimated variance-covariance matrix (denoted as S) and the model-implied variance-covariance matrix ($\Sigma(\Theta)$). This function can be written, again using the notation of Jöreskog, *et al.* (1999), as:

$$F_{ML}(\Theta) = \ln\left|\Sigma(\theta)\right| - \ln\left|S\right| + \mathrm{tr}\left[S\Sigma(\theta)^{-1}\right] - \omega + (\bar{z}-\mu)'\Sigma(\theta)^{-1}((\bar{z}-\mu),$$

where ω is the number of variables in $z = (y', x')'$.

Maximum likelihood (ML) estimation is derived from normal theory, and, as such, requires that the endogenous variables be jointly distributed multivariate normal and, as follows, distributed normal individually (Bentler and Dudgeon, 1996). The key data in this work, namely measures of Subjective Mobility, Travel Liking, and Relative Desired Mobility are categorical (as discussed in *4.1 Key Endogenous Variables*) and often not normally distributed. As a result, great care had to be taken in the estimation of the models.

For each of the models discussed in this dissertation, the first step in the estimation process is assessing the multivariate normality of the endogenous variables. AMOS (AMOS 7.0 is the software used for this study; see Arbuckle, 2006) provides a utility that presents a critical ratio of the skew and kurtosis for each variable as well as the critical ratio of the multivariate kurtosis, also known as Mardia's coefficient (Mardia, 1970). Under multivariate normality, the standardized third-order moment (skew) is zero and the fourth-order moment (kurtosis) is three (though, in practice, three is subtracted from empirical measures of kurtosis to measure the deviation from normality). Though guidelines vary, multivariate kurtosis values less than one indicate negligible non-normality, one to anywhere from 3.5 to 10.0 indicate moderate non-normality, and greater values indicate severe non-normality (Information Technology Services; Lei and Lomax, 2005; Kline, 2005; Curran, *et al.*, 1996; West, *et al.*, 1995).

The variables of the models estimated in this dissertation exhibited a wide range of non-normality (the multivariate kurtosis values and critical ratios are presented with the estimation results). As a result, the following estimation techniques were employed to best generate reliable parameter estimates and goodness-of-fit measures.

First, the models were estimated using maximum likelihood (ML). Though such an approach is not strictly theoretically appropriate with non-normal data, research does indicate that ML is relatively robust in the face of moderate non-normality when large sample sizes are present (Lei and Lomax, 2005; Chou and Bentler, 1995). Here, the sample sizes always exceed 1,300 observations, considered large by structural equation modeling standards.

The second approach utilizes Browne's asymptotic distribution free (ADF) estimation (Browne, 1984). ADF has the desirable property of not assuming a distribution – it is not based on normal theory. Rather, it entails a generalized least squares approach that assumes a weight matrix (simply the inverse of the observed variance-covariance matrix) that is responsive to second- and fourth-order terms. Creating the fitting function for the ADF approach is computationally demanding, requiring a combination of large sample sizes (on the order of 1,000 to 5,000) and few variables (less than 20) (West, *et al.*, 1995). ADF has been shown to yield incorrect χ^2 test statistics for small samples (Hu, *et al.*, 1992; Mueller, 1996). The relatively large number of observations (more than 1,300) and the relatively small number of variables (fewer than 15) in the specifications presented here make the ADF approach viable (West, *et al.*, 1995).

The third estimation approach is bootstrapping. Bootstrapping circumvents normal theory by sampling and re-sampling the data (with replacement) to generate parameter and standard error estimates, as well as goodness-of-fit measures. This is done by computing parameter estimates for each drawn sample. After numerous draws, a distribution of the parameter values can be estimated. In structural equation modeling, the Bollen-Stine bootstrap approach is used to correct the χ^2 test statistic, which, when estimated using maximum likelihood, is inflated by non-normality (Bollen and Stine, 1992). AMOS's naive bootstrapping method is used to estimate parameter coefficients.

The final estimation method uses the M*plus* software developed by Muthén (Muthén and Muthén, 2005; Muthén, 1983), in which a weighted least squares approach, similar to ADF, is employed. The unique aspect of the M*plus* estimation technique is that categorical variables, y, are assumed to represent approximations of an underlying latent variable, y^*, that is normally distributed (see Appendix 4 in Muthén, 2004). While this assumption is strong, West, *et al.* (1995) suggest that attitudinal variables, which are measured on a Likert-type scale of say "strongly disagree" to "strongly agree", could reasonably be said to meet this criterion. The key endogenous variables in the data used here, namely Subjective Mobility, Travel Liking, and Relative Desired Mobility, are all measured on five-point ordinal scales, similar to those described by West, *et al*. The additional complexity of the M*plus* technique requires the χ^2 test statistic and the model degrees of freedom to be corrected (Muthén, 2004).

In the maximum likelihood, bootstrapping, and asymptotic distribution free estimations, the ordinal variables are treated as continuous; in the M*plus* estimation, they are explicitly treated as ordinal (for further discussion of this point, see *4.1.5 Treating Ordinal Variables as Continuous*).

For further discussion of the use of ordinal variables in structural equation models, see Xie (1989), Skrondal and Rabe-Hesketh (2005), and Lee and Kimhi (2005).

Though each of the discussed estimation methods – ML, bootstrapping, ADF, and M*plus* – have their limitations, to the extent that each give consistent results, confidence in the results increases. As such, the *chosen* estimation method is all four: coefficient estimates, critical ratios, and goodness-of-fit measures from each of the estimation techniques are presented for the final ten category-specific models. Andreassen, *et al.* (2006) used a similar approach in analyzing bank satisfaction data; the authors conclude that such "estimation triangulation" provides a useful means of assessing model misspecification.

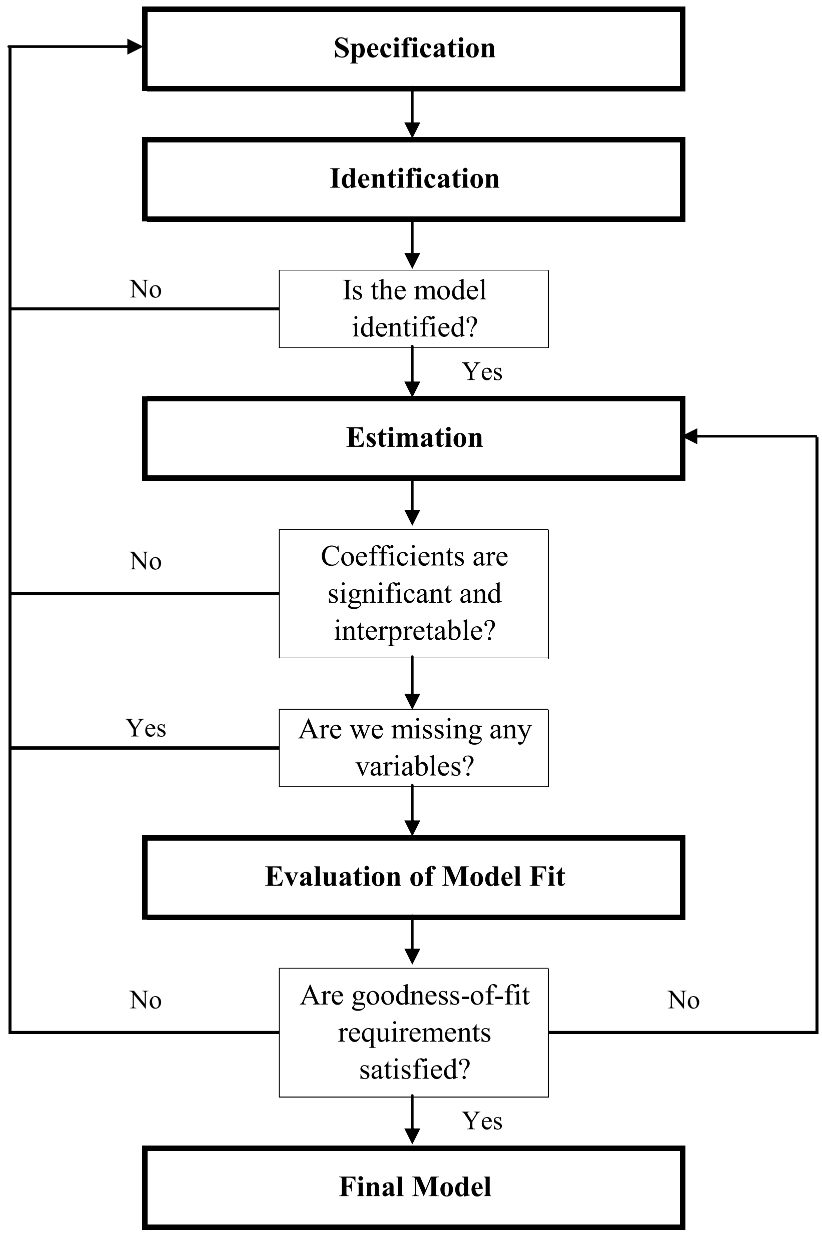
3.2.2.4 Latent Variables

As mentioned in the Introduction and elaborated on in *4.2 Explanatory Variables*, the travel Attitudes, Personality, and Lifestyle variables are collections of statements which respondents rated using five-point, Likert-type scales. To facilitate exploration of different specifications, these variables are first entered into the models as scores from a previously-estimated factor analysis. In doing so, these variables are considered to be externally measured (without error). After settling on a model specification, the factor score variables are replaced with latent constructs, modeled as generating the observed survey variables that originally loaded most heavily on each factor (see Table 4.2). Such simultaneous estimation of the latent variables as part of the system is another benefit of the structural equation modeling framework.

3.2.2.5 Model Fit

To assess the quality of a particular model specification (i.e. how well the model-implied variance-covariance matrix compares to the sample variance-covariance matrix), some measure of goodness-of-fit is needed. Certain transformations of the χ^2 test statistic are universally used for this task, including the χ^2 test statistic *p*-value, χ^2 test statistic divided by the model degrees of freedom, goodness-of-fit index (GFI), normed fit index (NFI), and comparative fit index (CFI). Other measures, such as the root-mean square error of approximation (RMSEA), are also recommended by various scholars. An entire body of literature is devoted to assessing the performance of goodness-of-fit measures under a host of conditions (see, e.g. Lei and Lomax, 2005; Bollen and Long, 1992). Because no consensus has been reached (i.e. no single goodness-of-fit measure has been shown to be superior over the others, as for the R^2 and adjusted R^2 values in linear regression), experts in the field recommend that a variety of measures be used to assess model fit. Most structural equation model software packages present numerous goodness-of-fit measures as part of their standard reporting (Byrne, 2001; Ullman, 1996; West *et al*. 1995; Satorra and Bentler 1988, 1994). Table 3.1 presents a summary of goodness-of-fit measures and presents typical values found in models from the fields of operations research (Shah and Goldstein, 2006) and marketing (Baumgartner and Homburg, 1996).

The following measures of goodness-of-fit are presented with the estimation results: χ^2 test statistic and *p*-value, relative fit index (RFI), comparative fit index (CFI), incremental fit index (IFI), and the root mean square error of approximation (RMSEA). Using a diversity of measures better describes the goodness-of-fit and presenting commonly-used measures, such as those selected, allows for a comparison to previously published studies.



Source: Adapted from Choo (2005)

Figure 3.1: Structural Equation Modeling Procedure

Table 3.1: Summary of Goodness-of-Fit Measures

Measure	Meaning*	Typical values from operations research† mean (range)	Typical values from marketing‡ mean (range)
χ^2	Discrepancy between observed and model-implied variance-covariance matrices	---	---
p-value	The null hypothesis states that the model reproduces the observed variance-covariance matrix well	---	---
χ^2 / degrees of freedom	Reduces the sensitivity of χ^2 to sample size	1.82 (0.02, 4.80)	1.62 (1.19, 2.26)
Goodness-of-fit Index (GFI)	An absolute fit index that estimates the proportion of variability explained by the model (similar to R^2 in regression models)	0.93 (0.75, 0.99)	0.95 (0.90, 0.98)
Adjusted Goodness-of-fit Index (AGFI)	GFI penalized for model complexity	0.89 (0.63, 0.97)	0.91 (0.84, 0.95)
Root Mean Square Residual	Difference between the observed and estimated covariance matrices	0.052 (0.01, 0.14)	0.05 (0.03, 0.06)
Root Mean Square Error of Approximation	Estimates the amount of error of approximation per model degree of freedom, correcting for sample size and penalizing model complexity	0.058 (0.00, 0.13)	0.06 (0.03, 0.08)
Normed Fit Index (NFI)	The proportion of baseline (independence) model χ^2 explained by the model of interest.	0.91 (0.72, 0.99)	---
Relative Fit Index (RFI)	NFI corrected for degrees of freedom	---	0.85 (0.78, 0.91)
Incremental Fit Index (IFI)	The incremental improvement of the model of interest over the baseline (independence) model	0.94 (0.88, 0.98)	0.95 (0.91, 0.97)
Comparative Fit Index (CFI)	Assumes a non-central χ^2 distribution for the baseline model discrepancy	0.96 (0.88, 1.00)	0.95 (0.91, 0.97)
Akaike Information Criterion (ACI)	Balances the discrepancy against complexity	---	---
Browne-Cudeck Criterion	Penalizes complexity more heavily than AIC	---	---

* Adapted from Mokhtarian and Meenakshisundaram (1999); † Shah and Goldstein (2006);
‡ Baumgartner and Homburg (1996)

4. DATA

The data analyzed in this study are collected from a fourteen-page self-administered survey of approximately 2,000 individuals in the San Francisco Bay Area. A total of 8,000 surveys were mailed (garnering a response rate of about 25%) to randomly-selected households in three neighborhoods, namely the Hayes Valley/Western Addition/University of San Francisco (USF) area in San Francisco proper (half of the surveys), Concord (one-quarter) and Pleasant Hill (one-quarter). Hayes Valley, Western Addition, and USF are adjacent urban San Francisco neighborhoods, located close to the regional central business district (CBD) and well-served by transit. Concord and Pleasant Hill, in contrast, are both contiguous but different suburban cities, located across the San Francisco Bay from the regional CBD. This dissertation focuses on a subset of the 2,000 respondents – those who work either part-time or full-time and commute at least once a month. The reason for that choice is that commuters have a markedly different transportation experience (and hence could be expected to have different perceptions, affections, and desires) than do non-commuters. This subset contains 1,358 respondents with relatively complete data on most variables of interest; some key Socio-demographic characteristics of the sample are shown in Table 4.1.

Table 4.1 indicates that the sample is relatively balanced in terms of gender and neighborhood location. The youngest and oldest age categories have few observations, but as the sample comprises full- and part-time workers, this is not surprising. Higher incomes are over-represented compared to the Census (see Curry, 2000 for further discussion). However, as the focus of the work is to model the impact of income and other variables on the behavioral constructs, rather than purely to ascertain the population distribution of such measures, it is more important simply to have a reasonable spread of incomes than that they be exactly representative (Babbie, 1998).

Table 4.1: Key Socio-demographic Characteristics of Sample (N=1,358)

Characteristic		**Number (percent)**
Concord		318 (23.4)
Pleasant Hill		369 (27.2)
San Francisco (Hayes Valley/Western Addition/USF)		671 (49.4)
Female[a]		692 (51.1)
Have a driver's license[b]		1,338 (98.7)
Work full-time		1,141 (84.0)
Household income[c]	< $15,000	31 (2.3)
	$15,000 – 34,999	141 (10.6)
	$35,000 – 54,999	269 (20.3)
	$55,000 – 74,999	250 (18.9)
	$75,000 – 94,999	220 (16.6)
	> $95,000	411 (31.1)
Age[d]	18 – 23	44 (3.2)
	24 – 40	584 (43.0)
	41 – 64	686 (50.5)
	> 65	43 (3.2)
Characteristic		**Mean (std. dev.)**
Total people in household		2.39 (1.22)
Total children under 18 in HH[e]		0.45 (0.84)
Total workers in HH (full/part-time)[f]		1.77 (0.80)
Number of personal vehicles in HH[g]		1.87 (1.08)
Total short distance travel (miles/week)[d]		219.46 (188.67)

[a] N=1,352; [b] N=1,356; [c] N=1,322; [d] N=1,357; [e] N=1,351; [f] N=1,354; [g] N=1,353

4.1 Key Endogenous Variables

As discussed in Chapter 1, this study includes four key endogenous variables, namely: Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility. Each of these variables is discussed in more detail below.

4.1.1 Objective Mobility

These questions asked about distance and frequency of travel by mode and trip purpose, as well as travel time for the commute trip. For short-distance trips, respondents were asked how often they traveled for each purpose, with six categorical responses ranging from "never" to "5 or more times a week". Respondents were also asked to specify how many miles they traveled each week, in total and by mode and purpose.

The long-distance Objective Mobility variables come from a section of the survey in which respondents were asked how often they traveled to various parts of the globe "last year", by purpose (for entertainment and work/school-related activities) and mode (personal vehicle, airplane and other) combinations, with an "other" category to catch any remaining travel. These responses indicated number of trips directly, and were also converted into approximate distances by measuring from a central position in the Bay Area to a central location within the destination region.

Trips were combined across world regions to obtain three different measures of distance:

- Total miles, the simple sum of the estimated miles for each reported trip;
- Log of miles, the natural logarithm of one plus the total number of miles. One mile was added to each total so that when zero miles were actually traveled in a given category, the log transformation would return the value zero (= $\ln(1)$) rather than $-\infty$ (= $\ln(0)$);
- Sum of the log-miles, obtained by taking the natural logarithm of one plus the number of miles of each trip in the category *separately*, and summing across all trips in the category.

Discriminating each of these variables by travel mode and purpose (personal vehicle, airplane, and other means; work/school-related, entertainment/recreation/social, and other), plus retaining the original "total" variables, yielded a set of 21 measures of distance that are considered during the model exploration stage.

4.1.2 Subjective Mobility

The survey captured the Subjective Mobility variables using the following question: "For each of the following categories, circle the number on the scale which best describes how *you* view the amount of travel *you* do." The five-point scale ranged from "none" (1) to "a lot" (5). Respondents were asked to answer this question for four different short-distance travel purposes (overall, commuting to work or school, for work/school-related activities, and for entertainment/ recreation/social activities), one short-distance travel mode (driver/passenger in any personal vehicle), three different long-distance (trips greater than 100 miles, one way, a threshold that is consistent with the American Travel Survey in use at the time of data collection) travel purposes (overall, for work/school-related activities, and for entertainment/recreation/social), and two different long-distance travel modes (driver/passenger in a personal vehicle and in an airplane); it should be noted that travel modes and purposes were treated independently (i.e. no question inquired about, for example, short-distance commute travel in a personal vehicle).

4.1.3 Travel Liking

The Travel Liking dependent variables were gathered directly from the survey via the question: "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." Respondents then rated their liking for travel in the same categories used for Subjective Mobility on a five-point Likert-type scale anchored by "strongly dislike" (1) and "strongly like" (5). The instructions emphasized consideration of the travel itself, rather than the activity at the end of the trip. Even with these explicit instructions, respondents certainly (to some degree) confounded their liking for the activity with the liking for travel (Ory and Mokhtarian, 2005). As discussed in Mokhtarian and Salomon (2001), someone who states a love for vacation travel is probably not referring to the hours spent in the airport, on the airplane, and in a rental car. However, I believe this bias to be diminished for questions regarding travel by specific modes (i.e. personal vehicle, bus) in contrast to travel by specific purposes (i.e. work, entertainment). In these questions, respondents may be more inclined to think directly about their mode of transport, which may then allow for a clearer recollection of traveling.

4.1.4 Relative Desired Mobility

An individual may consider that she travels “a lot”, but want to do even more. Thus, Relative Desired Mobility refers to how much a person wants to travel compared to what she is doing now. The structure of this question mirrors the structure for Subjective Mobility and Travel Liking, with respondents rating the amount of travel they want to do compared to the present for the various mode- and purpose-specific and overall categories described above, on a five-point scale from “much less” (1) to “much more” (5).

4.1.5 Treating Ordinal Variables as Continuous

As discussed in the previous sub-sections, variables in the Subjective Mobility, Travel Liking, and Relative Desired Mobility categories are ordinal, as are certain variables (e.g. trip frequency) in the Objective Mobility category. These variables will be treated as continuous (with the exception of the M*plus* estimation), with the following justification. First, each of the single-equation models developed for the key endogenous variables used, at least at the exploratory stage, ordinary least squares regression and assumed the dependent variables (e.g. Subjective Mobility, Travel Liking, and Relative Desired Mobility) to be continuous. Such a decision was based primarily on the superior commercial modeling software packages that allow for, after establishing "baseline" models, automated step-wise analysis of the large list of potential variables available in the dataset (step-wise analysis should be used carefully, as noted by Thompson (1995), among others). After estimating the ordinary least-squares models, more theoretically appropriate ordered probit models were estimated using the same specifications as the regression analysis, with minor variations also tested. For the most part, the significant variables in the least-squares regression models were also significant in the ordered probit models – in keeping with the reputation of linear regression for being robust with respect to departures from its technical requirements. Beyond the precedent in this work for treating ordinal variables as continuous, there are also practical reasons. The exploratory nature of this research makes an efficient estimation process crucial. As such, the variables will be treated as continuous for the maximum likelihood and asymptotic distribution free estimation, and as ordinal for the M*plus* estimation.

4.2 Explanatory Variables

The potential explanatory variables used in the models can be placed into five general categories, namely: Attitudes, Personality, Lifestyle, Mobility Constraints, and Socio-demographics. Each category is described in this section.

Attitudes: Attitudes towards travel, land use, and the environment were captured using responses on a five-point Likert-type scale, to 32 statements. Through factor analysis (see Redmond, 2000 or Mokhtarian, *et al.*, 2001 for details of the factor analyses on these as well as the Personality and Lifestyle variables), the statements were distilled into six basic dimensions, namely: travel dislike, pro-environmental solutions, commute benefit, travel freedom, travel stress, and pro-high density. Selected variables loading heavily on the Attitude, Personality, and Lifestyle factors are summarized in Table 4.2. These factor scores (along with those in the Personality and Lifestyle categories) are removed and latent variables estimated, using the variables shown in Table 4.2 directly, as the second step in the estimation process.

Personality: Respondents rated 17 attributes on a five-point scale (anchored by “hardly at all” to “almost completely”) in terms of how well the attributes described them. Here, the factor analysis revealed four dimensions that I am labeling personality types: adventure-seeker, organizer, loner, and the calm personality. It should be noted that the personality factors are not based on the so-called Big Five personality factors (see Norman, 1963), though similarities exist, but rather capture a narrower subset of traits specifically expected to relate to travel attitudes and behavior.

Lifestyle: The survey contained 18 statements related to work, family, money, status, and the value of time. Respondents agreed or disagreed with the statements using a five-point Likert-type scale. Four so-called lifestyle factors emerged: status seeker, workaholic, family/community related, and a frustrated factor.

Mobility Constraints: Here, participants selected, on a three-point scale (“No limitation”, “Limits how often or how long”, “Absolutely prevents”), the degree to which physical conditions or anxieties prevented them from engaging in a variety of travel forms, including: “driving on the freeway”, “driving at night”, and “flying in an airplane”. The percentage of time an automobile is available to the participant is also considered to be a Mobility Constraint (oriented in the reverse direction).

Socio-demographics: The survey captured an extensive amount of typical socio-demographic data to allow for comparison of the sample with more general populations. The data included measures of age, income, household size, employment type, number of household workers, education level, gender, and make/model of the vehicle driven most often by the respondent. The latter variable was allocated to one of nine major vehicle categories: small, compact, mid-sized, large, luxury, sport utility vehicle, minivan/van, pick-up truck, and sports (for more details, see Curry, 2000 and Choo and Mokhtarian, 2004).

Though one focus of this dissertation is examining the extent to which travel is not a strictly derived demand, I certainly accept that most travel is largely derived from the desire to participate in spatially-separated activities. The Socio-demographic data is used, in part, to explain the derived demand aspect of travel. For example, personal income will likely help explain the amount of entertainment travel in which an individual engages.

4.3 Detailed Clarifications to Conceptual Model

As indicated earlier, the conceptual model described in Figure 1.1 does not capture all the detailed relationships present in the model system. For example, neighborhood location is treated as a Socio-demographic variable (as was done in the previous analyses of the dataset cited in Chapter 1), a category not shown to be influenced by Attitudes. But it is quite likely that travel Attitudes influence neighborhood location choice (Schwanen and Mokhtarian, 2007). Also, the Mobility Constraint variables are considered to be strictly exogenous. However, when vehicle availability is placed in this variable category, that exogeneity is compromised – certainly income influences auto availability. With the sizeable number of variables present in the model system, certain relationships must move to the forefront and others be temporarily passed over. The focus of this effort is first to develop a modeling system that accounts for the endogenous relationships of Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility. A secondary goal is to sort out the myriad interrelationships present among the other variables in the dataset.

Table 4.2: Factor Loadings for Selected Attitude, Personality, and Lifestyle Variables

Variable category	Factor name	Survey variable	Factor loading
Attitudes	Travel dislike	Traveling is boring.	0.621
		I like exploring new places.	-0.537
		The only good thing about traveling is arriving at your destination.	0.525
	Pro-environmental solutions	To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle.	0.641
		We should raise the price of gasoline to reduce congestion and air pollution.	0.617
		We need more public transportation, even if taxes have to pay for a lot of the costs.	0.612
	Commute benefit	My commute is a real hassle.	-0.695
		My commute trip is a useful transition between home and work.	0.583
		The traveling that I need to do interferes with doing other things I like.	-0.530
		I use my commute time productively.	0.467
	Travel freedom	In terms of local travel, I have the freedom to go anywhere I want to.	0.511
		In terms of long-distance travel, I have the freedom to go anywhere I want to.	0.422
	Pro-high density	Living in a multiple family unit wouldn't give me enough privacy.	-0.617
		I like living in a neighborhood where there is a lot going on.	0.486
	Travel stress	I worry about my safety when I travel.	0.544
		Traveling makes me nervous.	0.537
		Traveling is generally tiring for me.	0.410
		I tend to get sick when traveling.	0.318
		I am uncomfortable being around people I don't know when I travel.	0.297
Personality	Adventure seeking	Adventurous	0.776
		Variety seeking	0.695
		Spontaneous	0.574
		Risk taking	0.557
	Organizer	Efficient	0.624
		On time	0.371
	Loner	Like being alone	0.935
		Like being independent	0.314
	Calm	Aggressive	-0.599
		Patient	0.532
Lifestyle	Frustrated	I often feel like I don't have much control over my life.	0.720
		I am generally satisfied with my life.	-0.618
	Family/ community oriented	I'd like to spend more time with my family and friends.	0.585
		My family and friends are more important to me than my work.	0.472
	Status seeking	To me, the car is a status symbol.	0.698
		A lot of the fun of having something nice is showing it off.	0.518
	Workaholic	I'm pretty much a workaholic.	0.652
		I'd like to spend more time on work.	0.373

Source: Redmond (2000).

5. COMMUTE TRAVEL

In this chapter, models of commute travel are presented and discussed. Due to the importance of the commute to both transportation infrastructure and individual lifestyle choices, special attention is provided this category of travel. Understanding what motivates and drives the often perplexing commute decisions of Californians and other Americans alike can go a long way toward making more informed transportation decisions.

5.1 Model Exploration and Specification

The relationships and behaviors that are described in this dissertation are not well established. Aside from the earlier analyses of the present dataset, no previous research examining the interrelationships of travel amounts, perceptions, affections, and desires exists, let alone research that undertakes the task with the statistical rigor offered in structural equation modeling. As such, the model specification process is exploratory by nature. In this section, that process is described in detail.

The exploration process begins with the conceptual model of Figure 1.1 and the previously-estimated single-equation models of Objective Mobility (Mokhtarian, *et al.*, 2001; Ory, *et al.*, 2004), Subjective Mobility (Collantes and Mokhtarian, 2002, 2007; Ory, *et al.*, forthcoming), Travel Liking (Ory and Mokhtarian, 2005), and Relative Desired Mobility (Choo, *et al.*, 2005). A structural equation model incorporating all of the relationships in the previously estimated single-equation models, as well as other reasonable relationships, is built and estimated. Though the single-equation models are potentially biased due to simultaneity (as discussed in Chapter 1), the logical relationships contained in those models serve as a reasonable collection of hypotheses, which act as a starting point for the structural model estimation. Insignificant coefficients are then removed, and other relationships tested, until a model with only significant coefficients (at a 95%

confidence level), is in place; this model is discussed in detail in *5.4 Expanded Model Estimation Results*.

This so-called "expanded" model includes myriad variables and relationships. As such, the predictive accuracy of the model (equation-specific R^2s) is quite good, but comes at the expense of model fit, i.e. the discrepancy between the model-predicted and empirically-observed covariance matrices is high. Should this model be "trimmed" of variables holding relatively minor explanatory power to improve the overall goodness-of-fit? The literature contains mixed advice with respect to this (quite common) situation. On the one hand, several scholars (e.g. Hayduk et al., 2007; McIntosh, 2007) argue that when a model does not fit the data adequately, parameter estimates, as well as the measures of predictive accuracy based on those estimates, are potentially bogus. On the other hand, other scholars (Tomarken and Waller, 2003, 2005) point out that the exclusion of relevant variables (when correlated with included variables, as is generally the case) constitutes an omitted-variables bias that renders coefficient and standard error estimates inaccurate – even, potentially, when goodness-of-fit is perfect. This dilemma makes it difficult, to say the least, to choose among competing specifications on the basis of *either* goodness-of-fit or parameter significance: apparently neither type of criterion for assessing model adequacy can be fully trusted if the other type of criterion is not also satisfied, and the two types of criteria inherently conflict. Because more fully-specified single-equation models of the key variables have already been studied exhaustively (whose parameter estimates may nevertheless be suspect due to simultaneity bias), the focus in this study is on the causal relationships among the key variables themselves, and I opt for parsimony with respect to the other relationships in the conceptual model. Accordingly, many of the direct effects found in the "expanded" model are excluded from the final model specification. However, I do not pretend to have necessarily achieved the single right or best model of these relationships, only one that is meaningful, satisfying, instructive, and consistent with typical SEM practice.

Upon approaching a final model specification, the dataset is examined for missing values in the variables that enter the final specification. This is done because to apply the bootstrapping methodology and to assess multivariate normality within AMOS (Arbuckle, 2006), the dataset must be free of missing data. The missing values in this dataset are relatively sparse, causing less than 4% of cases to be removed (across all 10 travel-category-specific models estimated in this dissertation) when using listwise deletion. Roth (1994) suggests that listwise deletion is appropriate under these circumstances. Removing missing data can alter the model results, which leads to further exploration of the specification space. Iteratively, models are estimated and missing data removed, until a preferred specification emerges.

The final model results are presented in *5.2 Preferred Model Estimation Results*, and more detailed specification issues are discussed throughout this chapter. In *5.4 Expanded Model Estimation Results*, the "expanded model", which is a model that includes many of the relationships found in the single-equation models, but fits the data poorly, by SEM standards, is presented and discussed.

5.2 Preferred Model Estimation Results

As described in *3.2.2.3 Model Estimation*, the final model specification is estimated using four different techniques, namely: maximum likelihood (ML), asymptotic distribution free (ADF), bootstrapping, and the M*plus* approach. The preferred model specification and maximum likelihood standardized coefficients are shown in Figure 5.1. Consistent with Figure 1.1, the error terms in Figure 5.1 are represented by small unlabeled circles and the endogenous variables are represented by labeled boxes. The estimation results, along with measures of goodness-of-fit, are presented in Table 5.1. The *unstandardized* coefficients (for each estimation technique) are presented in Table 5.1 and serve as an important record of the model results. The *standardized ML* coefficients are presented in the path diagram of Figure 5.1 and allow the reader to quickly compare the magnitude of the direct effects present in the structure as well as to compute the standardized indirect and total effects. All subsequent model results in this dissertation are summarized in a similar manner.

In general, the models fit the data well. The ML and ADF models have χ^2 test statistic divided by the model degrees of freedom (χ^2/d.f.) values near 1.2, which are slightly lower (i.e. better) than “typical” values (see Table 3.1) in the 1.7 range. The ML CFI is 1.000 (above the typical average of 0.95) and a RMSEA of 0.013 (better than the typical average of 0.060). The model only contains a single degree of freedom, which is not uncommon in structural equation models without latent variables (also referred to as “path analyses”) (Shah and Goldstein, 2006). The relationship between model degrees of freedom and the variability of goodness-of-fit measures is discussed in *8.5 Model Robustness*.

Specific model results are discussed by focusing on each key variable, in turn. Variables influencing the Objective Mobility (OM), Subjective Mobility (SM), Travel Liking (TL), and Relative Desired Mobility (RDM) variables are discussed in the sub-sections below. For the remainder of this chapter, “Subjective Mobility”, “Travel Liking”, and “Relative Desired Mobility” are used to describe the commute-specific incarnations of those variables. As discussed in *4.1 Key Endogenous Variables*, Subjective Mobility, Travel Liking, and Relative Desired Mobility variables were captured for numerous travel categories by the survey instrument. Here, the variables included in the model are the commute-specific versions of those measures.

5.2.1 Objective Mobility

Variables in the Objective Mobility (OM) category appear in each of the structural equations presented in Table 5.1. Two measures of Objective Mobility enter the final model specification, namely: the square root of one-way commute duration (one-way commute time is referred to as commute duration in this dissertation) and the square root of commute speed. The square root transformation is performed to increase the level of normality of the variables and to be consistent with previously estimated models (namely, the models of Subjective Mobility estimated by Collantes and Mokhtarian, 2002). Not surprisingly, the error terms of these two variables are positively, and significantly, correlated.

Other than the significant covariance with the other's error term, no other variables appear in the commute duration or speed equations – they are exogenous to the system. This is not to say that no variables in the dataset are able to describe these measures. Rather, the covariance introduced by potential explanatory variables is not capable of explaining sufficient variance in the system to warrant inclusion. As discussed in the previous section, the goal here is not to only explain the variability of the Objective Mobility measures, but to also efficiently model the structural relationships among the key variables.

5.2.2 Subjective Mobility

One goal of the work of Collantes and Mokhtarian (2002, 2007) was to determine what measures of Objective Mobility shaped commute-specific Subjective Mobility (SM). In common parlance: what measures of travel amounts (time, speed, distance, frequency, modal interactions with these measures, etc.) influence perceptions of the amount of travel? Collantes and Mokhtarian (2002) concluded that myriad measures did, rather than just one or two, which is broadly represented in the conceptual model of Figure 1.1 by the arrow pointing from Objective Mobility to Subjective Mobility.

The results of the present model estimation indicate that the square root of commute duration and the square root of commute speed shape the Subjective Mobility assessment of commute travel. Collantes and Mokhtarian (2002) found that these measures, along with commute frequency, weekly commute distance, square root of one-way commute distance, and measures of work/school-related and personal vehicle travel all impacted commute Subjective Mobility. These two findings are not necessarily inconsistent. In the structural equation modeling context, the impact of Objective Mobility on the larger system of Subjective Mobility, Travel Liking, and Relative Desired Mobility is being examined. Commute duration and speed are the two variables that have the most influence on this system as a whole. In the work of Collantes and Mokhtarian (2002), the goal in estimation was to describe the variation in the dependent Subjective Mobility variable (using single-equation methods), without regard to its role in explaining Travel Liking or Relative Desired Mobility. In that context, it is logical that several other Objective Mobility variables were significant covariates.

Interestingly, both the commute duration and speed variables enter the Subjective Mobility equation with positive coefficients. Such a result follows intuition with respect to the commute duration measure: the longer time one spends commuting, the greater one subjectively assesses his commute to be (the more I travel, the more I *think* I travel). The positive coefficient on speed may initially be contrary to expectation because traveling at higher speeds usually means traveling in less congestion, making a negative coefficient logical (the faster I travel, the less burdensome it is and therefore the lower the cognitive weight it has in my perceptions). But because the model contains both duration and speed, the coefficient on commute speed can be interpreted by assuming a constant duration. Consider, for example, two individuals, A and B, who both travel 20 minutes to work each day. Individual A travels at an average speed of 45 miles per hour (mph) and individual B travels at an average speed of 70 mph. Which of the two will consider his travel to be subjectively “greater” than the other? Since the coefficient on commute speed is positive, the model results indicate that it is person B, who travels at 70 mph. Because duration is constant, individual B is traveling a greater distance than individual A. Further, note that travel mode is not being held constant. Consider a more extreme example, in which commute duration is only 10 minutes. Here individual A travels on foot at 3 mph and individual B in an automobile at 60 mph. It would certainly be expected that individual A, who is merely walking down the block, will assess his travel to be of less magnitude than individual B, who is traveling six miles.

The speed variable in the model can be replaced by a measure of one-way commute distance, which yields a cleaner interpretation. However, this replacement considerably reduces the goodness-of-fit of the model, suggesting that the non-linear relationship of speed and duration contributes valuable information to the system. Similarly, one could replace duration in the final model specification with distance, which results in the expected positive coefficient on the distance variable and negative coefficient on the speed variable, but doing so again degrades the fit of the model.

A second goal of Collantes and Mokhtarian (2002) was, after first controlling for the effects of objective travel measures (time, distance, frequency, etc.), to determine what variables influence the Subjective Mobility of two people traveling the same objective amount. This answers the question: why would two people who travel basically the same objective amounts perceive their travel amounts to be different? The parsimonious structural equation model preferred here provides no answers on this front: although variables in categories such as Travel Liking, Attitudes, Lifestyle, Personality, and Socio-demographics were allowed to enter the model, in the final outcome only Objective Mobility measures shape Subjective Mobility. However, Travel Liking appears in the Subjective Mobility equation of the expanded model presented in *5.4 Expanded Model Estimation Results*.

5.2.3 Travel Liking

Ory and Mokhtarian (2005) estimated a single-equation model of commute Travel Liking (TL) that included variables in the Objective Mobility, Subjective Mobility, Socio-demographics, Attitudes, and Lifestyle categories; these findings are reflected in the conceptual model.

In the preferred structural equation model estimation, two measures, square root of one-way commute time and Subjective Mobility, influence Travel Liking. The negative coefficients on these measures suggest that those who are "forced" to commute long distances develop a relative dislike for commute travel. This finding supports the assertion in the literature that attitudes can be shaped by behavior, rather than vice versa (Golob, 2001; Tardiff, 1976). However, the negative coefficient on the Subjective Mobility variable adds another level of nuance to this relationship. If two individuals commute the same duration, a difference in travel perceptions can lead to a difference in travel affect. Given the discussion in *5.2.2 Subjective Mobility*, the model suggests that those traveling at faster speeds (holding duration constant) can increase these perceptions, which, in turn, decrease commute enjoyment. Of course, factors besides speed could also influence perception, though they are not captured in the model (or, perhaps, in the dataset). So, it is a combination of both the behavior (i.e. lengthy commute times, the Objective Mobility measure) and travel perceptions (i.e. the Subjective Mobility measure) that influence commute enjoyment (Travel Liking).

5.2.4 Relative Desired Mobility

The end measure of the model is conceptualized to be Relative Desired Mobility (RDM). That is, travel amounts, and how those amounts are subjectively assessed, as modified by enjoyment of travel, lead to a conclusion about how much more or less travel is desired. The estimation results support this conceptualized structure: measures of Objective Mobility, Subjective Mobility, and Travel Liking all influence the Relative Desired Mobility for commute travel.

The Objective Mobility variables (square root of commute duration and the square root of commute speed, interpreting speed, again, as distance) and Subjective Mobility (for commute travel) each enter with a negative coefficient, indicating that the more one actually travels and assesses her actual travel amounts to be, the less she desires to travel. This result is expected: those who commute large amounts logically desire to reduce that travel. The interpretation of the negative coefficient on the speed variable is identical to the discussion in the Subjective Mobility section (after controlling for time, higher speeds denote longer distances).

One of the hypotheses of this work is that travelers possess a subjective lens through which their travel is viewed. The output from such a lens determines to what degree more or less travel is desired, i.e. even if I travel a great deal, if I perceive that travel amount to be low, my desire to reduce my travel may not be that great. These relationships are operationalized through the impact of Objective Mobility on Relative Desired Mobility via Subjective Mobility (OM$\rightarrow^{+}$SM$\rightarrow^{-}$RDM). The standardized coefficients from the structural model can be examined in a path analysis to determine the degree to which the Subjective Mobility construct "filters" Objective Mobility to shape Relative Desired Mobility.

Looking first at the commute duration variable, Figure 5.1 shows that commute duration has a negative direct coefficient of -0.34 on Relative Desired Mobility (RDM), and a positive coefficient of 0.40 on Subjective Mobility (SM), which, in turn, has a -0.13 coefficient on RDM, leading to an indirect effect of duration on RDM of 0.40 * -0.13 = -0.05. Travel Liking (TL) is also acting as a filter in the model, as there is an indirect effect of duration on RDM via TL of -0.31 * 0.37 = -0.12. Moving to the other Objective Mobility (OM) variable in the specification, commute speed, Figure 5.1 shows a direct effect of commute speed on RDM of -0.07 and an indirect effect of commute speed, as filtered through SM, on RDM of -0.02. Therefore, for the commuting trip purpose at least, objective travel amounts are more important than "filtered" travel amounts in shaping desires (comparing -0.34 to -0.05 and -0.12 for duration; -0.07 to -0.02 for speed). One reason for this finding may be the societal standards placed on commute amounts (also see *6.5.6 Subjective Mobility Filtering* and *7.6.4 Subjective Mobility Filtering* for further discussion of this point). In contrast to recreational travel, everyone has an idea of what constitutes an acceptable amount of commuting. Commute distances are discussed with friends, neighbors, and coworkers, and media reports highlight those falling outside the norm. We have a sense of how much we *should* be commuting. Frequent comparisons are made to these standards each time we fill up the gas tank (informing us how much we traveled in the past week) or are late for work (reminding us of our commute duration). As such, it may well be that there is relatively little variation across the population in the filtering process for commute travel in particular.

However, even in the presence of more important direct effects from the commute duration and speed variables, the significant effect of perceptions on desires (SM→RDM) is still very important. It suggests that though two individuals who commute an hour each day may both desire a reduction in commuting, a difference in how those commute amounts are perceived can enhance or diminish these desires.

Travel Liking has a positive effect on Relative Desired Mobility. The result is both logical (the more someone enjoys traveling, the more of it is desired) and also intriguing. It shows that the desire to reduce commuting is influenced by the amount commuting is enjoyed. As the commute is stereotypically considered burdensome, this finding suggests that, at the very least, the degree to which that burden is ameliorated leads to a desire for more travel.

The entire model portrays a holistic and interesting picture of commute behavior. Looking at the upper half of the model in Figure 5.1, one can see how "soft" variables such as travel perceptions, travel enjoyment, and attitudes can lead to a desire for more commuting: those who psychologically diminish their perceived travel amounts, and those who enjoy travel, have a desire to commute more than those who do not have these attributes. Moving down the diagram, the actual characteristics of the commute come into play. Here, an increase in commute duration reduces the enjoyment of travel, which is not surprising, and an increase in commute duration and distance (through the speed variable) increase perceived travel amounts.

5.2.5 Notes on Estimation Techniques

The results across estimation techniques are highly similar. The χ^2 test statistic *p*-values for the ML, ADF, and M*plus* estimations are 0.265, 0.285, and 0.305, respectively, which are very close to the Bollen-Stine bootstrap p-value of 0.292. The coefficients in the ML, ADF, and bootstrap estimations are nearly identical. The M*plus* coefficients are uniformly larger in magnitude than those for the other three estimation techniques, suggesting a downward bias for those techniques in view of the measurement error inherent in treating the ordinal variables as continuous.

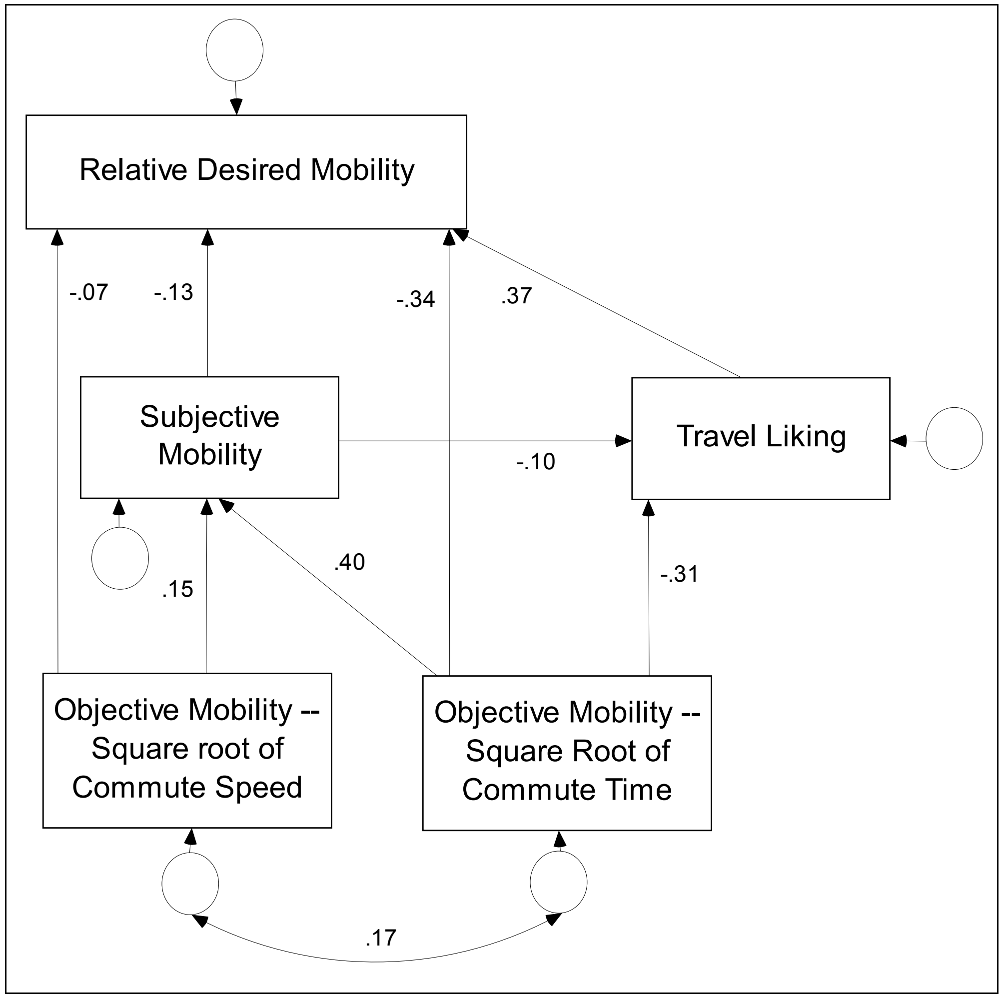


Figure 5.1: Commute Travel Model Structure and ML Standardized Coefficients

Table 5.1: Commute Travel Model Estimation Results (N=1,352)

Regression Weights [] -- range of observed values	**ML** **coeff**	 **crit ratio**	**ADF** **coeff**	 **crit ratio**	**Bootstrap** **coeff**	 **crit ratio**	**M*plus*** **coeff**	 **crit ratio**
→ Subjective Mobility -- Commute [1,…,5] (Equation R^2 = 0.206*)								
Objective Mobility -- Square root of one-way commute time [>=0]	0.276	16.422	0.275	17.596	0.276	17.250	0.288	16.646
Objective Mobility -- Square root of commute speed [>=0]	0.114	6.070	0.114	5.890	0.113	5.947	0.114	5.962
→ Travel Liking -- Commute [1,…,5] (R^2 = 0.131)								
Objective Mobility -- Square root of one-way commute time [>=0]	-0.167	-11.049	-0.168	-10.241	-0.167	-10.438	-0.196	-11.298
Subjective Mobility -- Commute [1,…,5]	-0.076	-3.401	-0.076	-3.224	-0.077	-3.348	-0.109	-3.528
→ Relative Desired Mobility -- Commute [1,…,5] (R^2 = 0.441)								
Objective Mobility -- Square root of one-way commute time [>=0]	-0.146	-14.275	-0.146	-13.757	-0.146	-13.273	-0.257	-15.276
Objective Mobility -- Square root of commute speed [>=0]	-0.036	-3.565	-0.036	-3.340	-0.037	-3.364	-0.078	-3.684
Subjective Mobility -- Commute [1,…,5]	-0.083	-5.697	-0.082	-5.282	-0.082	-5.125	-0.206	-6.781
Travel Liking -- Commute [1,…,5]	0.299	17.104	0.297	14.188	0.300	13.636	0.571	18.604
Covariances	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
Objective Mobility -- Square root of one-way commute time [>=0] Objective Mobility -- Square root of commute speed [>=0]	0.480	6.208	0.481	6.997	0.482	7.088	0.501	6.314
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =	1.241	(0.265)	1.144	(0.285)		(0.292)	1.053	(0.305)
Degrees of freedom =	1		1		n/a		1	
χ^2 test statistic / degrees of freedom =	1.241		1.144		n/a		1.053	
Fit indices: Relative, Incremental, Comparative =	0.991, 1.000, 1.000		0.928, 1.000, 1.000		n/a		---,---, 1.000†	
Root-mean square error of approximation (90 percent interval) =	0.013	(0,0.075)	0.010	(0,0.074)	n/a		0.006	(n/a)
Normality Measures								
Multivariate kurtosis =	2.068	(4.544)						

* Also known as the squared multiple correlation (SMC); † M*plus* does not report the Relative or Incremental Fit Index

5.3 Travel Liking Market Segmentation

As mentioned in Chapter 1, the relationship between Subjective Mobility and Travel Liking could very well be bidirectional, i.e. the more I enjoy travel, the less I perceive it to be (TL→SM), and, in the opposite direction, the more I perceive my commute travel to be, the less I enjoy it (SM→TL). In the current model, both directions of causality, when introduced individually, prove significant and have the same negative sign. The SM→TL direction provides a stronger statistical case, meaning it has both a higher t-statistic and the overall model fit is superior to the opposing direction of causality, and is therefore included in the final specification. Estimating both directions simultaneously, in the current structure, leaves the model unidentified; both directions do appear in the expanded model of *5.4 Expanded Model Estimation Results*. None of the other relationships in the final model have similar levels of ambiguity.

In a previous analysis of Subjective Mobility (Collantes and Mokhtarian, 2007), evidence for a U-shaped or quadratic relationship of Travel Liking (TL) to Subjective Mobility (SM) emerged: people who liked commuting, as well as those who disliked it, tended to have elevated perceptions of their commute mobility, relative to those with neutral feelings. In turn, this suggests that Subjective Mobility could have a different relationship to Relative Desired Mobility (RDM) depending on whether the respondent likes or dislikes commuting. If SM is high when TL is *low*, the respondent is likely to want to reduce commuting (RDM will be low, and SM will have a negative impact on RDM); conversely, if SM is high when TL is *high*, the respondent may wish to maintain or even increase her commuting (RDM will be neutral to high, and SM will have a negligible or possibly positive impact on RDM).

To further investigate the three-way relationship among Subjective Mobility, Travel Liking, and Relative Desired Mobility, the data were segmented into those who had positive commute Travel Liking responses and those with neutral or negative responses. That is, to the survey question

“How do you feel about *traveling* [when] commuting to work or school?”, those who responded with “Like” (253 cases), and “Strongly like” (37) are put into one segment, and those who responded with “Neutral” (517), “Dislike” (422) and “Strongly dislike” (123) into another (note that the distribution is not as heavily skewed in the dislike direction as may be expected; see Ory and Mokhtarian (2005) for further discussion of this point). The segmentation is made at this point because Collantes and Mokhtarian (2007) found that the minimum of their parabolic relationship between TL and SM occurred at TL=3.9, where “Neutral” is 3 and “Like” is 4. Though the same parabolic relationship could not be confirmed in the structural model, the findings of Collantes and Mokhtarian (2007) do motivate an independent examination of these two groups. If the relationship between TL and SM is, in fact, U-shaped, it would be expected for a linear term across both segments to be insignificant, or at least to fall between the two coefficients of opposite signs that could be expected for the two groups modeled separately. Segmenting the sample at the minimum point of the parabola should reveal a positive or neutral relationship between TL and SM for the “Like” and “Strongly like” (positive) segment and a negative relationship for the “Neutral”, “Dislike”, and “Strongly dislike” (neutral/negative) segment. Further, it would be expected for the neutral/negative TL sample to have a much stronger negative relationship between SM and RDM than the positive TL segment.

As a first step in exploring the Travel Liking segmentation, the full-sample model structure of Figure 5.1 is estimated on the positive and neutral/negative segments. As in the full-sample model, the directionality of the relationship between Subjective Mobility and Travel Liking is explored: both directions are estimated, and the direction with the stronger statistical case is included in the selected model.

The neutral/negative- and positive-segment models’ standardized ML coefficients are shown in Figure 5.2 (on the left and right, respectively) and Table 5.2. The neutral/negative-segment (N=1,062) has goodness-of-fit measures far superior to the full-sample model with a χ^2/d.f. value of 0.258 and a RMSEA of 0.000 (0.065 at the high end of the 90% interval). The positive (N=290) segment does not fit the data nearly as well: only three (duration on SM and RDM; speed on SM) of the coefficients are significant at the 95% confidence level. The χ^2/d.f. value is 1.828 and the RMSEA is 0.054.

As expected, the relationship between Subjective Mobility and Relative Desired Mobility is strongly negative for the neutral/negative segment. The standardized coefficient is -0.16, which is slightly larger than the value of -0.13 in the full-sample model. For the positive segment, the coefficient of -0.01 shown in Figure 5.2 is not statistically different from zero.

The relationship between Subjective Mobility and Travel Liking is negative, as expected, in the neutral/negative segment and goes from SM to TL, as in the full-sample model. The opposite direction of causality has a stronger statistical case for the positive segment. However, in the positive market segment, neither direction yields a statistically significant coefficient.

In sum, the two Travel Liking segments perform as expected. Those in the neutral/negative segment have negative relationships between SM and TL, and SM and RDM. As the perceived amount of travel increases, these individuals' enjoyment of, and desire for, travel diminishes. In the positive segment (i.e. for those who like commuting), perceived travel amounts have no significant impact on travel enjoyment or desire.

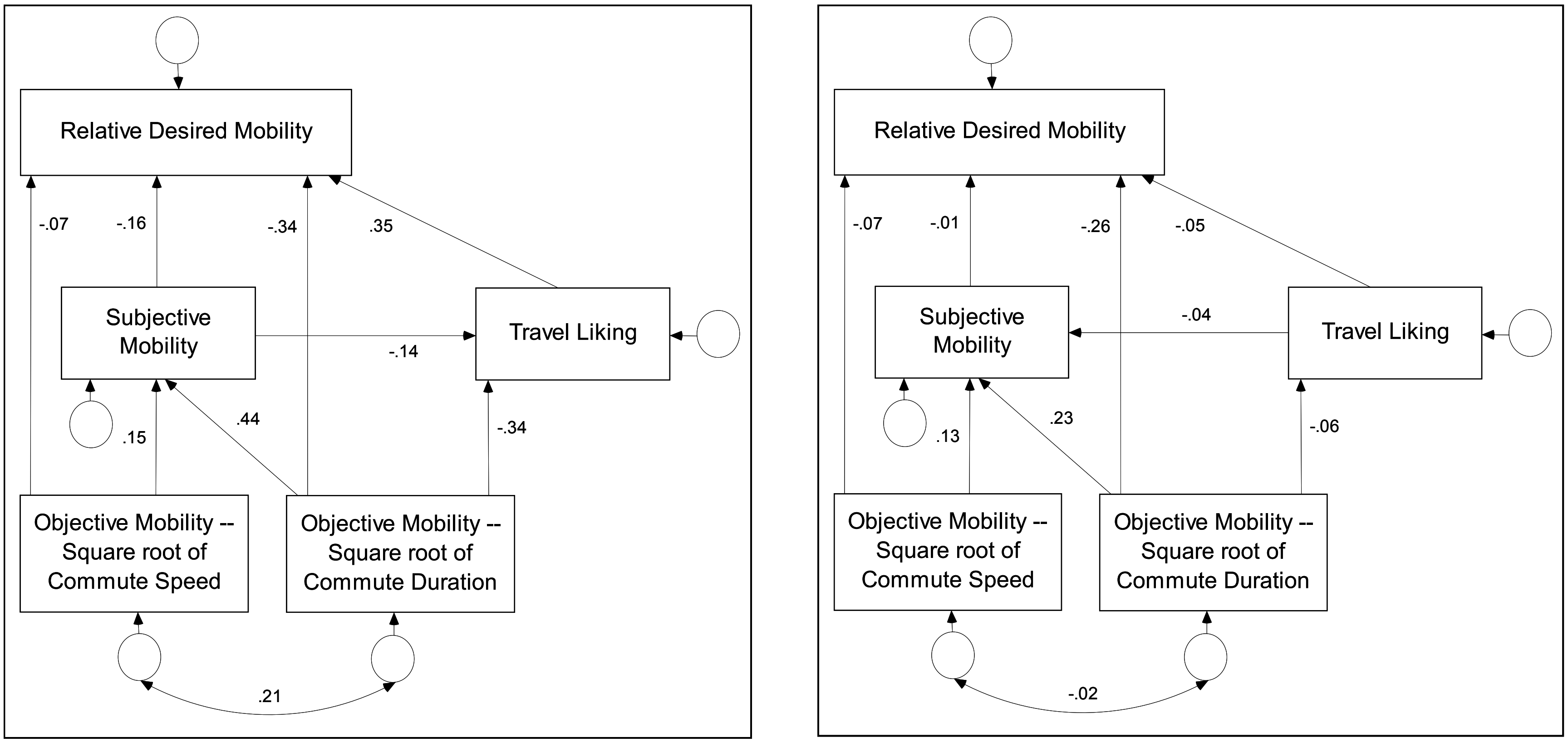


Figure 5.2: ML Standardized Coefficients for the Final Full-Sample Model Structure Estimated on Neutral/Negative (left, N=1,062) and Positive (right, N=290) Travel Liking Segments

Table 5.2: ML Estimation Results for the Final Full-Sample Model Structure Estimated on Neutral/Negative (left, N=1,062) and Positive (right, N=290) Travel Liking Segments

Regression Weights [] -- range of observed values	Neutral/Negative coeff	 crit ratio	Positive coeff	 crit ratio
→ Subjective Mobility -- Commute [1,…,5] (R^2 = 0.245, 0.071)*				
Objective Mobility -- Square root of one-way commute time [>=0]	0.297	16.186	0.178	4.123
Objective Mobility -- Square root of commute speed [>=0]	0.112	5.412	0.102	2.339
Travel Liking -- Commute [1,…,5]	---	---	-0.163	-0.782
→ Travel Liking -- Commute [1,…,5] (R^2 = 0.180, 0.005)				
Objective Mobility -- Square root of one-way commute time [>=0]	-0.129	-10.695	-0.013	-1.037
Subjective Mobility -- Commute [1,…,5]	-0.082	-4.561	---	---
→ Relative Desired Mobility -- Commute [1,…,5] (R^2 = 0.469, 0.076)				
Objective Mobility -- Square root of one-way commute time [>=0]	-0.145	-12.691	-0.100	-4.532
Objective Mobility -- Square root of commute speed [>=0]	-0.032	-2.910	-0.027	-1.230
Subjective Mobility -- Commute [1,…,5]	-0.099	-6.032	-0.005	-0.180
Travel Liking -- Commute [1,…,5]	0.390	14.163	-0.089	-0.864
Covariances				
Objective Mobility -- Square root of one-way commute time [>=0] Objective Mobility -- Square root of commute speed [>=0]	0.595	6.731	-0.051	-0.343
Goodness-of-fit Measures				
χ^2 test statistic (*p*-value) =	0.258	(0.611)	1.828	(0.176)
Degrees of freedom =	1		1	
χ^2 test statistic / degrees of freedom =	0.258		1.828	
Fit indices: Relative, Incremental, Comparative =	0.998, 1.001, 1.000		0.620, 0.982, 0.978	
Root-mean square error of approximation (90 percent interval) =	0.000	(0,0.065)	0.054	(0,0.176)
Normality Measures				
Multivariate kurtosis =	0.467	(0.909)	10.449	(10.634)

* (Neutral/negative segment R^2, positive segment R^2)

The good fit of the final model specification for the neutral/negative segment and the poor fit of the model on the positive segment suggest that respondents who like commuting have, to some degree, a different set of OM/SM/TL/RDM relationships than do their commute-disliking counterparts. This result motivated an independent exploration of the positive Travel Liking segment. Again considering all the variables in the dataset, I searched for the best specification of an OM/SM/TL/RDM model for the positive TL market segment. The ML standardized coefficients and model structure for the chosen model are presented in Figure 5.3 and Table 5.3. The model fits the data better than the full-sample model specification, with a χ^2/d.f. value of

1.046 and RMSEA of 0.013; each of the direct effect coefficients are significant at the 99% confidence level.

As previously hypothesized, there are no significant relationships between Subjective Mobility and Relative Desired Mobility, or Subjective Mobility and Travel Liking. Travel Liking plays no role in shaping the OM/SM/RDM structure, which is not surprising because the segmentation (only the "Like" and "Strongly Like" responses are included) leaves the measure with limited variability and explanatory power. The model results show that commute duration and frequency each positively affect Subjective Mobility. Note that frequency replaces the speed measure from the neutral/negative-segment and full-sample models. The two measures of OM have negatively correlated error terms: the longer the commute, the less frequently it is made. This finding suggests either that those with long commutes are mitigating the effects of such long trips by making them less frequently, or, conversely, that those who are able to commute less frequently are deciding to move farther from work, perhaps to a higher-amenity home location, and, in doing so, increasing their commute duration (for a discussion of this issue in the context of telecommuting, please see Ory and Mokhtarian, forthcoming). It may be that those who have the flexibility to adjust their commute frequency are thus able to enjoy their commute, motivating their inclusion in the positive Travel Liking segment. Duration is the sole influence on Relative Desired Mobility, estimating with the expected negative coefficient.

Comparing the positive-segment model of Figure 5.3 with the neutral/negative-segment model of Figure 5.2, the role travel enjoyment plays in shaping the relationship between perceptions and desires becomes evident. The interpretation is that between two people with the same Subjective Mobility (i.e. they assess their commute to be the same amount), the one who likes commuting will not desire a reduction in her commute amount, whereas the one with neutral or negative commute affections will desire a reduction. To the extent that these desires influence future behavior, measurements of travel enjoyment become important to travel behavior, even in the context of commute travel.

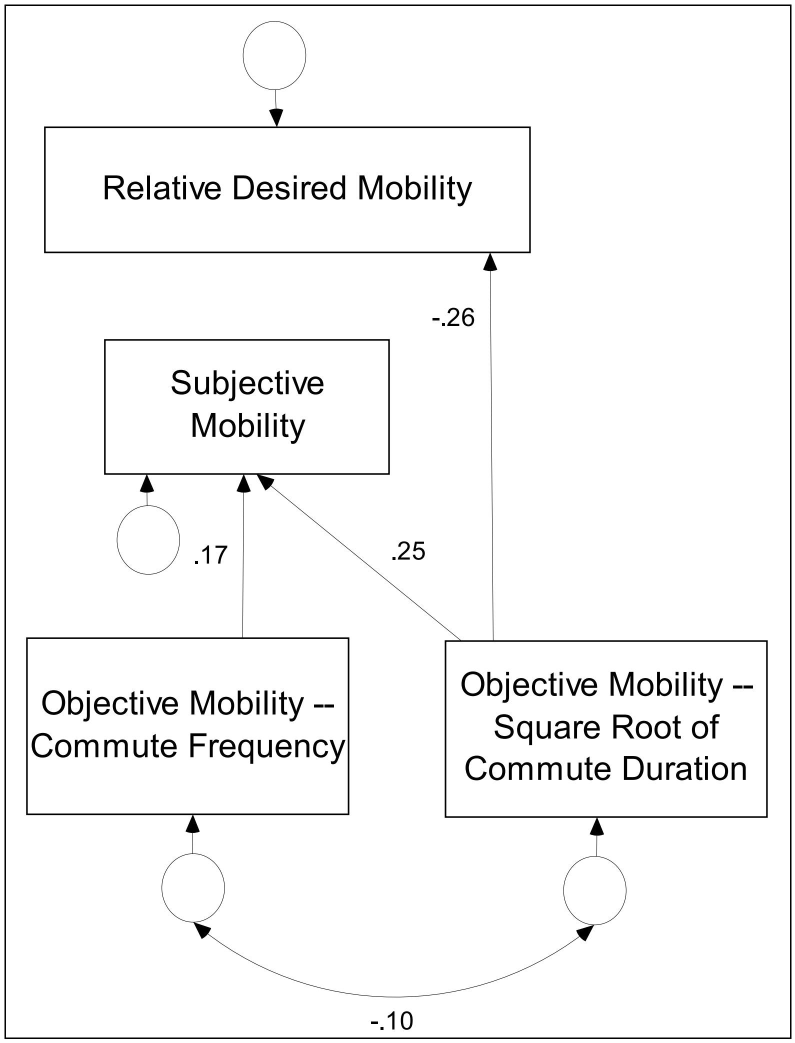


Figure 5.3: Improved Positive Travel Liking Segment Model Structure and ML Standardized Coefficients (N=290)

Table 5.3: ML Estimation Results for the Improved Positive Travel Liking Segment Model

Regression Weights [] -- range of observed values	**ML** **coeff**	 **crit ratio**
→ **Subjective Mobility -- Commute [1,…,5] (R^2 = 0.085)**		
Objective Mobility -- Square root of one-way commute time [>=0]	0.191	4.449
Objective Mobility -- Weekly commute frequency [1,…,6]	0.392	3.076
→ **Relative Desired Mobility -- Commute [1,…,5] (R^2 = 0.069)**		
Objective Mobility -- Square root of one-way commute time [>=0]	-0.099	-4.619
Covariances		
Objective Mobility -- Square root of one-way commute time [>=0] Objective Mobility -- Square root of commute speed [>=0]	-0.089	-1.723
Goodness-of-fit Measures		
χ^2 test statistic (*p*-value) =	2.092	(0.351)
Degrees of freedom =	2	
χ^2 test statistic / degrees of freedom =	1.046	
Fit indices: Relative, Incremental, Comparative =	0.878, 0.998, 0.998	
Root-mean square error of approximation (90 percent interval) =	0.013	(0,0.118)
Normality Measures		
Multivariate kurtosis =	10.13	(12.45)

5.4 Expanded Model Estimation Results

The results of the so-called "expanded model" are presented over two Tables, 5.4 and 5.5. The purpose in presenting this model is two-fold. First, it illustrates the model specification exploration process, in which the single-equation models are used as a starting point, and the model is systematically trimmed to reveal the structural relationships of the final model. This particular intermediate model represents the point at which all the estimated coefficients are significant and their signs logical. The second purpose is to motivate a discussion of how goodness-of-fit measures and model completeness (through additional variables) need to be balanced in the structural equation model context. This point is elaborated upon after the model description, presented next.

Table 5.4 presents the variables incident on the key measures of Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility. Table 5.5 presents the remaining relationships as well as goodness-of-fit measures. Both tables *italicize* the relationships that are present in the final full-sample model (referred to simply as "final model" for the remainder of this chapter) specification. Note that the tables summarize only the maximum likelihood (ML) estimation results.

Whereas the final model specification held two exogenous Objective Mobility variables, the expanded model has four, all of which are endogenous. These variables are logically functions of Socio-demographics (e.g. those with higher incomes commute at higher speeds) and lifestyle choices (e.g. workaholics tend to commute more frequently).

Each of the four measures of Objective Mobility positively influences Subjective Mobility, as expected. The two measures in the final model hold the same sign in this model and are *italicized* in Table 5.4. Unlike the final model, the Objective Mobility variables are not alone in shaping Subjective Mobility. Here, Travel Liking enters with the quadratic relationship of Collantes and Mokhtarian (2002, 2007). Interestingly, Relative Desired Mobility enters with a positive coefficient: those who desire more travel assess their travel amounts to be greater, perhaps reflecting the greater cognitive salience one's travel has to one who wants to do even more. Note that the structural equation model formulation is able to capture both directions of causality (SM$\rightarrow^{-}$RDM; RDM$\rightarrow^{+}$SM), with opposite signs.

Travel Liking is a function of commute duration and Subjective Mobility, as in the final model. Here, the relationship with Subjective Mobility is bidirectional. In addition to these variables, Attitudes and Lifestyles also shape Travel Liking, as hypothesized in the conceptual model.

The Relative Desired Mobility equation contains three of the four covariates of the final model. The lone absentee is commute speed, which does not have a significant impact in the expanded model. These variables are joined by the commute benefit Attitude factor score (note that the factor scores are not replaced with latent variables in this model only) which estimates with a positive coefficient (as expected).

Table 5.5 contains a host of logical and ancillary relationships, between measures of Objective Mobility, Attitudes, Lifestyle, and Personality. As these relationships have not been investigated in previous work with this data, more detailed investigations in either the single or structural equation context would be interesting, though not undertaken here.

It is expected that the expanded model will be superior to the final model in its ability to explain the variance of Relative Desired Mobility, in particular (as it is considered the "end measure" of the model), as well as Subjective Mobility and Travel Liking. As noted in Bentler and Raykov (2000), the squared multiple correlations, or equation-specific R^2 values, provided by software packages are not appropriate when the model structure is nonrecursive (i.e. contains loops). The expanded model is nonrecursive, as it contains bidirectional effects. An alternate method, proposed by Hayduk (2006), referred to as "blocked-error-R^2" (beR^2), is used to assess the proportion of variance explained in each of the key variables. The beR^2 value for commute Relative Desired Mobility is 0.601; for Subjective Mobility, 0.425; and for Travel Liking, 0.595. These values compare favorably to the R^2 values (beR^2 equals R^2 in recursive models) in the final model of 0.441, 0.206, and 0.131, respectively. The expanded model does, in fact, explain considerably more of the variance in each of the key measures (including the Objective Mobility variables which are exogenous, and hence not explained at all, in the final model) than the final model. However, the R^2 values in the final model are as good as or better than typical values for disaggregate models of travel behavior appearing in the literature.

The question is whether or not such superior proportions of variance explained makes the expanded model superior? To answer this question the overall fit of the model must also be examined. The expanded model has a χ^2 test statistic divided by model degrees of freedom (χ^2/d.f.) of 16.05 and a root mean square error of approximation (RMSEA) of 0.105. In comparison, the final model has values of 1.241 and 0.013, respectively. The goodness-of-fit measures of the expanded model are substantially outside the range of "typical" values found in the literature (see Table 3.1). So, while the expanded model does a good job of explaining the variance of the key variables, it does so at the expense of overall model fit.

In this chapter specifically and this dissertation generally, the "final" models selected to represent the structural relationships of each of the travel categories meet the goodness-of-fit standards present in the structural equation modeling (SEM) literature. As such, I am explicitly selecting models that do a poorer job of explaining the variance in each key variable individually, but are superior in explaining the structural relationships of the key variables in an efficient manner. This decision is made primarily to be consistent with the literature: the final commute model contains equation-specific R^2 values and overall structural goodness-of-fit measures that are consistent with the standards established in the travel behavior and SEM literature. The same cannot be said about the expanded model: it does not meet the SEM standards for goodness-of-fit. As mentioned at the beginning of this chapter, the single-equation models of OM, SM, TL, and RDM do a great job of explaining the variance in each construct individually. However, the expanded model is valuable in its own right, as its specification permits the identification of more complex structures than was possible in the final model – the two-way relationship between Travel Liking and Subjective Mobility being a case in point – and warrants further investigation in future research.

Table 5.4: Expanded Model ML Estimation Results – Key Variables (N=1,352)

Regression Weights [] -- range of observed values	ML coeff	 crit ratio	Standardized effects direct	 total
→ Objective Mobility -- Square root of one-way commute time [>=0]				
Socio-demographic -- Personal income [1,…,6]	0.181	5.864	0.149	0.129
Socio-demographic -- Single, no children [0,1]	0.282	2.998	0.069	0.069
Socio-demographic -- Commute mode - Private vehicle [0,1]	-0.937	-10.620	-0.256	-0.256
Socio-demographic -- Commute mode - Rail [0,1]	1.193	10.785	0.249	0.249
→ Objective Mobility -- Weekly commute frequency [1,…,6]				
Objective Mobility -- Square root of commute speed [>=0]	-0.023	-2.132	-0.058	-0.058
Lifestyle -- Workaholic factor score [-2.1, 2.7]	0.044	2.336	0.055	0.074
Socio-demographic -- Personal income [1,…,6]	0.038	3.256	0.091	0.082
→ Objective Mobility -- Square root of weekly commute travel distance [>=0]				
Objective Mobility -- Square root of commute speed [>=0]	-0.023	-2.132	-0.058	-0.058
Socio-demographic -- Personal income [1,…,6]	0.513	6.450	0.135	0.227
Socio-demographic -- Commute mode - Private vehicle [0,1]	-1.371	-6.188	-0.120	0.014
Socio-demographic -- Commute mode - Rail [0,1]	2.427	8.749	0.163	0.163
→ Objective Mobility -- Square root of commute speed [>=0]				
Socio-demographic -- Personal income [1,…,6]	0.159	6.088	0.146	0.163
Socio-demographic -- San Francisco neighborhood [0,1]	-1.149	-15.694	-0.367	-0.404
Socio-demographic -- Commute mode - Private vehicle [0,1]	0.702	8.927	0.216	0.216
→ Subjective Mobility -- Commute [1,…,5]				
Objective Mobility -- Square root of one-way commute time [>=0]	*0.324*	*8.663*	*0.492*	*0.339*
Objective Mobility -- Square root of commute speed [>=0]	*0.093*	*3.137*	*0.125*	*0.162*
Objective Mobility -- Weekly commute frequency [1,…,6]	0.408	5.912	0.214	0.153
Objective Mobility -- Square root of weekly commute travel distance [>=0]	0.038	4.104	0.177	0.127
Travel Liking -- Commute [1,…,5]	-2.006	-6.052	-1.615	-1.017
Travel Liking -- Commute squared [1,4,9,16,25]	0.277	5.020	1.277	0.916
Relative Desired Mobility -- Commute [1,…,5]	1.038	5.547	0.654	0.469
→ Travel Liking -- Commute [1,…,5]				
Objective Mobility -- Square root of one-way commute time [>=0]	*-0.028*	*-7.612*	*-0.053*	*-0.262*
Subjective Mobility -- Commute [1,…,5]	*0.022*	*2.414*	*0.027*	*0.017*
Attitude -- Travel freedom factor score [-3.0, 2.3]	0.117	3.881	0.092	0.079
Attitude -- Commute benefit factor score [-2.9, 2.6]	0.710	11.088	0.660	0.566
Lifestyle -- Family/community-related factor score [-3.9, 2.1]	-0.103	-3.502	-0.082	-0.070
→ Travel Liking -- Commute squared [1,4,9,16,25]				
Attitude -- Travel freedom factor score [-3.0, 2.3]	0.813	4.590	0.111	0.099
Attitude -- Commute benefit factor score [-2.9, 2.6]	3.890	10.645	0.632	0.543
Lifestyle -- Family/community-related factor score [-3.9, 2.1]	-0.537	-3.098	-0.075	-0.064
→ Relative Desired Mobility -- Commute [1,…,5]				
Objective Mobility -- Square root of one-way commute time [>=0]	*-0.073*	*-5.209*	*-0.175*	*-0.474*
Subjective Mobility -- Commute [1,…,5]	*-0.343*	*-7.584*	*-0.544*	*-0.386*
Travel Liking -- Commute [1,…,5]	*0.223*	*10.030*	*0.284*	*0.765*
Attitude -- Commute benefit factor score [-2.9, 2.6]	0.104	4.373	0.123	0.286

Note: *Italics* denote relationship also present in final model.

Table 5.5: Expanded Model Results cont. – Other Variables and Goodness-of-Fit Measures

Regression Weights [] -- range of observed values	**ML** **coeff**	 **crit ratio**	**Standardized effects** **direct**	 **total**
→ Attitude -- Commute benefit factor score [-2.9, 2.6]				
Objective Mobility -- Square root of one-way commute time [>=0]	-0.195	-10.431	-0.396	-0.331
Objective Mobility -- Square root of commute speed [>=0]	-0.044	-2.702	-0.079	-0.069
Travel Liking -- Commute [1,…,5]	-0.230	-2.630	-0.248	-0.207
Lifestyle -- Workaholic factor score [-2.1, 2.7]	-0.201	-5.833	-0.175	-0.164
→ Attitude -- Pro-high density factor score [-2.5, 2.3]				
Socio-demographic -- San Francisco neighborhood [0,1]	0.925	25.636	0.571	0.571
→ Attitude -- Travel freedom factor score [-3.0, 2.3]				
Socio-demographic -- Personal income [1,…,6]	0.124	9.186	0.244	0.244
→ Socio-demographic -- Full-time worker [0,1]				
Lifestyle -- Workaholic factor score [-2.1, 2.7]	0.049	3.772	0.102	0.102
→ Socio-demographic -- San Francisco neighborhood [0,1]				
Lifestyle -- Status seeker factor score [-1.7,2.7]	-0.055	-3.389	-0.090	-0.090
Personality -- Calm factor score [-2.9, 2.4]	-0.045	-2.754	-0.073	-0.073
→ Socio-demographic -- Commute mode - Private vehicle [0,1]				
Attitude -- Pro-high density factor score [-2.5, 2.3]	-0.092	-4.811	-0.155	-0.155
Socio-demographic -- Personal income [1,…,6]	0.025	2.841	0.076	0.076
Socio-demographic -- San Francisco neighborhood [0,1]	-0.083	-2.665	-0.086	-0.174
→ Socio-demographic -- Commute mode - Rail [0,1]				
Personality -- Calm factor score [-2.9, 2.4]	0.028	2.269	0.062	0.066
Socio-demographic -- San Francisco neighborhood [0,1]	-0.042	-2.086	-0.057	-0.057
→ Socio-demographic -- Personal income [1,…,6]				
Lifestyle -- Frustrated [-2.0, 2.7]	-0.264	-6.153	-0.151	-0.151
Lifestyle -- Workaholic factor score [-2.1, 2.7]	0.372	7.859	0.194	0.227
Personality -- Calm factor score [-2.9, 2.4]	-0.252	-5.742	-0.141	-0.141
Socio-demographic -- Full-time worker [0,1]	1.286	13.165	0.325	0.325
Covariances	**coeff**	**crit ratio**		
Socio-demographic -- Single, no children [0,1]	0.040	6.817		
Socio-demographic -- San Francisco neighborhood [0,1]				
Objective Mobility -- Square root of one-way commute time [>=0]	0.560	8.998		
Objective Mobility -- Commute Speed				
Travel Liking -- Commute [1,…,5]	3.776	21.535		
Travel Liking -- Commute squared [1,4,9,16,25]				
Objective Mobility -- Weekly commute frequency [1,…,6]	-0.300	-11.996		
Objective Mobility -- Square root of one-way commute time [>=0]				
Objective Mobility -- Weekly commute frequency [1,…,6]	1.065	14.946		
Objective Mobility -- Square root of weekly commute travel dist. [>=0]				
Goodness-of-fit Measures				
χ^2 test statistic (p-value) =	2808.869	(0.000)		
Degrees of freedom =	175			
χ^2 test statistic / degrees of freedom =	16.051			
Fit indices: Relative, Incremental, Comparative =	0.654, 0.772, 0.771			
Root-mean square error of approximation (90 percent interval) =	0.105	(0.102,0.109)		

6. SHORT-DISTANCE TRAVEL

In this chapter the following short-distance (SD) travel models are presented and discussed: overall, work/school-related, entertainment/social/recreation (labeled "entertainment" for the sake of brevity), and personal vehicle. In Sections 6.1 through 6.4, each of the models is introduced and briefly discussed. The heart of the chapter follows in Section 6.5, where comparisons are made across all of the short-distance models – those found in this chapter as well as the commute model of *5.2 Preferred Model Estimation Results*. Common themes and important differences are examined. Note that short-distance travel is defined as trips that have a one-way distance under 100 miles; a definition consistent with the American Travel Survey in place at the time of data collection (1998).

The generic variable names of Subjective Mobility (SM), Travel Liking (TL), and Relative Desired Mobility (RDM) are used in a category-specific context throughout this chapter. Meaning, if the term Subjective Mobility is used when discussing the overall travel model (*6.1 Overall*), the variable being discussed is the *overall* travel Subjective Mobility variable (i.e. the response to the statement, "I feel that I travel … **overall**, for **ALL** short-distance trips"). The variables in the Subjective Mobility, Travel Liking, and Relative Desired Mobility categories do not appear in models outside their travel categories in this chapter (they do in the long-distance models presented in Chapter 7).

6.1 Overall

The investigation of overall short-distance travel is at once both muddled and enlightening. On one hand, it is more difficult to conceptualize "overall" travel (e.g. "how much do you think you travel 'overall'?") than it is purpose- or mode-specific travel, such as commuting or personal vehicle travel. As such, interpreting the model results can be a bit muddled as overall travel may be shaped largely by commuting for some, and chauffeuring children for others. On the other hand, individuals' assessments of general travel may also best capture general feelings towards the act of traveling itself without the additional cognitive baggage of considering specific travel modes or purposes. Consider two questions: (1) would you like to travel more, overall? Or (2) would you like to travel more for leisure? Question (2) brings to mind both leisure activities (going fishing!) as well as constraints keeping one from those activities (I never have time to go fishing). Question (1), in contrast, invokes no such ancillary factors, and rather tends to focus one's thoughts on the act of traveling, be it in a car, bus, or on foot. In this regard, measures of overall travel may be "cleaner" assessments of feelings for the travel itself, in isolation from the activities at the destination.

It is expected that the model results for the overall travel category will be similar to the commute model of *5.2 Preferred Model Estimation Results* because it is likely that for most workers, their commute experiences will dominate their overall travel assessments. In particular, measures of commute Objective Mobility (e.g. duration, frequency, length) will likely influence overall travel perceptions (Subjective Mobility) and desires (Relative Desired Mobility).

The maximum likelihood (ML), asymptotic distribution free (ADF), bootstrap, and M*plus* estimation results for the overall short-distance travel model are presented in Table 6.1. The standardized coefficients from the ML estimation are shown in Figure 6.1. Recall from Chapter 5 that the *unstandardized* coefficients (for each estimation technique) are presented in Table 6.1 and the *standardized ML* coefficients are presented in the path diagram of Figure 6.1.

In general, the model fits the data very well. The ML and ADF χ^2 test statistic divided by model degrees of freedom (χ^2/d.f.) values are less than 0.11, the CFI is 1.000, and the RMSEA is 0.000. Such superior goodness-of-fit measures raise the concern that the model may be "overfit". Overfitting occurs when a model moves away from capturing general relationships and toward representing effects specific to the estimation dataset. Because the parameters estimated in this particular model lead to interesting and logical interpretations, and are consistent with the other nine model structures estimated as part of this dissertation (e.g. the structure of the commute model is very similar, for which goodness-of-fit measures are good, but not as good as these), overfitting does not appear to be a concern here (also see Chapter 8).

As in *5.2 Preferred Model Estimation Results*, each of the key variables is discussed individually, in turn. The variables incident to the key variables are discussed in each sub-section below.

6.1.1 Objective Mobility

Two measures of Objective Mobility (OM) enter into the final model specification. The first, demonstrating the influence of the commute on overall travel perceptions, is the square root of commute duration. No other variables in the system directly affect commute duration.

The second OM variable is a measure of total short-distance trip frequency. Interestingly, this variable is positively dependent on the overall Travel Liking variable. This result suggests that an overall enjoyment of travel can lead to increased trip making.

The two OM variables have a negatively correlated error term: an increase in commute duration corresponds to a decrease in overall short-distance trip making. This result is logical in that those with shorter commutes will likely have more time to make other trips, such as going out to eat dinner.

6.1.2 Subjective Mobility

The two measures of Objective Mobility (OM), commute duration and overall trip frequency, combine to shape overall travel perceptions (Subjective Mobility). Both of the OM measures have a positive influence on Subjective Mobility (SM), supporting the expected relationship that the more one travels, the greater one perceives his travel to be. These variables were also significant in the single-equation models of overall SM of Collantes and Mokhtarian (2002), along with other measures of work/school-related and personal vehicle travel. It is expected that a subset of the significant single-equation model covariates would be present in the structural equation models.

6.1.3 Travel Liking

The Travel Liking (TL) measure is negatively influenced by commute duration; the interpretation is logical: the more one is "forced" to commute, the less she enjoys travel overall. This result further confirms the hypothesis that commute travel shapes overall travel attitudes, specifically affections. Measures of commute distance appeared in the single-equation Travel Liking model of Ory and Mokhtarian (2005).

6.1.4 Relative Desired Mobility

The Relative Desired Mobility (RDM) variable is regarded as the "end measure" in the modeling: all the structural relationships influence how much more or less travel is desired. In the overall travel category model, RDM is positively impacted by Travel Liking and negatively impacted by Subjective Mobility and commute duration.

The presence of the Mobility variables suggests that high travel amounts and perceptions lead to a desire to reduce travel. Note that it is not just travel amounts that are important, but also travel perceptions. How travel is perceived influences the desire to reduce travel. This point is elaborated on in *6.5.1 Core Relationships*.

6.1.5 Notes on Estimation Techniques

As in the commute model, all four estimation techniques produced highly similar overall results. The χ^2 test statistic and Bollen-Stine bootstrap *p*-values for each estimation technique – ML, ADF, bootstrap, and M*plus* – are 0.886, 0.895, 0.897, and 0.864, respectively. Please see Chapter 8 for a detailed examination of the variation of goodness-of-fit measures across models and estimation techniques.

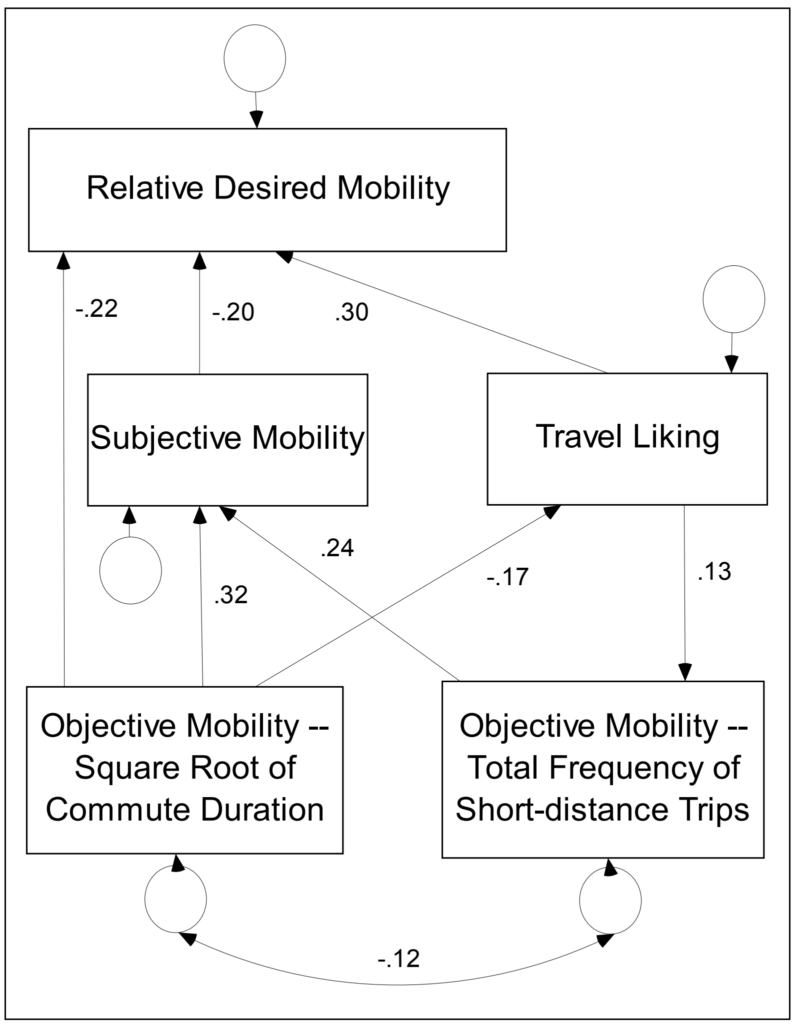


Figure 6.1: Overall SD Travel Model Structure and ML Standardized Coefficients

Table 6.1: Overall SD Travel Model Estimation Results (N=1,336)

Regression Weights [] -- range of observed values	ML coeff	 crit ratio	ADF coeff	 crit ratio	Bootstrap coeff	 crit ratio	M*plus* coeff	 crit ratio
→ Objective Mobility -- Total short-distance trip frequency [0,1,…] (R^2 = 0.022*)								
Travel Liking -- Overall [1,…,5]	0.138	4.810	0.137	4.133	0.136	4.121	0.110	5.053
→ Subjective Mobility -- Overall [1,…,5] (R^2 = 0.141)								
Objective Mobility -- Square root of one-way commute time [>=0]	0.182	12.635	0.182	12.857	0.182	13.000	0.217	11.696
Objective Mobility -- Total short-distance trip frequency [0,1,…]	0.309	9.396	0.309	9.421	0.310	9.688	0.369	8.867
→ Travel Liking -- Overall [1,…,5] (R^2 = 0.028)								
Objective Mobility -- Square root of one-way commute time [>=0]	-0.069	-6.176	-0.069	-5.595	-0.069	-5.750	-0.104	-6.661
→ Relative Desired Mobility -- Overall [1,…,5] (R^2 = 0.226)								
Objective Mobility -- Square root of one-way commute time [>=0]	-0.088	-8.556	-0.088	-8.728	-0.088	-8.800	-0.141	-8.063
Subjective Mobility -- Overall [1,…,5]	-0.142	-7.868	-0.142	-7.441	-0.142	-7.889	-0.255	-8.282
Travel Liking -- Overall [1,…,5]	0.291	12.268	0.290	10.854	0.292	10.815	0.421	13.368
Covariances	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
Objective Mobility -- Square root of one-way commute time [>=0]	-0.165	-4.356	-0.165	-4.375	-0.165	-4.342	-0.162	-4.064
Objective Mobility -- Total short-distance trip frequency [0,1,…]								
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =	0.242	(0.886)	0.221	(0.895)		(0.897)	0.294	(0.864)
Degrees of freedom =	2		2		n/a		2	
χ^2 test statistic / degrees of freedom =	0.121		0.111		n/a		0.147	
Fit indices: Relative, Incremental, Comparative =	0.998, 1.003, 1.000		0.997, 1.004, 1.000		n/a		---, ---, 1.000†	
Root-mean square error of approximation (90 percent interval) =	0.000	(0,0.026)	0.000	(0,0.024)	n/a		0.000	(n/a)
Normality Measures								
Multivariate kurtosis =	2.951	(6.446)						

* Also known as the squared multiple correlation (SMC); † M*plus* does not report the Relative or Incremental Fit Index

6.2 Work/school-related

Travel in the work/school-related category may include a service employee, such as a plumber, making daily visits to others' homes, or a downtown worker walking across the central business district (CBD) to the office of a client. It will be interesting to see how Objective Mobility and Travel Liking relate in the empirical model because work/school-related travel may be mandatory (e.g. a retail clerk must go to the bank each day to deposit the day's cash intake), but often may be discretionary (e.g. in a given retail store, numerous clerks may be capable of running to the bank, but the one who enjoys going to the bank, either to enjoy a walk in the sun or to converse with the handsome bank clerk, will end up making the trip more often than others).

The estimation results for the work/school-related travel model are presented in Table 6.2; the standardized coefficients from the ML estimation are included in Figure 6.2. Endogenous variables are represented in Figure 6.2 by labeled boxes; error terms by unlabeled circles; and latent variables by labeled circles.

The goodness-of-fit measures suggest that the models fit the data sufficiently well. The χ^2/d.f. measure for the ML and ADF estimations are near 2.4, the CFI is 0.985, and the RMSEA is 0.033. These measures are slightly "worse" than typical values found in the structural equation modeling (SEM) literature (see Table 3.1).

The data can be considered severely non-normal, as the multivariate kurtosis value is over 20. The non-normality of the data as a whole is largely a function of the Objective Mobility (OM) measures. Because many do very little travel in this category and others do quite a bit, the distribution is heavily skewed to the right. The multiple estimation techniques are valuable when the data are not multivariate normal because the standard estimation technique, ML, is not strictly valid (see Chapter 8 for a systematic comparison of multivariate kurtosis and goodness-of-fit variability).

The relationships found in the model are briefly discussed below, again organized by the key endogenous variables.

6.2.1 Objective Mobility

The final model specification contains two work/school-related and one commute-related measure of Objective Mobility (OM). The work/school-related variables include the square root of weekly work/school-related distance, which is exogenous to the system, and frequency of work/school-related travel (rated on an ordinal scale). Not surprisingly, these variables are significantly and positively correlated. The other OM variable is the square root of weekly commute distance traveled, which is also exogenous to the system.

The work/school-related Travel Liking (TL) variable estimates with a positive coefficient on the work/school-related frequency variable. This finding suggests that, to some degree, work/school-related travel is discretionary: an enjoyment leads to an increase in frequency. Consider, for example, the case of a junior employee volunteering to run to the post office or copy store, with an eye not for pleasing the boss (though that's certainly a benefit), but to escape the workplace for a spell. This finding is consistent with the OM models of weekly work/school-related distance in Redmond and Mokhtarian (2001b), who also found TL to have a positive effect on travel amounts.

6.2.2 Subjective Mobility

Consistent with the commute and overall models, the two Objective Mobility (OM) variables estimate positively on the Subjective Mobility (SM) variable: the more people actually travel, the more they think they travel. Interestingly, the commute distance variable does not significantly impact work/school-related SM, though it does impact Travel Liking (TL), as discussed in the next sub-section.

No significant direct relationships exist between Subjective Mobility and Travel Liking (also see *6.5.5 Relationship between Travel Liking and Subjective Mobility*). However, as in the overall model, there is a positive indirect effect from Travel Liking to Subjective Mobility through the trip frequency Objective Mobility variable. This result indicates that an enjoyment of work/school-related travel manifests itself in doing more of it, which leads to increased perceptions of amounts.

6.2.3 Travel Liking

The work/school-related measure of Travel Liking (TL) is impacted by the Objective Mobility (OM) variable square root of weekly miles commuting. Again, commute travel impacts the enjoyment of and desire for travel in another category. The interpretation is reasonable: those who are forced to commute long distances find less enjoyment in making trips while at work than do those whose commute distances are lower.

6.2.4 Relative Desired Mobility

In examining the variables that impact Relative Desired Mobility (RDM), consistent patterns across the commute, overall, and work/school-related models begin to emerge. The Subjective Mobility (SM) variable estimates on RDM with a negative coefficient, while the Travel Liking (TL) variable holds a positive coefficient. These effects have been present in each of the three models discussed so far (see *6.5.1 Core Relationships*).

The commute benefit latent variable, discussed in more detail in the next sub-section (also see *6.5.2 Latent Variables*), buttresses the Travel Liking variable by also estimating with a positive coefficient on Relative Desired Mobility. This variable's impact on RDM is further testament to the impact of commuting on work/school-related travel. Those who see their commute time as useful rather than burdensome desire more work/school-related travel relative to those without positive commute benefit attitudes. This may be because those who see their commute as useful are not as worn out by traveling and are willing to do more of it during the workday, or perhaps because, as with their commutes, they see work/school-related travel as a useful time for making phone calls or having time alone.

6.2.5 Commute Benefit Latent Variable

The commute benefit latent variable is manifested by three attitudinal statements from the survey, specifically: "My commute is a real hassle" (represented by "Hassle" in Figure 6.2); "My commute trip is a useful transition between home and work" ("Transition"); "The traveling that I need to do interferes with doing other things I like" ("Interferes"). Survey respondents used a five-point scale anchored by "strongly disagree" and "strongly agree" to record their level of agreement with these statements.

Commute distance has a negative effect on the commute benefit latent variable. The interpretation is that those who are "forced" to commute long distances are not as able to view their commute as a positive or productive time as those with shorter commutes.

There is seemingly a natural correlation between Travel Liking (TL) and commute benefit: both represent a general fondness (or, put another way, absence of disdain) for traveling. The question is, which direction of effect is more reasonable: does TL shape commute benefit attitudes or does the commute benefit latent variable influence TL? The direction of effect is not clear and, as such, the two variables are connected via correlated error terms in the structural model with the expected positive (and sizable) covariance.

In addition to the three attitudinal statements, the commute benefit latent variable estimates on Relative Desired Mobility (RDM) with a positive coefficient. The interpretation is: the more one sees the commute as a beneficial time, the more she wants to partake in work/school-related travel. It is likely that those who view commuting as positive desire more work/school-related travel so that they can further engage in whatever activity is making their commute useful (e.g. listening to a book on tape). The relationship may also reflect a general pro-work orientation.

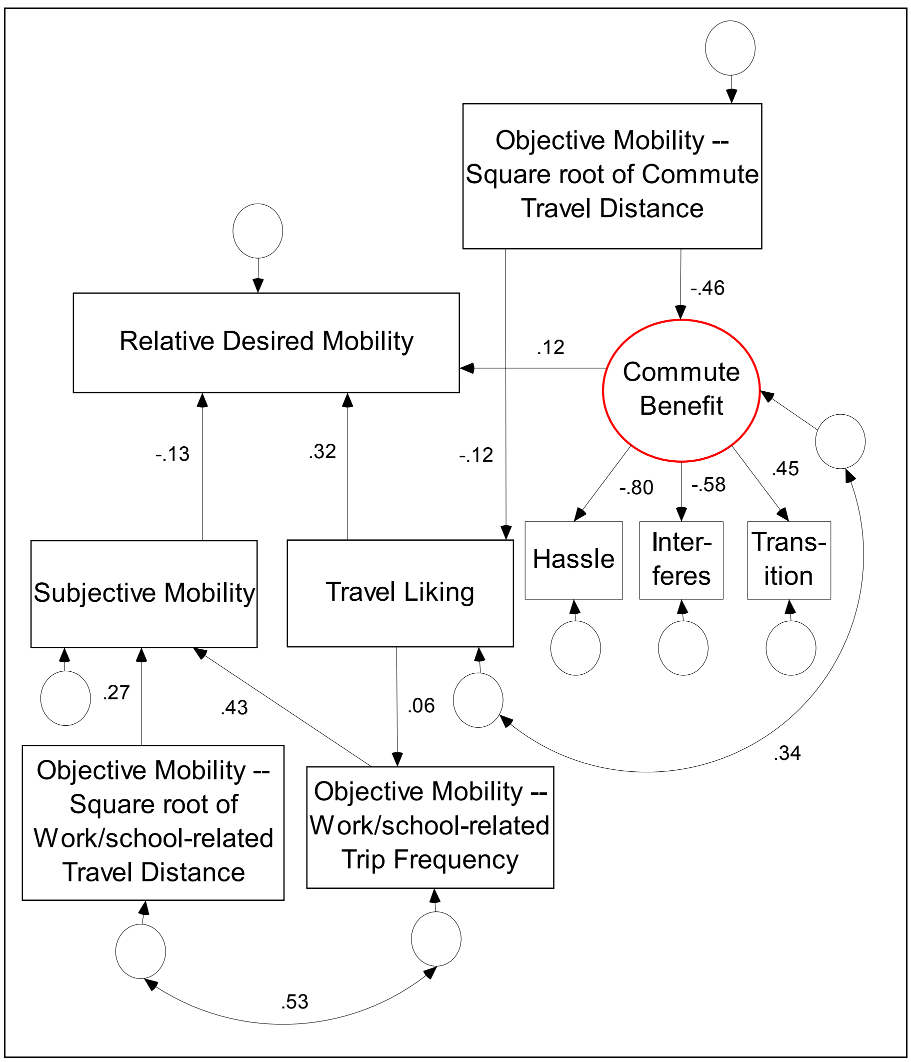


Figure 6.2: Work/school-related SD Travel Model Structure and ML Standardized Coefficients

Table 6.2: Work/school-related SD Travel Model Estimation Results (N=1,349)

Regression Weights	ML		ADF		Bootstrap		M*plus*	
[] -- range of observed values	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
→ Objective Mobility -- Work/school-related trip frequency [0,1,…] (R^2 = 0.000)								
Travel Liking -- Work/school-related [1,…,5]	0.106	2.406	0.097	2.053	0.105	2.059	0.077	2.528
→ Subjective Mobility -- Work/school-related [1,…,5] (R^2 = 0.373)								
Objective Mobility -- Work/school-related trip frequency [0,1,…]	0.335	16.732	0.339	14.624	0.336	14.609	0.671	18.474
Objective Mobility – Sqr. root of weekly work/school-related travel distance [>=0]	0.080	10.519	0.080	8.369	0.080	8.889	0.083	14.173
→ Travel Liking -- Work/school-related [1,…,5] (R^2 = 0.015)								
Objective Mobility -- Square root of weekly commute travel distance [>=0]	-0.018	-4.491	-0.020	-4.949	-0.018	-4.500	-0.024	-4.394
→ Relative Desired Mobility -- Work/school-related [1,…,5] (R^2 = 0.159)								
Subjective Mobility -- Work/school-related [1,…,5]	-0.077	-5.330	-0.080	-4.787	-0.077	-4.529	-0.137	-5.958
Travel Liking -- Work/school-related [1,…,5]	0.273	11.447	0.290	9.276	0.274	8.563	0.423	12.211
Latent Variable -- Commute Benefit	0.185	3.803	0.164	3.183	0.183	3.389	0.266	3.351
→ Latent Variable -- Commute Benefit (R^2 = 0.209)								
Objective Mobility -- Square root of weekly commute travel distance [>=0]	-0.039	-10.772	-0.042	-10.729	-0.039	-13.000	-0.042	-10.670
→ Attitude statement -- My commute trip is a useful transition between home and work [1,…,5] (R^2 = 0.199)								
Latent Variable -- Commute Benefit	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
→ Attitude statement -- The traveling that I need to do interferes with doing other things I like [1,…,5] (R^2 = 0.334)								
Latent Variable -- Commute Benefit	-1.246	-12.458	-1.248	-11.783	-1.248	-11.044	-1.460	-11.288
→ Attitude statement -- My commute is a real hassle [1,…,5] (R^2 = 0.638)								
Latent Variable -- Commute Benefit	-1.879	-12.764	-1.870	-12.338	-1.880	-12.789	-2.766	-8.350

Covariances	coeff	crit ratio	coeff	crit ratio	coeff	crit ratio	coeff	crit ratio
Objective Mobility -- Square root of weekly work/school-related travel distance [>=0]	3.214	17.200	3.068	17.059	3.216	16.926	2.269	35.679
Objective Mobility -- Work/school-related trip frequency [0,1,…]								
Travel Liking -- Work/school-related [1,…,5]	0.112	8.240	0.108	7.396	0.113	7.063	0.186	8.871
Latent Variable -- Commute Benefit								
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =	55.978	(0.000)	57.002	(0.000)		(0.001)	29.447	(0.003)
Degrees of freedom =	23		23		n/a		7	
χ^2 test statistic / degrees of freedom =	2.434		2.478		n/a		2.454	
Fit indices: Relative, Incremental, Comparative =	0.961, 0.985, 0.985		0.903, 0.962, 0.961		n/a		---, ---, 0.994	
Root-mean square error of approximation (90 percent interval) =	0.033	(.022,.044)	0.033	(.022,.044)	n/a		0.033	(n/a)
Normality Measures								
Multivariate kurtosis =	21.354	(27.869)						

6.3 Entertainment/Social/Recreation

Modeling the entertainment category allows for an examination of travel that can be considered more optional, or discretionary, than commute, overall, or work/school-related travel. The survey instrument directed respondents to assess each travel category in regard to the actual travel, as opposed to the activity at the destination. Even with these explicit instructions, it is likely that, as noted by Ory and Mokhtarian (2005), the travel is somewhat confounded with the activity at the destination (perhaps more so in this category than the others), though as the authors discuss at some length, the metric is still valuable and worth exploring in this context. It is expected that an enjoyment of entertainment travel (a high Travel Liking) will lead to higher travel amounts. It will be interesting to see if any Socio-demographic variables influence the entertainment structural relationships (e.g. does the presence of young children affect the relationships? What about higher incomes?).

During the model exploration stage, the San Francisco neighborhood dummy variable entered the entertainment model with numerous significant effects. Those results motivated segmenting the sample into those who reside in the Hayes Valley, Western Addition, or University of San Francisco neighborhoods in San Francisco proper and those who live in the suburban communities of Pleasant Hill and Concord. The two segment-specific models were estimated simultaneously in one "multigroup" estimation; selected coefficients across the two samples were constrained to be equal based on t- and χ^2-tests. Only one coefficient significantly differed across the segments: the positive effect from Travel Liking on Subjective Mobility (see the Subjective Mobility section below for a discussion of this point).

The ML and ADF estimation results, segmented by residential location, for entertainment short-distance travel are presented in Table 6.3; the bootstrap and M*plus* results are in Table 6.4. The standardized coefficients from the ML estimation are shown in Figure 6.3.

The models fit the data well with ML and ADF χ^2/d.f. values of 0.954 and 0.798, respectively. The multivariate kurtosis is around 7 for both segments, suggesting moderate to severe non-normality.

The rest of this section discusses each of the key endogenous variables in turn.

6.3.1 Objective Mobility

Two measures of Objective Mobility (OM), the square root of weekly entertainment travel distance and entertainment trip frequency, enter the models as endogenous variables; both are positively influenced by the Travel Liking (TL) measure. This result highlights the discretionary nature of entertainment travel: an enjoyment of travel directly leads to more travel, both in terms of trip frequency and travel distance. The directionality of this effect is reversed from the commute model, in which long commutes led to a decrease in travel enjoyment. A conclusion is that discretionary travel leads to a logical TL$\rightarrow^{+}$OM effect and mandatory travel an OM$\rightarrow^{-}$TL effect (see *6.5.4 Positive Utility of Travel*).

6.3.2 Subjective Mobility

Both measures of OM positively impact Subjective Mobility (SM), as expected (the more I actually travel, the more I think I travel), but have no direct effects on RDM. As mentioned previously, the effect of Travel Liking on Subjective Mobility differed by residential location market segment. This effect is not significantly different from zero for the San Francisco segment, suggesting that San Franciscans, unlike their suburban-dwelling counterparts, do not allow their enjoyment of entertainment travel (or lack thereof) to stretch or shrink their travel perceptions. Perhaps the shorter distances traveled by San Franciscans for entertainment make these perceptions more stable and, as such, less influenced by enjoyment. Note also that the covariance between weekly distance and frequency is not as strong in the San Francisco segment as it is in the suburban segment. This result is expected in that San Francisco residents have entertainment opportunities both close by and relatively far away (the latter being the only choice for many suburban residents).

6.3.3 Travel Liking

The entertainment Travel Liking (TL) variable acts exogenously to the entertainment model structure. This finding is not surprising in that entertainment travel is, by and large, discretionary. The implication is that enjoyment of entertainment travel is a fundamental attitude that is more inherent to the individual than influenced by external circumstances. The single-equation models of Travel Liking echo this position. The entertainment model in Ory and Mokhtarian (2005) had covariates in the Socio-demographics, Attitudes, Lifestyle, and Personality categories – none of which are included in the final structural model specification (though all were considered in the exploratory stage).

6.3.4 Relative Desired Mobility

As in each of the previously described models, Relative Desired Mobility (RDM) is positively impacted by Travel Liking (TL) and negatively impacted by Subjective Mobility (SM). The latter finding suggests that people can be satiated in their entertainment travel, and increases in travel can cause a desire to reduce travel amounts. Note that the negative coefficient on the SM variable in the RDM equation is of much smaller standardized magnitude (-0.07, as shown in Figure 6.3) than that in the commute (-0.13), overall (-0.20) or work/school-related (-0.13) models, suggesting, logically, that satiation of entertainment travel is more difficult to achieve than in commute, overall, or work/school-related travel.

Table 6.3: ML and ADF Entertainment SD Travel Model Estimation Results (N=1,344) by Residential Location Segment

Regression Weights	**ML**				**ADF**			
	SF Segment		**Sub. Segment**		**SF Segment**		**Sub. Segment**	
[] -- range of observed values	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
→ Objective Mobility -- Square root of weekly entertainment trip distance [>=0] (R^2 = 0.015 / 0.009*)								
Travel Liking -- Entertainment [1,…,5]	0.394	4.012	0.394	4.012	0.416	3.940	0.416	3.940
→ Objective Mobility -- Entertainment trip frequency [0,1,…] (R^2 = 0.017 / 0.016)								
Travel Liking -- Entertainment [1,…,5]	0.163	4.715	0.163	4.715	0.166	4.507	0.166	4.507
→ Subjective Mobility -- Entertainment [1,…,5] (R^2 = 0.208 / 0.278)								
Objective Mobility -- Square root of weekly entertainment trip distance [>=0]	0.085	10.074	0.085	10.074	0.083	8.724	0.083	8.724
Objective Mobility -- Entertainment trip frequency [0,1,…]	0.300	12.186	0.300	12.186	0.304	10.926	0.304	10.926
Travel Liking -- Entertainment [1,…,5]	0.053	1.275	0.132	3.242	0.056	1.195	0.138	3.195
→ Relative Desired Mobility -- Entertainment [1,…,5] (R^2 = 0.135 / 0.127)								
Subjective Mobility -- Entertainment [1,…,5]	-0.053	-2.832	-0.053	-2.832	-0.049	-2.321	-0.049	-2.321
Travel Liking -- Entertainment [1,…,5]	0.328	14.218	0.328	14.218	0.327	12.324	0.327	12.324
Covariances	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
Objective Mobility -- Square root of weekly entertainment trip distance [>=0] Objective Mobility -- Entertainment trip frequency [0,1,…]	0.766	8.071	1.209	10.002	0.753	7.730	1.205	9.987
Goodness-of-fit Measures								
χ^2 test statistic (p-value) =	9.538	(0.482)			7.981	(0.631)		
Degrees of freedom =	10				10			
χ^2 test statistic / degrees of freedom =	0.954				0.798			
Fit indices: Relative, Incremental, Comparative =	0.977, 1.001, 1.000				0.959, 1.005, 1.000			
Root-mean square error of approximation (90 percent interval) =	0.000	(0,0.029)			0.000	(0,0.025)		
Normality Measures								
Multivariate kurtosis =	7.119	(10.962)	7.268	(11.367)				

* San Francisco segment R^2 / Suburban segment R^2

Table 6.4: Bootstrap and M*plus* Entertainment SD Travel Model Estimation Results (N=1,344) by Residential Location Segment

Regression Weights	Bootstrap				M*plus*			
	SF Segment		Sub. Segment		SF Segment		Sub. Segment	
[] -- range of observed values	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
→ Objective Mobility -- Square root of weekly entertainment trip distance [>=0]								
Travel Liking -- Entertainment [1,…,5]	0.389	3.670	0.389	3.670	0.278	3.783	0.278	3.783
→ Objective Mobility -- Entertainment trip frequency [0,1,…]								
Travel Liking -- Entertainment [1,…,5]	0.163	4.289	0.163	4.289	0.143	4.879	0.143	4.879
→ Subjective Mobility -- Entertainment [1,…,5]								
Objective Mobility -- Square root of weekly entertainment trip distance [>=0]	0.085	9.444	0.085	9.444	0.110	8.548	0.110	8.548
Objective Mobility -- Entertainment trip frequency [0,1,…]	0.299	10.679	0.299	10.679	0.426	12.665	0.426	12.665
Travel Liking -- Entertainment [1,…,5]	0.056	1.191	0.134	2.913	0.074	1.713	0.156	3.233
→ Relative Desired Mobility -- Entertainment [1,…,5]								
Subjective Mobility -- Entertainment [1,…,5]	-0.053	-2.409	-0.053	-2.409	-0.117	-4.331	-0.117	-4.331
Travel Liking -- Entertainment [1,…,5]	0.329	12.185	0.329	12.185	0.499	15.625	0.499	15.625
Covariances	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
Objective Mobility -- Square root of weekly entertainment trip distance [>=0] Objective Mobility -- Entertainment trip frequency [0,1,…]	0.762	7.620	1.206	9.967	0.426	12.665	1.316	12.644
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =		(0.626)			5.594	(0.588)		
Degrees of freedom =	n/a				7			
χ^2 test statistic / degrees of freedom =	n/a				0.799			
Comparative fit index =	n/a				1.000			
Root-mean square error of approximation =	n/a				0.000			

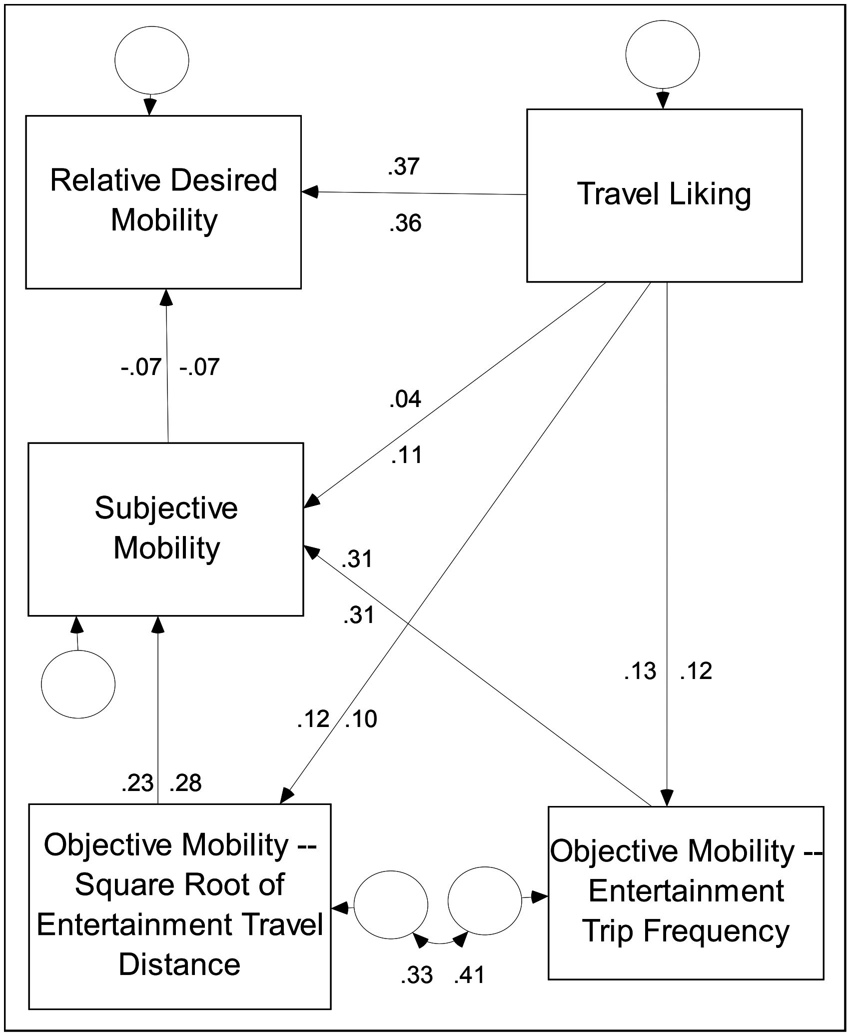


Figure 6.3: Entertainment SD Travel Model Structure and ML Standardized Coefficients for San Francisco (top/left of effect arrow) and Suburban (bottom/right) Market Segments

6.4 Personal Vehicle

This model concerns travel, for all purposes, in a personal vehicle (as either the driver or passenger) and has the capability to reveal interesting relationships regarding latent desires for automobile use. For example, would those who take transit on a routine basis prefer to use an automobile more frequently?

As in the entertainment model, the personal vehicle model is segmented by residential location: San Francisco or suburban. The detailed differences between the two segments are discussed in each of the key variable sub-sections below. The ML and ADF estimation results for both segments are presented in Table 6.5; the bootstrap and M*plus* results are in Table 6.6. The standardized coefficients are shown in the path diagram presented in Figure 6.4.

The non-normality of the data differs dramatically between the two segments. The San Francisco segment exhibits moderate-to-severe non-normality, with a multivariate kurtosis of slightly more than eight. The suburban segment, in contrast, has a value over 47, indicating severe non-normality. The source of this non-normality is the two Objective Mobility measures: weekly personal vehicle and bus distance. It is not surprising that those living in the suburbs have heavily skewed distributions of bus travel distance in particular.

The fit of the model to the data is in line with the guidelines put forth in Table 3.1. The ML and ADF RMSEA are 0.023 and the χ^2/d.f. value is near 1.7.

As in the previous sections, each of the key variable categories is discussed next.

6.4.1 Objective Mobility

Two measures of Objective Mobility (OM) enter the model as exogenous variables: the logarithm of weekly personal vehicle distance and the logarithm of weekly bus distance. The error terms of these two variables are significantly and negatively correlated, which is logical: the more I travel in a bus, the less I need to travel in a personal vehicle. Note that this correlation is much stronger for San Francisco residents than their suburban counterparts, suggesting that the dense transit networks in the City offer more reasonable substitution options to the personal vehicle than do the sparse networks of the suburbs.

6.4.2. Subjective Mobility

Similar to the previous models, the personal vehicle Subjective Mobility (SM) measure is a function of Objective Mobility (OM) and Travel Liking (TL). Here, the two measures of Objective Mobility work in opposing directions (also see *6.5.3 What Shapes Subjective Mobility?*): those traveling longer distances in a personal vehicle perceive their travel to be greater, while those traveling more in a bus perceive their personal vehicle travel to be reduced, all else equal.

The idea of bus travel influencing personal vehicle travel perceptions is intriguing. Consider two individuals, A and B, who travel 100 miles per week in a personal vehicle. If person A does no traveling by bus and person B travels 15 miles per week by bus (say to his favorite restaurant on the other side of the CBD to have lunch), then person B will tend to perceive her travel in a personal vehicle to be less than person A will, even though their actual automobile travel amounts are identical. This suggests that bus travel is seen as an unfulfilled opportunity to use a personal vehicle.

These effects differ by residential location segment. An extra mile in a personal vehicle has a greater perceptional effect on San Francisco residents relative to those in the suburbs; an extra mile in a bus, in contrast, has a lesser effect on City dwellers. These results are interesting and intuitive. For those living in the car-dominated suburbs, taking the bus is probably uncommon and may even be a topic of conversation among friends and coworkers. When thinking of how often one travels in a personal vehicle, the experience on the bus logically impacts the suburban traveler more than his urban counterpart, for whom taking the bus is more common.

The Travel Liking measure influences Subjective Mobility with a positive coefficient, suggesting that those who enjoy travel in a personal vehicle are more aware of the travel they do than those with lower levels of enjoyment.

The quadratic relationship between Subjective Mobility and Travel Liking found in Collantes and Mokhtarian (2002, 2007) could not be replicated here (including the terms greatly degraded the model fit). However, distance traveled by modes other than personal vehicle are found in their single-equation models, in which distance by bus, rail, and non-motorized modes all negatively influence personal vehicle Subjective Mobility.

6.4.3 Travel Liking

The personal vehicle Travel Liking measure has only one covariate, the latent pro-environmental solutions variable, which manifests in the following statements (with which respondents agreed or disagreed on a five-point scale): “We should raise the price of gasoline to reduce congestion and air pollution” (labeled as “Gas Price” in Figure 6.4), “To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle” (“Clean car”), and “We need more public transportation, even if taxes have to pay for a lot of the costs” (“Transit”) (also see *6.4.5 Pro-environmental Solutions Latent Variable* and *6.5.2 Latent Variables*). Ory and Mokhtarian (2005) also found this significant effect, among myriad others, in their single-equation models of Travel Liking.

Not surprisingly, the pro-environmental solutions variable estimates with a negative coefficient on the personal vehicle Travel Liking variable: those with pro-environment feelings enjoy, or say they enjoy, traveling in a personal vehicle less than those with less-strong pro-environment feelings.

6.4.4 Relative Desired Mobility

The end-measure of Relative Desired Mobility (RDM) is a function of Objective Mobility (OM), Subjective Mobility (SM), Travel Liking (TL) and two latent variables, pro-environment solutions and commute benefit. These results are a subset of the results found in the single-equation RDM models of Choo, *et al.* (2005).

The coefficient of personal vehicle distance on Relative Desired Mobility is negative, as expected, for both residential location segments, but not significantly different from zero for the suburban segment. This result suggests that even suburban residents who travel a great deal in their automobiles do not have a strong desire to reduce automobile travel. This finding probably reflects the difficulty of traveling by automobile in San Francisco relative to the suburbs, as well as the greater desire of San Francisco residents, again relative to their suburban counterparts, to drive less, both of which result in San Franciscans desiring much less automobile travel per mile of actual travel. Though other interesting differences do arise between the segments, all the remaining coefficients are statistically significant and have the same sign in both segments.

The negative coefficient of bus distance on SM combined with the negative coefficient of SM on RDM reveals a positive indirect effect between weekly bus distance and personal vehicle RDM. The end result is that the more bus travel one engages in, the more an individual desires to travel in a personal vehicle, all else, particularly actual personal vehicle distance, equal. This effect suggests that those traveling on the bus would, not surprisingly, prefer to travel in an automobile. The single-equation personal vehicle RDM model of Choo, *et al.* (2005) also contained a positive effect of bus SM on personal vehicle RDM.

The commute benefit latent variable and Travel Liking variable both have a positive influence on RDM. These findings suggest that those who see a benefit in commuting (often doing so in a personal vehicle) and those who enjoy driving, both desire more travel in a personal vehicle.

These effects are tempered by the pro-environmental solutions variable, which has a negative coefficient on RDM as well as an additional negative indirect effect through the Travel Liking variable.

Across the entire model, a desire for reduced personal vehicle travel is created by traveling a lot in a personal vehicle and by having pro-environmental attitudes.

6.4.5 Pro-environmental Solutions Latent Variable

As mentioned above, the pro-environmental solutions latent variable estimates with a positive coefficient on three survey statements ("We should raise the price of gasoline to reduce congestion and air pollution", "To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle", and "We need more public transportation, even if taxes have to pay for a lot of the costs"), to which respondents responded on a five-point Likert-type scale, from "strongly disagree" to "strongly agree".

The weekly personal vehicle and weekly bus travel distance variables impact the latent variable with opposing coefficients. Those traveling longer distances in personal vehicles tend to have less pro-environmental attitudes than those traveling more on the bus. Note that the stronger directional effect is from behavior to attitudes (in this model, the converse effect is not statistically different from zero), supporting the idea, as discussed in *2.1 Positive Utility of Travel*, that behavior can influence attitudes. Here, traveling on the bus "causes" (to the extent structural equation models can be said to suggest causality) pro-environmental feelings, rather than such feelings "causing" increased transit use. An alternative interpretation is that many people who express pro-environmental attitudes do not put them into practice by riding the bus, so the probability of having high pro-environmental attitudes if one rides the bus is much higher than the probability of riding the bus a lot if one has pro-environmental attitudes.

6.4.6 Commute Benefit Latent Variable

As in the work/school-related model, the commute benefit latent construct again shapes the responses to the following three survey statements: “My commute is a real hassle” (negative coefficient), “My commute trip is a useful transition between home and work” (positive coefficient), and “The traveling that I need to do interferes with doing other things I like” (negative coefficient).

The Travel Liking (TL) and commute benefit variables have positively-related error terms, suggesting the two variables are capturing similar attitudes. The construction of the latent variable and the relationship between the variable and the category-specific TL measure are identical to those found in the work/school-related model.

The weekly personal vehicle distance variable estimates on the commute benefit variable with a negative coefficient, suggesting that those who travel long distances in a personal vehicle are less able to see their commute as a beneficial time. Not surprisingly, this effect is of greater magnitude for the suburban segment than the San Francisco segment: those in the suburbs travel more in their automobiles and are likely able to reach a saturation point where having time alone in a vehicle is no longer seen as useful.

Table 6.5: ML and ADF Personal Vehicle SD Travel Model Estimation Results (N=1,354) by Residential Location Segment

Regression Weights	ML				ADF			
	SF Segment		Sub. Segment		SF Segment		Sub. Segment	
[] -- range of observed values	coeff	crit ratio	coeff	crit ratio	coeff	crit ratio	coeff	crit ratio
→ Subjective Mobility -- Personal Vehicle [1,…,5] (R^2 = 0.389 / 0.135*)								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	0.434	15.442	0.328	8.078	0.442	15.936	0.314	7.655
Objective Mobility -- Logarithm of weekly bus distance [>=0]	-0.093	-3.414	-0.226	-3.119	-0.090	-3.250	-0.372	-4.893
Travel Liking -- Personal Vehicle [1,…,5]	0.145	4.803	0.145	4.803	0.144	4.819	0.144	4.819
→ Travel Liking -- Personal Vehicle [1,…,5] (R^2 = 0.053 / 0.050)								
Latent Variable -- Pro-environmental solutions	-0.252	-6.701	-0.252	-6.701	-0.211	-6.140	-0.211	-6.140
→ Relative Desired Mobility -- Personal Vehicle [1,…,5] (R^2 = 0.355 / 0.216)								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-0.162	-8.613	-0.031	-1.119	-0.165	-7.611	-0.028	-1.019
Subjective Mobility -- Personal Vehicle [1,…,5]	-0.046	-2.564	-0.046	-2.564	-0.042	-2.456	-0.042	-2.456
Travel Liking -- Personal Vehicle [1,…,5]	0.373	12.767	0.289	9.678	0.362	12.356	0.282	7.850
Latent Variable -- Commute Benefit	0.249	5.033	0.249	5.033	0.259	5.106	0.259	5.106
Latent Variable -- Pro-environmental solutions	-0.129	-4.382	-0.129	-4.382	-0.144	-5.164	-0.144	-5.164
→ Latent Variable -- Commute Benefit (R^2 = 0.032 / 0.095)								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-0.050	-3.830	-0.163	-6.484	-0.050	-3.573	-0.181	-6.979
→ Latent Variable -- Pro-environmental solutions (R^2 = 0.069 / 0.016)								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-0.085	-3.740	-0.085	-3.740	-0.091	-4.015	-0.091	-4.015
Objective Mobility -- Logarithm of weekly bus distance [>=0]	0.072	2.941	0.072	2.941	0.072	2.799	0.072	2.799

→ Attitude statement -- My commute trip is a useful transition between home and work [1,…,5] (R^2 = 0.181 / 0.219)								
Latent Variable -- Commute Benefit	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
→ Attitude statement -- The traveling that I need to do interferes with doing other things I like [1,…,5] (R^2 = 0.272 / 0.338)								
Latent Variable -- Commute Benefit	-1.185	-12.234	-1.185	-12.234	-1.115	-11.662	-1.115	-11.662
→ Attitude statement -- My commute is a real hassle [1,…,5] (R^2 = 0.646 / 0.697)								
Latent Variable -- Commute Benefit	-1.923	-11.283	-1.923	-11.283	-1.864	-10.694	-1.864	-10.694
→ Attitude statement -- We should raise the price of gasoline to reduce congestion and air pollution [1,…,5] (R^2 = 0.379 / 0.451)								
Latent Variable -- Pro-environmental solutions	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
→ Attitude statement -- To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle [1,…,5] (R^2 = 0.395 / 0.293)								
Latent Variable -- Pro-environmental solutions	0.782	13.871	0.782	13.871	0.732	14.135	0.732	14.135
→ Attitude statement -- We need more public transportation, even if taxes have to pay for a lot of the costs [1,…,5] (R^2 = 0.515 / 0.366)								
Latent Variable -- Pro-environmental solutions	0.968	13.977	0.968	13.977	0.884	14.363	0.884	14.363
Covariances	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-1.302	-11.572	-0.121	-6.446	-1.361	-14.944	-0.111	-3.833
Objective Mobility -- Logarithm of weekly bus distance [>=0]								
Travel Liking -- Personal Vehicle [1,…,5]	0.074	3.869	0.081	4.412	0.061	2.946	0.068	3.544
Latent Variable -- Commute Benefit								
Goodness-of-fit Measures								
χ^2 test statistic (p-value) =	140.362	(0.000)			138.008	(0.000)		
Degrees of freedom =	81				81			
χ^2 test statistic / degrees of freedom =	1.733				1.704			
Fit indices: Relative, Incremental, Comparative =	0.926, 0.976, 0.976				0.852, 0.952, 0.951			
Root-mean square error of approximation (90 percent interval) =	0.023	(0.017,0.030)			0.023	(0.016,0.029)		
Normality Measures								
Multivariate kurtosis =	8.295	(6.339)	47.526	(36.803)				

* San Francisco segment R^2 / Suburban segment R^2

Table 6.6: Bootstrap and M*plus* Personal Vehicle SD Travel Model Estimation Results (N=1,354) by Residential Location Segment

Regression Weights	Bootstrap				M*plus*			
	SF Segment		Sub. Segment		SF Segment		Sub. Segment	
[] -- range of observed values	coeff	crit ratio	coeff	crit ratio	coeff	crit ratio	coeff	crit ratio
→ Subjective Mobility -- Personal Vehicle [1,…,5]								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	0.434	14.467	0.327	7.786	0.415	11.739	0.432	7.758
Objective Mobility -- Logarithm of weekly bus distance [>=0]	-0.092	-3.172	-0.220	-2.821	-0.229	-4.064	-0.171	-2.258
Travel Liking -- Personal Vehicle [1,…,5]	0.146	4.867	0.146	4.867	0.143	4.239	0.143	4.239
→ Travel Liking -- Personal Vehicle [1,…,5]								
Latent Variable -- Pro-environmental solutions	-0.253	-6.658	-0.253	-6.658	-0.289	-7.764	-0.289	-7.764
→ Relative Desired Mobility -- Personal Vehicle [1,…,5]								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-0.162	-7.043	-0.031	-1.069	-0.243	-6.952	-0.181	-5.152
Subjective Mobility -- Personal Vehicle [1,…,5]	-0.045	-2.500	-0.045	-2.500	-0.148	-3.595	-0.148	-3.595
Travel Liking -- Personal Vehicle [1,…,5]	0.371	11.594	0.290	8.056	0.588	10.565	0.525	9.506
Latent Variable -- Commute Benefit	0.252	4.582	0.252	4.582	0.389	4.817	0.389	4.817
Latent Variable -- Pro-environmental solutions	-0.129	-4.031	-0.129	-4.031	-0.177	-4.226	-0.177	-4.226
→ Latent Variable -- Commute Benefit								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-0.051	-3.188	-0.163	-6.520	-0.047	-2.844	-0.179	-6.041
→ Latent Variable -- Pro-environmental solutions								
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-0.086	-3.583	-0.086	-3.583	-0.074	-2.177	-0.074	-2.177
Objective Mobility -- Logarithm of weekly bus distance [>=0]	0.071	2.840	0.071	2.840	0.152	3.389	0.152	3.389

→ Attitude statement -- My commute trip is a useful transition between home and work [1,…,5]								
Latent Variable -- Commute Benefit	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
→ Attitude statement -- The traveling that I need to do interferes with doing other things I like [1,…,5]								
Latent Variable -- Commute Benefit	-1.192	-10.739	-1.192	-10.739	-1.481	-10.248	-1.481	-10.248
→ Attitude statement -- My commute is a real hassle [1,…,5]								
Latent Variable -- Commute Benefit	-1.932	-10.500	-1.932	-10.500	-2.776	-6.644	-2.776	-6.644
→ Attitude statement -- We should raise the price of gasoline to reduce congestion and air pollution [1,…,5]								
Latent Variable -- Pro-environmental solutions	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
→ Attitude statement -- To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle [1,…,5]								
Latent Variable -- Pro-environmental solutions	0.783	12.836	0.783	12.836	0.727	10.311	0.727	10.311
→ Attitude statement -- We need more public transportation, even if taxes have to pay for a lot of the costs [1,…,5]								
Latent Variable -- Pro-environmental solutions	0.972	12.000	0.972	12.000	1.086	8.743	1.086	8.743
Covariances	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
Objective Mobility -- Logarithm of weekly personal vehicle distance [>=0]	-1.299	-13.392	-0.121	-2.814	0.152	3.389	-0.118	-9.219
Objective Mobility -- Logarithm of weekly bus distance [>=0]								
Travel Liking -- Personal Vehicle [1,…,5]	0.075	3.261	0.080	3.810	0.114	3.928	0.170	6.133
Latent Variable -- Commute Benefit								
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =		(0.002)			150.060	(0.000)		
Degrees of freedom =	n/a				63			
χ^2 test statistic / degrees of freedom =	n/a				2.382			
Comparative fit index =	n/a				0.963			
Root-mean square error of approximation =	n/a				0.045			

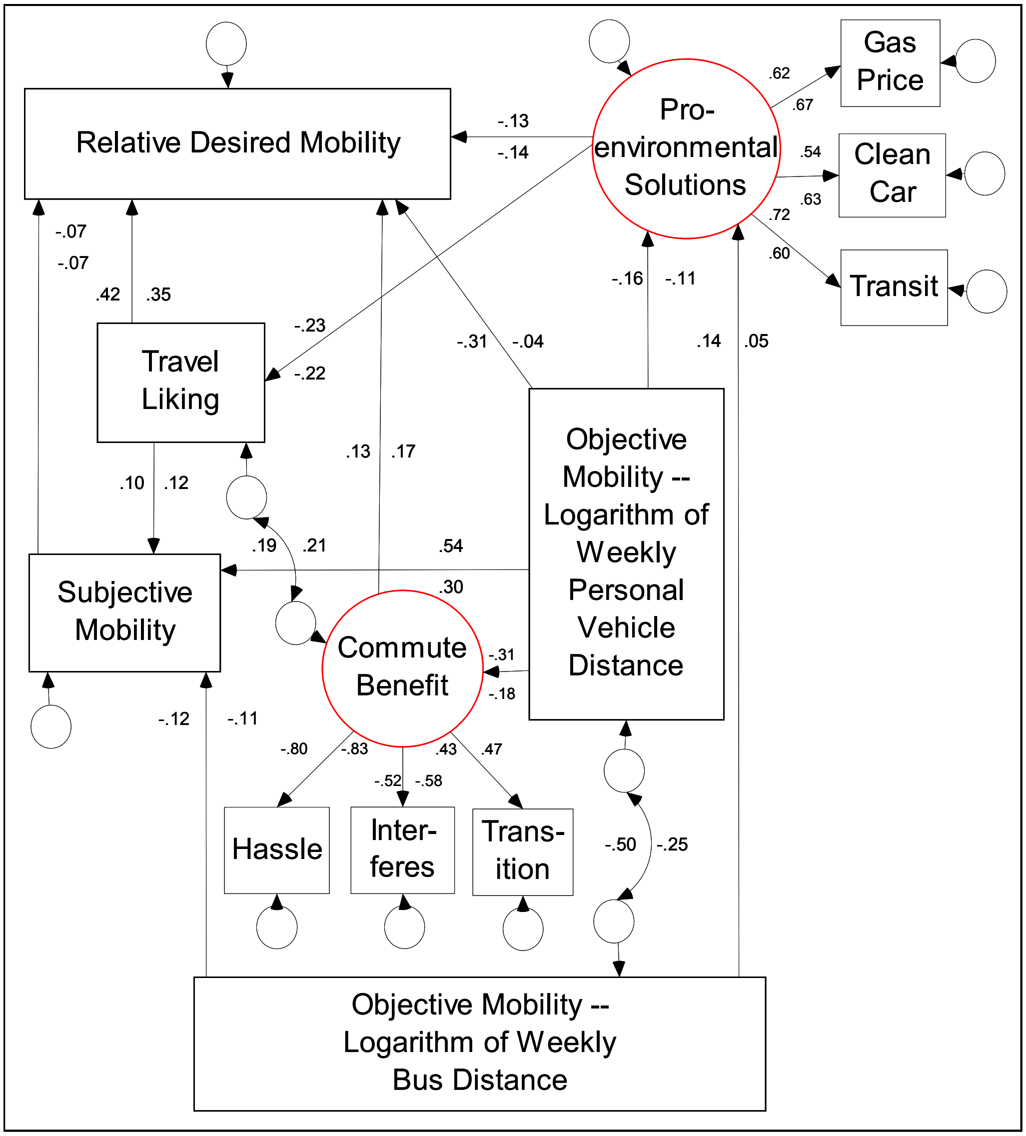


Figure 6.4: Personal Vehicle SD Travel Model Structure and ML Standardized Coefficients for San Francisco (top/left of effect arrow) and Suburban (bottom/right) Market Segments

6.5 Cross-model Comparisons

In this section, common themes across the four short-distance models presented in this chapter and the commute model of *5.1 Model Exploration and Specification* are discussed.

6.5.1 Core Relationships

Each of the five models contains three common relationships, namely: positive impacts of multiple measures of Objective Mobility on Subjective Mobility (OM$\rightarrow^{+}$SM); a negative impact of Subjective Mobility on Relative Desired Mobility (SM$\rightarrow^{-}$RDM); and a positive effect of Travel Liking on Relative Desired Mobility (TL$\rightarrow^{+}$RDM).

The relationship between OM and SM is discussed in a broader context in subsection *6.5.3 What Shapes Subjective Mobility?* Suffice it to say here that this finding is logical: the more I actually travel, the more I perceive my travel to be. Those in the sample have, as it turns out, a collective and common understanding of what constitutes "a lot" of travel across each of the five categories (see *6.5.6 Subjective Mobility Filtering* for more discussion of this point).

The negative relationship of SM to RDM means that high travel perceptions, in each of the five travel categories, lead to a desire to reduce travel. This finding supports the common-sense expectation that the desire to travel is not limitless: we may want to do more of it if we perceive that we are currently doing very little, but if we are traveling a lot, most of us become surfeited and would prefer to do less. Furthermore, the consistently significant effect of SM on RDM, competing against allowed-to-enter direct effects from OM to RDM, confirms that travel perceptions are important in shaping desires. It is not only the objective travel amounts that shape desires; it is also how those amounts are perceived. Two individuals who travel the same amount, therefore, may perceive these amounts differently, and, importantly, to the extent one perceives that travel to be less than the other, this same individual will not have the same motivation to reduce his/her travel when alternatives to travel, such as telecommuting, are presented. Interesting nuances of these relationships are found in *6.5.6 Subjective Mobility Filtering*.

The final common relationship is the positive effect of Travel Liking (TL) on RDM. Here, an enjoyment of travel leads to a desire for more of it; said another way, a lower dislike for travel lessens the desire to reduce one's travel. The strength of this relationship across the categories (it has among the largest standardized coefficients in each model), as shown in Figures 5.1 and 6.1 through 6.4, indicates the powerful role that enjoying travel can have in shaping desires (see *6.5.4 Positive Utility of Travel*).

6.5.2 Latent Variables

The work/school-related and the personal vehicle models each contain latent variables. These variables were included in the final specification via a two-step modeling process. In the first step, models were estimated using the previously-computed factor scores for the Attitude variables (see *4.2 Explanatory Variables*). After specifying a model, the factor score variables were replaced with latent constructs along with the observed survey variables that originally loaded most heavily on each factor.

The "commute benefit" factor score variable was part of the first-step model specification for both the work/school-related and personal vehicle models. In the second step, this variable was replaced with a latent representation of the commute benefit construct, and the optimal set of predictors was found. In both the work/school-related and personal vehicle models, the latent variable is related to the following three (out of 32) attitudinal statements to which survey respondents agreed or disagreed on a five-point scale: "My commute is a real hassle" (represented by "Hassle" in Figures 6.2 and 6.4); "My commute trip is a useful transition between home and work" ("Transition"); "The traveling that I need to do interferes with doing other things I like" ("Interferes"). For identifiability purposes (Kennedy, 1998), the "Transition" variable is fixed with an unstandardized coefficient of positive 1.0 (as it best embodies the previously-established name of the construct); both the "Hassle" and "Interferes" variables relate negatively to the latent variable. In the structural equation context, the latent variable moves away from being a function of attitudinal statements (as it is in factor analysis) and becomes part of the larger structure – directly influencing, and being influenced by, other variables in the system.

The pro-environmental solutions latent variable in the personal vehicle model estimates with a positive coefficient on the following three survey statements: “We should raise the price of gasoline to reduce congestion and air pollution” (“Gas Price” in Figure 6.4; fixed coefficient of 1.0), “To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicle” (“Clean Car”), and “We need more public transportation, even if taxes have to pay for a lot of the costs” (“Transit”).

6.5.3 What Shapes Subjective Mobility?

The primary purpose of the Objective Mobility variables, in the context of this work, is to determine what travel measures impact Subjective Mobility (SM). I am asking, in other words, what characteristic(s) of travel make(s) people think they are doing a lot of it? Is it traveling long distances? Is it making multiple trips? Is it traveling in congested conditions?

The modeling here, consistent with Collantes and Mokhtarian (2002, 2007), suggests that it is a combination of all these effects (see Table 6.7). In fact, essentially all the measurements of Objective Mobility captured in the survey proved significant in the modeling. For example, the only measurements taken of short-distance entertainment travel were trip frequency and travel distance. Both appeared with significant coefficients in the final specification. The same holds true for the work/school-related travel models.

In the overall, commute and personal vehicle models, OM variables (such as weekly travel distance specific to each of these categories) did enter the models with significant coefficients. However, although inclusion of these variables increased the predictive accuracy of the model (equation-specific R^2s), they also significantly degraded model fit, i.e. substantially increased the discrepancy between the model-predicted and empirically-observed covariance matrices. As discussed in *5.4 Expanded Model Estimation Results*, the literature contains mixed advice with respect to this (quite common) situation, but this dissertation chooses models with goodness-of-fit measures consistent with those found the SEM literature.

Perhaps the most interesting OM-SM relationship exists in the personal vehicle model. Here, the two measures of Objective Mobility, weekly travel distance in a personal vehicle and weekly travel distance in a public bus, work in opposing directions. Those traveling longer distances in a personal vehicle perceive their travel to be greater (a logical finding), while those traveling more in a bus perceive their personal vehicle travel to be lower, all else equal. This latter finding is intriguing and suggests that bus travel is seen as an unfulfilled opportunity to use a personal vehicle.

The relationships between Objective Mobility and Subjective Mobility also help answer the question: if two people travel the same objective amount, why would they perceive that travel differently? Because travel amounts (via the OM variables) are controlled for, the remaining variables affecting SM help answer this question. Collantes and Mokhtarian (2007) and Ory, *et al.* (forthcoming) address these issues in depth using the results from the single-equation models of Collantes and Mokhtarian (2002).

The SEM models estimated here are essentially consistent with the work of Collantes and Mokhtarian (2007). As shown in Table 6.7, only OM variables impact SM in three of the five models. Travel Liking has a positive impact on SM in the entertainment and personal vehicle models, suggesting that those who enjoy travel in these categories are more aware of the travel they do relative to those who do not enjoy these types of travel. The notion that travel perceptions are modified by travel enjoyment was one of the original hypotheses included in the conceptual model.

Table 6.7: Subjective Mobility Covariates

Model	Segment	Objective Mobility		Travel Liking Coefficient
		Measure 1, Coefficient†	Measure 2, Coefficient	
Commute	---	Commute duration 0.40	Commute speed 0.15	---
Overall	---	Commute duration 0.32	Trip frequency 0.24*	---
Work/school-related	---	Trip frequency 0.43*	Distance 0.27*	---
Entertainment	San Francisco	Trip frequency 0.31*	Distance 0.23*	0.04*
	Suburb	Trip frequency 0.31*	Distance 0.28*	0.11*
Personal vehicle	San Francisco	Distance 0.54*	Bus Distance -0.12	0.10*
	Suburb	Distance 0.30*	Bus Distance -0.11	0.12*

† All coefficients presented in the table are maximum likelihood standardized estimates; * Travel category-specific variable

6.5.4 Positive Utility of Travel

The Travel Liking variables appear in each of the five structural equation models. In the overall, work/school-related, and entertainment models, increased levels of Travel Liking lead directly to increases in trip making and, for the entertainment model, also lead to increases in travel distance. These results suggest that an enjoyment of travel, especially discretionary travel, can lead to an engagement in more of it. For mandatory travel, however, both the opposite direction of causality and the opposite sign appear as well. In the commute model of *5.2 Preferred Model Estimation Results*, as well as the overall and work/school-related models presented in Figures 6.1 and 6.2, increases in commuting cause a decrease in each of the category-specific measures of Travel Liking. Here, travel that one is “forced” to engage in causes a decrease in travel enjoyment across the three categories.

To summarize the relationships between TL and OM, (1) for entertainment travel, the TL$\rightarrow^{+}$OM relationship stands alone; (2) for overall and work/school-related, both TL$\rightarrow^{+}$OM(category-specific) and OM(commuting)$\rightarrow^{-}$TL are present; and for commuting, only the OM$\rightarrow^{-}$TL effect is significant. The opposite relationships of (1) and (3), with the opposite roles of OM as an effect and a cause, are just what would be expected for discretionary and mandatory travel, respectively. The fact that both relationships can be detected and estimated simultaneously in the two models that mix mandatory and discretionary travel is testimony to the ability of SEM to disentangle multiple directions of causality, having opposite signs.

The only other variable in the five models that has a direct effect on the Travel Liking variables is the pro-environmental solutions latent variable included in the personal vehicle model. This finding suggests (not surprisingly) that those who support environmentally-friendly solutions to transportation problems tend to state a greater dislike for travel in an automobile, relative to those without such feelings.

The commute benefit latent variable, included in the work/school-related and personal vehicle models, offers a more nuanced measure of Travel Liking (the two variables have positively correlated error terms in both models). Here, positive responses to the statement "My commute trip is a useful transition between home and work" (among others) manifest a higher commute benefit latent variable, which, in turn, increases the category-specific RDM variables. The idea is that those who see some value in commute time also see some value in time spent traveling for other, or, in the case of personal vehicle, more general, purposes, which ameliorates a desire to reduce travel amounts.

6.5.5 Relationship between Travel Liking and Subjective Mobility

One of the most difficult relationships to understand and predict among those in the dataset is that of Subjective Mobility (SM) and Travel Liking (TL). Both directions of causality are plausible (Ory and Mokhtarian, 2005; Collantes and Mokhtarian, 2007), with potentially opposite signs: those who enjoy or dislike travel may be more aware of the travel they do than those with neutral feelings (TL$\rightarrow^{+/-}$SM); those who perceive their travel amounts to be high may tend to dislike travel (SM$\rightarrow^{-}$TL).

Table 6.8 summarizes the direct and total effects of both the Travel Liking to Subjective Mobility and Subjective Mobility to Travel Liking directions of causality. The table shows that Travel Liking positively influences Subjective Mobility in all the models save the one for commuting, though it only does so directly in the entertainment and personal vehicle models. Subjective Mobility negatively influences Travel Liking in the commute model.

These results suggest that in mandatory travel, such as commuting, travel amounts are not seen as much of a choice (I *have* to commute each day) and, as such, high travel amounts, which lead to high travel perceptions, result in a decrease in travel enjoyment. The result is a negative impact from Subjective Mobility to Travel Liking (see *5.3 Travel Liking Market Segmentation* for further discussion of this issue in the commute model). In discretionary travel, such as for entertainment purposes, travel is more optional, and an enjoyment of travel leads to more awareness of those travel amounts. The result is a positive impact of Travel Liking on Subjective Mobility. The two travel types that are enjoyed the most, entertainment and personal vehicle (see Ory and Mokhtarian, 2005), show this result most clearly (see Ory, *et al.* (forthcoming) for a discussion of this issue in psychological terms).

These results are clear and understandable when comparing commute travel to entertainment travel. The difficulty in interpretation comes when examining the categories that mix mandatory and discretionary travel. The overall category, by definition, encompasses both types of travel and thus effects in both directions are expected – and, in fact, they are present, though not significantly different from zero and thus, not shown in the table. The same interpretation could be used for work/school-related travel where, as with the previous example of a retail clerk making a midday trip to the bank, trips can be both mandatory and discretionary.

Table 6.8: Subjective Mobility and Travel Liking Standardized Coefficients

Model	Segment	Direct Effects		Total Effects	
		TL → SM	SM → TL	TL → SM	SM → TL
Commute	---	---	-0.10	---	-0.10
Overall	---	---	---	0.03	---
Work/school-related	---	---	---	0.03	---
Entertainment	San Francisco	0.04	---	0.11	---
	Suburb	0.11	---	0.18	---
Personal vehicle	San Francisco	0.10	--	0.10	---
	Suburb	0.12	---	0.12	---

Note: The values shown are the MLE standardized coefficients

6.5.6 Subjective Mobility Filtering

Part of the conceptualization of the Subjective Mobility (SM) variables was for the measures to act as filters for actual travel amounts (the Objective Mobility (OM) variables) – the notion being that actual travel shapes perceptions, which, in turn, shape desires (OM→SM→RDM). I initially hypothesized that Travel Liking would modify these perceptions, TL→SM, and, as discussed in the previous subsection, ample evidence of this effect exists.

Here, I discuss the relationships between the direct effects of OM on RDM and the indirect effects of OM on RDM via SM. However, it should be noted that Travel Liking also acts as a "filter" for objective travel amounts, specifically mandatory travel amounts, to shape desires (OM→TL→RDM). In this case, the so-called "filtering" is simply a logical indirect effect: I am "forced" to commute, which causes me to enjoy commuting less, which causes me to desire less commuting.

To examine the OM→SM→RDM filtering, the standardized coefficients are used in a path analysis to quantify the direct and indirect effects of OM on RDM, as filtered by SM; a summary is presented in Table 6.9. Note first that the total effects of OM on RDM are strictly non-positive: the more I travel the less travel I desire. This result is logical and, as mentioned previously, shows that the desire to travel is not limitless: those who do a lot of it want to do less. However, the standardized coefficients on this effect are an order of magnitude larger for the commute purpose than the work/school-related or entertainment categories, suggesting, logically, that increased mandatory travel amounts lead to a stronger desire to reduce this type of travel, relative to more discretionary travel.

Each of the OM variables shown in Table 6.9 indirectly effects RDM via SM (note that the OM variable commute duration in the work/school-related model has neither a direct nor indirect effect on RDM, and, as such, is not included in the table). In the "Direct effects" column, the OM→RDM coefficients are significant for OM variables only in the commute, overall, and personal vehicle models and only for one of the two OM variables in the latter two. In each of these cases, the direct effects are of a much greater magnitude than the indirect effects. Thus, in the case of the commute, overall and personal vehicle models, actual travel amounts dominate "filtered" travel amounts in forming changes in desired travel amounts.

In the entertainment and work/school-related models, where the direct effects of OM on RDM are not significantly different from zero, the model appears to be working as conceived: travel amounts influence perceptions which then influence desires. A natural question is: what accounts for the difference in filtering across travel categories? Looking at Table 6.9, the variables having significant direct effects are commute duration, commute speed, and weekly personal vehicle distance. The variables having only indirect effects on RDM include overall short-distance trip frequency, entertainment weekly distance and trip frequency, work/school-related weekly distance and trip frequency, and weekly bus distance. The former group includes familiar measures that most individuals probably know rather well. The time one leaves home and arrives at work each day is a constant reminder of commute duration, and the weekly trip to the gas station is a reminder, in stark dollar terms, of weekly and daily travel distance (from which speed is computed). The variables in the latter category, those without significant direct effects, are probably less well known by the average traveler. How much entertainment travel, in terms of miles, does one do in an average week? This question is much more demanding than inquiring about the daily commute time and distance. There are no objective clues, such as being late for work or filling up the gas tank, that help with entertainment and work/school-related OM estimates.

Further, there are strong societal standards for commute duration and distance, as well as personal vehicle distance. Friends, coworkers, and the media all inform societal norms regarding “acceptable” commute times. For example, everyone in the office knows about the exurban-residing coworker who commutes over an hour each day (this person is commuting “too much”). Car manufacturers offer year- or mileage-limited warranties (e.g. ten years or 100,000 miles, whichever comes first) and oil changes should be done at time or mileage intervals (e.g. every three months or 3,000 miles); travel “should” conform to these norms. Regarding commute and personal vehicle travel, established standards have been set by society and users are aware of both these standards and their degree of compliance with them. As such, it is not surprising that objective travel amounts, for these travel categories, strongly shape desires. This finding suggests that society's "rules" regarding normal commute and personal vehicle usage play an important role in shaping desires.

Turning back to the OM variables with no direct effects, such as weekly entertainment travel distance, reveals measures that are both seldom thought of and non-controversial. The same exurban-dwelling coworker can tell his colleagues all about his weekend trips into the mountains without the same embarrassment he feels towards his long commute. There are no societal standards for these travel amounts. Logically, then, it is more reasonable that Objective Mobility in the entertainment and work/school-related categories is less important in shaping travel desires. Here, perceptions are the key determinant.

Table 6.9: Subjective Mobility Filtering of Objective Mobility

Model	Segment	OM Variable	Direct effects (OM→RDM)	Indirect effects (OM→SM→RDM)	Total effects† (OM→RDM)
Commute	---	Commute duration	-0.34	0.40 x -0.13 = -0.05	-0.51
		Commute speed	-0.07	0.15 x -0.13 = -0.02	-0.09
Overall	---	Commute duration	-0.22	0.32 x -0.20 = -0.06	-0.33
		Trip frequency (all short-distance trips)	---	0.24 x -0.20 = -0.05	-0.05
Work/school-related	---	Work/school-related weekly distance	---	0.27 x -0.13 = -0.04	-0.04
		Work/school-related trip frequency	---	0.43 x -0.13 = -0.06	-0.06
Entertainment	San Francisco	Entertainment weekly distance	---	0.23 x -0.07 = -0.02	-0.02
		Entertainment trip frequency	---	0.31 x -0.07 = -0.02	-0.02
	Suburb	Entertainment weekly distance	---	0.28 x -0.07 = -0.02	-0.02
		Entertainment trip frequency	---	0.31 x -0.07 = -0.02	-0.02
Personal vehicle	San Francisco	Weekly bus distance	---	-0.12 x -0.07 = 0.01	-0.01
		Weekly personal vehicle distance	-0.31	0.54 x -0.07 = -0.04	-0.37
	Suburb	Weekly bus distance	---	-0.11 x -0.07 = 0.01	0.00
		Weekly personal vehicle distance	-0.04	0.30 x -0.07 = -0.02	-0.08

Note: The "effects" are the MLE standardized coefficients; † Includes indirect effects through variables other than SM

7. LONG-DISTANCE TRAVEL

In this chapter the long-distance (LD) models for the following travel categories are presented and discussed: overall, work/school-related, entertainment, personal vehicle, and airplane. After presenting each model individually, comparisons across the models are made at the end of the chapter.

To be consistent with the definitions of the American Travel Survey in place at the time of data collection (1998), long-distance travel in the context of the survey instrument and, thus, the subsequent analysis is defined as one-way trips longer than 100 miles.

As in Chapter 6, the models are described through the four key variables of Objective Mobility (OM), Subjective Mobility (SM), Travel Liking (TL), and Relative Desired Mobility (RDM). Unless otherwise noted, the SM, TL, and RDM variables are specific to the category of travel being described in each section.

7.1 Overall

As in the short-distance modeling, the overall travel purpose allows for perhaps the cleanest examination of travel isolated from the activities associated with travel destinations. Here, respondents are asked how they feel about long-distance travel "overall", rather than for purpose- or mode-specific travel. This may remove the associated feelings of travel destinations (e.g. traveling abroad is always exciting) or modes (e.g. traveling long distances in airplanes is uncomfortable). The difficulty in interpretation is due to the wide variety in travel types this category could cover. For example, responses for long-distance overall travel can include anything from family automobile trips to a nearby mountain range and/or month-long business trips to Asia. It will be interesting to examine the relative roles of objective amounts of travel by automobile and airplane in shaping overall perceptions. Because air travel generally covers more distance than personal vehicle travel, will it be the primary influence on perceptions? Or, because personal vehicle travel is more physically demanding, will it be a stronger covariate?

During the model exploration stage, the San Francisco neighborhood dummy variable entered the overall long-distance model with numerous significant effects. These results motivated segmenting the sample into those who reside in the Hayes Valley/Western Addition/USF neighborhoods in San Francisco and those who live in the suburban communities of Pleasant Hill and Concord. The two segment-specific models were estimated simultaneously as one "multigroup" system of equations; selected coefficients across the two samples were constrained to be equal based on t- and χ^2-tests.

The results for the overall model are presented in Tables 7.1 and 7.2, and Figure 7.1. The first table summarizes the maximum likelihood (ML) and asymptotic-distribution free (ADF) estimation results (including unstandardized coefficients); the second table presents the bootstrap and M*plus* results. The figure contains a schematic of the model structure along with the standardized path coefficients from the ML estimation.

The χ^2 test statistic divided by degrees of freedom (χ^2/d.f.) measure for the ML estimation is 0.658, suggesting a good fit to the data; the CFI (1.000) and RMSE (0.000) also suggest a good to overfit model. As each of the coefficients provide for an interesting, logical, and consistent (in terms of the models presented in this dissertation) interpretation, overfitting is not a concern.

Each of the key variables' interactions in the model is described next.

7.1.1 Objective Mobility

A single measure of Objective Mobility (OM) enters the model: the logarithm of frequency for all long-distance trips. The logarithm transformation is used to improve the normality of the distribution. As discussed in *4.1.1 Objective Mobility*, the long-distance Objective Mobility variables are measured per year, rather than per week (as the short-distance OM variables are measured). A similar transformation was used in each of the five long-distance models; more details are included in *7.6.1 Core Relationships*.

Contrary to expectation, mode-specific measures, though allowed to enter the models during the exploratory stage, did not enter the final specification. Rather, a single measure of trip frequency proved more important, suggesting that being away from home during a long-distance trip is more important than the distance traveled or mode used (see *7.6.1 Core Relationships* for further discussion of this point).

The trip frequency variable is a function of the Travel Liking measure. This effect is stronger for the suburban segment than the San Francisco segment, though both effects are positive. The positive Travel Liking coefficient suggests that long-distance travel is, to some extent, discretionary, and enjoyment of it leads to more of it. The residential segmentation is likely acting as a proxy for a bundle of socio-demographic characteristics including age, family status, income, and auto ownership, in addition to urban form. Perhaps the effect of liking on engagement is higher in the suburbs because traveling by automobile, in particular, is easier, thus requiring less effort to make trips “on a whim”.

7.1.2 Subjective Mobility

The overall long-distance Subjective Mobility (SM) variable encounters familiar covariates in this model: Objective Mobility (OM) and Travel Liking (TL), each entering with a positive coefficient. As in the short-distance models, those who actually do travel a lot, think they travel a lot, leading to the positive coefficient of OM on SM (also see *7.6.1 Core Relationships*). The TL to SM relationship is significant (and positive) here, unlike in the short-distance overall travel model, suggesting that overall long-distance travel is viewed as discretionary for most, which is a logical finding (also see *7.6.3 Relationship between Travel Liking and Subjective Mobility*). Both these findings are consistent with Collantes and Mokhtarian (2002).

Note that the effect of TL on SM differs by residential segment: the effect is stronger for the San Francisco segment. Recall that the effect of TL on OM was stronger for the suburban segment. Thus, an enjoyment of travel in the suburbs tends to manifest in more travel, whereas in the City, it tends to manifest in higher travel perceptions.

7.1.3 Travel Liking

The Travel Liking (TL) variable is exogenous to the system. The TL models of Ory and Mokhtarian (2005) included primarily explanatory variables not present in the structural model, such as those in the Attitudes and Lifestyle categories. However, Ory and Mokhtarian (2005) did include a measure of work-related trip frequency, which entered their model with a negative coefficient, suggesting that "having" to travel frequently for work resulted in a reduction of overall travel liking (a finding consistent with the impact of commute travel on short-distance overall travel). Again, even though these results are not confirmed in the structural models, the results are not necessarily inconsistent. Rather, the goal in the structural equation modeling is different: explaining the patterns of covariation among a set of variables rather than explaining the variability in a single variable.

7.1.4 Relative Desired Mobility

Each of the other four variables in the system has a significant effect on Relative Desired Mobility (RDM). Consistent with each of the short-distance models, the OM and SM measures estimate with negative coefficients: if travel amounts are, or are perceived to be, high, less travel is desired (also see *7.6.1 Core Relationships*). The effects of OM on RDM are stronger for the San Francisco residential market segment as compared to the suburban segment. Again, the difficulty of traveling out of San Francisco may make each additional trip more burdensome, leading to a stronger desire to reduce travel per trip taken.

The Travel Liking variable influences RDM with the expected positive coefficient: the more travel is enjoyed, the more of it is desired (see *7.6.1 Core Relationships*).

These results are highly consistent with the single-equation models of Choo, *et al.* (2005), in which the SM and TL variables each estimate with a positive coefficient, as does a San Francisco neighborhood "dummy" variable. The trip frequency variable is not present, though a measure of work/school-related travel distance does enter with a negative coefficient.

7.1.5 Notes on Estimation Techniques

The M*plus* estimation technique results differed somewhat from the other methods. The χ^2 test statistic *p*-values for the ML, ADF, and M*plus* estimations are 0.658, 0.526, and 0.213, respectively, and the bootstrap *p*-value is 0.685. A cross-model comparison of estimation techniques is the focus of Chapter 8.

Table 7.1: ML and ADF Overall LD Travel Model Estimation Results (N=1,343) by Residential Location Segment

Regression Weights	ML				ADF			
	SF Segment		Sub. Segment		SF Segment		Sub. Segment	
[] -- range of observed values	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
→ Objective Mobility -- Logarithm of total long-distance trip frequency [>=0] (R^2 = 0.002 / 0.009*)								
Travel Liking -- Overall [1,…,5]	0.047	1.223	0.105	2.446	0.046	1.094	0.104	2.173
→ Subjective Mobility -- Overall [1,…,5] (R^2 = 0.243 / 0.265)								
Objective Mobility -- Logarithm of total long-distance trip frequency [>=0]	0.524	20.777	0.524	20.777	0.521	18.271	5.21	18.271
Travel Liking -- Overall [1,…,5]	0.136	3.665	0.064	1.664	0.139	3.477	0.060	1.337
→ Relative Desired Mobility -- Overall [1,…,5] (R^2 = 0.246 / 0.231)								
Objective Mobility -- Logarithm of total long-distance trip frequency [>=0]	-0.136	-3.701	-0.045	-1.387	-0.135	-3.235	-0.047	-1.400
Subjective Mobility -- Overall [1,…,5]	-0.108	-4.400	-0.108	-4.400	-0.108	-3.877	-0.108	-3.877
Travel Liking -- Overall [1,…,5]	0.474	19.522	0.474	19.522	0.474	16.477	0.474	16.477
Goodness-of-fit Measures								
χ^2 test statistic (p-value) =	1.973	(0.578)			1.579	(0.664)		
Degrees of freedom =	3				3			
χ^2 test statistic / degrees of freedom =	0.658				0.526			
Fit indices: Relative, Incremental, Comparative =	0.990, 1.001, 1.000				0.985, 1.003, 1.000			
Root-mean square error of approximation (90 percent interval) =	0.000	(0,0.039)			0.000	(0,0.036)		
Normality Measures								
Multivariate kurtosis =	4.104	(7.62)	5.119	(9.63)				

* Also known as the squared multiple correlation (SMC), San Francisco segment R^2 / Suburban segment R^2

Table 7.2: Bootstrap and M*plus* Overall LD Travel Model Estimation Results (N=1,343) by Residential Location Segment

Regression Weights	Bootstrap				M*plus*			
	SF Segment		**Sub. Segment**		**SF Segment**		**Sub. Segment**	
[] -- range of observed values	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
→ Objective Mobility -- Logarithm of total long-distance trip frequency [>=0]								
Travel Liking -- Overall [1,…,5]	0.049	1.167	0.106	2.163	0.055	1.602	0.085	2.494
→ Subjective Mobility -- Overall [1,…,5]								
Objective Mobility -- Logarithm of total long-distance trip frequency [>=0]	0.526	18.138	0.526	18.138	0.679	22.524	0.679	22.524
Travel Liking -- Overall [1,…,5]	0.139	3.475	0.065	1.413	0.180	4.459	0.096	2.379
→ Relative Desired Mobility -- Overall [1,…,5]								
Objective Mobility -- Logarithm of total long-distance trip frequency [>=0]	-0.136	-3.238	-0.044	-1.294	-0.206	-4.177	-0.048	-1.005
Subjective Mobility -- Overall [1,…,5]	-0.109	-3.893	-0.109	-3.893	-0.138	-4.889	-0.138	-4.889
Travel Liking -- Overall [1,…,5]	0.474	16.929	0.474	16.929	0.642	18.374	0.642	18.374
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =		(0.685)			3.080	(0.211)		
Degrees of freedom =	n/a				2			
χ^2 test statistic / degrees of freedom =	n/a				1.540			
Comparative fit index =	n/a				0.999			
Root-mean square error of approximation =	n/a				0.028			

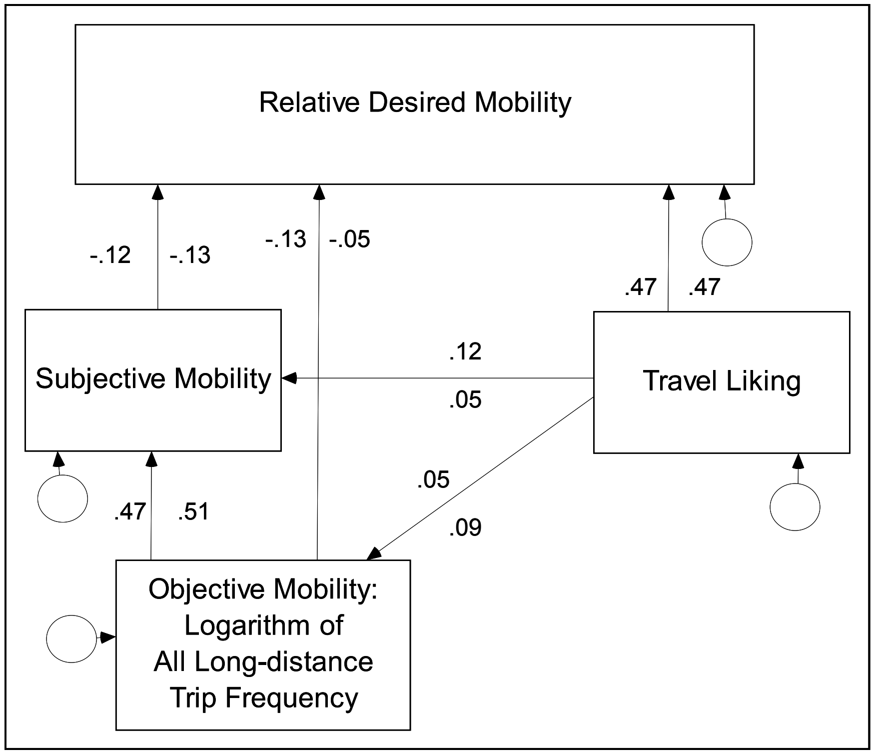


Figure 7.1: Overall LD Travel Model Structure and ML Standardized Coefficients for San Francisco (top/left of effect arrow) and Suburban (bottom/right) Market Segments

7.2 Work/school-related

In the sample about half of the respondents (48.8%) do not engage in any work/school-related long-distance travel in the calendar year previous to the survey administration. However, even those not participating answered questions regarding their affection and desire for travel in this category. As such, those not actually engaging in this type of travel are influencing the model results (of course, their past engagement in business travel is not known).

In this model it is expected that income will play an important role in shaping amounts; it will be interesting to see if income shapes perceptions and/or desires as well. The model will also hint at the extent to which work-related long-distance travel is discretionary for the sample. In the short-distance work/school-related model of *6.2 Work/school-related*, affections positively influenced trip making, suggesting that this type of travel is, to some extent, discretionary (i.e. an enjoyment of it leads to more of it, as opposed to commuting, in which more of it leads to less enjoyment). Will the same be true for long-distance work-related travel?

The model estimation results for each of the four techniques are presented in Table 7.4; the model structure and ML standardized coefficients are shown in Figure 7.2. The fit of the model is slightly "worse" than the standards presented in Table 3.1, as the χ^2/d.f. for the ML and ADF estimations are larger than 2.0.

The model contains only the four key variables and one latent construct, each of which is described below.

7.2.1 Objective Mobility

A log-transformed trip frequency variable is again the sole representative of Objective Mobility (OM), as in the overall long-distance model. Here, the variable is the logarithm of work/school-related trip frequency. Two variables enter with positive coefficients on the OM variable: Travel Liking and the workaholic latent variable.

The positive influence of Travel Liking on trip frequency suggests that, to some extent, work/school-related travel is discretionary, as more enjoyment for it leads to more engagement in it. This result is consistent with the short-distance work/school-related model and the interpretation is similar. Though some business trips must occur, those who prefer not to travel, such as parents (particularly mothers) of young children, are often able to send someone in their place or exchange information without face-to-face contact. Also, those who enjoy or do not mind long-distance business travel may be self-selected into careers where such travel is required.

The workaholic latent construct is manifested in the following Lifestyle statements from the survey: “I’m pretty much a workaholic” (labeled as “Pretty much” in Figure 7.2; estimates on the latent variable with a positive coefficient); “I’d like to spend more time on work” (“More work”; positive coefficient); “My family and friends are more important to me than work” (“Family”; negative coefficient) (see *7.2.5 Workaholic Latent Variable*). Those who indicated these statements described them well (to some degree) engaged in more long-distance work/school-related travel than those who indicated the statements did not describe them well. A dedication to one’s job often requires business travel, so this result is not unexpected.

The Travel Liking variable also enters the single-equation model of long-distance work/related travel distance (Redmond and Mokhtarian, 2001b), though the workaholic factor score variable does not. The trip frequency variables have not previously been modeled.

7.2.2 Subjective Mobility

The Subjective Mobility variable, as in the overall model, has Objective Mobility (OM) and Travel Liking (TL) variables as covariates, both with positive coefficients. The interpretations are both logical and, at this point, familiar. The positive coefficient on the Travel Liking variable again suggests that an enjoyment of business travel makes one more aware of those travel amounts, and, conversely, a distaste for business travel causes one to diminish, cognitively, those amounts. In terms of a stereotypical coping mechanism, this makes sense: pleasurable aspects of life are mentally enhanced and undesirable aspects diminished (see Ory, *et al.* (forthcoming) for further discussion of this point in the context of travel behavior). The positive influence of OM on SM suggests that the more one does travel, the more one thinks he travels. Both of these variables are also significant in the single-equation models of Collantes and Mokhtarian (2002).

7.2.3 Travel Liking

The Travel Liking (TL) variable is a function of the workaholic latent variable, which positively influences TL. The interpretation is that those who enjoy working, and want to spend more time working, like to travel for work-related purposes. The opposite direction of causality is also statistically plausible in the model structure: enjoyment of work travel leads to a general desire to work more. Though the latter interpretation is possible (if my job routinely sent me to Hawaii and the South of France for work, I would certainly be more inclined to become a workaholic), the former interpretation is preferred (in most cases, travel to Buffalo during the winter, for example, is probably viewed positively because of dedication to the job). The workaholic factor score variable appears in the single-equation TL models of Ory and Mokhtarian (2005).

7.2.4 Relative Desired Mobility

The Relative Desired Mobility variable is a function of only Subjective Mobility and Travel Liking, with the expected signs (negative and positive, respectively). Those who think they travel a lot for work hope to reduce that amount (SM$\rightarrow^{-}$RDM), and those who enjoy travel for work hope to do more of it (TL$\rightarrow^{+}$RDM). Because TL also has a positive effect on SM (TL$\rightarrow^{+}$SM), Travel Liking has an indirect negative effect on RDM via SM (TL$\rightarrow$SM$\rightarrow$RDM), in addition to the positive direct effect. The standardized coefficients for the ML estimation, displayed in Figure 7.2, can be used to compute the net effect of TL on RDM, which is positive and nearly equivalent to the positive direct effect, i.e. the indirect negative effect is negligible.

The lack of a direct effect of the trip frequency variable on RDM suggests that the SM measure is filtering actual travel amounts to form subjective travel amounts, which, in turn, form desired travel amounts. The possibility of this behavior motivated the idea of Subjective Mobility prior to the survey and seeing this relationship consistently operationalized in the modeling is encouraging (also see *7.6.4 Subjective Mobility Filtering*).

Though among numerous other measures, these two variables appear with coefficients of the same sign in the single-equation RDM models of Choo, *et al.* (2005).

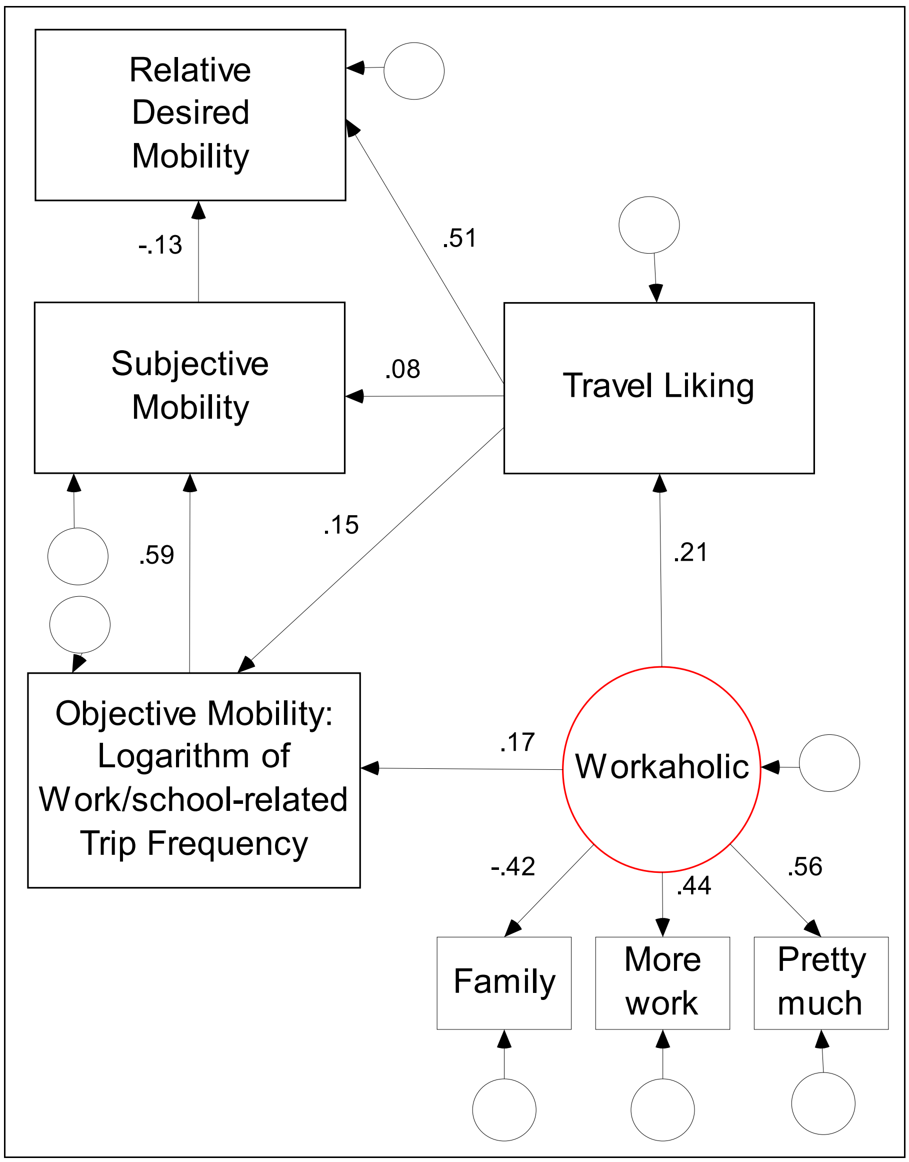


Figure 7.2: Work/school-related LD Travel Model Structure and ML Standardized Coefficients

Table 7.3: Work/school-related LD Travel Model Estimation Results (N=1,343)

Regression Weights [] -- range of observed values	**ML** **coeff**	 **crit ratio**	**ADF** **coeff**	 **crit ratio**	**Bootstrap** **coeff**	 **crit ratio**	**M*plus*** **coeff**	 **crit ratio**
→ Objective Mobility -- Logarithm of work-related long distance trip frequency [>=0] (R^2 = 0.063)								
Travel Liking -- Work/school-related [1,…,5]	0.182	5.410	0.179	5.903	0.183	5.903	0.160	4.705
Latent Variable -- Workaholic	0.330	3.908	0.330	4.317	0.330	4.231	0.283	3.956
→ Subjective Mobility -- Work/school-related [1,…,5] (R^2 = 0.376)								
Objective Mobility -- Logarithm of work-related long distance trip frequency [>=0]	0.625	26.980	0.623	22.014	0.626	22.357	0.686	23.571
Travel Liking -- Work/school-related [1,…,5]	0.103	3.722	0.091	3.267	0.104	3.714	0.207	6.220
→ Travel Liking -- Work/school-related [1,…,5] (R^2 = 0.042)								
Latent Variable – Workaholic	0.334	4.660	0.318	4.570	0.332	4.256	0.327	4.625
→ Relative Desired Mobility -- Work/school-related [1,…,5] (R^2 = 0.250)								
Subjective Mobility -- Work/school-related [1,…,5]	-0.090	-5.320	-0.084	-4.736	-0.089	-4.944	-0.159	-6.059
Travel Liking -- Work/school-related [1,…,5]	0.451	21.106	0.451	18.312	0.450	18.000	0.734	19.435
→ Lifestyle statement -- I'm pretty much a workaholic [1,…,5] (R^2 = 0.310)								
Latent Variable – Workaholic	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
→ Lifestyle statement -- I'd like to spend more time on work [1,…,5] (R^2 = 0.195)								
Latent Variable -- Workaholic	0.670	6.992	0.646	6.870	0.670	5.776	0.779	5.726
→ Lifestyle statement -- My family and friends are more important to me than work [1,…,5] (R^2 = 0.181)								
Latent Variable -- Workaholic	-0.634	-6.982	-0.607	-7.019	-0.635	-5.826	-0.782	-5.907
Goodness-of-fit Measures								
χ^2 test statistic (p-value) / (Bootstrap p-value) =	25.463	(0.008)	22.786	(0.019)		(0.008)	25.392	(0.001)
Degrees of freedom =	11		11		n/a		8	
χ^2 test statistic / degrees of freedom =	2.315		2.071		n/a		3.174	
Fit indices: Relative, Incremental, Comparative =	0.963, 0.989, 0.989		0.940, 0.983, 0.983		n/a		---, ---, 0.987†	
Root-mean square error of approximation (90 percent interval) =	0.031	(.015,.047)	0.028	(.011,.045)	n/a		0.040	(n/a)
Normality Measures								
Multivariate kurtosis =	8.289	(13.531)						

† M*plus* does not report the Relative or Incremental Fit Index

7.2.5 Workaholic Latent Variable

The workaholic latent variable acts exogenously to the system and is described in the Objective Mobility discussion above. Here, the reader is reminded that the estimation of these variables in the model system is done in two stages. First, the previously estimated factor score is used during the exploratory stage of the model specification. Second, the factor score is removed and replaced with the latent variable and any number of survey statements (from either the Attitude, Personality, or Lifestyle sections of the survey; Lifestyle in the present case). Those survey statements are expanded upon or removed during a second exploratory stage, where the best fit of the model including the latent variable is determined. Here, the following survey statement variables are included in the model: “I’m pretty much a workaholic” (represented by “Pretty much” in Figure 7.2); “I’d like to spend more time on work” (“More time”); “My family and friends are more important to me than work” (“Family”). The unstandardized coefficient on the “Pretty much” variable is chosen to be the one fixed at positive 1.0 for identifiability, as that statement most closely represents the name of the latent variable. The coefficient on “Family” is negative and “More work” is positive, as expected.

With respect to the influence of the latent construct on the other variables in the model, those who consider themselves to be workaholics make more business trips and enjoy traveling for business more than their non-workaholic counterparts – also as expected. This result is further confirmation of the role of attitudinal/lifestyle variables in generating travel that is normally considered mandatory (see Mokhtarian, *et al*. (2001) for further discussion of this point).

Note that the relatively poor fit (compared to the other models presented in this dissertation) of this model is largely due to the inclusion of the latent variable: a large share of the residual covariance is introduced by the latent indicator variables. Direct effects from these variables to the Objective Mobility (OM), Subjective Mobility (SM), Travel Liking (TL), and Relative

Desired Mobility (RDM) variables could have been included in the model structures, which would have resulted in an improved goodness-of-fit. Doing so, however, would have reduced the parsimony of the model while not adding any useful theoretical interpretations. For example, the standardized residual covariance matrix for the model is shown in Table 7.4 and residuals larger than 1.0 are bolded and italicized. Note that each of the marked cells is a covariance between an indicator variable and an OM, SM, or RDM variable. If I interpret the three indicator variables ("Family", "More work", and "Pretty much") in Figure 7.2 to be responsible only for shaping the "Workaholic" latent construct, and that latent construct, in turn, influences the Objective Mobility and Travel Liking variables, then adding a direct effect from, for example, the "Pretty much" indicator variable to Objective Mobility, does little to improve the explicative ability of the model, especially in regard to the four key variables. As such, these relationships are omitted; I am intentionally choosing a poorer fitting, but more parsimonious, model.

Table 7.4: Work/school-related Model Standardized Residual Covariance Matrix

	OM	SM	TL	RDM	Family	More work	Pretty much
OM	0.000						
SM	0.000	0.000					
TL	0.000	0.000	0.000				
RDM	-0.845	0.000	0.000	0.117			
Family	0.826	-0.642	-0.135	***-1.618***	0.000		
More work	***-1.554***	***-1.133***	0.367	***1.816***	-0.627	0.000	
Pretty much	***1.583***	***2.154***	-0.335	***-1.598***	0.272	-0.141	0.000

Abbreviations: OM = Objective Mobility: Logarithm of Work/school-related Trip Frequency; SM = Subjective Mobility; TL = Travel Liking; RDM = Relative Desired Mobility.

7.3 Entertainment/Social/Recreation

As in the short-distance entertainment model of *6.3 Entertainment/Social/Recreation*, there is perhaps more difficulty for the entertainment/social/recreation ("entertainment") category in distinguishing travel affection from affection for the activity at the destination. However, instructions were given in the survey to keep the focus on the travel, rather than the activity at the destination (see Ory and Mokhtarian (2005) for further discussion of this point). As discussed in Mokhtarian and Salomon (2001), someone who reports a love for vacation travel may not be referring to the hours spent in the airport, on the airplane, and in a rental car.

It is expected that income and other socio-demographic variables will play an important role in the entertainment structure, as those with higher incomes may have an easier time enjoying recreation travel due to a reduced concern of missing work or leaving children unattended at home.

The long-distance entertainment model includes only the four key variable categories of interest and contains each of the well-established relationships found throughout the modeling. Parameter and goodness-of-fit estimates are presented in Table 7.5; the model structure and ML standardized coefficients are shown in Figure 7.3. The model fit falls within the expected values established in the literature (see Table 3.1), with a χ^2/d.f. value near 1.3.

7.3.1 Objective Mobility

Consistent with the overall and work/school-related models, a single, category-specific, log-transformed trip frequency variable acts as the only measure of Objective Mobility (OM) in the modeling and is positively impacted by the category-specific Travel Liking (TL) variable. The interpretation is logical: entertainment travel is, by definition, completely discretionary and an enjoyment of the activity leads to more of it. Please see *7.6.1 Core Relationships* for details regarding the log-transformation of each of the OM variables included in the long-distance models.

7.3.2 Subjective Mobility

Also consistent with the previous two models, the Subjective Mobility (SM) variable is positively influenced by Objective Mobility (OM) and Travel Liking (TL). The interpretations are identical to those previously discussed. Both of these variables also appear in the single-equation models of Collantes and Mokhtarian (2002).

7.3.3 Travel Liking

The Travel Liking (TL) variable is exogenous to the system. This result is expected in that no Socio-demographic, Attitudes, or Lifestyle variables are included in the structure. These are the variables that impacted TL in the single-equation models of Ory and Mokhtarian (2005) and, along with Objective Mobility, were hypothesized to impact TL in the conceptual model of Figure 1.1.

7.3.4 Relative Desired Mobility

The Relative Desired Mobility (RDM) measure is again a function of only Subjective Mobility (SM) and Travel Liking (TL). The standard interpretations again apply here: SM is completely filtering the effects of OM on RDM (OM→SM→RDM) and the more one enjoys traveling, the more of it he desires (TL$\rightarrow^{+}$RDM).

Interestingly, the coefficient of SM on RDM is *positive* – meaning, the higher the travel amount perceptions, the higher the travel desires. This is the only model in which SM and RDM relate via a positive coefficient, suggesting that a desire for long-distance entertainment travel, in a manner of speaking, is insatiable (at least relative to current levels). Specifically, an increase in trip making (OM) causes an increase in travel perceptions (SM), which, in turn, causes an increase in travel desires (RDM). So, the more long-distance entertainment trips that are made, the more are desired. This result would be illogical if the OM measure were not trip frequency. Consider, for example, if the OM variable were yearly travel distance. If the same positive coefficients between OM, SM, and RDM held, this would mean that increases in travel distance increased the desire for more travel. And this would not be logical: certainly a 3,000 mile trip to Paris would not motivate a desire to return more than would a 1,000 mile trip to Paris. Such a finding would support the possible confounding of travel with destination activity, discussed at length in Ory and Mokhtarian (2005). Fortunately, the OM variable in the entertainment model is trip frequency rather than travel distance. The positive coefficients in this context are appealing: is it not likely that entertainment long-distance trips, subject to realistic constraints on time and money, are insatiably desired, on average, among those in the sample? It would certainly be reasonable to desire five annual trips to Paris rather than just one.

On the other hand, it should be noted that the magnitude of the coefficient is rather small. At a minimum, this suggests that the role of SM per se in generating the desire for more travel is relatively minor, once TL is accounted for. A stronger interpretation is that the SM coefficient is negative for some people and positive for others, with the average coefficient across the samples falling near zero (while still statistically significant). This hypothesis can be tested by segmenting the current dataset, perhaps by the Travel Liking variable, and doing so is a direction for future research.

While the TL variable is included in the single-equation RDM models of Choo, *et al.* (2005), the SM variable is excluded (as are all SM variables). The SM variable does estimate with a (marginally significant) positive coefficient in the single-equation model, which could have led the authors to exclude the variable from the estimation (of course, it could also have been excluded simply because it had marginal statistical significance). In the structural context, with trip frequency driving SM, the SM$\rightarrow^{+}$RDM result is reasonable.

7.3.5 Notes on Estimation Techniques

The coefficient estimates across all four estimation techniques are generally similar. As in the work/school-related model, the goodness-of-fit measures for the M*plus* estimation are slightly different than the ML and ADF measures, as well as different from the *p*-value for the bootstrap estimation. Specifically, the χ^2 test statistic *p*-values for the ML and ADF estimations are 0.253 and 0.250, respectively, and the Bollen-Stine bootstrap *p*-value is 0.267. In contrast, the M*plus* χ^2 test statistic *p*-value is 0.073. The goal of Chapter 8 is to try and understand the causes of exactly these types of inconsistencies.

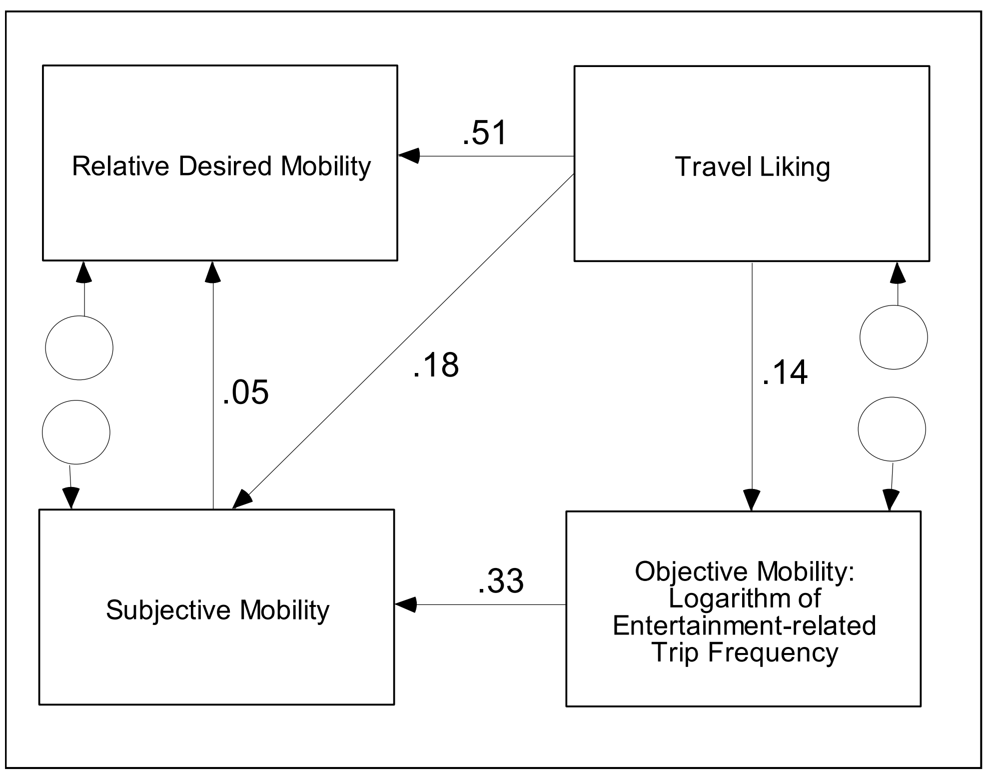


Figure 7.3: Entertainment LD Travel Model Structure and ML Standardized Coefficients

Table 7.5: Entertainment LD Travel Model Estimation Results (N=1,343)

Regression Weights [] -- range of observed values	**ML** **coeff**	 **crit ratio**	**ADF** **coeff**	 **crit ratio**	**Bootstrap** **coeff**	 **crit ratio**	**M*plus*** **coeff**	 **crit ratio**
→ Objective Mobility -- Logarithm of entertainment-related long distance trip frequency [>=0] (R^2 = 0.021)								
Travel Liking -- Entertainment [1,…,5]	0.136	5.368	0.138	5.220	0.134	4.963	0.119	4.902
→ Subjective Mobility -- Entertainment [1,…,5] (R^2 = 0.161)								
Objective Mobility -- Logarithm of entertainment-related LD trip freq. [>=0]	0.410	13.243	0.411	11.870	0.411	12.088	0.462	15.748
Travel Liking -- Entertainment [1,…,5]	0.206	7.093	0.203	6.676	0.208	6.710	0.247	7.852
→ Relative Desired Mobility -- Entertainment [1,…,5] (R^2 = 0.277)								
Subjective Mobility -- Entertainment [1,…,5]	0.040	2.037	0.042	1.880	0.040	1.818	0.031	1.037
Travel Liking -- Entertainment [1,…,5]	0.491	21.509	0.494	18.644	0.489	18.111	0.743	20.561
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =	1.305	(0.253)	1.323	(0.250)		(0.267)	3.217	(0.073)
Degrees of freedom =	1		1		n/a		1	
χ^2 test statistic / degrees of freedom =	1.305		1.323		n/a		3.217	
Fit indices: Relative, Incremental, Comparative =	0.989, 1.000, 1.000		0.997, 0.999, 0.999		n/a		---, ---, 0.998	
Root-mean square error of approximation (90 percent interval) =	0.015	(0, 0.076)	0.016	(0, 0.076)	n/a		0.041	(n/a)
Normality Measures								
Multivariate kurtosis =	3.947	(10.438)						

7.4 Personal Vehicle

The personal vehicle travel category is purpose independent. As such, the travel described in these models could be a family driving out to a nearby lake for a weekend camping trip, or an intrepid salesman traveling from city to city pushing his wares. Though different in important ways, they are similar in an important way: they both involve traveling a long distance in a personal vehicle – exactly the behavior I am trying to model. It will be interesting to see if any cross-relationships emerge between personal vehicle and airplane travel. Perhaps those accustomed to traveling in airplanes may find automobile travel too slow for their tastes. And vice versa: those who typically travel in a personal vehicle may find the luggage and security hassles associated with airplane travel unbearable. These relationships can be represented in the present models through the effects of Objective Mobility by one of these modes on the Travel Liking and Subjective Mobility of the other mode.

The estimation results are presented in Table 7.6 and the model structure and ML standardized coefficients are depicted in Figure 7.4. The model fits the data well, with a χ^2/d.f. around 0.60 and the RMSEA near 0.000 for each of the four estimation techniques. As in the overall model, because the model structure is consistent with those previously estimated, and the interpretations are logical, overfitting is not a concern. A description of the model results, segmented by the key variables, is presented below.

7.4.1 Objective Mobility

Consistent with each of the other long-distance models, the single Objective Mobility (OM) measure in the personal vehicle structural model is the logarithm of the category-specific trip frequency variable – long-distance personal vehicle trip frequency in this case. The Travel Liking

(TL) variable positively influences the OM variable, as in each of the previous long-distance models. This finding suggests that this type of travel is done more often if it is enjoyed.

The vehicle availability variable is an ordinal percentage (0, 20, 40, 60, 80, 100) response to the survey question: “About what percent of the time is a personal vehicle available to you when you want it?” This variable estimates with a positive coefficient on the trip frequency measure – an intuitive result. The more often a vehicle is available when it is desired, the more travel is done in it.

Both of these variables appear with the same sign in the single-equation model of personal vehicle distance (Redmond and Mokhtarian, 2001b).

7.4.2. Subjective Mobility

Unlike any of the previous models discussed in this dissertation (short- or long-distance), the Subjective Mobility (SM) variable in the personal vehicle model is the *overall* Subjective Mobility variable rather than the personal vehicle (i.e. category-specific) Subjective Mobility variable. Meaning, this variable is in response to the survey statement (emphasis original), “For long-distance trips (more than 100 miles *one way*), I feel that I travel … **overall**, for **ALL** long-distance travel” rather than the statement “… driver/passenger in any personal vehicle.” In the context of personal vehicle travel, the overall measure better explains the relationships between OM, SM, and RDM. This finding also holds for the long-distance airplane model discussed next (also see *7.6.1 Core Relationships*). In regard to the negative impact of SM on Relative Desired Mobility, it is interesting that the two mode-specific models have this in common. This finding suggests a “spillover” relationship between these two modes. If an individual thinks he travels long distances a lot, be it in a car or an airplane, he, in turn, wants to reduce that travel. If the travel in the two modes acted independently, only the mode-specific Subjective Mobility variable would matter. But the appearance of the overall Subjective Mobility variable in these two models suggests, indirectly, that a lot of perceived travel by airplane can lead to a desire for reduced travel in a personal vehicle, and vice versa.

Only the trip frequency Objective Mobility (OM) variable impacts the SM measure, with the expected positive coefficient. Breaking with the previous long-distance models, SM is not a function of Travel Liking: enjoyment for personal vehicle travel does not alter the perceived amount of automobile travel.

7.4.3 Travel Liking

The Travel Liking variable is exogenous to the system. Interestingly, the single-equation model of Ory and Mokhtarian (2004) includes the airplane-specific Subjective Mobility variable estimating negatively on personal vehicle Travel Liking. While this finding is not supported by the structural model, it does support the previous argument regarding the interrelated nature of long-distance airplane and personal vehicle travel.

7.4.4 Relative Desired Mobility

The Relative Desired Mobility (RDM) variable has the familiar covariates of Subjective Mobility (SM) and Travel Liking (TL). Subjective Mobility estimates with a negative coefficient, meaning increased travel perceptions lead to a desire to reduce travel, and Travel Liking estimates with a positive coefficient (the more travel is enjoyed, the more of it is desired).

The other variable impacting RDM is vehicle availability, estimating with a negative coefficient: the more a vehicle is available, the less travel is desired. Viewing this relationship from the opposite perspective gives a more logical interpretation: the less a vehicle is available, the more travel is desired. Thus, depriving someone of the opportunity to use an automobile when it is desired, leads to an increase in travel desires, even after accounting for travel amounts (though, in this case, only trip frequency is controlled for).

Each of these relationships is also present in Choo, *et al.* (2005).

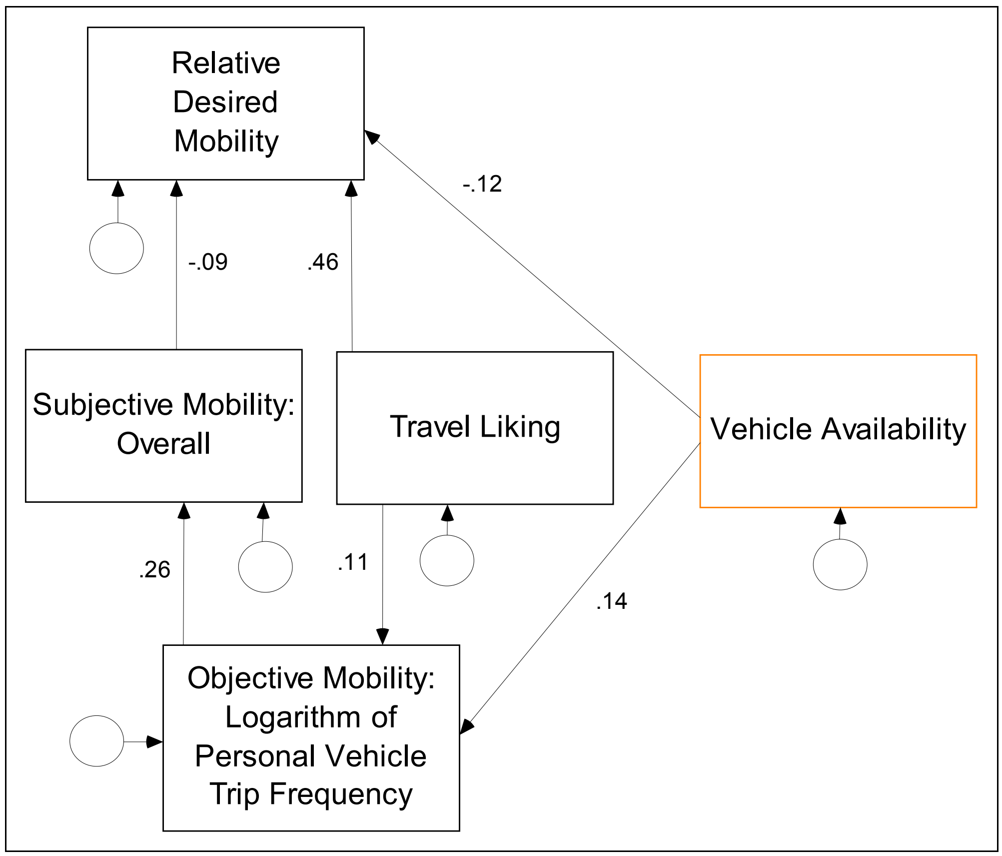


Figure 7.4: Personal Vehicle LD Travel Model Structure and ML Standardized Coefficients

Table 7.6: Personal Vehicle LD Travel Model Estimation Results (N=1,338)

Regression Weights [] -- range of observed values	**ML** coeff	crit ratio	**ADF** coeff	crit ratio	**Bootstrap** coeff	crit ratio	**M*plus*** coeff	crit ratio
→ Objective Mobility -- Logarithm of personal vehicle long distance trip frequency [>=0] (R^2 = 0.032)								
Travel Liking -- Personal Vehicle [1,…,5]	0.118	4.089	0.118	4.215	0.119	4.250	0.113	3.774
Socio-demographic -- Auto availability percentage [0,20,…,100]	0.006	5.292	0.006	6.347	0.006	6.000	0.229	5.421
→ Subjective Mobility -- Overall [1,…,5] (R^2 = 0.066)								
Objective Mobility -- Logarithm of personal vehicle long distance trip frequency [>=0]	0.246	9.778	0.244	8.975	0.245	8.750	0.294	10.741
→ Relative Desired Mobility -- Personal Vehicle [1,…,5] (R^2 = 0.235)								
Subjective Mobility -- Overall [1,…,5]	-0.072	-3.661	-0.073	-3.443	-0.072	-3.130	-0.111	-3.330
Travel Liking -- Personal Vehicle [1,…,5]	0.388	19.316	0.387	16.582	0.387	16.125	0.660	17.724
Socio-demographic -- Auto availability percentage [0,20,…,100]	-0.004	-4.800	-0.004	-4.453	-0.004	-4.000	-0.222	-4.539
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =	2.529	(0.639)	2.467	(0.651)		(0.672)	2.325	(0.676)
Degrees of freedom =	4		4		n/a		4	
χ^2 test statistic / degrees of freedom =	0.632		0.617		n/a		0.581	
Fit indices: Relative, Incremental, Comparative =	0.987, 1.003, 1.000		0.980, 1.005, 1.000		n/a		---, ---, 1.000	
Root-mean square error of approximation (90 percent interval) =	0.000	(0, 0.033)	0.000	(0, 0.033)	n/a		0.000	(n/a)
Normality Measures								
Multivariate kurtosis =	9.319	(20.356)						

7.5 Airplane

As in the personal vehicle model, the airplane model is purpose-independent, i.e. the model combines personal and business travel. This can be viewed as disadvantageous, in that conceptualizing the travel described by the model is not clear: traveling to Disneyland with the family is markedly different than traveling alone to Hong Kong for a convention. However, both types of travel involve spending a good deal of time in airplane, and it is that aspect of the trip that the models attempt to describe.

In the sample, more than 80% have done some airplane travel in the past year. As such, the majority of those giving their opinion about airplane travel have at least had some experience with the mode. It is also likely that many of those who have not traveled by air in the surveyed year have done so at some time in the past. It is expected that higher incomes will increase travel amounts on airplanes. The interesting question is the impact of income on perceptions, affections, and desires. Perhaps those with lower incomes may desire more air travel due to the relatively slow speeds associated with automobile travel.

The model results are presented in Table 7.7 and Figure 7.5. The fit of the models is among the worst in the long-distance group, with a χ^2/d.f. measure near 3.0 and RMSEA close to 0.040. As in the work/school-related model, the direct effects from the latent variable indicators to the key variables contribute the majority of the residual covariance and are primarily the cause of the poor model fit. As such, the low goodness-of-fit measures are not a major concern. Note that the RDM equation-specific R^2 value is 0.305, which is highest among the long-distance models, indicating that the model is adequately explaining the variation in the “end measure”.

7.5.1 Objective Mobility

Consistent with each of the five long-distance models, a single category-specific trip frequency Objective Mobility variable enters the model. This variable is influenced by the adventure-seeking latent construct, which estimates on trip frequency with a positive coefficient. The adventure-seeking variable shapes four Personality statements from the survey instrument. Respondents were asked to "… indicate how well each of the following words or phrases describes you" on a five-point scale: "hardly at all", "not very well", "moderately well", "very well", or "almost completely". The words forming the adventure-seeking construct include "risk-taking", "variety-seeking", "adventurous" (fixed coefficient of 1.0), and "spontaneous", all estimating with positive coefficients. Those who indicated these words described them well (to some degree) tend to make more long-distance airplane trips than those who indicated the words did not describe them well (to some degree) (also see *7.5.5 Adventure-seeking Latent Variable*).

7.5.2. Subjective Mobility

As discussed in the personal vehicle model, the airplane model also contains the *overall* Subjective Mobility variable rather than the airplane-specific Subjective Mobility variable. This finding suggests that airplane travel desires (RDM) are shaped by overall travel perceptions, rather than just the amount of travel done in an airplane (also see *7.6.1 Core Relationships*).

Similar to the personal vehicle model, there is no relationship between Subjective Mobility and Travel Liking in the airplane model. Subjective Mobility is a function of the Objective Mobility trip frequency measure, with the expected positive coefficient, and the adventure-seeking latent variable, also with a positive coefficient. The latter finding indicates that those who see themselves as adventurous and spontaneous tend to perceive their airplane travel to be in greater amounts than those who do not.

7.5.3 Travel Liking

The Travel Liking variable is also a function of the adventure-seeking latent variable: those who see themselves as adventurous tend to enjoy long-distance airplane travel more than those who do not. Statistically, the direction of this effect can go either way. The current direction, from adventure-seeking to Travel Liking, is chosen because it seems more reasonable that an inherent sense of adventure-seeking could lead to an enjoyment of traveling long-distances on airplanes, rather than an enjoyment of airplane travel stirring up a repressed adventuresome spirit.

7.5.4 Relative Desired Mobility

Airplane Relative Desired Mobility (RDM) is positively influenced by Travel Liking (TL) and the adventure-seeking latent variable, and negatively influenced by overall Subjective Mobility (SM). The TL and SM on RDM effects are expected and have been discussed previously.

The positive relationship between the adventure-seeking latent variable and RDM may suggest that there is some confounding between the travel itself and the destination activities the journey allows the traveler to access. These models are attempting to measure a desire for the travel itself, not the activities. Would those who seek adventure crave more airplane travel if they never left the destination airport? The answer is probably not: these results are likely influenced by the exciting destination activities. Of course, there is reason to think that the travel itself is also contributing. Though air travel is by now common, it is still reasonable that soaring through the sky at high altitudes and high speeds is invigorating for some and terrifying for others.

7.5.5 Adventure-seeking Latent Variable

The adventure-seeking latent construct appears in all four equations of the airplane structural model. Respondents who indicate “risk-taking”, “variety-seeking”, “adventurous”, and “spontaneous” describe them well (to some degree) tend to make more long-distance airplane trips, enjoy air travel more, desire more air travel, and perceive all their long-distance travel to be greater than those who indicate those words do not describe them well (to some degree). Though airplane travel is becoming more and more common, this result suggests there is still a sense of adventure associated with traveling by airplane.

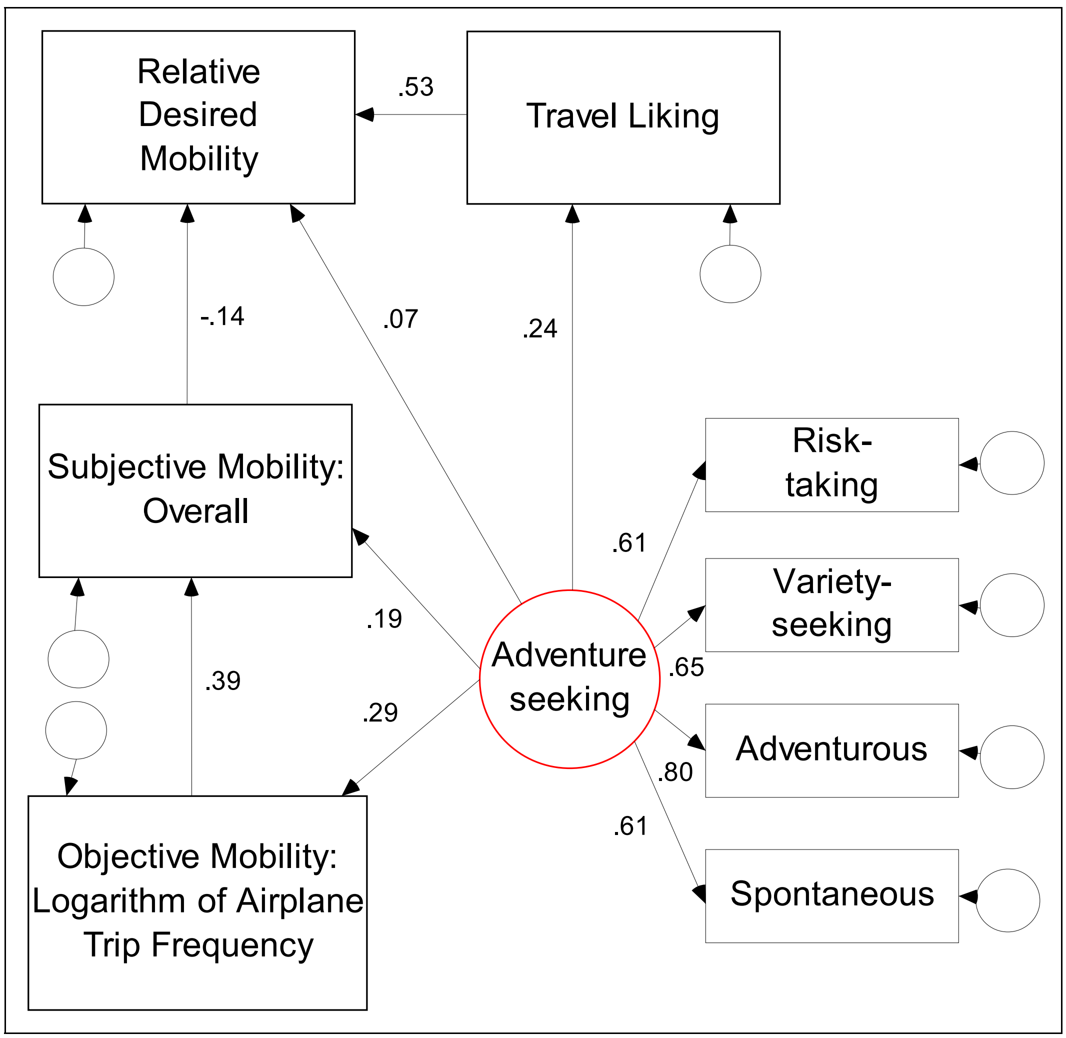


Figure 7.5: Airplane LD Travel Model Structure and ML Standardized Coefficients

Table 7.7: Airplane LD Travel Model Estimation Results (N=1,343)

Regression Weights	ML		ADF		Bootstrap		M*plus*	
[] -- range of observed values	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**	**coeff**	**crit ratio**
→ Objective Mobility -- Logarithm of airplane long distance trip frequency [>=0] (R^2 = 0.082)								
Latent Variable -- Adventure-seeker	0.403	9.323	0.393	9.240	0.403	8.761	0.174	8.288
→ Subjective Mobility -- Overall [1,…,5] (R^2 = 0.228)								
Objective Mobility -- Logarithm of airplane long distance trip frequency [>=0]	0.393	15.244	0.398	13.885	0.393	13.552	0.494	16.509
Latent Variable -- Adventure-seeker	0.267	6.465	0.253	6.123	0.268	6.537	0.142	6.181
→ Travel Liking -- Airplane [1,…,5] (R^2 = 0.058)								
Latent Variable -- Adventure-seeker	0.357	7.845	0.381	8.169	0.358	7.306	0.174	7.645
→ Relative Desired Mobility -- Airplane [1,…,5] (R^2 = 0.305)								
Subjective Mobility -- Overall [1,…,5]	-0.136	-5.837	-0.135	-5.428	-0.136	-5.440	-0.198	-6.010
Travel Liking -- Airplane [1,…,5]	0.487	22.296	0.481	17.995	0.485	18.654	0.761	20.310
Latent Variable -- Adventure-seeker	0.101	2.603	0.115	2.961	0.103	2.575	0.058	2.471
→ Personality statement -- Adventurous [1,…,5] (R^2 = 0.641)								
Latent Variable -- Adventure-seeker	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
→ Personality statement -- Risk-taking [1,…,5] (R^2 = 0.371)								
Latent Variable -- Adventure-seeker	0.804	19.316	0.832	18.814	0.804	17.867	0.531	11.471
→ Personality statement -- Variety-seeking [1,…,5] (R^2 = 0.418)								
Latent Variable -- Adventure-seeker	0.794	20.288	0.812	21.572	0.796	20.410	0.607	12.276
→ Personality statement – Spontaneous [1,…,5] (R^2 = 0.374)								
Latent Variable -- Adventure-seeker	0.798	19.394	0.807	18.582	0.801	18.205	0.533	12.193
Goodness-of-fit Measures								
χ^2 test statistic (*p*-value) / (Bootstrap *p*-value) =	48.136	(0.000)	44.716	(0.000)		(0.001)	47.722	(0.000)
Degrees of freedom =	17		17		n/a		13	
χ^2 test statistic / degrees of freedom =	2.832		2.630		n/a		3.671	
Fit indices: Relative, Incremental, Comparative =	0.966, 0.986, 0.986		0.912, 0.966, 0.966		n/a		---, ---, 0.989	
Root-mean square error of approximation (90 percent interval) =	0.037	(.025,.049)	0.035	(.023,.047)	n/a		0.045	(n/a)
Normality Measures								
Multivariate kurtosis =	8.908	(12.904)						

7.6 Cross-model Comparisons

In this section, comparisons are made across the five models, as well as to the short-distance models of Chapter 6.

7.6.1 Core Relationships

Three consistent relationships emerge across the five models. First, there is a positive relationship between a single category-specific log-transformed trip frequency variable and a measure of Subjective Mobility (OM$\rightarrow^{+}$SM). Since numerous transformations of the distance variables were considered in the model exploration stage and discarded on statistical grounds, this finding suggests that travel perceptions are shaped more by trip frequency than travel distance. At first glance, this consistent cross-model result may seem counterintuitive: surely bimonthly trips from San Francisco to Tokyo must be perceived to constitute a larger amount of travel than equally frequent trips from San Francisco to Seattle. The model results suggest otherwise. This finding could be a result of not having sufficient variation in the number of longer long-distance trips, of the San Francisco to Tokyo nature, to properly estimate the effect of travel distance on Subjective Mobility. But it may also be a logical perception. Consider a frequent traveler from San Francisco to Seattle. This individual may not even consider the possibility of traveling to Tokyo; it's something he has never done. As such, two trips a month, to this person, are "a lot" of travel. Similarly, someone traveling twice monthly to Tokyo also perceives this travel to be "a lot". The two universes within which these comparisons are made are simply different. But they don't need to be for this result to make sense. It may be that packing a suitcase, going to the airport, making one's way through security, and boarding the plane are what lead to the high perceptions. In this interpretation, the amount of time actually spent flying is largely irrelevant: it is the trip preparation and being away from home that leave a lasting impression. Anecdotally, I have found many frequent flyers who are extremely productive on, and therefore prefer, longer (often international) flights over ones that are "too short to get anything done" on, and hence are viewed as more of a nuisance.

As mentioned previously, each trip frequency variable is logarithmically transformed. The log transformation added one to the original value to avoid taking the logarithm of zero, which is undefined. To justify the use of the log-transformation, descriptive statistics for the "raw" and transformed variables are presented in Table 7.8. The untransformed variables are uniformly heavily skewed to the right, whereas the transformed variables are distributed close to normal.

Table 7.8: Trip Frequency Variable Transformation

Annual Trip Frequency Variable	Transfor-mation	Range	Mean	Standard Deviation	Skewness	Kurtosis
Overall	None	0, 273	12.5	18.0	5.94	59.0
	Logarithm	0.00, 5.61	2.15	0.917	0.190	0.256
Work/school-related	None	0, 230	5.28	14.9	8.50	101
	Logarithm	0.00, 5.44	0.951	1.15	1.03	0.205
Entertainment	None	0, 231	7.59	12.8	10.2	148
	Logarithm	0.00, 5.45	1.75	0.864	0.107	0.449
Personal vehicle	None	0, 270	6.40	14.5	9.76	138
	Logarithm	0.00, 5.60	1.39	1.02	0.457	0.0146
Airplane	None	0, 113	5.48	8.91	4.88	38.5
	Logarithm	0.00, 4.74	1.36	0.963	0.389	-0.265

Another interesting aspect of the trip frequency/SM relationship is that for the two mode-specific travel categories, personal vehicle and airplane, the *overall* Subjective Mobility variable enters the model rather than the expected category-specific Subjective Mobility variable. Meaning, this variable is in response to the survey statement (**bold**/*italic*/CAPITAL emphasis original), "For long-distance trips (more than 100 miles *one way*), I feel that I travel … **overall**, for **ALL** long-distance travel" rather than the mode-specific statement (e.g. "… driver/passenger in any personal vehicle"). For these two models, the overall SM measure better explains the relationships between trip frequency, SM, and Relative Desired Mobility (RDM) than the mode-specific measure. The outcome is that if an individual travels a lot in an airplane or a personal vehicle, her overall assessment of her amounts increases. These elevated perceptions (SM) then lead to a decrease in both personal vehicle and airplane travel desires (RDM). This suggests, indirectly, that travel by either of these two modes can lead to a desire to reduce long-distance travel by the other mode. If both personal vehicle and airplane category-specific measures of SM are included in each model together, the effect of both SM variables on the category-specific measure of RDM is not significant.

The second consistent relationship across the five models is the significant effect of Subjective Mobility (SM) on Relative Desired Mobility (RDM). This relationship is negative for each of the models save entertainment (see *7.3.4 Relative Desired Mobility*), suggesting that, as expected, those who travel large amounts desire to reduce those amounts. This finding is consistent with each of the short-distance models summarized in *6.5 Cross-model Comparisons* and supports the common-sense expectation that the desire to travel is not limitless: we may want to do more of it if we perceive that we are currently doing very little, but if we are traveling a lot, most of us become surfeited and would prefer to do less.

The final relationship that appears in each of the models is the positive effect of Travel Liking (TL) on Relative Desired Mobility (RDM). This finding is also consistent with the short-distance models summarized in *6.5 Cross-model Comparisons*. The interpretation is straightforward: those who enjoy traveling desire to do more of it, or, said another way, the less someone dislikes travel, the less the desire to reduce his travel amounts. The standardized coefficients of these effects range from 0.46 to 0.53, indicating the consistent strength of this effect across models. While the presence of this relationship is not surprising (certainly affect for anything could be expected to lead to a desire for more of the same thing), it is unique in the literature on travel behavior. The strength of this relationship makes a powerful argument for more carefully considering the role of a so-called positive utility of travel in shaping behavior.

7.6.2 Positive Utility of Travel

There is ample evidence of a positive utility of travel in the model estimation results. In addition to the positive coefficients of Travel Liking on Relative Desired Mobility (TL$\rightarrow^{+}$RDM) discussed previously, four of the five models have positive effects of Travel Liking on Objective Mobility (specifically, trip frequency). As such, an enjoyment of travel directly leads to the engagement in more travel. This finding holds for each model save airplane travel, in which an underlying personality construct, adventure-seeking, influences both an enjoyment of travel and the decision to engage in it (as well as positively impacting perceptions and desires). The airplane model results are appealing in that they quantify an aspect of personality that had a significant impact on each of the key variables. It seems logical that a measure of personality/lifestyle/attitudes could similarly impact the other four models. Meaning, in the airplane model, the variables describing adventure-seekers (risk taking, variety seeking, adventurous, and spontaneous) captured the personality of those who enjoy and seek out airplane travel. It seems reasonable that there are companion, though perhaps more complicated, constructs that describe the types of people who enjoy and seek out work/school-related, entertainment, and personal vehicle travel as well. The workaholic lifestyle variable included in the work/school-related model comes close, but does not have the same comprehensive effect as the adventure-seeking construct in the airplane model. This is one direction for future research: is there a combination of Attitude, Personality, and Lifestyle variables that yields a latent construct for each model that has the same explicative effect as the adventure-seeking variable in the airplane model?

The above discussion leads to the more general question of the relationship between attitudes and behavior. Though a common assumption in travel behavior research is that attitudes lead to behavior (e.g. a discomfort with public interactions leads to an avoidance of public transportation; see, e.g., Parkany, *et al.*, 2004), numerous authors (see, e.g., Tardiff, 1976; Golob and Hensher, 1998; Golob, 2001; Jakobsson, *et al*., 2000) have found the opposite direction of causality to hold. The models presented in this dissertation allow for a more nuanced view of the behavior/attitude relationship. Here, underlying personality traits, such as adventure-seeking, lead directly to behavior (e.g. traveling more frequently by airplane) and that same behavior, in turn, shapes variables that can broadly be considered "attitudes", such as a desire to reduce air travel amounts. This pattern holds throughout the models: affection leads to behavior, which then shapes perceptions, which, in turn, manifest in desires. Too often the relationship between generically named "attitudes" and behavior is presented as an either/or proposition: do attitudes shape behavior or vice versa? Including more detailed attitude, personality, and lifestyle variables in these models allow me to avoid picking a side to this false choice and, rather, tell a holistic and compelling story of travel behavior.

7.6.3 Relationship between Travel Liking and Subjective Mobility

Of all the relationships among the four key variables, the one between Travel Liking and Subjective Mobility is perhaps the most complex. As discussed in Chapter 1, both directions of causality are plausible (Ory and Mokhtarian, 2005; Collantes and Mokhtarian, 2007), with potentially opposite signs: those who enjoy or dislike travel may be more aware of the travel they do than those with neutral feelings (TL$\rightarrow^{+/-}$SM); those who perceive their travel amounts to be high may tend to dislike travel (SM$\rightarrow^{-}$TL).

To continue the examination of *6.5.5 Relationship between Travel Liking and Subjective Mobility*, a summary of the direct and total effects for each direction of causality in the present analysis are presented in Table 7.9. The results are consistent with the short-distance models in that the dominant direction of causality is TL on SM; in fact, there are no effects of SM on TL in any of the five long-distance models. Interestingly, the strongest effects, in terms of maximum likelihood standardized coefficients, appear in the work/school-related and entertainment travel categories. The presence of a strong coefficient in the entertainment model is expected: discretionary travel is optional and an enjoyment of travel logically leads to more awareness of travel amounts. The fact that the TL→SM standardized coefficient is of similar magnitude in the work/school-related model is another indication that this type of travel has a large discretionary component to it. If it were mandatory, I would expect high perceptions to lead to less enjoyment, which is the case for the commute model of *5.2 Preferred Model Estimation Results*, with the interpretation being: because the travel is mandatory, the more of it I have to do, the more I perceive I do, and thus, the less I enjoy it. That long-distance work/school-related travel is similar to entertainment travel in this regard is not totally unexpected. While employees can certainly be "forced" to make business trips when they would rather stay at home, over time, at least anecdotally, it seems that those who travel a good deal for business at best enjoy being out "on the road" and, at worst, do not seem to mind very much. This is yet another area that warrants further research.

Table 7.9: Subjective Mobility and Travel Liking Standardized Coefficients

Model	Direct Effects		Total Effects	
	TL → SM	SM → TL	TL → SM	SM → TL
Overall – San Francisco	0.12	---	0.14	---
Overall – Suburb	0.05	---	0.10	---
Work/school-related	0.08	---	0.17	---
Entertainment	0.18	---	0.23	---
Personal vehicle*	---	---	0.03	---
Airplane*	---	---	---	---

Notes: The values shown are the ML estimation standardized coefficients.
* The SM variable for these models is specific to the "overall" travel category

7.6.4 Subjective Mobility Filtering

Part of the conceptualization of the Subjective Mobility (SM) variables were for the measures to act as filters for the actual travel amounts (the Objective Mobility, or OM, variables) – the notion being that actual travel shapes perceptions, which, in turn, shape desires (OM→SM→RDM). The analysis in *6.5.6 Subjective Mobility Filtering* examined the degree to which this filtering took place in the short-distance models. I found that direct effects of OM on RDM are present for travel measures that have both frequent objective clues with respect to their quantities, and well-established cultural standards. For example, drivers are made aware of their personal vehicle distance every week when they fill up their gas tanks and are told repeatedly by automotive maintenance businesses that an oil change should take place every three months or 3,000 miles; one's personal vehicle distance is frequently compared to this cultural standard. The same cannot be said for other travel quantities, such as weekly entertainment or bus travel. It is hypothesized that fewer direct effects of OM on RDM would be present in the long-distance models, as fewer cultural norms are in place to influence desires, i.e. I am doing too much traveling, I need to reduce it.

As shown in Table 7.10, the hypothesis largely holds true. The only significant direct effect of OM on RDM is for the San Francisco segment of the overall model (the direct effect that appears in the table for the suburban segment is not significantly different from zero, but I retain it because it is included in the multigroup model estimation). This finding suggests that objective travel amounts are largely being filtered by perceptions to shape desires, as originally conceived. Here, individuals take in how much they travel, and, because of the significant coefficient of OM on SM in each model, there is, to some degree, a common understanding across the sample of how much travel is "a lot". These travel amounts shape perceptions, which, in turn, form desires. Travel perceptions, therefore, are a critical aspect of travel behavior. Without them, it cannot fully be understood how current travel amounts inform travel desires.

Table 7.10: Subjective Mobility Filtering of Objective Mobility

Model	OM Variable	Direct effects (OM → RDM)	Indirect effects (OM→SM→RDM)	Total effects (OM→ RDM)
Overall – San Francisco	Overall trip frequency	-0.13	0.47 x -0.12 = -0.06	-0.19
Overall – Suburb	Overall trip frequency	-0.05	0.51 x -0.13 = -0.06	-0.12
Work/school-related	Work/school-related trip frequency	---	0.59 x -0.13 = -0.08	-0.08
Entertainment	Entertainment trip frequency	---	0.33 x 0.05 = 0.02	0.02
Personal vehicle*	Personal vehicle trip frequency	---	0.26 x -0.09 = -0.02	-0.02
Airplane*	Airplane trip frequency	---	0.39 x -0.14 =-0.05	-0.05

Notes: The "effects" are the ML estimation standardized coefficients.
* The SM variable for these models is specific to the "overall" travel category

7.6.5 The Absence of Income and Other Notes on Model Exploration

The final model specifications presented in this dissertation are the result of an extensive model exploration effort. The exploratory process began by including the results of the single-equation models of Objective Mobility (Redmond and Mokhtarian, 2001), Subjective Mobility (Collantes and Mokhtarian, 2002, 2007), Travel Liking (Ory and Mokhtarian, 2005), and Relative Desired Mobility (Choo, *et al.*, 2005) into a structural model for each travel category. The structures were then trimmed and modified to find the model that best fit the data and explained the key relationships. During this process many variables were introduced and relationships considered.

Many of the hypotheses presented in the category-specific chapter sections speculated on the role income would play in the structural models. None of the final model specifications, however, included the household or personal income variables that are part of the dataset. During the exploratory stage of model development, personal income did enter each of the models with a significant coefficient on the category-specific Objective Mobility variable, but did not have a significant impact on variables in the other key categories. Although inclusion of the income variable increased the predictive accuracy of the model (equation-specific R^2s), it also significantly degraded model fit, i.e. substantially increased the discrepancy between the model-predicted and empirically-observed covariance matrices. As in the models estimated in *5.2 Preferred Model Estimation Results* and Chapter 6, the approach taken here is to find a model that both captures the relevant behaviors and fits the data at a level consistent with the structural equation modeling literature.

8. CROSS MODEL ECONOMETRIC ANALYSIS

A recent issue of *Personality and Individual Differences* (Volume 42, 2007) highlighted the often contentious debate on the best way to assess the fit of structural equation models (SEM). Barrett (2007) argued that the χ^2 test statistic is the only *statistic* available for comparing a model-implied covariance matrix to a sample covariance matrix and, as such, should be the primary (if not only) measure used to adjudge model fit. Numerous other eminent SEM scholars dispute Barrett's conjecture throughout the journal volume, pointing out the inherent flaws in the χ^2 test statistic as well as the benefits of other goodness-of-fit measures, such as fit indices.

It is common in the SEM econometric literature to use simulation studies to test the stability and reliability of both estimation techniques and goodness-of-fit measures (see, e.g., Hu, *et al.*, 1992; Curran, *et al.*, 1994; Chan, *et al.*, 1995; Hoogland and Boomsma, 1998). These studies typically assume a model structure – a confirmatory factor analysis (CFA) in most studies – and then simulate samples of various sizes and distributions (e.g., multivariate normal or not). Models are then estimated using a variety of estimation techniques, typically maximum likelihood (ML), asymptotic distribution free (ADF), and/or least squares, and the performance of each estimation technique, in terms of parameter estimates and fit statistics, is analyzed. It is difficult, however, to draw general conclusions from these myriad studies (see, e.g., Barrett, 2007). There are simply too many variations of structural equation models to draw conclusions for a particular empirical analysis. SEMs can have varying model structures, degrees of multivariate non-normality (skew and kurtosis), sample sizes, number of variables, and degrees of freedom. The inconsistencies in these studies are at the heart of the debate in the *Personality and Individual Differences* special issue.

Hoping to apply the proper tools to their problem, SEM practitioners are left to wade through this ample body of literature to first select, and then justify, both an estimation technique and goodness-of-fit measure(s). In this chapter, I suggest and implement a different approach. Using the specifications of the ten structural equation models presented in this dissertation, a cross-model, cross-estimation technique analysis is performed. Because the datasets used in the estimations are large, they are sampled to create hundreds of smaller datasets, which naturally vary in their degree of multivariate normality. The models are then reestimated on these sampled datasets using four different estimation techniques, namely ML, ADF, bootstrapping, and the M*plus* approach. The variability in two goodness-of-fit measures, the χ^2 test statistic and the root mean square error of approximation (RMSEA), is then examined.

The above procedure does not allow one to assess the "performance" of any given estimation technique because the "right" answer is not known, as it is in the simulation studies described above. However, it does inform as to when two given techniques diverge under "real data" conditions. In practice, such divergence should trigger the use of multiple estimation techniques in the hope that the resulting multiple solutions will triangulate, to some degree, the "correct" answer (Andreassen, *et al.*, 2006). This analysis also rigorously examines the "fit" of each of the model specifications, which has the potential to either increase or decrease the confidence in the model results.

This study is a valuable complement to the ample simulation-based literature because it uses real data and real models. Further, the models used are structural models with and without latent variables, which appear more frequently in the transportation literature than do the pure confirmatory factor analyses which are often the basis for the simulation literature, and which are common in psychology and other social sciences. It also presents a direct comparison of ML and ADF to the less-commonly used estimation techniques of bootstrapping and M*plus*.

The next section of this chapter discusses the details of the methods used in the analysis. Following, four sections of analysis results are presented. A recommendations section concludes the chapter.

8.1 Method

Four different estimation techniques were used to estimate each of the models presented in Chapters 5, 6, and 7 (excluding the segmented and expanded models of Chapter 5). The selection of the four estimation techniques – ML, ADF, bootstrapping, and M*plus* – was motivated by the fact that three of the four key variables, namely Subjective Mobility, Travel Liking, and Relative Desired Mobility, are ordinal rather than continuous, and that the variables included in each model structure were not always multivariate normal. Each of the four techniques is introduced briefly here (also see *3.2.2.3 Model Estimation*).

Maximum likelihood (ML), the most commonly used estimation technique (see, e.g., Golob, 2003), is based on normal theory and, as such, is not strictly theoretically appropriate when the data are not multivariate normal. However, the literature suggests that ML estimation is relatively robust in the face of moderate non-normality (defined below) when large sample sizes are present (Lei and Lomax, 2005; Chou and Bentler, 1995).

The asymptotic distribution free (ADF) estimation technique is advantageous in that it is not based on normal theory (Browne, 1984). The technique, in contrast to maximum likelihood (ML), does not require univariate and multivariate normality and is often a preferred alternative when data are non-normal. However, even a cursory glance at the literature will make a researcher aware that ADF is difficult to use in practice: researchers suggest that ADF not be used on small datasets or on models with numerous variables. For example, a simulation study performed by Hu, *et al.*, (1992) showed that ADF did not perform well on non-normal datasets with sample sizes less than 2,500, or on model structures with 30 or 40 variables. Numerous authors have made similar suggestions based on their own simulation studies (see, e.g., Curran, *et al.*, 1994; Chan, *et al.*, 1995; Hoogland and Boomsma, 1998). The problem is that unless the dataset and model structure a given researcher is working with are similar to those used in the simulation studies, the advice may or may not be relevant or helpful. For example, Hu, *et al*. (1992) used a confirmatory factor analysis model with 15 variables. The models presented in this work are structural equation models with and without latent variables, often referred to as "path analysis models" (without latent variables) or "models with structural and measurement components" (with latent variables) (Kline, 2005). These types of models are not typically used in simulation studies.

The Bollen-Stine bootstrap *p*-value is an alternative measure of goodness-of-fit that is not subject to normal theory constraints (Bollen and Stine, 1992) – as noted by Enders (2002), Beran and Srivastava (1985) deserve credit (in addition to Bollen and Stine) for introducing the transformation leading to the adjusted statistic. When data do not meet multivariate normal assumptions, bootstrapping can be used to assess model fit. The integration of bootstrapping techniques into standard estimation software, such as AMOS 7.0 (Arbuckle, 2006), one of the software packages used here, enhances the attractiveness of the bootstrap approach. However, the number of empirical tests on the performance of bootstraps in the structural equation modeling context is limited (see next paragraph). Even as more tests are conducted, the same problems that exist in the ADF literature will emerge: the experiments can only cover a finite number of conditions, which may or may not be directly relevant to the problem at hand.

Nevitt and Hancock (2001) present perhaps the most comprehensive assessment of bootstrapping in SEM to date. The authors use simulated data for a nine-variable, three-factor confirmatory factor analysis model with 21 parameters to investigate the impact of sample size and bootstrap sampling on goodness-of-fit and parameter estimations. The authors find that under moderate (multivariate kurtosis of 7.0) and severe (kurtosis of 21.0) non-normal conditions, the bootstrap approach rejects (at alpha=0.05) properly specified models at a much lower rate than maximum likelihood. Fouladi (1998), in a similar analysis, found that the bootstrap *p*-value out performed the maximum likelihood χ^2 test statistic in controlling for Type I errors (also see Ichikawa and Konishi, 1995).

West, *et al.* (1995) suggest that when attitudinal variables that are measured on a Likert-type scale of, for example, "strongly agree" to "strongly disagree", are included in a structural equation model, the M*plus* estimation technique can be useful. The M*plus* software package, developed by Muthén (Muthén and Muthén, 2005; Muthén, 1983), uses a weighted least squares approach, similar to ADF. The unique aspect of the M*plus* technique is that a categorical variable, *y*, is assumed to represent an approximation of an underlying latent variable, *y**, that is normally distributed (see Appendix 4 in Muthén, 2004). The key endogenous variables in the data, namely Subjective Mobility, Travel Liking, and Relative Desired Mobility are exactly these types of variables. The additional complexity of the M*plus* technique requires that the χ^2 test statistic and the model degrees of freedom be corrected (Muthén, 2004).

To examine the variability of goodness-of-fit measures across these four estimation techniques, I begin with the 10 model structures summarized in *6.5 Cross-model Comparisons* and *7.6 Cross-model Comparisons*. Each model is based on a model-specific dataset that is pruned of any missing data in the included variables. To measure the impact of sample size on goodness-of-fit, each model-specific dataset is sampled 100 times at each of four sample sizes, namely 250, 500, 750, and 1,000. This results in 401 datasets (the additional one being the full-sample dataset) for each of the ten model structures. The models are then estimated on the 401 model-specific datasets using the four estimation techniques.

The non-normality, as measured by multivariate kurtosis, varies naturally in the sampled datasets (Table 8.1 reveals an interesting association between multivariate kurtosis and sample size, in which the incidence of moderate kurtosis increases with sample size, while the incidence of both negligible and severe kurtosis decreases. However, these trends, while statistically significant, are not overly dramatic). This procedure, therefore, allows for the examination of the variability in the goodness-of-fit measures across estimation technique, sample size, and multivariate kurtosis. Though no definitive statements about the "performance" of the estimation techniques can be made from this analysis (because the "right" answer is not known), I can note, as previously mentioned, when the estimation techniques deviate from one another.

This procedure provides 4,010 model estimation results for each of the four estimation techniques. From these results, the following measures are extracted: multivariate kurtosis, χ^2 test statistic and *p*-value, root mean square error of approximation (RMSEA), Bollen-Stine *p*-value (for bootstrap), and model degrees of freedom.

Table 8.1: Cross-tabulation of Cases by Multivariate Kurtosis Range and Sample Size

Multivariate Kurtosis Range	Sample size				Total
	250	500	750	1,000+	
0 to <1.0	41	20	4	4	69
1.0 to <3.5	221	203	204	198	826
3.5 to <10.0	461	508	555	582	2,106
10.0+	277	269	237	226	1,009
Total	*1,000*	*1,000*	*1,000*	*1,010*	*4,010*

χ^2 test of independence: $\chi^2 = 78.3$; degrees of freedom = 9; significance = 0.00

The above extracted measures are cross-tabulated and compared across estimation technique. The following cross-model, estimation-technique comparisons are presented in the next three sections: ML to ADF; bootstrap to ML and ADF; and M*plus* to ML and ADF. I then examine the variability of the χ^2 test statistic by sample size within each model in an attempt to quantify the large-sample bias of the χ^2 test statistic and to check the robustness of the full-sample estimation results.

8.2 Comparison of ADF and ML Estimation

In this section, ADF and ML goodness-of-fit measures are segmented by multivariate kurtosis and sample size, and compared across models. Table 8.2 cross-tabulates the percent difference between the ADF and ML χ^2 test statistic and the absolute difference between the ADF and ML root mean square error of approximation (RMSEA) measure by multivariate kurtosis range. The kurtosis break points are motivated by the literature summarized in *3.2.2.3 Model Estimation*, which suggests that multivariate kurtosis values less than one indicate negligible non-normality, one to anywhere from 3.5 to 10 indicate moderate non-normality, and greater values indicate severe non-normality (Information Technology Services; Lei and Lomax, 2005; Kline, 2005; Curran, *et al.*, 1996; West, *et al.*, 1995). Though more than half of all the cases fall into the 3.5 to 10.0 kurtosis range, an adequate number of cases is present in each category, as shown in Table 8.2. Note that for models with two groups, the multivariate kurtosis for the Suburban group is used to represent the model (only in the short-distance personal vehicle model does the degree of non-normality differ significantly across segments). The absolute difference is used for RMSEA because the measure can be zero for well-fitting models.

The differences between the ADF and ML χ^2 test statistic do not vary dramatically as multivariate kurtosis increases: the average percent difference is less than 10% in each kurtosis category. On average, the ADF statistic is about four percent lower than the ML counterpart. The standard deviation of the percent difference does generally increase as multivariate kurtosis increases.

The difference between the ADF and ML RMSEA is negative, with an average of -0.000811. Note that this average is artificially reduced because models above a certain threshold of fit have an RMSEA value of zero. As such, comparing this measure does not inform the difference between two well-fitting models. Similar to the χ^2 test statistic results, the standard deviation of the difference between the ADF and ML RMSEA does increase as kurtosis increases, suggesting more consistency between the ML and ADF estimates at lower levels of kurtosis. Because the average difference between ADF and ML for these measures is negative, the ADF estimation, on average, suggests the model fits the data better than ML (for both the χ^2 test statistic and RMSEA, the lower the measure, the better the fit).

Table 8.2: Comparison of ADF and ML χ^2 Test Statistics and RMSEA by Multivariate Kurtosis

Multivariate Kurtosis Range	N	Percent difference between ADF and ML χ^2 statistics			Absolute difference between ADF and ML RMSEA		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
0 to <1.0	69	75.4%	-3.38	10.5	92.8%	-0.151×10^{-3}	2.95×10^{-3}
1.0 to <3.5	826	82.0%	-6.07	9.05	92.9%	-1.30×10^{-3}	4.50×10^{-3}
3.5 to <10.0	2,106	76.5%	-8.17	11.8	86.7%	-2.55×10^{-3}	6.45×10^{-3}
10.0 +	1,009	38.4%	5.57	18.6	42.4%	3.08×10^{-3}	10.5×10^{-3}
Total	*4,010*	*68.0%*	*-4.20*	*14.5*	*76.9%*	-0.834×10^{-3}	7.71×10^{-3}

A scatter plot of the χ^2 test statistic (CMIN in Figure 8.1) percent difference and RMSEA absolute difference, as a function of multivariate kurtosis, is presented in Figure 8.1. Note that at high levels of kurtosis (i.e. greater than 10.0) the differences in techniques consistently fall on one side (the "ML is better" side) of the horizontal axis. Since these are precisely the circumstances in which ADF would be assumed to be superior, i.e. to give a better estimate of the true fit, this suggests that the ML statistic is biased (downward) toward giving a more favorable result than is really the case, in just the situations where it should be trusted the least. Thus, this offers an important caution to structural equation modelers inclined to rely on the robustness of the ML approach.

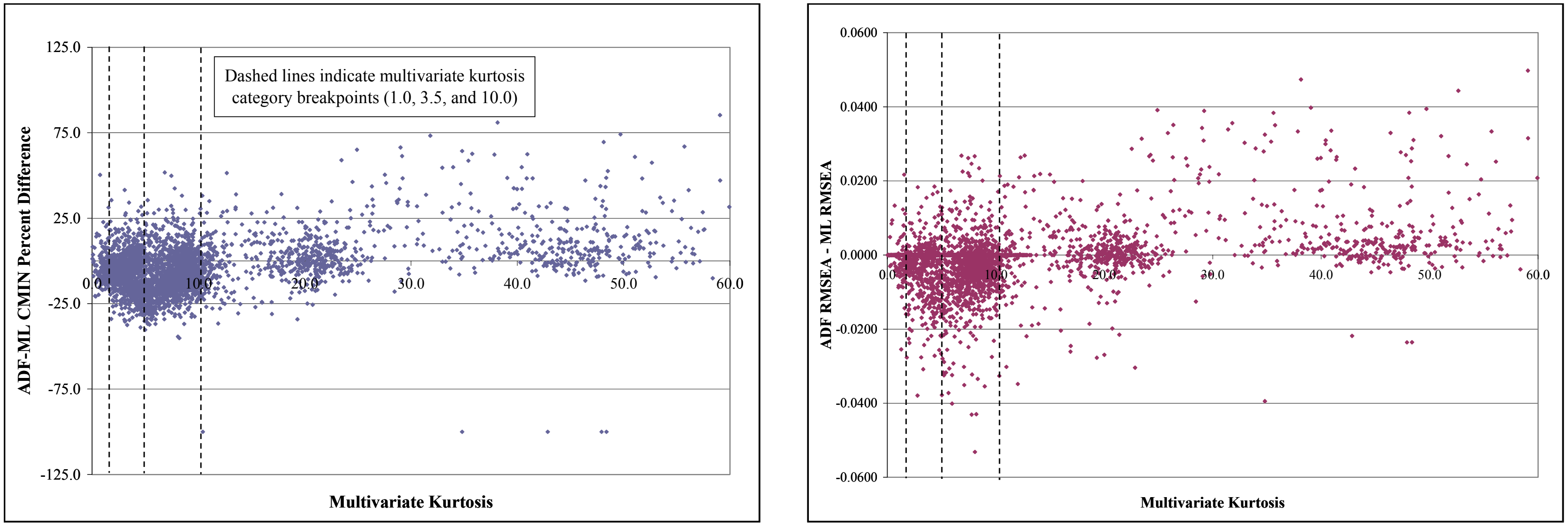


Figure 8.1: Percent Difference between ML and ADF χ^2 Test Statistics (left) and Absolute Difference between ML and ADF RMSEA (right) by Multivariate Kurtosis

Table 8.3 compares the χ^2 test statistic and RMSEA by sample size. Here, the pattern of deviation between the two estimation techniques is clear. As the sample size increases, the average percent difference between the ADF and ML χ^2 test statistics becomes increasingly negative, though the standard deviation of the percent difference decreases. A similar pattern holds for the RMSEA. These findings consistently show that the ADF technique suggests a better model fit for all sample sizes, and does so with more consistency as the sample size increases. For models estimated with a sample size of 1,000, the ADF technique produced a lower (i.e. better) χ^2 test statistic than ML 75% of the time, with an average improvement of 6.45% and a standard deviation of 9.03 percentage points. By contrast, at the smallest sample size of 250, the ML technique produced a better χ^2 test statistic almost as often as ADF (the latter winning 56.8% of the time), and the percent difference standard deviation was quite large, at 21.5 percentage points.

If it is assumed that the large sample ADF χ^2 test statistic is accurate, than the results support the common assertion in the literature that the ML χ^2 statistic is inflated at large sample sizes (see, e.g. Bollen and Stine, 1992).

Table 8.3: Comparison of ADF and ML χ^2 Test Statistics and RMSEA by Sample Size

Sample Size	N	Percent difference between ADF and ML χ^2 statistics			Absolute difference between ADF and ML RMSEA		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
250	1,000	56.8%	-0.0555	21.5	69.3%	0.426×10^{-3}	13.2×10^{-3}
500	1,000	67.7%	-4.27	13.1	77.6%	-1.28×10^{-3}	6.16×10^{-3}
750	1,000	72.0%	-5.98	10.2	79.1%	-1.37×10^{-3}	3.91×10^{-3}
1,000	1,000	75.5%	-6.45	9.03	81.6%	-1.12×10^{-3}	2.86×10^{-3}
Full sample	10	80.0%	-7.15	7.21	80.0%	-0.770×10^{-3}	1.38×10^{-3}
Total	*4,010*	*68.0%*	*-4.20*	*14.5*	*76.9%*	-0.834×10^{-3}	7.71×10^{-3}

The final comparison between ML and ADF is presented in Table 8.4. Here, the same two goodness-of-fit measures are tabulated against the number of measured (meaning non-latent) variables included in each model. No consistent pattern emerges in the results, though models with more variables, 9 and 11 specifically, seem to act differently than those with fewer variables. As this dataset contains only single models with 7, 8, 9 and 11 variables, respectively, no real conclusions can be reached from this summary.

Table 8.4: Comparison of ADF and ML χ^2 Test Statistics by Number of Measured (non-latent) Variables

Number of measured variables	N	Percent difference between ADF and ML χ^2 statistics			Absolute difference between ADF and ML RMSEA		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
4	802	69.3%	-9.99	14.6	87.8%	-2.65×10^{-3}	7.01×10^{-3}
5	1604	81.7%	-7.17	10.1	92.3%	-1.66×10^{-3}	5.43×10^{-3}
7	401	77.6%	-6.07	10.7	84.0%	-2.77×10^{-3}	-6.72×10^{-3}
8	401	74.8%	-4.84	10.3	76.8%	-2.27×10^{-3}	6.32×10^{-3}
9	401	43.1%	2.68	11.48	44.9%	1.05×10^{-3}	7.26×10^{-3}
11	401	19.7%	13.8	22.5	20.0%	7.82×10^{-3}	11.9×10^{-3}
Total	*4,010*	*68.1%*	*-4.31*	*14.7*	*77.0%*	*-0.811* $\times 10^{-3}$	*7.67* $\times 10^{-3}$

8.3 Comparing the Bootstrap Estimation with ML and ADF

The second analysis investigates the conditions under which the Bollen-Stine *p*-value, used to measure goodness-of-fit in the bootstrap estimation, deviates from the ML and ADF χ^2 test statistic *p*-values. Table 8.5 presents a summary of the absolute difference between the Bollen-Stine *p*-value and the χ^2 test statistic *p*-values for both the ML and ADF estimation techniques (the absolute difference is used because the *p*-value can be zero for poor-fitting models). The results show a rather clear pattern: as multivariate kurtosis increases, the average and standard deviation of the difference between the Bollen-Stine and χ^2 test statistic *p*-values increase.

Overall, the bootstrap technique suggested the model fit the data better (in the SEM context, the higher the *p*-value, the better the fit of the model) than ML in 89% of the cases and fit the data better than ADF in 67% of the cases.

Table 8.5: Comparison between Bollen-Stine *p*-value and ML/ADF χ^2 Test Statistic *p*-values by Multivariate Kurtosis

Multivariate Kurtosis Range	N	Absolute difference between Bollen-Stine and ML χ^2 *p*-values			Absolute difference between Bollen-Stine and ADF χ^2 *p*-values		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
0 to <1.0	69	30.4%	0.0110	0.0224	49.3%	0.00311	0.0212
1.0 to <3.5	826	23.8%	0.0173	0.0277	44.7%	0.00192	0.0214
3.5 to <10.0	2,106	10.1%	0.0483	0.0509	38.2%	0.00886	0.0483
10.0 +	1,009	2.08%	0.0505	0.0551	11.3%	0.0652	0.144
Total	*4,010*	*11.2%*	*0.0418*	*0.0497*	*33.0%*	*0.0215*	*0.0848*

Figure 8.2 presents a graphical summary of the ML and ADF comparison results of Table 8.5. The differences between the bootstrap and ML/ADF fit statistic *p*-values are dramatic as kurtosis increases, in some cases varying by more than 0.200 in the ML estimation and 0.300 in the ADF estimation. In general, the bootstrap approach always suggests a fit better than (or at worst about equal to) ML when the multivariate kurtosis is greater than approximately 15 and one better than ADF when multivariate kurtosis is greater than 25.

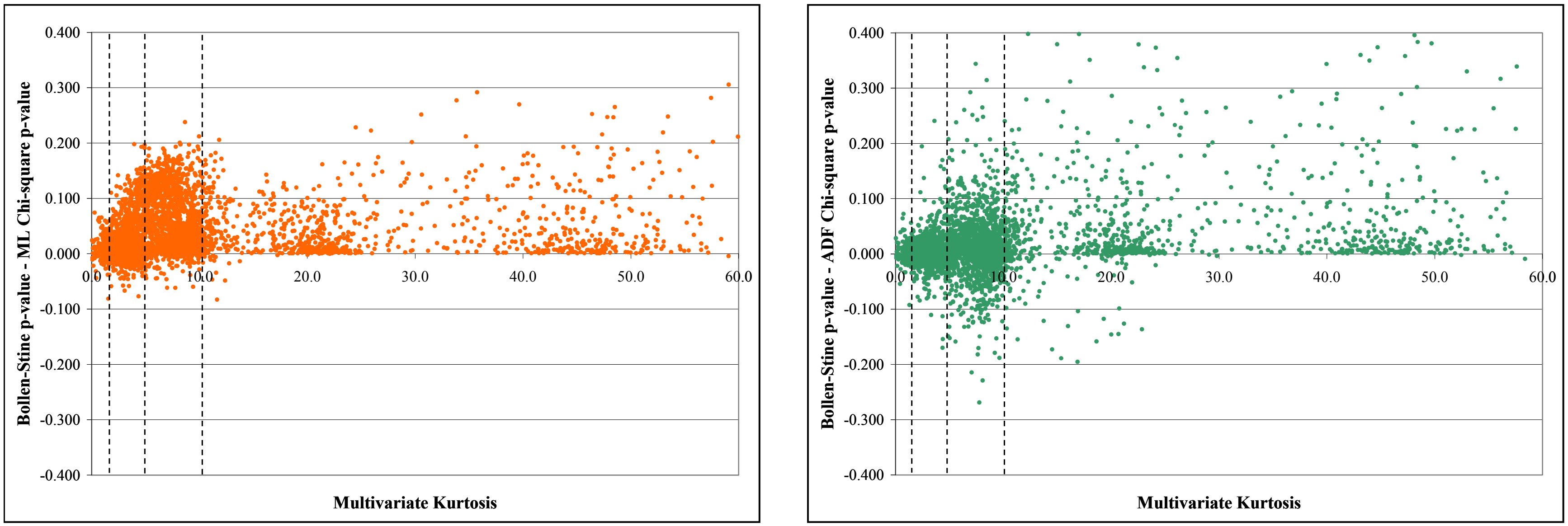


Figure 8.2: Difference between Bollen-Stine and ML χ^2 Test Statistic *p*-values (left) and Bollen-Stine and ADF χ^2 *p*-values (right) by Multivariate Kurtosis

The differences between the bootstrap and ML/ADF χ^2 test statistic *p*-values segmented by sample size are presented in Table 8.6. The table shows that, in general, the difference between the measures decreases as sample size increases, though the effect is relatively minor. The standard deviation of the differences decreases consistently and somewhat dramatically for the ADF estimation as sample size increases, suggesting that very different results can emerge when using ADF and bootstrap estimation with small samples.

Table 8.6: Comparison between Bollen-Stine *p*-value and ML/ADF χ^2 Test Statistic *p*-values by Sample Size

Sample Size	N	Absolute difference between Bollen-Stine and ML χ^2 *p*-values			Absolute difference between Bollen-Stine and ADF χ^2 *p*-values		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
250	1,000	16.5%	0.0506	0.0586	33.3%	0.0443	0.140
500	1,000	10.5%	0.0448	0.0493	34.2%	0.0232	0.0770
750	1,000	8.80%	0.0382	0.0441	33.4%	0.0120	0.0416
1,000	1,000	9.30%	0.0337	0.0440	31.1%	0.00669	0.0263
Full sample	10	0.00%	0.0343	0.0503	20.0%	0.00600	0.0113
Total	*4,010*	*11.2%*	*0.0418*	*0.0497*	*33.0%*	*0.0215*	*0.0848*

*8.4 Comparing the M*plus *Estimation with ML and ADF*

In this section, analyses similar to the bootstrap comparison are presented for the M*plus* estimation. As discussed previously, the M*plus* technique is similar to ADF though it has the additional feature of explicitly considering ordinal variables (Muthén and Muthén, 2005), of which at least three were present in each of the ten models.

Note that the M*plus* software requires that observations for each level of each ordinal variable be present in the dataset in order to estimate the models. This was not the case in 338 of the 4,010 datasets created for this analysis; these 338 cases are thus omitted from the following summaries.

Table 8.7 compares the M*plus* χ^2 test statistic *p*-value to the ML and ADF *p*-values. The most notable result in this table is the dramatic difference between the fit results in the 10.0+ kurtosis category. In this category, the average difference between the M*plus* and ML *p*-values is 0.241; the number is 0.248 when M*plus* is compared to ADF. Both these numbers are very high and suggest that the estimation techniques are highly inconsistent with each other when the data are non-normal. Because the *p*-value differences are positive, the M*plus* estimation is suggesting a substantially better model fit than either ML or ADF. To the extent that the M*plus* technique is adequately capturing the underlying latent variables that shape the ordinal revealed variables and the non-normality is being introduced by other (non-ordinal) variables, ML and ADF are underestimating model fit when the data are severely non-normal.

Table 8.7: Comparison between M*plus* χ^2 Test Statistic *p*-value and ML/ADF χ^2 Test Statistic *p*-values by Multivariate Kurtosis

Multivariate Kurtosis Range	N	Absolute difference between M*plus* and ML χ^2 *p*-values			Absolute difference between M*plus* and ADF χ^2 *p*-values		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
0 to <1.0	67	44.8%	-0.0117	0.0593	53.7%	-0.0184	0.0628
1.0 to <3.5	800	55.9%	-0.0257	0.0986	64.9%	-0.0398	0.100
3.5 to <10.0	1,847	51.6%	-0.00383	0.174	62.9%	-0.0357	0.175
10.0 +	958	21.7%	0.241	0.290	20.5%	0.248	0.318
Total	*3,672*	*44.6%*	*0.0551*	*0.227*	*52.1%*	*0.0379*	*0.244*

In Table 8.8, the M*plus* and ML/ADF RMSEA fit measures are compared by multivariate kurtosis. These results show that as the kurtosis increases, the average difference between the M*plus* and ML and ADF RMSEA increases, as does the standard deviation (more or less). Note here that the average difference between the M*plus* and ML RMSEA is positive (recall: the lower the RMSEA, the better the model fit); the same is true for the M*plus* and ADF RMSEA difference. These findings indicate that the M*plus* estimation suggests a worse model fit, on average, than do the other estimation techniques (aside from the 10.0+ kurtosis group, this is also the case for the χ^2 test statistic *p*-value). To complete the conclusion stated previously: to the extent that the M*plus* technique is adequately capturing the underlying latent variables that shape the ordinal revealed variables and the non-normality is being introduced by other (non-ordinal) variables, ML and ADF are *overestimating* model fit when the data are *not* severely non-normal.

Table 8.8: Comparison between M*plus* and ML/ADF RMSEA by Multivariate Kurtosis

Multivariate Kurtosis Range	N	Absolute difference between M*plus* and ML RMSEA			Absolute difference between M*plus* and ADF RMSEA		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
0 to <1.0	67	83.6%	0.200×10^{-2}	0.889×10^{-2}	80.6%	0.209×10^{-2}	0.946×10^{-2}
1.0 to <3.5	800	77.4%	0.387×10^{-2}	1.30×10^{-2}	71.8%	0.507×10^{-2}	1.44×10^{-2}
3.5 to <10.0	1,847	36.8%	1.17×10^{-2}	1.78×10^{-2}	36.1%	1.38×10^{-2}	1.97×10^{-2}
10.0 +	958	25.1%	1.34×10^{-2}	1.59×10^{-2}	29.0%	1.13×10^{-2}	1.63×10^{-2}
Total	*3,663*	*43.4%*	$\mathit{1.02 \times 10^{-2}}$	$\mathit{1.66 \times 10^{-2}}$	*42.8%*	$\mathit{1.10 \times 10^{-2}}$	$\mathit{1.80 \times 10^{-2}}$

A comparison of estimation techniques *p*-values across sample sizes are presented in Table 8.9. In general, the three techniques begin to converge as sample size increases, as both the average absolute difference and the standard deviation of the difference generally decreases as sample size increases.

The comparison of RMSEA is tabulated by sample size in Table 8.10. The differences here are relatively stable across sample size, though the average difference does decrease slightly as sample size increases.

Table 8.9: Comparison between M*plus* χ^2 Test Statistic *p*-value and ML/ADF χ^2 Test Statistic *p*-values by Sample Size

Sample Size	N	Absolute difference between M*plus* and ML χ^2 *p*-value			Absolute difference between M*plus* and ADF χ^2 *p*-value		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
250	845	44.9%	0.0931	0.266	48.0%	0.0865	0.300
500	908	44.1%	0.0653	0.241	50.6%	0.0496	0.261
750	939	44.8%	0.0383	0.215	54.2%	0.0178	0.224
1,000	970	44.6%	0.0288	0.179	54.9%	0.00438	0.178
Full sample	10	50.0%	0.0207	0.161	60.0%	-0.00762	0.145
Total	*3,672*	*44.6%*	*0.0551*	*0.227*	*52.1%*	*0.0379*	*0.244*

Table 8.10: Comparison between M*plus* and ML/ADF RMSEA by Sample Size

Sample Size	N	Absolute difference between M*plus* and ML RMSEA			Absolute difference between M*plus* and ADF RMSEA		
		Share ≤ 0	Average	Standard deviation	Share ≤ 0	Average	Standard deviation
250	845	46.4%	1.29×10^{-2}	2.16×10^{-2}	48.8%	1.27×10^{-2}	2.41×10^{-2}
500	908	43.2%	1.06×10^{-2}	1.70×10^{-2}	43.0%	1.16×10^{-2}	1.87×10^{-2}
750	939	42.5%	0.938×10^{-2}	1.44×10^{-2}	39.9%	1.06×10^{-2}	1.51×10^{-2}
1,000	970	42.1%	0.854×10^{-2}	1.27×10^{-2}	40.3%	0.960×10^{-2}	1.31×10^{-2}
Full sample	10	40.0%	0.854×10^{-2}	1.24×10^{-2}	50.0%	0.931×10^{-2}	1.21×10^{-2}
Total	*3,663*	*43.4%*	$\mathit{1.02} \times 10^{-2}$	$\mathit{1.66} \times 10^{-2}$	*42.8%*	$\mathit{1.10} \times 10^{-2}$	$\mathit{1.80} \times 10^{-2}$

8.5 Model Robustness

The purpose of this final analysis section is to examine the robustness of the model specifications and to attempt to quantify the large-sample bias of the χ^2 test statistic. This is done by comparing the χ^2 test statistic divided by the model degrees of freedom (χ^2/d.f.) goodness-of-fit measure across sample size and estimation technique for each of the ten model specifications. To the extent the goodness-of-fit measures are consistent, on average, across sample sizes and estimation techniques, the confidence I have in the model results increases.

Another benefit of this analysis is that the common large sample size bias of the χ^2 test statistic can be, to some degree, quantified. Because the statistic measures the discrepancy between the sample and model-implied covariance matrices, a large sample size gives the test great power, and thus makes the test difficult to pass (see, e.g., Kline, 2005). Comparing the average χ^2/d.f. statistics at each sample size can quantify the influence of sample size on the statistic for a particular model and dataset.

The χ^2/d.f. measure is chosen because it is both common and useful for comparing models with different degrees of freedom. Additionally, the M*plus* software corrects the degrees of freedom to account for the explicit treatment of ordinal variables (see Appendix 4 in Muthén, 2004) and, as such, does not necessarily have the same degrees of freedom as the ML and ADF techniques do for the same model structure.

A summary of the χ^2/d.f. values for each of the five short-distance models across four estimation techniques is presented in Table 8.11; the results for the five long-distance models are shown in Table 8.12.

The tables show that the χ^2/d.f. measure decreases as sample size decreases in only six of the ten models. The other four models (those for overall short-distance, short-distance entertainment, overall long-distance, and long-distance personal vehicle) show a relatively uniform increase in χ^2/d.f. as sample size decreases, which is contrary to expectation. Of course, this analysis does not control for actual model fit; the data is real, not simulated and, as follows, the χ^2/d.f. measure has no single expected value.

The differences by sample size between the χ^2/d.f. for a single model specification can be dramatic. The M*plus* estimation of the long-distance entertainment model, as an example, decreases from a full-sample value of 3.217 to a median 250-observation average of 0.714.

In general, each of the models appears to hold up across sample size and estimation technique. Perhaps the worst degradation of fit across sample size occurs for the short-distance overall model, which has a χ^2/d.f. of near 0.12 at the full sample, but closer to 0.70 at the 250 sample size. Of course, a χ^2/d.f. of 0.70 is still within the range, as established by the literature (see, e.g., Baumgartner and Homburg, 1998; Shah and Goldstein, 2006), of a well-fitting model. The tables give an estimate of the large-sample bias of the χ^2 test statistic for each of the ten models and reveal that the bias leans in the unexpected direction for four of the models.

One reason for the variation in fit is the degrees of freedom of the models. In Figure 8.3, the standard deviation of the ML χ^2/d.f. (labeled CMIN/DF on the chart) measure at each sample size is plotted against model degrees of freedom, i.e. each of the ten models has five points on the chart, one point for the standard deviation at each of five sample sizes (full, 1000, 750, 500, and 250). The figure shows that as model degrees of freedom increases, so does the stability of the χ^2/d.f. measure at each sample size. The model degrees of freedom compares the number of variables and number of free parameters in a model. If there are numerous relationships among a few variables, the model degrees of freedom is low. It is logical then that the deviation of the fit is larger for models with fewer degrees of freedom: a good deal of information is being extracted from only a few variables. Variability in the data, therefore, has a larger impact on model fit when the model has fewer degrees of freedom (MacCollum, *et al.*, 1996).

Table 8.11: Summary of Median χ^2/d.f. for Short-Distance Models by Estimation Technique

Model	Estimation	Sample Size				
		Full	1,000	750	500	250
Overall	ML	0.121	0.198	0.340	0.518	0.654
(full-sample N = 1,336)	ADF	0.111	0.185	0.323	0.494	0.616
	M*plus*	0.147	0.276	0.392	0.611	0.820
	Bootstrap	0.109	0.183	0.320	0.442	0.608
Commute	ML	1.241	1.019	0.910	0.497	0.405
(N = 1,352)	ADF	1.144	0.942	0.853	0.452	0.372
	M*plus*	1.053	0.842	0.846	0.442	0.409
	Bootstrap	1.110	0.914	0.829	0.470	0.362
Work/school-related	ML	2.434	2.088	1.815	1.526	1.421
(N = 1,349)	ADF	2.478	2.091	1.816	1.556	1.440
	M*plus*	2.454	2.158	1.864	1.651	1.720
	Bootstrap	2.162	1.846	1.620	1.397	1.336
Entertainment	ML	0.954	0.999	1.010	1.044	1.086
(N = 1,349)	ADF	0.798	0.827	0.861	0.928	1.005
	M*plus*	0.799	1.003	1.100	1.215	1.053
	Bootstrap	0.803	0.830	0.855	0.890	0.942
Personal vehicle	ML	1.733	1.549	1.449	1.372	1.201
(N = 1,354)	ADF	1.704	1.603	1.506	1.548	1.649
	M*plus*	2.382	2.055	1.894	1.750	1.560
	Bootstrap	1.512	1.382	1.312	1.236	1.114

Table 8.12: Summary of Median χ^2/d.f. for Long-Distance Models by Estimation Technique

Model	Estimation	Sample Size 1,343*	1,000	750	500	250
Overall	ML	0.658	0.689	0.771	0.855	0.951
	ADF	0.526	0.542	0.623	0.678	0.823
	M*plus*	1.540	1.338	1.226	1.243	1.379
	Bootstrap	0.496	0.508	0.607	0.653	0.758
Work/school-related	ML	2.315	1.964	1.784	1.452	1.226
	ADF	2.071	1.767	1.628	1.390	1.194
	M*plus*	3.174	2.606	2.207	1.792	1.429
	Bootstrap	2.276	1.811	1.641	1.339	1.200
Entertainment	ML	1.305	1.073	0.728	0.401	0.416
	ADF	1.323	1.084	0.729	0.424	0.516
	M*plus*	3.217	2.566	1.892	1.088	0.714
	Bootstrap	1.232	1.070	0.707	0.440	0.493
Personal vehicle	ML	0.632	0.680	0.758	0.887	0.916
	ADF	0.617	0.655	0.753	0.904	0.936
	M*plus*	0.581	0.703	0.793	0.960	1.046
	Bootstrap	0.583	0.629	0.732	0.876	0.849
Airplane	ML	2.832	2.305	1.980	1.710	1.398
	ADF	2.630	2.158	1.833	1.551	1.361
	M*plus*	3.671	3.022	2.541	2.120	1.650
	Bootstrap	2.399	2.023	1.768	1.528	1.208

* Overall N=1,341; Personal vehicle N=1,336

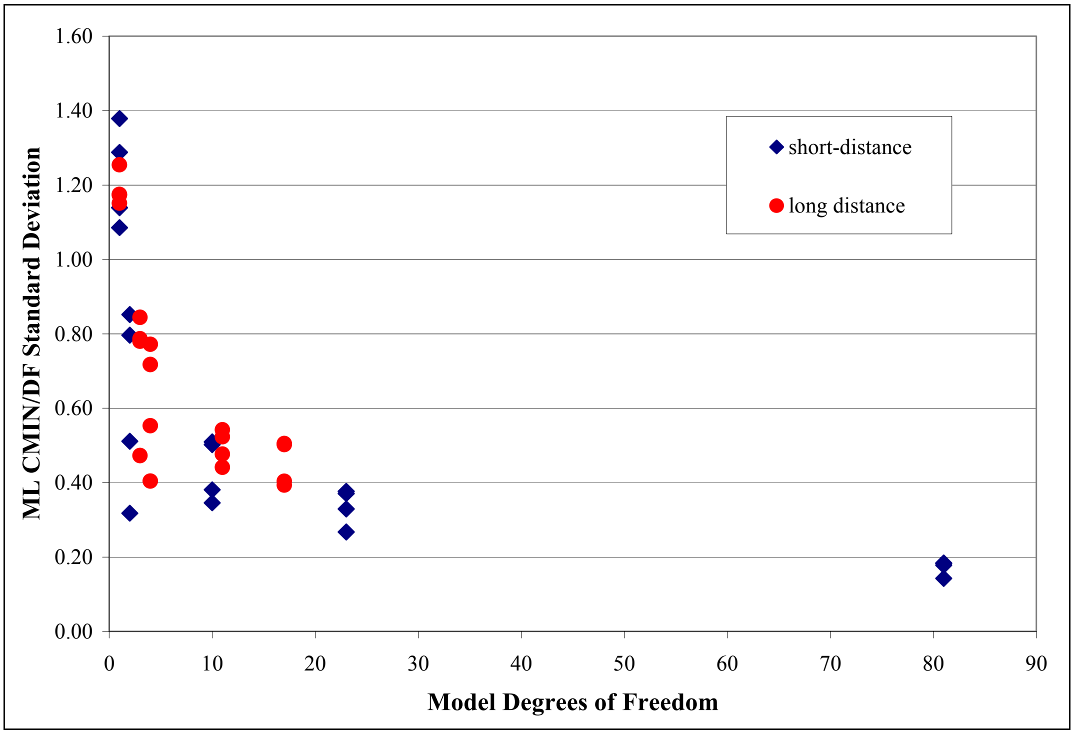


Figure 8.3: Standard Deviation of ML χ^2/d.f. by Model Degrees of Freedom

8.6 Recommendations

These results suggest that multiple estimation techniques should be used when possible. With the inclusion of ML, ADF, and bootstrapping techniques readily available in the AMOS (and other) software package(s), goodness-of-fit can easily be examined across estimation technique; when ordinal variables are present, the M*plus* software is a logical choice to buttress ML estimates. These results, which are suggestive rather than definitive, indicate that when sample sizes are small or multivariate kurtosis high, deviations across techniques become more likely.

If researchers are concerned that a large sample size is negatively influencing the χ^2 test statistic of their models, it is a relatively easy process to sample the dataset and estimate the specification on numerous smaller datasets. Though doing so cannot give a definitive quantification of the influence of sample size, it can give a rough idea. If the goodness-of-fit measures hold up across the sampled datasets, confidence in the fit of the models increases.

More than any quantifiable measure, estimating the data with different techniques and sampling the data to reestimate models provides an excellent opportunity to double check the model specifications and learn more about the data. This is especially true when using a different software package (M*plus* in this study). Though time consuming, rebuilding the models in M*plus* allowed for the opportunity to carefully consider all the relationships included in the model, such as covariances between exogenous variables. When the data is sampled and models reestimated, errors in the estimation are bound to occur, and investigating those errors can lead to learning more about datasets, such as the presence of outliers or unexpected correlations.

The recommendations from this chapter are that multiple estimation techniques should be used if non-normality or sample size (either large or small) is a concern. If time and effort permits, and the dataset is large, consider sampling the data to test the robustness of the model specifications, quantify the large-sample bias of the χ^2 test statistic, error check your work, and learn more about the dataset.

9. SUMMARY AND CONCLUSIONS

This chapter presents a summary of the findings, answers the motivating research questions of Chapter 1, discusses the implications of the work, and suggests some directions for future research. The first section gives a review of the literature and the empirical context in which this work is performed. The short-distance models of *5.2 Preferred Model Estimation Results* and Chapter 6 are summarized next, followed by a summary of the long-distance models of Chapter 7. Next, a summary section presents an overview of the econometric analysis of Chapter 8. The final two sections directly answer research questions and discuss the implications of the work. Directions for future research are presented throughout the chapter.

9.1 Empirical Context

The idea of measuring and modeling travel affect and desire is counterintuitive. Stereotypically, daily travel is universally disliked: no one enjoys traveling and we would all prefer to do less of it (keeping other preferences, such as home location, constant). Travel demand models, which are based on economic theory, reinforce this stereotype. Travel models uniformly assume that travel time is a cost to be minimized. For example, models of travel mode choice imply that, all else equal, the quickest trip is always preferable. This perspective, which has become axiomatic in the transportation field, views travel as a "derived demand" – derived from the demand to participate in spatially-separated activities. The act of traveling itself is traditionally not considered to offer any positive utility.

Recent research, however, has begun to challenge the derived-demand paradigm (Mokhtarian and Salomon, 2001). Though commentary on a so-called "positive utility for travel" is nascent, a number of transportation scholars have commented on the intrinsic benefits of travel for some time. Mokhtarian, *et al.* (2001) give a thorough summary of such literature, dating as far back as 1976, when Israeli geographer Shalom Reichman suggested that transportation may fulfill basic human needs in itself. Salomon and Mokhtarian (1998) present a list of reasons why individuals may enjoy travel for its own sake, including: adventure-seeking, variety-seeking, independence, control, status, buffer (between work and home), exposure to the environment, scenery and other amenities, and synergy. Ory and Mokhtarian (2005) empirically validate many of these reasons (using the same dataset as the current study) and add escape, curiosity, conquest, physical exercise, and the therapeutic value of movement/travel to the reasons proposed by Salomon and Mokhtarian.

The modern study of a positive utility of travel extends beyond the work of Mokhtarian and her colleagues, as illustrated by a special issue of *Transportation Research Part A* (Volume 39, Numbers 1-2, 2005). Using mixed logit models of mode choice, Hess, *et al.* (2005) examine the reasonableness of non-zero probabilities for positive coefficients for travel time. Larson and Lew (2005) also present an econometric argument in a study of the leisure travel of fishermen in Alaska, finding that the value of travel ancillary to the activity of fishing could be either positive or negative. The environmental psychologist Steg (2005) empirically investigates what motivates automobile travel, in the context of trying to better guide environmental policy; she found that instrumental motives (such as speed and convenience) play a secondary role to symbolic and affective motives (i.e. driving appeals to sensations of control, power, and status). Anable and Gatersleben (2005) took on a similar analysis and found that for work travel, individuals appreciate the instrumental aspects of travel modes, whereas for leisure travel, both instrumental and affective factors are important. In addition to these direct investigations of motivations, many others have commented on the “love affair” of travelers with their automobiles (see, e.g., Wachs and Crawford, 1992; Marsh and Collett, 1986; Sachs, 1992).

This dissertation further explores the arguments that a positive utility of travel does exist and that the effects of such a utility play a non-negligible role in describing travel behavior generally, and mandatory travel, such as commuting, specifically. I take a broader view than Steg (2005) by considering travel by all modes, not just the automobile, and expand on Anable and Gatersleben (2005) by measuring the enjoyment of travel generically (as well as mode-specifically).

In addition to building on the positive utility of travel literature, the models estimated in this study add to the larger body of work on the relationship between travel attitudes and behavior. The survey instrument used for the present study directly collected the amount, perception, affection, and desire data previously mentioned, as well as a host of attitude, personality, lifestyle, and socio-demographic variables. This aspect of the study follows the spirit of early work like that of Dobson*, et al.* (1978), who examined the mode choice behavior and bus attitudes and perceptions of freeway-accessible residents in Los Angeles. The authors used two-stage structural equation modeling to show that affect, which was influenced by perceptions, had an influence on behavior; the opposite direction of causality also held. In the absence of affect, behavior influenced attitudes/perceptions, but not the converse. This work expands on their ideas by measuring attitudes towards travel itself, in addition to travel desires, and including travel of various purposes, modes, and lengths.

Other studies that have examined the causal relationship between behavior and attitudes, though generally not directly considering affect, include the work of Tardiff (1976), who used simultaneous equations to investigate the relationship between mode choice attitudes and behavior in West Los Angeles. His results, though limited, suggest that behavior is more likely to cause attitudes than the converse. Similarly, Golob (2001) found stronger links of behavior to attitudes than vice versa, in his study of congestion pricing and attitudes in the San Diego area. In another study of road pricing, Jakobsson, *et al.* (2000) examined Swedish car users' willingness to accept pricing. The authors confirmed a model structure in which income and the expectation of others' car use reduction influenced the intention of car use reduction, which in turn influenced perceptions of fairness and infringement on freedom, which had a final impact on the acceptance of road pricing. Golob and Hensher (1998) examined the link between environmental attitudes, with a focus specifically on greenhouse gas emissions, and travel behavior in six Australian cities, finding that mode choice influences attitudes. Garling, *et al.* (2001) extend the study of attitudes further into the realm of psychology by examining the role of habits and past behavior in conjunction with the interaction of attitudes and behavior. The authors argue that initial attitude-based choices can lead to script-based (or habit-based) choices.

This dissertation adds to the travel behavior/attitudes literature by examining the causal relationship of attitudes and behavior in the presence of affect, perceptions and desires. The work is more general in that attitudes towards travel itself are measured. Analyzing the joint relationships among the key variables in this unique dataset inspires numerous research questions, such as: what measures of objective travel amounts (i.e. distance, time, frequency, speed) have the greatest influence on travel perceptions? Are these travel perceptions more important than actual travel amounts in shaping desires? Does a liking for travel lead to a desire for more of it? Does a liking for commuting influence travel perceptions? Each of these questions is addressed in this dissertation.

9.2 Short-distance Model Summary

Section *5.2 Preferred Model Estimation Results* and Chapter 6 present a total of five structural models of travel amounts, perceptions, affections, and desires for the following short-distance (one-way trips less than 100 miles) travel categories: overall, commute, work/school-related, entertainment, and personal vehicle.

Across the five models, three consistent relationships emerge. The first is the positive effect of travel amounts (Objective Mobility) on travel perceptions (Subjective Mobility): the more I actually travel, the more I think I travel. This result is logical and suggests that, to some extent, there is a common understanding across the sample of how much travel, in each category, constitutes "a lot". The second common finding is the negative relationship between perceptions and desires (Relative Desired Mobility). The higher the amount of travel is perceived to be, the more one wants to reduce that travel. Here, the more I think I do of it, the less of it I want to do – also a logical result, but pointing to the importance of perceptions in influencing (desired) travel behavior. The final robust relationship reveals evidence of a positive utility of travel, and *its* influence on (desired) behavior. In each of the five models, a strongly significant positive effect of Travel Liking (affections) on Relative Desired Mobility (desires) appeared. The more travel is enjoyed (or, put another way, the less it is disliked), the more travel is desired (or, the less a reduction in travel is desired).

An enjoyment of travel was also found to lead to increased actual trip making for the overall, work/school-related, and entertainment categories, and to an increased travel distance for the entertainment category. The fact that trip making is so consistently a function of stated travel enjoyment certainly motivates recognition that a positive utility of travel does exist, and should be given more attention.

Other findings include the idea that travel perceptions are a function of numerous objective measurements, including travel distances, frequencies, durations, choice of mode, and speeds. As indicated above, these perceptions, in turn, negatively influence travel desires. For mandatory travel, such as commuting, the models show that objective travel amounts play a more important role in shaping desires than perceptions do; the opposite is true for discretionary travel. I speculate that this is a result of travelers acquiescing to societal norms regarding commute distance and vehicle usage.

The role of perceptions in shaping desires is important. Travel demand management strategies will only be effective if travelers desire a reduction in travel. The results of this dissertation suggest that such desires are shaped by both objective travel amounts and perceptions for mandatory travel, but only perceptions for discretionary travel. As such, it is important to investigate not only how much travel is being engaged in, but also how that travel is being perceived. It also motivates further investigation into how travel perceptions are shaped, using both cross-sectional (see Ory, *et al.,* forthcoming and Collantes and Mokhtarian, 2007) and longitudinal studies.

As suspected from the outset (see Chapter 1), throughout the modeling, the most difficult relationship to represent was that between affections and perceptions. The issue is one of causality: do I like my travel in part because I am doing it an amount that is "right" for me? Or are my subjective evaluations of how much I am doing it influenced in part by how much I like it? The evidence from the modeling is not strong, but suggests that the latter direction of effect is stronger for all travel categories save commuting, in which the opposite direction is stronger. A psychological explanation of affections influencing perceptions in this context is discussed at length in Ory, *et al.* (forthcoming). The weak standardized coefficients between affections and perceptions found here could be because the two variables have a non-linear relationship. Collantes and Mokhtarian (2007) suggest that quadratic Travel Liking covariates best explain Subjective Mobility. Though quadratic transformations did not prove significant when included in the present models, segmenting the sample based on the commute Travel Liking variable showed that those who do enjoy commuting reveal a markedly different affection-perception effect on desire than those who do not enjoy commuting. It would be valuable for future research to look for similar effects in the models for other types of travel.

The coefficients and goodness-of-fit measures for the final model specifications were estimated using four techniques, namely maximum likelihood (ML), asymptotic distribution free (ADF), bootstrapping, and the M*Plus* approach. Each of the techniques produced similar parameter estimates. The goodness-of-fit measures varied a bit, but were more or less consistent across techniques.

9.3 Long-distance Model Summary

Chapter 7 presents five structural models of long-distance travel amounts, perceptions, affections, and desires for the following travel categories: overall, work/school-related, entertainment, personal vehicle, and airplane. The work continues the investigation of *6.5 Cross-model Comparisons*, which contains a summary of similar models for short-distance travel.

The key findings of *6.5.1 Core Relationships* are supported by the findings of Chapter 7. Specifically, the three key common relationships across the short-distance models also hold across the long-distance models. These include a positive effect of travel amounts (Objective Mobility) on perceptions (Subjective Mobility); a negative effect of perceptions on desires (Relative Desired Mobility); and a positive influence of affection (Travel Liking) on desires.

One of the most interesting findings in this portion of the analysis is the impact of trip frequency in shaping travel perceptions. Even more than measures of travel distance, the trip frequency variable emerged as the most important in shaping Subjective Mobility within the structural equation modeling context, in each of the five models separately. This finding suggests that travel perceptions and desires are motivated by the number of trips made each year, rather than by the distance traveled. This result makes sense in that preparing for a trip and being away from home could be more onerous than spending an extra hour on an airplane or in a car.

In each of the long-distance models save airplane travel, the travel enjoyment variable positively influenced the trip frequency variable; meaning that an enjoyment of travel leads to the engagement in more travel. This finding further supports the argument (see, e.g., Mokhtarian, *et al.*, 2001) of a non-negligible positive utility of travel playing an important role in travel behavior.

The model results also buttress the Chapter 6 assertion that perceptions are important. In each of the models, perceptions have a significant effect on desires, which suggests that two people who travel the same objective amount (i.e. make the same number of annual trips) will not necessarily desire the same reduction in travel; how the travel amounts are perceived is important.

As in the short-distance models, the coefficients and goodness-of-fit measures for the final model specifications were estimated using four techniques, namely maximum likelihood (ML), asymptotic distribution free (ADF), bootstrapping, and the M*plus* approach. Each of the techniques produced similar parameter and goodness-of-fit estimates.

The airplane model includes a latent measure of personality labeled “adventure-seeking” that is significant in each of the structural equations – meaning, a covariate of each of the four key constructs. This result motivates the speculation that some measure of attitudes, personality, and/or lifestyle has the potential to have similar explicative ability for each of the other four long-distance models. This is an area for future study that can be accomplished using the current dataset.

Another area for future research is the degree to which long-distance work/school-related travel is discretionary. In the current study, Travel Liking had a significant positive effect on both trip frequency and Subjective Mobility. These relationships were more similar to long-distance entertainment travel than to the model of commute travel in *5.2 Preferred Model Estimation Results*. It seems that, in my models at least, work/school-related travel is, at some level, more discretionary than mandatory. Anecdotally this result is logical, in that many business travelers do not seem averse to being “on the road”, and some even seem to enjoy it. It is reasonable to expect a certain amount of self-selection into occupations requiring a lot of travel, by those who enjoy such travel. A more rigorous analysis of this proposition would be interesting.

The striking consistencies between the model results presented here and the short-distance results of Chapter 6 make a compelling argument that there is something inherently true and basic about these relationships. It further emphasizes the need to measure travel perceptions in addition to objective travel amounts, and to recognize the importance that measures of attitudes, personality, and lifestyle possess in influencing travel behavior.

9.4 Econometric Summary

Chapter 8 uses the ten empirical models presented in *5.2 Preferred Model Estimation Results*, Chapter 6, and Chapter 7 to measure the variability of SEM goodness-of-fit measures (the χ^2 test statistic and root mean square error of approximation, or RMSEA, specifically) as a function of sample size, multivariate kurtosis, and estimation technique (ML, ADF, bootstrapping, and M*plus*). The analysis was performed by sampling the original ten datasets to produce more than 4,000 cases, at four different sample sizes and naturally varying degrees of non-normality, on which the ten model specifications were estimated.

The first examination compared the ML and ADF estimation techniques. The results showed that the techniques diverge most dramatically when sample sizes are small and multivariate kurtosis is high; both findings were expected and supported by the prior simulation studies discussed in Chapter 8. Interestingly, however, the ML technique suggested the model fit the data better than ADF when multivariate kurtosis was highest. Since these are precisely the circumstances in which ADF would be assumed to be superior, i.e. to give a better estimate of the true fit, this suggests that the ML statistic is biased (downward) toward giving a more favorable result than is really the case, in just the situations where it should be trusted the least. Thus, this offers an important caution to structural equation modelers inclined to rely on the robustness of the ML approach.

The relatively rarely used bootstrap technique was compared directly to both ML and ADF. As in the ML/ADF comparison, the techniques diverge when sample sizes are small and multivariate kurtosis high. Of particular note was the bootstrap technique almost always suggesting a better model fit than either ML or ADF when the multivariate kurtosis was larger than 25.

In a similar analysis, the M*plus* approach was shown to deviate from ML and ADF to a greater extent than bootstrapping, especially at high levels of multivariate kurtosis where the average difference between the M*plus* and ML χ^2 test statistic p-values was 0.233; the number was even higher, at 0.241, when comparing M*plus* to ADF. Such large differences do motivate the use of the M*plus* software when ordinal data are present.

The last examination compared the χ^2 test statistic scaled by degrees of freedom (χ^2/d.f.) for each of the ten model specifications individually, across both estimation technique and sample size. Surprisingly, the median χ^2/d.f. at the largest sample size (1,000) was smaller than the median value at the smallest sample size (250) in four of the ten models. It was expected that evidence of the large-sample bias of the χ^2 test statistic would appear in each of the ten models.

These results suggest that multiple estimation techniques should be used when possible. With the inclusion of ML, ADF, and bootstrapping techniques readily available in the AMOS (and other) software package(s), goodness-of-fit can easily be examined across estimation technique; when ordinal variables are present, the M*plus* software is a logical choice to buttress ML estimates. These results, which are suggestive rather than definitive, indicate that when sample sizes are small or multivariate kurtosis high, deviations across techniques become more likely.

If researchers are concerned that a large sample size is negatively influencing the χ^2 test statistic of their models, it is a relatively easy process to sample the dataset and estimate the specification on numerous smaller datasets. Though doing so cannot give a definitive quantification of the influence of sample size, it can give a rough idea. If the goodness-of-fit measures hold up across the sampled datasets, confidence in the fit of the models increases.

More than any quantifiable measure, estimating the data with different techniques and sampling the data to reestimate models provides an excellent opportunity to double check the model specifications and learn more about the data. This is especially true when using a different software package (M*plus* in this study). Though time consuming, rebuilding the models in M*plus* allowed for the opportunity to carefully consider all the relationships included in the model, such as covariances between exogenous variables. When the data is sampled and models reestimated, errors in the estimation are bound to occur, and investigating those errors can lead to learning more about datasets, such as the presence of outliers or unexpected correlations.

The recommendations from this chapter are that multiple estimation techniques should be used if non-normality or sample size (either large or small) is a concern. If time and effort permits, and the dataset is large, consider sampling the data to test the robustness of the model specifications, quantify the large-sample bias of the χ^2 test statistic, error check your work, and learn more about the dataset.

9.5 Answers to Research Questions

Five research questions were posed in Chapter 1 to motivate the study; each is directly addressed here.

Question 1: Does affection for travel increase travel amounts (Objective Mobility)? Or, do travel amounts determine affection for travel? Or, do both directions of causality hold? If so, what are the relative magnitudes of the opposing directions?

Evidence of all three possible relationships is found in the model results. Specifically, commute travel amounts (measures of Objective Mobility, OM) strictly determined commute affection

(Travel Liking, TL), with no effects in the reverse direction (OM$\rightarrow^{-}$TL). In the short-distance (SD) overall and work/school-related models, commute amounts negatively influenced category-specific Travel Liking (TL) measures ($OM_{commute}\rightarrow^{-}$TL), which, in turn, positively influenced category-specific trip frequency variables (TL$\rightarrow^{+}$OM). In the SD overall model, the bidirectional effects are of similar magnitude; in the work/school-related model, the negative impact of commute amounts on TL is roughly twice as large as the positive effect of TL on trip frequency. Therefore, commute amounts have a relatively stronger negative indirect effect on work/school-related trip making than on overall trip making. In the SD entertainment and all the long-distance (LD) models save airplane, the effect is strictly from TL to travel amounts (TL$\rightarrow^{+}$OM).

To summarize, for the most mandatory of all the travel categories, commuting, travel amounts determine affection (OM$\rightarrow^{-}$TL). For the categories that mix mandatory and discretionary travel, namely SD overall and work/school-related, significant effects hold in both directions ($OM_{commute}\rightarrow^{-}TL\rightarrow^{+}OM$). And, for more discretionary travel, such as SD entertainment and LD travel (even work/school-related), affections for travel determine amounts (TL$\rightarrow^{+}$OM). These results are quite natural, and point to the complex role of Travel Liking with respect to travel behavior: sometimes a cause and sometimes an effect, with opposite (and equally logical) signs depending on the direction of causality. Only structural equations modeling can sort out these possible relationships satisfactorily.

Question 2: The effect of Subjective Mobility on Travel Liking may be negative (the more I travel, the less I like it) while the converse effect may be positive (the more I like travel, the more I think I do it). Can these two counteracting effects be separately identified? Which is stronger?

This issue is discussed at length in *6.5.5 Relationship between Travel Liking and Subjective Mobility* and *7.6.3 Relationship between Travel Liking and Subjective Mobility*. The model results indicate that for mandatory travel, such as commuting, the more travel that is perceived to be done, the less it is enjoyed (SM→⁻TL). Conversely, in models of more discretionary travel, perceptions of travel amounts increase the more travel is enjoyed (TL→⁺SM). These results are parallel to those for Objective Mobility (Question 1), but the fact that they hold for Subjective Mobility in addition, even controlling for OM, points to a subjective amplification of objective reality that is important to understand.

For the sake of argument, let us define "subjectively mandatory" and "subjectively discretionary" travel based on the relationship between Travel Liking and Subjective Mobility: if the category-specific model contains a negative direct relationship of SM on TL (SM→⁻TL), then that category of travel is defined as subjectively mandatory; if TL positively influences SM (TL→⁺SM), then the category of travel is defined as subjectively discretionary. The ten travel categories analyzed in this study can be grouped using these definitions as follows:

- Strictly subjectively mandatory: SD commute;
- Slightly subjectively discretionary (standardized total effects less than 0.10): SD overall, SD work/school-related, LD personal vehicle;
- Strictly subjectively discretionary: SD entertainment, SD personal vehicle, LD overall, LD work/school-related, LD entertainment.

Obviously a lot of short-distance personal vehicle travel is mandatory. The model results are not suggesting that it is not. Rather, the model indicates that an enjoyment of SD personal vehicle travel leads to increased perceived amounts – a behavior more consistent with entertainment travel (a quintessentially discretionary category) than with commute travel (a quintessentially mandatory category). It may be that when considering travel in their automobiles, individuals conjure happy images of roaming about the countryside rather than the unpleasant memories associated with long commutes.

Another surprise in the above categorization is the presence of LD work/school-related travel in the strictly discretionary group. This issue is discussed in *7.2 Work/school-related* and warrants further investigation in future research.

Question 3: How are specific travel attitudes impacted by a general Travel Liking and vice-versa? Which direction of causality is strongest?

Of the ten models estimated in this dissertation (excluding the "expanded" and segmented models of Chapter 5), four contain latent measures of Attitudes, Personality or Lifestyle. The directions and signs of the direct relationship between these variables and the category-specific Travel Liking variables are as follows:

- SD work/school-related: Commute benefit Attitude $\leftarrow^{+}\rightarrow$ Travel Liking;
- SD personal vehicle: Commute benefit Attitude $\leftarrow^{+}\rightarrow$ Travel Liking;
- SD personal vehicle: Pro-environmental Attitude $\rightarrow^{-}$ Travel Liking;
- LD work/school-related: Workaholic Lifestyle $\rightarrow^{+}$ Travel Liking;
- LD airplane: Adventure seeking Personality $\rightarrow^{+}$ Travel Liking.

With the exception of the commute benefit Attitude, specific measures of Personality, Lifestyle, and Attitude influence category-specific measures of Travel Liking, rather than vice versa. As discussed in *6.2 Work/school-related*, the decision to relate the commute benefit latent variable and the Travel Liking measure via a covariance was theoretical, rather than statistical.

In general, the models support the position that measures of personality and lifestyle are inherent, with an enjoyment of travel (which itself can also be generically considered a "travel attitude") constituting one of their manifestations. In other words, a liking for travel has deeper roots in more fundamental personal characteristics. It would be valuable for future research to explore those roots of Travel Liking more thoroughly and systematically. Further commentary on the relationship between behavior and attitudes is included in *9.6 Implications*.

Question 4: The conceptual diagram shows Subjective Mobility impacting Relative Desired Mobility, both directly and indirectly through Travel Liking. Although both effects are expected to be negative, which one is stronger?

As discussed in Question 2, Subjective Mobility (SM) only directly affects Travel Liking (TL) in the commute model. Here, the direct effect (SM→RDM) has a standardized maximum likelihood coefficient of -0.13, and an indirect effect of (SM→TL→RDM) of -0.04. If the indirect effect were larger, I could conclude that, for the most part, perceptions influence liking, which, in turn, shapes desires. But because the direct effect is substantially larger, the dominant effect is rather perceptions directly influencing desires, with the indirect effect playing a (minor) supporting role.

Because the more common direction of effect across the models is from Travel Liking to Subjective Mobility (TL$\rightarrow^{+}$SM), rather than SM on TL, one could also ask: *the conceptual diagram shows Travel Liking impacting Relative Desired Mobility, both directly and indirectly through Subjective Mobility. Since we expect a positive direct effect (TL$\rightarrow^{+}$SM) and a negative indirect effect (TL$\rightarrow^{+}$SM$\rightarrow^{-}$RDM), which one is stronger?*

The answer to this question is that the direct effect of TL on RDM is dominant and the indirect effect of TL on RDM, via SM, is negligible, if it exists at all. Travel Liking, therefore, is more important in directly shaping desires than in influencing perceptions, which, in turn, shape desires. This result demonstrates the importance of Travel Liking: an enjoyment of travel is consistently a more important predictor of travel desires than is the perception of travel amounts.

Question 5: Does the Subjective Mobility construct proposed here actually "filter" the Objective Mobility construct to form Relative Desired Mobility? Or is a direct impact of Objective Mobility on Relative Desired Mobility a stronger effect?

This issue is discussed at length in *6.5.6 Subjective Mobility Filtering* and *7.6.4 Subjective Mobility Filtering*. The results suggest that for mandatory travel, such as commuting, objective travel amounts play a more important role in shaping desires than perceptions do; the opposite is true for discretionary travel, such as entertainment travel. I speculate that this is a result of travelers acquiescing to societal norms regarding commute distance and vehicle usage.

9.6 Implications

A common assumption in travel behavior research is that attitudes lead to behavior, e.g. a discomfort with public interactions leads to an avoidance of public transportation (see, e.g., Parkany, *et al.*, 2004). However, numerous authors (see, e.g., Tardiff, 1976; Golob and Hensher, 1998; Golob, 2001; Jakobsson, *et al*., 2000) have found the opposite direction of causality to hold in various circumstances. The models presented in this dissertation allow for a more nuanced view of the behavior/attitude relationship. Here, I show that specific attitudes such as Travel Liking, as well as more general underlying personality traits, such as adventure-seeking, lead directly to behavior (e.g. traveling more frequently by airplane) and that same behavior, in turn, shapes variables that can broadly be considered "attitudes", such as a desire to reduce air travel amounts. This pattern holds throughout the models: affection leads to behavior, which then shapes perceptions, which, in turn, manifest in desires. Too often the relationship between generically named "attitudes" and behavior is presented as an either/or proposition: do attitudes shape behavior or vice versa? Including more detailed attitude, personality, and lifestyle variables in these models allow me to avoid picking a side to this false choice and, rather, tell a holistic and compelling story of travel behavior.

The implications of this work are largely theoretical in that I am examining behavior (and its influences) outside the context of typical travel demand models. But the ideas can lead to very practical suggestions. For instance, those promoting travel demand management strategies, such as telecommuting, should pay attention to the travel perceptions of their target audiences. Even though someone may objectively be traveling a lot, if the individual does not perceive those amounts to be high, he may be more resistant to embracing a policy that reduces his travel. The three key findings outlined in *9.2 Short-distance Model Summary* and *9.3 Long-distance Model Summary* are presented alongside the implications of those findings to both the transportation research community and transportation planners charged with implementing travel demand management strategies in Table 9.1.

Perhaps most importantly, the models presented in this dissertation unequivocally demonstrate the importance of travel affection (or liking) to travel behavior. The Travel Liking variables played a primary role in shaping each of the other key measures (amounts, perceptions, and desires) across the category-specific structural models. Aside from the early work of Ramon (1981), the body of research from which this dissertation emerged marks the first time measures of Travel Liking have been captured and operationalized in models of travel behavior. That 21% of this sample “liked” or “strongly liked” the stereotypically-loathed travel category of commuting should not be ignored by the travel behavior research community – nor should the different OM→SM→RDM patterns that become apparent when segmenting the sample by the commute Travel Liking variable in *5.3 Travel Liking Market Segmentation*. The concept of a positive utility of travel should be accepted and further studied.

Table 9.1: Implications of Key Findings for Research and Travel Demand Management Strategies

Finding	**Research Implications**	**Travel Demand Management (TDM) Implications**
Objective Mobility $\rightarrow^{+}$ Subjective Mobility	There is a common understanding in the sample of how much travel is considered "a lot", across travel categories. More research is needed into how and why these commonalties exist and whether or not they can be manipulated.	Strategies that increase the awareness of travel amounts, such as congestion pricing, fuel taxes, "pay-as-you-go" automobile insurance, and other distance-sensitive pricing policies, have the potential to increase travel perceptions – not solely because of the cost per se, but additionally because of the enhanced salience of the amount of travel undertaken, and in particular by increasing the social undesirability of "excess" travel. This is important because, given the SM$\rightarrow^{+}$RDM relationship of the next row, increasing perceptions of the amount one travels could increase the desire to reduce one's travel.
Subjective Mobility $\rightarrow^{-}$ Relative Desired Mobility	While accepting the general OM$\rightarrow^{+}$SM relationship, it is important to understand the circumstances in which this relationship does not hold because travel perceptions (rather than amounts) are generally more important in shaping desires for more or less travel. Therefore, travel perceptions should be measured along with travel amounts.	Strategies targeting those with high travel amounts should focus more specifically on those who *perceive* their travel to be a lot, regardless of their actual amounts, because they are the ones who most want to reduce their travel.
Travel Liking $\rightarrow^{+}$ Relative Desired Mobility	Travel models should not uniformly impose the "derived demand" paradigm; travel does offer positive utility to certain individuals in certain situations. Further research is needed to better understand those individuals and those situations, and to assess implications such as how travel time (savings) is valued.	Strategies targeting those with high travel amounts should focus on the segment of that population that does not enjoy travel.

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