Title
The Impact of Transportation Infrastructure on the Value of Time

Author
Barrett, James

Publication Date
2010

UCTC-DISS-2010-03

The Impact of Transportation Infrastructure on the Value of Time

James Barrett
University of California, Davis
2010

The Impact of Transportation Infrastructure on the Value of Time

By

JAMES BARRETT
B.S. (Marquette University) 1982
M.S. (Marquette University) 1986

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

AGRICULTURAL AND RESOURCE ECONOMICS

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA DAVIS

Approved:

Dr. Douglas Larson (Chair)

Dr. Patricia Mokhtarian

Dr. Jeffrey Williams

Committee in Charge

2010

Acknowledgements

I would like to thank all those who have supported me in this effort. In particular I would like to thank my major professor Dr. Douglas Larson who has been instrumental by providing both theoretical and practical advice at nearly every turn. I especially wish to thank him for his patience. I know that this project has been stressful at times and Dr. Larson has been supportive from the start. I would also like to thank the other members of my committee including Dr. *Patricia* Mokhtarian and Dr. Jeffrey Williams who provided both and advice and encouragement.

I would also like to thank my family including my mother Mary Barrett, my sisters Mary and Kathy Barrett and my brother Patrick Barrett who provided both encouragement and aid. I never would have been able to accomplish this task without them.

In addition I would like to thank Gorm Kipperberg, Deborah Salon, Yuko Onozaka and the other fellow students at UC Davis who came to my aid when needed. Special thanks go to my friends who were always encouraging. In particular I want to thank Jim Duffy, Paul White, Jennifer Willis, Andy Jones, Matt Ziegler, Ningzi Sun, and Tangel Chang for their support and encouragement.

James Barrett
May 2010
Agriculture and Resource Economics

The Impact of Transportation Infrastructure on the Value of Time

Abstract

In this dissertation economic values time of are estimated as a function of public transportation infrastructure. These results provide insight into the value of improvements in transportation infrastructure that can be useful to policy-makers who need to consider the value of time saved when looking at the optimal allocation of transportation projects. This research contributes to our understanding of the value of time and in particular how the value of time is impacted by current levels of transportation infrastructure.

To analyze the value of time as a function of transportation infrastructure a combination of Geographical Information Systems (GIS), US census and survey data is employed. Empirical random utility maximization models in a mixed logit (MXL) framework are developed consistent with time and money-constrained choices. Both revealed preference (actual choice) and stated preference (hypothetical choice) models are analyzed.

The use of an internet based survey for this dissertation was especially important. In particular, the use of the internet based survey guaranteed that answers for questions related to time spent on various activities during the respondent's day added up to 24 hours. This ensured that the models of time developed in this study had a degree of accuracy that is much more difficult to achieve with other survey methods. In addition, the internet based survey made it possible to provide detailed instructions and examples that a respondent could view if she needed a fuller explanation of a particular question. Consequently, the survey employed in this study presented a complex set of questions that were easy for the respondent to answer.

Three communities are studied including the cities of San Francisco and Sacramento and Sonoma County in Northern California. Specifically, the value of time is modeled as a function of the currently available public transportation infrastructure. As such, the value of time is shown to vary between communities and within communities as a function of the level of transportation infrastructure in the immediate neighborhood of each individual's home. Using Contingent Valuation Methods (CVM), an economic welfare analysis shows that increases in levels of transit infrastructure have positive economic impacts that vary in relation to the current level of infrastructure.

Table of Contents

LIST OF TABLES

1 Introduction

1.1 Concept of time

“Time is an Ocean, but it ends at the shore.” - Bob Dylan

The idea of time and the derived notion of the value of time are elusive concepts that have concerned humanity for centuries. Over these centuries we have improved our ability to precisely and accurately measure time. At the same time we have become increasingly concerned with what and how much we can do during any particular time segment. This concern is reflected in commercial activities. In early history, time was measured in seasons, while farming was the dominant economic activity. Today time is routinely measured in nanoseconds, and economic value is often determined by how much can be accomplished in this much smaller increment of time. In the future, economic value may be limited only by Plank time, measured in increments of 10^{-43} seconds. What products are bought and sold to take advantage of this finer level of delineation is yet to be seen.

Each of us has some sense of how we value our time. A rational economic consumer or producer will evaluate the use of her or his time in terms of opportunity costs; sometimes exchanging labor for leisure and at other times choosing to work on the project due in 10 minutes, rather than the one due next week. Each of these tradeoffs implies that time spent in an activity has value and that time spent on one activity may be more valuable than other time spent doing an alternative activity. It is the need to get something done or the need to be somewhere at some point in time that imparts value to time. The more we try to do or need to do, the more we value time. Alternatively, the less demanding activities are on our time the less we value time. This is consistent with any constraint on utility or production. The shadow value of a constrained resource generally increases as the demand for the resource or the scarcity of the resource increases.

Ultimately our own time is finite. Consequently the resource of time is scarce and a worthy subject of economic analysis. In the standard economic model of consumption, a consumer maximizes her utility by consuming goods while constrained by a money budget. Extending this model to include constraints on time is now common in economic literature (Becker 1965, DeSerpa 1971, Hensher 2001, Larson 1993). In general these models have the perspective that utility, constrained by both money and time, is maximized by a rational consumer through the consumption of activities.

While similarities exist with all constraints on utility, there are some significant differences between the money and time constraints. Money is easily traded for any good or activity and consumers and producers can transfer money between each other. However, despite the common parlance that suggests that you can “give me a minute of your time” or that “I saved some time”, the transfer of time is not possible in the same manner as the transfer of money. One consumer cannot really give another consumer some of her time, nor can she save time in a bond or annuity redeemable at a later date. A consumer’s time is truly her own, and it will pass at a constant rate without regard to how she spends it.

However, the amount of time and money that individuals spend on any particular activity varies. These variations are partly determined by demographic characteristics such as age or number of children. These variations are also impacted by the levels of transportation services available, as this often facilitates the consumption of activities away from home.

The distribution of transportation infrastructure and services varies by geographical location. Those of us who live in a dense urban environment typically have many transportation options. Buses, light rail, intercity rail, the ubiquitous automobile and even walking or biking are available. Those who live in more suburban environments often have fewer choices. Suburbanites usually do not have the rail choices; buses are less frequent and more distant; and sidewalks are often absent. Residents of the less developed countryside see a transportation environment with a dearth of transportation services. There may be one or two buses per day; almost no sidewalks or bike lanes and a housing density low enough to generally preclude options such as carpooling.

This heterogeneous nature of the transportation environment seems likely to have a significant impact on a person's value of time. The greater the distance from work, schools, and other needs, the more time is required to reach these destinations. If transportation options are good, it may be relatively easy to get to all desired locations. On the other hand, if the transportation options are poor, it will be difficult and time consuming to get to destinations. Differences in transportation services are likely to result in differences in the trade-off between time and money and consequently in the value of time spent in transportation and other activities.

A consumer chooses her residence based on the values she places on the activities that are important in her life and the money and time prices of these activities. She will make decisions on how much she is willing to pay for housing and schools and how much time she is willing spend traveling to various locations. She will observe the available transportation services and given her value of time she will decide if she is willing to spend the time required for these activities. If the prices are wrong or if her value of time precludes living in a particular area she will opt to live somewhere else.

Yet once she has made her choice she is likely to stay in the same area for an extended period of time. Even though we live in a mobile society, the average time Americans reside at a particular address is still more than 6 years (US Census 2000). Once she has made her choices (signed a lease, put her children in school, and gotten to know her coworkers), she is not likely to move unless the situation becomes too onerous for comfort or an alternative is available in which the benefits outweigh the transaction costs associated with moving.

As such, we will live with the characteristics of our neighborhood for an extended period of time, often for years. If the population density grows and the roads and buses become more crowded, the original value of time that led an individual to choose a location could change. We may complain about the situation, lobby our local politicians, or modify our commute choices, but one is unlikely to move unless the situation becomes unbearable. Subsequently, even though people who live in an area may have originally moved there at different times and with different preferences, at any particular time all individuals in a region experience, broadly, the same level of transportation infrastructure.

Finally, the level of transportation services has an impact on all of a person's activities, not just their travel. A large amount of time spent commuting leaves less time for other activities. This suggests that the value of time spent in other activities may be higher or that people engage in fewer activities or spend less time spent in these activities in regions where transportation services are less available. Consequently, differences in peoples' values of time may be observable between areas which differ in the transportation amenities.

A decrease in the amount of time allocated to a particular activity can be seen as "saving time." A road improvement may allow a commuter to get to work in, say, ten fewer minutes than previously required. The ten minutes eliminated from her commute time can be spent on some other activity. In this sense, she "saved" time. She cannot put this time in the bank and use it tomorrow or next week, but she can do something during the actual 10 minutes that she no longer spends commuting. On the other hand, if the rest of her life has no other time constraints she could rearrange the remaining activities in the rest of her life and use the 10 minutes for any activity she wants. In general this won't occur since some other "obligation" will intervene, such as the need to be at work at 9:00 am that same morning. The work “requirement” will preclude rearranging of all of her activities. Consequently she is able to do some, but not all, activities during that particular 10 minute period. She could stop for a cup of coffee, make a phone call or “do nothing,” but she could not pick up her child from summer camp or eat in a Parisian restaurant (assuming she is not in Paris), since these would not be technically feasible.

1.2 General Framework

The topic of my dissertation is the economic effects of transportation infrastructure on the value of time. In particular, I compare models that demonstrate how the value of time is affected by the level of transportation infrastructure and services available to consumers. In addition, I examine the benefits of transportation policies in the context of these models.

The topic of this dissertation is especially relevant given the importance of transportation in everyday life. On average, Americans spend 300 hours per year, or 5% of their waking hours, engaged in transportation, and spend nearly one trillion dollars, more than 10% of GDP, on transportation-related activities (Bureau of Transportation Statistics, 2002). And even though transportation-related expenditures of time and money are at record levels, they continue to grow. Vehicle miles traveled (VMT) have increased in each of the last 20 years and this has led to increased congestion (United States Department of Transportation 2007). This increase in congestion is costly. A recent study by the Texas Transportation Institute estimates total congestion costs to be $78 billion per year. (TTI 2007)

This cost estimate of $78 billon assumes that the value of travel time is uniformly $14.60 per hour. This value does not account for any variations between communities or between individuals within a community. As such, a one hour reduction in congestion is valued at the same amount no matter where or for whom the reduction occurs. This is unlikely to true. In fact the TTI report warns; "Please do not place too much emphasis on small differences in the rankings. There may be little difference in congestion between areas ranked (for example) 6th and 12th. … The best congestion comparisons … are made between similar urban areas." (TTI 2007)

This study suggests that an accurate comparison between communities requires that the communities are similar. However, policy choices are often made in situations in which the impacted communities vary widely. This is particularly true for federal regulations or in the states, such as California, where the transportation environment and population is heterogeneous.

Ignoring these differences is likely to produce inaccurate estimates of the total costs and benefits that result from transportation changes, in particular those costs and benefits related to the value of time saved due to new construction or lost due to congestion. Also, studies generally report the value of time solely as a function of income (Train 1980, McFadden 1977). While it is clear that these values vary with income, ignoring other sources of heterogeneity may result in a less than adequate understanding of travel behavior by not capturing the impact of demographic characteristics: namely family size, work hour requirements and the availability of transportation options.

Individuals are likely to respond differently to changes in transportation infrastructure or services, in particular due to the effect of existing transportation services on the consumer's value of time. A similar-sized investment in transportation improvements might induce a different response from consumers who live in an area with a well-developed public transit infrastructure than it does from consumers who live in areas with poorly developed transit services. Subsequently, models that price time incorrectly or use 'correct' average values lack the robustness necessary to predict changes in behavior that result from changes in transportation services. The lack of delineation between various groups of travelers precludes policy instruments that could be targeted at different groups.

These considerations are particularly important since time saved from reduced congestion is often a reason for transportation investments. For example, Train (1980) and McFadden (1977) evaluated time spent in transportation as a justification for building the multibillion dollar San Francisco Bay Area Rapid Transit (BART) rail system.

Economic distortions that result from mispricing of time or an uneven distribution of benefits could lead to urban sprawl and other 'undesirable' effects. Given the magnitude of government investment and the subsequent effects on value of time and the urban environment, the problems associated with pricing time are potentially huge.

1.3 Dissertation objectives and contributions

The focus of this dissertation is to determine the impacts that public and private transportation infrastructure has on the value of time. I examine both actual choices (revealed preference) and hypothetical choices (stated preference) models to analyze these impacts.

Three different regions of Northern California were surveyed using a combination of an internet and paper based surveys. The three regions were chosen so that there would be variation in the levels of transportation infrastructure and amenities faced by the respondents. The three regions are the city of Sacramento, Sonoma County, and the city of San Francisco. San Francisco has the densest population and the greatest number of transportation services, whereas Sonoma County has the lowest population density and the smallest number of transportation services among the three regions. The value of time is calculated from models of commute mode choice in each of the three areas and compared across regions, while accounting for the effects of demographic characteristics, transportation infrastructure, and prices and budget levels, to allow for potential changes of the value of time with these.

The use of an internet based survey for this dissertation was especially important. In particular, the use of the internet based survey guaranteed that answers for questions related to time spent on various activities during the respondent's day added up to 24 hours. This ensured that the models of time developed in this study had a degree of accuracy that is much more difficult to achieve with other survey methods. In addition, the internet based survey made it possible to provide detailed instructions and examples that a respondent could view if she needed a fuller explanation of a particular question. Consequently, the survey employed in this study presented a complex set of questions that were easy for the respondent to answer.

1.4 Outline of the Dissertation:

The remainder of the dissertation is organized as follows:

Chapter 2 presents the theoretical framework for this study, including the implications of two-constraint models of consumer choice in general, the addition of variables to reflect the impacts of transportation infrastructure and demographics, and the basis for incorporating budget variables (i.e., prices and budget levels) in the models. Finally, the conditional indirect utility specification that reflects transportation, demographics, prices, and budget levels is incorporated into random utility models to facilitate empirical estimation.

Chapter 3 describes in detail the data collected for this study. The data sources include geographic information services (GIS) data that describes the transportation environment in three communities of Northern California (Sacramento, San Francisco and Sonoma county), census data that was used to determine values for choice experiments, and the household survey data collected. The combination of these three data sources is a particular strength of this study, particularly the use of two methods (internet and mail surveys) in gathering the survey data.

Chapter 4 provides the study's empirical results, including comparisons of models using mail versus internet data, actual choices (revealed preference) versus hypothetical choices (stated preference) data, and highlighting differences between the 3 communities. The impact of several transportation infrastructure variables (bus stop density, light rail density, road density, and the frequency of stops for public transportation options) is examined. In addition, the effects of various demographic characteristics, prices, and budget levels are investigated.

Chapter 5 illustrates the use of the commute mode choice model for policy evaluation, examining the welfare effects resulting from improvements in transportation infrastructure. Two types of improvements are considered: first, an increase in the number of stops on an existing bus line, and second, the introduction of a new commute mode. Chapter 6 concludes the dissertation with a summary of the main findings and limitations that must be attached to them.

2 Two-Constraint Activity Demand Models in Transportation

2.1 Introduction

In conventional consumer theory, the consumer's goal is to maximize utility through the consumption of utility-enhancing goods and services while constrained by a money budget. However, there is a rich literature in economics that goes beyond the single-constraint model; the most common applications recognize that consumers are constrained by both money and time[i]. In these models the consumer's utility-enhancing behavior is typically the consumption of "activities" that include not only the goods and services of conventional consumer theory, but also activities that require time but no money, money but no time, or a combination of both time and money.[ii] This dissertation analyzes two-constraint utility models with special attention paid to transportation activities.

Economic models that include time constraints typically have a single time constraint (Becker 1965. This specification has been the dominant perspective for the last three decades. Larson et al. (2004) state that "Essentially all the empirical models in use today that consider time as a constraint on choice in a utility-theoretic framework postulate a single time constraint, which implies a single value of time applicable to leisure (i.e., non-work) time." This approach is particularly attractive due to its simplicity. Although an individual's time can be broken up in to blocks of time that can result in more than one value of time, this dissertation examines simpler models that include only a single time constraint, consistent with the empirical focus on transportation infrastructure, commute mode choice, and the resulting implications for consumers' values of time.

In order to facilitate the discussion of the shadow value(s) of time, a series of utility theoretic models is introduced. Each of these models is designed to illustrate a set of principles and each recognizes the importance of time and money constraints on activities and consequently each follows the tradition of Becker's household production function (Becker, 1965). Special attention is paid to transportation activities recognizing the important role transportation in our lives, particularly in relation to the trade-off of time and money.

2.2 Literature Review

The major issues covered in this review are: modeling the value of time as it relates to a person's wage rate; recognizing the impact of mode choice and demographics on the value of time; and the evolution of model functional forms.

2.2.1 Values of time

Studies related to the value of time exist in several different literatures. In particular, studies of recreation demand and transportation mode choices are replete with analysis of the value of time.

There has been some theoretical work in the recreation demand literature specifying the shadow value of time (SVT), including *Bockstael* et al. (1987), Larson and Shaikh (2004) and McConnell (1992). Empirical studies have primarily determined values of time by assuming it is a linear function of the wage rate. Becker (1965) modeled the value of time as equal to the wage rate. Cesario (1976) and Beesley (1965) estimate the value of time saved in commuting to work at between one quarter and one half of the wage rate.

In the empirical recreation demand literature, several studies treat the SVT as the wage rate, including Cameron et al. (1996), Parsons and Hauber (1998), and Smith and Kaoru (1990). Most studies assume the SVT is a fraction of the wage rate, generally between one quarter and one half of the wage, including Brown and Mendelsohn (1984), Caulkins et al. (1985), Eom and Larson (2006), Parsons and Kealey (1995), Phaneuf et al. (2000) and Train (1998). And some studies simply don't model the role of time in recreation, assuming that the value of time is zero (e.g., Vaughn and Russell 1982; Bell and Leeworthy 1990; and Beal 1995).

The value of time is particularly important in transportation studies, where the value of time saved is a major justification for the construction of new transportation infrastructure. For example, Train (1980) and McFadden (1977) used discrete choice methods to evaluate time spent in transportation. These studies were used to justify the building of the multibillion dollar San Francisco Bay Area Rapid Transit (BART) rail system.

A significant percentage of studies present the value of time spent in travel as a percentage of the wage rate. Zamparini and Reggiani (2007) state that "Most of the studies conducted before 1995 expressed VTTS (Value of Travel Time Savings) as a percentage of the wage rate while most of the studies conducted since 1995 provided a monetary value for VTTS." This transition is likely related to increased computing power, which permit estimation of more complex models that allow for a variety of sources of heterogeneity within a population. Values expressed as a percentage of wage rate can vary by geographical region and by the transportation mode studied.

European studies[1] deduced values of time that are from a low of 13% of the wage rate to a high of 345% of the wage rate. North American studies[2] deduced values of time from a low of 13% to a high of 170% of the wage rate. Studies that have produced monetary values of time that are not explicitly tied to the individual's wage[3] derive values of time from $4.00 per hour to $22.00 per hour.

---

[1] These including EURET, 1994; Algers, 1996; Hansen, 1970; Ramjerdi et al., 1997; Dawson and Smith, 1959; Beesley,1965; Quarmby, 1967; Stopher, 1968; Lee and Dalvi, 1969; Dalvi and Lee, 1971; Wabe, 1971; Ghosh et al., 1975; MVA et al., 1987; Bates, 1987; Polak et al. , 1993; Gunn et al. ,1996; Atkins, 1994; Wardman and Mackie, 1997; HCG, 1998; PLANCO and Heusch-Boesefeldt, 1991; BMW, 1994; Transprice, 1997.

[2] Iincluding McFadden, 1977; Train and McFadden, 1978; Train, 1980; Mohring, 1961: Claffey, 1961: Becker, 1965: Lisco, 1967; Thomas, 1967; Oort, 1969; Thomas and Thompson, 1970; Talvittie, 1972; McFadden and Reid, 1975; McDonald, 1975; Guttman, 1975; Nelson, 1977; Chui and McFarland, 1985; Deacon and Sonstelie, 1985; Chui and McFarland, 1987; Cole Sherman, 1990.

[3] Leurent (1998), Algers et al. (1998), Hensher (1996), Calfee and Winston (1998), Ghosh (2000a), Sullivan (2000), Small and Sullivan (2001), Hultkrantz and Mortazavi (2001).

2.2.2 Impact of mode choice and demographics on the value of time

Various studies suggest that the value time is dependent on mode choice and other characteristics of travel. Some[4] derived values for commuting by car. Others[5] looked at values of time associated with car use other than for commuting. McFadden (1977), Train and McFadden (1978), Train (1980), Algers et al. (1996), Ramjerdi et al. (1997), and HCG (1998) look at values associated with riding the bus, and McFadden (1977), Train and McFadden (1978), Train (1980) Algers et al. (1996), Ramjerdi et al. (1997), Wabe (1971), HCG (1998) look at values associated with riding the train or light rail.

DeSerpa (1971) deduces different values of time for different transportation modes and components of a trip. . Beesley (1973) recognized the heterogeneity of the values of travel time for various travel segments including wait-time, walking-time and in-vehicle-time. Heckman (1974) shows that the unemployed value time and that household size and other demographic factors

---

[4] For example, (McFadden (1977), Train and McFadden (1978), Train (1980), Algers et al. (1996), Hansen (1970), Ramjerdi et al. (1997), Beesley (1965), Quarmby (1967), Stopher (1968), Lee and Dalvi (1969), Dalvi and Lee (1971), Bates (1987),Polak et al. (1993), MVA et al. (1987), Gunn et al. (1996), PLANCO and Heusch- Boesefeldt (1991), BMW (1994), HCG (1998),Wardman and Mackie (1997), Atkins (1994), Mohring (1961), Becker (1965), Lisco (1967), Thomas (1967), Oort (1969), Talvittie (1972), McFadden and Reid (1975), McDonald (1975), Guttman (1975), Cole Sherman (1990), Nelson (1977), Calfee et al. (1998), Lam and Small (2001) and Nakamura (2002)

[5] Claffey (1961), Thomas and Thompson (1970), Guttman (1975), Chui and McFarland (1985), Deacon and Sonstelie (1985), Chui and McFarland (1987), Cole Sherman (1990), Ghosh et al. (1975), BMW (1994), MVA et al. (1987), Bates (1987), Polak et al. (1993), Atkins (1994), Wardman and Mackie (1997), HCG (1998), Dawson and Smith (1959), Algers et al. (1996).

are important in determining values of time. McFadden (1977) delineates between wait time and in-vehicle time. Train (1980) shows significant differences in the value of time for auto and transit on-vehicle time, walk time, and transfer wait time. Hensher (2001) distinguishes between in-vehicle time, out of vehicle time, free flow time, slowed down time and stop/start time. Lam and Small (2001) separate the value of commute time from the value of the reliability of commute time, showing that expectations and gender are important in the value of time. Nakamura (2002) look at travel time and congested time as separate values.

McFadden (1977) shows that socioeconomic variables, in addition to transportation system attributes, (such as travel times and costs), improve the overall fit of his Multinomial Logit (MNL) model. Train (1980) distinguishes between commuters who drive alone and in car pools, those who use the bus and the BART. Additionally, Train (1980) distinguishes between transit, car, walk, and wait time. He suggests that previous studies that fail to decompose time spent out of vehicle lose the ability to design policies that may distinguish between these components.

Kitimura, Mokhtarian and Laidet (1997) find that land use, residential density, the presence of sidewalks, parking, and public transit accessibility are correlated with mode choice and the number of trips taken. Cervero (2002) examines mode choice as a function of land use. Castiglione et al. (2003) looked at mode choice segmented on household size and car availability. EXPEDITE (2002) analyzed mode–destination choice travel purpose. Jara-Dı´az (2001) concluded that the value of time in leisure and work activities is not equal.

Gupta et al. (2004) and Kalmanje and Kockelman (2004) looked at mode, destination and departure time choice and trip purpose. Koopmans and Kroes (2004) and De Raad (2004) analyzed mode, destination and departure time choice and travel purpose. Odeck et al. (2003) analyzed mode–departure time choice and trip purpose. USDoT (2004) looked at mode choice segmented on income and worker categories. Li (2003) measured differences in the value of time for perceived travel time versus actual travel time. Small et al. (2005) analyzed the value of time as a function of type of trip, travel conditions, and traveler preferences.

Cohan H and Southworth F (1999), Hollander Y (2006), Small K et al. (1999), Schweitzer LA, et al. (1998), Liu H, Recker W and Chen A (2004), and Batley, et al. (2008)found that the value of time increases with the uncertainty of travel time.

Several papers (including Young and Morris, 1981; Salomon and Mokhtarian, 1998; Richardson, 2003; Redmond and Mokhtarian, 2001; Mokhtarian and Salomon, 2001; and Sipress, 1999) suggest that the purpose of travel has an impact on the value of time to the point where the value (cost) of time in a particular activity is negative so that the consumer would actually prefer more time in the activity.

2.2.3 The evolution of model functional forms

By far the most common type of model used in transportation studies that look at the value of time is Random utility models. The original Random Utility Models (RUM) were based on the multinomial logit (MNL) model developed by McFadden (1974, 1978, 1981). This model, and most others that have followed, assume conditional indirect utility is linear in both parameters, and the limitations of early models regarding restrictions they impose on preferences has been addressed by generalizing the error structure of the model.

The simple MNL is limited due assumptions regarding the substitution patterns across alternatives[6] as well as the inability to model taste heterogeneity across subjects. The MNL model was used in the early work of in the study of the San Francisco Bay Area Rapid Transit (BART). Among the studies that employ RUMs are: Algers et al. (1998), Hensher (2001a,b,c), Lapparent and de Palma (2002), Cherchi and Ortuzar (2003), Jara-Diaz and Guevara (2003), Perez et al.(2003), Cirillo and Axhausen (2004).

The development of the family of Generalized Extreme Value (GEV) models, in particular the nested logit (NL), solved the first of these two problems. The NL was used in studies by (Williams, 1977); (Daly and Zachary, 1979) and (McFadden, 1978).

Other studies have used variations on the logit and probit models. Leurent (1998) used a binary logit model, Hensher (1996) used a heteroskedastic logit, and Hultkrantz and Mortazavi (2001) used probit models. Multinomial probit (MNP) models were used by Daganzo (1979).

The development of Random Parameter Logit (RPL) or Mixed Multinomial Logit (MMNL) solved the second problem and can model taste heterogeneity

[6] This is due to the IIA, Independence of Irrelevant Alternatives, property that is built into the structure of choice probabilities. This means that the relative probabilities of any two alternatives are independent of all others.

across subjects. Originally developed by Boyd and Mellman (1980), the RPL allows for the specification of coefficients that are randomly distributed across consumers. These models have become more common since 1995. This has much to do with increased computing power. Before the increased computing power that came in the last 2 decades the computational power required to run these models was unavailable.

Bhat (1997), McFadden and Train,(1997), Revelt and Train (1999), Train (1997, 1999), and Bhat (2000) are some of the many studies that utilize variations of RPL model in their studies of transportation and values of time associated with transportation choice. The power of the RLP was demonstrated by McFadden and Train (2000), who showed that the RPL can approximate any RUM

2.3 General Model

The consumer's choice problem used in this dissertation focuses on a subset of the activities consumers engage in, and thus is framed as an incomplete demand system. The activities of interest are denoted by the K-dimensional vector **a**, and the consumer may also choose labor supply (hours worked, h) jointly with **a**. **T**he consumer's choice of **a** and h can be represented by the Lagrangian

$$(2\text{-}1)\quad £ = \mathrm{U}(\mathrm{a}, \mathrm{h}, \mathrm{s}, \mathrm{q}) + \lambda[\mathrm{E} + \mathrm{w}\cdot\mathrm{h} - \mathbf{p}\cdot\mathbf{a} - z_M] + \mu[\,Ŧ - \mathrm{h} - \mathbf{t}\cdot\mathbf{a} - z_T]$$

where U(**a**,h,**s,q**) is a continuous, twice-differentiable quasi-concave utility function; the activity quantities (a_k, k = 1,…,K) have parametric money prices p_k and time prices $\mathbf{t}_k$; **q** is a r- dimensional vector of quality characteristics for the activities**;** λ and μ are Lagrange multipliers; E is the consumer's nonwage income; Ŧ is her total time budget; **s** is a vector of individual-specific shift factors; and z_M and z_T are numeraire goods representing expenditures of money and time, respectively, on goods outside the incomplete demand system.[iii] Income and prices are expressed in units of the money numeraire good (e.g., dollars) and time is expressed in units of the time numeraire good (e.g., hours or minutes).

2.3.1 First order conditions and the shadow value of time function.

The first order conditions for an interior solution to (2-1) are:

(2–5) $$\frac{\partial £}{\partial a_k} = \frac{\partial \text{U}}{\partial a_k} - \lambda \cdot p_k - \mu \cdot t_k$$

for k = 1, …, K (activity choices)

(2-6) $$\frac{\partial £}{\partial h} = \frac{\partial \text{U}}{\partial h} - \mu \cdot t_k - \lambda \cdot w = 0$$ (labor supply)

(2-7) $$\frac{\partial £}{\partial Z_T} = \frac{\partial \text{U}}{\partial Z_T} - \mu = 0$$

(2-8) $$\frac{\partial £}{\partial Z_M} = \frac{\partial \text{U}}{\partial Z_M} - \lambda = 0$$

Equations (2-5) and (2-6) explain the activity choices and labor supply, respectively, while equations (2-7) and (2-8) explain the determination of the shadow value of time, ρ. In particular, the marginal utility of time, μ, is the marginal (direct) utility of the time numeraire good, (i.e., $\mu = \partial U/\partial z_T$) and the marginal utility of money, λ, is the marginal utility of the money numeraire (λ =

$\partial U/\partial z_M$). Given preference non-satiation, the money budget constraint is binding, so that $\lambda > 0$, and the shadow value of time is

(2-9) $$\rho = \mu/\lambda,$$

which is the shadow value or opportunity cost of time in units of income. In addition, the time constraint is assumed to be strictly binding, so that $\mu > 0$, since this is far more likely than the alternative ($\mu = 0$) to reflect the reality of most people's lives, and is the only interesting case in any event.[iv]

Using the expressions for μ and λ, it can be seen that the shadow value of time is the ration of the marginal utilities of the numeraire goods in the time and money constraints.

Dividing equations (2-5) and (2-6) by λ and rearranging slightly, intuitive expressions for the activity choices and labor supply result. They are

(2–5') $$\mathrm{MV_k} = p_k + \rho \cdot t_k = 0$$

for k = 1, …, K (activity choices)

(2-6') $$\mathrm{MV_h} + w = \rho$$ (labor supply)

where $MV_k \equiv (\partial U/\partial a_k)/\lambda$ is the marginal value of activity k, and $MV_h \equiv (\partial U/\partial h)/\lambda$ is the marginal value of work.

Equation (2-5') says that an individual engages in each of the activities to the point where the marginal money value of each activity (left side) is equal to the full cost of the activity, i.e., the money price plus the shadow value (opportunity cost) of the time spent in the activity. Equation (2-6') indicates that the optimal hours decision is to equate the marginal value of work time, which consists of both the wage received and the monetized utility or disutility from working, to the opportunity cost of the time spent working.

When work is utility neutral (i.e., $MV_h = 0$), such that work provides no positive or negative utility other than the utility gained from the income earned, and the individual can freely chose her number if work hours, it follows that $\rho = w$. If $MV_h > 0$ then at the optimum hours worked, the wage received is less than the opportunity cost of time. Conversely, if $MV_h < 0$, then the wage received exceeds the opportunity cost of the time spent, in compensation for the fact that the job itself is unpleasant.

The most realistic cases are when work is not utility neutral, so the opportunity cost of time is not identified by the single parameter w (i.e., $\rho \neq w$). In general, ρ, being the ratio of two choice variables of the problem, depends on the parameters of the problem, and is written as

(2-9')

$$\rho(\mathbf{p}, \mathbf{t}, \mathrm{w}, \mathrm{E}, \mathrm{Ŧ}, \mathbf{s}, \mathbf{q}) = \mu(\mathbf{p}, \mathbf{t}, \mathrm{w}, \mathrm{E}, \mathrm{Ŧ}, \mathbf{s}, \mathbf{q}) \,/\, \lambda(\mathbf{p}, \mathbf{t}, \mathrm{w}, \mathrm{E}, \mathrm{Ŧ}, \mathbf{s}, \mathbf{q})$$

It is the dependence on these parameters that is relevant to this dissertation. Unlike most other treatments in the literature, the value of time for individuals is not restricted to be equal to the wage rate or a fraction thereof, as is the case in most transportation mode choice and recreation demand studies.

While the model in (2-1) includes labor supply chosen jointly with other activities, in this study labor supply is not modeled, and in addition we place focus on the consumer's choice of commute mode as it is influenced by the level of transportation infrastructure and their other characteristics. To reflect this, at this point two changes are made to the general formulation in (2-1). First, the labor supply decision is taken as given, which results in an exogenous money income M ≡ E + w · h and non-work discretionary time T ≡ Ŧ – h.

Then equation (2-1) can be rewritten as

(2-1') $$\mathrm{U}(\mathbf{a}, \mathrm{h}, \mathbf{s}, \mathbf{q}) + \lambda[\mathrm{M} - \mathbf{p} \cdot \mathbf{a} - \mathrm{Z_M}\ ] + \mu[\mathrm{T} - \mathbf{t} \cdot \mathbf{a} - \mathrm{Z_T}]$$

With these changes, the consumer's problem solves for the system of demands for activities,

(2-10) $$a_k\ = a_k\ (\mathbf{p}, \mathbf{t}, \mathrm{M}, \mathrm{T}, \mathbf{q}, \mathbf{s})\ \text{ for k = 1,…, K}$$

and the accompanying numeraire goods

(2-11) $$\mathrm{Z_T} = \mathrm{Z_T}(\mathbf{p}, \mathbf{t}, \mathrm{M}, \mathrm{T}, \mathbf{q}, \mathbf{s}) = \mathrm{T} - \mathbf{t} \cdot \mathbf{a}(\mathbf{p}, \mathbf{t}, \mathrm{M}, \mathrm{T}, \mathbf{q}, \mathbf{s})$$

and

(2-12) $$\mathrm{Z_M} = \mathrm{Z_M}(\mathbf{p}, \mathbf{t}, \mathrm{M}, \mathrm{T}, \mathbf{q}, \mathbf{s}) = \mathrm{M} - \mathbf{p} \cdot \mathbf{a}(\mathbf{p}, \mathbf{t}, \mathrm{M}, \mathrm{T}, \mathbf{q}, \mathbf{s})$$

Equation (2-1') can then be written as

(2-13)
$$U(\mathbf{a}(\mathbf{p},\mathbf{t},\mathrm{M},\mathrm{T},\mathbf{q},\mathbf{s}),\mathrm{h},\mathbf{s},\mathbf{q})$$

$$+\,\lambda[\mathrm{M}-\mathbf{p}\cdot\mathbf{a}(\mathbf{p},\mathbf{t},\mathrm{M},\mathrm{T},\mathbf{q},\mathbf{s})-\ \mathrm{Z_M}(\mathbf{p},\mathbf{t},\mathrm{M},\mathrm{T},\mathbf{q},\mathbf{s})]$$

$$+\,\mu[\mathrm{T}-\mathbf{t}\cdot\mathbf{a}(\mathbf{p},\mathbf{t},\mathrm{M},\mathrm{T},\mathbf{q},\mathbf{s})\ -\ \mathrm{Z_T}(\mathbf{p},\mathbf{t},\mathrm{M},\mathrm{T},\mathbf{q},\mathbf{s})]$$

which yields the indirect utility function:

(2-14)
$$V(\mathbf{p},\mathbf{t},\mathrm{M},\mathrm{T},\mathbf{q},\mathbf{s})\equiv\ max_a\,(\mathbf{a}(\cdot),\mathbf{s},\mathbf{q})$$

$$+\,\lambda[\mathrm{M}-\mathbf{p}\cdot\mathbf{a}(\cdot)-\ \mathrm{Z_M}(\cdot)]$$

$$+\ \mu[\mathrm{T}-\mathbf{t}\cdot\mathbf{a}(\cdot)-\ \mathrm{Z_T}(\cdot)]$$

Where $(\cdot)$ designates the arguments of the demand function $(\mathbf{p}, \mathbf{t}, \mathrm{M}, \mathrm{T}, \mathbf{q}, \mathbf{s})$

2.3.2 Comparative Statics

Applying the envelope theorem to (2-14) yields the following relationships for changes in the budget variables:

(2-15) $$V_M \equiv \frac{\partial V}{\partial M} = \lambda(\cdot)$$

(2-16) $$V_T \equiv \frac{\partial V}{\partial T} = \mu(\cdot)$$

And for each of the K activities

(2-17) $$V_{p_k} \equiv \frac{\partial V}{\partial p_k} = -\lambda(\cdot) \cdot a_k(\cdot)$$

(2-18) $$V_{t_k} \equiv \frac{\partial V}{\partial t_k} = -\mu(\cdot) \cdot a_k(\cdot)$$

Equations (2-15) and (2-16) state that an increase in money income or non-work time will increase utility, and increases in either the money or time prices of activities will decrease utility. In particular, for workers who work outside the home the k^{th} activity can be the commute to work. So that for the commute activity equations (2-17) and (2-18) imply that an increase in the money cost or length of time in the consumer’s commute will decrease utility. This is as expected since any increase in the price of commuting will leave less money for other utility enhancing activities.

Other properties of the primal problem in (2-14), such as homogeneity of activity demands, numeraire goods, and the shadow value of time with respect to changes in prices and budget levels have been derived by Larson (2004). The two dual minimum expenditure functions corresponding to (2-1) are introduced by Larson and Shaikh (2004) and their properties are similarly analyzed.

The results from this simple model illustrate a few important principles. In particular, changes in transportation infrastructure that affect either the cost or length of the commute have clearly predictable signs. Changes that go in opposite directions, such as an increase in money cost along with a decrease in commute time (or vice-versa) caused by a change in transportation infrastructure, will result in an ambiguous change to overall utility.

2.3.3 The Opportunity Cost of Time

It is common in transportation mode choice models to deduce a value of time for each mode choice (Train 1977, Train 1978, McFadden 1980), using discrete choice models. (Train 2003) describes this methodology. In the study of the proposed Bay Area Rapid Transit (BART) system, they estimated a single coefficient for cost divided by the post-tax wage equal to -0.0284 and coefficients for auto in-vehicle time (-0.0284), transit on-vehicle time (-0.0644) and additional coefficients for walk time and transfer wait time. The utility for activity j is then for an individual (with the subscript for the individual omitted) is: $U_j = \lambda_j \cdot p_j / w + \mu_j \cdot t_j$ where w is the wage rate for the individual. The total derivative with respect to time and is: $dU_j = \lambda_j / w \cdot dp_j + \mu_j \cdot dt_j$ which is then set to zero and solved for dp_j/dt_j to to find the change in price that keeps utility constant with a change in time. As such $dp_j/dt_j = (\lambda_j/\mu_j) \cdot w$ for each activity j. Consequently, the value of time for riding the bus = -0.0259/-0.0284 = 91% of the wage rate and the value of time for driving a car = -0.0644/-0.0284 = 227% of the wage rate. As such this method distinguishes separate values of time for each of the activities associated with commuting.

In contrast, the models in this dissertation estimate a single value of time for each individual. This value is the opportunity cost of time for the commute activity and there is no distinction made for a particular transportation mode.

2.4 Transportation and Demographic Variables

One contribution of this dissertation is to empirically analyze the structure of the value of time (ρ) with respect to the consumer's budget parameters, demographics, and available transportation infrastructure. Typically transportation studies deduce one value of time for the population studied, or at best values that vary by mode choice that are a function of normalized money price. The models in this dissertation model the marginal utility of money (λ), the marginal of time (μ), and subsequently the value of time (ρ) as functions of demographic and transportation variable.

The rationale for incorporating these variables into the value of time function is the expectation that variations in demographic characteristics such as gender, age, marriage, number of children and income are likely to have an impact on the consumer's utility function, as well as the time and money constraints on utility. Additionally, transportation is seen as a particularly important activity relative to the value of time. Many activities require transportation; consequently, variations in the availability of transportation infrastructure are likely to impact our ability to engage in utility-enhancing activities as well as our time and money budgets. The demographics and transportation characteristics are both represented by elements of the vector of preference shifters **s**.

Given that both the marginal utility of money and of time may be affected by transportation infrastructure, both the numerator and denominator of the shadow value of time can change as infrastructure changes. Writing $\rho(\mathbf{p},\mathbf{t},M,T,\mathbf{q},\mathbf{s}) \equiv \rho(\cdot,\mathbf{s})$ to simplify notation for this purpose, the effect of a change in the k^{th} infrastructure characteristic (s_k) on the shadow value of time is

(2-19) $$\frac{\left[\frac{\partial \rho(\cdot,s)}{\partial s_k}\right]}{\rho} = \frac{\left[\frac{\partial \mu(\cdot,s)}{\partial s_k}\right]}{\mu} - \frac{\left[\frac{\partial \lambda(\cdot,s)}{\partial s_k}\right]}{\lambda}$$

That is, the percentage change in the shadow value of time with the characteristic is the difference between the percentage changes in the marginal utility of time and the marginal utility of money that it causes.

In words, an increase in a transportation amenity or its level of service, such as bus stop density within a quarter mile of home, will increase the value of the consumer's time if the resulting percentage change in the marginal utility of time is greater than the percentage change in the marginal utility of money, and will decrease it otherwise.

Specifically, the transportation infrastructure variables (**TRANS**) that are examined in this research are:

BD - Density of bus stops in neighborhood of home location.

BF- Frequency of bus stops in neighborhood of home location.

RD- Density of roads in neighborhood of home location.

LD- Density of light rail stops in neighborhood of home location.

LF- Frquency of light rail stops in neighborhood of home location.

2.5 Empirical Functional Form for the Shadow Value of Time

In general, the shift variable **s** can have any effect on the value of time. This is not the case for the budget variables (prices and incomes in each constraint). The presence of two constraints on the consumer choice problem introduces additional structure on the choice functions, both for activities and for the shadow value of time. This additional structure was identified in Larson and Shaikh (2001) for the activity levels, and in Larson and Shaikh (2004) for the shadow value of time. This has led to the identification of structural relationships between the activity demands conditional on the shadow value of time, and the shadow value of time conditional on activity demands, that can be estimated econometrically.

The implications of the two- (or, more generally, multiple-) constraint structure for the functional forms for for activity demands conditional on the shadow value of time were set out in Larson and Shaikh (2001) and Hanemann (2004). It wasn't until more recently (Larson, 2009) that a functional form for the shadow value of time conditional on activity demands that meets the two-constraint requirements was identified.

The implications of these papers for specification of the econometric structure in this research is as follows. If both the conditional shadow value of time and the conditional activity demands are functions of *all* budget parameters (and, in particular, the time and money prices of all activities) in the incomplete demand system, a shadow value of time that is a function of the two numeraires is sufficient; i.e., a shadow value of time of the form

(2-20) $$\rho = f(Z_M, Z_T) = f(M - \mathbf{p} \cdot \mathbf{a}, T - \boldsymbol{t} \cdot \boldsymbol{a})$$

is sufficient to satisfy the two-constraint requirements. If, as may be more likely, the conditional shadow value of time is specified as a function of one subset of the incomplete demand parameters, and the conditional activity demands are specified as functions of another subset of these parameters, then a more specific functional form for the conditional shadow value of time is required; viz.,

(2-21) $$\rho = [\mu_0(s,q) + B(s,q) \cdot Z_M]/[\lambda_0(s,q) + B(s,q) \cdot Z_M]$$

will satisfy the two-, or (with notation appropriately adjusted), multiple-constraint requirements on both conditional activity demands and conditional shadow values of time. The conditional indirect utility which generates the shadow value in equation (2-21) is developed below in the discussion of functional forms for conditional indirect utility..

The term B(s,q), which is referred to hereafter as the full budget parameter, allows the conditional shadow value of time to vary with changes in budget variables (i.e., time and money prices of commute modes, and the time and money budgets available) in a theoretically-consistent manner, through the numeraires z_M and z_T. When B(s,q)=0, the conditional shadow value of time does not depend on budget parameters, but may (based on the empirical results in specific applications) depend on demographics and transportation infrastructure, since the resulting functional form is

(2-22) $$\rho = \mu_0(s,q)/\lambda_0\,(s,q)$$

In this case, as well as the more general case, the value of time varies across individuals.

Equation (2-22) is somewhat more general than most shadow value of time specifications in the transportation literature, because of its variation with demographics and transportation variables. This in turn is a special case of the specification in equation (2-22), which additionally allows the shadow value of time to vary systematically with money income (perhaps the most interesting of the budget variables in this context).

2.6 Developing a Model of Commute Mode Choice

Consumers typically have more than one commute mode available. The modes typically differ in terms of their time and money requirements. If an alternative is sufficiently unattractive, in the sense that the time or money price of this option cause it not to be chosen by the consumer, then a small decrease in price for the alternative, or a small increase in the price of the current *status quo* mode, are not likely to induce a mode shift. For instance, if the two options available are car and walking with p_{car} = \$5, t_{car} = 20 minutes, p_{walk} = \$0 and t_{walk} = 120 minutes; an increase in the time price of the car from 20 to 21 minutes is unlikely to induce a mode shift. From another perspective, individuals who are presented with alternatives with very large differences in time prices (or money prices) are likely behave as if they live in a world with only one alternative; a population faced with more than one alternative, in which one alternative requires an inordinate amount of time (money) will be willing to pay all money (time) prices offered in the market for the other alternative. This should result in an insignificant value for λ (μ).

The availability of multiple transportation mode options adds an additional level of complexity to the model. Most people have a “favorite” mode of transportation, given that most consumers in the United States routinely choose the car as their sole mode of transportation (TTI, 2007). However, in some regions, there a greater reliance on public transit, walking and bicycle riding. In addition to population density, geographical and climatic conditions other factors including the level of available transportation amenities such as the number of roads, bus stops and rail stops, and the frequency of busses and light rail have an impact on the consumer's choices. With this in mind, the models are now extended to include more than one choice of transportation.

This dissertation looks specifically at the activity of commuting to and from work. Consider an individual who commutes to work and has a fixed schedule. In addition, assume that the individual has more than one commute mode alternative available. Assume, for simplicity in exposition at this point, that there are 2 alternatives for the commute and that each of these alternatives is utility neutral. As such, the any impact on utility results from the effect that the mode choice has on the time and money budgets. Without loss of generality, label the two alternatives such that alternative 1 has a high money price and a low time price and alternative 2 has a low money price and a high time price. (If were otherwise, i.e., where one of the choices dominated by having both a low time and low money price, that option would always be chosen.)

This type of problem involves discrete choices between regimes that have distinct time and money costs, which is naturally addressed within the discrete choice framework. The next section discusses this class of models, as they apply to the research in this dissertation.

2.7 Random Utility Models

2.7.1 Introduction

The researcher is not able to observe the consumer's actual utility; he is able to observe the decisions the consumer makes, some of her attributes and some of the attributes of the alternatives she faces. Random utility models (RUMs), pioneered by McFadden (1975), are now commonly used to model the behavior of the consumer in situations when the choices are discrete. These models assume that a decision maker gets utility from each of a number of discrete alternatives that can be chosen, based on both characteristics that are observable to the outside researcher (the deterministic components) and those which are not (the stochastic components). To introduce this type of modeling, let the conditional indirect utility for a particular discrete choice j by an individual (suppressing the individual index) be

(2-23) $$V_j = U_j + \varepsilon_j$$

Where U_j are the observable components of utility and ε_j are the unobservable components of mode choice j. The individual then makes her choice of alternative j over all inferior alternatives k $\neq$ j such that

(2-24) $$V_j > V_k \; \forall_k \; k \neq j$$

which means that

(2-25) $$U_j - U_k > \varepsilon_k - \varepsilon_j$$

That is, the option with the highest utility is chosen.

McFadden (1973) that if the disturbances across all the alternatives are independent and identically distributed, as a Weibull distribution or type I extreme value, with cumulative distribution

(2-26) $$F(\varepsilon_j) = \exp(\exp(-\varepsilon_j))$$

the probability of choosing alternative j is

(2-29) $$\mathrm{p_j} = \exp(\mathrm{U_j}) \,/\, \textstyle\sum_{\mathrm{k}} \exp(\mathrm{U_k})\ \forall_{\mathrm{j}} \quad \mathrm{k} = 1, \ldots, \mathrm{J}$$

McFadden also developed a nested logit version of the model, to address a major limitation of this model with respect to the structure of choice among alternatives, often referred to as the Independence of Irrelevant Alternatives (IIA) property. The method used in estimation in this research generalizes this further, to allow parameters to vary randomly across the population, so the nested logit does not merit a separate discussion in development of the empirical model.

2.7.2 The Empirical Conditional Indirect Utility Specification

Most RUM applications use linear specifications for the indirect utility U_j, due to difficulties in calculating welfare estimates in non-linear models. While recent studies (e.g., Herriges and Kling, 1999; McFadden, 1999) employ simulation methods to model non-linear-in- parameters specifications of U_j, this dissertation instead investigates nonlinear-in variables (but linear-in-parameters) models, because of their relative simplicity in estimation and consistency with the underlying theory of choice and shadow values subject to multiple constraints.

The simplest indirect utility specification that is consistent with the dual-constraint framework for consumers that may have utility or disutility from work is (suppressing the person index for simplicity)

$$\text{(2-28)} \qquad V_j = \alpha + \lambda_0 \cdot (M - p_j) + \mu_0 \cdot (T - t_j) + \beta_{qj} \cdot q + \beta_{sj} \cdot s_j$$

where α, λ_0, μ_0, $\boldsymbol{\beta}_{qj}$ and $\boldsymbol{\beta}_{sj}$ are parameters to be estimated. The parameters λ and μ may themselves be functions of demographic and transportation attributes. If these relationships are linear in parameters and variables, indirect utility can be written as

(2-29)
$$V_j = \alpha + \left(\lambda_0 + \lambda_q \cdot \mathrm{q} + \lambda_\mathrm{s} \cdot \mathrm{s_j}\right) \cdot \mathrm{p_j}$$
$$+\left(\mu_0 + \mu_q \cdot \mathrm{q} + \mu_\mathrm{s} \cdot \mathrm{s_j}\right) \cdot \mathrm{t_j}$$
$$+\beta_{qj} \cdot \mathrm{q} + \beta_{sj} \cdot \mathrm{s_j}$$

where λ_0 and μ_0 are the intercept terms for the marginal utility of money and time respectively and $\boldsymbol{\lambda}_q$, $\boldsymbol{\lambda}_s$, $\boldsymbol{\mu}_q$, and $\boldsymbol{\mu}_s$ are vectors of coefficients associated with the individual specific attributes (**q**) and the alternative specific attributes ($\mathbf{s}_j$) for both money and time.

When the model includes a shadow value of time that varies with budget parameters, the specification of (2-29) generalizes to

(2-30) $$V_j = \alpha + \left(\lambda_0 + \lambda_q \cdot q + \lambda_s \cdot s_j\right) \cdot p_j + \left(\mu_0 + \mu_q \cdot q + \mu_s \cdot s_j\right) \cdot t_j + \beta_{qj} \cdot q + \beta_{sj} \cdot s_j + \mathrm{B(s,q)} \cdot \mathrm{Z_M}$$

The joint log-likelihood is the log of the product of the likelihoods for each individual, i.e.,

(2-31) $$\mathrm{LL} = \sum_{\mathrm{n}} \sum_{\mathrm{j}} \mathrm{d_{nj}} \cdot \ln\left(\mathrm{P_{nj}}\right) \qquad \mathrm{n} = 1, \ldots, \mathrm{N}, \mathrm{j} = 1, \ldots, \mathrm{J}$$

where N is the number of individuals and J is the number of alternatives, P_{nj} is the probability of the n^{th} individual choosing the j^{th} mode and d_{nj} equals 1 when the n^{th} individual choose the j^{th} mode and 0 otherwise.

2.7.3 Random Parameters (Mixed) Logit Models

The Mixed Logit or Random Parameters Logit (RPL) model eliminates the IIA problem inherent in the standard multinomial logit models (MNL). In fact the RPL model can approximate any random utility model (Train, 2003).

A RPL model is any model that can be expressed in the form:

(2-32) $$\int L_i(\beta) f(\beta) d\beta$$

where $L_i(\beta)$ is the logit probability evaluated at parameters β; i.e.,

(2-33) $$L_i(\beta) = \frac{\exp(v_i(\beta))}{\sum_{j=1}^{J} \exp(v_j(\beta))}$$

And f(β) is a density function that describes the distribution of the parameters β. Each element of β can be specified to have a unique distribution.

In the case where the mixing distribution $f(\beta)$ is degenerate such that $f(\beta)=1$ for $\beta = b$ and $f(\beta)=0$ for $\beta \neq b$ then the mixed logit is identical to the standard logit.

2.8 Towards the Empirical Model

All models in the empirical section are estimated as RPLs, because this is the most flexible version of the MNL. The computational burden is significantly heavier than for MNLs, though given the current state of computing technology, they often converge (if well-behaved) in a reasonable amount of time. However, the complexity of specification choice for RPL increases markedly, as the number of possible models is increased substantially, due to the rich set of possible distributions to choose from for each coefficient.

All of the models analyzed here are for commute choice for travel to work. The stated preference models are conditional, in that each individual has a set of mode options for her work commute, and chooses the one s/he likes best (in the revealed preference[7] case), or sees as set of options and selects the

[7] In this dissertation the terms “revealed preference” and “stated preference” are used consistent with the transportation literature. However, in the classic sense the use of these terms is incorrect. A more accurate description would be to refer to the revealed preference models as “actual choice” models and the stated preference models as “hypothetical choice” models. The classical use of the term “revealed preference” requires that there is an actual price change in the market from which the researcher can observe how the consumer’s preferences change. (Chalfant , J., Alston, J. 1988)

most preferred (in the stated preference case). The models are constructed so that each person's opportunity cost of time (the shadow value of time) is not required to be their wage rate. Thus, the marginal value (positive or negative) of work time itself is identified separately from the opportunity cost of time. Income is introduced into the models through the full budget variable and is allowed to influence mode choices, as is common in the transportation literature; it also is allowed to affect the shadow value of time, which is as yet not common in the literature. Transportation and demographic characteristics potentially affect indirect utility both directly through the utility function, and as a shifter of time and money prices. Consequently the value of time is modeled as a function of time and money prices and as a function of transportation infrastructure and demographic characteristics.

3 Data and Transportation Survey

3.1 Introduction

Northern California is a highly urbanized region, yet there is wide variation in population density and levels of transportation infrastructure that serve the various communities within this region. Although there is strong correlation[8] between population and the transportation infrastructure within the region, there is a wide variation in transportation services per capita. These variations are particularly relevant for this dissertation since the underlying hypothesis is that the level of available transportation infrastructure is a significant determinant for the opportunity cost of time.

In order to model the impacts of transportation infrastructure on the value of time, three sources of data were gathered that describe characteristics of three Northern California communities (the cities of Sacramento and San Francisco and Sonoma County). The first source of data is the US Census; the second is the various transportation agencies within these three communities;

[8] The correlation between population density and bus stop density within a quarter mile of home is 0.72.

the third is a survey conducted on the Internet and through the mail. These data were then combined to characterize the impact of transportation infrastructure on the value of time.

3.2 Census Data

According to the US Census, some of the most notable differences in variables affecting commutes to work between the three regions are: 1) the median travel time to work, which is highest for San Francisco and lowest for Sacramento; and 2) population density, which is much higher in San Francisco than in Sacramento and higher in Sacramento than in Sonoma.

Also, other attributes, including levels of education and income, vary between regions and are subsequently included in the models analyzed in this dissertation (chapter 4). Summary statistics related to these attributes are listed in the appendix in tables A.1 – A.2.

3.3 GIS and Transportation Services Data

There is wide variation in the number of transit services available in the three communities studied. San Francisco has the highest level of available service and Sonoma has the lowest, with Sacramento in between. Both San Francisco and Sacramento offer a light rail option that is not available in any part of Sonoma County. In particular the number of bus and light rail stops per square mile and the frequency of buses and light rail trains stopping to pick up passengers is greatest for all of these attributes in San Francisco and in smallest in Sonoma (See tables, A.3 - A.5 in the appendix). The data related to available transportation infrastructure are subsequently used in the models described in chapters 4 and 5 of this dissertation and is the basis for the underlying hypothesis of the study that suggests that the level of transportation infrastructure impacts the value of time.

3.4 Summary of Survey Development

This section describes the survey methodology and data collected in the transportation survey and activity diary. Two separate, yet similar, versions of the survey were conducted; the first version was Internet-based, and the second was mail- based. Both versions were conducted on a sample of randomly chosen households in the three regions between September 2007 and February 2008[9].

3.4.1 Basis for Using a Combination of Internet and Mail Surveys

The decision to conduct these two versions was based on an analysis of the benefits and problems associated with various survey methods. Phone, mail and Internet based surveys were evaluated. Four survey attributes: response rate, questionnaire construction and question design, accuracy of responses and administrative requirements were considered in the decision.

[9] All individuals were originally contacted with 2 solicitations through the mail prior to the holiday season. All individuals who did not respond to the original solicitations were sent an additional solicitation following the holiday season.

3.4.2 Response Rate

Response rates for telephone surveys are low and getting worse over time. In today's society most households have telephones, yet the number of households that have unlisted phone numbers, use cell phones as their only phone, or screen calls is substantial (Brick, et al., 2007). Also, the segment of the society that only uses a cell phone has different demographic characteristics than the segment with landline telephones or with no phone at all. The cell-phone-only segment is relatively young and wealthy and more likely to be renters and to live in urban or metropolitan areas. These trends have a significant impact on response rates and bias for telephone surveys (Dillman, 2000).

Response rates for mail surveys are typically higher than for Internet surveys, although web-based surveys have achieved response rates comparable to those from mail surveys when both were preceded by an advance mail notification and a reminder mail notification (Kaplowitz et al., 2004).

The lower response rates for Internet surveys are partly due to less than universal Internet access. (Nielsen, 2007) reports that the number of households in the United States with access to the Internet is approximately 75%. The

Internet is less prevalent among poorer and older members of the society (US Census 2000, Adler 2002).

Even with less than universal access to the Internet, there are situations in which use of the Internet as a survey tool can be appropriate. If the survey is restricted to a segment of the population that has broad access to the Internet or to segments of a population that have similar access to the Internet, then such a survey can be meaningful. It is this latter situation that is relevant for this study. In particular, subjects in the 3 regions of Northern California, who are demographically similar and have similar levels of access to the Internet differ in available levels of transportation infrastructure. For this group, Internet surveys can be administered and analyzed regarding the impact of transportation infrastructure on the value of time.

3.4.3 Questionnaire Construction and Question Design

3.4.3.1 Length, Complexity, Control Sequence and Item Non-response

Length of a questionnaire is a significant determinant of response rate. Response rates are constant for surveys up to a certain length, and then drop off significantly for longer surveys (Dillman, 1978). Error rates are likely to increase as a function of survey length (Goldenberg, 2002). Complex surveys can be difficult for respondents to answer, and different survey types can sometimes help the researcher to mitigate these difficulties. Mail surveys suffer from the inability to skip questions that are irrelevant are for a particular respondent, and in general do not have good control over how (e.g., in what order) the respondent answers. While it is possible to instruct respondents to skip irrelevant questions, some respondents may be confused and answer the questions anyway. Administrators of phone surveys can skip irrelevant questions and it is possible to construct the flow of questions in a computerized survey so that irrelevant questions are automatically skipped (Dillman, 2000).

Phone surveys generally need to be completed during a single phone call, whereas with mail surveys and Internet surveys, it is possible to answer a portion of the survey and return at a later time to fill out the remainder of the survey. This feature can help eliminate problems related to fatigue. Internet surveys are superior to both mail and phone surveys regarding complex questions. Not only can a computerized survey allow branching based on responses, but also on-line help or tutorials can be incorporated into the design to help explain difficult questions. Inconsistent responses can be rejected and re-asked. This is not possible for paper surveys, and can be difficult over the phone (Dillman, 2000).

Item non-response can be problematic and can occur for a variety of reasons, including concerns with anonymity in relation to sensitive questions. Internet surveys, due to perceived anonymity, produce better response rates than other vehicles when asking sensitive questions (Reneau, 2000, Tourangeau, 2003, Koch, 2001). Inadvertent skipping of questions and can be controlled in phone and Internet surveys but not in mail surveys. (Dillman, 2000)

3.4.3.2 Graphics, Visual Cues, Clarity and Explanation of Questions

Internet and paper mail surveys can include diagrams, graphics and other visible cues. This is not possible for phone surveys. The Internet is the most flexible in this regard. All surveys can offer explanations for questions. In phone surveys, repeated explanations can be offered if the respondent does not clearly understand a concept, whereas in mail and Internet surveys, the researcher has no way of knowing whether the explanation offered is sufficient. Internet surveys can offer on-line help that can incorporate many levels of help; examples can be made available, which is not practical for mail or phone based surveys.

3.4.3.3 Accuracy of Responses

Internet surveys can ensure greater accuracy compared to other methods if the respondent is expected to calculate a value or keep a running total of a quantity. This is particularly relevant in the activity diary section of this survey. Early tests of paper-based surveys, on highly educated and numerically competent economics graduate students, produced results that were unusable. In particular, the number of hours in an individual's day often did not add up to 24 hours. These results ranged from a low of 16 hours to a high of 32 hours. Inaccurate results of this nature are not reliable for use in any models. Since nearly 1/3 of the respondents in the early tests of the survey did not add the hours of their days correctly, it was apparent that using a paper-based survey alone would be problematic.

3.4.3.4 Administrative Requirements

Personnel costs are highest with phone surveys and lowest for Internet surveys. Data entry can be done while the survey is being conducted in a well-designed phone survey. Administration of mail surveys is relatively easy, yet data entry can be time consuming and requires attention to accuracy. In Internet surveys, data can be immediately stored in a predefined format that can easily be fed into econometric models.

Mail surveys take the most amount of time to obtain responses, while phone surveys can be completed in a relatively short period of time. Internet surveys can also be expedient and can be completed in a few days. Mail (for a domestic sample) and Internet costs do not vary with geographical distance. Phone costs have the highest variance, although costs are not exorbitant for short surveys, and vary with sample size, length, and complexity of the survey. Internet surveys have high design costs but low implementation costs. Mail surveys have lower design costs, but higher implementation costs. Phone surveys have low design costs, yet have high costs of training and for acquiring data. Overall, costs are determined partly by the size of the survey and the technical abilities of the researcher. (Dillman, 2000)

3.4.3.5 Final Choice of Survey Methods:

Based the considerations discussed above, an Internet survey was judged to be the preferred option. However, a small paper-based survey was also conducted primarily to determine if there are any differences in the distribution of values between the two survey methods. The overriding consideration in the decision to rely predominantly on an Internet survey was the concern with data accuracy, particularly regarding the activity diary. Additionally, the ability to incorporate online-help routines, logic that allowed irrelevant questions to be skipped and the ease of data entry were advantages with the Internet survey. The downside was the many hours of time required to develop the survey.

The survey was designed so that each person would report on the activities that occurred during one full 24 hour day. The day of the week was chosen so that it most likely fell mid-week (Tuesday, Wednesday or Thursday). This was done in order to maximize the probability that the individuals answering the survey commuted to work on the day of the reported activities. Pretests of the survey identified the number of days required for mail to arrive at the respondent's home. The posting of both the mail surveys and letters notifying respondents of the Internet survey were then timed to maximize the probability that they were received mid-week.

3.4.4 Internet Survey

The Internet survey was developed first and then the paper version was developed based on the design of the Internet version. The Internet version was developed using Macromedia® Dreamweaver 6.1 and Cold Fusion Macromedia® ColdFusion MX 7. A variety of web-based survey software was examined as possible platforms for the survey and all were rejected due to the lack of flexibility. In particular, none of the “canned” software allowed sophisticated error checking, and none were able to accommodate complex branching requirements.

3.4.4.1 Sections of the Survey

The seven sections of the survey are:

1. Commuting options and choices for work
2. Activity diary
3. Travel diary
4. Opinions regarding importance of transportation attributes
5. Opinions regarding attributes of available transportation
6. Choice experiments
7. Demographics and automobile questions

The following sections discuss the purposes and construction of each of these parts of the survey.

3.4.4.2 Commuting Options and Choices for Work:

The purpose of this section is to determine individual characteristics that potentially impact transportation choices. In particular, the availability of an automobile or the possession of a driver’s license or train pass can act as a constraint on transportation choices and can impact an individual’s value of time. Included in this section are the following questions: How often (Never, Seldom, Frequently, Always) do you use each of the following types of transportation **(**Bus, Light Rail, Train, Automobile Alone, Automobile with Others, Walk, Bicycle) as part of your commute to work? Do you have a driver's license (Yes/No)? Do you drive a car daily (Yes/No)? Do you own a current train or bus pass (or allowed to ride for free) (Yes/No)? How many people in your household have driver's licenses? Are you currently working (Yes/No)? Do you have a dedicated parking space at work (Yes/No)? Do you have a parking permit at work (Yes/No)? Do you have access to a car for use in commuting to work (Yes/No)? Do you have access to a bicycle for use in commuting to work (Yes/No)?

3.4.4.3 Activity Diary

This section, in conjunction with the following section on travel, collects data used in the revealed preference models. As a consequence of testing early versions of the survey with focus groups, the number of activity categories was limited to seven.

The activities are listed in table 3.1

Table 3.1 – Activities

Activity Category
Sleep
Work for pay
Household chores and tasks
Outdoor recreation (e. g. sports)
Leisure activities at home
Leisure activities away from home
Other activities

In addition, the ordering of questions was determined as a direct result of the focus groups and preliminary test runs of earlier versions of the survey. Ordering the activities as shown above appeared to reduce errors in adding hours in a person's day and subsequently reduced the need for respondents to modify their answers. For each activity, the following information was gathered: The amount of time spent on the activity (not including any travel time associated with the activity), a rating of how much the respondent enjoyed the actual time they spent in the activity, on a scale from 1 (lowest) to 10 (highest), a rating of how much the respondent felt they would enjoy having 15 more minutes of time available and spent in that activity, on the same scale of 1 to 10 and the amount of money the person spent while doing the activity, excluding any expenditures on travel to and from where the activity took place.

3.4.4.4 Travel Diary

In this section, respondents were asked to describe the travel they did on the day previous to when they received their survey. Respondents were instructed to report their travel in one-way trip segments, which is travel with a particular transportation mode, from a point of origin to the destination where a non-travel activity occurred. A round trip to and from the home, for example, will typically consist of at least 2, and often more, trip segments.

For each one-way trip segment the information was gathered on travel mode, destination, the time spent on the trip segment, the money cost for the trip, a rating of how much the activity was enjoyed, and a rating of how respondent felt about having 15 more minutes available for the activity. The Transportation Modes are listed in table 3.2 and the destinations are listed in table 3.3

Table 3.2 Travel Modes

Mode
Drive alone in car
Drive or ride with others in car
Bike
Walk
Ride light rail
Ride bus
Ride motorcycle
Ferry or other water transit
Airplane or other air transit

Table 3.3 Destinations

Destination
Airport
Bus Stop
Church, Temple or other religious or spiritual location
Day Care Center
Home
Gym
Movies
Political Event
Restaurant
School
Shopping
Sporting Event
Train or light rail Stop
Visit Friends
Work

3.4.4.5 Opinions Regarding Importance of Transportation Characteristics

This section asked respondents if they consider various mode choices listed in table 3.5 to have each of the characteristics listed in table 3.4 when they commute to work (e.g. is the light rail reliable?, is the light rail safe? etc.). The responses could be either yes or no. This series of questions were also presented as yes or no questions. The results of these questions are detailed in table A.18 and t-scores comparing each pairing of the three communities are listed in A.19. In general there are a number of differences between the three communities. In particular, those in Sonoma seem to have a negative attitude towards the light rail, even though they have none available. Also residents of San Francisco in general have more negative attitudes regarding the automobile and people in Sonoma have more positive attitudes regarding the automobile. However, this data is only listed as background information and this study does not evaluate whether these differences in attitudes are the result of variations in transportation infrastructure or are among the reasons why current residents of the various communities chose to live in those communities. This will be left for additional analysis at later time.

Table 3.4 Transportation Characteristics

Characteristics
Reliability
Safety
Cleanliness
How crowded it is
Reliability
Ease of use
Whether it's good for the environment
Whether the route is congested
The time it take
How much it costs

Table 3.5 Mode Options

Mode Options
Bus
Car
Train
Bike or Walk

3.4.4.6 Choice Experiments: Design Methodology

Respondents were presented with a series of choice experiments, to help better understand their tradeoffs between time and money for different transportation modes during their commute to work. The data obtained from the response in this section are at the heart of this study. In general models were developed for both actual transportation choices (revealed preference) and hypothetical choices (stated preference). The choice experiments described in this section were used to collect data for the stated preference models. The actual choices made by individuals on the day of the survey do not provide information on how individuals respond to changes in the time and money prices of their transportation options. However, the choice experiments allow variations in both time and money prices. As such, the choice experiments described in this section are able to elucidate the tradeoff of time and money and their underlying value of time.

Each experiment offered three primary transportation options for the work commute: Car, Bus, and Light Rail. Each of these choices varied in time (minutes) and money cost ($). Respondents were instructed to assume that in every other respect, the choices were equal, and that while some of the choices might resemble their current commuting options, others might not.

Each attribute (money price and time price) has 4 levels. Consequently there are 16 (4·4) possible combinations of time and money prices for each mode option. With 3 transportation modes, each of which have 16 possible combinations of money and time prices there are a total of 16·16·16 = 4,096 possible combinations of time and money that could be used in each choice experiment. Clearly, it is unreasonable to design an experiment based on a "full factorial design" in which each of these 4,096 treatment combinations is presented to every respondent. However, an "orthogonal design" reduces the number of comparisons to the fewest number necessary for efficient estimation of parameters (Dey, 1985). (Huber and Zwerina, 1996) list three properties of efficient designs:

a. Level balance: levels of an attribute occur with equal frequency
b. Orthogonality: the occurrences of any two levels of different attributes are uncorrelated
c. Minimal overlap: cases where attribute levels do not vary within a choice set should be minimized

In a sampling design for choice experiments, the attributes are represented as columns which contain as elements the levels offered. Each row of the design corresponds to a particular choice experiment presented to a respondent. An orthogonal design is sought, since it spans the space of attributes most efficiently.

In total there are 6 attributes in each choice experiment, namely the time and money costs for each of the three transportation modes.[10] In order to estimate non-linear effects, each of these 6 attributes requires L-1 degrees of freedom, where L is the number of levels the attribute takes. There are 4 levels for each of the time prices and 4 levels for each money price. Subsequently there are a total of 18 degrees of freedom (6·3) plus an additional degree of freedom required for the error component of the model for a total of 19. A blocking factor is added to the design, in which *n* blocks are defined of groups of choice experiments, and each block of experiments is administered to 1/*n* of the respondents. This is accomplished by adding an additional orthogonal column, with *n* levels. The number of blocks chosen was 4, which adds an additional 3 degrees of freedom for a total of 22, which is the minimal number of choices that must be asked to ensure identification.

An underlying consideration in the design was the number of choice experiments that would be "reasonable" for an individual to answer as part of the overall survey. From the point of view of the researcher, within the limits of a respondent's ability to process information, the more experiments offered, the

[10] Since each mode choice corresponds to a named attribute, and each experiment presents a choice of all three modes with various time and money prices, the mode choice is not treated as an attribute. However, each time and money price for each mode is treated as a separate attribute. This type of experiment is distinguished from experiments in which the mode itself is a separate attribute and the respondent is given a choice between a number of options in which the modes vary and some of the experiments present choices that may have redundant mode choices.

better. However, respondents prefer short surveys. Early tests of the survey resulted in the decision that a reasonable number of choice experiments is 9. This number of responses would be sufficient to identify parameters in the model and not be too onerous for most respondents.

Given that 36 choice experiments are sufficient to span the attribute space with a blocking factor is 4, each respondent was asked to respond to 9 choice experiments. The selection of choices presented to each block of respondents followed the methodology described in Huber and Zwerina (1996).

To determine the levels of the attributes, US Census data (US Census, 2003) were used. For the time cost, the distributions of travel time to work for each county were used, and are listed in Table 3.6.

Table 3.6 Travel Time to Work: US Census (2003)

Time to work	Sacramento Number of Commuters	San Francisco Number of Commuters	Sonoma Number of Commuters
Total:	578,052	383,996	220,049
Did not work at home:	560,136	359,556	212,260
Worked at home	17,916	24,440	7,789
Less than 5 minutes	18,794	5,897	10,273
5 to 9 minutes	50,856	16,303	23,659
10 to 14 minutes	70,055	38,218	35,311
15 to 19 minutes	87,417	45,583	34,134
20 to 24 minutes	96,936	59,985	29,935
25 to 29 minutes	52,933	24,494	10,251
30 to 34 minutes	91,672	71,926	27,548
35 to 39 minutes	10,682	10,420	3,336
40 to 44 minutes	22,472	18,761	6,258
45 to 59 minutes	30,790	37,860	13,258
60 to 89 minutes	19,387	24,602	11,434
90 or more minutes	8,142	5,507	6,863

The levels for time costs were chosen so that the high and low choices are 1.5 standard deviations from the mean for the particular county, and the middle choices are 0.5 standard deviations from the mean. Based on these criteria and Table 3.6, the levels used for time costs (rounding to the nearest minute) are displayed in table 3.7. These are one-way time costs.

Table 3.7 Travel Time to Work Options Rounded to Nearest Minute

	Sacramento Minutes	San Francisco Minutes	Sonoma Minutes
High	55	67	71
Middle High	28	31	28
Middle Low	15	19	13
Low	8	10	6

Money costs were similarly based on ranges of current one-way costs in the three regions. The rail costs for Sacramento and San Francisco were determined in a similar manner. Rail costs in Sonoma are hypothetical based on costs in the other communities. Bus and rail considered both local travel and including trips on a Greyhound, Amtrak or Bay Area Rapid Transit (Bart) for longer travel.[11] Car costs are based on average costs for operating a car in California. The rates at the time of the survey averaged $0.45 per mile (AAA Web Site, 2007), so that a 60 mile trip, which corresponds to the distance traveled for the High time trip, would cost $27 and would be considered "fairly normal". The low level of costs for car trips was set at the low levels determined for public transportation (discussed below) for each community. Again, these

[11] For Sonoma and San Francisco data for trip lengths and time were obtained from 511.org, which provides time and money cost information on local bus and light rail services in each local community. For Sacramento trip data was obtained from Sacrt.com. In addition Amtrak.com and Greyhound.com were used as sources of data for all three regions. The list of available transit services are provided in tables A.03, A.04 and A.05

values would appear to be in the normal range of actual costs for most respondents. The low level of Bus costs are based on actual rates for each of the three communities, which were obtained from local transit agencies.[12] Light rail costs were $1.75 in Sacramento and $1.50 in San Francisco.[13] Based on these, the lowest rail cost in Sonoma was set at $2.00. The high levels for Bus, Rail and Car were set at $10, $11 and $27 in each community.[14] Intermediate values were interpolated using even increments rounded to the nearest $1. Tables 3.8 to 3.10 present the levels of money cost, by mode, used in each region.

Table 3.8 Travel Cost to Work Options - Car[15]

	Sacramento Cost	San Francisco Cost	Sonoma Cost
High	$27.00	$27.00	$27.00
Middle High	$21.00	$21.00	$21.00
Middle Low	$8.00	$8.00	$8.00
Low	$2.00	$2.00	$2.00

[12] SacRT.org for Sacramento and 511.org for San Francisco and Sonoma
[13] SacRT.org for Sacramento and 511.org for San Francisco and Sonoma
[14] The costs for longer travel were based on public transit costs (Greyhound.com, Amtrak.com) for trips that required the amount of time for the High travel times for the various communities.
[15] Estimates for Automobile costs included parking costs

Table 3.9 Travel Cost to Work Options - Bus

	Sacramento Cost	San Francisco Cost	Sonoma Cost
High	$10.00	$10.00	$10.00
Middle High	$6.00	$6.00	$6.00
Middle Low	$4.00	$4.00	$4.00
Low	$1.00	$1.50	$1.10

Table 3.10 Travel Cost to Work Options – Light Rail

	Sacramento Cost	San Francisco Cost	Sonoma Cost
High	$11.00	$11.00	$11.00
Middle High	$7.00	$7.00	$7.00
Middle Low	$5.00	$5.00	$5.00
Low	$1.75	$1.50	$2.00

3.4.4.7 About You and Your Car

This section asks a series of demographic questions and questions regarding the respondent's car. The car information is designed to help determine the cost of driving in the revealed preference analysis. These questions are listed in table 3.11.

Table 3.11 Survey Questions – Demographic and Personal Transportation

Question Number	Question	Response Type
1	What is your Gender?	(Male/Female)
2	What is your Age?	Numeric
3	What is your Marital Status?	(Single/Married/Divorced/Widowed/Living with partner)
4	What is the Town or city of your work location?	Character string
5	What is the Zip code of your work location?	Numeric (5 digits)
6	What are the cross streets nearest to your work location?	Character string
7	How long have you lived at your current address?	(Years/Months) – Numeric
8	Do you own your own home or do	(Own/Rent)

	you rent?	
9	Including yourself, how many people live in your household?	Numeric
10	How many people living in your household are under 16 years of age?	Numeric
11	How many people in your household work for pay?	Numeric
12	How often do you make decisions about what type of transportation you will use to commute to work?	(Daily/Weekly/Monthly/Yearly/Less often than yearly/Never)
13	Are you currently working?	(Yes/No) (if no Skip to question 14)
13a	In your job, do you work on a fixed salary or does your pay vary by how many hours you work?	(Fixed/Vary)

13b	Do you work a fixed schedule or can you choose the hours or days you work?	Choose all that apply: Fixed schedule (I am not able to choose when and how much I work) I can vary the number of hours I work each day I can vary the number of hours I work each week I can choose which days I work each week I can choose my own start time each day
13c	Approximately what is your average wage per hour?	Numeric
14	Approximately what was your total annual <u>household</u> income last year (before taxes)?	Pull down menu of options
15	Approximately how many miles do you personally drive per year?	Numeric
16	Do you have one	(Yes/No)

	or more cars available to you for commuting or errands?	
17	What is the make of the car you drive most often?	Pull down menu of options
18	What is the model of the car you drive most often?	Character string
19	What is the year of the car you drive most often?	Numeric

Questions 4 – 6 were used to determine distance to work location. Although a question regarding the distance of commute was included in the travel diary, questions 4-6 were included in order to determine the accuracy of the respondent's estimate of commute distance. Question 7 was included in order to understand the "stickiness" of the consumer's transportation choices.

3.4.5 Mail Survey

After the Internet survey had been developed and tested on a small sample of randomly selected subject, the mail survey was developed. The only differences between the survey s regarded format and presentation. The questions were identical.

3.5 Implementation of surveys

3.5.1 Method

Both the mail and Internet surveys were conducted in accordance with standards described in the Tailored Design Method (Dillman, 2000). Included in the development of the survey were the following steps:

Early versions of the survey were developed in collaboration with individuals with knowledge in survey methodology, transportation, and economics. 8 personal interviews were conducted to evaluate the wording of questions as well as the structure of the Internet software. Six separate tests of the survey were conducted on university classes, with follow-up discussions regarding the content and structure of the survey

A pilot Internet survey was conducted on selected households in each of the three study regions and the results and comments received were evaluated. A pilot mail survey was conducted on selected households in each of the three study regions and the results and comments received were evaluated.

Results of the personal interviews, class tests, and pilot surveys were used to create the final survey versions, which modified specific question wording and placement based on comments received.

Certain characteristics, designed to insure adequate response rates and accuracy, were ultimately included in the Internet version. Among these characteristics are: 90% of all respondents are able to complete the survey in less than 30 minutes[16] and only subjects selected for the survey were allowed to enter data. [17]

---

[16] To determine the length of time required to take the survey, the start and end-time for each page in the survey was recorded for each respondent. In early tests of the survey, pages that took an excessively long time for many respondents were either shortened or otherwise modified to make them easier to understand. The total time required to complete each survey in pilot testing was calculated, and the mean was 27.52 minutes, with a standard deviation of 12.23 minutes.

[17] Subjects were sent a code required to proceed past the first page of the survey. This code was designed to avoid attempts by any individual to submit more than one response to the survey. Given that the code was simply constructed, it was never 100% guaranteed that someone with pernicious intent could not "hack" the web-site and undermine the integrity of the results. However, the code was designed to discourage capricious attempts to destroy or infect the data. Ultimately, there was no evidence suggesting that anyone entered more than one set

For the pretest, all solicitation letters asking potential respondents to answer the survey were mailed on the same day and at the same time (4:30 pm Tuesday June 12th, 2007) from Davis, California. When an individual responded to the survey, a file was created with a time and date stamp. The time and date stamp allowed us to track the time that each individual respondent started the survey. Each record in the file, which corresponded to a page of the survey, was also date stamped; we could determine when each page was completed and when entire survey was completed. From this information the length of time to deliver letters to each region was estimated. For the final survey, solicitation letters were mailed on the day of the week determined from information gathered from the pretest. This was designed so that all letters would arrive on a Tuesday.

3.5.2 Internet Survey

A random sample of 6,300 adults (age 18 or above) was used for this study. The names were purchased from Survey Sampling International Incorporated, a private sampling firm. 128 of the addresses were post office boxes; these names

---

of responses to the survey. However, there is no guarantee that the individual who answered the survey was the intended respondent, nor that the respondent was truthful. However, this is true of all surveys and in general cannot be avoided.

were eliminated from the list, leaving a total of 6,172 names. 300 names were used to pretest the Internet version of the survey, 100 names were used to pretest the mail version of the survey and 600 of the names were used for the mail survey. The remaining 5,712 names were used for the Internet survey. 5,112 letters (1,704 each to Sacramento, San Francisco and Sonoma) were sent on October 1, 2007, soliciting responses to the Internet survey. Of the 5,112 solicitations sent out in the initial mailing, 170 (60 from SAC, 72 from SAN, 30 from SON) were returned by the post office as undeliverable, and 551 surveys were completed. Subsequent to the original solicitation, all individuals who did not respond (5301 – 551 – 170 = 4580) were solicited a second time on October 15th, 2007 by postcard and then a second letter was sent on October 29th, 2007. The overall response rate,[18] calculated as the percentage of completed surveys relative to deliverable solicitations, was approximately 17.8%. Response rates overall and by community for the Internet survey are displayed in table 3.12.

---

[18] Following Dillman (1978).

Table 3.12 Response Rate Internet Survey

Region	Sent	Rejected	Received	Returned	Percent
Sacramento	1704	60	1644	242	14.7%
San Francisco	1704	72	1632	322	19.7%
Sonoma	1704	38	1666	315	18.9%
All	5112	170	4942	879	17.8%

3.5.3 Paper Survey

The steps taken in implementing the mail based survey, and their timeline, were:

On October 1st, 2007 the survey, along with a stamped return envelope, a letter of solicitation and an additional page of instructions, was sent to 600 randomly selected individuals in Sacramento, San Francisco and Sonoma. On October 15th, 2007 a follow up postcard was sent to the 500 individuals who did not respond to the surveys sent on October 1st, 2007 and for whom the survey was not returned as undeliverable by the post office. On January 1st, 2008 a second paper survey, along with supporting materials, was sent to 448 individuals that neither responded to the first solicitation nor had the postcard or original solicitation returned by the post office. On February 2nd, 2008 2/1/2008 a third paper survey, along with supporting materials, was sent to 360 individuals who did not respond to either the first two solicitations and had none of the previous mailings returned by the post office. The overall response rate for the mail survey is shown in table 3.13.

Table 3.13 Response Rate Paper Survey

Region	Sent	Rejected	Received	Returned	Percent
Sacramento	200	18	182	67	36.8%
San Francisco	200	22	178	80	44.9%
Sonoma	200	12	188	90	47.9%
All	600	52	548	237	43.2%

3.5 Comparison of Response Rates, Time to Respond and Accuracy

Clearly the response rate for the paper based survey (43.2%) was better than the response rate for the internet based survey (17.8%). However, 38% of the respondents who answered the paper based survey reported times for the activities in their day that did not add up to 24 hours. Consequently, this data was not useable for the revealed preference models. It was impossible to know for certain what day individuals responded to the paper based survey although most (82%) did record the day of their response. In the case of the internet survey the actual time and day the survey was answered was recorded automatically. Also, the time required to answer the survey was recorded. The average time required to answer the internet survey was 28 minutes with a standard deviation of 8.6 minutes. 72.2% of the respondents answered the survey within 24 hours of the day the solicitation was targeted to reach their home. 15.2% of those who responded did so between 24 and 48 hours of the solicitation. Another 6.1% of the respondents responded between 48 to 72 hours after the solicitation. The goal was to have the solicitation arrive at the respondent's home in the middle of the week so that the day of their recorded activities would also fall midweek. As such this aspect of the survey was substantially successful.

3.6 Calculation of costs for revealed preference models

Only work trips were analyzed in the mode choice models. The choice experiments (stated preference data) presented three mode options, with a time and money price associated with each option. However, the revealed preference data only contained information on the time and money that individuals reported for their actual work trip. Respondents were asked to exclude gasoline costs in their reported costs. Gasoline costs were added based on reported automobile type, information on gas mileage from AAA, and reported distance to work.

Data for the "counter-factual" alternatives to the commute mode the person actually used had to be constructed. This was done by using the respondents' reported work location and home, along with information from local transit agencies. For example, for each individual who used a car to get to work, the cost and time for bus, light rail and walking alternatives were constructed. Walking speed was assumed to be 3.0 miles per hour in all cases. Individuals living in San Francisco were assumed to take a combination of SF Muni, Bart or the appropriate public transportation available. In all cases the option that requires the least time was used for the bus and light rail alternatives. Residents of Sacramento usually had the Regional Transit (RT) bus and light rail system available, and residents of Sonoma could use their local transit option if it existed. In all cases, online software (511.org for San Francisco and Sonoma and SacRt.com for Sacramento) was used to calculate trip time and cost. In cases where public transit was used for the actual work trip, reported data on vehicle type and distance to work was used to calculate the cost for the automobile option.

3.7 Summary Statistics

Summary statistics from the survey are listed in the appendix. Tables A.9 – A.11 lists summary statistics for age, years of school, income, number of persons in the household, gender and marital status. Tables A.12 – A.14 lists statistics on home ownership, car ownership and work status. Tables A.15 – A.16 details information on work schedules. These demographic characteristic were subsequently used in the models described in chapters 4 and 5. In general the respondents living in San Francisco were a bit younger (48.1 years old as compared to 50.6 years in Sacramento and 54.0 years old in Sonoma) made more money ($285 per day as compared to $235 in Sonoma and $230 per day in Sacramento) and somewhat more educated (16.2 years of school as compared to 15.9 years in Sacramento and 15.3 years of school in Sonoma). Most striking is the difference in home ownership. Respondents from San Francisco owned their own home in only 50% of the cases whereas in Sonoma 81% of the respondents own their own home and 79% of respondents from Sacramento.

3.8 Summary

This chapter describes the data used in this dissertation, which come from three principal sources: census data, Graphical Information Services (GIS) data from transportation agencies and from general population surveys conducted on both the Internet and through the mail. The reasoning behind choosing a combination of mail and Internet based surveys, and the design methodology for the choice experiments, were explained. And finally, summary statistics derived from each of the three data sources are presented. These data are used in discrete choice models to analyze peoples' transportation choices for work trips and to model the value of time.

4 Estimation of Values of Time

This chapter presents estimation results for the two-constraint discrete choice transportation value of time models developed in chapter 2.

First a general model is described that incorporates, and tests for similarities and differences between, stated preference information on preferred commute choices, along with revealed preference data from the respondent's own commute. Two different survey instruments were used for these purposes, an internet-based survey and a mail survey, and residents from three regions in northern California were sampled (Sacramento, San Francisco and Sonoma).

The first step in analyzing the data of different types, from different sources and from residents of different areas, is to consider the degrees to which they can be combined in estimation; that is, for a given model specification, whether the parameter estimates using the different sources and types of data are the same or not. Likelihood ratio tests are used to evaluate restrictions on a general model where each of the data sources, survey instruments, and regions have their own parameter vectors, which impose equality of parameters across various combinations of these data cells. Principal questions that this addresses includes (1) whether models using revealed preference data are the same as those using stated preference data, (2) whether data from the two different survey techniques, mail and internet, give the same parameter estimates; and (3) whether residents of different regions have the same preferences or the same weights to their preferences.

The models selected after this testing process are presented and analyzed. A variety of models is presented, ranging from simple specifications that model the marginal utilities of time and money as constants (consistent with much of the existing transportation literature) to richer specifications that allow indirect utility, and the resulting shadow values of time, to vary based on an individuals' characteristics, the level of transportation infrastructure available to them for commuting to work, and the budget variables (prices, money income, and time budget) they face.

4.1 The Empirical Specification

4.1.1 Random Parameters Logit Models

All of the economic models used in this dissertation are random parameters or mixed logit (MXL) models.[19] These models relax a strong restriction inherent in standard multinomial, the Independence of Irrelevant Alternatives (IIA) property. In particular, MXL models allow for random taste variations and have

[19] See Chapter 2 for a more complete description of MXL models.

unrestricted substitution patterns; thus eliminating the problem of Independence of Irrelevant Alternatives (IIA). In these models each individual faces a set of transportation mode choices for her work commute, and chooses the mode that delivers the most utility.

4.1.2 Transportation Arguments of the Indirect Utility Function

In the more general models, in addition to the economic determinants used in the simplest models (i.e., time and money price of each transportation alternative), the conditional utility of a commute mode is assumed to be a function of characteristics of both the person making the choice and her local transportation environment.

The transportation environment characteristics considered in these models are designed to reflect the degree of availability of transportation alternatives to the respondent. Each characteristic is measured, for each respondent, as a number or frequency of occurrence within the vicinity of the respondent's home, that is, a circle of given radius around the respondent's home. Radii of an eighth mile, quarter mile, half mile and one mile were used in the empirical analysis.

The transportation availability variables are:

Bus stop density (BD) – The number of bus stops;

Bus Stop Frequency (BF) – The number of times on the day of the survey that any bus stopped to pick up passengers;

Light rail stop density (LD) – The number of light rail stops;

Light rail stop frequency (LF) – The number of times on the day of the survey that any light rail stopped to pick up passengers;

Public Transit Stop Density (PD) – The number of bus stops and light rail stops; i.e., *BD* + *LD*; within the radius around the respondent's home

Public Transit Stop Frequency (PF) – The number of times on the day of the survey that any bus or light rail stopped to pick up passengers; i.e., *BF* + *LF*

Road Density (RD)[20] – The number of lane-miles (the sum of the product of the number of lanes and number of center-line miles of all roads in the vicinity)

The demographic characteristics considered are *Car Ownership* (a dummy variable with *OC* = 1 indicating that the commuter had access to a car on the day of the commute, and *OC* = 0 otherwise); *Age; Gender* (Gender=1 if male and 0 if female); *Fixed Work Hours* (a dummy variable with *FH* = 1 indicating that the

[20] The effects of road density, nonlinear effects of age, home ownership, and the number of children in the family were investigated but not included in the models presented in this dissertation, since these variables were insignificant in all cases.

respondent had fixed work hours on the day of the commute, and *FH* = 0 otherwise); *Home Ownership* (a dummy variable taking the value *OWN* = 1 if the respondent owned her home, and *OWN* = 0 otherwise); *Number of People in Household under the Age of 16;* and *Number of Years in School*.

4.1.3 The Value of Time Implied by Indirect Utility Functions

All of the utility functions analyzed in this dissertation are linear in parameters, as is standard in the discrete choice literature, though most are nonlinear in the variables (which is less commonly seen in the standard literature, but more general). The utility obtained from choosing a particular mode is assumed to be a function of attributes of the individual making the choice and transportation environment characteristics; these characteristics include the variables described above. This linear function, in its most generic form, allows the marginal utility of time and of money to vary with both demographic characteristics and transportation availability for the person making the commute mode choice. A sample specification of the conditional indirect utility for person *i* using commute mode *j*, U_{ij}, might be

$$(4\text{-}1)\quad U_{ij} = -(\mu_0 + \mu^F \cdot FH_i + \mu^{BD} \cdot BD_i) \cdot t_{ij}$$
$$-(\lambda_0 + \lambda^{FH} \cdot FH_i + \lambda^{BD} \cdot BD_i) \cdot p_{ij} + \beta^{FH} \cdot FH_i + \beta^{BD} \cdot BD_i$$

where BD_i is bus stop density for person *i*, $FH_i$is a dummy variable indicating whether the respondent had a fixed work schedule on the day of the survey,[21] p_{ij} and $t_{ij}$are the money and time price of using mode *j* for person *i*, and the Greek symbols are parameters to be estimated.

Equation 4-1 hypothesizes that the utility for mode j is a function of the time required for the commute, the money price of the commute and a function of both the density of bus stops in a specified neighborhood of the residence of the commuter (i.e. quarter mile) and whether or not she has a fixed schedule (*FH*) at work. The time and money required for mode j are each a linear function of the bus stop density and fixed hours components of the utility function. [22] Given this specification, the marginal utility of the time price of commute mode *j* is

[21] This is consistent with the literatures in labor supply and recreation demand analysis which show conceptually, and find empirically, that a individuals' value of time depends on the flexibility of their work schedule.

[22] In most stated preference models, the functions included each of the three terms (constant, time related, and money related). For the revealed preference models, in most cases some of the terms were not included due lack of convergence.

(4-2) $$U_{t_{ij}} \equiv \frac{\partial U_{ij}}{\partial t_{ij}} = -(\,\mu_0 + \,\mu^{FH} \cdot FH + \,\mu^{BD} \cdot BD)$$

while the marginal utility of the money[23] price of commute mode *j* is

(4-3) $$U_{p_{ij}} \equiv \frac{\partial U_{ij}}{\partial p_{ij}} = \,-(\lambda_0 + \,\lambda^{FH} \cdot FH + \,\lambda^{BD} \cdot BD)$$

Equations (4-2) and (4-3) imply that person *i*'s shadow value of time is

(4-4) $$\rho \equiv \frac{U_{t_{ij}}}{U_{p_{ij}}} = \frac{\mu_0 + \mu^{FH} \cdot FH + \mu^{BD} \cdot BD}{\lambda_0 + \lambda^{FH} \cdot FH + \lambda^{BD} \cdot BD}.$$

4.1.4 Mode Options in Choice Sets People Face

The data used in the stated preference models were collected through choice experiments, where all respondents were presented with the same choice set, which includes car, bus and light rail. Since the revealed preference models are based on what people actually chose as their commute modes, the choice set for these models is broader, and in addition to the car, bus, and light rail options, a non-motorized option (referred to as *walking* for short) was also

---

[23] The notation $U_{t_{ij}}$ is used to designate the partial derivative of U with respect to t_{ij}.

included.[24] The car option was also broader than in the stated preference models, encompassing all private motorized transportation modes, including motorcycles and mopeds.[25]

4.1.5 Value of Time Estimates for the Sample and Corresponding Populations

For all models the value of time was calculated by two methods. The first was to generate individual-specific estimates of the value of time using each respondent's values of the covariates, and the sample distribution of these values was summarized. Variation in this value of time is due to the distribution of covariates across the sample, but does not take account of variation due to parameter uncertainty. To address this, the second value of time measure held covariates at the means of the samples, and identified the distribution of values of time based on the joint distribution of the parameters, as summarized by their variance-covariance matrix, using the Krinsky-Robb approach (Krinsky and Robb, 1986).

---

[24] *Walking* also includes riding a bicycle.
[25] No distinction was made between driving alone and driving with others in the car.

4.2 Estimation Results

The first step in the analysis is to determine whether the different data sets can be pooled; i.e., whether they are mutually consistent with a presumed form of the preference function, which in this case is linear-in-parameters indirect utility. There are as many as 12 different models differentiated by source of data (stated or revealed preference), method of data collection (via the internet or mail), and city of residence (San Francisco, Sacramento, Santa Rosa), and it is useful to reduce this number if possible. Likelihood ratio tests were used to determine whether there are statistically significant differences between models defined by these criteria, by comparing unrestricted and restricted models of conditional utility. These are discussed further below.

4.2.1 A General Model for All Data

In its most general form, an unrestricted model that combines all the data, including the internet and mail versions of the survey, revealed and stated preference data, and data from all three regions, is described by the conditional utilities of different commute modes below. In this model R and P are dummy variables for which R=1 denotes revealed preference data and R=0 denotes stated preference data; while P=1 denotes data from the paper (or mail) version of the survey and P=0 denotes data from the internet version of the survey. SC, SF and SN are regional dummy variables for which SC=1 denotes data from the Sacramento region, SF=1 denotes data from the San Francisco region and SN=1 denotes data from the Sonoma region. The term $\alpha_j^{DT,SM,RE}$ is an alternative-specific constant whose subscript designates the transportation mode (*j* = Car, Bus, Light Rail, Walk) and whose superscript refers to the data type *DT* (where *DT* = *R*, *S*, for revealed preference data and stated preference data, respectively), the survey method SM (where P = paper and I= Internet) and *RE* refers to the region (where RE=SC, SF, SN, for Sacramento, San Francisco, and Sonoma, respectively). The alternative specific constants were included for all modes except for bus. As such, bus is considered the base alternative.

Car:

$U_{i1} =$

$$\alpha_1^{RPSC} \cdot R \cdot P \cdot SC + \alpha_1^{RPSF} \cdot R \cdot P \cdot SF + \alpha_1^{RPSN} \cdot R \cdot P \cdot SN$$

$$+\alpha_1^{SPSC} \cdot (1-R) \cdot P \cdot SC + \alpha_1^{SPSF} \cdot (1-R) \cdot P \cdot SF + \alpha_1^{SPSN} \cdot (1-R) \cdot P \cdot SN$$

$$-\begin{bmatrix} \lambda^{RPSC} \cdot R \cdot P \cdot SC + \lambda^{RPSF} \cdot R \cdot P \cdot SF + \lambda^{RPSN} \cdot R \cdot P \cdot SN \ + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN + \lambda^{SSF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot p_{i1}$$

$$-\begin{bmatrix} \mu^{RPSC} \cdot R \cdot P \cdot SC + \mu^{RPSF} \cdot R \cdot P \cdot SF + \mu^{RPSN} \cdot R \cdot P \cdot SN + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN + \mu^{SPSF} \cdot (1-R) \cdot P \cdot SF + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot t_{i1}$$

$$+$$

$$\alpha_1^{RISC} \cdot R \cdot (1-P) \cdot SC + \alpha_1^{RISF} \cdot R \cdot (1-P) \cdot SF + \alpha_1^{RISN} \cdot R \cdot (1-P) \cdot SN$$

$$+\alpha_1^{SISC} \cdot (1-R) \cdot (1-P) \cdot SC + \alpha_1^{SISF} \cdot (1-R) \cdot (1-P) \cdot SF$$

$$+\alpha_1^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN$$

$$-\begin{bmatrix} \lambda^{RISC} \cdot R \cdot (1-P) \cdot SC + \lambda^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \lambda^{RISN} \cdot R \cdot (1-P) \cdot SN \quad + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \lambda^{SISF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot p_{i1}$$

$$-\begin{bmatrix} \mu^{RPIC} \cdot R \cdot (1-P) \cdot SC + \mu^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \mu^{RISN} \cdot R \cdot (1-P) \cdot SN + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \mu^{SISF} \cdot (1-R) \cdot (1-P) \cdot SF + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot t_{i1}$$

Bus:

$U_{i2} =$

$$-\begin{bmatrix} \lambda^{RPSC} \cdot R \cdot P \cdot SC + \lambda^{RPSF} \cdot R \cdot P \cdot SF + \lambda^{RPSN} \cdot R \cdot P \cdot SN \ + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN + \lambda^{SSF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot p_{i2}$$

$$-\begin{bmatrix} \mu^{RPSC} \cdot R \cdot P \cdot SC + \mu^{RPSF} \cdot R \cdot P \cdot SF + \mu^{RPSN} \cdot R \cdot P \cdot SN + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN + \mu^{SPSF} \cdot (1-R) \cdot P \cdot SF + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot t_{i2}$$

$$-\begin{bmatrix} \lambda^{RISC} \cdot R \cdot (1-P) \cdot SC + \lambda^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \lambda^{RISN} \cdot R \cdot (1-P) \cdot SN \quad + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \lambda^{SISF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot p_{i2}$$

$$-\begin{bmatrix} \mu^{RPIC} \cdot R \cdot (1-P) \cdot SC + \mu^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \mu^{RISN} \cdot R \cdot (1-P) \cdot SN + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \mu^{SISF} \cdot (1-R) \cdot (1-P) \cdot SF + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot t_{i2}$$

Light Rail:

$U_{i3} =$

$$\alpha_3^{RPSC} \cdot R \cdot P \cdot SC + \alpha_3^{RPSF} \cdot R \cdot P \cdot SF + \alpha_3^{RPSN} \cdot R \cdot P \cdot SN$$

$$+\alpha_3^{SPSC} \cdot (1-R) \cdot P \cdot SC + \alpha_3^{SPSF} \cdot (1-R) \cdot P \cdot SF + \alpha_3^{SPSN} \cdot (1-R) \cdot P \cdot SN$$

$$-\begin{bmatrix} \lambda^{RPSC} \cdot R \cdot P \cdot SC + \lambda^{RPSF} \cdot R \cdot P \cdot SF + \lambda^{RPSN} \cdot R \cdot P \cdot SN \ + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN + \lambda^{SSF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot p_{i3}$$

$$-\begin{bmatrix} \mu^{RPSC} \cdot R \cdot P \cdot SC + \mu^{RPSF} \cdot R \cdot P \cdot SF + \mu^{RPSN} \cdot R \cdot P \cdot SN + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN + \mu^{SPSF} \cdot (1-R) \cdot P \cdot SF + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot t_{i3}$$

$$+$$

$$\alpha_3^{RISC} \cdot R \cdot (1-P) \cdot SC + \alpha_3^{RISF} \cdot R \cdot (1-P) \cdot SF + \alpha_3^{RISN} \cdot R \cdot (1-P) \cdot SN$$

$$+ \alpha_3^{SISC} \cdot (1-R) \cdot (1-P) \cdot SC + \alpha_3^{SISF} \cdot (1-R) \cdot (1-P) \cdot SF$$

$$+ \alpha_3^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN$$

$$-\begin{bmatrix} \lambda^{RISC} \cdot R \cdot (1-P) \cdot SC + \lambda^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \lambda^{RISN} \cdot R \cdot (1-P) \cdot SN \quad + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \lambda^{SISF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot p_{i3}$$

$$-\begin{bmatrix} \mu^{RPIC} \cdot R \cdot (1-P) \cdot SC + \mu^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \mu^{RISN} \cdot R \cdot (1-P) \cdot SN + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \mu^{SISF} \cdot (1-R) \cdot (1-P) \cdot SF + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot t_{i3}$$

Walk:

$U_{i4} =$

$$\alpha_4^{RPSC} \cdot R \cdot P \cdot SC + \alpha_4^{RPSF} \cdot R \cdot P \cdot SF + \alpha_4^{RPSN} \cdot R \cdot P \cdot SN$$

$$+\alpha_4^{SPSC} \cdot (1-R) \cdot P \cdot SC + \alpha_4^{SPSF} \cdot (1-R) \cdot P \cdot SF + \alpha_4^{SPSN} \cdot (1-R) \cdot P \cdot SN$$

$$-\begin{bmatrix} \lambda^{RPSC} \cdot R \cdot P \cdot SC + \lambda^{RPSF} \cdot R \cdot P \cdot SF + \lambda^{RPSN} \cdot R \cdot P \cdot SN + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN + \lambda^{SSF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot p_{i4}$$

$$-\begin{bmatrix} \mu^{RPSC} \cdot R \cdot P \cdot SC + \mu^{RPSF} \cdot R \cdot P \cdot SF + \mu^{RPSN} \cdot R \cdot P \cdot SN + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN + \mu^{SPSF} \cdot (1-R) \cdot P \cdot SF + \\ \mu^{SPSN} \cdot (1-R) \cdot P \cdot SN \end{bmatrix} \cdot t_{i4}$$

$$+$$

$$\alpha_4^{RISC} \cdot R \cdot (1-P) \cdot SC + \alpha_4^{RISF} \cdot R \cdot (1-P) \cdot SF + \alpha_4^{RISN} \cdot R \cdot (1-P) \cdot SN$$

$$+\alpha_4^{SISC} \cdot (1-R) \cdot (1-P) \cdot SC + \alpha_4^{SISF} \cdot (1-R) \cdot (1-P) \cdot SF$$

$$+\alpha_4^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN$$

$$-\begin{bmatrix} \lambda^{RISC} \cdot R \cdot (1-P) \cdot SC + \lambda^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \lambda^{RISN} \cdot R \cdot (1-P) \cdot SN \quad + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \lambda^{SISF} \cdot (1-R) \cdot P \cdot SF + \\ \lambda^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot p_{i4}$$

$$-\begin{bmatrix} \mu^{RPIC} \cdot R \cdot (1-P) \cdot SC + \mu^{RISF} \cdot R \cdot (1-P) \cdot SF + \\ \mu^{RISN} \cdot R \cdot (1-P) \cdot SN + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN + \mu^{SISF} \cdot (1-R) \cdot (1-P) \cdot SF \ + \\ \mu^{SISN} \cdot (1-R) \cdot (1-P) \cdot SN \end{bmatrix} \cdot t_{i4}$$

Within this general structure, a series of more specific comparisons between the different types of data and the regions were conducted.

4.2.2 Comparison of Revealed Preference and Stated Preference

The first tests analyzed whether the data collected from the individual,s actual commute decision (revealed preference data) can be combined with her responses to choice experiments asking which choice shewould make from among specific commuting choices that differ in the time and money required for the commute as well as the commute mode (stated preference data).

To determine whether these two sets of data could be pooled, an unrestricted model, in which both data sets are included but the parameter vectors pertaining to each are different, was first estimated, treating residents of each of the three cities separately. This was compared to a restricted model in which all coefficients are restricted to be the same for both data sets. The null hypothesis that both parameter vectors are the same was tested with a likelihood ratio test, which has a test statistic

(4-5) $$LR = -2 \cdot \ln \frac{L_R}{L_U}$$

which is distributed as a chi-squared variate with degrees of freedom equal to the number of restrictions placed on the model.

For reasons of space, the likelihood ratio tests reported here are for simple models of the sort usually seen in the transportation economics literature, and they are representative of the findings for all models. Conditional utilities in the unrestricted model used for this are

Car: $U_{i1} = [\alpha_1^R \cdot R + \alpha_1^S \cdot (1-R)] - [\lambda^R \cdot R + \lambda^S \cdot (1-R)] \cdot p_{i1}$

$$-[\mu^R \cdot R + \mu^S \cdot (1-R)] \cdot t_{i1}$$

Bus: $U_{i2} = -[\lambda^R \cdot R + \lambda^S \cdot (1-R)] \cdot p_{i2}$

$$-[\mu^R \cdot R + \mu^S \cdot (1-R)] \cdot t_{i2}$$

Light Rail: $U_{i3} = [\alpha_3^R \cdot R + \alpha_3^S \cdot (1-R)] - [\lambda^R \cdot R + \lambda^S \cdot (1-R)] \cdot p_{i3}$

$$-[\mu^R \cdot R + \mu^S \cdot (1-R)] \cdot t_{i3}$$

Walk: $U_{i4} = [\alpha_4^R \cdot R + \alpha_4^S \cdot (1-R)] - [\lambda^R \cdot R + \lambda^S \cdot (1-R)] \cdot p_{i4}$

$$-[\mu^R \cdot R + \mu^S \cdot (1-R)] \cdot t_{i4}$$

In estimation, the parameters α_1^R and α_1^S are modeled as randomly distributed with normal distributions,[26] and the remaining parameters are modeled as constants. When the restrictions that: $\lambda^R = \lambda^S$, $\mu^R = \mu^S$, $\alpha_1^R = \alpha_1^S$, $\alpha_3^R = \alpha_3^S$, $\alpha_4^R = \alpha_4^S$, and $\sigma^{\alpha_1^R} = \sigma^{\alpha_1^S}$ (where $\sigma^{\alpha_1^R}$ and $\sigma^{\alpha_1^S}$ are the standard deviations for $\alpha_1^R$and α_1^S respectively) are imposed, the conditional utilities in the restricted model simplify to

Car: $U_{i1} = \alpha_1^R - \lambda^R \cdot p_{i1} - \mu^R \cdot t_{i1}$

Bus: $U_{i2} = -\lambda^R \cdot p_{i2} - \mu^R \cdot t_{i2}$

[26] The other alternative specific variables were also modeled as randomly distributed with normal distributions but these models did not converge to solutions.

Light Rail: $U_{i3} = \alpha_3^R - \lambda^R \cdot p_{i3} - \mu^R \cdot t_{i3}$

Walk: $U_{i4} = \alpha_4^R - \lambda^R \cdot p_{i4} - \mu^R \cdot t_{i4},$

The results from this test are presented in table 4.1.

Table 4.1. Tests of Differences between the Revealed and Stated Preference Data Sets, by City

		Unrestricted Model			Restricted Model		
Variable Name	Coefficient	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
-R·t $-R \cdot t_j$	μ^R	0.0307 (2.60) ***	0.0236 (5.62) ***	0.0029 (0.46)	0.0640 (15.55) ***	0.0626 (22.49) ***	0.0498 (17,47) ***
$-(1-R) \cdot t_j$	μ^S	0.0664 (15.51) ***	0.0623 (21.98) ***	0.0189 (13.80) ***	___	___	___
$-R \cdot p_j$	λ^R	0.1980 (1.88) *	0.2462 (5.62) ***	0.0668 (1.32)	0.1793 (10.81) ***	0.2199 (14.91) ***	0.1245 (10.73) ***
$-(1-R) \cdot p_j$	λ^S	0.1887 (10.71) ***	0.2078 (13.21) ***	0.0046 (1.66) *	___	___	___
R·Car	α_1^R	4.2621 (2.00) **	0.9227 (2.72) ***	3.6850 (3.28) ***	2.1772 (12.60) ***	-0.1514 (-1.06)	1.5465 (12.67) ***
	$\sigma^{\alpha_1^R}$	1.6526 (1.03)	0.0295 (0.05)	0.6359 (0.37)	2.5098 (7.41) ***	2.940 (9.49) ***	2.3015 (7.11) ***
(1-R)·Car	α_1^S	2.2286 (12.26) ***	-0.0532 (-0.37)	1.7707 (1.90) *	___	___	___
	$\sigma^{\alpha_1^S}$	2.8083 (7.62) ***	2.5966 (7.80) ***	0.0658 (0.05)	___	___	___
R·Trn	α_3^R	1.4332 (1.31)	0.3725 (1.30)	___	0.4038 (4.94) ***	0.2037 (3.45) ***	0.7472 (11.01) ***
(1-R)·Trn	α_3^S	0.4096 (4.90) ***	0.1802 (3.03) ***	-0.164 (-3.19) ***	___	___	___

R·Wlk	α_4^R	2.8463 (12.256) ***	-1.5993 (-3.06) ***	-25.74 (0.00)	1.8647 (2.19) **	-1.5426 (-2.60) ***	-0.4278 (-0.48)
Log-Likelihood		-1669	-2189	-2238	-1677	-2207	-2705
Number of Responses		2164	2985	2833	2164	2985	2833

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively.

The values for the test statistics are: Sacramento = 16.2, San Francisco =36.4 and Sonoma = 934. For each city, the restricted model places 5 restrictions on the unrestricted model, so in each case the degrees of freedom are equal to 5. The critical χ^2 values are χ^2_c = 9.24 for p = 0.10, χ^2_c = 11.07 for p = 0.05, and χ^2_c = 15.09 for p = 0.01.

In all cases the null hypothesis that there is no significant difference between the two models is rejected. Given that the real world situations that face individuals differ substantially from those in the choice experiments, especially the lack of variation in available public commute modes, it is not too surprising that the models based on this data produce significantly different results than models based on the stated preference data that, by design, have a large amount of variation in choices. Because of these differences, the revealed and stated preference data were not pooled in subsequent estimation.

4.2.3 Comparison of Internet Survey Data and Mail Survey Data

The null hypothesis that the Internet and mail survey data sets can be pooled was tested in a manner similar to that for comparing the stated preference data and revealed preference data. Results from simple models (including only the terms for μ^P, μ^I, λ^P and λ^I and the alternative specific constants) are displayed in table 4.2. These models are illustrative of the results for other models based on paper and internet data.

Table 4.2 Tests of Differences between the Mail and Internet Stated Preference Data Sets, by City

		Unrestricted Model			Restricted Model		
Variable Name	Coefficient	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
$-P \cdot t_j$	μ^P	0.0493 (6.32) ***	0.0455 (11.57) ***	0.0508 (7.12) ***	0.0660 (15.36) ***	0.0621 (21.89) ***	0.0528 (18.44) ***
$-(1-P) \cdot t_j$	μ^I	0.0718 (13.95) ***	0.0697 (20.03) ***	0.0539 (16.86) ***	—	—	—
$-P \cdot p_j$	λ^P	0.1461 (4.33) ***	0.1361 (10.55) ***	0.0824 (3.97) ***	0.1883 (10.60) ***	0.2062 (13.52) ***	0.1334 (11.26) ***
$-(1-P) \cdot p_j$	λ^I	0.2027 (9.67) ***	0.2418 (12.93) ***	0.1464 (10.37) ***	—	—	—
$P \cdot Car$	α_1^P	1.9257 (5.60) ***	0.4922 (3.15) ***	1.6848 (5.47) ***	2.2246 (12.19) ***	-0.0585 (-0.41)	1.5087 (11.88) ***

	$\sigma^{\alpha_1^P}$	1.9147 (7.14) ***	0.0757 (0.14)	2.4872 (3.30) ***	2.7883 (7.45) ***	2.5764 (7.66) ***	2.5735 (8.19) ***
(1-P)·Car	α_1^I	2.3367 (10.77) ***	-0.2847 (-1.49)	1.4731 (10.51) ***	—	—	—
	$\sigma^{\alpha_1^I}$	3.0597 (7.14) ***	3.3429 (8.62) ***	2.5917 (7.33) ***	—	—	—
P·Trn	α_3^P	0.2284 (1.32)	0.1124 (0.96)	0.4264 (2.61) ***	0.4067 (4.87) ***	0.1780 (3.02) ***	0.7475 (10.83) ***
(1-P)·Trn	α_3^I	0.4789 (4.94) ***	0.2230 (3.20) ***	0.8222 (10.62) ***	—	—	—
Log-Likelihood		-1631	-2061	-2157	-1638	-2075	-2177
Number of Responses		2012	2782	2630	2012	2782	2630

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively.

The values for the χ^2 test statistics are: Sacramento = 14, San Francisco = 28 and Sonoma = 40. In each case the degrees of freedom are equal to 5. The critical χ^2 values are $\chi^2_c = 9.24$ for p = 0.10, $\chi^2_c = 11.07$ for p = 0.05, and $\chi^2_c = 15.09$ for p = 0.01. The null hypothesis is rejected in all cases at the 95% level and in both Sonoma and San Francisco at the 99% level. Subsequently the data was modeled separately for each region.

4.2.4 Revealed Preference Data

Results for the tests on revealed preference data are displayed in table 4.3.

Table 4.3 - Tests of Differences between the Mail and Internet Revealed Preference Data Sets, by City

		Unrestricted Model			Restricted Model		
Variable Name	Coefficient	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
$-P \cdot t_j$	μ^P	0.4085 (1.73) **	-0.3411 (-0.24)	0.0213 (0.00)	0.0322 (2.60) ***	0.0236 (4.33) ***	0.0149 (1.52)
$-(1-P) \cdot t_j$	μ^I	0.0292 (2.48) **	0.0382 (6.07) ***	0.0153 (1.50)	—	—	—
$-P \cdot p_j$	λ^P	0.9066 (1.22)	0.6545 (0.03)	-0.023 (-0.00)	0.2230 (1.89) *	0.2461 (5.62) ***	0.0300 (0.41)
$-(1-P) \cdot p_j$	λ^I	0.1970 (1.73) *	0.3255 (10.41) ***	0.0297 (0.39)	—	—	—
$P \cdot Car$	α_1^P	-7.3255 (-0.96)	15.114 (0.03)	21.174 (0.00)	5.0698 (1.85) *	0.9220 (2.71) ***	5.5832 (1.79) *
	$\sigma^{\alpha_1^P}$	4.7731 (0.82)	56.107 (0.03)	2.9149 (1.20)	2.2153 (1.29)	0.0798 (0.14)	2.7549 (1.20)
$(1-P) \cdot Car$	α_1^I	4.7658 (2.09) **	0.7403 (1.58)	5.6063 (1.71) *	—	—	—
	$\sigma^{\alpha_1^I}$	4.7731 (0.92)	0.0142 (0.00)	2.9149 (1.20)	—	—	—
$P \cdot Trn$	α_3^P	12.1384 (2.99) ***	9.1792 (0.03)	—	1.6504 (1.30)	0.3728 (1.30)	—
$(1-P) \cdot Trn$	α_3^I	1.8126 (1.41)	0.3260 (0.72)	—	—	—	—

P·Wlk	α_4^P	-22.5357 (-0.72)	-97.919 (-0.03)	-0.800 (-0.00)	3.1826 (1.92) *	-1.600 (-3.06) ***	0.8010 (1.20)
(1-P)·Wlk	α_4^I	3.7270 (2.24) **	-1.3517 (-2.21) **	0.8676 (0.81)	___	___	___
Log-Likelihood		-31.9	-110.6	-30.3	-36.4	-127.6	-31.7
Number of Responses		152	203	203	152	203	203

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively.

The values for the test statistics are: Sacramento = 9.00, San Francisco = 34.00, and Sonoma = 2.80. The degrees of freedom are equal to 6 for Sacramento and San Francisco and 5 for Sonoma.[27] `1 Subsequently the critical values are for Sacramento and San Francisco are for p = 0.10 is χ^2_c = 10.64, for p = 0.05 is χ^2_c = 12.59 and for p =0.01 is χ^2_c = 16.81.and for Sonoma for p = 0.10 is χ^2_c = 9.24, for p = 0.05 is χ^2_c = 11.07 and for p =0.01 is χ^2_c = 15.09.

The results of the likelihood ratio tests for the revealed preference data suggest that there is a difference between the mail and internet data for San Francisco but not for Sacramento or Sonoma. Consequently for San Francisco the internet data was treated separately, whereas for Sonoma and Sacramento the full data set was used. However, in the case of Sonoma revealed preference

[27] Sonoma County does not have the train or light rail mode available

models, all of the models produced almost entirely insignificant results or did not converge.

4.2.5 Including Transportation Infrastructure in the Model

The next step in the description of the models estimated is the introduction of terms related to transportation infrastructure in the neighborhood of the commuter. The first of these variables is the bus stop density in the neighborhood of the commuter's home, which is the number of bus stops within a quarter mile of home. [28, 29]

The bus stop density (and, later, frequency) variables appear in conditional utility in 3 ways: as alternative-specific variables and as part of the marginal utilities of time and money, for 2 of the 3 modes. Thus transportation

---

[28] These distances were calculated as the Euclidean distance from the home of the respondent to the position of the bus stop. There was no consideration made for the actual streets that someone would have to walk in order to get to the bus stop. While the actual distance traveled may be slightly longer than the calculated in some cases, the number of bus stops within a given distance does reflect the level of bus service available. However, when times were determined for travel by bus, on-line services from the various transit agencies in the 3 communities were used. In these instances the travel times and distances traveled were determined by the travel agencies and dependent on the actual routes available.

[29] Additional models were analyzed that incorporated terms for Bus Stop Density within ½ mile, 1/8 mile and 1 mile of the commuter's home. The results produced were similar with the magnitude or the coefficients diminishing with increased distance from home. The models that include the density of bus stops within ¼ mile radius were preferred since this distance is considered a "reasonable" distance for most individuals to walk to the bus stop

infrastructure (as represented by this variable) has a fairly flexible effect on both conditional utility and the opportunity cost of time. The inclusion of bus stop density as alternative-specific variables for 2 of the 3 modes reflects the hypothesis that the density of bus stops helps explain the propensity to use a particular mode relative to the others. The coefficients on these two terms are allowed to differ; suggesting that the existence of bus stops will impact the various modes in different manners and magnitudes.[30]

For the revealed preference models, the transportation infrastructure enters somewhat less flexibly, as a shifter of the marginal utility of money but not of the marginal utility of time. In most[31] of the subsequent models this convention is adopted and consequently the revealed preference models generally have fewer terms than the stated preference models. This was done due to the lack of convergence and instability of most of the revealed preference models that included all of the terms.

---

[30] It is reasonable to hypothesize that the number of bus stops has an impact on the utility derived from choosing the bus. A more highly developed level of service, in part captured by the number of bus stops, could impact utility in a number of ways; particularly by reducing risk and increasing the number of options. The number of bus stops could also impact the utility of light rail travel, in as much as the light rail is part of a public transit network that includes buses. Finally, the number of bus stops can impact the utility of automobile travel, either positively or negatively. This impact could be due to the diminishing the stress of driving due to other individuals riding the bus or it could lead to increased stress of driving if a commuter has a negative interaction with bus travelers. As such the magnitude and sign of the coefficients is determined empirically.

[31] The model with the numeraire interaction term, the bus stop density and no demographic determinants has transit density appearing in both the time and money terms.. In all subsequent models, with or with the numeraire interaction term, the money related term is omitted

4.2.6 Estimation Results for the Stated Preference Models

Table 4.4 presents the parameter estimates for the complete stated preference models, including transportation infrastructure, demographic shifters, and the numeraire interaction term. Not surprisingly, inclusion of the full set of demographic variables resulted in insignificant parameter estimates for many, including the nonlinear age effect (age squared), gender, home ownership, and number of children. Consequently, these demographics were omitted from the final models. In addition, a number of other terms such as C*Age (the impact of age on the Car choice as an alternative-specific constant) were insignificant and were also omitted from the final models

Table 4.4 Econometric Results for the Stated Preference Model, By City and Opportunity Cost of Time Specification – Including Car Ownership

		Opportunity Cost of Time Specification:					
		Independent of Income			Varies With Income		
Variable Name	Coefficient	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
$X_{M_j} \cdot X_{T_j}$	β^{FB}	——	——	——	0.00017 (3.61) ***	0.0002 (4.39) ***	0.0001 (3.63) ***
	$\sigma^{\beta^{FB}}$	——	——	——	0.00019 (5.25) ***	0.0001 (5.74) ***	0.0001 (5.69) ***
$-t_j$	μ	0.0404 (2.69) ***	0.1216 (6.23) ***	0.0386 (4.24) ***	0.0252 (1.55)	0.1222 (5.37) ***	0.0282 (2.24) **
$-p_j$	λ	0.1229 (2.54) **	0.4072 (4.86) ***	0.0844 (2.69) ***	-0.1051 (-1.32)	0.3545 (3.40) ***	-0.0295 (-0.47)
$-t_j \cdot BD$	μ^{BD}	0.0012 (1.40)	-0.0004 (-0.64)	0.0002 (0.14)	0.0013 (1.34)	-0.0003 (-0.53)	-0.0001 (-0.01)
$-p_j \cdot BD$	λ^{BD}	0.0058 (1.87) *	0.0055 (2.18) **	0.0022 (0.61)	0.0049 (1.78) *	0.0055 (2.08) **	0.0011 (0.31)
$-t_j \cdot OC$	μ^{OC}	0.1067 (4.32) ***	0.0784 (4.29) ***	0.0861 (5.36) ***	0.565 (2.75) ***	0.0386 (2.29) **	0.0638 (3.68) ***
	$\sigma^{\mu^{OC}}$	0.1089 (4.49) ***	0.0758 (5.28) ***	0.0800 (6.28) ***	0.0752 (3.59) ***	0.0598 (4.07) ***	0.0645 (4.80) ***
$-p_j \cdot OC$	λ^{OC}	0.1799 (3.80) ***	0.1178 (2.11) **	0.2151 (5.45) ***	0.1309 (2.45) ***	0.0137 (0.25)	0.1441 (2.87) ***
	$\sigma^{\lambda^{OC}}$	0.3176 (4.70) ***	0.3363 (6.27) ***	0.2770 (6.50) ***	---	0.2929 (5.31) ***	0.1634 (2.68) ***
$Car \cdot OC$	β^{COC}	----	0.7329 (1.79) *	____	---	0.0048 (0.01)	----
Car	α_1	3.0127 (6.83) ***	0.3394 (0.43)	2.0479 (8.98) ***	2.6119 (6.89) ***	0.0048 (0.01)	2.0583 (8.74) ***
	σ^{α_1}	3.0732 (3.33) ***	1.5436 (2.37) **	2.6223 (3.81) ***	1.9800 (2.59) ***	2.4234 (3.41) ***	2.4461 (3.43) ***

$Bus \cdot BD$	β^{BBD}	0.0303 (1.42)	0.0569 (2.24) **	0.0021 (0.08)	0.0282 (1.47)	0.0597 (2.33) **	0.0034 (0.13)
$LRail \cdot OC$	β^{LOC}	----	0.6924 (3.29) ***	------	---	0.6445 (2.84) ***	----
$LRail \cdot BD$	β^{LBD}	----	0.0262 (1.08)	------	---	0.0258 (1.07)	----
L	α_3	0.8354 (4.58) ***	0.4254 (1.57)	1.2613 (8.33) ***	0.8181 (4.48) ***	0.5379 (1.85) *	1.3130 (8.14) ***
$-t_j \cdot AGE$	μ^{AGE}	----	-0.0010 (-3.33) ***	-----	----	-0.0012 (-3.70) ***	----
$-p_j \cdot AGE$	λ^{AGE}	----	-0.0032 (-2.54) ***	------	----	-0.0047 (-3.49) ***	----
Log-Likelihood		-1235	-1377	-1322	-1223	-1360	-1302
Number of Responses		1590	2072	2186	1590	2072	2186

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively.

It is useful to interpret the implications of the signs on estimated parameters for their effects on the shadow value of time. The three broad categories of variables of interest are transportation infrastructure, demographics, and the budget variables, principally money income. They may enter either the marginal utility of time (the numerator of the shadow value of time) or the marginal utility of money (the denominator).

To illustrate the effects on comparative statics, we can consider two of the principal variables of interest: bus stop density, which appears in both the numerator and denominator of the shadow value of time, and money income, which appears only in the numerator. Writing the opportunity cost of time as

$$(4\text{-}18) \qquad \rho \equiv \frac{\mu}{\lambda} = \frac{\mu(s)+\mu^{BD}\cdot BD+\beta\cdot M}{\lambda(s)+\lambda^{BD}\cdot BD},$$

where $\mu(s)$ and $\lambda(s)$ are covariates other than the variables of interest (bus stop density *BD* and income *M*) entering the marginal utilities of time and money, respectively. As bus stop density (*BD*) changes, for example, the comparative static effect is

$$(4\text{-}19) \frac{\partial\rho}{\partial BD} = \frac{\mu^{BD}-\lambda^{BD}\cdot\rho}{\lambda}.$$

For San Francisco residents, the effects of bus stop density on the marginal utility of time (μ^{BD}) is negative and its effect on the marginal utility of money (λ^{BD}) is positive. Consequently, their value of commute time unambiguously decreases with bus stop density, since with $\mu^{BD} < 0$ and $\lambda^{BD} > 0$, $\frac{\partial\rho}{\partial BD} < 0$.

For Sacramento, both μ^{BD} and λ^{BD} are greater than 0. While in general this is indeterminate, for the estimated parameter values, $\frac{\partial \rho}{\partial BD} < 0$, consistent with expectations.

For the Sonoma region both μ^{BD} and λ^{BD} are insignificant. This is either the result of insufficient data or because bus stop density does not have an impact on the marginal value of time or the marginal value of money. Consequently, the level of bus stop density has no impact on the opportunity cost of time in this region.

Similarly, from (4-18), it can be seen that the change in the shadow value of commute time with money income is

(4-19) $$\frac{\partial \rho}{\partial M} = \frac{\beta}{\lambda},$$

and since the marginal utility of money (λ) and β are positive for all estimated models, the effect of an increase in income is to increase the shadow value of commute time.

Evaluation of the effects of demographics is similarly straightforward. For example, it can be verified that the opportunity cost of time increases with home ownership and decreases with age.

Tables 4.5 and 4.7 present the two different summary measures of the distribution of the opportunity cost of time implied by the stated preference models. Table 4.5 summarizes the sample distribution of predicted values of time for each person in the sample. The variation in these estimates is due to differences in the covariates across people. Table 4.7 presents the distribution of the shadow value of time evaluated at the means of the covariates, using the Krinsky-Robb simulation approach. The estimates here reflect the effect of accounting for estimation uncertainty, as they reflect the precision with which the parameters are estimated.

The t-scores that that are the result of hypothesis tests that compare the mean values of time for the three communities are displayed in table 4.6 and 4.8.

For both sets of estimates all comparisons of means are statistically significant for $p<0.001$. The value of time is lowest in San Francisco and highest in Sacramento. This result is similar for models that vary with income and those that are independent of income. In the regions in which the bus stop density terms are significant (Sacramento and San Francisco) the value of time decreases with bus stop density. This is consistent with the expectation that higher levels of transportation infrastructure will relax the constraints on time.

Table 4.5 Distribution of Sample Point Estimates of the Values of Time – Stated Preference Models

	Opportunity Cost of Time Specification					
	Independent of Income			Varies With Income		
	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
ρ	\$26.38	\$18.22	\$24.78	\$24.99	\$16.52	\$23.82
σ^{ρ}	\$2.93	\$3.41	\$2.67	\$6.50	\$6.23	\$3.55
MIN	\$16.47	\$3.51	\$21.85	\$12.44	\$3.12	\$11.23
MAX	\$29.15	\$24.36	\$28.36	\$37.10	\$27.86	\$34.44

Table 4.6 Test Statistic – Difference in Mean Value of Time

	Regions Compared		
Model	Sacramento – San Francisco	San Francisco – Sonoma	Sacramento – Sonoma
	T-Score	T-Score	T-Score
Independent of Income	77.72	-69.64	17.19
Varies with Income	39.79	-46.64	6.51

Table 4.7 – Mean and Variation in the Shadow Value of Time (ρ) Due to Parameter Uncertainty – Stated Preference Models

	Opportunity Cost of Time Specification					
	Independent of Income			Varies With Income		
	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
ρ	$27.37	$18.29	$24.68	$25.76	$17.43	$25.03
σ^{ρ}	2.45	1.18	1.86	2.17	0.97	1.90

Table 4.8 Test Statistic – Difference in Mean Value of Time

	Regions Compared		
Model	Sacramento – San Francisco	San Francisco – Sonoma	Sacramento – Sonoma
	T-Score	T-Score	T-Score
Independent of Income	136.16	-134.57	36.75
Varies with Income	142.53	-165.63	10.75

4.2.7 Revealed Preference Model - San Francisco

The revealed preference models include fewer terms overall than in the stated preference models. Preliminary tests were made of models that included the same set of parameters included in the stated preference models, but these models either failed to converge or produced results in which there were no significant coefficients. Subsequent models were run using primarily the time-related terms for each of the attribute functions. A final model was developed only for San Francisco, and it contained a smaller set of covariates - bus stop density and car ownership along with time and money prices and the alternative specific constants. The econometric estimates from this model are presented in Table 4.9, and the resulting shadow values of time are summarized in Tables 4.10 and 4.11.

The estimates of the value of time displayed in table 4.10 are similar for the model that is independent of income ($8.07) and the model that varies with income ($8.04). While the full budget parameter (β^{FB}) is significant, the inclusion of this variable does not impact the distribution of the values of time significantly.

Table 4.9. – San Francisco - Revealed Preference Data Set – All Attributes – Including Car Ownership

Variable Name	Coefficient	Opportunity Cost of Time Specification: Independent of Income	Opportunity Cost of Time Specification: Varies With Income
$XMXT_j^{'}$	β^{FB}	———	0.00007 (1.29)
$-t_j$	μ	0.0566 (2.59) ***	0.0432 (1.93) *
$-p_j$	λ	0.3897 (5.41) ***	0.3062 (3.21) ***
$-t_j \cdot BD$	μ^{BD}	-0.0039 (-2.59) ***	-0.0036 (-2.39) **
$-t_j \cdot OC$	μ^{OC}	0.0599 (3.72) ***	0.0496 (2.94) ***
Car	α_1	-0.8795 (-0.79)	-0.7569 (-0.68)
$Bus \cdot BD$	β^{BBD}	-0.1095 (-1.81) *	-0.1036 (-1.71) *
$LRail \cdot BD$	β^{LBD}	-0.1341 (-1.88) *	-0.1288 (-1.80) *
$LRail$	α_3	0.6845 (0.68)	0.7294 (0.72)
$Walk \cdot BD$	β^{WBD}	-0.7086 (-2.41) **	-0.6931 (-2.62) **
	$\sigma^{\beta^{WBD}}$	0.2452 (2.17) **	0.2639 (2.38) **
$Walk$	α_4	4.1579 (1.28)	3.6494 (1.15)
Log-Likelihood		-71	-70

Number of Responses	167	167

The numeraire interaction term is not significant at the 90% level. μ^{BD} is significant and negative for both models. Given the absence of the parameter λ^{BD} in this model, a negative value for μ^{BD} implies that a change in $\mu(\cdot)$ with respect to BD is negative and subsequently the value of time decreases with BD. This is as expected, implying that an increase in the level of the transportation service will relax the constraint on time and subsequently lower the value of time.

μ^{OC} is positive and significant implying that ownership or access to a car tends to increase the value of time. This is an interesting contrast to public transportation infrastructure which tends to lower the opportunity cost of time rather than increasing it. This suggests that car ownership is endogenous.[32] Additional models that exclude car ownership as a variable impacting the value of time are included in the section 4.2.15.

[32] Further analysis of the endogeneity of car ownership in the context of models of the value of time will be the basis for future work.

Table 4.10– Distribution of Sample Point Estimates of the Shadow Value of Time – Revealed Preference Model for San Francisco

	Opportunity Cost of Time Specification	
	Independent of Income	Varies With Income
ρ	\$8.07	\$8.04
σ^{ρ}	\$4.15	\$4.06
MIN[33]	\$0.00	\$0.00
MAX	\$17.95	\$15.58

Table 4.11 – Mean and Variation in the Shadow Value of Time (ρ) Due to Parameter Uncertainty – Revealed Preference Model for San Francisco

	Opportunity Cost of Time Specification	
	Independent of Income	Varies With Income
ρ	\$8.04	\$8.04
σ^{ρ}	2.34	2.25

4.2.8 Stated Preference Model for All Regions

Because the random parameters logit model is a fairly flexible way to represent preferences, and differences in preferences across people, a final set of models was estimated for each type of preference data, pooling the

[33] 4 cases had value of time less than 0. These values were set to 0.

observations from all regions. Estimation results are presented in table 4.12, while tables 4.13 and 4.15 present summaries of the distribution of the shadow value of time, reflecting variation in covariates across the sample (Table 4.13) and estimation uncertainty (Table 4.15).

The value of time decreases with bus stop density, increases with car ownership, and decreases with age. In addition this model implies that the value of time is higher for men than for women, and is lower for those who have fixed work schedules, *ceteris paribus*.

The t-scores resulting from hypothesis tests that compare the mean values of time for the three communities are displayed in table 4.14 and 4.16.

For both sets of estimates all comparisons of means are statistically significant for $p<0.001$ except for the comparison of Sacramento and Sonoma in terms of the variation of covariates (table 4.13) which is insignificant. The value of time is lower in San Francisco than the other two communities. This result is similar for models that vary with income and those that are independent of income. In the regions in which the bus stop density terms are significant (Sacramento and San Francisco) the value of time decreases with bus stop density.

Table 4.12. – Estimation Results for the Stated Preference Model—All regions —Including Car Ownership

		Opportunity Cost of Time Specification	
Variable Name	Coefficient	Independent of Income	Varies With Income
$XMXT_j'$	β^{FB}	———	0.0001 (11.28) ***
$-t_j$	μ	0.0739 (5.79) ***	0.0583 (4.65) ***
$-p_j$	λ	0.2095 (10.04) ***	0.0717 (2.15) **
$-t_j \cdot BD$	μ^{BD}	00004 (1.19)	0.0003 (0.98)
$-p_j \cdot BD$	λ^{BD}	0.0091 (8.21) ***	0.0093 (8.38) ***
$-t_j \cdot OC$	μ^{OC}	0.0643 (7.21) ***	0.0523 (6.00) ***
	$\sigma^{\mu^{OC}}$	0.0731 (9.80) ***	0.0675 (9.51) ***
$-t_j \cdot AGE$	μ^{AGE}	-0.0004 (-1.91) *	-0.0004 (-1.99) **
$-p_j \cdot Male$	λ^{Gen}	-0.0335 (-2.23) **	-0.0294 (-2.06) **
$-p_j \cdot FH$	λ^{FH}	0.0425 (2.94) ***	0.0407 (2.94) ***
Car	α_1	1.6515 (11.12) ***	1.6090 (11.28) ***
	σ^{α_1}	3.9934 (9.80) ***	3.7572 (10.92) ***
$Bus \cdot BD$	β^{BBD}	0.0397 (5.24) ***	0.0391 (5.26) ***

LRail	α_3	0.9756 (10.32) ***	0.9490 (10.92) ***
Log-Likelihood		-3695	-3684
Number of Responses		5748	5748

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively

Table 4.13 – Distribution of Sample Point Estimates of the Values of Time – Stated Preference Model for All Regions

	Opportunity Cost of Time Specification					
	Independent of Income			Varies With Income		
	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
ρ	\$29.27	\$21.16	\$30.70	\$29.27	\$21.57	\$30.65
σ^{ρ}	\$7.02	\$5.46	\$6.06	\$8.14	\$6.29	\$6.95
MIN	\$11.18	\$8.03	\$11.28	\$8.59	\$6.90	\$9.95
MAX	\$43.50	\$33.32	\$43.64	\$50.09	\$39.07	\$47.93

Table 4.14 Test Statistic – Difference in Mean Value of Time

Model	Regions Compared Sacramento – San Francisco	San Francisco – Sonoma	Sacramento – Sonoma
	T-Score	T-Score	T-Score
Independent of Income	8.11	-9.54	-1.43
Varies with Income	7.70	-9.08	-1.38

Table 4.15 – Mean and Variation in the Shadow Value of Time (ρ) Due to Parameter Uncertainty – Stated Preference Data Set – One Population

	Opportunity Cost of Time Specification					
	Independent of Income			Varies With Income		
	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
ρ	\$27.54	\$20.01	\$29.76	\$27.04	\$20.15	\$29.41
σ^{ρ}	1.42	1.03	1.73	1.39	0.99	1.70

Table 4.16 Test Statistic – Difference in Mean Value of Time

Region Compared	Regions Compared Sacramento – San Francisco	San Francisco – Sonoma	Sacramento – Sonoma
	T-Score	T-Score	T-Score
Independent of Income	7.53	-9.75	-2.22
Varies with Income	6.89	-9.26	-2.37

4.2.9 Revealed Preference Model for All Regions

Treating all three regions as one population for the revealed preference data resulted in models that either did not converge or with coefficients that were insignificant for nearly all variables of interest. In particular the inclusion the Sonoma data was problematic. Consequently, models were created in which Sacramento and San Francisco were treated as one population. Even with this simplification, models containing the numeraire interaction term failed to converge. Thus, the model presented does not include this term.

In this model, the value time decreases with bus stop density, decreases with fixed hours and decreases with years of school (SY). Estimation results for this model are presented in table 4.17, while tables 4.18 and 4.19 present the summaries of the distributions of the shadow value of time. The hypothesis test that compared the mean for the values of time in table 4.18 resulted in a T score of 4.34 and the same comparison for the values of time in table 4.19 resulted in a T score of T score 10.46. In both cases the means are statistically significant for p<0.001.

The value of time is higher in Sacramento than it is in San Francisco. This is consistent with the results from all of the other models in this study and suggests that the level of transportation infrastructure is a significant determinant of the opportunity cost of time for the commute activity.

Table 4.17 – Revealed Preference Model for Sacramento and San Francisco

Variable Name	Coefficient	Parameter Estimate
$-t_j$	μ	-0.0136 (-1.16)
$-p_j$	λ	-0.0464 (-2.44) **
$-t_j \cdot BD$	μ^{BD}	0.0205 (3.97) ***
$-p \cdot FH$	λ^{FH}	0.2200 (2.75) ***
$-t_j \cdot SY$	μ^{SY}	0.0032 (3.43) ***
$-p \cdot BD$	λ^{SY}	0.0307 (4.23) ***

Car	α_4	1.8371 (4.23) ***
$LRail$	α_3	0.5174 (1.51)
	σ^3	0.0340 (0.07)
$Walk$	α_4	0.5174 (1.51)
	σ^{α_4}	6.9211 (2.34) **
Log-Likelihood		-112
Number of Responses		167

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively

Table 4.18 - Distribution of Sample Point Estimates of the Values of Time - Revealed Preference Model for Sacramento and San Francisco

	Sacramento	San Francisco
ρ	$18.71	$6.51
σ^{ρ}	23.11	$6.07
MIN	$0.60	$0.63
MAX	$148.26	$66.00

Table 4.19 – Mean and Variation in the Shadow Value of Time (ρ) Due to Parameter Uncertainty – Revealed Preference Model for Sacramento and San Francisco

	Sacramento	San Francisco
ρ	\$9.81	\$5.21
σ^{ρ}	\$3.51	\$1.38

4.2.10 Models that Exclude Car Ownership Terms that Impact the Value of Time

In the previous models, car ownership was found to decrease the value of time. In the short run transportation choices are made, conditional on public infrastructure and the car ownership decision which is predetermined in this time frame. However, a full treatment of car ownership in this context requires that the endogeneity of car ownership must be accounted for. Simply omitting this variable is likely to results in significant bias in the other variables.

Tables 4.20, 4.21 and 4.22 display the results of the models for stated preference for each region individually, the revealed preference model for San Francisco and the stated preference model in which all regions are treated as one population. These results are in contrast to the results for similar models (table 4.4, table 4.9 and table 4.12 respectively) that include time and money components that are functions of car ownership. Most of the coefficients that were significant in the models when the car ownership terms are included remain significant and have the same signs. However, there are significant differences. Most notably the value of μ for Sacramento is not significant in the stated preferences model that includes the full budget. Most coefficients differ slightly and are either more or less significant than in the models that include the car ownership terms. In each case the log likelihood is significantly higher in magnitude when the car ownership terms are omitted. This suggests that there is bias due to the omitted variables.

Table 4.20 Econometric Results for the Stated Preference Model, By City and Opportunity Cost of Time Specification – Excluding Car Ownership Terms that Impact the Value of Time

		Opportunity Cost of Time Specification:					
		Independent of Income			Varies With Income		
Variable Name	Coefficient	Sacramento	San Francisco	Sonoma	Sacramento	San Francisco	Sonoma
$X_{M_j} \cdot X_{T_j}$	β^{FB}	——	——	——	0.00014 (4.76) ***	0.00018 (6.34) ***	0.0001 (4.92) ***
	$\sigma^{\beta^{FB}}$	——	——	——	0.00015 (7.19) ***	0.0001 (8.33) ***	0.0015 (8.17) ***
$-t_j$	μ	0.0656 (11.49) ***	0.1251 (7.88) ***	0.0539 (15.10) ***	0.0443 (5.36) ***	0.1141 (6.60) ***	0.0449 (7.34) ***
$-p_j$	λ	0.1737 (7.99) **	0.3312 (4.25) ***	0.1415 (9.63) ***	-0.0111 (-0.26)	0.2549 (3.62) ***	0.0431 (1.27)
$-t_j \cdot BD$	μ^{BD}	0.0009 (1.42)	-0.0007 (-1.83) *	0.0004 (0.05)	0.0006 (0.92)	-0.0004 (-0.90)	-0.0001 (-0.18)
$-p_j \cdot BD$	λ^{BD}	0.0044 (2.39) **	0.0032 (1.80) *	0.0016 (0.89)	0.0043 (2.13) **	0.0035 (1.81) *	0.0012 (0.49)
$Car \cdot OC$	β^{COC}	----	1.3717 (3.52) ***	____	---	1.1015 (2.93) ***	----
Car	α_1	2.3588 (10.55) ***	0.3394 (-0.367)	1.4900 (10.01) ***	2.1566 (10.66) ***	-0.0475 (-0.70)	1.7488 (11.00) ***
	σ^{α_1}	2.8743 (6.72) ***	1.9753 (1.69) *	2.5907 (7.29) ***	1.2151 (2.64) ***	2.2450 (5.03) ***	1.5876 (3.68) ***
$Bus \cdot BD$	β^{BBD}	0.0170 (1.14)	0.0534 (2.21) **	0.0070 (0.38)	0.0201 (1.30)	0.0475 (2.29) **	0.0090 (0.43)
$LRail \cdot OC$	β^{LOC}	----	0.5801 (3.12) ***	------	---	0.5941 (2.91) ***	----
$LRail \cdot BD$	β^{LBD}	----	0.0361 (1.57)	------	---	0.0213 (1.09)	----

LR	α_3	0.5635 (4.63) ***	0.0859 (0.37)	0.8494 (8.99) ***	0.6885 (5.14) ***	0.3137 (1.22)	1.1052 (9.25) ***
$-t_j \cdot AGE$	μ^{AGE}	----	-0.0008 (-2.95) ***	-----	----	-0.001` (-4.24) ***	----
$-p_j \cdot AGE$	λ^{AGE}	----	-0.0025 (-1.56) *	------	----	-0.004` (-4.00) ***	----
Log-Likelihood		-1303	-1423	-1374	-1269	-1376	-1727
Number of Responses		1590	2072	2186	1590	2072	2186

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively.

Table 4.21 – San Francisco - Revealed preference Data Set – All Attributes – Excluding Car Ownership Terms that Impact the Value of Time

		Opportunity Cost of Time Specification	
Variable Name	Coefficient	Independent of Income	Varies With Income
$XMXT_j'$	β^{FB}	———	0.00007 (2.04) **
$-t_j$	μ	0.0860 (3.43) ***	0.0588 (2.87) ***
$-p_j$	λ	0.3855 (5.80) ***	0.2037 (2.58) ***
$-t_j \cdot BD$	μ^{BD}	-0.0028 (-2.22) **	-0.0022 (2.04) **
Car	α_1	-0.0108 (-0.01)	-0.2982 (-0.38)
	σ^{α_1}	———	0.0392 (0.08)
$Bus \cdot BD$	β^{BBD}	-0.0608 (-1.34)	-0.0488 (-1.23)
$LRail \cdot BD$	β^{LBD}	-0.1009 (-1.88)	-0.0832 (-1.35)
$LRail$	α_3	0.9225 (0.97)	0.8520 (0.92)
$Walk \cdot BD$	β^{WBD}	-0.5658 (-2.82) ***	-0.2727 (-1.60)
	$\sigma^{\beta^{WBD}}$	0.2030 (2.58) **	———
$Walk$	α_4	3.7440 (1.60)	2.0430 (0.08)
Log-Likelihood		-81	-81

Number of Responses		167	167

Table 4.22 – Estimation Results for the Stated Preference Model—All regions — Excluding Car Ownership Terms that Impact the Value of Time

		Opportunity Cost of Time Specification	
Variable Name	Coefficient	Independent of Income	Varies With Income
$XMXT_j'$	β^{FB}	______	0.0008 (5.79) ***
$-t_j$	μ	0.0804 (10.01) ***	0.0631 (7.61) ***
$-p_j$	λ	0.1344 (10.15) ***	0.0217 (0.97)
$-t_j \cdot BD$	μ^{BD}	0.0005 (2.24) **	0.0004 (1.67) *
$-p_j \cdot BD$	λ^{BD}	0.0071 (8.91) ***	0.0071 (8.88) ***
$-t_j \cdot AGE$	μ^{AGE}	-0.0004 (-2.64) ***	-0.0004 (-2.79) ***
$-p_j \cdot Male$	λ^{Gen}	-0.0207 (-1.98) **	-0.0189 (-1.80) *
$-p_j \cdot FH$	λ^{FH}	0.0336 (3.32) ***	0.0321 (3.18) ***
Car	α_1	1.3192 (12.94) ***	1.3234 (12.92) ***
	σ^{α_1}	2.5820 (11.23) ***	2.5877 (11.04) ***

Bus·BD	β^{BBD}	0.0304 (5.10) ***	0.0299 (5.02) ***
LRail	α_3	0.7401 (10.42) ***	0.7395 (10.39) ***
Log-Likelihood		-3813	-3795
Number of Responses		5748	5748

[a] Asymptotic Student's-t statistics in parentheses.
[b] *, ** denote significance at the 10%, 5%, and 1% levels (two-tailed test), respectively

4.2.11 Light Rail Alone

Light rail density was included as a transportation infrastructure variable for Sacramento and San Francisco; it is omitted in the Sonoma models since that region has no light rail service available. It was included only in the stated preference models, since models using revealed preference data did not converge.

The most interesting outcome concerning light rail density is the difference in sign of the coefficient (λ^{LD}) for San Francisco and Sacramento. In Sacramento λ^{LD} is positive, similar to the models that include variables for bus stop density (i.e. the term λ^{BD} is positive in these models). However, in San

Francisco the sign for λ^{LD} is negative[34]. This result at first glance seems anomalous. However, there is a difference in the distribution of light rail stops in relation to bus stops in the two cities. In Sacramento, there is a positive correlation (Corr = 0.5761) between the number of bus stops and light rail stops in the vicinity of peoples' residences, whereas in San Francisco there is a negative correlation (Corr = -0.1411). The implication is that in Sacramento the light rail and bus systems act like complements and tend to serve the same areas, whereas in San Francisco they act more as substitutes, wherein some regions are dominated by bus service and some are more dominated by the light rail. In Sacramento, the downtown and Midtown regions have high densities of both bus and light rail service. However, regions such as Natomas area have no light rail and very sparse bus service. In San Francisco there is either some bus or light rail service in nearly every part of town. However, in areas such as the Richmond district that are not serviced by the light rail, the density of bus stops and number and frequency of routes is particularly dense.

4.2.12 Bus Stop Density and Light Rail Density – Stated Preference

Inclusion of the bus stop density and light rail stop density as separate variables in the same model produces results consistent with the results from

---

[34] Coefficients for light rail stop density are positive, suggesting that light rail stops do not detract from overall utility. The coefficient for (-time cost)·(Light rail stop density) is negative.

the models where only one of the two variables is considered. Again, the value of time decrease with light rail density in Sacramento and increases with light rail density in San Francisco.

4.2.13 Public Transit Density

Since light rail and bus systems are part of the a region's overall public transit network, a single variable representing the density of all public transportation (where bus stops and light rail stops in a household's vicinity are added together) was also explored. Results obtained were consistent with the models where the bus stops are considered separately. Increases in the public transit density caused decreases in the value of time in both Sacramento and San Francisco. Its effect on the marginal utilities of time and money was the same as with the bus stop models: μ^{PD} and λ^{PD}were both positive for Sacramento and μ^{PD} was positive and λ^{PD} was negative for San Francisco.

The similarity between the results for this model and the models that contain only Bus Stop density is not unexpected, since in all of the communities the bus service is more extensive than the light rail service. The bus system either feeds into the light rail system or vice versa depending on the location of the nearest stop. This is particularly true in Sacramento where the bus and light rail systems act as complements.

4.2.14 Bus Stop Frequency

Models that included Bus Stop Frequency instead of Bus Stop Density produced results similar to the models that include the bus stop density.[35] The coefficients[36] μ^{BF} and λ^{BF} are insignificant for both the revealed preference and stated preference models for Sonoma, indicating that there is no statistically significant impact of bus stop frequency on the value of time for this region. However, for both stated and revealed preference models for the Sacramento and San Francisco regions the value of time decreases with bus stop frequency similar to the results for models that include Bus Stop Density.[37]

4.3 General Conclusions and Observations

This chapter presents the empirical results from implementing the random parameters discrete mode choice models developed in chapter 2. These models are more general than those found in the transportation economics literature with respect to their treatment of transportation infrastructure,

---

[35] Models with both bus stop density and bus stop frequency are not included due to the high correlation between stops and frequency

[36] These coefficients are similar to the coefficients μ^{BD} and λ^{BD} described in the models that included bus stop density.

[37] While the models in this study mainly analyzed the impact of bus stop density as a determinant of the value of time, it is clear that density is only one component of the level of transportation service available. The frequency of service, in particular the frequency at certain times a day is likely to be as important if not more important. Additional work in the area will examine for fully the impact of both frequency and reliability of transportation services.

consumer demographics, and the way in which the shadow value of time varies with the consumer's full budget.

One finding, consistent with other commute mode choice literature, is that stated preference commute choice data cannot be pooled with revealed preference data within the linear-in-parameters conditional utility structure. Because of this, models for the stated preference and revealed preference data are estimated and presented separately.

In general, all of the models suggest that the value of time is a function of the level of transportation infrastructure available to the commuter. The value of time decreases with increases in the level of public transportation infrastructure, consistent with the idea that better availability of transportation services relaxes the constraints on a consumer's travel choices. This is consistent with expectations and with the general theory of resource constraints. Generally, one would expect an increase in a resource important to utility will lead to a lower shadow fail of the resource. In this case, however, the resource (time) is not made available in a direct manner but instead time is less constrained due an increase in the number of commute options. However, the results for car ownership and light rail stop density suggest that the relationship between all transportation infrastructure and the value of time is more complicated than is indicated by this simple explanation. Light rail systems are part of an overall network of public transportation services. The results from this study suggest that more complicated models that incorporate the relation between bus and rail services are warranted.

The results related to car ownership suggest that models that consider both the short and long term time frame are interesting and necessary. The results of this study are in the context of models that control for public transit and imply that car ownership in itself has an impact on the value of time. This of course, could be effect rather than cause: there is likely some endogeneity of car ownership, as it may be determined partly by a high value of time, where a premium is placed on having a short commute time to work. Certainly there are pronounced differences in car ownership across communities: people living in Sonoma and Sacramento are much more likely to own a car than people in San Francisco. As such, the choice of whether or not to own a car is not exogenous to the value of time and must be considered in this context. Additionally the models in this chapter show that some demographic characteristics are important in distinguishing differences in the value of time across people. It is shown that gender, age, and years of school have some impact on the value of time in individual models, although these results were not consistent across all models.

In addition to demographic influences, the models of this chapter show a pronounced effect of money income on a person's value of time. This is intuitive, since the logic of increasing the availability of a constrained resource (in this case, money income) will tend to lower the corresponding shadow value, and this shadow value (the marginal utility of money) is the denominator of the shadow value of time. That said, the effects of increasing a constrained resource are broader, and will also affect the shadow prices on other constraints, and in addition does not necessarily act to reduce the marginal utility of money. However, the empirical results of this chapter clearly indicate that the shadow value of time increases with money income.

In all comparisons between revealed and stated preference, the estimated values of time were lower for the revealed preference model when compared to a similar stated preference model. Finally, all of the models show that the mean value of time is lowest in San Francisco. San Francisco has the highest level available transportation services, the densest population and the most services such as restaurants that are available by public transportation. Additional implications of these results will be discussed in chapters 5 and 6, which examine the implications of transportation infrastructure changes and overall conclusions of this study.

5 Welfare Implications of Transportation Improvements

The primary policy goal of this research is to help determine the impact of changes in existing transportation infrastructure on peoples' commute choices and two measures of the benefits to society from transportation: their economic valuation of (willingness to pay for) commute transportation modes, and their values of commuting time saved. Three separate policies are examined. The first two are illustrative of the kinds of policy changes the model can be used for, and the third is based on a current proposal, for a SMART Train in Sonoma and Marin counties in Northern California.

5.1 Welfare Measures in Two-Constraint Discrete Choice Models

One measure of individual welfare change for a change in price of a good or service is the willingness to pay, or compensating variation (CV). The CV associated with a general change in money prices (**p**), time prices (**t**), and transportation characteristics (**tr**) of a commute trip, from initial levels ($\mathbf{p}^0$, $\mathbf{t}^0$,$\mathbf{tr}^0$) to subsequent levels ($\mathbf{p}^1$, $\mathbf{t}^1$,$\mathbf{tr}^1$), can be defined implicitly as

(5-2) $$V(M + \rho \cdot T, \mathbf{p}^0 + \rho \cdot \mathbf{t}^0, \mathbf{tr}^0) = V(M + \rho \cdot T - CV, \mathbf{p}^1 + \rho \cdot \mathbf{t}^1, \mathbf{tr}^1)$$

where the term $\mathbf{p}^0 + \rho \cdot \mathbf{t}^0$ is the vector of full prices (i.e., money price plus the time cost monetized at the person's shadow value of commute time, ρ) for all commute modes considered, and the term $M + \rho \cdot T$ is the person's full income, defined analogously to full prices. In equation (5-2), the compensating variation is a change in money the consumer has that leaves her as well off after a change in prices and transportation characteristics as she was before the change.

Equation (5-2) is written presuming that the individual's shadow value of value of commute time (ρ) is constant, which is typical of standard transportation commute choice models. However, in the most general specifications of Chapter 4, with both transportation characteristics and the budget interaction term, the marginal utilities of time and money, and consequently the individual's value of time, vary with changes in prices, budgets, and transportation characteristics. In this case, equation (5-2) does not fully capture the compensating variation, which is again defined implicitly as

(5-3) $$V(M + \rho^0 \cdot T, \mathbf{p}^0 + \rho^0 \cdot \mathbf{t}^0, \mathbf{tr}^0) = V(M + \rho^1 \cdot T - CV, \mathbf{p}^1 + \rho^1 \cdot \mathbf{t}^1, \mathbf{tr}^1),$$

where ρ^0 and ρ^1 are the initial and subsequent levels of the value of time.

In discrete choice models, the welfare measure is expected compensating variation (ECV), defined (e. g., Hanemann 1984) as

(5-2) $$CV = \left(\ln \sum_j e^{V_{j1}} - \ln \sum_j e^{V_{j0}}\right)/\lambda$$

where the marginal utility of money, λ, is constant and where V_{j0} and V_{j1} are the initial and subsequent utility levels for mode choice *j*. When the marginal utility of money is not constant, the general convention is to use the initial marginal utility of money λ_0, so that compensating variation is

(5-3) $$CV = \left(\ln \sum_j e^{V_{j1}} - \ln \sum_j e^{V_{j0}}\right)/\lambda_0,$$

consistent with the definition of willingness to pay with reference to initial expected utility level.

5.2 Estimates of Welfare Change for Transportation Infrastructure Changes

The three scenarios examined in this chapter are:

a. Uniform increases in the number of bus and public transit stops in each of the three communities of 0.25, 0.5 and 1.0 stops per quarter mile.

b. Targeted increases in the number of bus and public transit stops in each of the three communities, where the targets are determined by current density of transit stops. In areas with both high densities of bus stops and low densities of bus stops, the number of stops in a quarter mile was increased by 0.25, 0.5 and 1.0 stops per quarter mile. These hypothetical increases were increases in the absolute number of stops per quarter mile rather than a percentage increase.

c. The addition of the SMART Train in Sonoma County.

5.2.1 Welfare Impacts of Uniform Increases in the Number of Transit Stops

This section looks at the impact of a uniform increase in the number of transit stops in each of the three communities.

Three scenarios were considered including an addition of 0.25 bus stops per quarter mile for each person in each of the three regions, and addition of 0.5 bus stops per quarter mile for each person and an addition of 1 bus stop per quarter mile for each person.

For each of these scenarios and for each region,[38] the mean CV was calculated using the formula in Equation 5.5 above. In addition a “low” value

[38] For Sacramento and San Francisco the Stated preference models for the individual regions were used. For Sonoma the model for all three regions was used.

was calculated for each region for individuals who lived in neighborhoods with bus stop densities less than 2.0 per quarter mile, and a “high” value was determined for people who live in neighborhoods with bus stop densities greater than 8.0 bus stops per quarter mile. These results are presented in table 5.01.

Signs for the CV associated with an increase in bus stop density (see table 5.1) are positive in all cases, indicating a welfare gain from the addition of bus stops. In all cases, the CV associated with an increase of 0.50 bus stops per quarter mile was larger than the CV associated with an increase of 0.25 bus stops per quarter mile and similarly the CV associated with an increase of 1.00 bus stops per quarter mile was greater than the CV associated with an increase of 0.50 bus stops per quarter mile. This is expected, since the higher the level of bus stop density, the lower the overall time price for a given trip. The CV for an increase in bus stop density of 0.50 bus stops per quarter mile is approximately twice the value of the CV for an increase in bus stop density of 0.25 bus stops per quarter mile and in turn the CV for increase of 1.0 bus stops per quarter mile is twice the CV for an increase of 0.50 bus stops per quarter mile.

Within each community the CV associated with an increase of bus stops of similar magnitude (e.g. an increase of 0.25 bus stops per quarter mile) was larger in areas of the community where the current bus stop density is high (greater than 8.0 bus stops per quarter mile) than in areas where the bus stop density is low (less that 2.0 bus stops per quarter mile). However, between communities the CV associated with an increase in bus stop density was highest in the region with the lowest overall bus stop density (Sonoma) and lowest for the region that currently has the highest overall bus stop density (San Francisco). The implication is that within a given community the greatest benefit, as measured by CV, is achieved by adding infrastructure (bus stops) to the regions that already have a large density of infrastructure. Yet the benefit per person is still greater in the community with the lowest overall density.

However, the average CV per trip, per person associated with an increase in bus stop density of 0.25 bus stops per square mile is much greater in Sacramento ($0.37) than it is in San Francisco ($0.05) but lower than in Sonoma ($0.58). In a similar manner the CV associated with an increase in bus stop density of 0.5 bus stops per mile is $0.75 in Sacramento, $0.10 in San Francisco and $1.19 in Sonoma, whereas the CV associated with an increase of 1.0 bus stops per square mile is $1.56 in Sacramento, $0.20 in San Francisco and $2.47 in Sonoma. In general, the regions with the lowest level of infrastructure receive the largest benefit per trip from a uniform increase in bus stops, but within a community, the aggregate benefits are greatest in the areas that have the most infrastructure. This result suggests that a community that that has a low level of transportation infrastructure (e.g. Sonoma) will benefit substantially from increases in overall infrastructure, but within all communities additional infrastructure is most beneficial if concentrated in areas with the highest existing levels of transportation infrastructure and population densities.

In addition, the percentage of the population that changed their commute mode to the bus as a consequence of the increase in bus stop density was determined using NLOGIT discrete choice simulation routines.[39] These results are presented in table 5.2. An increase in bus stop density of a similar magnitude (0.25 bus stops per quarter mile) has a larger impact (1.26% of the population switching to bus) in San Francisco than in either of the other two regions (0.91% switching to bus in Sacramento and 0.92% switching t bus in Sonoma). This result was consistent for increases of 0.25, 0.50 and 1.00 bus stops per quarter mile.

[39] For each model a simulation was run that simulated each of the hypothetical increases in Bus Stop Density for each region.

Table 5.1 CV per Trip per Person for Increases in Bus Stop Density

Increase In BD	Sacramento Mean	Sacramento Density Low	Sacramento Density High	San Francisco Mean	San Francisco Density Low	San Francisco Density High	Sonoma Mean	Sonoma Density Low	Sonoma Density High
0.25	$0.37	$0.25	$0.52	$0.05	$0.04	$0.05	$0.58	$0.46	$0.73
0.50	$0.75	$0.51	$1.04	$0.10	$0.08	$0.10	$1.19	$0.95	$1.55
1.00	$1.56	$1.08	$2.09	$0.20	$0.16	$0.21	$2.47	$2.03	$3.17

Table 5.2 Mode Shift to Bus Due to Increase in Bus Stop Density

BD Increase	Sacramento % Shift	San Francisco % Shift	Sonoma % Shift
0.25	0.92%	1.26%	0.91%
0.50	1.84%	2.52%	1.81%
1.00	3.72%	5.02%	3.64%
Commuters	158,000	399,000	518,000

The total CV for the impacted population (all commuters who live within a quarter mile of an added bus stop) was calculated along with the actual number of bus stops that would have to be added to achieve the increase in density. Subsequently the CV per day per added bus stop was calculated.[40] This information is presented in tables 5.3 – 5.5.

[40] In each quarter mile section of each region the current bus stop density was determined using data from 411.com and SacRT.com. US census data was used to determine the population density in each census tract. The segment of the population that commute in each region (US Census) was used to determine the impacted population.

The greatest aggregate benefit is for Sonoma County, which currently has the lowest density of infrastructure. And the smallest overall benefit goes to San Francisco which is the community with the highest level of transportation infrastructure. In fact the overall benefit in Sonoma is nearly 15 times the benefit in San Francisco. Sacramento falls in between the other two communities both in terms of current density of transportation infrastructure and aggregate benefit from a geographically uniform increase in the density of infrastructure.

However, geographical areas of these three regions are significantly different. Sonoma County encompasses 1,575 square miles while the City of Sacramento is 97 square miles and San Francisco is 47 square miles. As such the addition of a bus stop per quarter mile requires many more bus stops in Sonoma than it does in San Francisco. In order to achieve this increase in density the number of bus stops required in Sonoma is over 16 times the number required for Sacramento and 32 times the number required for San Francisco.

If the total CV per bus stop is calculated for each community (tables 5.3 – 5.5), the benefit per added bus stop is nearly uniform within each community. However there are substantial differences between the three regions. In Sacramento the CV per bus stop for a uniform increase of 0.25 bus stops per quarter mile is $151; an increase of 0.50 bus stops results in a benefit of $153 per added stop and an increase of 1.00 stop per quarter mile results in a benefit of $159 per stop. In San Francisco the benefit is $106 per bus stop regardless of the density of the increase in stops. While in Sonoma an increase of 0.25 bus stops per quarter mile results in a benefit of $48 per added stop; an increase of 0.50 bus stops results in a benefit of $49 per added bus stop and an increase of 1.0 bus stops per quarter mile results a benefit of $51 per added stop. As such, the benefit per added bus stop in Sacramento 1.4 times the benefit per stop in Sacramento and more and 6 times the benefit per added bus stop in Sonoma.

San Francisco currently has a high level of bus service so that the addition of additional bus stops does not, at the margin, benefit each individual resident by a great amount, yet the number of additional bus stops is not large to increase the stated increase in density for each household.

The opposite extreme exists in Sonoma. There is currently a low level of service overall, and additions to bus stop density have a large impact at the margin on each individual. However, since the number of people affected is much smaller, providing the additional stops is likely to be expensive relative to the benefits generated.

Sacramento is in the middle ground for each of these characteristics. It does not have such a high level of service that additions will not be noticed by those who wish to take public transit, and the community is small enough that increasing the level of service to all residents does not require the same investment as would be necessary in Sonoma.

Table 5.3 Sacramento – Total CV for Impacted Population and CV per Added Stop

Increase BD	Total CV	Total stops	CV per Stop
0.25	$58,460	388	$151
0.50	$118,500	776	$153
1.00	$246,480	1552	$159

Table 5.4 San Francisco – Total CV for Impacted Population and CV per Added Stop

Increase BD	Total CV	Total stops	CV per Stop
0.25	$19,950	188	$106
0.50	$39,900	376	$106
1.00	$79,800	752	$106

Table 5.5 Sonoma – Total CV for Impacted Population and CV per Added Stop

Increase BD	Total CV	Total Stops	CV per Stop
0.25	$300,400	6,300	$48
0.50	$616,420	12,600	$49
1.00	$1,279,460	25,200	$51

5.2.2 Welfare Impacts in Sonoma County from the Sonoma Marin Area Rail Transit Train

Sonoma and Marin Counties in Northern California have recently agreed to create a new rail transportation system known as the Sonoma Marin Area Rail Transit[41] (SMART) system. The train will run along the US Highway 101 corridor from Northern Sonoma County to Southern Marin County, just North of San Francisco.

The Sonoma County segment of this train system will have 9 separate stops. These stops and some characteristics of their immediate area are presented in table 5.6.[42]

The census tract encompassing each stop and population density of each census tract was determined using the location for each stop and US Census data. The CV was calculated for the addition of each of these stops[43] and the results are presented in table 5.7. The CV per commute trip was fairly uniform, ranging from $2.31 to $2.76, with the highest values obtained for areas that already had higher densities of public transit stops.

[41] http://www.sonomamarintrain.org/

[42] http://www.sonomamarintrain.org/, US Census (2000)

[43] The model for the entire population was used and transit stops were treated as generic transit stops since Sonoma currently has no rail transit.

Table 5.6 Characteristics of Proposed SMART Stops in Sonoma County

Transit Stop	Latitude	Longitude	Zip Code	Population Within (1/4 mile)	Bus Stop Density
Cloverdale	38.7989	123.0117	95425	8	2.04
Healdsburg	38.6066	122.8658	95448	8	1.40
Windsor	38.5478	122.8170	95492	25	2.37
Santa Rosa Jennings	38.4516	122.7318	95401	316	5.98
Santa Rosa Railroad Sq.	38.4371	122.7215	95401	403	5.98
Rohnert Park	38.3634	122.7111	94928	260	3.77
Cotati	38.3317	122.6913	94928	318	3.77
Petaluma Corona	38.2669	122.6550	94954	337	2.70
Petaluma Downtown	38.2372	122.6356	94952	533	2.04

Using the 2000 census data on percentage of the population that commutes in this region, the total CV was determined for each stop by multiplying the CV per trip by the number of commuters within a quarter mile of each stop. This result was then doubled to account for a round-trip commute. These results are presented in table 5.7. The overall total value per day for all 9 stops was determined to be $11,313.

Table 5.7 Impact of the Addition of SMART Stops

Transit Stop	CV per trip	Population Within (1/4 mile)	Total CV Per Day (2 Trips per commuter)
Cloverdale	$2.54	8	$41
Healdsburg	$2.46	8	$39
Windsor	$2.43	25	$122
Santa Rosa Jennings	$2.76	316	$1,744
Santa Rosa Railroad Sq.	$2.76	403	$2,225
Rohnert Park	$2.55	260	$1,326
Cotati	$2.55	318	$1,622
Petaluma Corona	$2.57	337	$1,732
Petaluma Downtown	$2.31	533	$2462
Total			$11,313

5.3 Discussion

Increases in transit stop density have a positive impact on commuters. This impact varies and is determined in part by the current level of available transportation infrastructure. Dollars spent in one community will have benefits that are sharply different from similar-sized investments in other communities, since the prevailing level of transportation infrastructure has a large effect on both per capita and aggregate benefit. In particular the benefit per person in a community that has a sparse level of infrastructure (Sonoma) may be high, but the overall benefit and the benefit per dollar spent are likely to tell a different story.

A community that is "reasonably compact" (Sacramento being the best example among the 3 communities studied here), and does not have a transportation infrastructure that is dense (e.g. San Francisco), will benefit more in aggregate from each dollar spent on improvements than a sprawling community (e.g. Sonoma).

However, since the benefits per person in sparsely populated communities are higher relative to other communities, targeted investments in regions such as Sonoma can have positive benefits. This was demonstrated for the case of the Sonoma SMART Train. It is clear in this case (see table 5.07) that the greatest benefit for a transit stop is for a stop added to a location with higher population density (e.g. Petaluma) relative to the other locations (e.g. Cloverdale). In general, given that the cost of providing uniform increases throughout a region such as Sonoma is likely to be quite expensive and the benefit per added stop is low relative to other communities such as Sacramento or San Francisco it particularly important to determine which locations will provide the largest overall benefit. This analysis can help elucidate the benefits derived from changes in the value of time that vary in part due to variations in the current level of transportation infrastructure.

6 Summary and Conclusions

This dissertation uses discrete choice econometric models of commute mode choice in conjunction with geographic information systems (GIS) and household surveys to provide empirical estimates of the impact that transportation infrastructure has on the value of commute time. This study extends the current literature in three important areas. First and foremost it models the value of time in transportation as a function of the transportation environment, including the density of roads, bus stops and light rail stops, and the frequency with which buses and light rail trains pick up passengers in the neighborhood of their residences. Additionally, the impact of impact of including demographic characteristics as variables in the value of time function is examined. Finally, the impacts of full prices and full budgets on the shadow value of time are examined theoretically and then modeled empirically. I employ both stated preference and revealed preference models to characterize these impacts.

This study relied substantially on an internet based survey. The use of this survey method was particularly important since it guaranteed that answers for questions related to time spent on various activities during the respondent's day added up to 24 hours. This ensured that the models of time developed in this study had a degree of accuracy that is much more difficult to achieve with other survey methods. In addition, the internet based survey made it possible to provide detailed instructions and examples that a respondent could view if she needed a fuller explanation of a particular question. Consequently, the survey employed in this study presented a complex set of questions that were easy for the respondent to answer.

The underlying hypothesis of this dissertation is that the level of public transportation infrastructure available to a consumer has an impact on their value of time. In particular, the expectation is that a higher level of transportation infrastructure should make the task of getting from one place to another easier. As such, someone who is faced with very few transportation options or transportation options that require long walks, huge amounts of time or are infrequent will have significantly tighter constraints on her time and money as compared to a similar consumer in a different environment that offers a much wider range of options or better options. The tighter constraint should affect the trade-off between time and money that the consumer makes when deciding how to get to and from a particular location. This hypothesis is substantially verified by this study, which focuses on one aspect of transportation from home, the choice of commute mode. However, the sign on the coefficients related to the density and frequency of the light rail stops suggest that the interaction between various types of public transportation are somewhat more complicated; it appears that some urban centers (e.g., Sacramento) have a variety of public transportation modes (e.g. bus and light rail) acting as complements to each other while others cities have these various types of transportation acting more like substitutes (e.g., San Francisco).

The most significant results of this analysis, in chapter 5, underscore the idea that the current level of transportation infrastructure impacts the value of time for the residents of a community. As a consequence, changes in levels of infrastructure will have different impacts on both the value of time and welfare of communities that have different levels of transportation. Also, the number of people affected is important. Changes in infrastructure in communities that have high population density may result in relatively small individual welfare benefits that nonetheless in the aggregate produce a greater benefit than might be experienced in a smaller community with larger individual benefits from transportation improvements. In particular, it is shown that increases in transportation infrastructure, such as bus stop density, are predicted to have a smaller impact on an individual resident of the population in the bus stop- dense community of San Francisco than the same change will have on a resident of Sonoma; yet the aggregate benefit of the improvement in San Francisco is larger than the aggregate benefit in Sonoma. This has implications in terms of policy, underscoring the point that it is aggregate benefits, not individual benefits, that must be counted when considering the benefits and costs of transportation infrastructure improvements. And while the individual enthusiasm for improvements in San Francisco may be less than the individual enthusiasm for changes in Sonoma, the overall benefits may be the greater.

Secondly, this dissertation hypothesizes and supports the proposition that the value of time is influenced by a variety of demographic characteristics. Most obvious of these characteristics is car ownership and availability. Car ownership tended to increase the value of time.

Finally, this dissertation contains theoretical development of models that incorporate the full budget into models of transportation choice. The empirical results suggest that the full budget is a significant determinant in transportation choices and ultimately in the value of time associated with those choices, and that, as would be expected, the value of time increases with money income and decreases with increases in one's time budget

6.1 Shortcomings

The number one shortcoming, as is the case for most studies, is the lack of data to adequately test all of the hypotheses that are of interest. In particular, the insignificant results for the revealed preference models for the Sonoma region suggest that more data may have been helpful in order to use this source of information in combination with stated preference information for this region. Also, despite all the care taken to ensure that that data obtained is accurate, it is likely that responses to questions in the previous-day activity diary are subject to some recall bias. It is always desirable to have data that is known to be accurate, though in many applied economic studies in transportation and environmental economics, where household survey data must be used, results are often subject to the vicissitudes of subjective memory.

The second most severe shortcoming is also data-related. Despite the clear significance of the transportation environment in the commuter's neighborhood, it is clear that this is not the only factor that impacts the decisions and values related to the commute choice. It is likely that the transportation environment in the vicinity of the commuter's place of work is also important; and while the distance to the work location was taken into account when determining the time for the commute, data regarding to the transportation infrastructure in the neighborhood of the work location was not included in the models.

Finally, all of the models in the current study are linear in parameters, as is standard in the random parameters discrete choice literature. There are numerous reasons to believe that these linear models are merely approximations of a more complicated, non-linear reality.

6.2 Next Steps

The survey data are sufficiently rich to define a research program above and beyond this individual dissertation. The data include responses to questions in which the respondents were asked to rate the time spent in each activity and to rate how much they would have liked to have more time for the activity. These data can also be used model the value of time, and a longer-term research objective is to combine these data with the stated and revealed preference data, where possible, to provide additional perspective on peoples' commute mode choices. In addition, data were collected regarding attitudes towards transportation options that can also be used to provide a more sophisticated explanation of how transportation preferences affect mode choice and the value of time.

As always, more and better data is desirable. One could, with their permission, track commuters by using GPS technology. The current data set relies on peoples' recollections of their activities from the previous day. It is likely that many respondents omitted trips or did not remember accurately the details of their trips. GPS tracking technology can be used to accurately record the movements of individuals willing to be the subjects of experiments. This in turn would likely prompt people to provide better information about other aspects of their trips.

Other regions can be examined, including a contiguous region of Northern California along the Interstate 80 on Highway 101 corridors, as well as cities and regions from other states. Further work will incorporate a richer set of non-linear in parameters models. And finally, additional work can be done regarding how the value of commute time varies with the changes in the commuter's time and money constraints.

Bibliography

Algers S, Dillen J, Widlert S (1996) The national Swedish value of time study. Value of Time Seminar, PTRC England

Algers, S., Bergstroem, P., Dahlberg, M., Dillen, J.L., 1998. Mixed logit estimation of the value of travel time. Working Paper, Department of Economics, Uppsala University, Uppsala, Sweden.

Atkins W. (1994) Cambridgeshire County Council: stated preference project. W. S. Atkins, Epsom, Surrey, England

Batley, R. Grant-Muller, S., Nelthorp, J., De Jong, G., Watling, D., Bates, J. (2008), Multimodal Travel Time Variability, Institute of Transport Studies, University of Leeds for the Department of Transport, at www.dft.gov.uk/pgr/economics/rdg/jtv/finalreport.pdf.

Bates, J., 1987. Measuring travel time values with a discrete choice model: a note. The Economic Journal 97, 493–498.

Becker, G.S., 1965. A theory of the allocation of time. The Economic Journal 75, 493–517.

Beal, D. J. 1995. "A Travel Cost Analysis of the Value of Carnarvon Gorge National Park for Recreational Use." Review of Marketing and Agricultural Economics 63 (2): 292-303

Beesley, M. E. 1965. "The Value of Time Spent Travelling: Some New Evidence." Economica 32 (May): 174-185.

Beesley, M. E. (1973): Urban Transport: Studies in Economic Policy, Butterworths, London.

Bell, F. W., and V. R. Leeworthy. 1990. "Recreational Demand by Tourists for Saltwater Beach Days." Journal of Environmental Economics and Management 18: 189-205.

Ben-Akiva, M., Lerman, S.R., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press, Cambridge, Massachusetts.

Bhat, C.R., 1998. Accommodating variations in responsiveness to level-of-service measures in travel mode choice modeling.Transportation Research 32A (7), 495–507.

Bhat, C.R., 2000. Incorporating observed and unobserved heterogeneity in urban work travel mode choice modeling. Transportation Science 34 (2), 228–238.

BMW (1994) Calculations of the social costs of congested traffic. BMW – Munich, mimeo

Bockstael, N.E., I.E. *Strand, and W. M. Hanemann*. 1987. "Time and the Recreation Demand. Model." American J. of Agricultural Economics 69: 293-302.

Boyd J, Mellman J . 1980. The effect of fuel economy standards on the U.S. automotive market: a hedonic demand analysis. Transportation Research 14A(5-6): 367-378.

Brown, G. Jr., and R. Mendelsohn. 1984. "The Hedonic Travel Cost Method." Review of Economics and Statistics 66(3): 427-433.

Bureau of Transportation Statistics: http://www.bts.gov/

Calfee, J., Winston, C. "The Value of Automobile Travel Time: Implications for Congestion Policy" Journal of Public Economics 69 (1998) 83-102.

Cameron, T.A., W. D. Shaw, S. E. Ragland, J. MacCallaway, and S. Keefe. 1996. "Using Actual and Contingent Behavior Data with Differing Levels of Time Aggregation to Model Recreation Demand." Journal of Agricultural and Resource Economics 21(1):130-149

Castiglione, J., Freedman, J., Davidson, W., 2003. Application of a tour-based microsimulation model to a major transit investment. San Francisco County Transportation Authority and PBConsult, San Francisco.

Caulkins, P.P., Bishop, R.C., and Bouwes, N.W. 1985. "Omitted Cross-Price Variable Biases in the Linear Travel-Cost Model: Correcting Common Misinterpretations." Land Economics 61: 182 – 187.

Cervero, R. "Built Environments and Mode Choice: Towards a Normative Framework." Transportation Research Part D 7 (2002) 265-284.

Cesario, F.J. 1976. "Value of Time in Recreation Benefit Studies." Land Economics 52: 32-41.

Chalfant, J.A. and J.M. Alston. 1988. "Accounting for Changes in Tastes" Journal of Political Economy 96(1988):391-410.

Cherchi E (2003) Il Valore del Tempo nella Valutazione dei Sistemi di Trasporto (The Value of Time in Travel Systems Evaluation). FrancoAngeli, Milano

Cherchi, E., Ortuzar, J. de D., 2003. Alternative specific variables in non-linear utilities: influence of correlation, homoscedasticity and taste variations.Paper presented at the 10th International Conference on Travel Behaviour Research, Lucerne, Switzerland.

Chui MK, McFarland WF (1985) Value of travel time: new estimates developed using a speed choice model. Texas Transport Institute, College Station, Texas

Chui MK, McFarland WF (1987) Value of travel time: new estimates developed using a speed choice model. Final report. Federal Highway Administration (FHWA), Washington D.C.

Cirillo, C., Axhausen, K.W., 2006. Evidence on the distribution of values of travel time savings from a six-week diary. Transportation Research Part A 40, 444–457.

Claffey PJ (1961) Characteristics of passenger car travel on toll roads and comparable free roads. Highway Research Board, National Academy of Sciences, Washington D.C

Cohan H and Southworth F (1999), “On the Measurement and Valuation of Travel Time Variability Due to Incidents on Freeways,” Journal of Transportation and Statistics, Bureau of Transportation Statistics Dec., pp. 123-131; www.gcu.pdx.edu/download/2cohen.pdf

Cole, Sherman Inc. (1990) Attitudinal survey: tradeoff analysis. Excerpt from draft report prepared for VIA Rail Canada

Daganzo, C.F., 1979. Multinomial Probit: The Theory and its Applications to Demand Forecasting. Academic Press, New York.

Dalvi MQ, Lee N (1971) Variations in the value of travel time: Further analysis. Manchester School of Economics and Social Studies 39:187-204

Daly, A.J., Zachary, S., 1978. Improved multiple choice models. In: Hensher, D.A., Dalvi, M.Q. (Eds.), Determinants of Travel Choice. Saxon House.

Dawson RFF, Smith NDS (1959) Evaluating the time of private motorists by studying their behavior: report on a pilot experiment. Research Note 3474, Road Research Laboratory, Crowthorne, UK

Deacon, R.T., Sonstelie, J. “Rationing by Waiting and the Value of Time: Results From a Natural Experiment” Journal of Political Economy 1983 vol. 93 no. 4.

De Raad, P.M., 2004. Congestion costs closer examined, Monetarising adaptive behaviour using the Logsum-method. M.Sc. Thesis, TU Delft.

DeSerpa, A. C. “A Theory of the Economics of Time” Economic Journal 81-324 (1971) 828-846.

Dey, A.. 1985. *Orthogonal Fractional Factorial Designs*. New York: Halstead Press.

Eom, Y.-S., and D. M. Larson. 2006. “Improving environmental valuation estimates through consistent use of revealed and stated preference information.” Journal of Environmental Economics and Management 52: 501–516.

EURET (1994) Cost benefit and multicriteria analysis for new road construction: final report. Report to the Commission of the European Communities, Directorate General for Transport, Doc. EURET/385/94

EXPEDITE Consortium, 2002. EXPEDITE Final Publishable Report. Report for European Commission, DGTREN, RAND Europe, Leiden.

Ghosh D, Lees D, Seal W (1975) Optimal motorway speed and some valuations of life and time. Manch Sch Econ Soc Stud 73:134–143

Ghosh, A., 2000. To Pay or Not to Pay: Commuters' Mode Choice under Real Time Congestion Pricing. Working Papers, University of California, Irvine, USA.

Gunn H, Bradley M, Rohr C (1996) The United Kingdom value of time study. Value of Time Seminar, PTRC England

Gupta, S., Kalmanje, S., Kockelman, K.M., 2004. Road pricing simulations: traffic, land use and welfare impacts for Austin, Texas. Paper Presented at the 84th Annual Meeting of the Transportation Board.

Guttman, JM (1975) Implicit assumption and choices among estimates of the value of time. Transp Res Rec 534:63–68

Hansen S (1970) Value of commuter travel time in Oslo. Slemdal, Institute for Transport Economics

HCG (1998) The second Netherlands' value of time study: final report. The Hague Consulting Group for AVV, Rijkswaterstaat

Heckman J. "Shadow Prices, Market Wages and Labor Supply" Econometrica 42 (1974) 679-694.

Hensher, D.A., 1996. Extending valuation to controlled value functions and non-uniform scaling with generalized unobserved variances. In: Proceedings of the Theoretical Foundations of Travel Choice Modeling, Stockholm.

Hensher, D. A., 2001a. Measurement of the valuation of travel time savings. Journal of Transport Economics and Policy 35 (1), 71–98.

Hensher, D. A., 2001b. The sensitivity of the valuation of travel time savings to the specification of unobserved effects. Transportation Research 37E, 129–142.

Hensher, D. A., 2001c. The valuation of commuter travel time savings for car drivers: evaluating alternative model specifications.Transportation 28, 101–118.

Hensher, D.A., and L.W. Johnson. 1981. Applied Discrete Choice Modelling. London: Croom - Helm/New York: John Wiley.

Hensher, D.A., J. M. Rose, and W. H. Greene. 2005. Applied Choice Analysis. A Primer. Cambridge: Cambridge University Press

Herriges, J.A. and C. L. Kling. .”Nonlinear Income Effects in Random Utility Models” Review of Economics and Statistics, 81(1), 62-72, 1999

Hollander Y (2006), “Direct Versus Indirect Models For The Effects Of Unreliability,” Transportation Research A, Vol. 40, Issue 9 (www.elsevier.com), November, pp. 699-711.

Huber, J., and Zwerina, K. (1996), “The Importance of Utility Balance in Efficient Choice Designs,” *Journal of Marketing Research*, 33 (August) 307-317.

Hultkrantz, L., Mortazavi, R., 2001. Anomalies in the value of travel-time changes. Journal of Transport Economics and Policy 35 (2), 285–300.

Jara-Dı´az, S.R., 2001. On the Goods-Activities Technical Relations in the Time Allocation Theory. ITS Working Papers, 2001.

Jara-Diaz, S.R., Guevara, C.A., 2003. Behind the subjective value of travel time savings: the perception of work, leisure and travel from a joint mode choice-activity model. Journal of Transport Economics and Policy 37, 29–46.

Kalmanje, S., Kockelman, K.M., 2004. Credit-based congestion pricing: travel, land value and welfare impacts. Paper Presented at the 2004 Annual Meeting of the Transportation Board.

Kitamura, R., Mokhtarian, P.L., Laidet, L. "A Micro analysis of land use and travel in five neighborhoods in the San Francisco Bay area" Transportation 24: 125-158 1997.

Koopmans, C.C., Kroes, E.P., 2004. Werkelijke kosten van files tweemaal zo hoog (The real cost of queues twice as high). Article in ESB April 2004, pp. 154–155.

Lam, T.C., Small K.N. "The Value of time and reliability: Measurement from a Value Pricing Experiment." Transportation Research Part E 37 (2001) 231-251.

Lapparent, M.D., de Palma, A., 2002. Non-linearities in the valuations of time estimates. In: Proceedings of the PTRC Annual Meeting, 2002, PTRC, London.

Larson D. M. "Joint Recreation Choices and Implied Values of Time" Land Economics 69(3) (1993): 270-86

Larson, D.M., and S.L. Shaikh. 2004. "Recreation Demand Choices and Revealed Values of Leisure Time." Economic Inquiry 42: 264–78.

Lee N, Dalvi MQ (1969) Variations in the value of travel time. Manch Sch Econ Soc Stud 37:213 236

Leurent, F., 1998. The distribution of car commuters' values of time in Marseilles. Recherche Transports Securite 60, 19–38.

Li Y (2003), "Evaluating the Urban Commute Experience: A Time Perception Approach," Journal of Public Transportation, Vol. 6, No. 4, pp. 41-67; at www.nctr.usf.edu/jpt/pdf/JPT%206-4%20Li.pdf.

Lisco TE (1967) The value of commuters' travel time. PhD dissertation, Department of Economics, University of Chicago

Liu H, Recker W and Chen A (2004), "Uncovering the Contribution of Travel Time Reliability to Dynamic Route Choice," Transportation Research, Vol. 38A, No. 6, July, pp. 435-453.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behaviour. In: Zarembka, P. (Ed.), Frontiers in Econometrics.Academic Press, New York.

McFadden, D. “The Urban Travel Demand Forecasting Project Phase 1 Final Report Series” Institute of Transportation Studies, University of California, Berkeley, June 1977.

McFadden, D. and K. Train (1997): Mixed MNL models for discrete response, Applied Econometrics.

McConnell, K. E. 1992. “The Problem of Onsite Time in the Demand for Recreation," American Journal of Agricultural Economics 74:918–25.

McDonald JF (1975) Some causes of the decline of Central Business District retail sales in Detroit. Urban Studies 12:229–233

McFadden D, Reid F (1975) Aggregate travel demand forecasting from disaggregated behavioral models. Transp Res Rec 534:24–37

McFadden, D., 1978. Modelling the choice of residential location. In: Kar-Iquist, (Ed.), Spatial Interaction Theory and Planning Models.North Holland, Amsterdam, pp.75–96 (Chapter 25).

McFadden, D., 1981. Econometric models of probabilistic choice. In: Manski, C.,

McFadden, D., Train, K., 2000. Mixed MNL models of discrete response. Journal of Applied Econometrics 15, 447–470.

Mohring H (1961) Land Values and the Measurement of Highway Benefits. J Polit Econ 69(3):236–249

Mokhtarian, P.L., Salomon, I., 2001. How derived is the demand for travel? Some conceptual and measurement considerations. Transportation Research 35A, 695–719.

MVA Consultancy, Institute of Transport Studies University of Leeds, and Transport Studies Unit University of Oxford (1987) The value of travel time savings. Policy Journals, Newbury, Berks, U.K.

Nakamuara, K., Kockelman, K.M. “Congestion Pricing and Roadspace Rationing: An Application to the San Francisco Bay Bridge Corridor” Transportation Research Part A 36 (2002) 403-417.

Nelson JP (1977) Accessibility and the value of time in commuting. Southern Econ J 43:1321 1329

Odeck, J., Rekdal, J., Hamre, T.N., 2003. The socio-economic benefits of moving from cordon toll to congestion pricing: the case of Oslo. Paper Presented at TRB Annual Meeting.

Oort, O., 1969. The evaluation of travelling time. Journal of Transport Economics and Policy 3, 279–286.

Parsons, G.R., and M.J. Kealy. 1995. "A Demand Theory for Number of Trips in a Random Utility Model of Recreation. Journal of Environmental Economics and Management 29: 357–367.

Parsons, G. R., and A. B. Hauber. 1998. "Spatial Boundaries and Choice Set Definition in a Random Utility Model of Recreation Demand." Land Economics 74(1): 32-48

Perez, P.E., Martinez, F.J., Ortuzar, J. de D., 2003. Microeconomic formulation and estimation of a residential location choice model: implications for the value of time.Journal of Regional Science 43 (4), 771–789.

Phaneuf, D. J., C. L. Kling, and J. A. Herriges. 2000. "Estimation and Welfare Calculations in a Generalized Corner Solution Model with an Application to Recreation Demand." Review of Economics and Statistics 82(1): 83–92.

PLANCO and Heusch-Boesefeldt (1991) Aktualisierung der Kosten für die BVWP. Schlussbericht. Im Auftrag des Bundesministeriums für Verkehr. FE-Nr. 90228 A/90

Polak JW, Jones PM, Vythoulkas PC, Wofinden D, Sheldon R (1993) Travellers choice of time of travel under road pricing. PTRC, London

Quarmby, D.A. (1967): Choice of travel mode for the journey to work: some findings, Journal of Transport Economics and Policy, 1(3), 273-297.

Ramjerdi F, Rand L, Saetermo AF, Salensminde K (1997) The Norwegian value of time study: some preliminary results. Institute of Transport Economics, Oslo, Norway

Redmond, L.S., Mokhtarian, P.L "The Positive Utility of the Commute: Modeling ideal commute time and relative desired commute amount" Transportation 28: (2001) 179-205.

Redmond, L.S., Mokhtarian, P.L., 2001. The positive utility of the commute: modeling ideal commute time and relative desired commute amount.Transportation 28, 179–205.

Revelt, D. and K. Train (1996): Incentives for appliance efficiency: random parameters logit models for households' choices, Department of Economics, University of California, Berkeley.

Revelt, D. and K. Train (1999): Customer-specific taste parameters and mixed logit, Department of Economics, University of California, Berkeley.

Richardson, A.J., 2003. Some evidence of travelers with zero value-of-time. Transportation Research Record 1854, 107–113.

Salomon, I., Mokhtarian, P.L., 1998. What happens when mobility-inclined market segments face accessibilityenhancing policies? Transportation Research 3D (3), 129–140.

Schweitzer LA, et al. (1998), Highway Performance and Time-Sensitive Industries, University of Iowa (www.ppc.uiowa.edu);

Sipress, A., 1999. Not all commuters driven crazy. Washington Post, pp. Al and A12.

Small K et al. (1999), Valuation of Travel-Time Savings and Predictability in Congested Conditions for Highway User-Cost Estimation, NCHRP 431, TRB (www.trb.org);

Small, K., Sullivan, E.C., 2001. Choice models of route, occupancy, and time-of-day with value priced tolls. In: Transportation Research Board 80th Annual Meeting, Washington, DC.

Small K, Winston C and Yan J (2005), Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability: Implications for Road Pricing, University of Irvine
www.socsci.uci.edu/note.pdf.

Smith, V., and Kaoru, Y. 1990 Signals or Noise? Explaining the Variation in Recreation Benefits Estimates. American Journal of Agricultural Economics 72(2): 419-433

Stopher PR (1968) A probability model of travel mode choice for the work journey. Highway Research Record 283. Highway Research Board, Washington D.C.

Sullivan, E., 2000. Continuation Study to Evaluate the Impacts of the SR 91 Value-Priced Express Lanes. Final Report, State of California, Department of Transportation, USA.

Talvittie A (1972) Comparison of probabilistic modal choice models: estimation methods and system inputs. Highway Research Record 392. Highway Research Board, Washington D.C.

Thomas TC (1967) Value of time for commuting motorists. Highway Research Record 245. Highway Research Board, Washington D C.

Thomas TC, Thompson GI (1970) The value of time for commuting motorists as a function of their income level and amount of time saved. Highway Research Record 314. Highway Research Board, Washington D.C.

Train KE, McFadden DL (1978) The goods/leisure trade-off and disaggregate work trip mode choice models. Transp Res 12:349–353

Train, KE "A Structured Logit Model of Auto Ownership and Mode Choice" Review of Economic Studies 47 (1980) 357-370.

Train, KE (1997): Mixed logit models for recreation demand. In C. Kling and J. Herriges (eds): Valuing the Environment Using Recreation Demand Models, Elgar Press, New York 141-160.

Train, KE 1998. "Recreation Demand Models with Taste Differences Over People." Land Economics 74(2): 230-239.

Train. KE (1999): Halton sequences for mixed logits, Department of Economics, University of California at Berkeley, August. War

Transprice (1997) Deliverable 1: review of issues and options. Transprice, Goteborg/London

Texas Transportation Institute (TTI) (2007) The 2007 Urban Mobility Report http://tti.tamu.edu/documents/ums/mobility_report_2007_wappx.pdf

U.S. Census Bureau (2000). 2000 Decennial United States Census of Population and Housing. Washington D.C. http://factfinder.census.gov/

U.S. Department of Transportation, Federal Highway Administration, 2004. Case Study: Sacramento, California Methodology Calculation of User Benefits, www.fhwa.dot.gov/planning/toolbox/sacramento_methodology_user.htm

Vaughn, W. J., and C. S. Russell. 1982. "Valuing a Fishing Day: An Application of a Systematic Varying Parameter." Land Economics 58 (Nov.): 450-463.

Wabe JS (1971) A study of house prices as a means of establishing the value of journey time, the rate of time preference, and the valuation of some aspects of environment in the London metropolitan region. App Econ 3:247–253

Wardman MR, Mackie PJ (1997) A review of the value of time: evidence from British experience. PTRC European Transport Conference, England

Williams, H.C.W.L., 1977. On the formation of travel demand models and economic evaluation measures of user benefit. Environment and Planning A 9 (3), 285–344.

Young, W., Morris, J., 1981. Evaluation by individuals of their travel time to work. Transportation Research Record 794, 51–59.

Zamparini L, Reggiani A (2007) The value of travel time in passenger and freight transport: an overview. In: van Geenhuizen M, Reggiani A, Rietveld P (eds) Policy analysis of transport networks. Ashgate, Aldershot, pp 145–161

Appendix - Census, GIS and Survey Data

Table A.1 Demographic Characteristics US Census

Characteristic	Sacramento	San Francisco	Sonoma
Population, 2000	407,018	776,733	458,614
Population Change (1995-2000)	9.4%	-4.2%	1.8%
Persons under 5 years old	7.1%	5.4%	6.2%
Persons under 18 years old	27.3%	14.8%	23.7%
Persons 65 years old and over	11.4%	14.8%	12.6%
Females	51.4%	49.3%	50.6%
Living in same house 1995 – 2000	48.6%	54.2%	52.0%
Bachelor's degree, pct of persons age 25+	23.9%	45.0%	28.5%
Homeownership rate	50.1%	35.0%	64.1%
Median value of owner-occupied housing units	$128,800	$396,400	$273,200
Households	154,581	329,700	172,403
Persons per household	2.6	2.3	2.6
Median household income	$37,049	$51,815	$53,645
Total number of firms	25,562	91,873	48,290
Land area, 2000 (square miles)	97	47	1,575
Persons per square mile	4,196	16,635	291

Table A.2 Travel Characteristics for Workers (US Census – 2000)

Characteristic	Sacramento Amount	Sacramento Percent	San Francisco Amount	San Francisco Percent	Sonoma Amount	Sonoma Percent
Workers 16 and over	536,310	100%	418,553	100%	536,310	100%
Worked not at home	518,020	96.6%	399,177	95.4%	518,020	96.6%
Worked at home	18,290	3.4%	19,376	4.6%	18,290	3.4%
By Mode Choice						
Drive alone	404,130	75.4%	169,508	40.5%	404,130	75.4%
Car Pool	77,021	14.4%	45,152	10.8%	77,021	14.4%
Bus	12,678	2.4%	89,443	21.4%	12,678	2.4%
Light rail, or railroad	3,485	0.6%	39,130	9.3%	3,485	0.6%
Walk	10,999	2.1%	39,192	9.4%	10,999	2.1%
Bicycle	4,573	0.9%	8,302	2.0%	4,573	0.9%
Motorcycle	1,197	0.2%	3,951	0.9%	1,197	0.2%
Other	3,917	0.8%	4,499	1.1%	3,937	0.8%
Work travel minutes	24.5		29.3		24.5	

Table A.3 Public Transit Serving San Francisco

Name	Mode
AmTrak	Train
Super Shuttle	Shuttle
San Francisco Muni	Bus
San Francisco Muni	Light Rail
AC Transit	Bus
BART	Rail
CalTrain	Train
Greyhound	Bus
Golden Gate Park Weekend Shuttle	Bus
Golden Gate Transit	Bus
Golden Gate Transit	Ferry
Oakland-Alameda Ferry	Ferry

Presidio Shuttle Service	Bus
SamTrans	Bus
San Francisco Paratransit	Shuttle
Vallejo Transit bus	Bus
Vallejo Transit ferry	Ferry

Table A.4 Public Transit Serving Sacramento

Name	Mode
Amador Regional Transit System	Bus
Amtrak	Train
CSUS Hornet Express	Bus
El Dorado Transit	Bus
Fairfield/Suisun Transit	Bus
Folsom Stage Line	Bus
Greyhound	Bus
Placer County Transit	Bus
Roseville Transit	Bus
Sacramento Regional Transit	Bus
Sacramento Regional Transit	Light Rail
Yolobus	Bus

Table A.5 Public Transit Serving Sonoma

Name	Mode
Golden Gate Transit	Bus
Healdsburg In-City Transit	Bus
Petaluma Transit	Bus
Santa Rosa City Bus	Bus
Sonoma County Transit	Bus

Table A.6 Transportation Infrastructure in Neighborhood of Survey Respondents – Mail and Internet Combined Sample

	All (N=898)		Sacramento (N=240)		San Francisco (N=327)		Sonoma (N=331)	
Variable	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
POPDEN	10,366	12,181	4,961	2,188	23,571	11,083	1,280	1,459
BD125	2.1	2.6	1.1	1.8	4.3	2.8	0.7	1.3
BD25	8.3	8.8	4.6	5.7	16.4	8.5	3	3.8
BD5	31	30.9	17.5	18.7	60.8	28.4	11.2	11.5
BD1	110	102	64	59	218	79	37	35
BMIN	0.2	0.5	0.2	0.4	0.1	0.1	0.4	0.7
BF125	850	1,542	73	150	2,263	1,837	18	64
BF25	3,282	5,222	323	510	8,694	5,347	81	187
BF5	12,240	18,715	1,311	1,812	32,352	17,960	295	490
BF1	43,403	62,335	4,719	5,399	114720	51,370	996	1,366
LRD125	0.11	0.5	0.02	0.16	0.29	0.79	-	-
LRD25	0.5	1.5	0.1	0.5	1.3	2.2	-	-
LRD5	1.7	3.8	0.4	1.3	4.4	5.1	-	-
LRD1	6.0	9.3	1.3	2.7	15.6	9.4	-	-
LRMIN	22.7	28.5	1.7	1.3	0.4	0.4	-	-
LRF125	18	100	3	36	47	159	-	-
LRF25	77	266	17	79	200	408	-	-
LRF5	272	658	55	190	707	930	-	-
LRF1	976	1,586	187	409	2,542	1,706	-	-
RDEN	8.1	4.4	8.8	3.7	9.9	4.6	5.8	3.6

Table A.7 Transportation Infrastructure in Neighborhood of Survey Respondents – Internet Sample

	All (N=738)		Sacramento (N=198)		San Francisco (N=264)		Sonoma (N=276)	
Variable	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
POPDEN	9,896	11,464	5,126	2,013	22,485	10,495	1,321	1,475
BD125	2.1	2.6	1.3	1.9	4.1	2.6	0.7	1.3
BD25	8.1	8.5	5.1	6.1	15.7	8.0	3.0	4.0
BD5	30.0	29.1	19.5	19.8	57.7	26.5	11.1	11.8
BD1	108.3	97.4	70.5	62.3	209.4	76.8	38.6	35.8
BMIN	0.2	0.5	0.2	0.4	0.1	0.1	0.4	0.7
BF125	790	1,431	83	162	2,126	1,709	19	70
BF25	3,047	4,839	363	548	8,160	4,946	83	201
BF5	11,337	17,427	1,475	1,944	30,275	16,934	296	520
BF1	40,521	58,786	5,297	5,740	108,32	49,836	1,023	1,424
LRD125	0.1	0.5	0.0	0.2	0.3	0.8	-	-
LRD25	0.5	1.5	0.1	0.5	1.3	2.3	-	-
LRD5	1.7	3.7	0.4	1.4	4.5	5.1	-	-
LRD1	6.0	9.3	1.5	3.0	15.6	9.5	-	-
LRMIN	23.0	28.6	1.6	1.3	0.4	0.3	-	-
LRF125	18	102	4	40	48	163	-	-
LRF25	79	271	20	86	206	418	-	-
LRF5	272	647	63	207	712	914	-	-
LRF1	950	1,553	218	441	2,492	1,695	-	-
RDEN	8.1	4.5	8.6	3.4	10.1	4.8	6.0	3.8

Table A.8 Transportation Infrastructure in neighborhood of Survey respondents – Mail sample

	All (N=160)		Sacramento (N=42)		San Francisco (N=63)		Sonoma (N=55)	
Variable	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
POPDEN	12,534	14,900	4,184	2,773	28,107	12,347	1,073	1,367
BD125	2.2	3.0	0.5	0.9	4.9	3.3	0.6	0.9
BD25	9.3	10.5	2.2	2.5	19.4	9.8	3.1	3.0
BD5	35.5	37.7	8.4	6.6	74.2	32.0	11.9	10.3
BD1	120.0	122.5	31.1	20.0	256.2	79.8	31.7	28.2
BMIN	0.2	0.6	0.4	0.5	0.06	0.1	0.4	1.0
BF125	1,128	1,958	26	57	2,838	2,222	13	21
BF25	4,364	6,626	136	177	10,932	6,345	69	87
BF5	16,405	23,389	541	496	41,052	19,607	286	298
BF1	56,694	75,410	1,993	1,539	14,1907	49,092	857	1,028
LRD125	0.1	0.5	0.00	0.0	0.3	0.8	0.0	0.0
LRD25	0.4	1.4	0.0	0.2	1.1	2.0	0.0	0.0
LRD5	1.6	4.0	0.1	0.5	4.1	5.5	0.0	0.0
LRD1	6.3	9.6	0.3	0.9	15.8	9.3	0.0	0.0
LRMIN	21.4	28.0	2.3	1.1	0.5	0.6	0.0	0.0
LRF125	17	88	0.0	0.0	44	137	0.0	0.0
LRF25	70	244	3	20	175	366	0.0	0.0
LRF5	275	708	19	61	687	1,000	0.0	0.0
LRF1	1,094	1,731	41	117	2,752	1,752	0.0	0.0
RDEN	8.0	4.2	9.8	5.0	9.3	3.6	5.1	2.2

Variable Description TableA.6, A.7, A.8

POPDEN – Population Density – Persons per square mile

BD125 – Number of bus stops within an eighth mile of home

BD25 – Number of bus stops within a quarter mile of home

BD5 – Number of bus stops within a half mile of home

BD1 – Number of bus stops within a mile of home

BMIN – Minimum distance from home of bus stop – Miles

BF125 – Frequency of bus stopping within an eighth mile of home – Stops per day

BF25 – Frequency of bus stopping within a quarter mile of home – Stops per day

BF5 – Frequency of bus stopping within a half mile of home – Stops per day

BF1 – Frequency of bus stopping within a mile of home – Stops per day

LRD125 – Number of light rail stops within an eighth mile of home

LRD25 – Number of light rail stops within a quarter mile of home

LRD5 – Number of light rail stops within a half mile of home

LRD1 – Number of light rail stops within a mile of home

LRMIN – Minimum distance from home of light rail stop – Miles

LRF125 – Frequency of light rail stops within an eighth mile of home – Stops per day

LRF25 – Frequency of light rail stops within a quarter mile of home – Stops per day

LRF5 – Frequency of light rail stops within a half mile of home – Stops per day

LRF1 – Frequency of light rail stops within a mile of home – Stops per day

ROADDENS – number of lanes of roads within mile of home

Table A.9 Survey Responses – Internet and Mail Combined

	All (N=898)		Sacramento (N=240)		San Francisco (N=327)		Sonoma (N=331)	
Variable	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
AGE	50.9	14.6	50.6	15.6	48.1	13.9	54.0	13.8
SCHYRS	15.8	3.6	15.9	3.6	16.2	3.9	15.3	3.1
PERDAY	$252	$131	$230	$124	$285	$139	$235	$121
TOTMONS	149	147	148	156	142	144	156	143
PEOPLE	2.5	1.7	2.6	2.4	2.3	1.2	2.6	1.3
UNDER16	0.4	1.2	0.5	1.1	0.3	1.4	0.5	1.0
NUMPAY	1.5	1.0	1.5	0.9	1.6	1.0	1.5	1.0
MALE	66%		64%		69%		65%	
MARRIED	65%		63%		57%		75%	

Table A.10 Survey Responses - Internet Only

	All		Sacramento		San Francisco		Sonoma	
	(N=738)		(N=198)		(N=264)		(N=276)	
Variable	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
AGE	50.6	14.1	50.6	15.7	48.2	13.7	53.0	12.8
SCHYRS	15.9	3.4	16.0	3.4	16.3	3.6	15.4	3.0
PERDAY	$253	$130	$233	$125	$284	$139	$236	$119
TOTMONS	149	144	153	160	143	139	153	137
PEOPLE	2.5	1.8	2.5	2.6	2.3	1.2	2.7	1.4
UNDER16	0.5	1.2	0.5	1.1	0.4	1.5	0.5	1.0
NUMPAY	1.6	0.9	1.4	0.8	1.7	1.0	1.6	0.9
MALE	69%		70%		72%		66%	

Table A.11 Survey Responses – Mail Only

	All		Sacramento		San Francisco		Sonoma	
	(N=160)		(N=42)		(N=63)		(N=55)	
Variable	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
AGE	52.3	16.4	50.6	14.9	47.6	15.1	59.1	17.1
SCHYRS	15.3	4.4	15.1	4.3	15.6	4.9	15.0	3.8
PERDAY	$247	$133	$215	$122	$288	$137	$226	$127
TOTMONS	147	160	124	131	140	167	174	172
PEOPLE	2.3	1.1	2.7	1.1	2.0	1.0	2.3	1.0
UNDER16	0.3	0.9	0.7	1.3	0.2	0.7	0.2	0.6
NUMPAY	1.4	1.1	1.7	1.3	1.4	0.9	1.3	1.1
MALE	52%		39%		53%		60%	

Variable Description – Tables A.9, A.10, A.11

AGE – age of respondent at time of survey

SCHYRS – Number of years in school

PERDAY – Income per day

TOTMONS – Total months living at current location

PEOPLE – Number of persons in household

UNDER16 – Number of persons in household under 16 years old

NUMPAY – Number of persons in household working for pay

MALE – Gender (Male=1/Female=0)

MARRIED – Married at the time of survey

Table A.12 Respondent Characteristics – Mail and Internet Sample

Variable	ALL (N=854) Percent	Sacramento (N=234) Percent	San Francisco (N=313) Percent	Sonoma (N=326) Percent
OWN	69%	81%	50%	79%
RENT	31%	19%	50%	21%
OWNCAR	91%	92%	85%	95%
WORKPAY	82%	80%	86%	78%

Table A.13 Respondent Characteristics – Internet Sample

Variable	ALL (N=709) Percent	Sacramento (N=194) Percent	San Francisco (N=253) Percent	Sonoma (N=271) Percent
OWN	70%	80%	53%	79%
RENT	30%	20%	47%	21%
OWNCAR	91%	92%	84%	95%
WORKPAY	84%	81%	88%	81%

Table A.14 – Respondent Characteristics – Mail Sample

Variable	ALL (N=152) Percent	Sacramento (N=42) Percent	San Francisco (N=60) Percent	Sonoma (N=55) Percent
OWN	66%	90%	40%	79%
RENT	34%	10%	60%	21%
OWNCAR	92%	90%	92%	95%
WORKPAY	72%	76%	78%	62%

Variable Description – Tables A.12, A.13. A.14

OWN – Do you own your home (1=Yes/0=No)
RENT - Do you rent home (1=Yes/0=No)
OWNCAR – Did you have a car available on the day of the survey?
WORKPAY – Did you work for pay on the day of the survey?

Table A.15 Respondent Characteristics – Internet and Mail Combined Sample

Variable	All (N=692)	Sacramento (N=181)	San Francisco (N=270)	Sonoma (N=242)
FIXSAL	57%	59%	63%	50%
FIXHRS	40%	45%	36%	41%
HOURSDAY	42%	38%	46%	41%
HOURWEEK	34%	25%	37%	36%
DAYWEEK	23%	18%	24%	26%
STARTIME	38%	30%	44%	37%

Table A.16 Respondent Characteristics – Internet Sample

Variable	All (N=580)	Sacramento (N=149)	San Francisco (N=223)	Sonoma (N=209)
FIXSAL	58%	61%	63%	51%
FIXHRS	40%	42%	38%	41%
HOURSDAY	42%	40%	43%	41%
HOURWEEK	34%	27%	36%	36%
DAYWEEK	23%	18%	23%	25%
STARTIME	37%	32%	42%	36%

Table A.17 Respondent Characteristics – Mail Sample

Variable	ALL (N=112)	Sacramento (N=32)	San Francisco (N=47)	Sonoma (N=33)
FIXSAL	54%	50%	66%	42%
FIXHRS	43%	63%	28%	45%
HOURSDAY	44%	25%	60%	39%
HOURWEEK	35%	19%	43%	39%
DAYWEEK	26%	16%	28%	33%
STARTIME	41%	22%	53%	42%

Variable Description: Tables A.15, A.16, A.17

FIXSAL – Do you have a fixed salary or get paid by the hour?

FIXHRS – Do you have a fixed schedule (not able to choose when and how much you work)?

HOURSDAY – Can you vary the number of hours you work each day ?

HOURWEEK – Can you vary the number of hours you work each week?

DAYWEEK – Can you choose which days you work each week?

STARTIME – Can you choose your own start time each day?

Table A.18 Attitudes towards Transportation Alternatives

	All (N=824)		Sacramento (N=240)		San Francisco (N=27)		Sonoma (N=314)	
Variable	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
AUTCLN	0.94	0.23	0.96	0.20	0.93	0.26	0.94	0.23
AUTCON	0.44	0.50	0.46	0.50	0.45	0.50	0.42	0.50
AUTCOS	0.48	0.50	0.43	0.50	0.55	0.50	0.46	0.50
AUTCRO	0.11	0.31	0.12	0.33	0.10	0.31	0.11	0.31
AUTEAS	0.94	0.24	0.94	0.23	0.88	0.32	0.98	0.14
AUTENV	0.17	0.38	0.19	0.39	0.11	0.32	0.21	0.41
AUTREL	0.97	0.16	0.97	0.18	0.95	0.21	1.00	0.00
AUTSAF	0.91	0.29	0.91	0.29	0.83	0.39	0.97	0.17
AUTTIM	0.19	0.40	0.17	0.38	0.15	0.36	0.25	0.43
BUSCLN	0.50	0.50	0.51	0.50	0.38	0.49	0.63	0.48
BUSCON	0.47	0.50	0.45	0.50	0.64	0.48	0.31	0.47
BUSCOS	0.20	0.40	0.22	0.42	0.13	0.34	0.26	0.44
BUSCRO	0.54	0.50	0.52	0.50	0.75	0.44	0.36	0.48
BUSEAS	0.41	0.49	0.30	0.46	0.64	0.48	0.28	0.45
BUSENV	0.73	0.45	0.68	0.47	0.80	0.40	0.69	0.46
BUSREL	0.54	0.50	0.56	0.50	0.49	0.50	0.57	0.50
BUSSAF	0.79	0.41	0.69	0.46	0.85	0.36	0.80	0.40
BUSTIM	0.77	0.42	0.80	0.40	0.71	0.45	0.80	0.40
TRNCLN	0.59	0.49	0.67	0.47	0.69	0.46	0.39	0.49
TRNCON	0.26	0.44	0.32	0.47	0.31	0.46	0.15	0.36
TRNCOS	0.28	0.45	0.34	0.48	0.25	0.44	0.25	0.43
TRNCRO	0.33	0.47	0.42	0.49	0.39	0.49	0.17	0.37
TRNEAS	0.39	0.49	0.41	0.49	0.60	0.49	0.13	0.34
TRNENV	0.74	0.44	0.81	0.39	0.85	0.36	0.54	0.50
TRNREL	0.52	0.50	0.62	0.49	0.68	0.47	0.25	0.43
TRNSAF	0.69	0.46	0.73	0.44	0.86	0.35	0.47	0.50
TRNTIM	0.56	0.50	0.69	0.47	0.55	0.50	0.42	0.50
WLKCLN	0.76	0.43	0.76	0.43	0.77	0.42	0.73	0.44
WLKCON	0.11	0.31	0.10	0.30	0.09	0.28	0.13	0.34
WLKCOS	0.03	0.18	0.03	0.17	0.03	0.16	0.05	0.21
WLKCRO	0.07	0.26	0.08	0.27	0.07	0.25	0.08	0.27
WLKEAS	0.61	0.49	0.58	0.50	0.73	0.44	0.51	0.50
WLKENV	0.92	0.27	0.92	0.28	0.96	0.20	0.89	0.32
WLKREL	0.67	0.47	0.64	0.48	0.80	0.40	0.58	0.50

WLKSAF	0.54	0.45	0.51	0.50	0.63	0.48	0.48	0.50
WLKTIM	0.67	0.47	0.66	0.48	0.63	0.48	0.70	0.46

Table A.19 Comparison of Attitudes Towards Transportation Alternatives (T – Scores)*

Variable	Sacramento - San Francisco T-Score	Sacramento - Sonoma T-Score	San Francisco - Sonoma T-Score
AUTCLN	1.32	-0.71	0.69
AUTCON	0.15	0.64	0.78
AUTCOS	**-2.61**	**2.23**	-0.55
AUTCRO	0.54	-0.07	0.49
AUTEAS	**2.37**	**-4.39**	**-2.10**
AUTENV	**2.32**	**-2.99**	-0.46
AUTREL	0.85	**-3.69**	**-2.87**
AUTSAF	**2.69**	**-5.50**	**-2.85**
AUTTIM	0.46	**-2.77**	**-2.21**
BUSCLN	**2.67**	**-5.71**	**-2.57**
BUSCON	**-4.08**	**7.67**	**2.89**
BUSCOS	**2.58**	**-3.87**	-1.01
BUSCRO	**-5.33**	**9.80**	**3.45**
BUSEAS	**-7.65**	**8.89**	0.63
BUSENV	**-2.92**	**2.98**	-0.14
BUSREL	1.55	**-1.99**	-0.29
BUSSAF	**-3.90**	1.49	**-2.55**
BUSTIM	**2.36**	**-2.43**	0.06
TRNCLN	-0.61	**6.44**	**5.65**
TRNCON	0.25	**3.74**	**3.89**
TRNCOS	**1.94**	0.12	**1.99**
TRNCRO	0.59	**5.12**	**5.59**
TRNEAS	**-3.81**	**11.1**	**6.50**
TRNENV	-1.02	**6.96**	**5.84**
TRNREL	-1.36	**10.0**	**8.20**
TRNSAF	**-3.03**	**8.82**	**5.51**

TRNTIM	**3.07**	**2.42**	**5.45**
WLKCLN	-0.28	1.07	0.75
WLKCON	0.43	-1.51	-1.03
WLKCOS	0.24	-1.16	-0.89
WLKCRO	0.27	-0.41	-0.12
WLKEAS	**-3.49**	**5.19**	1.39
WLKENV	-1.73	**2.93**	1.09
WLKREL	**-3.80**	**5.73**	1.56
WLKSAF	**-2.69**	**3.34**	0.49
WLKTIM	0.60	-1.61	-0.95

*Boldface implies significant at p<0.10

Variable Description: Tables A.18, A.19

AUT – Automobile

BUS – Bus

TRN – Light Rail

WLK – Walk or Bike

REL – Is the Mode reliable?

SAF – Is the Mode Safe

CLN – Is the Mode Clean?

CRO – Is the Mode crowded?

EAS – Is the Mode easy to use?

ENV – Is the Mode good for the environment?

CON – Is the route for the Mode congested?

TIM – Does the Mode take too much time?

COS – Does the Mode cost too much?