NON-MOTORIZED TRAVEL

IN THE

SAN FRANCISCO BAY AREA

by

Chandra R. Bhat

Jessica Y. Guo

Rupali Sardesai

Department of Civil Engineering

The University of Texas at Austin

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CHAPTER 1.
INTRODUCTION

1.1. Motivation

Walking and bicycling are not used extensively as a means of transportation in the United States today. This is especially the case for utilitarian trips, which are trips undertaken with the purpose of reaching a particular destination for accomplishing an activity. The low usage of walk and bicycle modes of transportation, and the concomitant increasing usage of motorized vehicles for transportation, may be associated with the sprawling land use patterns in the US cities as well as the relatively low cost of operating motorized automobiles. In any case, the increasing reliance on motorized vehicles in this country has contributed to serious traffic congestion and air quality problems. According to the Urban Mobility Report (Texas Transportation Institute, 2004), the travel time index, which is defined as the ratio of travel time in the rush hour to the travel time during the free flow period, in 85 urban areas across the nation for 2002 was 1.3 times greater than that for 1982; and this figure is on the rise. The peak congested hours have increased from 4.5 hours per day in 1982 to 7.1 hours per day in 2002. 58% of the major road system was congested, compared to only 34% in 1982, resulting in 46 hours of average delay per peak traveler per year. Moreover, the impact of traffic congestion was found to be more severe in larger cities with more vehicular traffic. The average travel time index for each individual population group varies from 1.5 for the very large urban areas to 1.1 for the small urban areas. In areas with a population of more than 3 million, the annual delay per peak traveler exceeded 50 hours in 2002. Traffic congestion not only causes inconvenience to the travelers, but also results in considerable loss of resources. In 2002, wasted fuel and time due to congestion was estimated to be monetarily equivalent to $63.2 billion in 85 urban areas (Texas Transportation Institute, 2004).

In addition to the monetary losses incurred from congestion, there are serious environmental implications associated with increasing levels of traffic congestion in the urban areas. One of the most serious environmental implications is the steady deterioration of air quality caused by the combustion of fuel in automobiles. The levels of hazardous air pollutants are increasing at an alarming rate. For example, the World Health Organization at the European Region (1999) reported that auto-generated pollution is responsible for more deaths than all traffic crashes. In order to mitigate the current situation, the Federal Government has enforced the Clean Air Act Amendments of 1990 (CAAA), which requires the Metropolitan Planning Organizations (MPO) to demonstrate the conformity of their transportation development and investment plans with the National Ambient Air Quality Standards (NAAQS). Under this act, the MPOs are required to ensure that the levels of ozone, respirable particulate matter, nitrogen dioxide, sulfur oxides, volatile organic compounds, carbon monoxide, and other pollutants are maintained within certain prescribed limits. Non-compliance with the regulations leads to a cut in the funding provided to the MPO by the federal government. At present, many of the regions are not in attainment of the NAAQS, with more than 90 million Americans living in such non-attainment regions. It is, therefore, crucial for the MPOs in such regions to achieve healthy air standards by reducing vehicular emissions. One effective way to reduce vehicular emissions would be to encourage more non-motorized travel to reduce vehicular trips.

Aside from planning and transportation authorities, the topic of non-motorized travel, also referred to as “active-transport”, is gaining attention from health agencies. This is because physically inactive lifestyles are posing significant health hazards to present day society. Insufficient physical activity has been identified as being among the ten leading causes of death and disability in the world (World Health Organization, 2002). It is a serious risk factor for chronic physical and emotional diseases (such as coronary heart disease, stroke, some cancers, diabetes, and depression), which are among the leading causes of mortality among most Americans (US Department of Health and Human Services, 1996; Sallis et al., 2004). Sedentary lifestyles are responsible for about 300,000 deaths each year in the US alone (World Health Organization, 2002). Nationwide, the medical costs and lost productivity incurred from physical inactivity was estimated to be about 75 billion dollars in 2000. Sources from the World Health Organization recommended that, to maintain a healthy lifestyle, individuals should undertake a minimum of 30 minutes of moderate intensity physical activity each day. Yet at least 60 percent of the global population fails to do so and the risk of these people getting a cardiovascular disease is 1.5 times higher than those who follow the minimum physical activity recommendations. In addressing the above-mentioned health problems, health agencies around the world have identified active transport as a pivotal means to boost the levels of physical activity among individuals.

The community problems associated with traffic congestion, air quality, and health has led many local, regional and state authorities to consider non-motorized travel as a way to alleviate these problems. At the same time, as the resources for funding transportation improvements are limited, planners and policy makers need to assess the usage and benefits of improvements in non-motorized transportation options against other alternative transportation projects. Such assessments require a good understanding of non-motorized travel behavior to estimate the impact of policy actions aimed at encouraging bicycle and pedestrian travel. In contrast, evaluating the effects of bicycle and pedestrian infrastructure and programs on travel behavior and emissions is in general a poorly developed science (Replogle, 1997). Several recent reviews of non-motorized travel methods such as Turner et al. (1997), Porter et al. (1999), Cambridge Systematics and Bicycle Federation of America (1999), and USDOT BTS (2000) point to the need to collect accurate data on non-motorized travel, understand the behavioral elements of non-motorized travel, and develop quantitative models of non-motorized travel for both planning purposes (prioritizing projects, estimating reduction in automobile emissions, time and cost savings to travelers, etc.) as well as for safety analysis (for example, developing exposure rates from which measures of accident risk can be developed).

1.2. Objectives

This study is motivated by the background and importance of the need for a detailed and comprehensive analysis of non-motorized travel. The study has three objectives. The first objective is to review the state-of-the-art of existing research on transportation by non-motorized modes and to identify possible directions for further research. The second objective is to contribute to the general understanding of non-motorized travel behavior. This will entail conducting an extensive descriptive analysis to examine the relationships between the use of non-motorized modes and the characteristics of the travelers and their surrounding environment. The third objective is to develop and estimate a set of disaggregate models of non-motorized trip frequency as a function of individual level characteristics. The disaggregate modeling approach is the most accurate tool available for predicting travel behavior impacts, enabling us to isolate the effects of a full spectrum of factors on non-motorized travel behavior. Separate models are developed for walk and bicycle modes, and for different trips purposes.

1.3. Outline of Report

The rest of the report is structured as follows. Chapter 2 presents a review of the past literature on non-motorized travel, and discusses the ways in which the current study attempts to advance the existing body of knowledge on the topic. Chapter 3 describes the data assembly process for generating the sample for analysis of non-motorized travel patterns and discusses the characteristics of the resulting sample. The primary data source for the analysis is the 2000 San Francisco Bay Area Travel Survey. Chapter 4 presents an exploratory analysis of non-motorized travel patterns. Chapter 5 describes the development of, and the results obtained from, ordered response probit models to predict the frequency of walk and bicycle trips made by an individual for different activity purposes. Finally, chapter 6 summarizes the findings of the study and identifies promising policy actions for promoting non-motorized travel.

CHAPTER 2.
LITERATURE REVIEW

Over the past decade, the body of literature relating to non-motorized (or active) transportation has begun to grow. There have been a number of review articles summarizing past studies in the transportation and public health fields about why people do and do not walk or bicycle (see Replogle, 1997; Schwartz, 1999; Humpel et al, 2002; Saelens et al, 2003; Sallis et al, 2004). The objective of this chapter is to provide a brief overview of the state-of-the-art of research on non-motorized transportation and to identify possible directions for further research. The reader is referred to the aforementioned review articles for detailed discussions on the methodologies and findings of past studies on the subject.

This chapter is organized as follows. Section 2.1 describes the fields of studies in which the topic of non-motorized transportation has received significant attention. Section 2.2 discusses the different types of data commonly used in past studies on the topic. Section 2.3 explains the alternative methods used in past studies to analyze non-motorized travel data. The section also describes the advantages and limitations of the methods, and highlights the empirical findings from past studies. Section 2.4 concludes the chapter by identifying the gaps in the literature.

2.1. Fields of Studies

The subject of non-motorized transportation has been studied mainly in two fields: transportation and public health. The interests in the two fields have been generated by differing concerns, and researchers from the two fields have taken slightly different approaches to study the same topic. Below, we describe the motivation behind, and the characteristics of, the studies in the two fields.

2.1.1. *Transportation*

Studies of non-motorized travel in the fields of urban planning and transportation are driven by the desire to predict the usage of walk and bicycle modes of travel under various circumstances. The predictions are used to help determine how public resources can be best prioritized and allocated to achieve the planning goals of a region. With this objective in mind, transportation planning professionals have studied non-motorized travel in the context of conventional travel demand models, by relating observed aggregate bicycle/walk use at the zonal level to other aggregate variables, such as residential density or number of individuals employed in a zone (see Section 2.3.2 for examples of this aggregate approach). The approach provides a rough estimate of the market share of non-motorized modes, and is useful mainly for exploratory research to evaluate the factors that may influence travel modal dependencies in different regions (Replogle, 1997). The alternative, disaggregate, approach of modeling non-motorized travel behavior of individual travelers has been used in more recent studies (see Section 2.3.3 for examples of this disaggregate approach). By using statistical models, such as regression models and discrete choice models, the disaggregate approach focuses on the tradeoffs that people make among various factors influencing the use of non-motorized modes. The disaggregate approach is therefore more suitable for evaluating projects or programs aimed at influencing the use of non-motorized modes.

2.1.2. *Public Health*

While transportation researchers are interested in non-motorized travel as a way to reduce vehicular travel and the resulting environmental implications (Frank and Engelke, 2001; Litman, 2003), health professionals view non-motorized travel as a vehicle to improve public health. Public health researchers have studied the extent of influence of walking and bicycling on the physical activity levels of individuals, and explored the potential of non-motorized transportation to increase the level of physical activity. The early studies in this area focused on how psychological and social variables are associated with physical activity (Sallis et al, 2004). More recently, the relationship between physical activity behavior and perceived and objectively determined physical environment attributes, such as safety and aesthetics, has also been gaining attention in the health literature (see Humpel et al, 2002, for a detailed review of these studies). Another body of literature in the health field is devoted to examining the effect of non-motorized mode commuting or transit use on biological health outcomes, such as body mass index, blood lipid profiles, and blood pressure (see Sallis et al, 2004, for a review of six such studies). These studies suggest that individual's use of non-motorized modes for utilitarian travel (which is more traditionally studied in the transportation literature) has similar health benefits as recreational physical activity (which is more traditionally studied in the health literature). Thus, it becomes clear that non-motorized transportation is beneficial to a community's health as well as its transportation system performance. Hence, transportation and health professionals are beginning to join forces to create an environment to increase non-motorized transportation (Frank and Engelke, 2002; Sallis et al, 2004).

The data used in past studies of physical activity are usually collected from surveys designed to obtain information on physical activity levels. The data tend to be disaggregate in nature, allowing the analysts to relate an individual's level of physical activity to various self-reported or objectively measured variables. The methodologies used in the studies usually involve descriptive statistics and logistic regression analysis (for example, see Plotnikoff et al, 2004, and Duncan and Mummery, 2005).

2.2. Data Sources

Depending on the nature and objective of the studies, the data used in past studies of non-motorized (or active) transportation usually fall into one of four categories: conventional travel surveys and census data, non-motorized travel surveys, attitudinal surveys, and health surveys. Each type of data source is described in turn in the subsequent sections.

2.2.1. Conventional Travel Surveys and Census Data

In the past, transportation professionals' data collection efforts have usually focused on vehicular travel. The household travel surveys often classify "auto-walk" or "walk-bus-walk" trips simply as "auto" or "transit", leaving the supplementary non-motorized trips unrecorded. Census data, which is a common source for studying commute behavior, also suffers from a similar problem. The exclusion of supplementary non-motorized trips in the travel and census surveys results in an underestimation of non-motorized modal share (usually ranging from 5% to 10%; see Sallis et al, 2004). The underreported share of non-motorized trips also leads to the lack of sufficient data for estimating statistical models specifically developed for non-motorized travel. As Litman (2003) suggests, if, instead of asking "what portion of trips involve *only* non-motorized travel", we ask "what portion of trips involve *some* non-motorized travel", 20-30% of non-motorized urban trips would be included and active modes would be recognized as common and important.

2.2.2. Non-motorized Travel Surveys

In view of the underreporting problem associated with the conventional travel and census surveys, a few surveys have been specifically designed to collect information about users of walk and bicycle modes and their characteristics. For example, Antonakos (1994) targeted cyclists at four recreational bicycle tours in Michigan and studied their environmental and travel preferences. Since the universe of the survey excluded cyclists who bicycle only for utilitarian transportation and non-cyclists, the findings from this study may not be generalized. Another example is the 2002 National Survey of Pedestrian and Bicyclist Attitudes and Behaviors conducted by the U.S. Department of Transportation's National Highway Traffic

Safety Administration and the Bureau of Transportation Statistics (2002). The survey collected data on non-motorized travel frequency, nature of trips, reasons for not biking/walking, perception of safety, safety practice, facility availability, community design, safe routes to school, and sociodemographics. Respondents were asked to provide information about their overall non-motorized travel behavior during the past 30 days, with a focus on individual trips made on the most recent day they walked or bicycled. The data provided a rich source of information to help planning for non-motorized travel.

2.2.3. Attitudinal Survey

The planning of non-motorized travel can also benefit from attitudinal survey data. These surveys involve asking hypothetical questions to identify the relative importance people place on environmental and other factors. However, as Dill and Carr (2003) cautioned, the results of this type of surveys are "influenced by the wording of the questions and they only reveal what people might do, rather than what they actually do." Thus, unless carefully designed, the surveys can significantly overestimate the actual response to a bicycle or pedestrian improvement. This is because people are likely to overstate their use of non-motorized modes after potential improvement (Goldsmith, 1992; Porter et al, 1999).

2.2.4. Health Survey

Studies of non-motorized travel from the field of public health typically use data from heath surveys. This type of survey is typically conducted to collect information about the health status of the population, the sociodemographic and geographic variations in health status, and the determinants of major causes of morbidity and mortality. The design of the survey – in terms of the target respondents, the sampling method, and the questions to ask – often vary from study to study depending on the objective of the study.

2.3. Analytic Methods

We describe in this section three popular types of quantitative methods that have been used in past studies to analyze or forecast pedestrian and bicycle travel: descriptive analysis, aggregate models, and disaggregate models. We describe examples of how these methods have been applied to the modeling of, and how the findings could help the planning for, non-motorized travel.

2.3.1. Descriptive Analysis

Descriptive statistics (such as means, percentages, variances, and correlation coefficients) have been used to analyze survey data related to non-motorized travel or physical activity. One of the earliest empirical studies of this kind was conducted by Hanson and Hanson (1977), who related data collected from a travel survey with weather data. They found that, at the aggregate level, the percentage of daily trips by bicycle is correlated with temperature and cloud coverage. Moreover, the strength of the correlation differs for different trip purposes: discretionary travel by bicycle is more sensitive to temperature changes and less sensitive to cloud coverage than bicycle use for commuting. The authors concluded that "… attitudes constitute a more formidable deterrent to bicycle use than the weather does" (p.48). Goldsmith (1992) also employed descriptive statistics to analyze aggregate levels of bicycling and walking. He compared data from twenty cities across the nation, and identified subjective and objective factors that may influence individuals to choose or avoid non-motorized transportation. These factors included the size of the urban area, population density, trip distance, land use, and facilities designed for bicycling and walking. As opposed to a comparative analysis across cities, Williams and Larson (1996) examined American workers as a whole and developed a demographic profile of bicycle commuters based the 1990 public use micro-data sample (PUMS) files compiled by the Census Bureau. The researchers found that bicycle commuters tend to be male, young (aged 15 to 24), single, non African-American, live close to work, have low levels of income and education, and live in the Pacific or the Mountain regions of the country.

Beck and Immers (1994) used a telephone survey of Amsterdam residents to examine non-motorized travel behavior and attitudes, including bicycle ownership, bicycle use by trip purpose, reactions to proposed measures to promote bicycle use, attitude of interviewee toward bicycles, and general background questions. The study found that the distribution of bicycle use differs over different areas. In most cases, the main reason for bicycling is the associated (fast) speed, health benefits, not having to depend on public transport, and not having to worry about (car) parking. The main reason that people did not use the bicycle was the distance to be traveled. For commute, besides the distance factor, (the lack of) comfort, low speed, and the absence of luggage-carrying facilities are reasons for not cycling. For non-work utilitarian travel, people choose not to bicycle mainly because of the absence of luggage-carrying facilities and the lack of comfort.

Stinson and Bhat (2004) also conducted a detailed descriptive analysis of the deterrents and facilitators of bicycle commuting. Among the most dominant deterrents for bicycle commuting are unpleasant weather, personal issues, and not enough daylight to ride safely. When comparing bicycle commuters against the non-bicycle commuters, the former group more often cites unpleasant weather and an injury/illness as being deterrents than does the latter group. On the other hand, the non-bicycle commuters have a much higher likelihood of identifying lack of daylight, unsafe neighborhoods, long distance to work, dangerous traffic, and lack of bicycle facilities as bicycle use deterrents. Among the bicycle commuters, the dominant reasons for using the bicycle to commute are the fitness/health benefits and the pleasure/enjoyment accruing from bicycle use.

A number of descriptive analysis studies have specifically targeted bicyclists. For example, Hope (1994) used data on commuter cyclists from Ottawa, Canada. The objective was to develop a profile of cycling and cycling characteristics to better plan the city for bicycles. Similarly, Antonakos (1994) surveyed only recreational cyclists, with the intention of providing recommendations for designing bicycle facilities. Her study used analysis of variance and correlation techniques to examine the environmental and travel preferences of cyclists. She found that commute distance is negatively correlated with the likelihood and frequency of commuting by bicycle. The more experienced a cyclist, the more likely she/he is to commute and run errands by a bicycle. On the other hand, the less experienced a cyclist, the less likely she/he is to bicycle for recreational purposes because of concerns related to safety and traffic conditions.

As evident in the above mentioned studies, descriptive analysis is useful for identifying the factors that are related to individuals' decision of traveling by bicycle or walk. However, because of the simple nature of the statistical measures used and the possible multi-way correlation among the underlying factors, the empirical findings are not easy to interpret. Methods that are capable of accounting for the complex interactions among many relevant variables are better suited for isolating the effect of individual factors.

2.3.2. Aggregate Models

Aggregate models relate observed aggregate (zone level) bicycle/walk use data to aggregate "exogenous" variables, such as residential density, topography of towns, and/or area size. The aggregate nature of the approach makes it particularly useful for evaluating factors that may influence differences in travel modal dependencies in different regions (Replogle, 1997). In the past, because the majority of travel data have overlooked and/or under-counted non-motorized modes (as discussed in Section 2.2.1), only a few regional travel demand models have included aggregate models for non-motorized modes. It was only in the 90's that aggregate models of non-motorized use began to emerge.

Baltes (1996) used regression analysis of the 1990 census journey-to-work data from 284 metropolitan statistical areas (MSA) to estimate the effects of demographic and climate factors on the percent of commuters traveling by bicycle in a MSA. He found that an MSA is more likely to have a relatively high share of bicycle commuters if (a) it is a college community and has a high percentage of people without a car, (b) employed primarily in agriculture, (c) has a large share of unemployed individuals and home renters, (d) has a significant fraction of workers living and working in central city, and (e) has a sizable Asian population. Interestingly, perhaps due to correlation among variables, median family income, population density, and gender were not statistically significant determinants.

Nelsona and Allen (1997) also used regression analysis to study bicycle use from data collected in 18 cities in the U.S.. They modeled the number of bicycle commuters in a city as a linear function of bicycle pathways per capita, terrain, number of rainy days, mean high temperature, and percentage of college students in the city. Of these variables, terrain and mean high temperature were dropped because of statistical insignificance. The authors found that each additional mile of bikeway per 100,000 people is associated with a 0.69 percent increase in bicycle commuting, holding other factors constant. Dill and Carr (2003) later built upon the work of Nelson and Allen (1997) by using the Census 2000 supplemental Survey (C2SS). They controlled for variables such as state spending per capita on bike/pedestrian, vehicle per household, and days of rain. Their research suggested that, for typical U.S. cities over 250,000 population, each additional mile of on-street bike lanes is associated with a roughly one percent increase in the share of workers commuting by bicycle. The authors concluded that, even though the finding does not suggest a cause-effect relationship, commuters will use bicycle lanes if provided.

The aggregate models discussed above provide a means to estimate regional non-motorized travel demand, but have been criticized because they ignore important factors that may influence actual demand (Porter et al, 1999). In addition, these models do not consider the demographic and urban form diversity within each aggregate spatial unit and, therefore, are subject to the familiar aggregation bias.

2.3.3. Disaggregate Models

Instead of relating aggregate levels of observed non-motorized travel to other aggregate variables, many recent studies of walking and bicycling behavior use a disaggregate approach to model an individual's mode choice or non-motorized trip frequency as a function of relevant individual-level characteristics. These disaggregate models are usually estimated using local survey data and are the most accurate tool available for predicting travel behavior impacts (Schwartz et al, 1999). They are particularly useful for isolating and quantifying the effects of specific factors on travel behavior and for examining the interaction of each factor with other factors.

Several disaggregate models have been developed to examine why individuals choose to travel by non-motorized modes as opposed to other modes. For example, Cevero (1996) developed three binomial mode choice models (one for each of private auto, mass transit, and walking/bicycling modes) using data collected for eleven MSAs from the 1985 American Housing Survey. Cervero expressed the probability of commuting by a given mode as a function of land-use variables as well as other variables such as residing within central city of MSA, vehicle ownership, household income, and commute distance. He found that the presence of low density housing (single-family detached, single-family attached and low-rise multi-family buildings) in the immediate vicinity (300 feet) of one's residence and the presence of grocery or drug stores beyond 300 feet but within 1 mile deter walk and bicycle commuting. On the other hand, the presence of high density housing (mid- and high-rise multi-family buildings) and the presence of commercial and other non-residential buildings within 300 feet induce walking or bicycling to work.

A limitation of Cervero's (1996) models was that they did not consider several important variables, such as personal characteristics of the commuters and factors that may contribute to the "walkability" or "bikeability" of the neighborhood. Cervero and Duncan (2003) overcame this limitation in a later study by examining a more comprehensive set of variables in two binomial mode choice models, one for walking and the other for bicycle. These two mode choice models were developed for non-work trips that were unlikely to involve carrying large amount of goods. The models considered person/household attributes (disability, gender, ethnicity, and vehicle ownership), trip characteristics (weekend vs. weekday, purpose), physical constraints (distance, slope, rainfall, dark, and neighborhood affluence), and environment factors at both the trip origins and destinations. The environment factors included one factor representing the pedestrian/bike friendliness and one factor representing the land-use diversity within 1-mile radius of trip origins and destinations. The factors were obtained using factor analysis and were used to replace the potentially correlated vector of environment variables. Interestingly, the model estimation results revealed that the only environmental factors significant at the 5% level is the land-use diversity variable within 1 mile of the trip origin, suggesting that land use has an impact on the use of non-motorized modes at the trip origin end but not the destination end. The results also showed that (a) trip distance, steed terrain and rain deter walking, (b) weekends are favored for walking, (c) walking is a more prevalent mode for social and recreational purposes, (d) vehicle ownership has a significantly negative impact on non-motorized mode use, and (e) African-Americans are more likely to walk than are other ethnic groups after other socio-demographic variables are controlled for. The bicycle model produced similar results to the walk model, except that the slope and land-use diversity at the origin are no longer significant at the 5% level. Additional significant factors in the bicycle model included gender (males are more likely to ride) and number of bicycles owned (which increases the likelihood of bicycling).

Based on the assumption that the land-use or attractiveness at the trip ends impacts non-motorized travel, Eash (1999) first developed a set of destination choice models for walk trips and subsequently used the log-sums obtained from the destination choice models as explanatory variables in his mode choice models. The main source of data was the 1990 household travel survey for Northern Illinois that included trips made exclusively by walking, but grouped bicycle trips into the "other" category. Separate walk destination choice models were estimated for workers, non-workers, and children. The models were further stratified by trip type: home-based, work-based, and non-home non-work based trips. The explanatory variables included the distance to destination, the number of census blocks in the zone (as a proxy measure of street connectivity), and the number of retail, non-retail, and residential opportunities in the zone. The distance variable is consistently and far more statistically significant than the other variables across all the walk destination choice models. In the binomial logit models of mode choice between walk and auto, the log-sums from the destination models were used as measures of accessibility by walking. Other variables considered included transit availability, average vehicle availability per person in the household, and number of workers in the household. The mode choice models were stratified by household vehicle ownership and by trip purpose (work/home/shop/other). The non-home based models revealed that the vehicle availability at the start of the trip is the dominating factor for using the walk mode. Because of the limited number of variables considered in the study, the author acknowledged that the models were not suitable for scenario analysis of changes in land-use or urban design (e.g. facility) factors.

Rajamani et al (2003) developed a multinomial logit mode choice model for non-work activity travel using data from the 1995 Portland Metropolitan Area Activity Survey. The choice set comprised drive alone, shared ride, transit, walk and bicycle. The variables examined include household and individual demographics, level-of-service variables, and land use characteristics. Among the individual socio-demographic variables, ethnicity was the single most important determinant of the likelihood to walk. The authors also found that mixed land use leads to considerable substitution between motorized modes and walk mode. Lower density and cul-de-sacs increase the resistance to walking as compared to other modes. The share of walking is also very sensitive to walk time. Improved accessibility by walk/bicycle increases the walk/bicycle share for recreational trips.

Rodriguez and Joo (2004) also developed a multinomial mode choice model, with the objective of examining the relationship between travel mode choice and attributes of the local physical environment such as terrain slope, sidewalk availability, residential density, and the presence of walking and cycling paths. Of the individual characteristics considered in the model, age did not have a significant impact on mode choice, while students, males, and individuals with lower number of vehicles at home have a higher propensity to walk relative to non-students, females, and individuals with more vehicles in their households, respectively. Of the physical environment variables, flat terrain and presence of sidewalk significantly increased the odds of walking/bicycling. Surprisingly, land use (residential density) and presence of walking and bicycling paths were found to be statistically insignificant.

In the literature discussed above, several findings about the effect of environment variables are inconsistent across studies. Cervero and Radisch (1996) attributed this inconsistency to the high multi-collinearity between residential density and the other built environment variables (e.g. mixed land use, average shorter block lengths), and to the little variation across individual observations (because of the lack of spatially detailed land use and urban design data). Once density is introduced into the model, the other land-use and urban design variables usually add little significant marginal explanatory power. Cervero and Radisch (1996) overcame the multi-collinearity problem by introducing a subjectively defined location indicator in their mode choice models, as opposed to using multiple environment variables. The location indicator is used to identify the very different built environment of the two study areas. In their study, two binomial mode choice models − one for work trips and the other for non-work trips − were estimated to examine the choice between the automobile mode and the other modes (including transit, walk, and bicycle). The authors found that the residents from the compact, mixed land-use, study area are more likely to make work trips using the non-automobile modes relative to the otherwise-similar residents from the other study area. Since the two study areas produce similar number of non-work trips per day, and that the area with compact, mixed land-use setting has higher rates of walking trips than the other study area, the authors concluded that the residents of the compact study area substitute internal walk trips for external automobile trips. In the case of work trips, the subjectively-defined location indicator was not statistically significant, suggesting that the built environment does not impact the commute mode choice.

Handy and Clifton (2001) also overcame the problem of multi-collinearity problem by examining the differences in non-motorized travel behavior between residents of neighborhoods that differed in environmental characteristics. They selected two "traditional", two "early-modern", and two "late-modern" neighborhoods in Austin, Texas. Using data from residents in these neighborhoods, they developed a regression model to examine the tradeoffs between distance and other considerations for frequency of walks to stores. Three shopping-related urban form measures that reflect the respondents' perception as customers and pedestrians were considered: quality of stores, walking incentive (within walking distance, difficult to park), and walking comfort (safety and convenience). Other variables included distance to the nearest store, socio-demographics, frequency of strolling around the neighborhood (to reflect basic preference for walking), and location constants. The model showed that distance to shopping location is a highly significant predictor of shopping trip frequency. Also, people who are older, live with young children, are women, or have higher incomes tend to walk to the store less frequently than others. The more positively one rates the shopping-related urban form measures, the more likely s/he is to walk. Finally, the frequency of strolling around the neighborhood was also a significant explanatory variable, suggesting the importance of intrinsic preference for walking in explaining the frequency of walking to stores.

2.4. Factors Influencing Non-Motorized Mode Use

The past studies of non-motorized transportation have collectively identified a broad range of factors that influence the level of non-motorized travel. In this section, we provide a list of these relevant factors, which include four categories: demographic and socioeconomic characteristics, trip characteristics, environment factors, and attitude and perception. We describe each category in a subsequent subsection. For a detailed review of the empirical evidence associated with each factor, we refer the readers to Goldsmith (1992), Frank and Engelke (2001), and Saelens et al (2003).

2.4.1. Demographic and Socioeconomic Characteristics

Age, gender, and ethnicity of individuals are found in most studies to correlate with non-motorized travel behavior. Young people are more likely to bicycle, while both the young and the elderly tend to rely more on walking than other age groups. Men are consistently found to bicycle more than women, for both recreation and transportation purposes. African-Americans and Caucasians have been associated with lower levels of non-motorized travel than other ethnic groups.

At the household level, the presence of transportation alternatives (particularly, access to private cars) reduces the likelihood of walking or bicycling. Also, households with lower income level (even after vehicle availability is controlled for) are more likely to walk and bicycle than those with higher income.

2.4.2. Trip Characteristics

Trip distance is a well-established determinant of non-motorized travel: all else being equal, the farther away one is from a destination, the less likely one is to use bicycling or walking. Although distance is objectively measurable, its effect may vary for individuals depending on their physical condition, attitudes, perception of distance, and trip purpose. Compared to other trip purposes, bicycling is used the most for recreational pursuits.

2.4.3. Environment Factors

Environment factors that influence non-motorized travel can be further divided into a number of categories: land development, topography and connectivity, micro-scale urban design, and weather.

Land development

Urban sprawl negatively impacts non-motorized travel since distance between trip generators is lengthened. All else being equal, a compact environment can help make walking and bicycling viable options as it reduces the distance between points of interest. However, higher density often results in higher volume of traffic on the streets, thereby making roadways unsafe for bicyclists and pedestrians. Hence, compact land use must be accompanied by appropriate walk/bicycle facilities that address traffic safety concerns.

A factor closely related to compactness is high density development. Higher density has been found to attract more utilitarian cycling trips, since the destinations are within short distances. Denser business developments inherently bring commuters closer to their work place, making it more feasible for individuals to bicycle or walk to work. Closely related to land use density is the mix of land use. Policies that promote dense and mixed land use are found to discourage urban sprawl, reduce the dependence on automobiles to pursue errands, and encourage walking and bicycle use. However, the impact of land use diversity may be limited to within a one mile radius around an individual's residence. Beyond that radius, mixed land use may have a counter effect and may results in more auto trips (Cevero, 1996).

Topography

The topography of an area is also directly related to the propensity of using non-motorized modes. Sloping and hilly terrain are deterrents to walking and bicycling. Similarly, street networks with low connectivity (i.e. curvilinear and cul-de-sac street layouts), typically found in modern suburbs, are also barriers to walking and bicycling. In comparison, grid street networks maximize direct access, making it easy for pedestrians and cyclists to move between origins and destinations using the existing streets and sidewalks (Frank and Engelke, 2001; Cervero and Duncan, 2003; Sallis et al, 2004).

Micro-scale design

Micro-scale urban design factors, such as the presence and continuity of sidewalks, bike lanes and trails, and proper street lighting, encourage the use of non-motorized modes. Other factors that contribute to the "attractiveness" or aesthetic quality of a neighborhood (for example, scenery, landscaping, park or water features, shopping opportunities, and recreation sites) also increase the propensity for walking and bicycling in the neighborhood for pure-recreation or other non-utilitarian purposes. Given the dependency of children on parental transportation, availability of play space within walking distance is also expected to increase children's physical activity and to reduce the necessity for parents to drive children to recreational opportunities.

Weather

Finally, weather also plays a role in the decision to travel by non-motorized modes. This is because rainy or snowy weather results in an uncomfortable environment and poses safety risks for walking and bicycling.

2.4.4. Attitude and Perception

The physical activity literature has shown that health benefits are a key reason why people walk or bicycle, for recreation as well as commuting. An environment that is perceived as safe to walk and bicycle is also an important determinant. Pedestrians and cyclists perceive busy traffic, absence of pedestrian crossings, and presence of major arterials as important safety hazards. In the U.S., safety is of special concern because our non-motorized fatality rates are much higher than countries such as the Netherlands and Germany. Appropriate actions are needed to create safe environments for pedestrians and cyclists.

2.5. Summary

This chapter has reviewed prior research on non-motorized travel in the field of transportation planning and public health. The complementary nature of the transportation and health researchers' efforts emerges from the similarities in their planning goals, their analytic approaches, and their findings. As Sallis et al (2004, p. 261) contend, "[t]here is a public health imperative to evaluate environmental and policy variables and their association with active transport, recreational physical activity, and total physical activity. The results of such studies can … promote population shifts in physical activity as well as improve transportation systems." Hence, in order to support the interdisciplinary collaboration between transportation and public health fields, further research on the topic needs to examine the full spectrum of environmental and policy variables relevant to both fields.

The literature review revealed that studies from both areas have collectively identified a range of variables that may influence an individual's decision to walk or bicycle. Yet, empirical evidence of the relationship between non-motorized travel behavior and some of these factors remains inconsistent (Frank and Engelke, 2001, Rodriguez and Joo, 2004). For example, while age is found to correlate with walking or bicycling in many descriptive analyses and mode choice models, it is not the case in Rodriguez and Joo's study (2004). The inconsistency may be attributed to the fact that past studies include and exclude different independent variables, use different data sources, rely on different levels of data aggregation, employ different analytic methods, and define the variables differently. For example, in studies that adopt the neighborhood comparison approach, the selection of neighborhoods as "walkable" or "compact" is subject to the researchers' perception. The lack of a consistent measure of "walkablility" or compactness means that the findings from different studies are likely incomparable.

The same reasons that have resulted in the inconsistent findings across past studies have also led to inconsistent conclusions about the relative impact of the influencing factors. In order to maximize modal shifts to non-motorized travel, policy makers most likely need to take the integrated approach of simultaneously improving multiple aspects of the travel environment to meet the differing needs and preferences of the population. The success of this integrated approach will depend on a thorough understanding of the interactions among, and the relative impact of, the full spectrum of influencing variables. This calls for a comprehensive examination of all relevant variables in a single analysis framework.

The current study is designed to contribute to the existing body of literature on non-motorized travel behavior analysis in two ways. First, our descriptive analysis will examine the relationships among a broad range of relevant variables to help clarify some of the past contradictory findings. Second, our trip frequency models will provide important insights into walk and bicycle trip generation behavior, which has received very little attention in the past literature. Most disaggregate models found in the existing literature have been developed for analyzing individuals' mode choice behavior. The work of Handy and Clifton (2001) is one of the few studies to estimate a generation model for walk trips to stores. The current study will expand this limited body of work by developing separate trip frequency models for walk and bicycle modes and for commute, maintenance shopping, and pure recreation. Also, as opposed to using a linear regression modeling approach (as adopted by Handy and Clifton, 2001), which unrealistically treats trip frequency as a continuous variable, we employ more appropriate econometric models to account for the ordinal nature of trip frequency.

CHAPTER 3.
DATA ASSEMBLY AND SAMPLE DESCRIPTION

This chapter describes the sources, the assembly process, and the characteristics of the data used for the two stages of analysis to be presented in the next two chapters. Section 3.1 describes the study area and the data sources. Section 3.2 explains the process involved in compiling the various spatial data that describe the travel environment. Section 3.3 describes the formation and the classification of the sample data. Section **Error! Reference source not found.** presents the characteristics of the sample at the household, person, and trip levels.

3.1. Data Sources

The primary data for our analysis was acquired from the 2000 Bay Area Transportation Survey (BATS) conducted by MORPACE International Inc. for the Metropolitan Transportation Commission (MTC), California. The survey collected information on all activity and travel episodes undertaken by individuals from over 15,000 households in the nine counties in Bay Area (as illustrated in Figure 3.1) for a two-day period (see MORPACE International Inc., 2002 for details on survey, sampling, and administration procedures). The information collected on activity episodes included the type of activity, start and end times of activity participation, and the geographic location of activity participation. Travel episodes were characterized by the mode used, and the start and end times of travel. For all out-of-home activity episodes, additional information on the name of the activity participation location and the type of location were collected. Furthermore, data on individual and household socio-demographics, individual employment-related characteristics, household auto ownership, household location, and internet access and usage were also obtained.

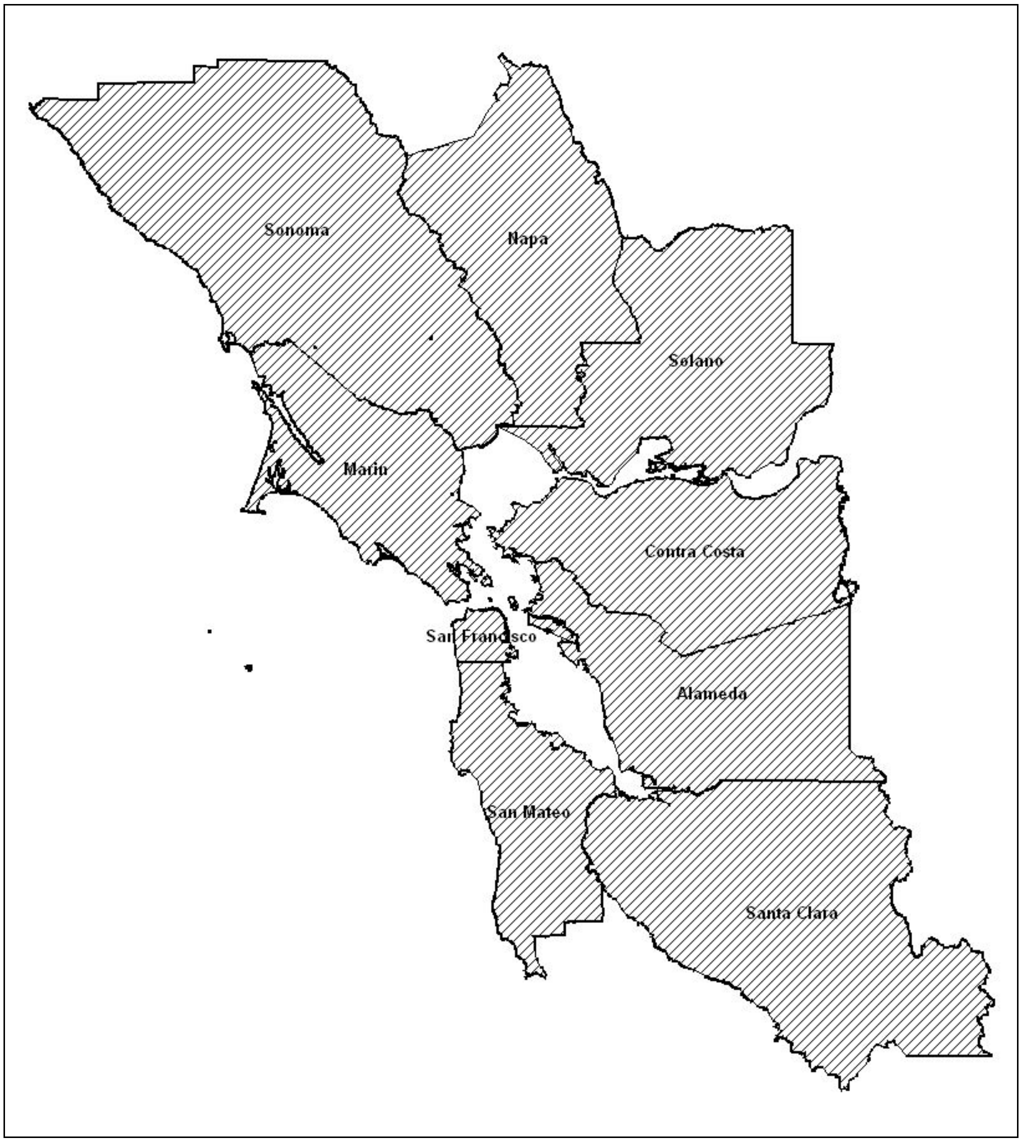


Figure 3.1 The study region covers the nine counties in the San Francisco Bay Area.

The BATS data is ideally suited for our analysis of metropolitan area non-motorized travel for several reasons. First, the 2000 BATS collected information from more than 15,000 households and is perhaps the most extensive metropolitan area travel survey to date. Due to the large size of the dataset, there is a large number of walk and bicycle trips to support a comprehensive analysis of non-motorized trips. Second, unlike many conventional travel surveys, the BATS is a time-use survey that captures travel pursuits without any specific destination to perform activities (such as walking or jogging around a neighborhood). Third, the BATS obtained activity diary information on all members of a household, including children. This alleviates the problem of underreporting of short non-motorized trips undertaken by children. Fourth, the BATS data collection period spanned all the months of the year 2000. This enables a detailed study of seasonal fluctuations in non-motorized travel and the effect of weather conditions on non-motorized travel use. Fifth, the trips in the BATS survey have been geo-coded to latitude and longitude. This facilitates analysis at a high spatial resolution.

In addition to the 2000 BATS data, a number of other data sources are used to derive measures about the urban environment within which the survey respondents undertake their activities and travel. The MTC provided Traffic Analysis Zones (TAZ) -level data on: (1) area coverage by land-use purpose, (2) number of housing units, (3) employment levels by sector, (4) zonal population, income and age distribution of the population, and (5) area type of the zone (central business district, urban, suburban, or rural). The MTC also provided a GIS line layer describing all existing bicycle facilities in the Bay Area region. It includes class 1 facilities (separate paths for cyclists and pedestrians), class 2 facilities (painted lanes solely for cyclists), and class 3 facilities (signed routes on shared roads). Another source of data is the Census 2000 TIGER files, from which two GIS line layers were extracted for the Bay Area region: one is the highway network (including interstate, toll, national, state and county highways) and the other is the local roadways network (including local, neighborhood, and rural roads).

3.2. Processing of Spatial Data

In order to examine the influence of environmental factors on non-motorized travel, we compiled a set of urban form variables using units of analysis consisting of concentric circles of 1/4, 1, and 5 mile radii around the residence of each individual in the sample. These variables include those from the TAZ data, the total length of bikeway, the total length of highway, and the total length of local roadways. The compilation of measures for the circular units from TAZ-level data and the transportation network layers involved using TransCAD to perform overlay operations as follows:

1. Assume that the TAZ attributes follow a uniform distribution within each zone so that data for a given zone can be disaggregated uniformly over the zone. For instance, if the number of service employment opportunities in a 10 square-mile zone is 100, then every squared-mile area in the zone is assumed to have 10 service employment opportunities. The disaggregate data are then projected onto, and re-aggregated over, the circular buffers created around the geo-coded location of each household to produce the corresponding measures for the circular units.
2. Project each of the network layers onto the circular units and sum up the lengths of the line segments falling within each circular unit.

A number of additional variables were further computed for the circular units. These include density measures (population and employment), land-use composition measures (percentage of coverage by land-use type), and a more complex measure of land-use diversity defined by:

$$LUMIX_i = 1 - \frac{\left|\frac{R_i}{T_i} - \frac{1}{3}\right| + \left|\frac{CI_i}{T_i} - \frac{1}{3}\right| + \left|\frac{O_i}{T_i} - \frac{1}{3}\right|}{\frac{4}{3}}$$

where T_i is the total area of the circular unit i; and R_i, CI_i, and O_i are the acreage of residential, commercial and industrial, and other land use type. This land-use mix index takes a value between 0 and 1, where 1 indicates perfect mixing of land uses and 0 indicates that the land in a particular area is completely dedicated to a single land use (see Bhat and Gossen, 2002).

The result of the aforementioned process is a table of spatial measures for circular units of ½, 1, and 5 mile radii around the residence of each individual in the BATS data. The spatial measures include numbers of single- and multiple-family dwelling units, area type variables classifying zones into one of 4 categories (central business districts, urban, suburban, and rural), land use composition, residential density, employment density, land-use mix index, length of highways, length of roads, and length of bikeways.

3.3. Sample Formation

Three data tables were assembled from the BATS data and the spatial measures described in the previous section to support different levels of analysis. First, we extracted information about the travel episodes to form a table of trip records. There were 4,05,541 such records, each characterized by the purpose, mode, time of day, day of week, number of stops made and other attributes of the trip. For the purpose of our subsequent analyses, we defined trip purpose by a four-way categorization: (1) primary job, (2) maintenance shopping, (3) pure recreation, and (4) other purposes. "Primary job" refers to trips made for the purpose of commuting to an individual's primary employment location. "Maintenance shopping" refers to trips made to groceries, gas stations, laundry stores and dry cleaners. "Pure recreation" refers to trips made by the walk and bicycle modes for recreation that started and ended at an individual's home. Second, we identified the attributes of the trip makers to form the person table. The attributes include individual socio-demographics, employment-related characteristics, study-related characteristics, and internet access and usage. The trip patterns of each traveler (such as the total number of trips undertaken by mode and by trip purpose) are also aggregated from the trip table and added to the person table. Third, the first two tables were appropriately aggregated to the household level, and additional household attributes (such as household structure, auto ownership level and location attributes) were appended to form the household table. Fourth, several screening and consistency checks were performed, and records with missing or inconsistent data were eliminated. The final sample for analysis included data from 14,529 households, 33,402 individuals, and 209,069 trips.

Three types of households can be identified in the dataset (see Figure 3.2). Households with persons making only non-motorized trips and no motorized trips (henceforth referred to as "non-motorized households") constituted a share of 3.5% in the entire sample. Households with individuals making non-motorized as well as motorized trips (the "mixed households") accounted for 35.2% of the sample. Households with individuals making only motorized trips and no non-motorized trips (the "motorized households") accounted for 61.3% of the sample. Also, as shown in Figure 3.2, about three quarters of the trip makers used motorized modes for all their trips, while a quarter of the surveyed trip makers made at least one non-motorized trip.

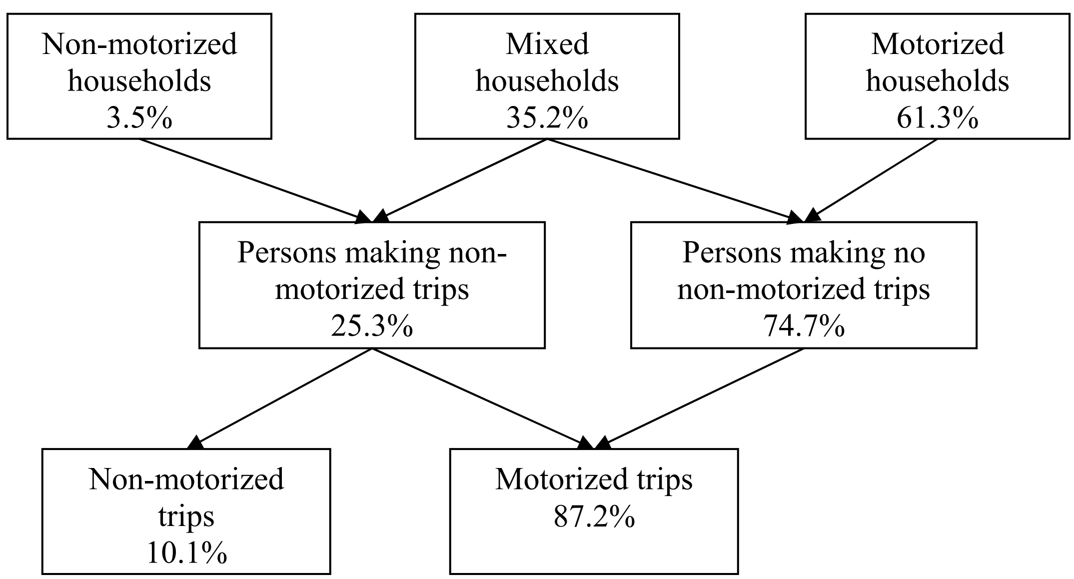


Figure 3.2 Categorization of the trip, person and household records in the sample for analysis

3.4. Sample Characteristics

The aggregate characteristics of the three data tables are as follows.

3.4.1. Household Level Characteristics

Table 3.1 shows the household characteristics for the non-motorized households, mixed households, motorized households, and all households. These results are quite intuitive. The non-motorized households have the smallest household size on average, lower vehicle ownership, lower number of children, and also low income.

Table 3.1: Household level characteristics

	Non-motorized HH		Motorized HH		Mixed HH		All HH	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
HH size	1.5	0.7	2.2	1.2	2.6	1.3	2.3	1.3
Number of vehicles	0.6	0.7	1.9	0.9	1.9	0.9	1.9	1.0
Number of bicycles	0.8	1.4	1.3	1.5	1.8	1.8	1.4	1.6
Number of children	0.1	0.5	0.4	0.8	0.7	1.1	0.5	0.9
Number of active adults	1.1	0.7	1.5	0.8	1.7	0.8	1.6	0.8
Number of senior adults	0.2	0.5	0.3	0.6	0.2	0.5	0.2	0.5
Household income (dollar)	49,155	35,602	80,613	47,519	84,704	49,538	80,686	48,398

3.4.2. Individual Level Characteristics

At the individual level, the non-motorized subset of the sample, which includes individuals making at least one non-motorized trip, has a significantly higher share of individuals under the age of 16, lower license holding, and a higher fraction of unemployed individuals and full-time students (see Table 3.2).

Table 3.2 Individual level characteristics

Survey Respondent characteristics	Non-motorized modes		All
	Users (%)	Non-users (%)	Individuals (%)
Gender			
Males	49.4	48.1	48.4
Females	50.6	51.9	51.6
Total	100.0	100.0	100.0
Age			
Age 0-16	24.0	18.5	19.8
Age 17-30	15.9	12.6	13.3
Age 31-50	35.1	36.7	36.6
Age 51-66	17.1	21.3	20.3
Senior citizens (age > 66)	8.0	10.9	10.3
Total	100.0	100.0	100.0
Disability			
No	98.2	97.2	97.4
Yes	1.8	2.8	2.6
Total	100.0	100.0	100.0
Licensed to Drive			
No	29.4	21.9	23.6
Yes	70.6	78.1	76.4
Total	100.0	100.0	100.0
Employment Status			
Unemployed	44.7	41.6	42.3
Employed			
Full time employee	45.0	49.0	48.1
Part time employee	10.3	9.4	9.6
Total	100.0	100.0	100.0
Student Status			
Non-student	66.4	73.3	71.7
Student			
Full time student	26.1	19.0	20.6
Part time student	7.6	7.8	7.7
Total	100.0	100.0	100.0
Ethnicity			
Caucasian	76.1	74.2	74.7
African American	2.9	3.1	3.0
Hispanic	4.3	5.3	5.0
Asian	8.5	9.5	9.3
Other	8.1	7.9	8.0
Total	100.0	100.0	100.0

3.4.3. Trip Level Characteristics

As summarized in Table 3.3, the overall mode choice shares in the trip table are as follows: 1.3% for bicycling, 8.8% for walking, 87.2% for motorized modes and 2.7% for other modes. When compared across the four different trip purposes of primary job, maintenance shopping, pure recreation and other (as defined in section 3.3), the use of non-motorized modes is highest for pure recreational trips (38.5% of such trips are walk trips and 6% are bicycle trips). Be definition, the travel undertaken for pure recreation is solely for the purpose of the utility derived from the travel. Travelers are not as concerned about factors such as travel speed as they would be when traveling for other purposes. Also, since the trip starts and ends at home, there is no chaining of activities, making the choice of non-motorized modes more probable in terms of comfort and convenience. For these reasons, it is not surprising that the share of non-motorized modes is highest for the pure recreation purpose.

Trips related to the primary job have the second highest share of walk and bicycle trips. The lowest percentage of non-motorized trips is for maintenance shopping trips. It is evident that the use of walk and bicycle modes are very much dependent on the trip purpose, suggesting the need to develop models of non-motorized travel behavior that are segmented by trip purpose.

Table 3.3 Distribution of mode shares across trip purposes

Mode	Trip Purpose				All Purposes (%)
	Primary Job (%)	Maintenance Shopping (%)	Pure Recreational (%)	Other (%)	
Bicycle	1.7	1.1	6.0	1.4	1.3
Walk	8.8	6.1	38.5	8.9	8.8
Motorized	85.4	91.9	45.1	87.0	87.2
Other	4.1	0.9	10.4	2.7	2.7
Total	100.0	100.0	100.0	100.0	100.0

3.5. Summary

In this chapter, we have described the process of assembling the sample from the San Francisco Bay area for our subsequent analysis. The sample consists of three separate tables: (1) a trip table that describes the characteristics of the trips observed in the BATS data; (2) a person table that describes the characteristics of the trip makers and their trip making pattern; and (3) a household table that describes the characteristics of the households to which the trip makers belong, the composition of the households, and the characteristics of the environment surrounding the household residences.

This chapter also presented a scheme for categorizing the trips, the persons, and the households based on the usage of transportation modes. The percentage of households which rely solely on non-motorized modes is very small. The percentage of households which use both motorized and non-motorized modes is a little over half of the percentage of households which do not use non-motorized modes at all. The 61% of motorized households, or equivalently the 75% of the population making no non-motorized trips at all, presents a major challenge for advocates of active transportation and for agencies trying to reduce vehicular trips.

CHAPTER 4.
EXPLORATORY ANALYSIS

Using the 2000 BATS dataset described in the previous chapter, we conducted an exploratory analysis relating non-motorized forms of travel to trip attributes, traveler socio-demographics attributes, and the attributes of the activity travel environment. The purpose of this analysis is to understand how the usage of non-motorized travel modes is impacted by these various attributes. The exploratory analysis provides a broad perspective about the preferences of individuals toward the mode chosen for different trip purposes. The findings will enable us to gain important insights into the inter-relationship of the various factors affecting the choice of non-motorized modes. Such insights will be used to guide the model specification for the empirical analysis discussed in Chapter 5.

Section 4.1 describes the correlation between trip characteristics and the use of non-motorized modes. Section 4.2 describes the relationship between the socio-demographic characteristics of travelers and non-motorized mode use. Section 4.3 discusses the impact of the built environment on non-motorized travel behavior.

An important point to note here. The exploratory analyses of the next few sections do not control for the effect of variables all at the same time. Thus, the interactions and correlations among variables are not considered. As a result, caution should be exercised in inferring a strict causal effect of explanatory variables on the behavior of interest.

4.1. Impact of Trip Characteristics

The trip characteristics that are likely to influence non-motorized mode use include day of the week of travel, time of the day of travel, and weather at the time of travel. The following sections discuss in detail the relationship between each of these trip characteristics and the use of non-motorized forms of travel.

4.1.1. Day of the Week

Table 4.1 presents the shares of motorized, bicycle, and walk modes in the overall and by trip purpose. Interestingly, for maintenance shopping trips, the results show little variation in mode shares between weekdays and weekends. However, the mode shares of walk and bicycle are higher during the week, as compared to the weekend, for trips related to primary job, pure recreation and other purposes. Thus, in the overall, the share of non-motorized modes is slightly higher on weekdays than on weekends.

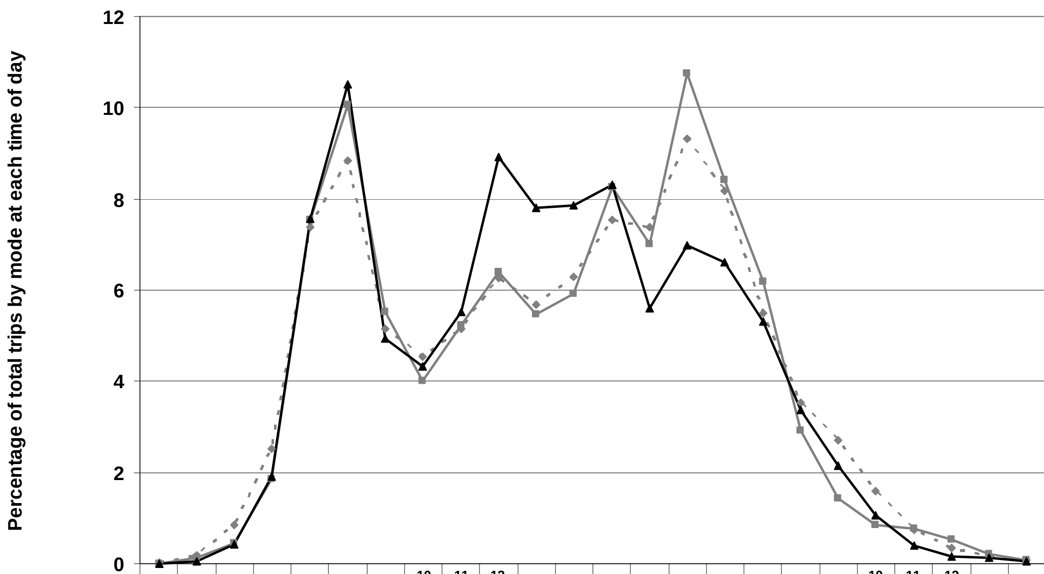
Table 4.1 Mode share by trip purpose by day of the week

Trip Purpose	Travel Mode	Day of the Week	
		Weekdays (%)	Weekend (%)
Overall	Motorized	89.7	91.1
	Bicycle	1.4	1.1
	Walk	8.9	7.8
	Total	100.0	100.0
Primary Job	Motorized	89.6	88.3
	Bicycle	1.6	2.2
	Walk	8.7	9.5
	Total	100.0	100.0
Maintenance Shopping	Motorized	92.9	92.5
	Bicycle	1.1	1.0
	Walk	6.0	6.5
	Total	100.0	100.0
Pure Recreation	Motorized	55.1	60.0
	Bicycle	6.0	6.7
	Walk	38.9	33.3
	Total	100.0	100.0
Other Purposes	Motorized	89.6	91.0
	Bicycle	1.4	1.1
	Walk	9.0	7.9
	Total	100.0	100.0

4.1.2. Time of Day

Figure 4.1 presents the distributions of motorized, bicycle, and walk trips across the different times of the day. That is, the trips by each mode for each time of day are computed as a percentage of total trips by that mode during the entire day. Clearly, the distributions of motorized trips and bicycle trips are very similar, resembling the usual commute pattern. The distribution of the walk trips, on the other hand, has a morning peak at the same hours as the other two modes. But its afternoon peak starts much earlier than the other two modes and spreads out across the afternoon hours of the day.

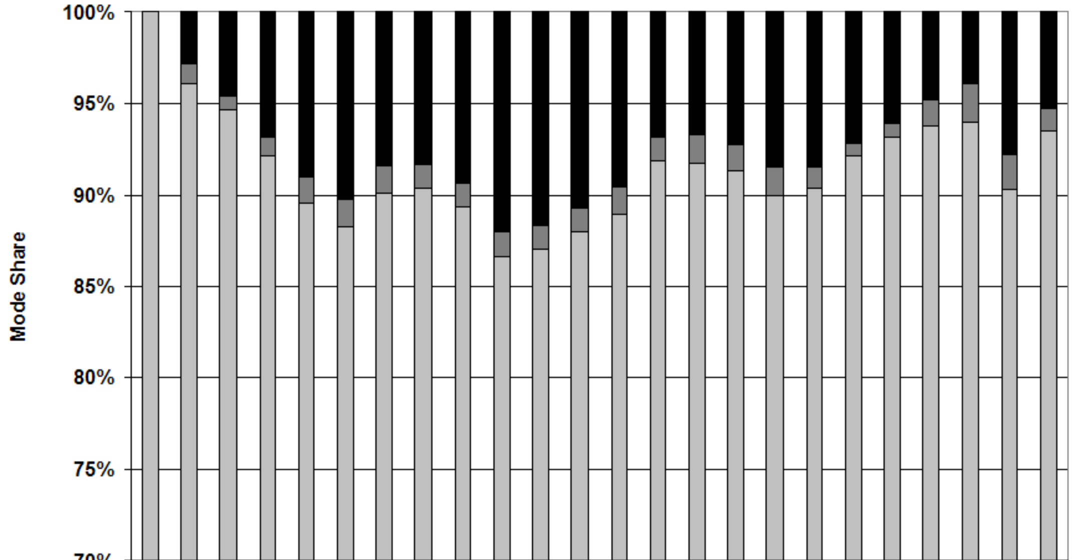
Figure 4.2 shows the modal shares by hour of day, thus controlling for overall trip-making levels at different time of the day. The combined share of walk and bicycle modes is higher during the morning peak hours (7am ~ 9am), mid-day (12pm ~ 2pm), and evening peak hours (7pm ~ 9pm).



	3am	4am	5am	6am	7am	8am	9am	10 am	11 am	12 pm	1pm	2pm	3pm	4pm	5pm	6pm	7pm	8pm	9pm	10 pm	11 pm	12 am	1am	2am	total
Motorized	0.0	0.2	0.9	2.5	7.4	8.8	5.1	4.5	5.2	6.3	5.7	6.3	7.5	7.4	9.3	8.2	5.5	3.5	2.7	1.6	0.8	0.3	0.1	0.1	100
Bicycle	0.0	0.1	0.5	1.9	7.5	10.1	5.5	4.0	5.2	6.4	5.5	5.9	8.2	7.0	10.7	8.4	6.2	2.9	1.4	0.8	0.8	0.5	0.2	0.1	100
Walk	0.0	0.1	0.4	1.9	7.6	10.5	4.9	4.3	5.5	8.9	7.8	7.8	8.3	5.6	7.0	6.6	5.3	3.4	2.2	1.1	0.4	0.1	0.1	0.0	100

Time of day

Figure 4.1 Percentage of trips at each time of day



	3am	4am	5am	6am	7am	8am	9am	10 am	11 am	12 pm	1pm	2pm	3pm	4pm	5pm	6pm	7pm	8pm	9pm	10 pm	11 pm	12 am	1am	2am
walk	0.0	2.9	4.6	6.8	9.0	10.2	8.4	8.4	9.3	12.0	11.7	10.7	9.6	6.8	6.7	7.2	8.5	8.5	7.1	6.1	4.8	3.9	7.8	5.3
bicycle	0.0	1.0	0.8	1.0	1.4	1.5	1.5	1.2	1.4	1.3	1.3	1.3	1.5	1.3	1.6	1.4	1.5	1.1	0.7	0.7	1.5	2.2	1.9	1.2
motorized	100.0	96.1	94.6	92.1	89.6	88.2	90.1	90.4	89.3	86.7	87.1	88.0	88.9	91.9	91.7	91.3	90.0	90.4	92.1	93.2	93.8	93.9	90.3	93.5
total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

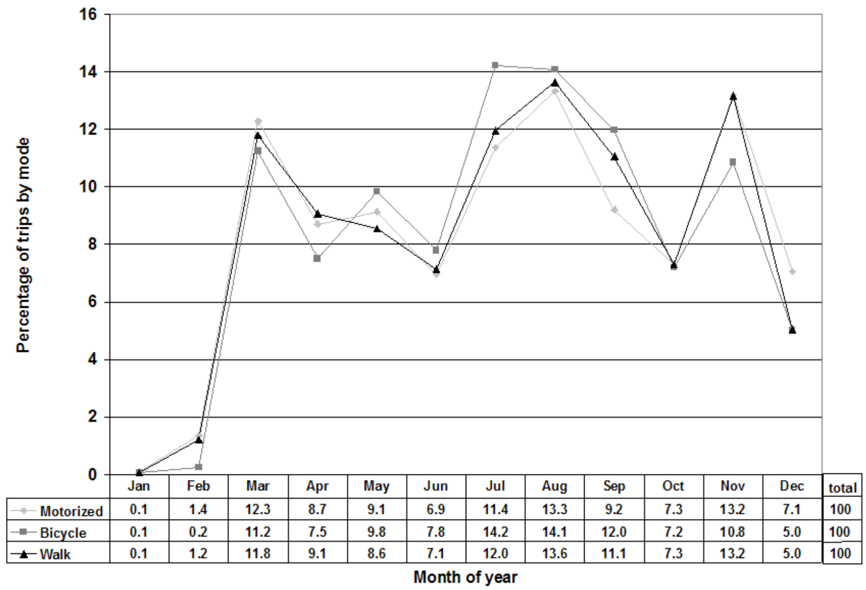
Time of Day (hr)

Figure 4.2 Modal shares by time of day.

4.1.3. Weather

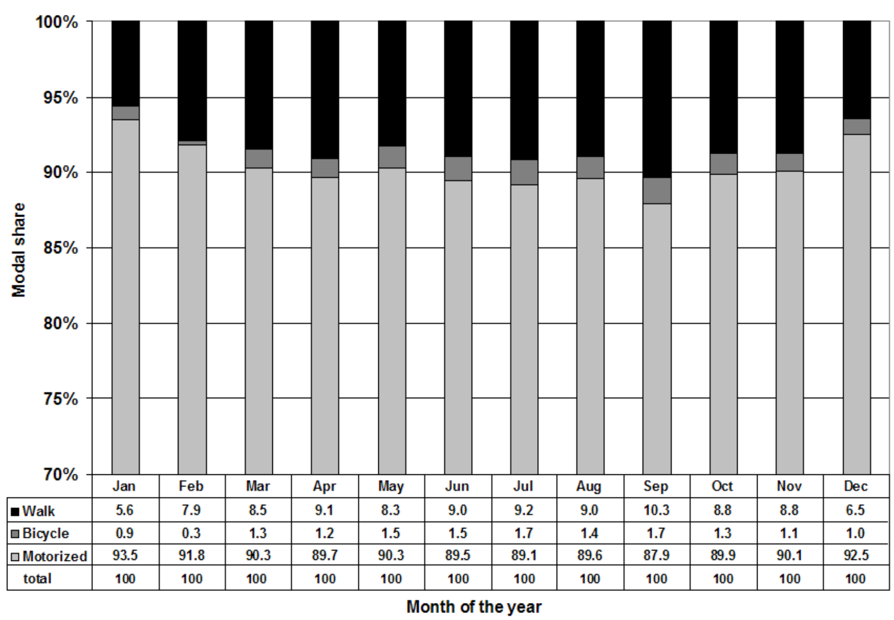
As data about the daily weather conditions associated with the BATS was not available, we infer the weather condition at the time of travel from the month in which each trip took place. Figure 4.3 presents the distributions of the motorized, bicycle and walk trips over the twelve months of a year. It shows that all three modes share very similar seasonal distributions, characterized by overall trip making levels during different seasons of the year. The coldest months of the year, i.e. January and February, have the lowest percentages of trips for all three modes. The warmest time of a year, i.e. during July and August, has the highest percentage of trips of all times. The other two months that are also associated with relatively high trip shares are March and November.

In comparing the modes against each other for different months of the year, we find that the month of September has the highest share of walk and bicycle modes (see Figure 4.4). The share of the walk mode is also relatively high in April, Jun, July and August, while the share of the bicycle mode is relatively high from May through August. In general, the summer and fall seasons have a higher non-motorized modal share compared to the winter and spring seasons.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	total
Motorized	0.1	1.4	12.3	8.7	9.1	6.9	11.4	13.3	9.2	7.3	13.2	7.1	100
Bicycle	0.1	0.2	11.2	7.5	9.8	7.8	14.2	14.1	12.0	7.2	10.8	5.0	100
Walk	0.1	1.2	11.8	9.1	8.6	7.1	12.0	13.6	11.1	7.3	13.2	5.0	100

Figure 4.3 Percentage of trips in each month of the year



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Walk	5.6	7.9	8.5	9.1	8.3	9.0	9.2	9.0	10.3	8.8	8.8	6.5
Bicycle	0.9	0.3	1.3	1.2	1.5	1.5	1.7	1.4	1.7	1.3	1.1	1.0
Motorized	93.5	91.8	90.3	89.7	90.3	89.5	89.1	89.6	87.9	89.9	90.1	92.5
total	100	100	100	100	100	100	100	100	100	100	100	100

Figure 4.4 Modal shares by month of the year

4.2. Impact of Demographic and Socioeconomic characteristics

Our description of the sample characteristics in section 3.4 has indicated that the demographic and socioeconomic characteristics at the household and person level are correlated with the use of non-motorized modes of travel. Below, we present a more in-depth descriptive analysis of how gender, age, ethnicity, employment status, student status, household income, automobile ownership, household structure, and the number of children in the household are related to the aggregate level of non-motorized travel.

4.2.1. Gender

Figure 4.5 shows the percentages of walk and bicycle trips made by males and females. It can be observed that the frequency of walk trips made by men is comparable to that made by women. However, the percentage of bicycle trips made by men is higher than that of women. This is consistent with previous findings in the literature (as discussed in section 2.4.1 of this report). A possible explanation is that women are more concerned with safety issues related to walking and bicycling. Also, perhaps the work apparel for women may not be convenient for bicycling to work.

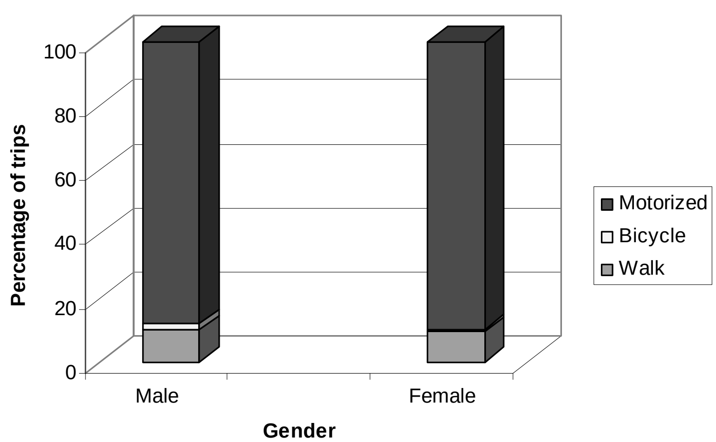


Figure 4.5 Effect of gender on walk and bicycle trips

4.2.2. *Age*

Since non-motorized travel essentially involves exertion of physical energy, the age of an individual is likely to play a role in the decision of an individual to choose non-motorized travel. Table 4.2 shows the effect of age on levels of walking and bicycling. Children up to the age of 10 are dependent on their parents for transportation to physical activity participation locations and other locations (Sallis et al., 1992b; Hoefer et al., 2001). This explains the lower percentages of walk and bicycle trips in the age group of less than 10 years compared to above 10 years. Above the age of 10, children are relatively more independent and they generally bicycle or walk to their school or playgrounds and/or parks near their homes. Among adults (age greater than 16 years), individuals less than 35 year old use non-motorized modes more than individuals older than 35 years.

Table 4.2 Effect of age

Age	Mode			
	Walk (%)	Bicycle (%)	Motorized (%)	Total (%)
Less than 4 years	9.8	0.6	89.5	100
5 thru 10 years	10.6	1.6	87.8	100
11 thru 15 years	15.8	3.5	80.7	100
16 thru 25 years	11.3	2.0	86.7	100
26 thru 35 years	12.4	2.1	85.6	100
36 thru 50 years	7.8	1.3	90.9	100
51 thru 65 years	8.1	0.8	91.1	100
66 years or more	9.5	0.5	90.0	100

4.2.3. *Ethnicity*

Table 4.3 shows shares of motorized versus non-motorized trips by ethnicity and trip purpose. The table indicates that African-Americans make more non-motorized trips than Caucasians, Hispanics, and Asians/Pacific Islanders, irrespective of the trip purpose. On the other hand, Hispanic-Americans are more likely to travel by motorized modes than the other ethnic groups. While this could be due to the intrinsic inclination of the ethnic groups, it could be related to the low vehicle ownership levels among African-Americans and/or the poor walk/bicycling accessibility to jobs and shopping opportunities experienced by the Hispanic population.

Table 4.3 Effect of ethnicity

Trip Purpose	Travel Mode	Ethnicity				
		Caucasian (%)	African American (%)	Hispanic (%)	Asian/Pacific Islander (%)	Other (%)
Primary Job	Non-motorized	10.7	12.5	6.1	7.8	32.1
	Motorized	89.3	87.5	93.9	92.2	67.9
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Non-motorized	7.0	9.8	4.5	5.7	11.9
	Motorized	93.0	90.2	95.5	94.3	88.1
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Non-motorized	45.7	50.0	40.0	45.5	87.0
	Motorized	54.3	50.0	60.0	54.5	13.0
	Total	100.0	100.0	1000	100.0	100.0

4.2.4. Employment Status and Flexibility of Working hours

The employment status and work schedule of an individual has an impact on the mode chosen (see Table 4.4). Compared to the unemployed population group, employed individuals are more inclined toward motorized modes and less inclined toward non-motorized modes. Those with a totally or partially flexible work schedule are more predisposed to using non-motorized modes than those with no flexibility in work schedule. This may be because individuals with a flexible schedule may not need to travel during the peak hour, thereby avoiding traveling in the busy traffic – which can be a serious deterrent for choosing non-motorized modes.

Table 4.4 Effect of employment status

Mode	Unemployed (%)	Employed (%)	Totally Flexible (%)	Partially Flexible (%)	No Flexibility (%)
Walk	10.2	8.6	8.9	9.1	8.0
Bicycle	1.3	1.5	1.7	1.2	1.4
Motorized	88.5	89.9	89.4	89.7	90.6
Total	100.0	100.0	100.0	100.0	100.0

4.2.5. Students

Table 4.5 shows the effect of student status on levels of walking and bicycling. Students make a higher share of their trips by walk and bicycle relative to non-students. This is perhaps because students tend to be younger and more physically active. Also, students enrolled in high school are independent and many of them walk or bicycle to school. Further, students attending college or university stay close to the campus, making walking or bicycling easier and convenient. Compared to full time students, part time students contribute to more motorized trips and fewer non-motorized trips. In fact, the mode shares of part-time students are about identical to non-students. This is intuitive, since most part-time students are employed at locations that are not as conductive to non-motorized mode use as college campuses.

Table 4.5 Effect of student status

Mode	Non-Student (%)	Student (%)	Full time student (%)	Part time student (%)
Walk	8.0	10.9	12.1	8.0
Bicycle	1.2	1.8	2.1	1.1
Motorized	90.9	87.3	85.8	90.9
Total	100.0	100.0	100.0	1000

4.2.6. Income

Table 4.6 presents the impact of household income level on walk and bicycle trips. For primary job and maintenance shopping, low income households (below 50K) clearly use the walk and bicycle modes more than the higher income households.

This higher proportion of bicycle and walk trips among the lowest income bracket is very likely due to their relatively lower vehicle ownership levels. For pure recreation trips, though the medium income households (between 50K and 125K) do not walk as much as low income households, they are more likely to bicycle than the other income groups.

Table 4.6 Effect of income

Trip Purpose	Travel Mode	Income			
		< 50K (%)	≥ 50K and < 75K (%)	≥ 75K and < 125K (%)	≥ 125K (%)
Primary Job	Walk	9.9	8.6	8.5	8.9
	Bicycle	3.3	0.8	1.1	1.0
	Motorized	86.9	90.6	90.4	90.1
	Total	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	9.1	7.1	4.7	3.9
	Bicycle	1.7	1.2	0.7	0.5
	Motorized	89.2	91.7	94.6	95.6
	Total	100.0	100.0	100.0	100.0
Pure Recreation	Walk	44.9	37.5	38.5	29.6
	Bicycle	4.1	15.0	5.8	0.0
	Motorized	51.0	47.5	55.8	70.4
	Total	100.0	100.0	100.0	100.0

4.2.7. Automobile availability

Table 4.7 shows the influence of automobile availability – defined as the number of vehicles per licensed driver in a household – on levels of walking and bicycling. Individuals with low (≤0.5) automobile availability are more likely to walk and bicycle than individuals with higher automobile availability. This negative impact of automobile availability on non-motorized use is found for all three trip purposes.

Table 4.7 Effect of automobile availability

Trip Purpose	Travel Mode	Average number of vehicles per licensed individual in a household				
		=0 (%)	>0 and ≤0.5 (%)	>0.5 and ≤1.0 (%)	>1.0 and ≤1.5 (%)	>1.5 (%)
Primary Job	Walk	43.9	23.6	7.4	4.3	8.0
	Bicycle	13.4	5.6	1.1	0.7	0.5
	Motorized	42.7	70.8	91.5	95.0	91.5
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	55.4	16.5	4.6	2.8	4.6
	Bicycle	12.5	2.9	0.7	0.7	0.6
	Motorized	32.1	80.6	94.7	96.5	94.8
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Walk	60.0	52.6	34.2	36.8	25.0
	Bicycle	6.7	26.3	4.5	0.0	0.0
	Motorized	33.3	21.1	61.3	63.2	75.0
	Total	100.0	100.0	100.0	100.0	100.0

4.2.8. Family type

The family structure of an individual's household can be a significant determining factor of mode usage, especially for utilitarian trips. Table 4.8 shows the modal shares by trip purpose and household structure. It shows that, due to the presence of children in the households, the nuclear families and the single parent families rely on motorized modes for utilitarian trips more than the other types of households. On the other hand, single individual households use the walk and bicycle modes for primary job and maintenance shopping trips more than the other types of households. This is intuitive, as single individuals do not need to coordinate their trips with other members of the household, making non-motorized modes more feasible. In the case of travel for pure recreation, couples and nuclear families have higher shares of walk and bicycle trips than the single parent and single individual households. This is perhaps related to the difference in the life style preferences between the household types.

Table 4.8 Effect of household structure

Trip Purpose	Travel Mode	Household structure				
		Couple (%)	Nuclear Family (%)	Single Parent (%)	Single Individual (%)	Other (%)
Primary Job	Walk	8.2	7.8	7.4	11.5	9.5
	Bicycle	1.0	0.8	0.0	2.1	2.8
	Motorized	90.9	91.5	92.6	86.4	87.8
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	5.8	4.2	6.0	10.7	5.8
	Bicycle	0.7	0.9	0.4	1.5	1.5
	Motorized	93.4	94.9	93.6	87.8	92.7
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Walk	48.0	48.9	25.0	31.0	22.5
	Bicycle	6.0	4.4	0.0	0.0	15.0
	Motorized	46.0	46.7	75.0	69.0	62.5
	Total	100.0	100.0	100.0	100.0	100.0

4.2.9. Number of children

Table 4.9 shows the effect of presence of children in the household on walk and bicycle trips made for each trip purpose. As the number of children in the household increases, the share of trips by non-motorized modes increases for commuting to primary job. This result is rather surprising, and needs further exploration. For maintenance shopping, however, the percentage of walk trips decreases as the number of children in the household increases (except for the few households that have more than three children).

Table 4.9 Effect of number of children

Trip Purpose	Travel Mode	Number of children in household				
		0 (%)	1 (%)	2 (%)	3 (%)	> 3 (%)
Primary Job	Walk	7.0	7.8	9.4	10.8	9.6
	Bicycle	0.2	0.8	2.2	0.0	2.1
	Motorized	92.8	91.4	88.5	89.2	88.2
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	5.8	3.7	3.3	1.3	7.5
	Bicycle	0.7	1.0	0.2	3.2	1.2
	Motorized	93.5	95.2	96.5	95.5	91.4
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Walk	46.4	50.0	33.3	50.0	34.9
	Bicycle	3.6	10.0	8.3	0.0	6.6
	Motorized	50.0	40.0	58.3	50.0	58.5
	Total	100.0	100.0	100.0	100.0	100.0

4.3. Impact of the Built Environment

4.3.1. Land Use

The land use mix defines the diversity or mix of the types of land use present in the area. As described in section 3.2, the value of land use mix index varies between 0 and 1. A value of 0 means that there exists only one type of land use in the area, whereas a value of 1 indicates that there is a perfect balance between the proportions of the different land use types. Table 4.10 and Table 4.11 show the relationship between the level of walk and bicycle trips and the land use mix within one mile and five miles, respectively, around each household residence.

Table 4.10 suggests that individuals in households with medium level of land use mix (between 0.25 and 0.75) around 1 mile of their residence make a larger fraction of their primary job and maintenance shopping trips by non-motorized modes than individuals in households with low or high levels of land use mix.

Table 4.11 show that, when measured up to 5 miles around each household, higher levels of land use mixing are associated with a greater proportion of walk and bicycle trips for primary job and maintenance shopping travel. For pure recreation travel, this trend holds for the walk mode, but is less clear for the bicycle mode.

Table 4.10 Effect of land use mix within 1 mile around the residence

Trip Purpose	Travel Mode	Land Use Mix			
		≤ 0.25 (%)	> 0.25 and ≤ 0.5 (%)	> 0.5 and ≤ 0.75 (%)	> 0.75 (%)
Primary Job	Walk	6.7	8.5	10.3	5.9
	Bicycle	1.6	1.6	1.7	1.1
	Motorized	91.7	89.9	88.0	93.1
	Total	100	100	100	100
Maintenance Shopping	Walk	3.3	6.1	7.5	3.5
	Bicycle	0.7	1.3	1.0	0.6
	Motorized	96.1	92.5	91.5	96.0
	Total	100	100	100	100
Pure Recreation	Walk	25.0	32.6	42.6	50.0
	Bicycle	6.3	6.5	6.4	8.3
	Motorized	68.8	60.9	51.1	41.7
	Total	100	100	100	100

4.3.2. Bikeway Density

Since bikeways are facilities designed specifically for cyclists and pedestrians, areas of denser bikeway network would be expected to generate more non-motorized trips than areas of lower density of bikeways. This is indeed observed from Table 4.12 and Table 4.13, in which bikeway density is computed as the total length (in miles) of bikeways within ¼ mile and 1 mile, respectively, around each household's residence. The tables show that, as bikeway density increases, there is a clear shift from motorized modes to non-motorized modes. The shift is more pronounced for primary job and maintenance shopping trips.

Table 4.11 Effect of land use mix within 5 mile around the residence

Trip Purpose	Travel Mode	Land Use Mix ≤ 0.25 (%)	> 0.25 and ≤ 0.5 (%)	> 0.5 and ≤ 0.75 (%)	> 0.75 (%)
Primary Job	Walk	5.3	6.3	10.3	10.8
	Bicycle	1.2	0.4	1.4	3.0
	Motorized	93.5	93.4	88.3	86.2
	Total	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	3.1	2.9	6.8	9.6
	Bicycle	0.7	0.8	0.7	2.2
	Motorized	96.1	96.3	92.5	88.2
	Total	100.0	100.0	100.0	100.0
Pure Recreation	Walk	28.6	20.0	35.4	54.0
	Bicycle	0.0	20.0	4.9	8.0
	Motorized	71.4	60.0	59.8	38.0
	Total	100.0	100.0	100.0	100.0

Table 4.12 Effect of bikeway density within ¼ mile

Trip Purpose	Travel Mode	Bikeway Density (mile) ≤ 0.25 (%)	> 0.25 and ≤ 0.5 (%)	> 0.5 and ≤ 0.75 (%)	> 0.75 ≤ 1.5 (%)	>1.5 (%)
Primary Job	Walk	6.2	9.3	11.0	11.6	17.2
	Bicycle	1.2	0.7	2.8	2.0	2.8
	Motorized	92.6	90.0	86.2	86.4	80.0
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	4.0	5.1	7.3	8.5	16.6
	Bicycle	0.9	0.3	1.4	1.3	2.4
	Motorized	95.1	94.6	91.3	90.2	81.0
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Walk	29.0	55.6	33.3	50.0	39.1
	Bicycle	4.3	0.0	16.7	12.5	0.0
	Motorized	66.7	44.4	50.0	37.5	60.9
	Total	100.0	100.0	100.0	100.0	100.0

Table 4.13 Effect of bikeway density within 1 mile

Trip Purpose	Travel Mode	Bikeway Density (mile)				
		≤ 5 (%)	> 5 and ≤ 10 (%)	> 10 and ≤ 15 (%)	> 15 ≤ 20 (%)	> 20 (%)
Primary Job	Walk	5.5	8.3	7.9	8.0	29.7
	Bicycle	1.4	0.8	2.1	2.9	3.2
	Motorized	93.1	90.9	90.0	89.1	67.2
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	3.8	4.8	4.9	9.7	25.0
	Bicycle	0.9	0.5	1.2	0.9	3.1
	Motorized	95.2	94.7	93.9	89.4	71.9
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Walk	32.8	32.4	41.9	25.0	60.7
	Bicycle	4.7	8.1	6.5	25.0	3.6
	Motorized	62.5	59.5	51.6	50.0	35.7
	Total	100.0	100.0	100.0	100.0	100.0

4.3.3. Highway Density

Highways are barriers for walking and bicycling. Thus, neighborhoods that are close to highways are expected to generate fewer non-motorized trips than neighborhoods that are further away. However, Table 4.145 and Table 4.15, which show the mode shares by purpose for five levels of highway density (computed as the total length of highways) within 1 mile and 5 miles of each household's residence, do not support this hypothesis. Instead, the tables display a slight increase in the shares of walk and bicycle trips as highway density increases. A possible explanation is that a denser highway network is often accompanied by denser development, which could encourage walking and bicycling.

Table 4.14 Effect of highway density within 1 mile

Trip Purpose	Travel Mode	Highway Density (mile)				
		≤ 1 (%)	> 1 and ≤ 2 (%)	> 2 and ≤ 3 (%)	> 3 ≤ 4 (%)	> 4 (%)
Primary Job	Walk	7.9	9.0	9.0	8.8	12.2
	Bicycle	1.1	1.5	2.4	1.3	2.0
	Motorized	91.0	89.5	88.6	90.0	85.8
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	5.0	6.2	7.3	5.7	8.9
	Bicycle	0.6	1.1	1.5	1.1	1.4
	Motorized	94.4	92.7	91.2	93.2	89.8
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Walk	34.1	30.2	39.5	50.0	50.0
	Bicycle	0.0	9.3	10.5	3.6	11.1
	Motorized	65.9	60.5	50.0	46.4	38.9
	Total	100.0	100.0	100.0	100.0	100.0

Table 4.15 Effect of highway density within 5 mile

Trip Purpose	Travel Mode	Highway Density (mile)				
		≤ 20 (%)	> 20 and ≤ 40 (%)	> 40 and ≤ 60 (%)	> 60 ≤ 80 (%)	> 80 (%)
Primary Job	Walk	4.9	10.7	11.0	5.4	10.7
	Bicycle	1.2	1.3	2.5	1.0	0.0
	Motorized	93.9	88.0	86.5	93.6	89.3
	Total	100.0	100.0	100.0	100.0	100.0
Maintenance Shopping	Walk	3.9	7.5	7.4	4.3	8.9
	Bicycle	0.7	0.7	1.9	1.1	2.2
	Motorized	95.5	91.7	90.7	94.6	88.9
	Total	100.0	100.0	100.0	100.0	100.0
Pure Recreation	Walk	29.7	35.0	46.7	50.0	0.0
	Bicycle	2.7	8.3	6.7	10.0	0.0
	Motorized	67.6	56.7	46.7	40.0	100.0
	Total	100.0	100.0	100.0	100.0	100.0

4.4. Summary

The exploratory analysis conducted in this chapter provides interesting insights into the existing behavioral patterns among the population. The mode chosen for a particular trip is fundamentally related to the trip characteristics, household and individual characteristics of the person making the trip, and the attributes of the built environment in which the trip is made. However, these various factors may be correlated to each other in intricate ways and thus their effect on non-motorized trip making behavior is more difficult to isolate.

In order to explain the relative effects of the many influencing factors discussed in this chapter, an analytic approach which examines the full spectrum of factors simultaneously is required. This is the focus of the following chapter.

CHAPTER 5.
ORDERED RESPONSE PROBIT MODELS FOR NUMBER OF WALK AND BICYCLE TRIPS

In this chapter, we develop a suite of models for predicting walk and bicycle trip frequencies for three different trip purposes: primary job, maintenance shopping, and pure recreation. While the first two trip purposes correspond to utilitarian trips that have traditionally been the focus of transportation professionals, our interest in travel for pure recreation is motivated by the concerns of the health professionals. The models presented in this chapter not only provide both transportation and health professionals more insight into the determinants of non-motorized trip generation, but also serve as predictive tools for analyzing the impact of future policies targeted at promoting non-motorized travel.

The remainder of this chapter begins with section 5.1 that presents the structure of the trip frequency models. Section 5.2 describes the sample data used for model estimation. Section 5.3 discusses the empirical results obtained from estimating the models using the Bay area data. Section 5.4 concludes the chapter with a summary of the findings.

5.1. Modeling Structure

A model structure that recognizes the ordinal nature of trip frequency is the ordered-response formulation. The ordered-response formulation was initially proposed by McKelvey and Zavonia (1975) and has been used extensively in the transportation literature for analyzing the frequency of stop-making and trip-making (see, for example, Agyemang-Duah and Hall, 1997, and Bhat and Zhao, 2002).

In the context of trip frequency by a non-motorized mode m for trip purpose p, the ordered-response mechanism postulates the presence of a latent continuous trip making propensity y_{imp}^{*} for individual i. This latent propensity is assumed to be a linear function of a relevant vector of exogenous variables x_i and a standard normally distributed error term ε_{imp}:

$$y_{imp}^{*} = \beta_{mp}{}' x_i + \varepsilon_{imp},$$

where ε_{imp} is normally distributed, $\varepsilon_{imp} \sim N(0,1)$. The latent propensity y_{imp}^{*} characterizes the actual reported frequency of trips by mode m for purpose p, y_{imp}, through a set of threshold bounds:

$$\begin{array}{lll}
y_{imp} = 0 & \text{if} & y_{imp}^{*} \leq 0 \\
y_{imp} = 1 & \text{if} & 0 < y_{imp}^{*} \leq \psi_{mp,1} \\
 & . & \\
 & . & \\
 & . & \\
y_{imp} = J_{mp} & \text{if} & y_{imp}^{*} > \psi_{mp,J_{mp}-1}
\end{array}$$

where J_{mp} indicates the maximum value y_{imp} can take. The ψ_{mp}'s, are the $(J_{mp} - 1)$ unknown threshold bounds, where $\psi_{mp,1} < \psi_{mp,2} < \ldots < \psi_{mp,J_{mp}-1}$.

Following from the standard normal assumption of ε_{imp}, the response probabilities are as follows:

$$P(y_{imp} = 0) = P(y_{imp}^{*} \leq 0) = \Phi\left(-\beta_{mp}{}' x_i\right)$$

$$P\left(y_{imp}=1\right)=P\left(0<y_{imp}^{*}\leq\psi_{mp,1}\right)=\Phi\left(\psi_{mp,1}-\beta_{mp}{}'x_i\right)-\Phi\left(-\beta_{mp}{}'x_i\right)$$

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$$P\left(y_{imp}=J_{mp}\right)=P\left(y_{imp}^{*}>\psi_{mp,J_{mp}-1}\right)=1-\Phi\left(\psi_{mp,J_{mp}-1}-\beta_{mp}{}'x_i\right)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. The parameters to be estimated in the ordered probit model are the threshold parameters, ψ_{mp}'s, and the vector β_{mp}. The estimation is performed using the maximum likelihood method. While the β_{mp} estimates represent the relative impacts of the exogenous variables on the propensity to make trips, the threshold parameters ψ_{mp} do not have any substantive behavioral interpretations and simply serve the purpose of associating the observed frequency categories to the underlying propensity to travel by mode m for purpose p.

5.2. Sample for Estimation

The ordered probit models for non-motorized trip frequency are estimated using the data described in chapter 3 for the San Francisco Bay area. Specifically, the three tables (trip, person, and household tables) obtained at the end of the data assembly process described in Chapter 3 are further combined into one sample. This is achieved by first computing from the trip table the total number of trips by walk and by bicycle for each of the three trip purposes. The trip counts are accordingly appended to each record in the person table. Variables describing the household characteristics of each individual are also appended from the household table to the person table. This new person table forms the final sample for the purpose of model estimation, where the individuals are the units of analysis. Each individual record is therefore characterized by variables ranging from household socio-demographics, individual socio-demographics, internet-use characteristics, location variables, and trip frequencies by trip purpose and mode.

5.3. Empirical Results

A total of five ordered probit models have been estimated for five mode-purpose combinations. Specifically, the five models correspond to (1) frequency of walking trips to primary job, (2) frequency of bicycling trips to primary job, (3) frequency of walking trips for maintenance shopping, (4) frequency of bicycling trips for maintenance shopping, and (5) combined frequency of walking and bicycling trips for pure recreation. Model (5) is estimated for the combined frequency of walking and bicycling trips for pure recreation because the number of individuals undertaking pure recreational trips is very low, especially for bike trips.

The best specifications for the five models were obtained after systematically eliminating the statistically insignificant variables. The final specifications are shown in Table 5.1. We discuss the final specification of each of the five models in the subsequent sections.

Table 5.1 Ordered probit models of trip frequency by mode and trip purpose

	Primary Job				Maintenance Shopping				Pure Recreation	
	Walk		Bicycle		Walk		Bicycle		Walk and Bicycle	
	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.
Household level Characteristics										
No. of motorized vehicles	-0.0717	-2.48	-0.1689	-2.36	-0.2013	-7.94	-0.2448	-4.83	-0.1553	-2.93
No. of bicycles			0.1428	5.31			0.1630	9.25	0.0457	2.05
No. of children			-0.2664	-3.61	-0.0916	-3.86				
No. of active adults									0.1227	2.20
Household structure (other types as base)										
Couple (dummy)			-0.3426	-2.19					0.2597	2.99
Nuclear (dummy)							-0.3220	-3.08		
Single Parent (dummy)							-0.7673	-2.20		
Single individual (dummy)			-0.4732	-2.53						
Household income (above 125k as base)										
Between 0 and 50k (dummy)			0.3634	2.91	0.0841	1.92	0.2800	2.78		
Between 50k and 75k (dummy)							0.1915	1.90		
Individual level Characteristics										
Gender (male as base)										
Female (dummy)			-0.2803	-2.37			-0.1889	-2.38		
Age (below 16 as base)										
Between 16 and 17 (dummy)					0.4043	2.93				
Between 18 and 65 (dummy)	0.5689	6.04					0.4581	3.30		
Above 65 (dummy)										
Disabled (dummy)	-0.3333	-1.70			-0.3006	-2.52				
Ethnicity (Caucasian as base)										
Asian (dummy)	-0.2455	-2.36			-0.2400	-3.28	-0.4736	-2.02		
Hispanic (dummy)					-0.2406	-2.21				
African American (dummy)					-0.2399	-1.96			0.4084	2.71

Licensed to drive (dummy)	-0.2434	-2.70			-0.2371	-3.69	-0.3552	-2.83		
Internet use										
Use for shopping (dummy)							0.2756	1.78		
Use for social chat (dummy)	0.1953	3.38	0.3983	3.42	0.2297	5.36				
Employed fulltime (dummy)	-0.2848	-4.88			-0.3128	-6.86				
No. of jobs			0.1598	4.63						
Attending school (dummy)					-0.2804	-5.03				
Location Characteristics										
CBD within 1 mile (dummy)	0.3211	4.35			0.3102	5.50				
CBD within 5 mile (dummy)									0.3067	3.63
Urban area within 1 mile (dummy)	0.1855	2.95			0.1260	2.38				
Ln(no. retail employment within ¼ mile)					0.0279	1.70				
Ln(total no. employment within ¼ mile)			0.0758	1.92						
Length of bikeways within 1 mile	0.0062	2.28			0.0051	2.56			0.0059	1.67
Length of roadways within ¼ mile					0.0735	3.41				
Length of roadways within 1 mile							0.0071	3.15		
Trip Making Pattern										
No. walk trips for primary job			0.4963	3.94						
No. bike trips for primary job	0.6380	4.03								
No. walk trips for maintenance shopping							0.3881	3.04		
No. bicycle trips for maintenance shopping					0.4236	2.77				
Threshold Parameters										
Threshold 1	3.3612	17.83	3.9175	10.76	2.5526	13.45	3.5141	13.82	3.177	22.36
Threshold 2	3.7328	19.53	4.3317	11.63	3.5450	18.06	4.2271	15.65	3.904	22.06
Threshold 3	4.4794	20.60	4.8855	11.70	4.4541	16.53	4.8733	13.33	4.1986	18.39
Threshold 4	5.0229	15.78	5.1131	10.88	-	-	-	-	-	-
Mean log-likelihood	-0.03965		-0.00785		-0.07572		-0.01683		-0.01468	

5.3.1. *Walk Trips to Primary Job*

As shown in the second column of Table 5.1, the number of vehicles in a household is the only household level factor found to statistically significantly impact the number of walking trips to work. The associated negative sign suggests that individuals in households with a higher number of motorized vehicles have a lower propensity to make walk trips to their primary work location than individuals in households with a lower number of motorized vehicles. It is interesting to observe that the other household characteristics, particularly household structure and household income, do not affect the frequency of non-motorized trips for the primary job.

Several individual level attributes influence the propensity to walk to primary jobs. Individuals who are active adults (aged between 18 and 65) are likely to walk more often to their work location than people of other age groups, presumably because this age group is the working group of the population. The parameter associated with disability has the expected negative sign, suggesting that disability reduces the likelihood for, or prevents all together, an individual from making walk trips to work. Compared to other ethnicity groups living in the Bay area, the Asian population living in the area is found to make a lower number of walk trips to work. This is different from what is commonly found in the literature: that African-Americans and Caucasians are usually associated with lower level of non-motorized travel than other ethnicity groups. The lower walk trip rate associated with the Asians in the Bay area could be due to factors related to the nature of their employment or work location.

Individuals with a license to drive have a lower propensity to make walk trips to work as compared to non-license holders. This is intuitive because individuals without a license would have to use modes other than driving. Interestingly, individuals using internet for social chatting are found to be more predisposed to walk to work. This could be because such individuals are more social and therefore prefer walking to their job locations. Also, individuals who are full time workers, presumably because of their more rigid schedules and the early (late) hours that they travel to go to work (go home), are less likely to make walk trips to work compared to the part time workers.

Several location factors are considered at three different spatial scales: around ¼, 1 and 5 miles around the individuals' residence (but not at the work end). The factors that turn out to be significant all correspond to the 1 mile radius. This is intuitive as 1 mile is often considered as the maximum walk distance. Living within 1 mile from the CBD or an urban area increases the likelihood of walking to the work location. This is perhaps because the traffic congestion typically found in CBD and urban areas makes walking a convenient and time-saving option compared to driving. Good connectivity, as reflected by the positive sign associated with the length of bikeways (which include pedestrian pathways) within 1 mile of an individual's residence, also encourages an individual to walk to work.

Lastly, the parameter associated with the number of bicycle trips an individual makes to get to work is statistically significant and has a positive sign, indicating that individuals who often ride to work also walk to work. Moreover, for these individuals, the walking and bicycling modes do not appear to be substitutes of each other. These individuals are predisposed to making high numbers of commute trips by non-motorized modes because of their inherent preference towards active transport. Such inherent preferences may be attributed to their attitudes towards non-motorized modes and/or other factors related to their commute trips that have not been observed.

5.3.2. Bicycle Trips to Primary Job

The third column in Table 5.1 shows the best specification for the model of bicycle trip frequency to primary job. Similar to its expected effect on walk trips to work, the number of vehicles in the household reduces the propensity to use the bicycle to work. The positive sign associated with the number of bicycles in the household is also intuitive, because having access to bicycles is necessary for someone to ride to work and because households with individuals who enjoy riding to work would own more bicycles than others. Contrary to their lack of influence on commute trips by walk, household composition factors are found to have significant impacts on the number of commute trips by bicycle. Individuals who are from households with a high number of children, are from couple families, or live alone are less likely to bicycle to work. The parameter on household income indicates that low income households have a higher propensity to undertake bicycle trips to work even after vehicle and bicycle ownerships are controlled for. This could be due to the fact that an otherwise similar individual from a higher income household can afford other modes of transportation, such as taxi, while an individual from a more economically disadvantaged background has few alternatives.

The negative sign associated with gender indicates that females are more adverse to commuting by bicycling than men. This is perhaps because females are more sensitive to issues such as safety than men; or because most females' work clothes may not be suitable for bicycling. Similar to that found for the frequency of walk trips, individuals who use the internet for social chatting also generate higher number of commute trips by bicycle. Another individual-level factor that has a significant influence is the number of jobs.

The only location factor found to impact an individual's number of bicycle trips to the primary job is the log of the total number of employment within ¼ mile around the individual's residence. This is intuitive, as higher employment density offers job opportunities that are closer to home. However, it is unclear why employment density measured over a larger 'bikable' range (i.e. 1 or 5 miles) does not show the same effect.

Lastly, the parameter associated with the frequency of walk trips to work is positive, indicating that individuals who often walk to work also ride to work more often than others.

5.3.3. Walk Trips for Maintenance Shopping

The effects of several variables on walk frequency for maintenance shopping are similar to those found on the walk frequency for commuting to primary job. These effects include the negative impact of high number of vehicles in the household, disability, and full-time employment status. Internet use for social chat, CBD within 1 mile, urban area within 1 mile, length of bikeways within 1 mile, and the number of walk trips for the same purpose are found to lead to higher number of maintenance shopping trips by walking.

Two household level variables are found to induce walk trips for maintenance shopping that do not affect walk trips for primary job. The first variable is the number of children in the household. The negative sign indicates that an increase in the number of children in the household reduces the propensity to pursue maintenance shopping by walking. This is understandable since, with more children, it would be easier to go shopping with the children in a car than walking with them. If driving is not an option, then the individual may avoid the need to take the children out by reducing the number of maintenance shopping episodes. The parameter associated with household income indicates that individuals from a low income household make more utilitarian trips by walk as compared to those from higher income households. This is consistent with the literature survey in section 2.4.1.

Individuals who go to school are less likely to perform maintenance shopping trips on foot, presumably because they are either too young, or cannot afford the time, to do so. However, children who are aged between 16 and 17, and even if they attend school, make a higher number of walk trips for maintenance shopping than individuals in any other age group. This is reasonable, because young teenagers have shopping needs, but can not yet drive legally without adult supervision, making the walk mode an attractive alternative.

The parameters associated with ethnicities suggest that, all else being equal, Asians, Hispanics and African Americans are about equally unlikely to pursue maintenance shopping by walk relative to Caucasians. This differential preference based on ethnicity requires further investigation to examine any correlations with unobserved characteristics of the locations where the ethnic groups cluster.

For walk trip frequency, there are more location factors impacting the frequency for maintenance shopping than the frequency for commute. The propensity to walk for maintenance shopping increases as the number of retail employment and the total length of roadways within ¼ mile around an individual's residence increase. This finding is intuitive, as the two variables together reflect the accessibility to shopping within a comfortable walk distance from home.

5.3.4. Bicycle Trips for Maintenance Shopping

As in the case of trips to the primary job location, individuals who ride often for maintenance shopping are more likely to be male and belonging to households with lower number of vehicles, higher number of bicycles, and lower income level. Moreover, individuals from nuclear and single parent households make fewer maintenance trips by bicycle, presumably because of the presence of children.

All else being equal, individuals who are active adults (i.e. aged between 18 and 65) are associated with a higher propensity to pursue maintenance shopping by bicycle compared to other age groups. A very probable explanation is that the physically active nature of bicycling and the need to carry a shopping load on the bicycle require the strength and riding skill that other age groups are less likely to possess.

Ethnicity is found to impact the number of maintenance trips by bicycle. The negative parameter associated with the Asian indicator suggests that Asians are less likely to make a maintenance shopping trip by bicycling. Individuals with a license to drive are also less likely to pursue maintenance shopping by bicycle as compared to licensed drivers. This is obvious because bicycle presents an attractive alternative mode given these individuals' inability to drive. Those who use the internet for shopping are more predisposed to pursuing maintenance shopping trips by bicycle. This could be because these individuals are the environmentally conscious ones and are therefore supporters of non-motorized modes such as bicycling as well as "cyber-travel".

Compared to the walk trip frequency for maintenance shopping, bicycle trip frequency for maintenance shopping is less influenced by location factors, possibly suggesting that cyclists are more driven by their intrinsic preference for cycling and are less influenced by the environment. The only location parameter found to be statistically significant is the length of road ways within 1 mile radius of an individual's home. Since a dense road network reflects good accessibility and is often associated with denser development that provides maintenance shopping opportunities, it is enough to encourage the already cycling-inclined individuals to pursue maintenance shopping by cycling.

5.3.5. Walk and Bicycle Trips for Pure Recreation

The last column of Table 5.1 shows the estimation results for the trip frequency model of pure recreation trips by walk or bicycle. The first two parameters associated with the number of vehicles and the number of bicycles have the expected effects on trip frequency similar to those found for the preceding four models. Two other household-level parameters also suggest intuitive effects on the frequency of pure recreation trips: (1) The parameter associated with the number of active adults in the household indicates that the propensity to pursue pure recreation trips by non-motorized modes increases as the number of active adults in the household increases; and (2) The parameter associated with couple households suggests that, all else being equal, couples walk or bicycle more for pure recreation pursuits than other types of households. Both parameters imply that the companionship from a partner or other active adults in the households induces more walking and bicycling for leisure.

The estimation results also indicate that ethnicity is the only individual-level factor that has a significant impact on pure recreation non-motorized travel. Specifically, the positive sign associated with the African American indicator implies that African Americans are more likely to walk and bicycle for pure recreational purposes than otherwise similar individuals of other ethnicity. Whether this is due to the predisposed preference of the African American population or due to additional factors associated with this ethnic group that are not available in the sample data requires further investigation.

The spatial extent over which the location factors are found to influence non-motorized travel for pure recreation is generally larger than that found in the previous models. Individuals are found to undertake more walking and bicycling trips for pure recreation if they live within 5 miles of a CBD area or if the total length of the bikeways within 1 mile from their home is relatively high. This is not necessarily an intuitive finding because, even though the CBD area is likely to provide individuals with better access to various recreational facilities, the traffic and the density may work as deterrents to pursuing pure recreational activities on foot or on bicycle. However, further examination of the data suggests that, due to the coastal setting of the study area, individuals who live close to the CBD often also have good access to the beach and hence can pursue recreational walking and bicycling there. The effect of the second influencing location factor, the length of bikeways, is more obvious because, the denser the bicycle facility, the safer and more comfortable an environment is for encouraging pure recreational trips.

5.4. Summary and Discussion

This chapter has discussed the structure and estimation of five ordered response probit models for the frequency of walk and bicycle trips for three trip purposes: primary job, maintenance shopping, and pure recreation. The estimation results reinforce many of the findings from chapter 4, but provide a more in-depth understanding about who walks or cycles and for what purpose.

The estimation results show that vehicle ownership level is the only determinant common to all five models. That is, higher vehicle ownership levels are associated with lower propensity to walk and bicycle for all three trip purposes. It is, however, an open question whether a lower number of motorized vehicles *causes* a higher non-motorized trip making propensity or whether individuals (as part of their household) decide on the number of cars based on their propensity to travel by non-motorized modes. Other factors found to influence trip frequencies include bicycle ownership, household age composition and structure, household income, gender, age, disability, ethnicity, license holding status, internet use, employment status, schooling status, and location factors such as area type, employment density, and transportation network density. However, the relative effects of these factors differ for each of the five models.

Between the two bicycle-specific trip frequency models for primary job and maintenance shopping, higher bicycle ownership levels, lower household income, and being male are consistently associated with higher bicycle trip rates. After road density and shopping opportunity are controlled for, the area type of one's neighborhood does not affect one's bicycle trip frequency. On the other hand, the two walk-specific trip frequency models suggest that individuals with disability, of an Asian origin, without a driving license, employed full-time, and not using the internet for social chat make fewer walk trips for the purposes of commuting to primary work location as well as for maintenance shopping. The walk models also show that higher walk trip rates occur in CBD and urban settings, and in neighborhoods (up to one mile from one's residence) where the density of dedicated bikeways and pedestrian walkways is high. The commonalities found between the models for the same mode and the differences found between the modes suggest that the walk-inclined population and the bicycle-inclined population are different. Also, an urban form design that supports walking does not necessarily promote bicycling.

Compared to the degree of similarity found between models for the same mode, models for the same trip purpose have fewer variables in common. For the purpose of commuting to primary job, the only variable (in addition to vehicle ownership) that shows up as a significant determinant in both the walk model and the bicycle model is the use of internet for social chat. As for maintenance shopping, individuals from households with lower income levels, and individuals who do not drive, make more trips by both walking and bicycling than other population groups. Roadway density is a key location factor that influence maintenance shopping trip frequency for both walk and bicycle modes. When the walk mode is concerned, it is within ¼ mile around one's residence that roadway density has impact on maintenance shopping trip frequency; whereas when the bicycle mode is concerned, the spatial extent of influence of roadway density increases to one mile around one's residence. This is consistent with the fact that people would cycle for longer distances than they would walk.

For the purpose of pure recreation, a single combined model for walk and bicycle was developed because of sample size considerations. The model suggests that (1) African-American individuals, (2) individuals from households with lower vehicle ownership level, (2) households with higher bicycle ownership, (3) households with more active adults, and (4) individuals who live within 5 miles of the CBD area or near dense bikeway networks are more predisposed to making walking and bicycling trips for pure recreation compared to other individuals.

The above discussion about the factors influencing the trip frequencies for different purpose and different non-motorized modes suggest that, in order to effectively increase the overall use of non-motorized modes, policy makers need to be clear about the specific purpose(s) and the specific non-motorized mode(s) that they want to target and develop improvement strategies accordingly.

CHAPTER 6.
SUMMARY AND CONCLUSIONS

Pedestrian and bicycle travel planning has been receiving increasing attention in the past decade at the local, regional and national levels because of the potential environmental, social, and health benefits of non-motorized travel. Specifically, pedestrian and bicycle travel can provide a safe and convenient alternative to automobile travel, thus reducing traffic congestion problems and mobile source emissions. Similarly, non-motorized travel can contribute to the improved health of society, serve as a recreational outlet, and foster a socially vibrant community through increased opportunities for interaction among individuals. At the same time, however, the limited resources for funding transportation improvements requires that planners and policy makers estimate the usage and benefits of improvements in non-motorized transportation options against other alternative transportation projects. Such estimations require a good understanding of non-motorized travel behavior and the development of non-motorized travel demand models to predict future travel needs as well as to assess the impact on travel mode of policy actions aimed at encouraging bicycle and pedestrian travel.

The current study was motivated by the need to delve deeper into non-motorized travel behavior and the need for predictive models of non-motorized travel needs. The objectives were to (1) review existing literature on the topic of non-motorized travel behavior to identify the state-of-the-art of research, (2) conduct an exploratory analysis to examine the variations in the characteristics of non-motorized travel by activity purpose, key demographic, spatial, and temporal attributes, and (3) develop econometric models of trip frequency for different trip purposes by walking and bicycling.

Our literature review revealed that non-motorized travel behavior analysis and demand forecasting is in its infancy relative to motorized travel. However, the research on this topic is gaining momentum in the fields of transportation planning and public health. Depending on the motivation and the focus of their studies, past researchers have employed different sources of data, ranging from conventional travel surveys to attitudinal surveys specifically designed for studying non-motorized travel behavior.

They have also used different analytic tools, ranging from descriptive statistical analysis, aggregate models, and the more behaviorally-realistic disaggregate models. These past studies have collectively identified a range of variables that may influence an individual's decision to walk or bicycle. Yet, they have not all led to consistent conclusions about the effect of various factors on non-motorized travel behavior. The inconsistency in their findings could be a result of their differences in the data sources and the analytical methods employed. It could also be attributed to the difference in the subset of variables being considered in each study, in the level of data aggregation, and in how the variables are defined or quantified. Our review pointed to the need for the comprehensive examination of all relevant variables in one analysis framework. It also identified trip frequency analysis of non-motorized travel as one of the under-developed area.

The exploratory analysis that we conducted based on the 2000 BATS data involved cross tabulating the use of non-motorized forms of travel against a wide range of trip attributes, traveler socio-demographics attributes, and attributes of the activity travel environment. Our results confirmed many of the findings in the existing literature, especially in terms of the effects of socio-demographic factors such as gender, vehicle ownership, income, and family structure. We also provided new insights into the effects of the other attributes. We found that the purpose of a trip is a crucial determinant of the mode choice. In the San Francisco Bay area, about 45% of all pure recreational trips are pursued using non-motorized modes, compared to only 10% for the trips to prime jobs and 7% for the maintenance shopping trips. We found significant temporal variation in non-motorized travel. The percentage of walking and bicycling trips is higher on weekdays than weekend days, and during the warmer months of the year than the colder months. We also found correlation between the use of non-motorized modes and the urban form characteristics, such as land use mix and bikeway density, around individuals' place of residence.

The empirical results obtained from our development of five trip frequency models reiterated many of the correlation effects we found during the exploratory analysis. Consistent across all five models is the influence of vehicle ownership on the frequency of walking and bicycling, irrespective of the trip purpose. For the primary job and maintenance shopping purposes, the frequencies of bicycle trips are influenced by bicycle ownership levels, household income, and gender; the frequencies of walk trips are impacted by disability, ethnicity (Asian), license holding status, employment status (full-time), the use of internet (for social chat), area type (CBD and urban), and bikeway density.

The models for the same trip purpose have fewer variables in common than the models for the same mode. For the commute purpose, the only variable (besides vehicle ownership) common to both the walk model and the bicycle model is the use of internet for social chat. For maintenance shopping, the common variables are income level, license holding status, and roadway density. For the purpose of pure recreation, one combined model for walk and bicycle has been developed because of the under representation of individuals who make such trips. The frequency of non-motorized trips for pure recreation is found to depend on ethnicity (African-American), vehicle ownership, bicycle ownership, household composition (number of active adults), area type (CBD) and bikeway density.

The appropriate utilization of the current study's findings would enable transportation authorities to formulate policies to attract people towards the use of non-motorized modes. For instance, our models provide strong evidence to support the importance of pedestrian and cycling facilities, suggesting that the provision of well-connected walkways, pedestrian friendly intersections, bicycle lanes, sufficient and reliable bicycle parking, and better street lighting will increase the levels of walking and bicycling among people. These facilities would induce people to use non-motorized modes not only for pure recreation – thereby raising the level of public health – but also for utilitarian trip purposes – thereby help relieving congestion and pollution problems. Our modeling results also suggest that the walk-inclined population and the bicycle-inclined population are different. Moreover, the spatial scale of urban form design that supports walking is more micro than that for bicycling. Therefore, in order to effectively increase the overall use of non-motorized modes, policy makers need to devise their actions targeted at travel for specific trip purpose(s) by specific non-motorized mode(s).

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