Enhancing Transportation Equity Analysis for Long-Range Planning and Decision Making

By

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Abstract

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Metropolitan Planning Organizations (MPOs) regularly perform equity analyses for their long-range transportation plans, as this is required by Environmental Justice regulations. These regional-level plans may propose hundreds of transportation infrastructure and policy changes (e.g. highway and transit extensions, fare changes, pricing schemes, etc.) as well as land-use policy changes. The challenge is to assess the distribution of impacts from all the proposed changes across different population segments. In addition, these agencies are to confirm that disadvantaged groups will share equitably in the benefits and not be overly adversely affected. While there are a number of approaches used for regional transportation equity analyses in practice, approaches using large scale travel models are emerging as a common existing practice. However, the existing methods used generally fail to paint a clear picture of what groups benefit or do not benefit from the transportation improvements. In particular, there are four critical shortcomings of the existing transportation equity analysis practice. First, there is no clear framework outlining the key components of a transportation equity analysis at the regional-level. Second, the existing zonal-level group segmentation used for identifying target and comparison groups are problematic and can lead to significant biases. Third, the use of average equity indicators can be misleading, as averages tend to mask important information about the underlying distributions. Finally, there is no clear guidance on implementing scenario ranking based on the equity objectives.

In addressing the first shortcoming of existing equity analysis practices, we present a guiding framework for transportation equity analysis that organizes the components of equity analysis in terms of transportation priorities, the model, and the equity indicators. The first component emphasizes the need to identify the priority transportation improvement(s) relevant for communities, as this guides the transportation benefits (or costs) to be evaluated. The second component is the model to be used for facilitating scenario analysis and measuring the expected transportation and land-use changes. The third component refers to the selection of equity indicators (ideally selected based on the transportation priorities identified), and the evaluation of these indicators. This three-part framework is also useful for outlining the research needs for transportation equity analysis. Among other key research needs, the literature indicates that the development of meaningful distributional comparison methods for transportation planning and decision-making and the use of more comprehensive measures of transportation benefit (for use as equity indicators) are critical.

The primary contributions of this dissertation relate to the third component; we develop an advanced approach for evaluating transportation equity outcomes (as represented by the equity indicator(s)). Our proposed analytical approach to transportation equity analysis addresses the existing shortcomings with respect to zonal-level group segmentation and average measures of transportation equity indicators. In addition, our approach emphasizes the importance of scenario ranking using explicit equity criteria. Our approach leverages the disaggregate functionality of activity-based travel demand models and applies individual-level data analysis to advance the existing equity analysis practices.

There are four steps in our proposed equity analysis process. The first step is to select the equity indicators to be evaluated and segment the population into a target group and comparison group(s). In this case we advocate for an individual -unit of segmentation and therefore individual-level equity indicators. This minimizes the biases associated with aggregate group segmentation and average equity indicators. The second step is to calculate the indicators from the model data output, which involves determining the exact measures (formulas) for the selected equity indicators. Here we advocate for measures that are comprehensive and sensitive to both transportation system changes and land-use factors, such as the logsum accessibility and consumer surplus measure. The third step in the process is to generate and evaluate distributions of the individual-level equity indicators. In particular, we advocate for the use of what we refer to as the “Individual Difference Density” comparison, which compares distributions of individual-level changes for the population segments across the planning scenarios. This comparison allows for the “winners” and “losers” resulting from the transportation and land-use plans to be identified. The fourth and final step in the process is to identify equity criteria (associated with the chosen equity standard (objective)) and rank the planning scenarios based on the degree to which they meet the equity criteria.

We present two conceptual demonstrations of the advantages of distributional comparisons, relative to average measures. The first case uses a synthetic data set and simple binary mode choice model to show and the second case uses an empirical data set (the 2000 Bay Area Travel Survey) and more sophisticated mode choice model. These demonstrations show that distributional comparisons are capable of revealing a much richer picture of how different population segments are affected by transportation plans, in comparison with average measures. Further, distributional comparison provides a framework for evaluating what population’s characteristics and conditions lead to certain distribution transportation outcomes.

Our proposed process for regional transportation equity analysis is subsequently applied in a case study for the San Francisco Bay Area. We evaluate joint transportation and land-use scenarios modeled using the Metropolitan Transportation Commission’s state-of-the-art activity-based travel demand model. We demonstrate the power of individual-level data analysis in a real-world setting. We calculate individual-level measures of commute travel time and logsum-based accessibility/consumer surplus using the model output and compare the scenario changes across income segments. We generate empirical distributions of these indicators and compare the changes associated with the planning scenarios for low and high income commuters. Further, we apply criteria for a set of equity standards (which represent alternative equity objectives) and rank the planning scenarios. There are four key takeaways from this case study. First is that our results show a significant difference in equity outcomes when using the individual-level population segmentation approach, compared to using the zonal segmentation approach done in practice. In fact we find opposite results. For average commute travel time, the Metropolitan Transportation Commission's zonal segmentation approach indicates that low income commuters are worse off than all other commuters, while the individual segmentation approach (in our case) indicates that low income commuters are significantly better off than high income commuters. While the underlying causes for these results warrant further investigation, we hypothesize that this difference is due to the fact that the zone-based approach only captures 40% of the target (low income) group. The individual-level segmentation approach is able to capture 100% of the target group. Second is regarding the equity indicators evaluated. The commute travel time indicator results indicate that low income commuters are better off than high income commuters, while the accessibility/consumer surplus results indicate that low income commuters are worse off than high income commuters. The underlying causes for these results warrant further investigation, but we hypothesize that this difference in results to due to the fact that the logsum accessibility/consumer surplus measure by design is able to capture transportation and land-use related factors, while the travel time measure only captures one dimension of transportation user factors. Focusing on travel time may be misleading because it does not fully capture the true benefits of the transportation scenarios. Third is regarding the use of distributional comparisons, relative to average measures. We find that distributional comparisons are much more informative than average measures. The distributional measures are capable of providing a much richer picture of individuals-level transportation impacts, in terms of who gains and who loses due the transportation planning scenarios. Using the accessibility/ consumer surplus measure, the Individual Difference Densities show that as many as 33.3% of low income commuters experience losses, compared to 13.4% for high income commuters. Finally, we make the case that the use of equity standards for scenario ranking plays an important role in the equity analysis process. Our results show that different equity standards result in different rankings for the transportation planning scenarios. This points to the need for agencies (and communities) to make conscious decisions on what equity standard(s) should be used and apply this/these in the scenario ranking process.

This dissertation work includes the first known full-scale application of a regional activity-based travel model for transportation equity analysis that involves distributional comparisons of individual-level equity indicators and scenario ranking based on equity criteria. We find that while the existing practice is to use average measures to represent how different groups are affected by transportation plans, distributional comparison are able to provide for a richer evaluation of individual-level transportation impacts. Distributional comparisons provide a framework for quantifying the "winners" and "losers" of transportation plans, while average measures may be misleading and uninformative. We make significant progress with regard to evaluating equity indicators (part three of the guiding framework). However, our proposed process is flexible and can be extended to include a number of additional advances, including more environmental and long-term land-use related equity indicators (e.g. emissions exposure, gentrification and displacement risk, employment participation, etc.) and additional population segments (e.g. age, ethnicity, household type, auto-ownership class, etc.). Among other important research directions, our analytical framework for regional transportation equity analysis can be applied to investigating *why* certain groups are more likely to be "losers" and *what* factors of transportation planning scenarios to modify in order to arrive at a more equitable transportation and land-use plan.

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Chapter 1 . Introduction

This dissertation aims to advance the methods for *transportation equity analysis* of regional level long range transportation plans. This is the process of analyzing social equity outcomes resulting from multiple large scale transportation improvements. The methods presented herein leverage the power of activity-based travel demand modeling, which represents the best practice in travel demand modeling. In particular, we propose a process for regional equity analysis that makes use of individual and household level data generated from these models, and among other things, emphasizes the use of distributional comparisons to reveal individual-level equity outcomes.

1.1 Introduction

Addressing inequities across all areas of society is critical for thoughtful public policy. The global financial crisis of 2008 drove the subject of inequity into the forefront of public discourse, as income inequity was arguably a key trigger of this financial meltdown (Vandemoortele, 2009). In the United States, where income inequity is drastically pronounced relative to the world's other developed nations and rising (Tomaskovic-Devey and Lin, 2013), evidence of inequities can be found in numerous areas of society.

Equity concerns are particularly relevant in the transportation realm. Current conditions of inequitable transportation accessibility levels among society have resulted from transportation planning processes which place unfair weight on the preferences of the more advantaged members of society. We are left with the reality that disadvantaged members of society have experienced less-than-fair shares of transportation benefits and disproportionately high shares of transportation externalities. These are long recognized concerns and have led to federal Environmental Justice legislation and directives (1994 Executive Order 12898, and Title VI of the Civil Rights Act of 1964) calling for government agencies (e.g. the US Department of Agriculture (USDA), the US Environmental Protection Agency (EPA), US Department of Transportation (DOT), State DOTs, and Metropolitan Transportation Organizations (MPOs)) to investigate the expected outcomes of proposed infrastructure and policy changes, and confirm that low income and minority (disadvantaged) groups will share equitably in the project benefits and not be overly adversely affected.

The critical issues addressed in this dissertation lie with the approaches taken to analyze equity outcomes of transportation infrastructure and policy improvements. In spite of the regulations mandating equity analysis for long range transportation plans for many years now, the approaches generally fail to paint a comprehensive picture the various transportation experiences that result from transportation plans. In many cases the measures themselves are insensitive to the heterogeneity of transportation experiences across different groups.

The remainder of this chapter is organized as follows: In Section 1.2, we give the dissertation research scope. We then give the dissertation objectives, contributions, and chapter outline in Sections 1.3, 1.4, and 1.5, respectively.

1.2 Research Scope

This research focuses on enhancing the methodology for transportation equity analysis of regional-level transportation plans. These plans may include hundreds of transportation and land-use investments, including large scale highway and transit improvements, fare changes and tolling/pricing schemes (e.g. bridge tolling, variable tolling lanes, cordon pricing), land development incentives, growth boundaries, etc. Because of this scale and great number of projects, it is necessary to use large scale transportation models in order to evaluate the overall impact of a transportation plan on travel in the region. As will be discussed throughout this dissertation, activity-based travel demand models are particularly useful for equity analysis of regional transportation, because of their use of micro-simulation and ability to generate population and travel-related data at disaggregate (individual and household) levels. Activity-based travel models represent the best practices in travel demand modeling and have great potential for disaggregate level transportation equity analysis. That is, the disaggregate population and travel-related data from these models enable us to explore the use of distributional comparison tools and reveal the "winners" and "losers" resulting from transportation plans.

The Use of Travel Demand Models for Regional Equity Analysis

The equity analysis process proposed in this dissertation falls under what we define as a modeling approach to regional equity analysis (as will be discussed in Section 2.4), where large scale travel models are applied to measuring the impact of transportation plans on regional travel. The literature indicates that equity analyses using large scale regional travel models are becoming more prevalent (Johnston, et al., 2001; Rodier et al., 2009; Castiglione et al., 2006; MTC, 2001; MTC, 2013). Further, more and more MPOs are adopting activity-based travel models for evaluation their Regional Transportation Plans (RTPs) (Bowman, 2009). The concern is that methods used for regional transportation equity analyses are lagging behind. The advantages of using disaggregate data from activity-based models for equity analysis are well cited in the literature (e.g. Walker, 2005); although to date, there are no examples of an application that uses disaggregate level indicators for regional equity analysis. Further, only one other example is found in the literature where disaggregate population segmentation is applied for regional transportation equity analysis (Castiglione et al, 2007).

1.3 Objectives

The objective of this dissertation is to develop a quantitative methodological approach for regional transportation equity analysis that leverages the power of activity-based travel demand modeling. Our proposed equity analysis method, compared to prior methods used, will extend the capacity to analyze transportation equity impacts by taking advantage of the individual and household level data from an activity-based model. Our method further emphasizes and the usefulness of distributional comparison methods (among other tools) in understanding transportation equity outcomes.

This objective is carried out in the following two steps:

- Develop an enhanced analytical framework for transportation equity analysis
- Execute an application of this proposed analysis process via a real world case study

With this improved framework, we endeavor to provide guidance for regional level transportation equity analysis, as well as provide a richer understanding of the equity impacts of regional transportation plans.

1.4 Contributions

This dissertation work makes three primary contributions. These contributions relate to multiple bodies of literature, including policy analysis, transportation planning, and travel demand modeling.

Developing an Enhanced Methodology for Transportation Equity Analysis of Regional Transportation Plans

Our first contribution is in developing an analytical process for regional-level transportation equity analysis. Our process leverages the disaggregate functionality of activity-based travel demand models and distributional comparisons to gain a fuller and more accurate understanding of individual-level equity outcomes across population segments. Our methods emphasize the significance of distributional comparison methods, relative to the existing practice of using average measures. Our methods also emphasize the need to adopt an equity standard and rank planning scenarios based on the defined equity standard. This serves to link the outcome of the equity analysis to the equity goals outlined by the agency, stakeholders, and/or practitioners.

Demonstrating Equity Analysis Using a Real World Activity-Based Modeling System and Transportation and Land-Use Scenarios

The second contribution is that we demonstrate our proposed equity analysis process in a full scale, real world case study using the San Francisco Bay Area Metropolitan Transportation Commission's activity-based travel model and recently developed transportation and land-use scenarios. We detail the considerations and challenges with applying this advanced equity analysis process in practice, and we provide some solutions to these challenges. There are four key findings from this case study:

- While a zonal segmentation approach for distinguishing the target and non-target groups is used in most regional transportation equity analyses, this approach only allows for 40% of the target (low income) group to be captured in the Metropolitan Transportation Commission's case. In comparison, the individual-level segmentation approach allows for 100% of the target group to be captured. This difference in approach results in opposite findings in our case, relative to comparable results from the San Metropolitan Transportation Commission's 2013 regional transportation equity analysis. Using the commute travel time indicator, we find that low income commuters experience significantly higher gains than high income commuters, while the Metropolitan Transportation Commission finds that low income commuters experience lower gains than all other commuters.

- The accessibility/consumer surplus indicator produced opposite results than the travel time indicator in our case. That is, the accessibility/consumer surplus results show that low income commuters are worst off and most likely to experience losses greater than high income commuters, while the travel time results show that low income commuters are better off and most likely to experience gains than high income commuters. We attribute this difference in results to the fact that the accessibility/consumer surplus indicator is capable of capturing both transportation level-of-service and land-use factors, while travel time only captures level-of-service.

- Distributional comparisons (in comparison with the existing practice of using average measures) are more informative and capable of providing a much richer picture of how individuals-level transportation impacts, in terms of who gains and who loses due the transportation planning scenarios.

- While not common in practice, the use of equity standards for ranking transportation planning scenarios is an important step in transportation equity analysis and powerful approach to linking equity objectives for regional transportation and the results of the equity analysis. In our demonstrations we find that application of different equity standards results in different scenario rankings. This points to the need for agencies (and communities) to make conscious decisions on what equity standard should be used and apply this standard in the scenario ranking process.

Documenting an Application of Disaggregate Data Analysis using Data from Activity-Based Travel Models

Since the early development and application of activity-based models for regional transportation planning (in practice), the disaggregate-level data enabled through micro-simulation has been touted as one of the key advantages of activity-based modeling. Yet no studies have demonstrated individual-level measures for regional transportation planning applications. To the author's knowledge, this dissertation work documents the first such application using a full scale activity-based travel model to generate and evaluate individual and household-level transportation measures.

1.5 Dissertation Outline

The remainder of this dissertation is organized as follows. In Chapter 2, we provide discussions on the background, literature, and existing practice for regional transportation equity analysis. Chapter 3 presents a new analytical framework for equity analysis of regional transportation plans. First, we provide an overview of activity-based travel modeling, and then we discuss the proposed equity analysis process. Chapter 4 works through two examples to demonstrate the usefulness of distributional comparisons for transportation equity analysis. To do this, we employ a combination of synthetic and real-world travel datasets and some simplistic travel demand models to calculate individual (logsum) consumer surplus measures. In Chapter 5, we present a full scale case study of the proposed equity analysis process. In this case study for the San Francisco Bay Area, we use a full scale activity-based travel modeling system to evaluate a set of transportation and land-use scenarios. The travel demand model and planning scenarios were all developed by the Metropolitan Transportation Commission (the Metropolitan Planning Organization for the nine-county San Francisco Bay area). In the final chapter we summarize the findings and contributions of this dissertation and give a discussion of future research needs.

Chapter 2 . Transportation Equity Analysis: Background, Literature, and Existing Practices

2.1 Introduction

In this chapter, we provide the background information for transportation equity analysis. The existing challenges with understanding transportation equity analysis (of transportation infrastructure and policy changes) stem from the inconsistencies in the literature. We aim to organize of the literature starting with a discussion of the definitions, dimensions, and interpretations of transportation equity. We then provide a guiding framework for transportation equity analysis that relates three important components of transportation equity analysis: equity priorities, modeling system, and equity indicators. In addition, these three equity analysis components serve as a useful framework for reviewing and critiquing the academic literature supporting transportation equity analysis. We finish with a discussion of the existing practices for equity analysis of regional transportation plans. These discussions set the foundations for how transportation equity is defined for this dissertation work, and the existing shortcomings of current regional transportation equity analysis practices that we address in subsequent chapters.

This chapter is organized as follows. In Section 2.2 we provide some background discussions for transportation equity analysis, including the origins of equity concepts in transportation planning, definitions of transportation equity, the significance of equity in transportation planning, and federal requirements for transportation equity analysis. In Section 2.3 we present a guiding framework for transportation equity. In Section 2.4 we discuss and critique the existing practice for transportation equity analysis, and in Section 2.5 we provide the chapter conclusions.

2.2 Background

2.2.1 Origins of Equity in Transportation Planning

Equity finds its roots in the philosophical and political concept of *justice*. Justice, is an important and fundamental moral concept, and refers to conformity with the principles of righteousness and fairness. The related concept of s*ocial justice* refers to the application of these principles of justice to the functions of society, with emphasis on fairness among social classes. These principles are viewed as desired qualities of ethical and social decision making, and they characterize the desired qualities of the political system. Further, regarding the relationship between citizens and government, justice is commonly discussed in terms of distributive justice (concerning the fairness of outcomes), and procedural justice (concerning the fairness of processes), with the former being more emphasized in the literature and discourse (Konow, 2003).

From an economic perspective, the principle of equity is paired with economic efficiency, which represent the fundamental criteria by which the performance of the economy is evaluated (as is the objective in Welfare Economics) (Just et al., 2004). Much of the study on how to define and measure an equitable distribution of goods and services across various markets falls under the umbrella of Welfare Economics. However, the emphasis here has primarily been on the income distribution of society, and whether income groups accrue their fair share of total national wealth (i.e. gross domestic product).

The evaluation of equity outcomes in noneconomic domains has increasingly a central topic in the evaluations of public programs and investments (Konow, 2003). Transportation policies are an example of where policy makers and practitioners seek to apply principles of equity. As will be discussed below, Environmental Justice regulations require equity analysis for all government funded investments (including infrastructure and policies). Our concern is with the distribution of transportation costs and benefits that result from such transportation-related investments. These cost and benefits include a mix of economic, environmental, and transportation system related factors. While federal transportation regulations attempt to outline equity principles for transportation programs, the challenge of measuring and evaluating transportation equity outcomes remains.

2.2.2 Defining Transportation Equity

A number of definitions for transportation equity can be found in the literature. To date, there seems to be no consensus among academics on how transportation equity should be defined (Levinson, 2010). In effort to bring organization to these definitions and provide a clearer understanding of what is meant by *transportation equity* in this dissertation, we have structured the definitions in terms of a general equity concept, equity dimensions, and equity standards.

Concept: Transportation Equity generally refers to the fair or just distribution of transportation costs and benefits, among current (and future) members of society. (Note that there are a number of distributions that may be considered *fair*, and these will be referred to as *equity standards*, as discussed below.) Transportation costs include the actual costs of building, operating, and maintaining the transportation infrastructure, as well as transportation user costs and environmental costs that result from the transportation operations and use. These environmental costs may include the direct emissions from auto use, traffic congestion, and noise pollution, etc. Transportation benefits range from improvements in accessibility, mobility, and economic vitality on the general scale, to reductions in travel time and travel user costs. Improved consumer surplus is also an indication of transportation benefit.

Dimensions: Transportation equity can be defined along two primary dimensions: Horizontal and Vertical equity (Musgrave and Musgrave, 1989; Litman, 2002). Horizontal equity, which may include spatial and generational equity, refers to the distribution of impacts (costs and benefits) across groups that are considered to be equal in ability and need. Vertical equity refers to the distribution of transportation impacts on sub-populations that differ in ability and needs, such as different social and income classes, and disabled or special needs groups. In some cases spatial and generational equity are seen as separate dimensions, but for simplification purposes we group them with the Horizontal equity dimension.

Standards[1]: We refer to competing principles of equity as equity standards. A number of different standards have been discussed in the academic literature. These standards represent alternative ideas of what distribution (regarding rights, opportunities, resources, wealth, primary goods, welfare, utility, etc.) is accepted as *fair* or most desired.

2.2.3 Transportation Equity Analysis and Environmental Justice Regulations

Transportation Equity Analysis (sometimes referred to as Environmental Justice Assessment) refers to the process of evaluating the distribution of outcomes resulting from transportation plans (Lui, 2010). Beyond the evaluation of the transportation costs and benefits to various population segments, the objective is to confirm that some desired equity standard (fair distribution of transportation costs and benefits) is met. It is mandated that all federally-funded transportation agencies perform equity analyses in evaluating proposed infrastructure and policy changes. This mandate was established as a result of the 1994 Executive Order 12898, "Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations," as well as Title VI of the Civil Rights Act of 1964. The Executive Order directs Federal agencies to make Environmental Justice a part of their mission by identifying and addressing the impacts of all programs, policies, and activities, on minority and low-income populations. Additionally, Title VI states that "No person in the United States shall, on the grounds of race, color, or national origin, be excluded from participation in, be denied the benefits of, or be subjected to discrimination under any program or activity receiving Federal financial assistance."

The three basic goals of Environmental Justice are as follows:

1. To avoid, minimize, or mitigate disproportionately high and adverse human health and environmental effects, including social and economic effects, on minority populations and low-income populations.
2. To ensure the full and fair participation of all potentially affected communities in the transportation decision-making process.
3. To prevent the denial of, reduction in, or significant delay in the receipt of benefits by minority and low-income populations

Although our focus is on Environment Justice requirements for transportation planning, it is important to recognize that Environmental Justice regulations apply to all other Federal agencies, such as the Environmental Protection Agency (EPA) and the US Department of Agriculture (USDA). A full review of Environmental Justice analysis in other such areas is provided by Lui (2010).

[1] A subset of these equity standards, seen frequently in the literature, has been compiled and is shown Table 3.10 (in Chapter 2 of this dissertation).

2.2.4 The Significance of Equity Analysis in Transportation Planning

The U.S. Department of Transportation requires equity analysis for all projects that it helps to fund, and for this reason transportation equity analysis is a federal requirement for MPOs. However, there are broader reasons that equity analysis is critical for evaluating transportation plans. The transportation system, largely funded by public dollars, plays a significant role in supporting quality of life and social welfare. The infrastructure that facilitates the movement of people and goods is also influential in shaping land-use patterns, livability of communities, and economic interactions. In addition to mobility and accessibility improvements, transportation investments can improve safety, health, and environmental conditions. There are also negative externalities associated with transportation investments, including emissions exposure and noise. However, the reality is that all of society will not experience the same level of transportation impacts. Some will gain from transportation investments (winners) and some will be made worse off (losers). Individuals will be affected differently by transportation changes, given the variance in population and transportation conditions (income level, residential and work locations, accessibility to alternative travel modes, etc.). Further, we know that historically, negative transportation externalities have been born disproportionately by disadvantaged segments of society (Ward, 2005; Schweitzer and Stephenson, 2007). For these reasons, it is inappropriate to ignore that transportation plans will result in a distribution of impacts across members of society. Planning organizations have a responsibility to fully evaluate and disclose the expected impacts of transportation plans, for all segments of society.

2.3 A Guiding framework for Transportation Equity Analysis: Literature Review and Research Needs

Here, we organize the literature and research needs within a general guiding equity analysis framework. While federal Environmental Justice regulations require equity analysis for regional transportation plans, little methodological guidance is provided. This has resulted in a wide range of equity analysis methods (varying by scale, approaches, etc.). There has been some effort around establishing goals for the distribution of transportation benefits (Martens, et al. 2012), but no efforts have been found on providing clear outline on the process for conducting equity analysis. With this framework, we seek to address two needs. The first is to define the important components of equity analysis, which will guide this dissertation work going forward. The second aim is to summarize the literature with respect to these components. This guiding framework is illustrated in Figure 2.1 and the research areas are discussed below.

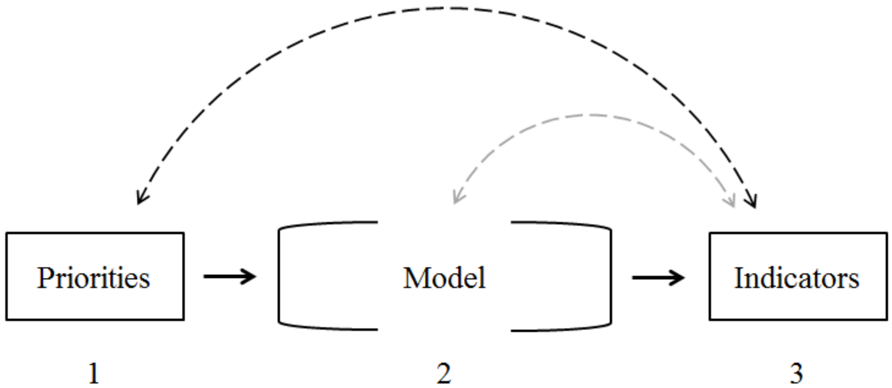

Figure 2.1 Equity Analysis Framework

2.3.1 Component 1: Priorities

The first component and research area ("Priorities") is regarding the types of transportation objectives that are most important to communities. Given the full range of possible transportation benefits to society, which are most important for which communities? In many cases, accessibility to employment is viewed as a primary transportation objective for low income and minority groups of interest. Other priority objectives may be accessibility to health care resources or grocery stores, shorter travel times, reduced traffic congestion and delay, improved walkability, etc. A clear understanding of the transportation priorities, based on the needs of communities is critical for selecting appropriate equity indicators (as will be discussed in Section 2.3.4).

There are two general approaches that practitioners can use to go about identifying the transportation priorities for different communities, one qualitative and one quantitative. In the qualitative approach, surveys, interviews, focus groups, etc., can be conducted to engage the different communities and directly record what they view as transportation needs and priorities. In the quantitative approach, travel behavior data can be analyzed to glean the travel limitations and constraints for disadvantaged communities, relative to the majority population. The two methods are complementary and participation requirements mandate that community members be engaged and not simply treated as objects of study. In other words, qualitative methods for involving communities are expected to shape and inform quantitative analysis. The transportation needs and priorities of different communities would be based on their own assessments, and not that of transportation practitioners. This dissertation focuses on advancing quantitative methods for equity analysis but recognizes that in a real world application this would have to be coupled with participatory processes whose findings would shape the priorities, indicators, and model runs done.

There are a number of related studies which have sought to understand the differences in travel behavior for different communities. A large number of studies have assessed the gender differences in travel behavior (White, 1986; Mauch and Taylor, 1997; Pucher and Renne, 2003; Nobis and Lenz, 2005; Zhou et al., 2005; Rogalsky, 2010). Some studies have also emphasized the travel constraints of women, relative to their male counterparts (Astrop et al., 1996). These studies have generally found that the travel behavior of women is heavily influenced by household-serving responsibilities (grocery shopping, other non-work trips, etc.) and child chauffeuring necessities, resulting is a greater number of trips with shorter trip lengths, and more trip chaining. Other studies have assessed the travel behavior characteristics of the elderly and disabled (Pucher and Renne, 2003; Alsnih and Hensher, 2003; Rashidi and Mohammadian, 2009). The elderly and disabled are found to have lower modality rates and greater dependence on transit. This literature is one example of where the transportation needs have been assessed for the purpose of recommending transportation improvements. Some studies have also focused on travel behavior differences across various ethnicities and income classes (Mauch and Taylor, 1997; Giuliano, 2003; Tal and Handy, 2005; Srinivasan and Rogers, 2005; Agrawal et al., 2011), with some further emphasizing the travel behavior differences by immigration status (Srinivasan and Rogers, 2005). While there doesn't seem to be a strong causal link between ethnicity and travel behavior (Mauch and Taylor, 1997), there is a higher instance of residential clustering among ethnic minorities as well as recent immigrants, resulting in high trip densities (the majority of trips are made within a smaller radius of home). Lower income residents are also more likely to be transit dependent, although the majority of trips are still made by automobile (Astrop et al., 1996; Pucher and Renne, 2003; Alsnih and Hensher, 2003). In addition, the travel behavior of lower income residents is generally characterized by fewer trips, with shorter trip lengths, although it is unclear whether this is an indicator of transportation disadvantage (i.e. low levels of accessibility), or simply a characteristic of low income traveler behavior. This body of literature on the travel behavior of different communities is rather large; however, few studies were found that have linked these travel behavior evaluations to transportation needs and how these may vary across communities.

2.3.2 Component 2: Model

This component and research area ("Model") focuses on the modeling tool to be used for scenario analysis. The used of large scale travel demand models of regional level transportation equity analysis is becoming more widespread, although this modeling tool can vary based on the scale of the transportation investments being evaluated. This scenario analysis tool may refer to a process or tool used to calculate the expected transportation, economic, land-use, and/or environmental related changes due to transportation investments. Here, the task is to identify which model (or process) is most suitable, and whether this model is accurate and comprehensive with respect to the expected changes.

Using regional level analysis as an example, the literature indicates that more and more regional planning authorities are applying travel demand models for transportation equity analyses, yet few efforts have been done to assess whether output from these models effectively represents the heterogeneity of travel behavior observed in the real world. These differences are critical for equity analysis. This is, for example, because a model that is insensitive to the differences in travel behavior between different income groups is likely unable to accurately model the differences in equity outcomes between high and low income travelers. In practice, the statistical significance of socio-demographic variables (in travel models) and the use of model calibration processes (confirming that model forecasts to match some empirical control totals) is seen as sufficient for assessing model sensitivity. However, for activity-based travel models, which are able to generate person-level data, validation at the across population segments is not common.

One such study (Bills et al., 2012) compared distributions of travel time generated from a real world activity-based model and the travel diary data used to estimate the travel model. In this case, the tests of distributional equality fail, although the comparisons of the general shape of the distributions and central tendencies indicate that the relative difference between the low and high-income travelers is maintained. As this is only one example of such a study, there is a need from more evaluations this kind.

It is important to note the influence of the travel diary data that is used to estimate activity-based models. These models are estimated and calibrated on a sample of data (on individuals and their travel patterns), and quality of this data has implications for the sensitivity of the model to the differences between groups. That is, the model's sensitivity is undoubtedly tied to how well the sample data reflects the true characteristics of these groups of interest. In other words, the model estimates are only as good as the travel diary survey data. This is certainly a research area that is critical for making progress is the area of activity-based travel modeling for transportation equity analysis.

2.3.3 Component 3: Indicators

The third component and research area focuses on the equity indicators used to measure equity impacts (transportation-related costs and benefits). These indicators are quantitative representations of the transportation priorities (described under component 1). For example, if we determine that the transportation priority is to improve employment accessibility, then we should use the change in employment accessibility (due to the transportation plan) as an equity indicator. This third component in the framework deals with what equity indicators to use, as well as how to compare the equity indicator measurements across communities or population segments. The existing practice for regional level transportation equity analysis is to calculate average measures of the indicators for the difference population segments and evaluate the percentage change across these segments and across scenarios. The use of averages tends to mask important information about the change in the distribution of transportation experiences (as measured by the equity indicators). In particular, changes in the shape of a distribution may have equity implications that can't be fully captured using a mean measurement (Franklin, 2005). In this dissertation, we emphasize the important of distributional comparisons of these indicators, for different communities. However, few examples of distributional comparisons in equity analysis are found in practice.

In one example, Franklin (2005) used Relative Distribution methods to do transportation equity analysis. A Relative Distribution is a non–parametric and scale–invariant comparison between two distributions (Handcock and Morris, 1999; Handcock and Aldrich, 2002; Franklin, 2005). Accompanying statistical summary measures (polarization measures) provide a way to decompose and interpret the differences between the distributions. Franklin (2005) clearly demonstrates that more can be understood about equity outcomes (i.e. the progressivity and regressivity of a policy) using distributional comparison measures, as opposed to comparing mean values. However, Relative Distribution methods are very mathematically complex and difficult for practitioners as well as academics to understand. Thus, there is a need to research distributional comparison methods which are more readily usable in practice. Beyond the Franklin example, no studies were found to have emphasized alternative methods for measuring the changes in distributions, and apply these methods to equity analysis. Given that the purpose of transportation equity analysis is to access the distribution of transportation costs and benefits, it is understandable that the application of such methods (i.e. Relative Distribution methods) would provide for a richer understanding of equity outcomes. In this dissertation, we take the first steps toward developing distributional comparison methods for use in practice.

2.3.4 Feedback: Linking Equity Indicators and Transportation Priorities

An important criterion for identifying equity indicators, as represented by the black dashed curve, is whether the chosen equity indicators are truly representative of the transportation priorities for the groups of interests. As an example, accessibility is a widely used indicator of transportation equity, but there is little in the literature that describes the direct link between access and the desired societal benefits; economic opportunity or the probability of employment. This question of whether job accessibility in linked to employment outcomes has been tackled in the number of studies (O'Regan and Quigley, 1998; Cervero and Appleyard, 1999; Aguilera, 2002; Ory and Mokhtarian, 2005; Gurmu et al., 2006), but there doesn't seem to be a consensus on whether a measurable causal link exists, nor the direction of this relationship. Some studies have found no evidence of a relationship between accessibility and employment (Cervero and Appleyard 1999), while others (Gurmu et al., 2006) have found that accessibility to jobs and child care resources are significant indicators of the probability of employment. This same question can be asked of other commonly used equity indicators (accessibility to health care, consumer surplus, travel time savings, etc.). There is some evidence in the literature on the positive relationship between increased healthcare accessibility and the uptake of healthcare services, among minority groups (Guendelman et al., 2000). This certainly represents a step in the right direction, in terms the potential to identify equity indicators most relevant and meaningful, and linked to the transportation priorities of different communities. However, there is a need for more research efforts to develop the larger understanding of how different transportation priorities link to societal benefits, and apply this understanding to the selecting transportation equity indicators.

2.3.5 Summary and Critique of Literature and Existing Equity Analysis Practice

In summary, the equity analysis framework illustrated in Figure 2.1 serves as a useful and standard guide for identifying the key components of transportation equity analysis, as well as overviewing the current state of equity analysis practices and identifying the research needs. These research needs are as follows:

- There is a large body of literature focusing on the differences in travel behavior across ethnicities, income levels, genders, etc., but has yet to be applied is the equity analysis realm for identifying transportation needs and constraints, and thereby prioritizing transportation improvements, for various population segments.

- The use of activity-based travel models for equity analysis is becoming more common, but there is a need to fully assess how well these models represent the differences in travel-related outcomes for different groups of interest at the disaggregate level. This is important for confirming the suitability of these models transportation equity analysis. Further, given that the use of activity-based travel models in practice is relatively new, there is a need to outline clear steps for effectively applying such models for equity analysis.

- The use of average measures of equity indicators is problematic, as they mask important information underlying distributions (and changes in these distributions). Distributional comparisons can provide for a richer understanding of equity outcomes at the individual and household levels, but there is a need to develop more practical distributional comparison methods.

- The equity measures and indicators used are weakly linked to transportation costs and benefits. For example, travel time is a commonly equity indicator used in practice, but only captures one dimension of total transportation benefits. A more comprehensive measure of would capture multi-dimensions, including costs, quality, satisfaction, etc. There is a great need to identify more meaningful and comprehensive equity indicators capable of representing true transportation benefits.

2.4 The Existing Practice for Regional Transportation Equity Analysis

The development and assessment of Regional Transportation Plans (RTP) are regular practices for MPOs, usually taking place every three to five years. This periodic practice involves an assessment of long-term transportation needs and proposals for transportation (and land-use) improvements to address these needs. Among other foci, this process involves assessments of equity impacts. Planning agencies (i.e. Metropolitan Planning Organizations (MPOs)) have applied a range of methods for transportation equity analyses of Regional Transportation Plans. The literature points to two primary analysis approaches. The first approach, which we refer to as a "Modeling" approach, analyzes equity impacts using regional travel demand models, and second approach, which we refer to as a "Non-modeling" approach does not apply travel demand models to evaluate equity outcomes.

2.4.1 "Non-modeling" Approach to Regional Transportation Equity Analysis

The non-modeling approach, which tends to be most common among planning organizations (Amakutzi et al., 2012), is characterized by the use of spatial analysis tools to map the residential locations of low income and minority communities in relation to the location of the proposed transportation project(s). This is done to discern the level of benefits to these communities based on spatial proximity. In some cases, these analyses include determining whether the communities are being overly exposed to transportation externalities (air or noise pollution, traffic congestion, etc.) (e.g. MTC, 2001; Rodier et al., 2009).

2.4.2 "Modeling" Approach to Regional Transportation Equity Analysis

In the modeling approach to equity analyses, transportation and land-use scenarios are modeled using a regional travel demand model. The general approach is to measure the expected impacts of transportation and land use improvements on the travel behavior of defined population segments, calculate some indicators of the costs and/or benefits to these segments (due to the transportation and land-use improvements), and then compare these costs and/or benefits across the segments in order to judge whether the distributions of costs and/or benefits is equitable.

Existing Equity Analysis Practice

As further description of this modeling approach to regional transportation equity analysis, we summarize the process in three steps below. Following, we give brief descriptions for population segmentation and equity indicators, and then two examples of transportation equity analyses done using travel demand models, as this approach is the focus of this dissertation.

Overview

This general equity analysis process (using travel demand models) is summarized in the following three steps:

1. Select equity indicators (such as travel times, transit mode share, accessibility to jobs, etc.) and segment the population into two categories: target group(s) and comparison group(s).
2. Calculate indicators for the population segments (the target and non-target groups).
3. Compare the changes in these measured values across the groups, and across scenarios (simulating changes after some transportation policy or project has been implemented).

Population Segmentation

This refers to the defining of target and comparison groups, and involves the use one or more *variables of segmentation* (e.g. income, ethnicity, gender, etc.) and a *unit of segmentation* (e.g. individuals, households, census blocks, travel analysis zones, etc.). Most commonly, the target group is defined in terms of "communities of concern". These are zones or census blocks that are identified based on high concentrations of low income and minority residents. In this case, the variables of segmentation are commonly income and ethnicity, and units of segmentation are zones or census tracts (MTC, 2009; MTC, 2013b).

Equity Indicators

These are measures of the costs or benefits resulting from the transportation plan. There is a range of indicators used in equity analysis of regional transportation plans. These will be outlined in more detail in Section 5.4.1, but the most common are work travel time, accessibility to jobs, emissions exposure, and project investments by population segment (MTC, 2009; SANDAG, 2011; MTC 2013).

Equity Analysis Examples
To illustrate the comparison process common for equity analyses done using travel demand models, two examples are taken from equity analyses done by the Metropolitan Transportation Commission (MTC), for their 2035 and 2040 Regional Transportation Plans. We use MTC's analyses as example for two primary reasons. The first is that they are one of the more experienced MPOs with regard to applying travel demand models for transportation equity analysis. Second is that MTC's methodology represents to best practices in equity analysis of regional transportation plans, given that they are currently the only MPO known to have applied an activity-based travel model[2] for regional transportation equity analysis.

MTC 2035 Equity Analysis (2009)
In this analysis, four scenarios are modeled to represent transportation and land-use improvements and the (expected) resulting travel-related changes. These scenarios include a "No-Project" scenario, the "Project" scenario (the agency's "preferred" scenario), and two additional alternative scenarios. These are modeled using a 4-step Travel Demand Model[3]. For this analysis, the variables of segmentation were income and ethnicity, and the units of segmentation were travel analysis zones. The zones were selected as communities of concern based on the presence of high concentrations of low income or minority residents. The zones with high concentrations of low income and minority populations are defined as communities of concern, and a comparison is made between these communities of concern (target group) and the remainder of the region (comparison group).

MTC evaluated a number of indicators, including work and non-work accessibility, vehicle emissions exposure, and transportation/housing affordability[4]. The results for the work accessibility measure (the weighted average of total low income employment opportunities, within 30 minutes by transit) for the target group (communities of concern) and comparison group (the remainder of zones in the Bay Area.) are shown Figure 2.2 and Figure 2.3. The comparison was done by calculating the average change in the indicators (for each population segment, and for the "Project", "Pricing", and "Land Use" scenarios relative to the "No-Project" scenario). Focusing on the right-most column in Figure 2.3, they found that Communities of Concern would accrue a similar level of accessibility benefits as would the Remainder of the Region, although on average the Remainder of the Regional would experience slightly higher gains in accessibility compared to the Communities of Concern.

MTC 2040 Equity Analysis (2013)
In MTC's more recent equity analysis (MTC, 2013a), five scenarios are modeled, including a No-Project scenario, Project (preferred) scenario, and three additional alternative scenarios. These scenarios were modeled using their recently developed activity-based travel demand model. In this case, the target (and comparison) groups are defined using zones as the units of segmentation (as in the previous example), but using more variables of segmentation than previously. In addition to ethnicity and income, these variables of segmentation include English

[2]It is important to note the MTC also applied a disaggregate land-use model (UrbanSim) in developing the transportation and land-use scenario. For more details, see Waddell (2002) and Waddell (2013).
[3]For a description of MTC's 4-step travel demand model, see Purvis (1997).
[4]For more details on the measurement of these indicators, see MTC (2013a).

proficiency, auto ownership, senior citizen status, disability status, number of parents in the home, and rent burden. Zones with high concentrations for at least four of these variables are classified as Communities of Concern. The indicators evaluated in this analysis were commute and non-commute travel time (for all modes), transportation/housing affordability, displacement risk, and vehicle miles traveled (VMT) and emissions density (exposure to vehicle emissions).

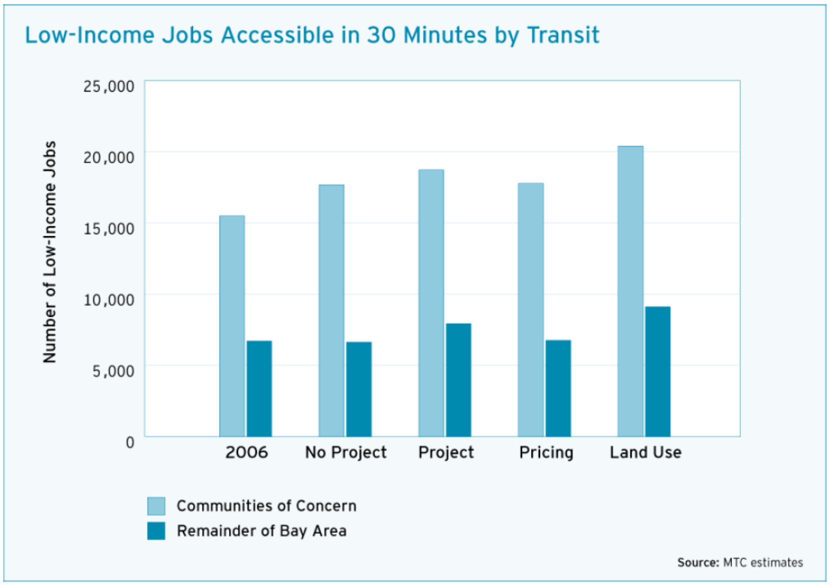

Figure 2.2 MTC Equity Analysis of 2035 RTP Example:
(Cumulative) Job Accessibility within 30 Minutes by Transit (MTC, 2009).

Table B2. Low Income Jobs Accessible in 30 Minutes by TRANSIT
Averages by Household Income Group and Community Type

	Income Group	2006	No Project	Project	Change: *2006 to Project*	Change: *No Project to Project*
Communities of Concern						
	Low	17,272	20,234	21,337	4,065	1,103
	Moderately Low	12,589	14,833	15,817	3,228	983
	Moderately High	10,723	12,200	13,115	2,392	914
	High	11,310	13,014	13,994	2,684	980
Remainder of Bay Area						
	Low	6,959	6,871	8,171	1,212	1,300
	Moderately Low	6,499	6,483	7,795	1,296	1,312
	Moderately High	6,030	6,017	7,104	1,075	1,088
	High	6,600	6,607	7,764	1,164	1,157
Bay Area Total						
	Low	11,692	13,700	14,899	3,207	1,199
	Moderately Low	8,555	9,723	10,907	2,352	1,184
	Moderately High	7,272	7,926	8,960	1,687	1,034
	High	7,317	7,834	8,957	1,640	1,123

Figure 2.3 MTC Equity Analysis of 2035 RTP Calculations Example (MTC, 2009)

The comparison is done using the same methods from the previous example, where the average change in the indicators are calculated and compared across population segments and across scenarios. It is also important to note that this analysis included some mapping of Communities of Concern vs. the planned investments, which is characteristic of the qualitative approach to regional equity analysis. Figure 2.4 gives the results for the commute travel time indicator. From this analysis, MTC concluded that although Communities of Concern experienced a slightly smaller reduction in travel time, overall they fair comparably to the Remainder of the Region. This is because the reductions in travel cost to Communities of Concern (due to some shifting to less expensive travel modes) likely offset the negative travel time outcomes.

	2010	1	2	3	4	5	% Change	
	Base Year	No Project	Project	Transit Priority	Network of Comm.	Env., Equity & Jobs	Base Year to Project	No Project to Project
Communities of Concern	25	26	26	25	26	25	5%	-1%
Remainder of Region	27	29	27	26	27	27	2%	-6%
Regional Average	26	28	27	26	27	27	2%	-5%

Figure 2.4 MTC Equity Analysis of 2040 RTP/SCS Example: Commute Time (Minute), based on individual modes taken (MTC, 2013a)

Overall, we emphasize key takeaways. The first is that the type of travel model used to forecast the MTC scenarios and applied for equity analysis was upgraded from a 4-step model to an activity-based model in recent years, as is the new direction in regional travel modeling practices. The second point is that the methodology (i.e. using zones as the unit of analysis and using average measures of equity indicators) for these regional equity analyses have remained relatively the same, even though activity-based models enable new and significant advantages in these areas.

2.5 Critiquing the Existing Equity Analysis Process

Here we elaborate on the shortcomings of the existing practice for regional transportation equity analysis. Recall from earlier that the first step in the existing practice is to identify transportation equity indicators and define the population segments, the second step is to calculate the indicators for the population segments, and the third step is to compare these indicators across the population segments. There are three critical issues with the existing practice emphasized here. These are regarding the unit of analysis by which the population is segmented, the indicators used in the group comparison, and the method of comparison.

Regarding the unit of population segmentation, MPOs commonly classify the target group into what are called “communities of concern” or Environmental Justice communities (MTC, 2009; SANDAG, 2011; MTC 2013a). While the variables of segmentation vary some, these are generally selected to capture high concentrations low income and minority households. Further, the units of segmentation used are aggregate spatially-based units, such as travel analysis zones (TAZs) or census tracts. In this case, the communities of concern represent the target group, while all other zones in the regional represent the comparison group. The issue here is with the use of zones as the unit of analysis, as this will likely lead to a degree of aggregation bias in evaluating the impacts on population segments. Take the case that we are interested in vertical equity and we want to compare impacts on low income travelers, relative to high income travelers. Using a zone-based unit of segmentation is clearly problematic, as there would likely be some share of other income groups living in the same zones. In this case, it is impossible to isolate the impacts for the difference groups[5]. Activity-based travel models are capable of measuring disaggregate impacts, which would alleviate issues with aggregation bias.

The second step in the existing process in to calculate equity indicators for the different population segments, for the different planning scenarios. While our focus is not on discussing which equity indicators are best, it is important to note a key challenge with common equity indicators used in practice. This is regarding the extent to which the equity indicators represent transportation-related benefits (or costs). For example, while travel time indicators are attractive and intuitive mobility-based measures, they only capture a portion of transportation benefits. On the other hand, accessibility measures are more comprehensive and capable of capturing land-use related impacts, in addition to mobility impacts. As will be discussed in Chapter 3, the logsum accessibility and consumer surplus measure is particularly desirable for its sensitivity to individual costs and preferences.

The third and final step in the existing practice is to compare the indicators measured for the population segments, across the different planning scenarios. As seen earlier, the common approach is to calculate an average value of the equity indicator and compare the percentage change across the population segments, from the base-case scenario to another project scenario. The concern is that the use of average measures is problematic, because averages tend to mask the individual level outcomes. For example, the average may indicate that overall, all groups are better off as a result of the scenario, when in reality only 80% of individuals benefit and 20% are made to be worse off.

2.6 Conclusion

In this chapter we have discussed the background, literature, and existing practice for transportation equity analysis. Transportation equity analysis is a process undertaken to determine how different groups will be affected by transportation plans, with an emphasis in verifying that disadvantaged groups are not overly adversely affected. Although this analysis can be done using a range of modeling and non-modeling approaches, the modeling approaches for equity analysis becoming more prevalent. Overall, there are three key components to transportation equity analysis, including transportation priorities, modeling tool, and equity indicators. Our review of the literature and the existing practice for transportation equity analysis points to a number of research needs and shortcomings. Regarding research needs, there are three primary takeaways. First, the literature indicates the need to further verify that travel models sufficiently represent the behavioral differences in travel behavior, observed in the real world. Second is that there is a need to develop more useful distributional comparison methods for

[5]There are certainly some cases where spatial units of analysis are more appropriate: such as in the case of "horizontal equity" analyses.

evaluating individual level equity outcomes. Third is that considerations for long-term transportation and land-use impacts have largely been left out of transportation equity analyses. Regarding the existing practice, the key shortcomings are related to the using of zones as units of populations segments, weaknesses in how well the equity indicators represent transportation benefits (or costs), and the use of average measure for equity indicators. The proposed equity analysis process presented in Chapter 3 aims to address these shortcomings.

Chapter 3 . Methodology: An Analytical Framework for Transportation Equity Analysis of Long-Range Transportation Plans

3.1 Introduction

Here we present an analytical framework for regional transportation equity analysis that advances the existing equity analysis practice, and address the shortcomings discussed in Chapter 2. This analysis framework draws on the power of activity-based travel demand models, which represents the state-of-the-art in modeling and forecasting. We use these models to measure the expected changes in travel behavior to result from transportation and land-use plans. Among other things, this proposed process leverages the disaggregate functionality of activity-based travel models, and the usefulness of distributional comparison for transportation equity analysis.

The remainder of this chapter is organized as follows: Section 3.2 give an overview of the activity-based modeling process, including model estimation, scenario forecasting, and data analysis. In Section 3.3, we discuss each step in the proposed equity analysis process, including some considerations for implementing such a process in practice. In Section 3.4, we discuss some issues with implementing the proposed equity analysis process in practice. Finally, we give concluding statements in Section 3.5.

3.2 Activity-Based Travel Demand Modeling for Transportation Equity Analysis

Travel demand models serve as the primary transportation planning tools for measuring and forecasting changes in travel behavior that result from large scale transportation investments. These models measure the effects of transportation system and land-use changes, as well as travel and residential costs, and demographic changes on travel behavior (mode, destination, time-of-day, and other travel choices). In this case, the model to be estimated in an activity-based travel demand model. Activity-based travel models, described in this section, represent the best practices in travel demand modeling and have tremendous potential for transportation equity analysis. The disaggregate population and travel-related data from these models enable us to explore the use of distributional comparison tools for transportation equity analysis, which are capable of revealing the “winners” and “losers” resulting from transportation plans. In this way, we can provide a clearer and more accurate understanding of equity outcomes across groups.

3.2.1 Modeling Process

From start to finish, the full modeling and analysis process used in transportation equity analysis includes development and estimation of the travel demand models, forecasting of the transportation and land-use scenarios, and then processing of the data. These three phases are illustrated in the Figure 3.1. The primary contribution of this dissertation is with the Data Processing phase, and will be detailed in Section 3.3. However, it is important to review the Model Estimation and Scenario Forecasting phases from an equity analysis perspective. For these two initial phases, the emphasis with respect to equity analysis is on capturing the heterogeneity across population segments, such that the (expected) behavioral responses to transportation and land-use changes can be modeled. These are critical for accurately measuring the differences between population segments, and therefore equity outcomes across population segments.

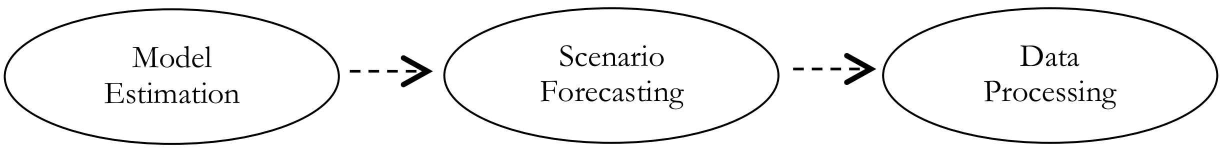

Figure 3.1 Full Modeling and Analysis Process Supporting Transportation Equity Analysis

3.2.2 Model Estimation

This description of the Model Estimation phase includes the following: a general overview of activity-based modeling systems, description of each model component, and a brief introduction to utility theory and discrete choice modeling.

Model Description

Activity-based travel models were developed on the basic principle that one's travel is derived from their desire to participate in various activities (Bhat and Koppelman, 1999). Therefore, individuals' make their daily travel decisions based on their (individual and household) established daily activities. This approach further aims to model travel from a more behaviorally realistic (choice-based) perspective. It therefore breaks travel actions into a set of travel-related choice dimensions and models each type of travel behavior using (logit) discrete choice models. These travel choice dimensions generally include work location, auto ownership, (daily) activity pattern, time-of-day, stop location, and mode choice dimensions. Figure 3.2 shows a schematic for a typical activity-based travel demand model. These model components are linked together in a "nested-like" structure, using feedback variables[6].

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[6]These "feedback" variables are logsums, which can be generated from any (logit) choice dimension in the activity-based modeling system. The significance of these logsums is further discussed in Section 3.3.3.

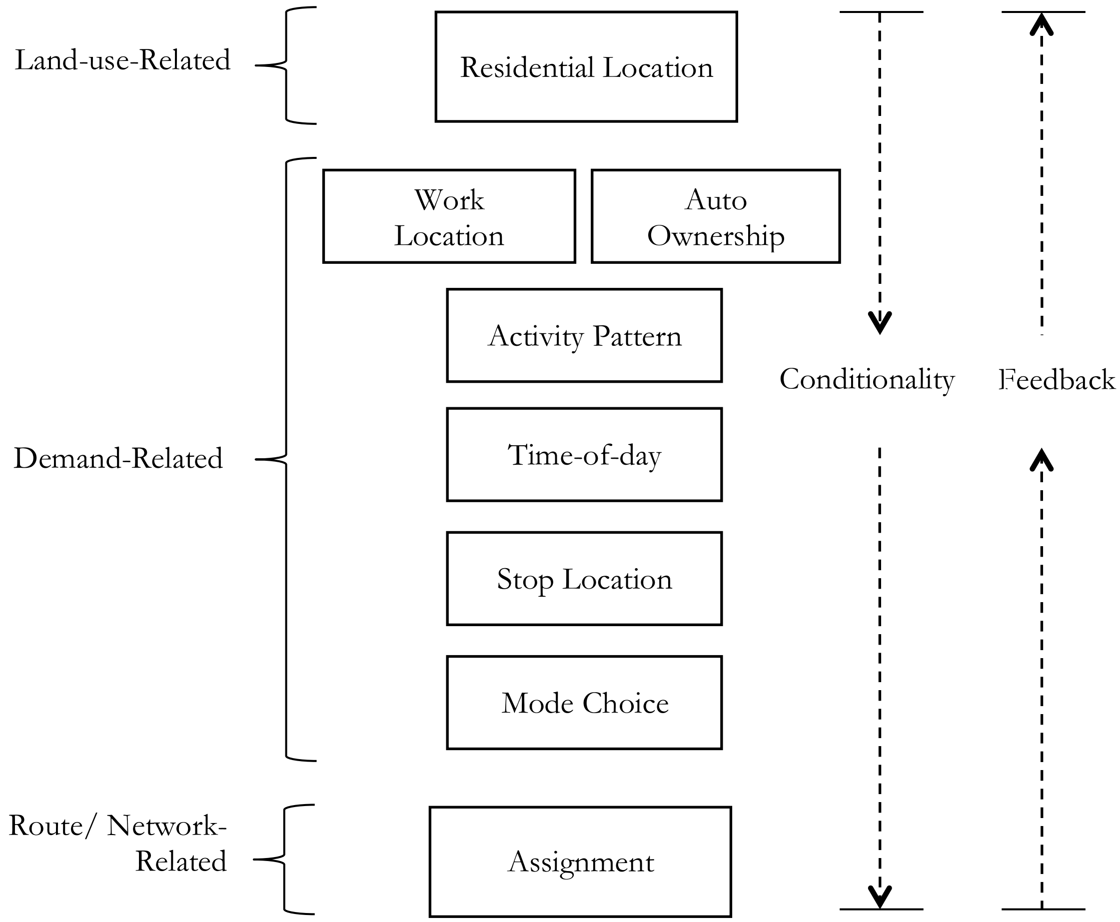

Figure 3.2 Generic Activity-Based Travel Model Schematic

The activity-based model components fall into three general groupings; land-use, demand, and assignment. In addition, the modeling system includes a population synthesizer. Given the discrete choice framework of the activity-based modeling system, it is necessary to enumerate a sample of individual agents, with as full set of population characteristics.

Model Components

Each demand-related component of the activity-based travel demand model represents a different travel choice dimension. Although the land-use and route/network related components are key travel related dimensions, the emphasis here is on the demand-related components of the model. This is because these capture the majority of the travel behaviors that are important for generating transportation equity indicators. We emphasize the use of land-use indicators a key topic in further research direction. Following are descriptions for Population Synthesis, as well as the demand-related travel model components.

Population Synthesis: The purpose of the population synthesizer is to generate a sample of individual agents that is representative of the real-world population. This population sample is typically generated for the base year or forecast year scenario. Each individual record generated has a set of characteristics (identification number, age, gender, etc.) and is assigned to a household with a set of characteristics (size, number of workers, income, number of vehicles, etc.). Further, (in the absence of a residential location choice model) each household is assigned to a residential location in the region (travel analysis zone (TAZ)). Associated with each TAZ is the location's size, population, employment, and other land-use related information.

Work Location Choice Model: The work location choice model seeks to answer the question of "Where in geographic space will a particular individual work?" Among other things, this choice will be a function of the "size" (e.g. amount of employment by sector), and impedance or level-or-service (LOS) associated with traveling to an alternative location. The alternatives for this choice are all possible locations in geographic space, which are partitioned into TAZs[7]. The model specification is multinomial logit. Further, location choice model alternations (the choice set) can be partitioned by person type (e.g. workers, college, high school, and elementary school students.)

Auto Ownership Choice Model: This model predicts the household level choice of "How many automobiles to own?" The alternatives represent the range of number of automobiles (e.g. 0 to 4+ automobiles). This choice is a function of various household level characteristics and the model is specified as a multinomial logit model.

Full-Day Activity Pattern Model(s): These models predict each individual's tour patterns. This information includes the tour purpose class (Mandatory[8], non-mandatory[9], and home), tour frequency (including for sub-tours), trip-chain pattern (whether there will be stops on the out-bound and/or in-bound legs of the tour), and stop frequency. It is also possible to model joint tour patterns among house members[10]. These models are commonly specified as binary and multinomial logit models.

Time-of-Day Choice Models: These models predict to departure and arrival times for each leg of each tour, and for each tour purpose class. The choice set here is comprised of different combinations of departure and arrival times. These models are specified as multinomial logit.

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[7] As a computational simplification, the location choice-set is a selected subset of the full set of alternatives. For a more detailed review of the aggregation theory that supports the sampling of alternatives, see Ben-Akiva and Lerman (1985).

[8] Mandatory tour purposes include work, college, high school, and elementary school.

[9] Non-Mandatory tour purposes include shopping, maintenance, dining, dining, visiting, recreational, and other.

[10] See and Bradley and Vovsha (2005) for description of household interactions activity pattern modeling.

Stop Location Choice Model: This model predicts the location of stops made along each leg of each tour (given the number of stops predicted by the stop frequency model). The choice set for this model is sampled from possible locations in geographic space. The location of a particular stop will be a function of various tour pattern characteristics, the "size" of the location, and the impedance or cost[11] associated with reaching that destination. This model specification is multinomial logit.

Tour and Trip Model Choice Models: Travel mode is modeled at the tour and trip levels. The tour mode choice model predicts the primary mode of travel for each tour, and the trip mode choice model predicts the model of travel for each trip made along the tour (mode for travel between each stop made along the tour). The choice set for the trip mode choice model represents all possible modes of travel, while the choice set for the tour mode choice is typically a set of aggregated categories of these (trip-level) travel modes; representing the primary mode of travel. For example, the tour level transit mode may be associated with bus, train, and ferry modes at the trip level. These models are specified as nested logit. It is important to note that these models are commonly used to generate the LOS variables used precedent choice models, representing the level of impedance associated with traveling to a particular destination, by all travel modes.

Utility Theory and Discrete Choice Models

Each of the demand-related choice dimensions modeled in the activity-based travel demand model is formulated as a logit discrete choice model. The objective of the choice modeling process is to understand the behavioral process that leads to a particular choice being made. Here we do not engage in a full introduction to utility theory and discrete choice model estimation, but it is important to highlight how the different data types (person, transportation, and land-use data) enter into the choice model formulation, and therefore the transportation demand modeling framework. This is because the sensitivity of the equity indicators generated from the models, will be a function of the data types that enter the choice models specifications.

The principle of utility maximization guides the mathematical form of the discrete choice model. The general concept is that decision making agents (individual, household, firms, etc.) select the alternative that provides the highest utility, among all alternatives available in the choice set. A choice model consists of utility functions; one for each alternative in the choice set (e.g. travel modes, work destination, etc.). The expression for each utility function includes parameterized observable variables, which are characteristics of the decision maker and attributes of the alternative. The parameter(s) associated with each of the variables, which are known to the decision maker and unknown to the researcher, are estimated[12] from a data sample (representing choices made by the decision makers when presented with a choice situation). These parameters represent the "tastes" or value that the decision maker associates with the factors. Because there are always factors which influence the choice of alternative, but are unknown to the researcher,

[11]The "cost" of reaching a particular location is typically represented using the highway distance between the origin and the particular location (Castiglione et al., 2006).

[12] In this case, the parameters are estimated using Maximum Likelihood Estimation (MLE), although there are difference estimation protocols possible.

there is an independent and identically distributed (*iid*) error term ε associated with each utility function. This unobservable component of the utility is considered random and follows some density $f(\varepsilon)$.

Mathematically, the utility U_{in} of alternative *i*, for individual *n*, is expressed as:

$$U_{ni} = h(\boldsymbol{x}, \varepsilon) \;=\; V_{ni} + \varepsilon_{ni} \;=\; \boldsymbol{x_{ni}\beta_i} + \varepsilon_{ni} \qquad (3.1)$$

where, *h* denotes the generic functional form, V_{ni} is the systematic utility for decision maker *n* and alterative i, $\boldsymbol{x_{ni}}$ is a row vector of observed attributes of alterative i and characteristics of the decision maker *n*, $\boldsymbol{\beta_i}$ is the column vector of parameters associated with the attributes and characteristics, and ε_{ni} is the random unobserved portion of the utility function. Assumptions on the distribution of the error term guide the mathematical form of the probability equation (3.2). In this case, the error terms are assumed to follow an Extreme Value distribution, which gives rise to the logit probability equation (3.2). The probability that the decision maker chooses a particular alternative is the probability that the unobservable factors, given the observable factors, result of the alternative being selected. The formula for the logit probability equity is as follows:

$$P_{ni}(i|\boldsymbol{x}, C_n) = {exp\ (\boldsymbol{x_{ni}\beta_i})}\Big/{\sum_{j \in C_n} exp\ (\boldsymbol{x_{nj}\beta_j})}$$

(3.2)

where, $P_{ni}(i|\boldsymbol{x}, C_n)$ denotes the probability of alternative i, conditional on the attributes and characteristics $\boldsymbol{x}$, and choice set C_n presented to the decision maker n, and j denotes any alternative in the choice set.

The types of data that enter the utility specification of a discrete choice model will vary according to the choice dimension that is being modeled. For example, the specification for mode choice model utilities will include attributes of the travel modes in the choice set (e.g. travel time and travel cost for each travel mode) and characteristics of the decision maker (income, gender, age, etc.), while destination choice model utilities would include attributes of the destination (e.g. employment by industry sector, number of households, LOS, etc.).

3.2.3 Scenario Forecasting

Once the models of individual travel behavior of are estimated, they are used to forecast the changes in travel behavior that will result from changes in the attributes of the alternatives. These scenarios are new instances of the travel model, where the input data[13] have been altered to reflect the implementation of various transportation and land-use changes. That is, these scenarios represent the influence on the transportation system and land-use patterns of various transportation projects (e.g. highway expansion, transit extension, etc.), transportation policies

[13]The key types of input data to the travel model include level-of-service data (travel times, costs, and distances, etc.) for each link in the transportation network and land-use data (zone level population, employment, etc.)

(e.g. fare changes, pricing schemes, etc.), and land-use policies (e.g. transit oriented development incentives, growth boundaries, etc.). These changes are specified as adjustments to the transportation system parameters. For example, in the case of a new transit project where a rail transit alternative is made available in areas that previously did not have access to transit; this would be reflected in the mode choice model availabilities, indicating to decision makers that a new transit alternative is now available for particular links in the network. In addition, the attributes of the new alternative, would be added to the various model input files.

Once the scenarios have been specified for evaluation, the modeling system is run to generate the model outputs[14]. Running the model primarily involves the assignment of travel-related choices (for each choice dimension) to the individual decision-making agents of the model. These choices reflect the individual behavior expected to occur in response to the scenario specifications. Activity-based models use Monte-Carlo simulation to generate choice realizations for each individual agent and for each choice dimension. That is, a realization is randomly drawn from a probability distribution (estimated from the choice model), for each individual. For example, say that an individual's mode choice probability is 0.15 for the first of two mode alternatives (and 1- 0.15 for the second alternative); if the random number drawn is less than or equal to 0.15, then the first alternative is assigned to that individual. From a system perspective (given that all the choice models together comprise the travel demand modeling system), we can view the choice simulations for all model components together as one draw from a complex joint distribution, which results in a sequence of random draws (relative to some initial "seed" value). In this case, there is one draw per iteration of the modeling system. Ultimately, this Monte-Carlo simulation process results in the assignment of travel-related choices to each individual in the population, which together are representative of the choice probabilities at the aggregate level.

Each run of the model results in new data files being generated. These data include work destination choices, daily travel pattern data for individuals and households, times-of-day for tours and trips, tour and trip more choices, other variables related to the travel choice dimensions. The organization of these data files are further described in Section 3.3.2. Once these new data are generated for each scenario run, equity indicators can be calculated for each population segment and for each scenario, for the purpose of equity analysis.

3.2.4 Data Processing

The primary contribution of this dissertation is with regard to the Data Processing phase of transportation equity analysis. This phase involves developing equity indicators from the activity-based travel model, and comparing and evaluating these indicators across population segments. In the following sections, we present our proposed equity analysis process, which whish address the shortcomings with existing equity analysis practice, discuss in Chapter 2. We also discuss some issues of implementation and outline some solutions for these issues.

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[14] The model output is generated in the form of transportation link volumes, number of tours taken at the individual (and sometimes household) level, number of stops on each tour, tour and trip purposes, tour and trip modes, etc. These are generated as new tour and trip files, origin-destination matrices, etc.

3.3 Proposed Equity Analysis Process

This proposed equity analysis process seeks to address the shortcomings of the existing practice, by leveraging the power of activity-based travel models. Among other steps, this process involves generating and comparing distributions of equity indicators, in order to reveal the individual level equity outcomes of transportation plans. This is to reveal a clearer and fuller picture of equity outcomes across segments of society. Further, we advocate for the adoption of scenario ranking criteria which reflect the transportation equity goals for the region.

3.3.1 Overview of Proposed Equity Analysis Process

In developing a method of applying activity-based travel models for regional equity analysis, it is necessary to determine the step-by-step process, starting with the model output, through the data processing phase, and culminating in a ranking of the scenarios being evaluated. Note that this process assumes that transportation and land use scenarios have previously been generated using the activity-based model. Therefore, this proposed equity analysis process refers to the post processing of the travel model data. The steps of the proposed analysis process are summarized in Table 3.1. We also give a general comparison of the existing vs. the proposed equity analysis process is presented in the Table 3.2 The third column in this table describes the improvements that the proposed equity analysis process makes, relative to the existing equity analysis practice.

Table 3.1 Summary of Proposed Process for Regional Transportation Equity Analysis

Process	Description
Step 1. Who and What:	Identify the equity indicator(s) and determine how to segment the population (How are the target and comparison groups identified?).
Step 2. Calculations:	Determine how to calculate the indicator(s) from the travel model data, for each unit (individual, household, etc.)
Step 3. Distributional Comparison:	Generate distributions of the indicator(s), and evaluate to determine what the distributions indicate about the impacts on the target and comparison groups.
Step 4. Rank via Equity Criteria:	Select the equity criteria by which the scenarios should be ranked, and rank the scenarios based on this criteria.

Table 3.2 Existing vs. Proposed Equity Analysis Process

Existing Practice	**Proposed Process**	**Improvements**
Segment population and identify indicators	1. Segment population and identify indicators	The population is segmented using individuals and households as the units of analysis, rather than zones.
Calculate indicators	2. Calculate indicators	The logsum accessibility and consumer surplus measure is emphasized as a more comprehensive measure of user benefits.
Compare changes in indicators across groups	3. Compare changes in indicators across groups	Distributional comparison measures are used, rather than average measures.
	4. Rank scenarios using equity criteria	This is emphasized as an important final step, in order to select a scenario that best meets the transportation equity goals for the region.

3.3.2 Step 1: Define Population Segments and Identify Equity Indicators

This first step in our proposed equity analysis process deals with the initial questions of "who?" and "what?" That is, this step involves segmentation the population into target and non-target groups, and identifying the equity indicators to evaluate. Our contribution here is not in recommending the best variables of segmentation or equity indicators, but we give important considerations for approaching population segmentation and identification of equity indicators. We begin with presenting the data variable types typically available from activity-based travel models, as this is relevant to the population segmentation and indicators possible for analysis. Following, we give considerations for determining the population segments and equity indicators. The choice of variable of segmentation is closely tied to the agencies adopted equity dimensions, while the selection of equity indicators requires some initial thought on the types of costs and/or benefits to result from the transportation plan, and potential confounding factors associated with the indicators of these costs and/or benefits.

Data Available from Activity-Based Travel Demand Models

The input and output data from an activity-based travel model sets the foundation for data available for transportation equity analysis. These data guide the populations to be segmented and well as the indicators to be evaluated. For understanding the data available from activity-based travel models, we categorize the data into population, travel behavior, travel network, and spatial data. The population data, travel behavior, and travel network data are generated from the activity-based modeling system. In particular, the population data are generated from the population synthesizer, the travel behavior data are simulated from the travel model, and the travel network data are generated from a combination of travel model output and input data. In addition, the forth data type, which serves as input into the modeling system, is the spatial data. From these data, there are numerous ways of segmenting the population and a range of possible equity indicators.

Table 3.3 Population Data

Population Data Element	Features
Individual	Ethnicity, age, gender, employment status, employment sector
Household	Size, income, residential location, # workers, # children, # vehicles

Table 3.4 Travel Behavior Data

Travel Data Element	Features
Stop	Location, Purpose
Trip	Mode, time-of-day, travel time, cost, distance
Tour	Tour class (home-based mandatory, home-based non mandatory work-based, etc.), stop frequency, primary mode, Primary origin and destination
Full-Day Pattern	Tour frequency

Table 3.5 Travel Network Data

Travel Network Element	Features
Travel Time Skims	In-vehicle time, wait times, access times
Travel Cost Skims	Vehicle operating cost, tolls, parking costs, transit fare
Travel Distance Skims	Auto network distance, transit network distance, walk and bike distance
Network-link Volumes	Vehicle-Miles-Traveled

Table 3.6 Spatial Data

Spatial Data Element	Features
Zone Neighborhood City County Region	Location, # households, Employment, by sector, amenities (shopping, hospitals, banks, etc.)

Population Segmentation

Here we discuss population segmentation for defining the target and comparison groups. The population segmentation involves the use of one or more variables of segmentation, a unit of segmentation, and a definition or threshold(s) for distinguishing the target and non-target (comparison) groups. Most commonly, variables of segmentation include income and ethnicity, and zones or census blocks as the units of segmentation. The target and comparison group thresholds vary significantly, as it depends on how transportation disadvantage is defined.

Variable of Segmentation

The dimension of equity adopted for a particular evaluation will guide the selection of the variable(s) of segmentation. Equity is commonly defined along two dimensions; “vertical” and “horizontal” equity. Vertical equity refers to the distribution of transportation impacts on sub-populations that differ in ability and needs, such as different social and income classes, and disabled or special needs groups; while horizontal equity refers to the distribution of impacts across groups which are considered to be equal in ability and need. Table 3.7 gives some examples of variables associated with vertical and horizontal equity dimensions. Note that it is also possible to segment by a combination of vertical and horizontal equity variables, as is done by MTC for their selection of communities of concern.

Table 3.7 Example Population Segmentation Variables for Equity Dimensions

	Vertical Equity	Horizontal Equity
Segment By:	Income	Location
	Gender	Travel Mode
	Age	Time-of-Day

Unit of Segmentation

The unit of segmentation refers to “what” we are segmenting. The most common for large scale equity analyses are zones (i.e. travel analysis zones) and census blocks. However, the use of zones (and other spatial units) can be problematic and lead to biased indicator measurements. For example, say that we are interested in vertical equity impacts across income class. Even if a particular zone has a very high share of households or individuals of a particular income class, there will certainly be some households of other income classes located in that same zone. Therefore, such an analysis would lead to some degree of aggregation bias, as there would be no way to fully isolate and evaluate the impacts within income classes.

For this reason, disaggregate (individual and household level) units of segmentation are most desirable. It is possible to generate most population, travel behavior, travel network data at the individual level, although some measures (which do not vary significantly across individuals) may be more appropriately generated at higher aggregation levels, such as households. We particularly caution against the use of zonal units, when considering vertical equity. In the case of MTC's equity analyses (MTC, 2009; MTC, 2013a), as much as 50% of the target group reside outside of the target zones (communities of concern). In comparison, the use of disaggregate units of segmentation available from an activity-based modeling system would allow for 100% of the target group to be captured and evaluated, alleviating issues with aggregation bias.

Definition of Target and Comparison Groups
Once the variable(s) and unit of segmentation have been identified, it is necessary to determine thresholds for the target and comparison groups. These thresholds define exactly what portion of the population units (i.e. individual, households, or zones) falls in and outside of the target and comparison groups. For example, say that our variable and units of segmentation are income and individuals, respectively. Regarding income, it is common to select low income individuals as the target group, with the comparison group being any other income group or all other income groups in the population. The threshold for defining the low income group can take a number of forms. For example, the low income group can be defined using the first quartile of the income distribution or some other general poverty class definition, such as the federal poverty threshold (established by the U.S. Department of Human and Health Services). Ideally, the thresholds for defining the target and comparison groups will be a function of how transportation disadvantage is defined[15].

Equity Indicators

Equity indicators are measures of the costs or benefits associated with implementing a transportation plan. We have established that the data types available from the activity-based travel modeling system can be used to generate a wide range of equity indicators, at all levels of data aggregation: from the individual level to neighborhood and higher levels. A list of equity indicators used in practice is given in Table 3.8. This list is compiled from regional equity analysis (done using travel demand models) from across the US. By far the most common indicators used are work travel time and accessibility to jobs.

Considerations of Selecting Equity Indicators
The primary consideration for identifying equity indicators is regarding the extent to which the indicators represent costs or benefits of the transportation plan. It is important that the change in these indicators (due to the transportation plan) reflect whether travel conditions are actually being made better or worse. One approach to determining whether the indicators reflect transportation benefits (or costs) is to consider the conceptual definition of a transportation benefit. Another approach to determining whether an indicator represents true transportation benefits (or costs) is to check and control for factors that may confound the relationship between the indicator and the expected benefit. Further discussions and examples of these two approaches are given below.

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[15] For more discussion of transport disadvantage, see Currie (2011).

Table 3.8 Common Equity indicators used for Regional Transportation Equity Analysis[16]

Indicator Type	Details
Accessibility (by auto and transit modes)	To jobs
	To Schools
	To Shopping
	To Medical Services
	To Parks
Travel Time	For All purposes
	For Mandatory Purposes (including work, and school Purposes)
	For Shopping Purposes
	For Other purposes
	To the Central Business District
Travel Distance	To Work
Mode Share	For Transit Modes
	For Walk and Bike Modes
Project Investments	By Population Segment
Environmental Quality	Exposure to Vehicle Emissions
	Noise
Congested Vehicle Miles Traveled (VMT)	During Peak Hours
Displacement	Due to Highway Projects

Considerations for "True' Transportation Benefits

An example regarding the definition of a transportation benefit is rooted in the debate of mobility vs. accessibility (objectives and performance measures) in transportation planning. Are mobility-centric indicators such as travel time truly an adequate measure of user benefit (or cost), or are accessibility-centric indicators more appropriate? For many years, transportation planning goals and system performance evaluations have been dominated by a mobility-centric perspective. That is, the goals and criteria for evaluating the performance of transportation systems, has been centered on how fast we can move vehicles through the transportation network, or reducing travel delay. However, over there past 30 years the literature indicates a gradual paradigm shift from mobility-centric transportation planning, to accessibility-centric planning. This is, transportation researchers and practitioners are now arguing that transportation planning goals (and system and social performance measures) should be centered on increasing the ease is reaching opportunities that are scattered across geographic space, as opposed to simply increasing the ease of traveling (mobility) (Cervero, 1996; Cervero and Appleyard, 1999; Handy, 2002).

[16]This list of equity indicators is compiled from recent equity analyses of Regional Transportation Plans in California (MTC, 2013a; SCAG, 2011; SACOG, 2012; and SANDAG, 2011). A more comprehensive summary of equity indicators is given by Rodier and Spiller (2012).

Another example regarding the definition of a transportation benefit is with the use of transit mode share as an equity indicator. As we indicate in the Table 3.8, transit mode share is commonly used as an equity indicator in regional analysis, although it is not clear that an increase in transit mode share can be understood as a benefit to all population segments. It is true that increasing the use of public transportation has long been an objective for transportation investments; therefore, transit mode share serves as an important performance measure for justifying transit investment. However for equity analysis, if transit mode share for low income travelers increases relative to high income travelers (for example), can this be considered a true benefit? We argue that changes in transit model can have ambiguous interpretations. While increases in transit mode share could mean that improvements in transit service, accessibility, and quality are drawing more users, these increases could also be interpreted user being forced to use a less expensive or low-accessibility travel mode (relative to auto) because of rising automobile costs (i.e. gas, insurance, parking and toll/pricing costs). Because of this uncertainty as to whether an increase in transit mode share can be understood as a benefit or a cost, the use of this as an equity indicators can be problematic.

Consideration for Confounding Factors

Regarding confounding factors, it is important to consider possible preferences, constraints, and travel characteristics that may be correlated with the expected transportation costs/benefits. In further describing possible issues with confounding factors, we give examples using consumer surplus, and travel time indicators to describe preference, constraint, and travel behavior related confounding factors.

The question of how individuals value a given benefit (or cost), or willingness-to-pay, is particularly relevant for selecting equity indicators (of transportation costs/benefits). Another way of wording this question is whether the utility gains (or losses) due to the change in a given equity indicator varies significantly across population segments or individuals. Indicators of consumer surplus serve as good examples for describing such preference related confounding factors is. A fuller discussion of considerations for applying consumer surplus measures is given in Section 3.4. Here we simply want to describe how heterogeneous willingness-to-pay across population segments can be very problematic is equity analysis. The fact the higher income corresponds to a higher willingness-to-pay for goods and services, is well known in the literature (Kickhofer et al., 2011). Further, given that consumer surplus is theoretically the difference between ones willingness-to-pay and the price of a given commodity, this implies that a higher willingness-to-pay (and higher income level) is associated with higher gains in consumer surplus. From an equity analysis perspective where the focus may be on comparing outcomes across income categories, this means that high income groups are inherently more likely to experience higher gains (or higher loses) in consumer surplus relative to low income groups, which is highly problematic.

Regarding confounding factors related to travel behavior, the travel time indicator serves as a useful example. Travel-time measures (or travel delay) are commonly used as indicators of transportation user benefit. However, increases in average travel time can also be associated with differences in travel frequency or system usage across income groups. Given that higher income groups exhibit higher rates of travel (Astrop et al., 1996; Pucher and Renne, 2003), there is likely a bias associated travel time comparisons across income groups. For this reason, it is important to control for trip/travel frequency when comparing travel times across income groups. This is similar to the problem of averaging impacts without controlling for the size of the comparison group. Without controlling for travel frequency, an evaluation of travel time/costs for high income travelers vs. low income travelers may falsely conclude that high income travelers are more likely to gain (or lose) in terms of travel time benefits.

3.3.3 Step 2: Indicator Calculations

For the second step in the analysis process, the task is to calculate the equity indicators using data from the activity-based travel model. This involves determining how to measure the equity indicators (selecting and computing the formula for the measure(s)), and assigning the computed values to the individual records. Here we describe the calculation processes using travel time and accessibility indicators. The immediate outputs of these calculation processes are tables (for each indicator) that contain the computed values of the measure, along with the value of the segmentation variable (e.g. annual income). These tables are ultimately used to generate distributions for comparison across the population segments.

Measures of Equity Indicators

Here we emphasize the need to determine how to measure the pre-identified equity indicators. This key initial step in calculating the equity indicators is to identify the formulas to be calculated, as there will likely be a number of approaches to calculating each indicator. In the following sections, we summarize the various types of travel time and accessibility measures.

Travel Time Measure
There are a number of travel time measures possible from activity-based travel model data. At a very basic level, travel time is the estimated time of travel between two locations, which is a function of distance and speed. Further, distance and travel speed vary by mode of transportation. For example, rail transit generally runs at slower speeds and at longer distances (along a fixed network) compared to automobiles. In addition, time-of-day (the time that the trip is taken) affects travel time, given that congestion levels tend to be significantly higher during peak travel periods, relative to off-peak times. Travel times can be further categorized by travel activity type. That is, travel time can be represented at the trip, tour, and daily-travel pattern levels[17]. Therefore, travel time measures can vary along three general dimensions: travel mode, time-of-day, and travel activity type.

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[17]Using these basic activity-based travel types, the tour is the primary unit of travel, which is the summation of all trips from primary origin to primary destination. For example, a home-based work tour would include the residential location as the primary origin, and the work location as the primary destination. This tour may also include a number of trips (or stops). For example the out-bound leg of the tour may include a stop to drop off children at daycare before continuing on to work. In this case, the out-bound leg of the tour is made up of two trips (or one stop). A daily-travel pattern would be comprised by aggregating an individual's tours taken throughout the day.

Accessibility Measure

Accessibility is generally defined as the "ease with which any land-use activity can be reached from a location, using a particular transport system" (Dalvi and Martin, 1976). Conceptually, accessibility is considered to be an important indicator of social welfare. A number of studies have shown that greater accessibility is associated with improved economic opportunity and social welfare (Kain, 1968; Wachs and Kumagai, 1973; O'Regan and Quigley, 1998). There are a number of accessibility measures found in the transportation literature, including infrastructure-based, location-based, person-based, and utility-based accessibility measures. Examples of these are given in Table 3.9.

Table 3.9 Types of Accessibility Measures

Group	Type	Description
Infrastructure-based	Infrastructure	These measures use transportation level-of-service characteristics (i.e. traffic congestion levels, operating speed, average travel time, etc.) to access the infrastructure's level of accessibility. (Thill and Horowitz, 1997; Geurs and Wee, 2004).
Location-based	Gravity	Location-based measures generally analyze the accessibility from a particular location to spatially distributed activities, given a transportation mode. (Handy and Neimeier, 1997). The gravity-based accessibility measure, first introduced by Hansen (1959), is derived by weighting the opportunities in an area by a measure of attraction, and discounting each opportunity by a measure of impedance.
Location-based	Contour	These measures sum the number of activities (e.g. jobs) that can be reached in a given time period (e.g. 30 minutes) and using a specific travel mode (Handy and Neineier, 1997; Cervero, 2005).
Person-based	Time-Space	Person-based measures analyze individuals' level of access to activities, given their temporal and spatial constraints. These measures, are based on Hägerstrand's (1970) proposed time-space prism (Kwan, 1998; Geurs and Wee, 2004)
Utility-based	Logsum	These measures calculate individuals' level of access as the maximum utility derived from a set of transportation alternatives. (Ben-Akiva and Lerman, 1985; Geurs and Wee, 2004; Dong et al., 2006)

The logsum measure has a number of desirable qualities relative to other accessibility measures. In addition to being flexible across various travel purposes and capable of sensitivity to time and space factors, the logsum measure is sensitive to individual-level costs and preferences. Given our emphasis on individual level measures for equity analysis, this measure is particularly useful. We discuss the logsum measure in the following sections.

The Logsum Measure

The "logsum" measures the expected maximum utility or welfare derived from a choice situation. This utility-based measure takes the mathematical formulation of the denominator of the logit discrete choice probability. The basic expression for the logsum is as follows:

$$Logsum_n = E\left[max_j \ (V_{nj} + \varepsilon_{nj})\right] = \left[ln\left(\sum_j exp\ (V_{nj})\right) + C\right]$$

(3.3)

where $Logsum_n$ is the expected maximum utility for individual n, j is the subscript for all possible alternatives, V_{nj} is the systematic utility expression, ε_{nj} is the random error term, and C is the constant[18]. While the logsum can be a useful measure of transportation accessibility, it is also mathematically equivalent to a measure of consumer surplus (Train, 2003). These two interpretations of the logsum measure (accessibility and consumer surplus) are discussed further in the following sections.

Logsum Accessibility Measure

The logsum (generated from a travel-related logit choice model) is interpreted as a measure of accessibility because it measures the expected "worth" of a set of travel alternatives (Ben-Akiva and Lerman, 1985). The logsum accessibility measure can be calculated from a number of different choice models of travel choice dimensions, including destination, mode, joint destination-model, and full activity-based choice models.

Usually, the logsum accessibility measure is calculated from a nested destination-mode choice model. In this case, the logsum would measure the ease of reaching all possible activities, relative to the origin location. The systematic utility for each destination alternative takes the following form:

$$V_{nij} = mcLogsum_{nij}\beta_{mcLogsum} + ln\ (size_j)\beta_{size} \qquad (3.4)$$

where, V_{nij} denotes the systematic utility for individual n and from origin i to destination alterative j, $\beta_{mcLogsum}$ is the parameter associated with the mode choice logsum $mcLogsum_{nij}$, and β_{size} is the parameter associated the log-size variable ln $(size_j)$. As shown in Equation 3.4, a logsum accessibility measure generated from a destination choice model measures two important factors: travel impedance and the "size" of opportunities. Note that Equation 3.4 represents the simple case where the log-size term does not vary across individuals. However, this can be extended to vary for different person-types (e.g. employees in different work sectors,

[18] The unknown constant C represents that the absolute level of utility cannot be measured (Train, 2003).

grade school students and university students), as well as for different activity types (e.g. employment, shopping, and recreation). For travel impedance, that standard is to use a mode choice logsum (Ben-Akiva, 1973) to represent the hardship of traveling to a particular destination by all mode of travel (in the mode choice set). This can be simplifies to measure impedance by a particular travel mode, using a level-of-service variable (e.g. travel time, cost, and distance). The generic mode choice logsum expression is as follows:

$$mcLogsum_{nij} = ln(\sum_k exp\,(V_{nijk})) \tag{3.5}$$

where, $mcLogsum_{nij}$ is the mode choice logsum impedance for individual n, from origin i to destination j, k denotes the travel mode, and V_{nijk} is the systematic utility in the mode choice model. The interpretation in this case would be the ease of reaching the opportunities in location j using all travel modes, from an origin location i. The "size" measure associated with each possible destination represents the attractiveness of the destinations based on the area allocated to a given activity type or amount of activities available in the zones. These activities are typically distinguished by activity type (e.g. employment, school, shopping, and recreational activities). The general expression for the size function is as follows:

$$size_j = \#opportunities_j \tag{3.6}$$

where, $size_j$ is the size variable for destination j and individual n, and $\#opportunities_j$ is the number of opportunities of the particular activity type available in location j. In the case that we are measuring accessibility to total employment, the size term for each destination would be the log of the number of employment opportunities available is that particular destination location. This functional form of the log follows from theory on aggregation of the alternatives in the location[19].

Not only can the logsum accessibility measure be simplified in terms of the size and impedance terms, but the measure can be extended to more complex choice dimensions. Notably, there are cases of logsum accessibility measures generated from joint mode-destination models (Handy and Niemeier, 1997), and full activity-based models (Dong et al., 2006), where the measures are sensitive to activity pattern behaviors such as scheduling, trip-chaining, and time-of-day travel choices.

Logsum Consumer Surplus

Consumer surplus is a welfare economics concept that generally refers to the total value (in monetary terms) that individuals place on goods and services (Just et al., 2004). For any particular group, the consumer surplus can be understood as the summation of the difference in individuals' willingness to pay, relative to the market prices for goods.

The logsum measures the Compensating Variation (CV), which is a Hicksian (compensated demand) measure of consumer surplus, as opposed to a Marshillian or uncompensated demand

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[19] For more on the theory of aggregating alternatives, see Ben-Akiva and Lerman (1985).

measure. We do not present a full introduction to CV here, but this measure of consumer surplus is interpreted as the maximum amount of money given to (or taken from) a particular consumer, in order for them to maintain their existing level of utility before a commodity price change (a function of the old utility level and the new) (Just et al., 2004).

The expression for this logsum consumer surplus measure is as follows:

$$CS_n = (\frac{1}{\alpha_n})\left[ln\left(\sum_j exp\ (V_{nj})\right) + C\right]$$
(3.7)

where the difference here relative to equation (3.3) is that the expression is divided by the marginal utility of income α_n, which converts the measure to monetary units.

Calculate and Assign Measures to Individual Records

This last step involves computing the measures of the indicators and assigning them to the appropriate individual or household level records. In the case of the travel time measure, it is clear that variables from multiple model output files need to be managed and assigned to individual records. This process is described below.

Estimated travel times for all possible origin-destination pairs (in the planning region) are made available in the travel time skim files. The locations of the origin and destination locations (for a given individual tour) reflect a number of factors: travel purpose, the travel tour type and patterns, destination choice, etc. This means, for example, that a primary origin and destination pair for an individual's work tour, will be related to outcomes from the work destination choice model, activity pattern models, and mode choice (as the distance may vary for transit vs. highway networks, for example). Further, time-of-day for travel will be a reflection of the time-of-day choice model. Therefore, the assignment of travel times requires model output from these travel model components. In the case of a work tour travel time, it is necessary to assign the appropriate travel time to each worker's origin-destination pair(s), based on time-of-day, and travel model taken.

3.3.4 Step 3: Generate and Analyze Distributions of Indicators

The primary task in this third step is to compare the disaggregate indicators across the population segments and for each scenario relative to the "No-Project" scenario conditions. We have established that taking averages of the indicators will likely mask important information about the distribution of travel impacts due to transportation plans, resulting in misleading equity analysis results. Alternatively, we emphasize the use of distributional comparisons, where distributions[20] of the selected indicator(s) are generated and analyzed for the different population segments. In this section, we discuss categories of distributional change and how these changes

[20]Here, a distribution or density refers to a graph that maps the frequency of values of an indicator, for all individuals or agents in the population.

are interpreted. We follow up with descriptions of two types of distributional comparisons: one of the aggregate densities and one of individual differences.

With distributional comparisons, there are two basic questions: 1) In what ways are the distributions different across planning scenarios, and 2) how do these changes compare across the population segments? As a first step, it is important to understand how to interpret the differences or changes in two distributions. In most cases, there will be graphical differences in the distribution, which can provide meaningful information beyond parametric measures. In addition there are methods of quantifying the changes in the distributions, ranging from simple quantile comparisons, to more sophisticated methods. We discuss two types of distributional comparisons in particular. The first comparison is of the aggregate density of the equity indicator measured for the No-Project scenario and the indicator measured for alternative scenario conditions. The Figure 3.4 shows a hypothetical example of this type of comparison, referred to as the "Aggregate Density" comparison. The second type of comparison is of the individual or household level differences in the indicator. For this comparison, we calculate the differences in the given indicator across planning scenarios and generate distributions of these values for the different population segments. We refer to this comparison as the "Individual Difference Density" comparison. This is shown in Figure 3.5.

Comparing Distributions

Graphical Differences: Understanding the Basics

An initial step in comparing distributions is to characterize graphical differences. The differences between any two distributions can generally be characterized in terms of shifts in location (central tendency) and shifts in shape (Handcock and Morris, 1999).

The locational shift (illustrated in Figure 3.3A) can be understood as the horizontal movement of a distribution. Consider a case where we are evaluating the changes in travel time for a group of travelers, after a new transit link is built. We have recorded the travel times from before (sample *A*) and after (sample *B*) the new transit link is constructed[21]. If the relationship between the values of *A* and *B* is purely a locational shift, then the *B* values are simply the *A* values plus a constant, *C*. In this case, a purely locational shift in the travel time distribution means that all travelers experience the same amount of change in travel time.

The shape shift of a distribution (illustrated in Figure 3.3B) refers to changes in higher distributional moments, such at variance, skew, etc. The variance captures the spread of the distribution. Using our commute travel time example from above, an increase in the variance of the distribution would indicate some degree of disparity in travel time impacts. That is, some travelers experience a positive change (longer travel times), while other travelers experience a negative change (shorter travel times). It is also possible that some travelers experience no change in travel time while others experience positive and negative changes, or that travelers

[21]Note that sample A and sample B need not only represent the indicator (e.g. travel time) measured under two different circumstances. These may, for example, be of an indicator measured for two groups (e.g. income groups, age groups, neighborhoods, etc.).

experience different rates of change (some small and some large changes in travel time). A decrease in the variance, on the other hand, would indicate that travelers' experiences (travel times) are growing more similar. The skewness captures the asymmetry of a distribution. A right-skewed distribution (a long tail extending to the right and the bulk of the values to the left of the mean) indicates there is a higher probability of travelers experiencing shorter travel times, while a left-skewed distribution has the opposite interpretation.

In reality, transportation policy actions will most likely result in a combination of locational and shape shifts. There may be shorter travel times experienced overall (locational shift), while some travelers are not affected and some experience much longer travel times (shape shift).

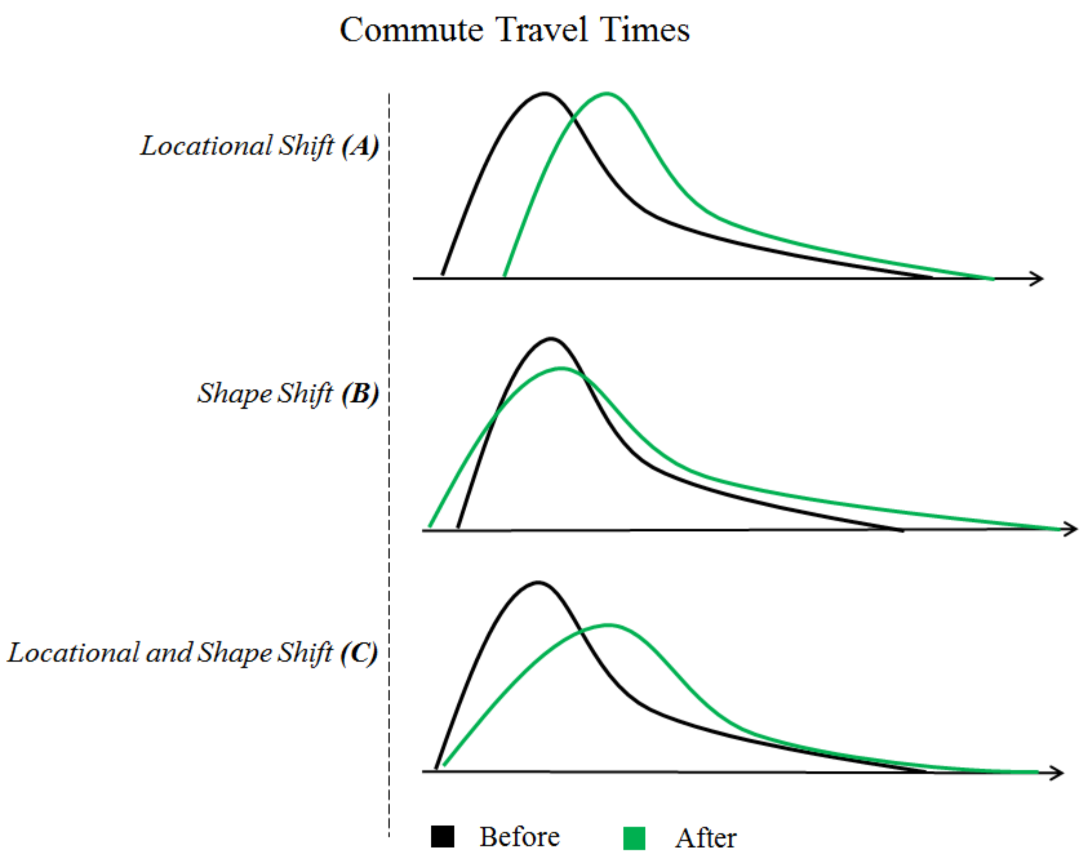

Figure 3.3 (A-C). Hypothetical Commute Travel Time Distributions

Quantifying Differences

The next step beyond graphical comparisons of distributions is to quantify the differences. That is, we want to understand the magnitude of the differences between distributions. Our interest here is not simply in parametric comparisons (of the central tendency and variance) of the distributions, but of the distributional differences overall. With this special focus, there are few tools to quantify differences in distributions, as common statistical tests for distributions (e.g. Mann-Whitney U test, Wilcoxon Signed-Ranks test, etc.) are unable to explain overall differences in distributions. Some tests are able to judge equality of two distributions e.g. Kolmogorov–Smirnov test, Pearson Chi-Square test), but are still unable to quantify overall differences in the distributions. A simple approach involves using data binning to group to data and then comparing across these groups. A more sophisticated approach is known as the Relative Distribution Method and is one of few statistical approaches to quantifying distributional differences (Liao, 2002).

Data Binning and Comparisons

The data binning approach involves reducing the data into groups, and comparing the group frequencies. In this way, the distributional differences in specific data ranges of can be evaluated. This can be useful particularly in cases where graphical comparisons fall short of showing the direction of overall change or differences in the distributions. As an example, consider the case that we want to compare distributions of travel time for two different groups of travelers; a reference distribution and comparison distribution. The aim is to measure how the travel time distributions are different. We first define the bins as some fixed interval of data for the reference distribution. These can be quantiles, some classes of equal width, or other meaningful classes defined based on the type of data (Larose, 2005). In this case, we define the bins as quartiles, which divide the data for each distribution into four equal parts. In this hypothetical case, say that the range of travel times for the first quartile of the reference distribution is 0 to 10 minutes in travel time. Next we calculate and compare the share of data points (travel times) that fall into the 0 to 10 minute range for the two distributions. This is also done for the remaining travel time bins. In this way, we can measure precisely how the bin frequencies differ across the distributions.

Relative Distributions Methods

Relative distribution methods were developed for use in the social sciences, where differences among groups or changes over time are commonly the focus of study. Traditionally, parametric measures of distributions (i.e. means) are used at the basis for comparing data samples. However in many cases, there are questions that are only fully addressed through understanding the underlying properties of the distributions which cannot be captured by these summary measures. Relative distribution methods (i.e. the relative density and polarization measures) provide for a full comparative distributional analysis. These methods compare two distributions based on the changes in the location and shape of the distribution. A more through discussion of the calculation process for relative distribution tools can be found in Handcock and Morris (1998).

The relative density itself serves as a graphical component that simplifies exploratory data analysis and display, and provides a basis for calculating more robust distributional comparison metrics of change: polarization measures. These polarization measures decompose the relative density in terms of the degree that the comparison distribution shifts in location and the degree that the shape changes, relative to the reference distribution. These polarization measures are useful for equity analysis given the ability to capture the changes in the upper and lower tails and indicate the regressive or progressive tendencies of the relative distribution (Franklin, 2005).
While relative distribution tools can be powerful measures of overall distributional differences, there is a need for tools that are capable of evaluating changes at the individual level. Relative distribution methods operate at the aggregate distribution level, where changes at the individual level go undetected. Further regarding application for equity analysis, relative distributions can

be difficult to interpret for practitioners and decision-makers. Therefore, there is a need for distributional measures that are both able to evaluate disaggregate level changes and more accessibility to transportation practitioners and decision-makers.

Two Types of Distributional Comparisons

Figure 3.4 gives a hypothetical example of the "Aggregate Density" comparison using travel time. This shows a case where there is an overall reduction in travel times, as indicated by the left-ward locational shift of the green "After" distribution, relative to the black "Before" distribution. However, the right tail of the green distribution indicates that some travelers experience an increase travel times. While the Aggregate Density comparison can provide practitioners with a general sense of how a scenario is impacting travelers, further processing can be done to better quantify the change in conditions for target and comparison groups. For example, the data binning approach described above can be useful for more precise measurement of distributional differences.

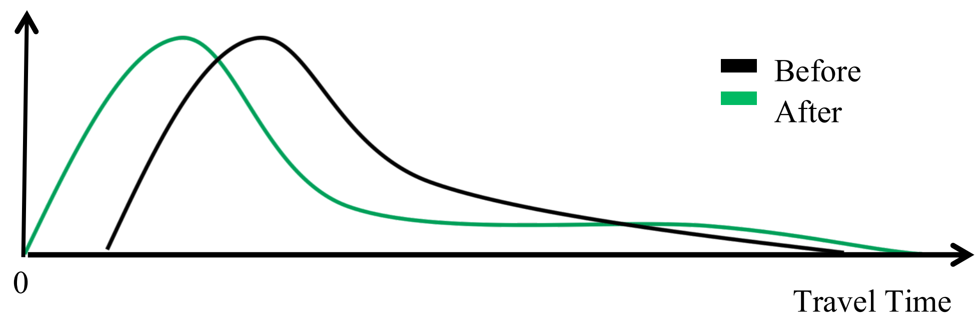

Figure 3.4 Hypothetical Aggregate Density Comparison

The "Individual Difference Density" comparison evaluates the individual level changes across the population. With this type of comparison, it is possible to identify the portion of the segment likely to experience positive or negative changes: "winners" and "losers". Figure 3.5 gives a hypothetical example of the Individual Difference Density comparison, using the individual level changes in travel time for a target group vs. comparison group. Values to the right of the origin (0) represent increases in travel time (losers), while values to the left of the origin represent decreases in travel time (winners). In this hypothetical case, a significant share of the target group experiences a losses in travel time, while very few in the comparison group experience losses. This type of finding is not possible using the Aggregate Density comparison. The graphical Individual Difference Density comparison provides a meaningful picture of how population segments will be affected. This distributional comparison also lends itself nicely to cases where the impacts of several groups need to be compared. Further, there are a number of summary measures that can be generated from this type of comparison, including the share of winners, share of losers, total gains, total losses, and relative losses/gains.

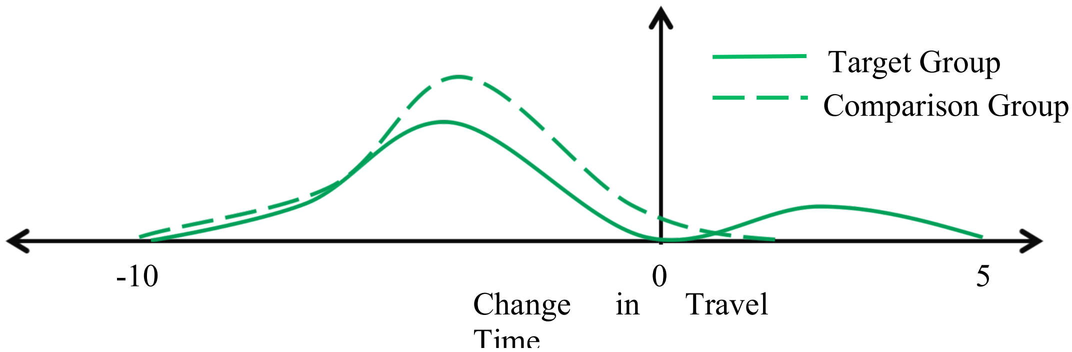

Figure 3.5 Hypothetical Individual Difference Density Comparison

3.3.5 Step 4: Equity Criteria and Scenario Ranking

With transportation equity analysis, the question is not so much whether or not a plan results in equitable outcomes, but the degree to which a plan results in equitable outcomes (Levinson, 2010). This principle lends itself to a ranking strategy, rather than an absolute determination of whether a plan is equitable or not. We address this as a final step in the analysis process and rank the alternative scenarios based on a defined equity standard. The tasks are to first identify some equity standard(s) or criteria by which to rank the scenarios. It is then necessary to determine the degree to which these criteria are satisfied using the comparison results from Step 3. In the literature, we find a number of proposed equity standards. These are various proposals for what should be considered "fair' with regard to the distribution of benefits. A sample of these is presented in the Table 3.10. Ultimately, the selection of equity criteria is at the discretion of the practitioner and agency, based on consultation with community members and stakeholders, as well as federal regulations.

Significance of Adopting Equity Standard

The explicit use of equity criteria is critical in transportation equity analysis. In practice, our review of existing equity analysis practices suggests that some type of rubric is used to judge the acceptability of planning scenarios, from an equity perspective. However, it is unclear whether MPOs actually adopt a particular equity standard and apply it.

Equity Criteria in Practice

While equity standards are primarily discussed from a theoretical perceptive in the literature, it is important to consider how to express these standards and operationalize the criteria for ranking scenarios. One example has been found literature of these equity criteria being operationalized for evaluating planning scenarios (LeGrand, 1991). Although MPOs are mandated to adopt Environmental Justice (EJ) regulations, these seem to serve primarily as general guidance over the planning process and not as specific criteria for ranking planning scenarios. We present examples of operationalizing equity criteria in the case study presented in Chapter 5 of this dissertation.

Table 3.10 Descriptions of Equity Standards

Equity Standard	Description
Basic Needs	A compromise between egalitarian and market–based equity; first the basic needs to each group are satisfied, then the remainder of the benefits are distributed according to market-based equity (Khristy, 1996; Duthie et al., 2007).
Equality/ Egalitarian	Providing an equal level of benefits among all groups of interest. Note that given the different levels of need and value that individuals place on these benefits, equality of benefits may be achieved without the actual amount of benefits being equal (Miller, 1979; Forkenbrock, 2001; Rosenbloom, 2009).
Market-based	"You get what you pay for": an allocation in proportion to the price paid for the use of facilities. This is typically evaluated by comparing the amount a group pays in taxes and fees with the level of benefits receive (Forkenbrock, 2001; Levinson, 2009).
Maximum Average Net Benefit	Maximizing the average benefit, using a certain amount as a constraint, to ensure that certain groups of interest (the most neglected groups) receive a certain minimum amount of benefit (Frohlich and Oppenheimer 1992, Khristy 1996).
Pareto	A change in benefits that results in at least one individual or group benefiting, without making anyone else worse off (Juran, 1950; Just, et al 2004).
Proportionality	Distributing benefits is proportion to the share that a group represents of the total population (Young, 1995; Forkenbrook and Sheeley 2004, Martens, et al 2010).
Restorative Justice	A distribution of benefits that calls for the "equalizing" of existing differences between groups of interest; that is remediating the existing disproportionality of transportation benefits (Martens, et al 2010).
Utilitarianism	Providing a distribution that produces the greatest utility or level of satisfaction, for the greatest number of people (Hensher, 1977).
Rawls-Utilitarianism	Providing the greatest level of benefits to those who are the most disadvantaged (Rawls, 1972).

3.4 Issues of Implementation

In our investigation of how to apply activity-based models for regional level transportation equity analysis, we expose a number of challenges. There are concerning three important topics: 1) the size and complexity of activity-based travel demand models, 2) the generation of the "Individual Difference Density" described in Sections 3.3.4, and 3) the use of the logsum accessibility/consumer surplus as an equity indicator. First, the size and complexity of activity-based models presents the challenge of defining the scope of equity analysis, particularly regarding to the selection of equity indicators. Second, the activity-based model's use of micro-simulation limits the ability to generate "winners" and "losers". Third, the use of a utility-based measure, given the previously documented issues with heterogeneous willingness-to-pay in welfare analysis, calls for the use of a simplified consumer surplus measure used in this proposed equity analysis process. Because of these challenges, we make a number of constraints to the model data when calculating equity indicators and performing the distributional comparisons. These constraints will vary based on the particular questions that need to be answered.

3.4.1 Size and Complexity of Activity-Based Travel Demand Models

Because of the size and complexity of activity-based travel models, it is important to make efforts toward defining the scope of the evaluation. This is for the following general reasons:

- The population synthesis generates a sample of decision-makers that is fully representative of the real world population, including a wide range of socio-demographic factors. This implies that there are numerous dimensions by which to evaluate indicators (numerous ways of population segmentation).

- The model is designed to be behaviorally realistic, which implies a high level of complexity given linkages (conditionality) between the different travel choice dimensions.

- The output from the activity pattern models are an example of the vast potential for travel indicators from activity-based models. The question of how to calculate travel time, for example, can be very complex. It is possible to calculate, trip level, tour level, and daily travel time measures, for various travel modes, travel purposes, and times-of-day. It is also possible to calculate direct primary origin-destination travel times or tour level travel times accounting for all stops along the tour, among other things. So the question of how to calculate travel time or any other indicator is nontrivial to say the least.

3.4.2 Micro-simulation and Individual Level Comparisons

The activity-based travel model uses a Monte Carlo micro-simulation protocol to assign choices to the decision-making agents, for each choice dimension in the modeling system. This means that although the choice share for any particular travel choice dimension will reflect the probability distribution at the aggregate level, for each model run, a different outcome is likely to be drawn and assigned to a particular decision-maker. Because of this, we cannot assume that a particular decision maker maintains the same residential location, work location, mode choice, or any other travel-related choice across scenario runs.

This challenge with micro simulation does not impact the aggregate densities, but has implications for the generation of the "Individual Difference Density" and the calculation of winners and losers. For this disaggregate level of comparison where the distribution of differences (in a given indicator) across decision makers is generated, is it necessary that the values of the indicators across the scenarios be comparable. For example, if we aim to measure the losses or gains in accessibility (a location-related measure) due to a transportation investment for a given household, then it is necessary that the household's location remains the same for the comparison scenarios. Using similar logic, the constraints used in calculating individual level changes in other indicators (such as travel time) will vary.

3.4.3 Logsum Accessibility and Consumer Surplus Measure

There are two relevant challenges with applying the logsum measure in our proposed equity analysis process. The first challenge is regarding the need to compare utility-based measures across individuals. The second challenge is regarding the use of a constant marginal utility of income in calculating the compensating variation (CV) derived from a choice model (the logsum measure).

The logsum is the expected maximum utility derived from a choice situation. In economic terms, an individual's utility represents their level of satisfaction or pleasure received from their consumption of goods and services. Therefore, it is not meaningful to compare one individual's level of utility to another individual's, as these values are of different (individual specific) scales. That is, one individual may derive a much higher level of utility for consuming a particular good, relative to her neighbor. This has implications for the generation of aggregate densities of any utility based indicator, as this would assume that the utility values are of a consistent and comparable scale. This however, does not impact the generation of individual difference densities, as the values that are distributed are only compared for individuals. For example, an individual's utility in scenario 2 is compared to the value of that individual's utility in scenario 1, and the distribution of this difference value is evaluated across decision makers.

The second issue is regarding the use of a constant vs. heterogeneous marginal utility of income in the calculation of consumer surplus. In equation (3.4), the logsum is converted into monetary units using the marginal utility of income (α_n). In theory, it is possible and more realistic that this marginal utility of income be individual specific and vary according to income level, as denoted by the subscript *n*. However this would introduce a significant challenge with respect to comparing welfare changes across income categories (as is frequently done in transportation policy analyses). The issue is that high income individuals are known to have a higher willingness' to pay for travel-related factors (e.g. value of time). Therefore, an analysis of welfare variations across income groups would assign greater weight to impacts on higher income individuals, relative to low income individuals. This outcome is particularly disturbing from an equity analysis perspective, given the explicit objective of providing fair distribution of outcomes for all groups.

This issue is not new to transportation policy analysis, as these objections to welfare-based analyses of user benefits are well cited in the literature on Cost-Benefit Analysis (Frank, 2000; Martens, 2009). However, few if any satisfying solutions have been proposed and tested. The most common method of overcoming this issue is the use of a constant marginal utility of income (for all individuals), effectively constraining the willingness-to-pay of all income groups to be the same. Although unrealistic, this "quick fix" allows for some level of useful welfare change comparison across income categories.

3.5 Conclusion

In this chapter we have presented a review of the activity-based modeling process and outlined the steps for applying such a modeling system for regional transportation equity analysis. This proposed equity analysis process takes advantage of disaggregate level output from the activity-based travel model and emphasizes the use of distributional comparisons to evaluate equity outcomes are the individual level. This includes the calculation of the shares of winners and losers that result from the transportation and land-use scenarios being evaluated.

The steps in the proposed equity analysis process include 1) Identifying the equity indicator(s) and determining how to segment the population into groups, 2) determining how to calculate to indicator(s) from the model output, 3) comparing the indicator(s) across population segments and across scenarios using distributional comparisons tools, and 4) selecting equity criteria and ranking the scenarios based on this criteria. We have provided a discussion of each of these steps.

Finally, we have exposed a number of challenges with operationalizing the proposed equity analysis process, and presented some solutions to these challenges. These challenges involve making individual level comparisons, given the activity-based model's micro-simulation framework, comparing utility-based measure across individual, and calculating a measure of consumer surplus, given the questions around using constant vs. heterogeneous marginal utility of income.

Chapter 4 . Distributions and Transportation Equity Analysis: Conceptual Evaluations

4.1 Introduction

The proposed process for regional transportation equity analysis presented in Chapter 3 emphasizes the use of distributional comparisons for evaluating individual level equity impacts, among other improvements. The micro-simulation framework of activity-based travel models makes the calculation of individual level equity indicators possible, from which a number of distributions can be generated and evaluated. In this chapter, we give conceptual evaluations of our proposed equity analysis process and highlight the explanatory power of distributions. Here we are particularly concerned with Step 3 in the proposed analysis process, which calls for the generation and evaluation of distributions of individual level equity indicators. Operating in controlled settings, we aim to provide clear demonstrations of how distributions are derived. This addresses the question of what individual level factors lead to various distributional outcomes. Second, we seek to explore the relationships between the population characteristics of a sample in conjunction with transportation changes, and the distribution of outcomes resulting from these transportation changes. In this way, we provide a foundation for interpreting various distributional changes possible in the real world setting, which is the subject of Chapter 5 of this dissertation. These objectives are carried out in two steps. In addressing the first objective, we evaluate distributions derived from a hypothetical transportation planning context and scenarios using a simplistic model of travel behavior and a synthesized dataset. We address the second objective using a real world dataset and realistic model of travel behavior to generate and evaluate empirical distributions.

The remainder of this chapter is organized as follows. In Section 4.2 we discuss distributions derived in a hypothetical setting. This involves the use of a synthesized sample of individuals and assumed mode choice parameters to generate individual level measures of consumer surplus. As a next step we generate distributions of consumer surplus from a mode choice model estimated using a real world travel dataset (the 2000 Bay Area Travel Survey). This is described in Section 4.3. We give concluding remarks in Section 4.4.

4.2 Distributional Comparisons Using a Hypothetical Setting

The idea of using a large scale travel model and a fully representative population to generate distributions equity indicators for equity analysis can be off-putting. There are numerous population and environmental (transportation and land-use) factors that together shape the transportation experiences of individuals. In a real world setting, for example, one's income level, age, gender, ethnicity, residential location, work location, and access to various travel modes all play key roles in determining how one is affected by the transportation system. In such a complex system where numerous population, land-use, and transportation factors are at play, the influence of these factors on distributional outcomes can be difficult to disentangle. For this reason, our analysis approach is to start by reducing much of this complexity to a simplified case. We synthesize a population sample with a basic set of socio-demographic characteristics and limited options for residential location. Our variable of segmentation is income and we compare the impacts on low income individuals to high income individuals. We apply a simple (hypothetical) transportation scenario and calculate the change in (logsum) consumer surplus for each individual. The consumer surplus measures are calculated from a basic model of travel behavior: a binary mode choice model. We then generate and evaluate distributions of individual changes in consumer surplus. In the following sections we discuss the development of the synthetic data set, consumer surplus calculations, transportation scenarios, and the comparison results.

4.2.1 Data Synthesis

Synthetic Data Setting and Sample Generation

Ultimately, the variation in traveler characteristics and experiences is what allows us to generate distributions. Therefore the objective here is to develop a sample with some basic level of heterogeneity. We do this by varying the characteristics along three dimensions: population, land-use, and transportation. Each individual is assigned one population variable (income level), land-use variable (residential location), and four transportation variables (travel mode, travel time, transit wait time, and travel cost).

There are two simplified income categories (low income and high income), three residential location options (neighborhoods 1-3), and two travel mode alternatives (auto and bus) which make up the dataset. In this hypothetical setting, all individuals travel to work in the Central Business District (CBD) during the morning peak commute period (there is no variation in travel time-of-day). For the three residential locations, one is characterized as an urban neighborhood that is located closest to the CBD, one is a suburban neighborhood located farthest from the CBD, and one is a neighborhood with mixed urban and suburban characteristics that is located medium distances from the CBD. Each neighborhood varies with respect to population size, share of income groups, availability of travel modes, and mean distance to the CBD. The total sample size is 1500. This hypothetical city setting is illustrated in Figure 4.1, and the population parameters for each neighborhood are given in Table 4.1.

The income levels and travel characteristics (travel time, transit wait time, and travel cost) are drawn from different log-normal distributions. For the travel time calculations, we first draw log-normally distributed travel distances. This is to simulate residences that are scattered across geographic space for each zone. A mean travel distance is selected for each neighborhood, from which the neighborhood's travel distance distribution is generated. The travel times are calculated from the assigned travel distances for each individual, using fixed travel speeds: 60 miles/hour for auto and 35 mile/hour for transit. These speeds represent the average highway travel speed and bus network speed. The transit wait times follow a truncated log-normal distribution, with a minimum wait time of 1 minute and a maximum wait time of 25 minutes. Similarly, the auto travel costs are calculated from the travel distances using a fixed unit auto operation cost of $0.30 per mile. The transit fares follow a truncated log-normal distribution, with a minimum fair of $0.50 and a maximum fair of $4.00.

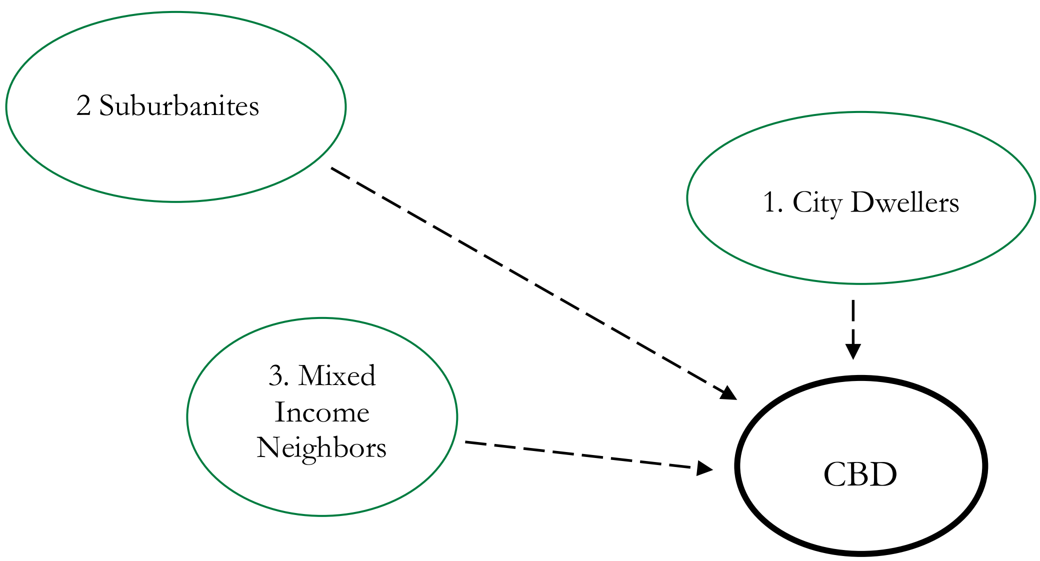

Figure 4.1 Hypothetical City Setting for Generating Synthetic Population.

Table 4.1 Synthetic Data Parameters

	Neighborhood	Population Size	% Low Income	% High Income	Mean Travel Distances (Miles)	Modes Available
1	**City Dwellers**	650	80%	20%	10	Transit
2	**Suburbanites:**	350	20%	80%	15	Auto*, Transit
3	**Mixed Income Neighbors:**	500	40%	60%	12	Auto, Transit

*Only high income individuals have access to auto in neighborhood 2.

Mode Choice Simulation

Here we describe the process taken to simulate mode choices for each individual in the sample. Using a discrete choice framework, we develop binary mode choice utilities using the synthetic data variables (travel times, cost, and income) to determine the choice that generates the greatest level of utility for each individual. In this case, the mode choice model is not only important for assigning the mode choices, but also for calculating the change in the mode choice logsum which results from implementing the planning scenario.

Our process for developing the model and assigning mode choices is similar to those documented in Williams and Ortúzar (1982) and Raveau et al,. (2010). There are two rules used in identifying the mode choice parameters. The first is that the resulting value of time be within a range of reasonable values of time. The rule of thumb for values of time in the San Francisco Bay Area is that on average, ones value of time is equal to 25-50% of their wage rate (Purvis, 1997). Given the average wage of $16.5 in our synthetic sample, this indicates an approximate range of $4 to $8. The second rule used is that the wait time parameter be 2-3 times the travel time parameter, as a number of studies have found that travelers tend to be much more sensitive to out-of-vehicle travel times, relative to in-vehicle travel time (Iseki et al., 2006).

Once initial values for the parameters are selected, we assign a mode choice to each travel record (based on the mode that generates the greatest level of utility) and verify that the model is estimable by recovering the parameters. That is, we estimate the parameters using the synthetic sample to determine if the original parameters can be recovered. Note that these parameters have a generic specification. The software used for estimation is Biogeme (Bierlaire, 2003). This iterative process in done in the following steps:

1. Select ideal parameters based on rules of thumb
   a. Is the value-of-time reasonable?
   b. Is the ratio of in-vehicle to out-of-vehicle time parameters reasonable?
2. Generate mode choices
   a. If the utility of auto is greater than the utility of bus, choose auto; otherwise choose bus.
3. Estimate parameters
   a. If estimates are not within one standard error of the original parameter, adjust parameters and repeat process (starting at step 2).

4.2.2 Equity Indicator: Logsum Measure

We use the logsum accessibility/consumer surplus measure as the equity indicator, which has been previously described in Section 3.3.3. Other possible indicators could be calculated based on travel time or cost, given that they are available in the simulated dataset. However, in the absence of a full travel modeling system to generate travel skims, it is necessary to calculate the expectation of travel time or cost changes; neither of which give realistic or meaningful representations of transportation benefits. In this case, the logsum measure, which is the expected maximum benefit derived from the individuals' mode choices, it is a comprehensive measure that captures all changes in utility due to the policy change.

4.2.3 Scenario

Our objective for developing this hypothetical policy is to demonstrate positive impacts overall, but negative impacts for a small population segment. In this way, we intend to give a clear example of how average measures of indicators can be grossly misleading. These (contrived) policy changes are developed to reflect a relocation of transit services (in an efficient manner), where some bus services from Neighborhoods 2 and 3 are moved to Neighborhood 1. The policy changes result in an average 10% reduction in all travel times and 15% reduction in transit wait times overall. For Neighborhood 1, bus riders experience a 50% reduction travel time. Further, because the bus frequencies for Neighborhoods 2 and 3 are drastically reduced, results in a 100% increase in transit fare, a 100% increase in wait time, and 50% increase in transit travel time. In this way, we directly introduce vertical inequity (given that low income residents in Neighborhood 2 only have access to bus) and horizontal inequity (spatial differences in travel times and costs), resulting in winners and losers. Note that this scenario is not intended to be realistic, but to demonstrate the distributional changes resulting from a (controlled) transportation investment scenario.

4.2.4 Results

Here we discuss the results of the hypothetical transportation investment scenario introduced above. As a first step, we calculate the average change in the logsum measure, due to the scenario. These values are given in Table 4.2. In this case we find that although both groups experience positive gains, high income commuters experience relatively higher gains.

Table 4.2 Average Change in Logsum Consumer Surplus Measure

	Average Change in Logsum Consumer Surplus	
	Low Income	*High Income*
Change per person	$0.80	$0.92

Next, we generate the Individual Difference Densities for high and low income commuters, using the process described in Section 3.3.4. We calculate the change in the logsum measure due the scenario and convert the values to consumer surplus, in units of dollars ($). This comparison is shown in Figure 4.2.

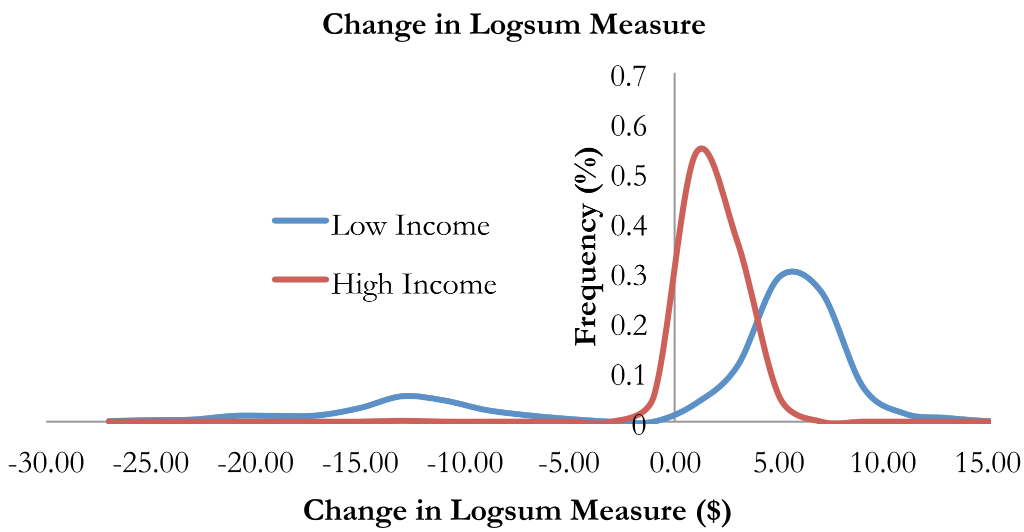

Figure 4.2 Individual Difference Density Comparison for a Hypothetical Setting

The results show that most commuters experience an increase in consumer surplus (winners). Further, the relative positions of the curves for low income and high income commuters indicate that many low income commuters are more likely to experience higher gains, relative to high income commuters. However, it is also the case that low income commuters are more likely to experience loses in consumer surplus (losers). This distributional comparison is not only useful for visual comparison and identifying winners and losers across population segments, but it can also be used to calculate the shares of winners and losers for each population segment. As shown in Table 4.3, we find that approximately 21% of low income commuters experience a reduction in consumer surplus, relative to less than 2% for high income commuters. We can further calculate the amount of loss experienced for each group. The low income commuters experience a loss of approximately $14.00 per person, relative to $0.45 for high income commuters, which represents a considerable disparity in transportation impacts.

Table 4.3 Share of Workers Who Experienced a Reduction in Consumer Surplus (Losers) and Magnitudes of Loss

	Experienced a Reduction in Logsum Consumer Surplus	
	Low Income	*High Income*
Share of Segment	20.9%	1.6%
Loss per person ($)	-$14.31	-$0.45

4.3 Distributional Comparisons Using a (More) Realistic Setting

In the previous example we employed a simplistic travel model of travel behavior and an unrealistic planning scenario to demonstrate the advantages of distributional comparisons. Now we turn our attention to generating these distributions from a more realistic travel model, estimated from empirical data, and using less orchestrated scenarios. The emphasis here is on highlighting the distributional changes resulting in a real world context (the San Francisco Bay Area) and possible transportation changes (reductions in travel time and cost). To do this, we estimate a nested logit mode choice model, using the 2000 Bay Area Travel Survey.

4.3.1 Data: 2000 Bay Area Travel Survey

The 2000 Bay Area Travel Survey (BATS) was used for model estimation. This is a regional-scale household travel survey collected by MTC to support modeling and evaluation of travel across the Bay Area. For this survey, travel diary data for over 14,000 households was collected. This includes household population data (location, income, size, # workers, # children, # vehicles, etc.) and personal travel records over a two-day period (travel destinations, time-of-day, purpose, travel mode, etc.). For our purposes, we use the work tour data and some household characteristics to estimate our mode choice model. Note that the raw BATS travel records are in the form of person-trips. However, we make use of the San Francisco Metropolitan County Authority's (SFCTA) version of the data, in which the trips are processed into tours (linked trips from primary origin to primary destination) and corresponding level-of-service skims (travel times and costs) are attached. A total of 26701 work tours from across the Bay Area are used for model estimation. Of these tours, 12% are made by low income commuters (earning less than $30,000 annually) and 30% are made by high income commuters (earning more than $100,000 annually).

4.3.2 Mode Choice Model

We specify and estimate a tour-level mode choice model for home-based work tours. For the purpose of employing a more realistic representation of travel behavior and adding travel complexity, the model is developed to resemble the structure of MTC's mode choice model. The model structure is nested logit with three nests. The first nest includes Drive Alone, Shared Ride 2, and Shared Ride 3 mode alternatives; the second nest includes Drive-Transit and Walk-Transit mode alternatives; and the third nest includes Walk and Bike mode alternatives. This nested logit specification allows for a more realistic correlation structure between the choice alternatives, relative to multinomial logit. The estimation results are given in Appendix A.

4.3.3 Setting and Planning Scenarios

The setting for this evaluation is the nine-county San Francisco Bay region. The region is spatially divided into travel analysis zones. Based on MTC's zonal system, there are a total of 1454 zones representing the region. The residential and employment locations of commuters are scattered across the region, in contrast to the previous example where all commuters lived in three neighborhoods and all traveled to the same employment destination. There are a number of travel modes available. There include three auto modes, which are distinguished by occupancy level: single occupancy (Drive-Alone), double occupancy (Shared-Ride 2), and three or more occupants (Shared-Ride 3). The transit modes are distinguished by access mode: drive-to-transit or walk-to-transit. Walk and bike modes are also included in the mode choice set. As with MTC's model and other mode choice models used in practice, the choice set varies across individuals. For example some individuals may not have access to the Drive-Alone or Walk alternatives due to a disability, or if they simply do not own a vehicle. Similarly, some individuals may not have access the Bike mode if they do not own a bike, or if there is poor bike infrastructure between their residential and work locations. Further, travel takes place at various times-of-day, based on individual needs. Regarding mode share, there are significant differences across income groups. The low income group is much more likely to take Transit and Walk/Bike modes, relative to the high income group. This is shown in Figure 4.3.

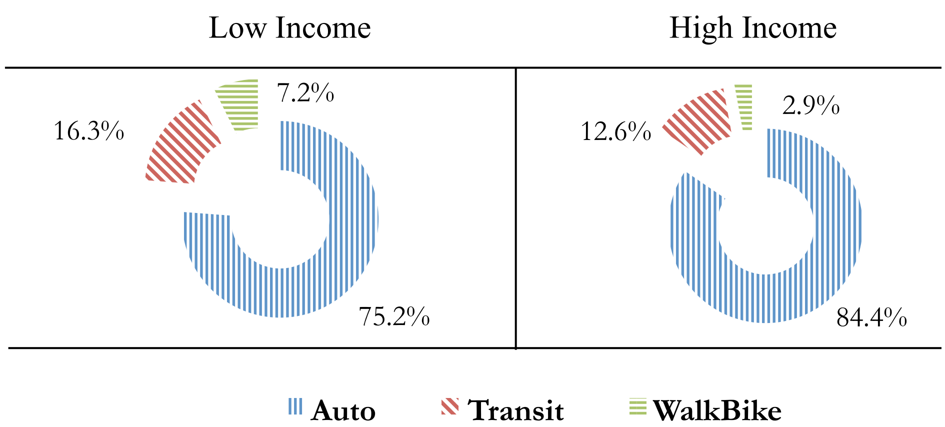

Figure 4.3 Mode Shares for Low Income and High Income Workers

4.3.4 Results

Here we present the results from two planning scenarios. For the first scenario, there is a 20% reduction in travel costs. As with the previous example, we start by calculating the average change in the logsum measure, and then follow with the Individual Difference Density comparison. The average changes in the losgum measure for low and high income commuters are given in Table 4.4. In this case, we find that the average effects for income groups are similar: a small but positive change. Higher income commuters experience a (slightly) greater positive impact.

Table 4.4 Average Change in Consumer Surplus due to Scenario 1 (20% Travel Cost Reduction)

	Average Change in Consumer Surplus	
	Low Income	*High Income*
Change per person	$0.14	$0.15

The findings with the distributional comparison are consistent with the finding from the average measures. In Figure 4.4, we see that relative positions of the curves for low income and high income commuters indicate that high income commuters are likely to experience higher gains, relative to low income commuters.

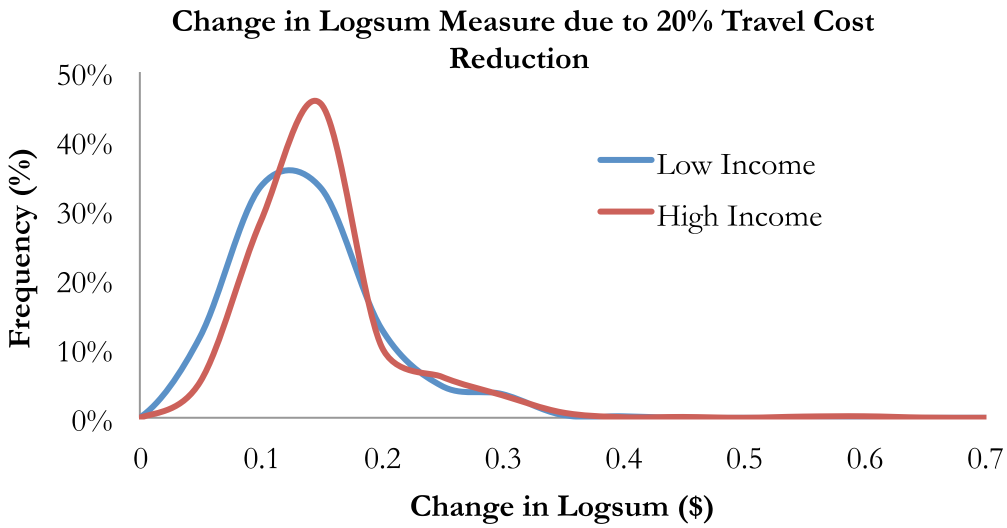

Figure 4.4 Individual Difference Comparison for Scenario 1 (20% Travel Cost Reduction)

For the second scenario, there is a 20% reduction in travel times for all commuters. The results from the average change in the logsum measure for low and high income commuters are given in Table 4.5, and the Individual Difference Density comparison results are given in Figure 4.5. As with the first scenario, we find positive average changes in the logsum measures for both low and high income commuters. However in this case, low income commuters experience a higher average benefit relative to high income commuters. Further, the magnitudes of the average changes are (approximately) two times greater than those resulting from the first scenario.

Table 4.5 Average Change in Consumer Surplus due to Scenario 2 (20% Travel Time Reduction)

	Average Change in Logsum Consumer Surplus	
	Low Income	*High Income*
Change per person	\$0.30	\$0.25

Regarding the Individual Difference Density comparison, this scenario produces more interesting results. In Figure 4.5, we see that this scenario results in a multi-modal distribution with two peaks. In the first and taller peak (ranging approximately from \$0.10 to \$0.30), the curve for high income commuters is positioned above the curve for low income commuters, indicating that the higher income commuters are more likely to experience gains ranging from \$0.10 to \$0.30. For the second peak area (ranging approximately from \$0.30 to \$0.50), the low income curve is positioned to the right of the high income curve, indicating that lower income commuters are more likely to experience higher gains. A relevant question here is why the travel cost changes result in a uni-modal distribution (with one peak), while the travel time changes result is a multi-modal distribution (with two peaks). In contrast to the travel cost reductions imposed in the first scenario, all travel modes contribute to the logsum (utility) gains due to the travel time reductions. Only auto and transit modes contribute to the logsum gains that are due to travel cost reductions, as walk and bike mode have no travel costs (in our mode choice model specification). In the case of the travel time reductions in Scenario 2, we find that the first and taller peak (shown in Figure 4.5) corresponds to the commuters who derive a significant portion of their utility gains from auto or transit modes, while the second and shorter peak corresponds to those commuters who derive a significant portion of their gains from walk or bike modes. Given the positions of the low income and high income curves, we find that high income commuters derive much more of their utility gains from auto and transit modes, while low income commuters gain significant levels of utility from auto and transit modes, and walk and bike modes. These findings are supported by the mode shares for low and high income commuters; while the majority of work tours (for both groups) are made by auto modes, low income commuters are much more likely to travel by walk and bike mode (relative to high income commuters).

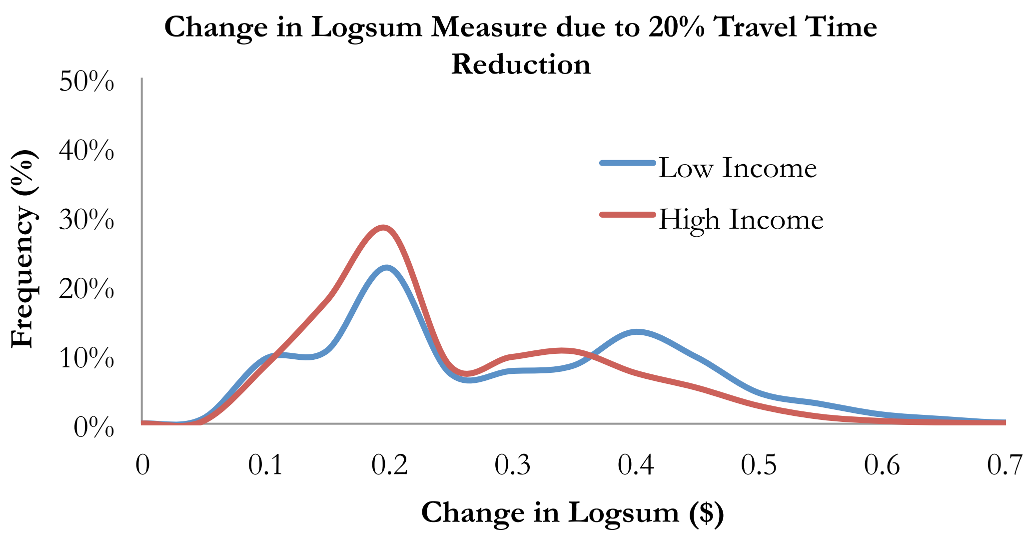

Figure 4.5 Individual Difference Comparison for Scenario 2 (20% Travel Time Reduction)

4.4 Conclusion

In this chapter, we have demonstrated distributional comparisons of (hypothetical) transportation impacts, using disaggregate (synthetic and empirical) travel data. The synthetic data are generated from a hypothetical setting, while the empirical data is taken from the 2000 Bay Area Travel Survey dataset. Using these data and simplistic models of travel behavior (mode choice models), we have shown the advantages of distributional comparisons, relative to comparisons using average calculations. In particular, we emphasize the relationships between characteristics of the populations segments and the distributional outcomes due to the (hypothetical) scenarios.

The hypothetical evaluation results (Section 4.2) points to two data variables that strongly influence the distributional disparities between population segments. There are travel mode availability and residential location. The disparity with regard to winners and losers could not be achieved simply by varying travel network variables: travel times and costs (e.g. a 10% increase or reduction in travel costs). This produces locational distribution shifts only, meaning that all individuals experience very similar effects. However, disparities are pronounced in the presence of travel mode constraints by residential location. The implication here is that the presence of residential clustering by income class (or other segmentation dimensions) in a region may be associated with higher disparities in transportation investment outcomes.

The empirical evaluation results (Section 4.3) show a clear relationship between the travel behavior characteristics of low income and high income workers, and the resulting scenario outcomes. In particular, the shapes of the Individual Difference Densities are reflective of the mode shares for the low and high income groups. While high income commuters derive much more of their utility gains from auto and transit modes, low income commuters gain significant levels of utility from auto and transit modes, and walk and bike modes. In this case, the policy implication is that bicycle and pedestrian investments may provide significant improvements, in terms equitable transportation benefits in the region.

Overall, we find that distributional comparisons are capable of providing a fuller picture of individual travel experiences due to transportation investments. Further, they provide a means of reverse-engineering the scenario impacts and determining specifically what factors lead to various transportation (equity) outcomes. This level of analysis is otherwise limited using average measures.

Chapter 5 . San Francisco Bay Area Case Study: Real-World Evaluation of Proposed Transportation Equity Analysis Process

5.1 Introduction

Thus far, we have presented an advanced methodology for regional transportation equity analysis using activity-based travel demand models (in Chapter 3), and demonstrated the usefulness of distributional comparisons in hypothetical settings (Chapter 4). Here we apply our proposed equity analysis process in a full-scale evaluation of real-world regional transportation planning scenarios. For this case study, we use the Metropolitan Transportation Commission's (MTC) regional activity-based travel model and perform an equity analysis of their recently developed transportation and land-use planning scenarios. The primary objective for this chapter, beyond the application of a full-scale activity-based travel model for regional transportation equity analysis, is to detail the advantages and challenges with such an application. We compare the results of this case study to the results of MTC's 2013 equity analysis of their regional transportation plans, in which they evaluate the same set of planning scenarios as evaluated here. This latest MTC equity analysis is one of very few cases where a full-scale activity-based travel model has been applied for equity analysis of regional transportation plans. Through this comparative perspective, we aim to demonstrate the advantages of our proposed equity analysis process, relative to the existing practices for regional transportation equity analysis.

The remainder of the chapter is organized as follows: Section 5.2 gives a brief overview of MTC's activity-based modeling system and describes the transportation and land-use scenarios being evaluated. Section 5.3 provides a description of the case study data. Section 5.4 gives the evaluation results for each step in the proposed equity analysis process. Section 5.5 presents some important methodological extensions relevant to this case study, and Section 5.6 gives the concluding remarks.

5.2 Bay Area Transportation and MTC's Regional Activity-Based Travel Demand Model

In this section, we give a description of transportation in the San Francisco Bay Area and how it is modeled. MTC uses an activity-based travel model to forecast the transportation and land-use planning scenarios evaluated in this case study: MTC's Travel Model One (MTC, 2013b). We have given a general discussion of activity-based models in Section 3.2. Here we first emphasize important features that are specific to MTC's activity-based modeling system. This is for the purpose of understanding the structure of the model data evaluated herein. For example, the presence of household interaction for travel choices for MTC's model affects the household data output from the model. This is to say that in some cases, the type and organization of the data are simply a construct of the model and may vary for other activity-based modeling systems.

Second, we briefly discuss the Bay Area's transportation system and how it influences transportation affordability for different population segments in the regions. This sets a foundation for understanding existing equity related issues in the Bay Area. Third and finally, we discuss some of the basic population, travel, and land-use characteristic for different population segments.

5.2.1 MTC Model Design

Development for Travel Model One started in 2005 as a joint initiative between MTC and Parsons Brinckerhoff, Inc. The model is estimated and calibrated using a combination of Bay Area Travel Survey (BATS) data for the year 2000, census data, and local transit operator data. The design of the model is intended to realistically represent travel behavior, and it is based on a number of analytical approaches, including multinomial and nested logit models, activity duration models, and entropy-maximization models. The travel model components are grouped into five model component categories; population synthesizer, long-term decisions, daily decisions, tour-level decisions, and trip-level decisions. These groupings, which are for demand-related choice components, are illustrated in the Figure 5.1.

A prominent feature of MTC's model relates to the third grouping of model components: daily decisions. These components model the individual and household daily travel activities, which include the daily activity pattern, tour frequency, scheduling, party size and participation (for joint-tours), and location choice (for all but individual mandatory tours). The daily activity pattern (DAP) model predicts the tour type (mandatory, non-mandatory, or home (no-tour)) for each member in a household. The choice of activity pattern represents a household level choice for single or multiple (possible) individual participants. The tour frequency, scheduling, party and participation (for joint tours), and location choices are predicted (where applicable) for the mandatory and non-mandatory tour types. In particular we want to highlight that these daily pattern-type components for the MTC model capture the influence of household interactions on travel choices. For example, the daily activity pattern model predicts the probability of different combinations of household members' choice of travel pattern. That is, the choice set for this model is the enumeration of all possible combinations of household members and activity pattern types. Further, a joint tour model is included to predict the household level choice of engaging on a joint tour.

While the overall model structure is typical of other existing activity-based models, the household interactions in travel decision-making are not necessarily standard for activity-based travel models. In this case, the design of MTC's model results of joint-tour output files, which contain information on the tours in which multiple household members have decided to participate. These are included for this case study evaluation.

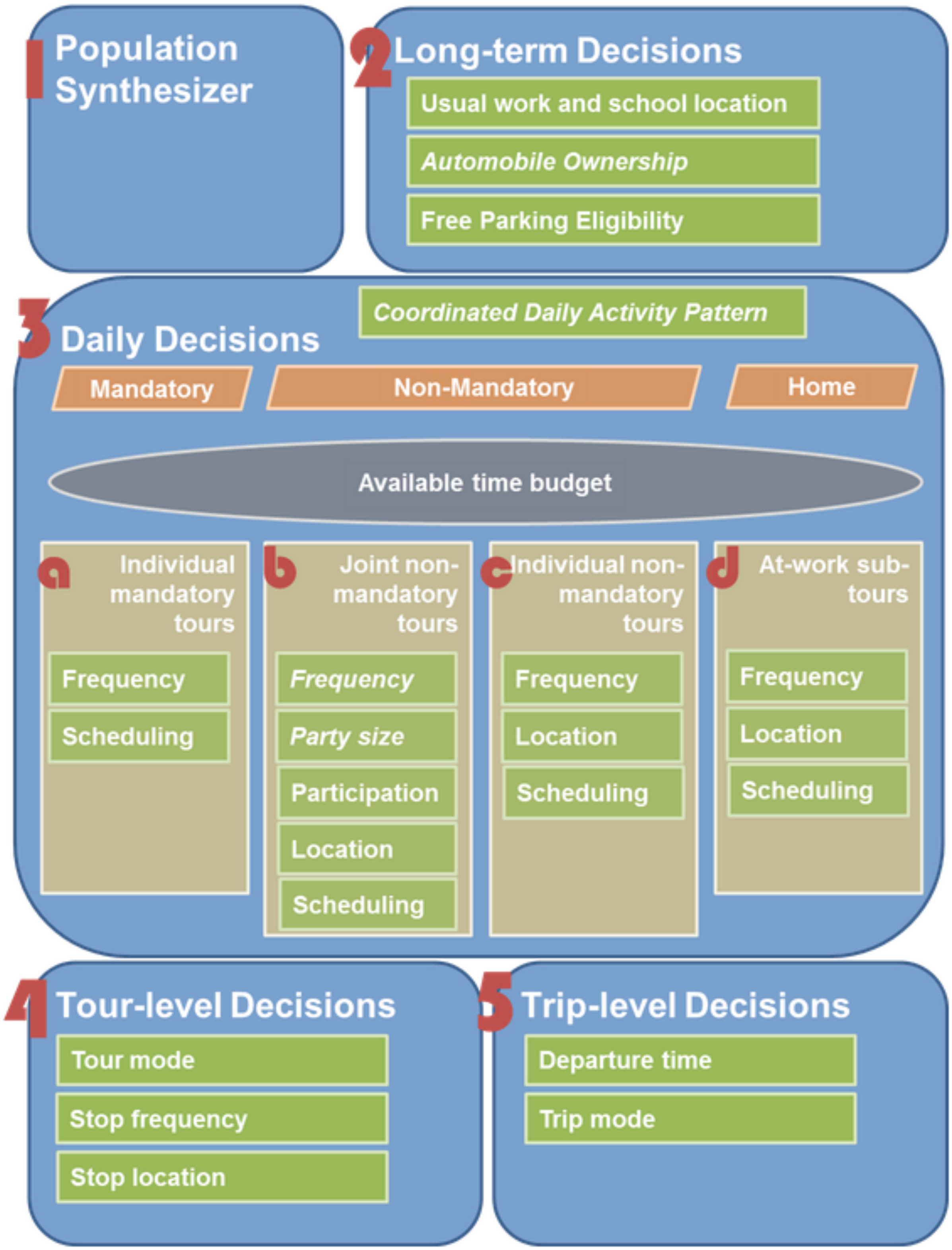

Figure 5.1 Model Schematic for MTC's Activity-Based Travel Demand Model ("Travel Model One") (Ory, 2012)

5.2.2 Transportation and Affordability in the Bay area

The San Francisco Bay Area has a population of some 7.1 million residents in an area encompassing nine counties and over 100 cities. The metropolitan region has three primary central business districts, with San Francisco to the west of the Bay, Oakland to the east, and San Jose to the south. The CBDs are connected to each other and to residential and suburban locations via a complex multimodal transportation network. The transportation network includes an extensive highway system, numerous bus services, eight toll bridges, heavy rail, light rail, commuter rail, and ferries.

The Bay Area's vast transit network helps to provide for significantly lower household transportation expenditures for the region, as compared to other major metropolitan areas (Haas et al., 2006; CNT, 2009; Urban Land Institute, 2012). However, the Bay Area is also among the most expensive of U.S. metropolitan areas regarding housing expenditures. Haas et al. (2006), a study by the Center for Neighborhood Technology, calculated household transportation and housing expenditures as a share of the median household income for 28 major US metropolitan regions. They found that for the San Francisco Bay Area, 15% of the median household income is spent on transportation, while 30% is spent on housing. This is shown in Figure 5.2.

In CNT (2009), a joint study with MTC, they further investigate what this means for low income households earning less than $35,000 annually. According to this study, the conventional rule that housing and transportation expenditures should consume no more that 48% of a household's total income implies that the Bay Area's low income households are in a particularly vulnerable and constrained condition. The high housing costs in the Bay Area in conjunction with the rule of 48% suggests that only 4% of Bay Area housing would be affordable to low income households (CNT, 2009), which are approximately 30% of the region's population. These residential choices are mostly concentrated in eastern San Francisco and some parts of Oakland. This places significant constraints on where low income households are able to reside, as compare to options for higher income households. These higher transportation and housing costs have direct and significant impacts on household budgets, limiting opportunities for (among other activities) saving and creating wealth (CNT, 2009). Further, the constraints on residential location choices directly influence the quality of services and amenities to low income households, as well as accessibility to desired activities and destinations.

The Bay Area's low income residents live under particularly constrained housing conditions. These high housing costs in the Bay Area not only limit where low income residents can afford to live, but limits their opportunities and ability to create wealth. Further, these constraints in residential location likely have implications on their level of access to transportation modes and clustering patterns in the region. As we discuss in Chapter 4, residential clustering patterns can have great impacts of how these residents are affected by transportation plans. Again, this implies that low income residents are particularly vulnerable with regards to transportation and land-use changes. It is supports the need to place some emphasis on low income residents (among other groups) and evaluate equity effects of on low income groups due to transportation plans.

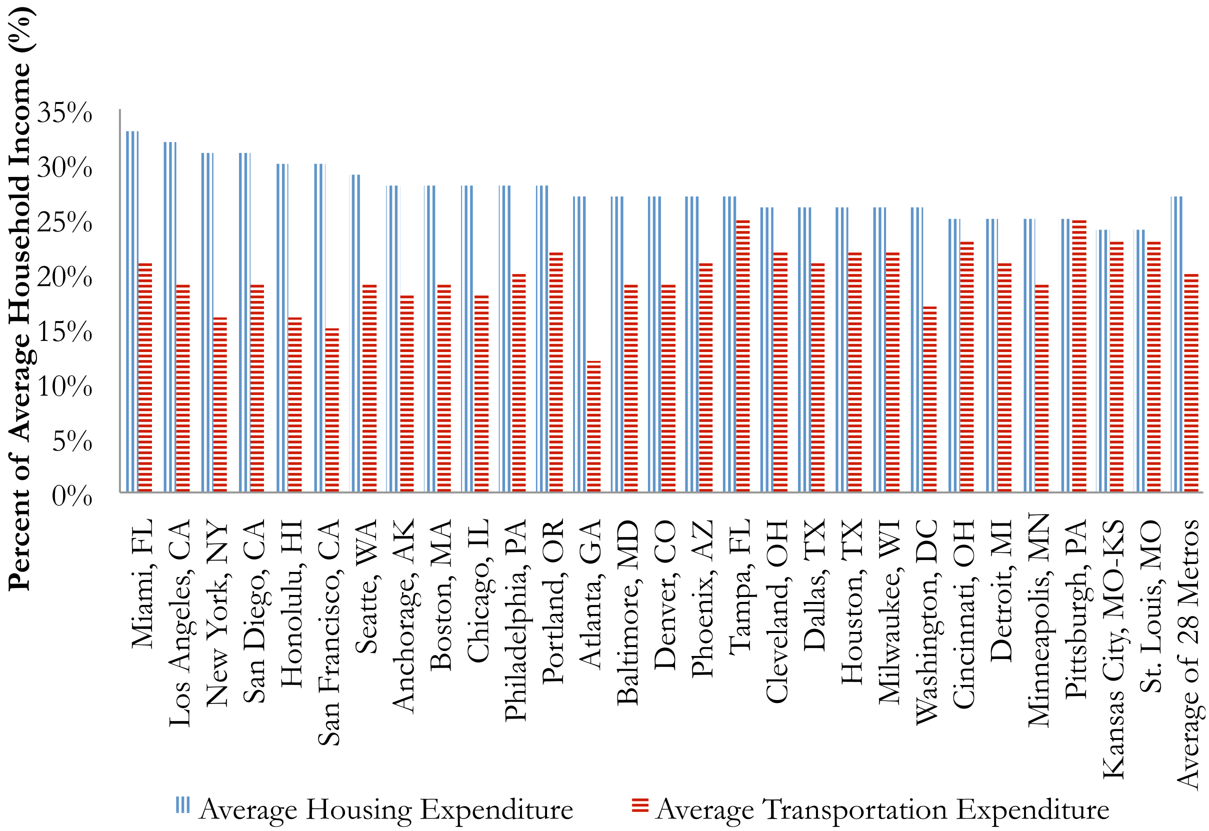

Figure 5.2 Average Transportation and Housing Costs at a Percent of Average Household Income, for 28 US Metropolitan Regions (Haas et al., 2006)

5.2.3 Case Study Context and Data Set

Now that we have given some context on equity related issues in the San Francisco Bay Area, we move on to describing each of the transportation and land-use scenarios evaluated in this case study. We also give a data description of the basic population (exogenous) and travel (endogenous) characteristics exhibited in the data. These scenario and data descriptions will serve to support the discussion of the case study results, as the equity impacts on population segments will be a reflection of the basic population and travel characteristics of these segments, as well as the expected transportation and land-use changes.

Transportation and Land-use Planning Scenarios

MTC developed five planning scenarios for their 2013 Regional Transportation Plan evaluation; one being a "No-Project" scenario and the remaining being four "Project" scenarios that are composed of different transportation investments and land-use policy alternatives (MTC, 2013, Waddell, 2013). The investments included in all scenarios are fiscally constrained, meaning that the investments are feasible from a financial perspective. The travel model data associated with each scenario includes the full regional-scale forecasts for travel behavior changes that are likely to arise due to the combinations of projects and policies specified in the scenarios. In this case study, we evaluate equity outcomes from each of the four "Project" scenarios, relative to the "No-Project" scenario.

Each planning scenario can be summarized in terms of transportation investments (i.e. infrastructure changes), transportation policy investments (e.g. fare changes and congestion pricing schemes), and land-use policy investments (e.g. urban growth boundaries and transit-oriented development). These scenarios have been specified for a 30-year planning horizon (from 2010 to 2040). The total population in the Bay Area in 2010 was 7.15 million, and this is expected to grow to 9.30 million residents by 2040[22]. Table 5.1 provides summaries of the five scenarios[23], using these categories.

Table 5.1 Summary of Transportation and Land-use Scenarios

	Transportation Investments	**Transportation Policies**	**Land-use Policies**
No-Project	Existing	Existing	Existing
Jobs-Housing	Majority Maintained investments and upgrades	No Policy Changes	PDA[24]-Concentrated Growth, and PDA Subsidies
Transit Priority	Jobs-Housing project list with fewer HOV lanes, and VMT tax	Higher Peak Bridge Tolls	TPP[25]-Concentrated Growth, and Urban Core Subsidies
Environmental Justice	Additional service for all major transit operators	Higher Peak Bridge Tolls and VMT tax	PDA-Concentrated Growth, PDA and Urban Core Subsidies
Connected	Same as Jobs-Housing	Higher Peak Bridge Tolls	PDA-Concentrated Growth, PDA Subsidies

No-Project (Base Case) Scenario: This scenario represents the expected changes, based on the 2010 existing transportation system and project list[26], and existing land-use patterns and policies. This can be interpreted as the "business as usual" scenario; there are no new transportation investments (beyond what was fully approved as of May 1, 2011) no new fees, subsidies, or, land-use incentives, and growth/ relocation patterns follow the historic rates and trends.

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[22]This growth total is consistent for all scenarios except the Connected scenario.
[23]For more detail on these planning scenarios, see MTC (2013b).
[24] Priority Developments Area (PDA)
[25] Transit Priority Project (TPP) Areas
[26] For a full list of the projects represented in the scenarios, see MTC (2013b)

Jobs-Housing Connection (Jobs-Housing) Scenario: Regarding transportation investments, this scenario dedicates close to 90% of future revenues to operating and maintaining the (2010) existing road and transit system. This scenario includes major capital investments, such as a San Jose BART extension, Caltrain electrification projects, and Bus Rapid Transit lines plan for some of the region's urban core areas. These improvements correspond to a 27% increase in daily transit capacity from existing conditions across the region, due to transit expansion and frequency improvements. This scenario also includes some highway improvements what will result in a 3% increase in highway capacity. Regarding landuse policy, the Jobs-Housing scenario tests a development pattern that concentrates housing and job growth in areas identified as Priority Development Areas (PDAs), which were identified by local jurisdictions. With this development strategy, 80% of new housing and 66% of new employment will be concentrated in PDAs.

Transit Priority Focus (Transit Priority) Scenario: For this scenario, the transportation investments are similar to those outlined for the "Jobs-Housing" scenario, but have a greater emphasis on strengthening travel and connectivity in the urban core areas of the region. Here, investment are scaled back from highway enhancements and invested for additional BART and AC Transit services in the urban core. Transportation policies for this scenario include an increase of the San Francisco-Oakland Bay Bridge toll to $8 during peak hours. Regarding land-use policies, this scenario tests the potential for more efficient land uses areas called Transit Priority Project (TPP) areas (as defined by Senate Bill 375 (PRC Section 21155)). These TPPs would be developed at higher densities than existing conditions to support high quality transit. There is also a Regional Development Fee based on development in areas that generate high levels of vehicle miles traveled.

Environment, Equity, and Jobs (Environment Justice) Scenario: This scenario reflects a joint proposal developed by a group of transportation equity advocates in the Bay Area: Public Advocates, Urban Habitat, and TransForm (MTC, 2013a). The transportation investments for this scenario generally support increased transit service to historically disadvantaged communities and a reduced roadway network. Regarding transportation policies, this scenario tests a Vehicle Miles Traveled (VMT) tax, as well as an increase of the San Francisco-Oakland Bay Bridge toll to $8 during peak hours. Regarding land use policies, this scenario seeks to maximize affordable housing in "opportunity rich" urban and suburban areas through incentives and housing subsidies in these areas.

Enhanced Network of Communities (Connected) Scenario: For this scenario, the transportation investment strategy is consistent with that of the Jobs-Housing Scenario. Regarding transportation policies, this scenario tests an increase of the San Francisco-Oakland Bay Bridge toll to $8 during peak hours. Regarding land-use policies, this scenario seeks to provide sufficient housing for all Bay Area residents, with no in-commuters from other regions. This scenario also allows for more dispersed residential and employment growth patterns than in the Jobs-Housing Scenario, although development is still primarily focused in PDAs.

5.3 Model Data Description

Here we briefly describe the data used in this case study evaluation. A more thorough discussion is provided in Appendix B. Note that although the travel characteristics will vary due to the (transportation and land-use) changes specified for each scenario, our aim here is simply to provide a general picture of the data trends. As this general picture does not vary significantly across the scenarios, we describe only the "No-Project" scenario data here.

There are two data types available from activity-based travel demand models. The first data type is referred to as population data, and includes exogenous data from economic and population forecasts of individual and household level characteristics. These are relatively the same across all scenarios[27]. The second data type is simply referred to as travel behavior data, and includes the endogenous data that is predicted from the travel model. These include destination choices, auto ownership, tour and stop frequency, tour type, and mode choice, among other variables. We also include a description of residential choices. Given that we evaluate the equity outcomes from groups segmented by income class (for this case study), we particularly emphasize the differences in these population and travel behavior data variables across income classes. The income class definitions are given in Table 5.2. Note that these income classes (roughly) represent income quartiles, and we adopt these income class definitions in order to be consistent with how income is specified for the MTC travel model.

It is important to note that the travel patterns and trends described here are artifacts of the model specification. While the synthetic population and travel behavior features are designed to represent what is observed for actual commuters in the San Francisco Bay Area, it is not our objective to validate how well the model data represents empirical data, specifically across income groups. Nevertheless, we acknowledge that this is an important research direction. Our point here is to give a description of the model output evaluated, and support subsequent discussions of the case study results.

Table 5.2 Household Income Class Definitions

Income Class	Annual Household Income Range (in year 2000 dollars)	Share of 2040 Population
Low Income	0 - $30,000	28.6%
Medium Income	$30,000 – 60,000	24.5%
Medium-High Income	$60,000 - $100,000	23.5%
High Income	$100,000 and greater	23.4%

[27] Only the Connected scenario has a different population forecast.

5.3.1 Summary of Population and Travel Characteristics

Population Data

The population related data used for this case study are contained in the person and household output files. The relevant person file contents include age, gender, and employment status characteristics. There is a household identification number associated with each person record in the person file, which links an individual to a household. The relevant household file contents include income level, household location, household size (e.g. total household members, # workers, # minors, and # seniors), and number of automobiles. Each household's residential location is represented as a travel analysis zone (TAZ) in the region. There is a total of 1454 travel analysis in MTC's zonal system.

The population data (see Appendix B) shows that the lower income individuals are characterized as mostly retirees, non-workers, part-time workers, or university students, while higher income individuals are most likely to be full-time workers than any other person type. Low income household tend to live closer to transit rich areas, relative to high income households. Further, low income households are characterized as smaller households with zeros or few workers, few minors, and are more likely to have seniors, relative to all other income classes. On the other hand, high income households are characterized as larger households, with one or more workers, more minors and fewer seniors, relative to all other households.

Travel Data

The relevant travel behavior related data used in this case study includes the individual and joint tour files, and the travel time skim files. The individual tours comprise approximately 98% of all tours taken, and the file contents include the tour category (mandatory, non-mandatory, or at-work), tour purpose (eat out, escort, school, university, shopping, social, work, etc.), primary origin and destination, origin and destination time-of-day, and number of stops. Note that the mandatory tour type includes work, university, high school, and grade school travel purposes. The joint tours, are non-mandatory tours with multiple household participants. This tour file contains a similar list of variables as the individual tour file. The travel time skim files contain the estimates of travel time between each origin-destination zone pair (1454 x 1454 pairs), for each mode[28], and each time-of-day[29]. Also, the transit time are broken down into types (e.g. wait times, in-vehicle time, transfer times, etc.).

We characterize the travel behavior across income classes in terms of tour frequency (for households and individuals), stop frequency (the number of stops made on a given tour), mode share for mandatory and non-mandatory tours, and household auto ownership. There are a total

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[28] There are a total of 17 available travel modes in the dataset. These include Drive Alone (toll), Drive Alone (no toll), Shared-Ride 2 (toll), Shared-Ride 2 (no toll), Shared-Ride 3 (no toll), Walk, Bike, Walk-Transit (Local Bus), Walk-Transit (Light Rail/Ferry), Walk-Transit (Express Bus), Walk-Transit (BART), Walk-Transit (Commuter Rail), Drive-Transit (Local Bus), Drive-Transit (Light Rail/Ferry), Drive-Transit (Express Bus), Drive-Transit (BART), and Drive-Transit (Commuter Rail).

[29] There are five time-of-day categories; early morning, morning peak, mid-day, afternoon peak, and evening.

of 5,585,018 individual and joint tours contained in the tour files. This represents a 50% sample of all Bay Area tours on a daily basis. Of these, 43% are mandatory tours.

The travel data (see Appendix B) shows that lower income commuters tend to take fewer tours (for mandatory and non-mandatory tour types), relative to high income commuters. Further, lower income households are more likely to own zero or one automobile, and they have a higher tendency toward transit, walk, and bike modes. Higher income households have relatively higher trips frequencies, although the majority of higher income households stay within one to two mandatory and non-mandatory tours daily. In contrast, higher income households are much more likely to travel by auto models, relative to lower income households. Regarding residential location choices, there are high concentrations of low income households primarily in the inner north, east and south bay areas. These areas tend to have higher transit network densities, although there are certainly some low income households residing in less transit accessible areas. Higher income households are more concentrated in the outer south and east bay areas.

5.4 Methodology and Results: Proposed Equity Analysis Process

In the following sections, we present the proposed equity analysis process as it has been applied for this San Francisco Bay Area case. As described in Chapter 3, our proposed process includes four steps. The first step is to identify the equity indicator(s) and determine how to segment the population. The second step is to calculate the indicator(s) from the travel model output. The third step is to generate the distributions from the disaggregate indicators (calculated in step 2) and determining the winners and losers that result from the transportation scenarios. The fourth and final step is to select the equity criteria and apply these criteria to rank the scenarios.

We provide detailed descriptions for each step in our analysis process. In addition, we discuss the evaluation results and limitations where applicable. Further, we take a comparative perspective and discuss our results of each step in relation to the results from the Metropolitan Transportation Commission's Equity Analysis of their 2040 Regional Transportation Plan[30]. This MTC equity analysis represents the current state of best practices for regional transportation equity analysis. With this comparison we aim to make the case that the proposed equity analysis process of this dissertation improves significantly on the existing best practices.

5.4.1 Step 1: Population Segmentation and Indicators

Here we describe the population segmentation approach and indicators used for this case study evaluation. Population segmentation involves the use of one or more variables of segmentation, a unit of segmentation, and a definition or threshold(s) to distinguish the target and non-target groups. For the selection of equity indicators, it is important to consider of whether the indicator truly represents a transportation user benefit (or cost), as well whether there are factors that may confound the expected benefit (or cost) to result from the transportation plan. Note that a more thorough discussion of the considerations for selecting a segmentation approach and indicators is provided in Section 3.3.2.

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[30] For more detail on the MTC's recent equity analysis, see MTC (2013a).

Population Segmentation

Our focus for this case study evaluation is on the vertical equity dimension, and we use income as the variable of segmentation. We focus on vertical equity primarily because this is a dimension of equity emphasized in the Environmental Justice regulations, and adopted commonly for regional transportation equity analyses. We select income as the variable of segmentation for two reasons. The first is that income is one of two primary variables for characterizing transportation disadvantage groups for Environmental Justice issues; with the other variable being ethnicity. The second reason is related to the MTC travel model specification; ethnicity is not included as a socio-demographic variable in the population synthesis for the MTC model, therefore this leaves us to adopt the income variable for segmentation.

We use individual and household level units of analysis in the case study evaluation. In comparison to other more aggregate units such as zones and census blocks, these disaggregate units provide for a more accurate analysis. We give a more thorough discussion in Section 3.3.2; but here disaggregate data analysis is a key advantage of using activity-based travel demand models or the traditional four-step travel models.

We define the low income class as the target group and the high income class as the comparison group. We define low income commuters as the target group to be consistent with how protected groups are defined by Environmental Justice regulations. The high income commuters are selected as the comparison group because they are the least financially constrained; by virtue of their higher income levels, they are afforded more advantages regarding travel. In this way, we are comparing the extreme groups in the population: the lowest and highest income groups. This deviates from MTC's segmentation approach, given that we do not define the comparison group as all other income groups (except low income individuals). While is it certainly important to consider the impacts on middle income groups, our emphasis in this case study demonstration is on presenting the results for the most and least financially constrained income groups. Although not presented in this dissertation, we have done all calculations for the middle income groups and their impacts will range between those of the low income and high income two groups. We use MTC's income class definitions[31] (shown in Table 5.2) in order to be consistent with how income variables are specified for the MTC model. However, it is certainly possible to select any number of other classifications (e.g. quintiles, deciles, etc.).

Indicators

The indicators evaluated for this case study are commute tour travel time (for the outbound leg of the tour), and logsum accessibility/consumer surplus, which is generated from the work destination and mode choice models. While work purpose is the standard travel purpose evaluated in regional transportation equity analyses, other travel purposes can and should be evaluated. Here we aim to evaluate and compare the performance of these two indicators, travel time (mobility) and logsum measure (accessibility), for regional transportation equity analysis. One reason for using these measures in the case study is that they are two of the most common indicators used in regional transportation equity analyses (as shown in Table 3.8). Travel time is

[31] Note that MTC's income class definitions approximate income quartiles.

arguably the most common equity indicator used. Regarding accessibility, there are a number of approaches to measuring accessibility. The accessibility measure used most common is the cumulative opportunity measure (the number of opportunities that can be reaching within a certain travel time). The logsum accessibility measure is selected because of its sensitivity to individual preferences, which makes it suitable as an individual level transportation measure of user benefit. Further the discrete choice framework of activity-based travel demand models makes the calculation of the logsum measure quite convenient. As a final point, the equation of these two indicators will provide some additional insight into the debate on mobility vs. accessibility based measures in transportation planning.

Comparison with MTC Equity Analysis

Regarding equity indicators (specifically those generated using the travel model), MTC evaluates average commute travel time, average non-commute travel time, transportation/housing affordability, and emissions exposure. It is important to note that in a previous MTC equity analysis (MTC, 2009), they evaluated an average cumulative transit accessibility measure for low income jobs as an equity indicator. These equity indicators measure the number of low income jobs that can be reached within 30 minutes by transit. In comparison to our proposed equity analysis process, travel time indicators are used in both studies, while the remaining equity indicators differ (between MTC's study and the current case study).

MTC's equity analysis uses the zonal segmentation approach and defines disadvantaged groups as communities of concern. These communities of concern are geographic units (travel analysis zones) that are defined along multiple dimensions, including minority status, income, English proficiency, auto ownership, senior citizen status, disability status, number of parents in the home, and rent burden. These criteria are given in Table 5.3, along with the concentration thresholds. A zone is classified as a community of concern if four or more of these criteria are met. MTC also provides a version of their results for each dimension separately. Overall, we emphasize that MTC's method of segmentation differs from the approach taken in this case study. MTC uses a multi-criteria definition for the disadvantaged group, while we define the disadvantaged group along one dimension; income. In addition, MTC's unit of analysis (communities of concern) is tied to geographic zones, while we use individuals and households as the units of analysis. MTC also provides a version of their results for each dimension separately. Overall, we emphasize that MTC's method of segmentation differs from the approach taken in this case study. MTC uses a multi-criteria definition for the disadvantaged group, while we define the disadvantaged group along one dimension; income. In addition, MTC's unit of analysis (communities of concern) is tied to geographic zones, while we use individuals and households as the units of analysis.

Table 5.3 MTC Communities of Concern Selection Criteria

Disadvantage Factor	% of Regional Population	Concentration Threshold
1. Minority Population	54%	70%
2. Low Income (<200% of Poverty) Population	23%	30%
3. Limited English Proficiency Population	9%	20%
4. Zero-Vehicle Households	9%	10%
5. Seniors Aged 75 and Over	6%	10%
6. Population with a Disability	18%	25%
7. Single-Parent Families	14%	20%
8. Rent-Burdened Households	10%	15%

5.4.2 Step 2: Indicator Calculations

We evaluate two indicators in this case study: commute tour travel time and mandatory (logsum) accessibility. In the following sections, we detail the calculations for these measures from the MTC travel model data. It is important to note here that these calculations are a reflection of the MTC model specification, as the calculation processes would vary somewhat using output from a different model. For this case study we calculate the indicators using data that are output directly from the MTC travel models. That is, we do not alter the specification of the models in any way, but adopt methods and calculations based on what is available from the travel models.

Travel Time Measure
We evaluate the outbound tour-level commute travel times from primary origin to primary destination[32]. These outbound commute tour travel times are calculated for each individual (commute) tour. They are a function of the household and work locations, travel mode, and time-of-day of travel. These data are available from the travel model output; however, some processing is necessary, given that the individual, household, tour, and travel time data are all output into separate files. This processing involves merging the relevant variables from these files (income, travel mode, primary origin, primary destination, travel time-of-day (for the outbound travel)) for each worker's (first) work tour of the day. The appropriate travel time then needs to be assigned to each work tour record. Several scripts were developed to execute this processing. These scripts were developed using R Statistical and Matlab programming software.

Logsum Measure from MTC Model
Our second equity indicator is the logsum accessibility/consumer surplus measure for mandatory tours (including work, university, high school and grade school purposes). Note that it is also possible to generate a similar measure for non-mandatory tours (for shopping, dining, entertainment, maintenance, and other purposes), using similar calculation processes. The generation of this indicator involves calculating the destination choice logsum for the base case scenario and a given project scenario. The difference between these two logsums is then divided

[32] Note that these are simplified tour travel times, as we ignore all stops made on each tour and use the direct primary origin to primary destination travel times.

by the marginal utility of income, α, which converts the logsum (originally in utils) to dollar ($) units.

The formula for this is as follows:

$$CS_{iaep} = (\frac{1}{\alpha})\left[ln\left(\sum_j exp\ (V_{ijaep}^1)\right) - ln\left(\sum_j exp\ (V_{ijaep}^0)\right)\right]$$
(5.1)

$$\alpha = \beta_{mcLogsum}\beta_{OPcost}^{*} \quad (5.2)$$

$$V_{ijaep} = mcLogsum_{ijae}\beta_{mcLogsum} + ln\left(size_{jep}\right)\beta_{size} \quad (5.3)$$

$$mcLogsum_{ijae} = ln\ (\textstyle\sum_k exp\ (V_{ijkae}))$$
(5.4)

$$V_{ijkae} = \alpha_{ka} + \boldsymbol{time_{ijk}\beta_{time}} + \boldsymbol{cost_{ijk}\beta_{cost,e}} + \boldsymbol{landuse_{ijk}\beta_{landuse}} \quad (5.5)$$

$$size_{jep} = \begin{Bmatrix} \boldsymbol{emp_j\beta_{emp,e}}, if\ p = worker \\ universities_j\beta_{universities}, if\ p = university\ student \\ highSchools_j\beta_{highSchools}, if\ p = highschool\ student \\ gradeSchools_j\beta_{gradeSchools}, if\ p = grade\ school\ student \end{Bmatrix} \quad (5.6)$$

, where *i* is the subscript for the origin (home) zone; *j* is for the destination zone; a is for auto ownership class; *e* is for income class; *p* is for person-type; *k* is for each mode; superscript 1 is for the project scenario; and 0 is for the No-Project scenario.

For equation (5.1), CS_{iaep} is the consumer surplus for zone *i,* auto-ownership class a, income class *e*, and person-type *p*; α is the marginal utility of income; the superscripts 0 and 1 refer to the No-Project scenario and a project scenario, respectively; V_{ijaep} is the systematic utility (regarding the base case or project scenarios) for travel between origin *i* and destination alternative *j*. Note that equation (5.1) shows the total calculations performed. Although the MTC model directly generates the logsum accessibility values (which vary by residential location, income class, and auto-ownership class) from the destination choice model, the consumer surplus calculation is completed manually. That is, once the logsum values are calculated by the MTC model, a series of further calculations are done manually. Each household is assigned an accessibility value for each scenario. Then, the difference in each household's project scenario logsum value is calculated relative to their base case (No-Project) scenario value. This difference value (for each household) is then divided by the (constant) marginal utility of income, as shown in equation (5.1).

Typically, the marginal utility is simply the negative of the cost parameter. However, given that the destination choice utilities do not directly include travel cost, we use the cost parameter from the mode choice model. The mode choice cost parameter enters the destination choice utilities indirectly, via the mode choice logsum. That is, the travel costs enter directly into the mode choice model, and the logsums from the mode choice model enter into the destination choice model utilities[33]. Because of this nested-like model structure, it is necessary to modify the scale of mode choice cost parameter (or marginal utility of income) to the scale of the destination choice utilities. The expression for the (re-scaled) marginal utility of income is given in equation (5.2) (Kalmanje and Kockelman, 2004), where, α is the marginal utility of income, $\beta_{mcLogsum}$ is the mode choice logsum coefficient (parameter associated with the mode choice logsum), and β^*_{OPcost} is the parameter associated with travel operation costs from the mode choice model. The superscript * indicates that this cost parameter is fixed and does not vary by income class, as does the cost parameter of the mode choice model. This formulation can be easily understood if we consider that β^*_{OPcost} is actually multiplied by the mode choice scale parameter μ_{mc} and $\beta_{mcLogsum}$ is actually the ratio of the destination choice scale parameter to the mode choice scale parameter, μ_{dc}/μ_{mc}. Therefore mathematically, equation (5.2) gives us the re-scaled mode choice cost parameter: $\mu_{dc}\beta^*_{OPcost} = \mu_{mc}\beta^*_{OPcost} * \mu_{dc}/\mu_{mc}$. For a fuller discussion of scale parameters of discrete choice models, see Train (2003).

It is important to note that the marginal utility of income may in reality vary according to the income levels of the decision makers (Abouchar, 1982; Jara-Díaz and Videla, 1988**.** However, the use of heterogeneous marginal utilities of income (the inclusion of income effects) would lead to the issues outlined in Section 3.4.3. That is, the use of heterogeneous marginal utilities of income would result in greater (positive or negative) weight to the impacts on high income travelers. The use of a constant value for the marginal utility of income has been validated and is common, particularly in the case of welfare changes in discrete choice situations (Williams, 1976; Rosen and Small, 1981). Therefore, we apply a constant marginal utility of income for this case study evaluation. Although this measure (using a constant marginal utility of income) is inconsistent with the theoretical consumer surplus measure (using heterogeneous marginal utilities), this approach allows for useful consumer surplus comparisons across income groups.

The systematic destination choice utility takes the formulation given in equation (5.3), where V_{ijaep} is the systematic utility for origin i and destination alternative j, auto-ownership class a, income class e, and person-type p; $\beta_{mcLogsum}$ is the parameter associated with the mode choice logsum, $mcLogsum_{ijae}$, and β_{size} is the parameter associated with the log-size term, $\ln(\mathrm{size_{jep}})$. As indicated in equation (5.1), the systematic destination choice utilities are calculated for the No-Project ($\mathrm{V^0_{ijaep}}$) and Project scenarios ($\mathrm{V^1_{ijaep}}$).

The mode choice logsum takes the general formulation given in equation (5.4), where $mcLogsum_{ijae}$ is the mode choice logsum value for origin i and destination alternative j, auto-ownership class a, and income class e, and V_{ijkae} is the systematic utility for mode alternative k. There are five (simplified) mode alternatives included in the mode choice logsum; single occupancy vehicle (SOV), high occupancy vehicle (HOV), walk-transit (WT), drive-transit (DT), and non-motorized.

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[33] Note that the mode choice logsum is included in the destination choice utilities as a measure of level-of-service.

The systematic utilities for the simplified mode choice alternatives take the form given in equation (5.5), where, V_{ijkae} again is the systematic utility from origin *i* to destination alternative *j*, for mode alternative *k,* auto-ownership class a, and income class *e;* α_{ka} is the alterative specific constant; $\boldsymbol{\beta_{time}}$ is the vector of parameters associated with travel times $\boldsymbol{time_{ijk}}$, $\boldsymbol{\beta_{cost}}$ is the vector of parameters associated with travel costs $\boldsymbol{cost_{ijk}}$, and $\boldsymbol{\beta_{landuse}}$ is the vector of parameters associated with land-use variables $\boldsymbol{landuse_{ijk}}$. The travel time variables include in-vehicle and/or walk access for all modes, and access, auxiliary, egress, and wait times for transit modes. Travel costs variables include operating cost for all motorized modes, and toll and parking costs for single and high occupancy vehicle modes. There are no costs included for the non-motorized mode. Finally, the land use variables include area density[34] and topology measures for non-motorized and transit modes. These land-use variables are not included for single and high occupancy vehicle modes.

Finally, the formulation for the mandatory size term $size_{jep}$ is given in equation (5.6). Here, $size_{jep}$ is the linear combination of mandatory activities for destination zone j, income class *e*, and person-type p. The variable $\boldsymbol{\beta_{emp,e,p}}$ represents the vector of parameters associated with employment types, $\boldsymbol{emp_j}$; $\beta_{universities,p}$ is the parameter associated with the number of universities, $universities_j$; $\beta_{highSchools,p}$ is the parameter associated with the number of high schools, $highSchools_j$; and $\beta_{gradeSchools,j,p}$ is the parameter associated with the number of grade schools, $gradeSchools_j$. The employment types (sectors) include trade and retail, financial and professional services, health, educational and recreational services, agricultural and natural resources, and manufacturing and transportation. The person types include workers, and university, high school, and grade school students. Additionally, the size term (for workers only) varies by income.

5.4.3 Step 3: Distributional Comparisons

Here we present the distributional comparison results for the two equity measures: commute tour travel time and logsum accessibility/ consumer surplus. The emphasis here is on showing the level of information gained from distributional comparisons, beyond the comparison of average measures. We first present some results from MTC's average commute travel time measure. These results are taken directly from MTC's equity analysis report for their 2040 Regional Transportation Plan. We then present similar calculations for average commute travel time, but using our own processing scripts. The key difference here is with the group segmentation approach (their zonal vs. our individual-level segmentation). We then compare our results for the average measures to our distributional measures of commute travel time change. Next, we present the results for our accessibility/ consumer measure. MTC does not evaluate the logsum accessibility/consumer surplus measure in their analysis, so we are unable to make a comparison using this indicator. However, we calculate measures of average change in accessibility/consumer surplus and compare these results to the distributional comparison results

[34] The area density is a measure of population and employment density. For more on this see (MTC, 2013a).

for the accessibility/consumer surplus measure. The two types of distributional comparisons used here are the Aggregate Density comparison and the Individual Difference Density comparison.

Constraints and Implications

The activity-based travel models' use of micro-simulation for forecasting travel behavior makes it necessary to make constraints on the calculation of the equity indicators. In the micro-simulation process, realizations of the outcomes for each choice dimension are drawn randomly from a distribution for each model run. This means we cannot assume that fundamental individual and household level characteristics such as work locations or residential location, are consistent across model runs. For these reasons, we make some constraints on the calculations of commute tour travel time and mandatory logsum accessibility/ consumer surplus. These constraints apply specifically to the Individual Difference Density comparisons and not the Aggregate Density comparisons. The types of constraints vary based on the equity indicator. Before proceeding with the distributional evaluation results, it is important to revisit the constraints made on calculating the two indicators and discuss the implications of these constraints.

Travel Time Indicator: Regarding commute tour travel time, the household residential location, work location, travel mode, and travel time-of-day are constrained to be the same across model runs. This means that for the different scenarios, only the travel time skim (a function of level-of-service) varies. The implication here is that the choices of residential location, work location, travel time-of-day, and travel mode are not influenced as a result of transportation and land-use changes. However, in reality an individual may certainly (for example) decide to take rail transit to work (instead of auto), leave for work at an earlier time, or even (over time) change work locations due a new congestion pricing policy. Regarding the impact of these constraints on evaluation results, it is likely that the share "losers" calculated, as well as their magnitude of loss is over estimated.

Logsum Indicator: Regarding the accessibility/consumer surplus measure, the household location is constrained to be the same across scenario runs. This means that the transportation and land-use changes for each scenario have no impact on residential location choice. This may introduce a bias, as in reality, households may choose to relocate due to transportation and/or land-use changes. Therefore, it is likely that the share of "losers" (as well as "winners"), and the magnitudes of losses and gains are over or underestimated. The direction of this bias is not immediately clear and will require further investigation.

Results for Commute Travel Time Measure

MTC Equity Analysis Results (Averages)

MTC results for commute travel time are shown in Figure 5.3. Note that MTC generally uses multiple segmentation variables (listed in Table 5.3) to segment the population. However, the results shown in Figure 5.3 are segmented along single variables as opposed to the full multi-criteria definitions. These results show that on average low income communities[35](for the Project scenario relative to the No-Project scenario) will experience a 3% reduction in mandatory travel time, while all other (higher) income communities will on average experience a 6% reduction in mandatory travel time. That is, low income groups benefit only half as much from the Project scenario relative to all other income groups. Note that the Project scenario emphasized here refers to the "Job-Housing" scenario. Further, MTC focuses on this scenario because it is ultimately selected as the preferred scenario for their Regional Transportation Plan.

Scenario			1	2	3	4	5	% Change	
	Community Type	Base Year	No Project	Project	Transit Priority	Network of Comm.	Env. Equity & Jobs	Base Year to Project	No Project to Project
Minority	Minority Pop. > 70%	25	27	27	26	27	26	6%	-1%
	Minority Pop. < 70%	27	29	27	26	27	27	1%	-7%
Low-Income	Low-Income Pop. >30%	25	27	26	25	26	25	3%	-3%
	Low-Income Pop. < 30%	27	29	27	27	28	27	2%	-6%
Limited-English	LEP Pop. > 20%	24	26	25	25	26	25	5%	-2%
Proficiency	LEP Pop. < 20%	27	29	27	26	27	27	2%	-5%
Zero-Vehicle	Zero-Vehicle HHs > 10%	25	26	26	26	26	25	4%	-1%
Households	Zero-Vehicle HHs > 10%	27	29	27	26	28	27	2%	-6%
Seniors 75+	75+ Pop. > 10%	26	31	27	27	27	27	1%	-13%
	75+ Pop. < 10%	26	28	27	26	27	27	2%	-4%
Persons w/	Pop. w/ Disability > 15%	25	27	26	25	26	25	5%	-1%
a Disability	Pop. w/ Disability < 15%	27	29	27	26	27	27	2%	-5%
Single-Parent	Single-Parent Fam > 15%	26	27	27	25	26	26	3%	-2%
Families	Single-Parent Fam < 15%	27	29	27	27	27	27	2%	-6%
Rent-Burdened	Rent-Burdened HHs > 15%	25	27	26	25	26	25	5%	-3%
Households	Rent-Burdened HHs < 15%	27	29	27	27	27	27	2%	-6%
6+ Disadv.	6+ Disadvantage Factors	25	26	26	25	26	25	5%	-1%
Factors	<6 Disadvantage Factors	27	29	27	26	27	27	2%	-5%
	Regional Average	26	28	27	26	27	27	2%	-5%

Figure 5.3 MTC Equity Analysis of 2040 RTP/SCS Example:
Commute Time (Minute), based on individual modes taken (MTC, 2013).
Note that 40% of the low income population is represented in the "Low-Income Pop. > 30%" community type (see Appendix C).

[35] Here, low income communities are defined as zones where 30% or more of households earn less than $50,000 per year (MTC, 2013a).

SF Bay Area Case Study Equity Analysis Results (Averages)
Table 5.4 shows the results for average commute travel time, for low income and high income individuals, for all scenarios. Note that the key differences relative to the MTC results (above) is that these are averaged across individuals instead of zones, and the low income group here is defined as any individual living in a household earning less than $30,000 annually, as opposed to $50,000 annually. Overall, the evaluation of the percentage change in commute travel times indicates that on average, low income and high income commuters will experience a reduction in travel time, relative to the No-Project scenario. Further, the savings benefits accrued to low income commuters is greater than the benefits to high income commuters for all scenarios. The exception is with the "Connected" scenario results for High income commuters. In this case, they experience an increase in travel time (on average).

Table 5.4 Average Travel Time Results

Scenarios	Average Commute Travel Time			%Change in Commute Travel Time	
	All Individuals	Low Income	High Income	Low Income	High Income
No-Project	28.4	28.3	28.6	--	--
Transit Priority	26.3	24.1	28.0	-14.7%	-2.1%
Environmental Justice	26.9	24.8	28.5	-12.2%	-0.5%
Connected	27.1	24.2	29.3	-14.4%	2.5%
Jobs-Housing	27.0	25.2	28.1	-11.0%	-1.8%

SF Bay Area Case Study Equity Analysis Results (Distributional Comparisons)

Aggregate Density Comparison
Here we present graphical and quantitative comparisons of the Aggregate Densities, for low income (Figure 5.4) and high income commuters (Figure 5.5). The graphs in each figure are frequency plots, where the frequency of travel times has been plotted for one-minute bins. (Note that these graphs are similar to histograms, but the points are connected in a continuous fashion instead of vertical bars.) For the graphical comparisons, we are interested in the position of the scenario (dashed) curves, relative to the No-Project (solid) curve. This gives an overall indication of whether travel times are increasing or decreasing. For the quantitative comparisons, we group the travel times into bins and calculate the shares of tours that fall into each bin. The bins[36], which are marked on the figures using vertical dashed lines, are quartiles that have been slightly adjusted to correspond with more meaningful travel time ranges.

Figure 5.4 (A) through (D) show the graphical Aggregate Density comparisons for commute travel time for low income commuters. The dotted curves representing the distributions of

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[36] Data binning refers to the categorization of data into a manageable intervals which are convenient for analysis (Larose, 2005).

commute travel time under the different scenarios generally fall just above the solid (No-Project scenario) curve. This indicates an overall reduction in travel times. However, there is very little visual difference in the aggregate densities.

We do observe some noticeable differences when we compare travel time bins for low income commuters. For each travel time group, we calculate the share of observations associated with each bin. These are presented in the Table 5.5. Again, we do not observe much change when comparing across the Project scenarios, but relative to the No-Project scenario, we observe a more noticeable reduction in the frequencies of tours longer than 40 minutes. Of the four Project scenarios, the Transit Priority scenario resents in the greatest reduction in times over 40 minutes, with 15.7% for the Transit Priority scenario vs. 20.8% for the No-Project scenario.

Overall we find a positive trend for low income commuters: commute travel times are being reduced as a result of the scenarios. The quantitative comparisons (using travel time bins) provide useful information about the types of tours that are affected in the different scenarios. We see that at the aggregate level, the distributions shift away from longer travel times (40+ minutes) and toward shorter travel times (ranging from 0 to 40 minutes), particularly in the case of the Transit Priority scenario.

Table 5.5 Travel Time Group Results (Low Income)

Bins	**Low Income Travel Time Groupings**				
	No-Project	Transit Priority	Env. Justice	Connected	Jobs-Housing
0-10 Minutes	25.5%	27.6%	27.2%	28.1%	27.7%
10-20 Minutes	28.0%	30.1%	28.8%	29.3%	29.0%
20-40 Minutes	25.6%	26.6%	26.6%	26.5%	26.5%
40+ Minutes	20.8%	15.7%	17.4%	16.1%	16.8%

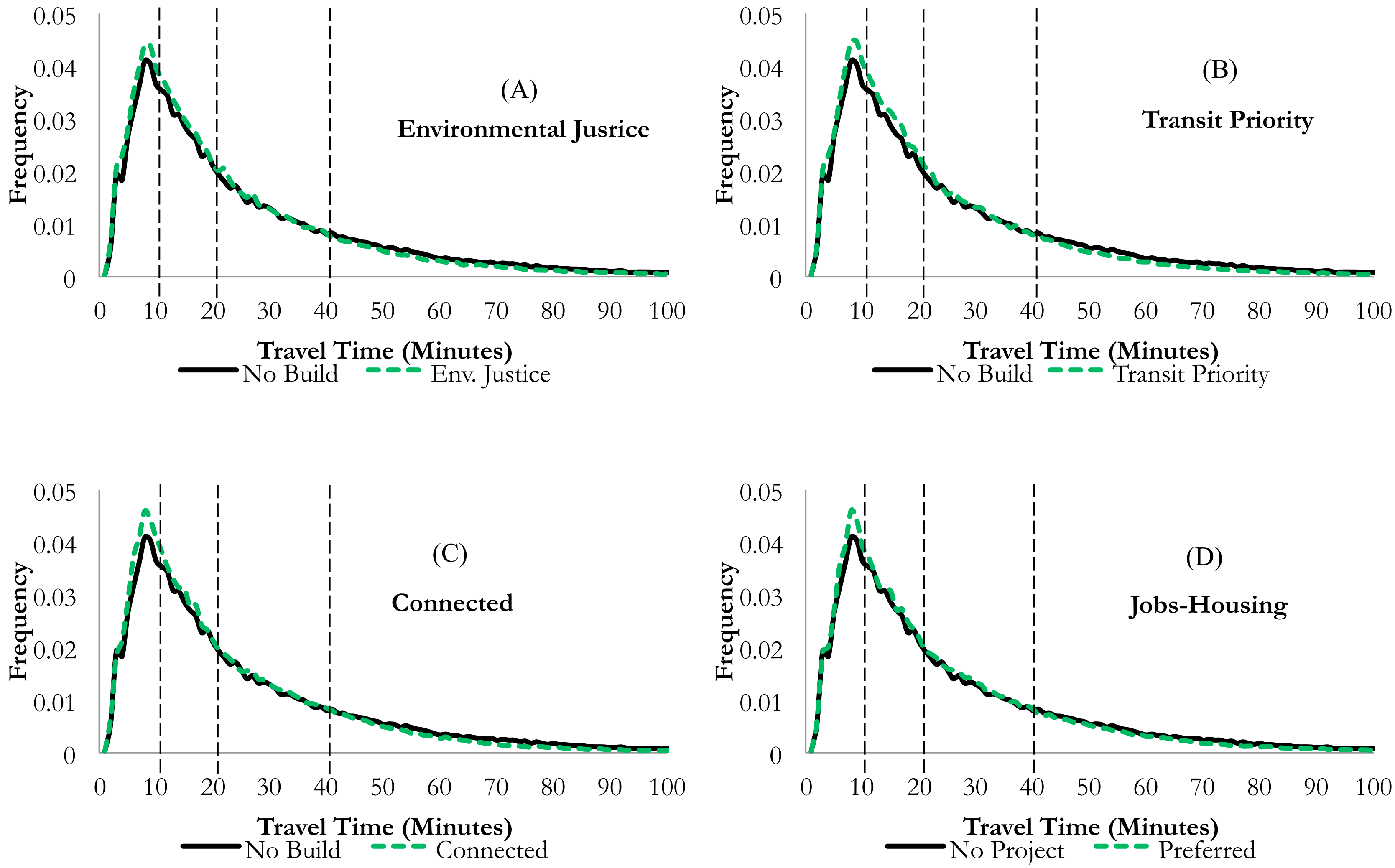

Figure 5.4 (A-D) Aggregate Commute Travel Time Densities (Low Income). Environmental Justice Scenario (A), Transit Priority Scenario (B), Connected Scenario (C), Jobs-Housing Scenario (D).

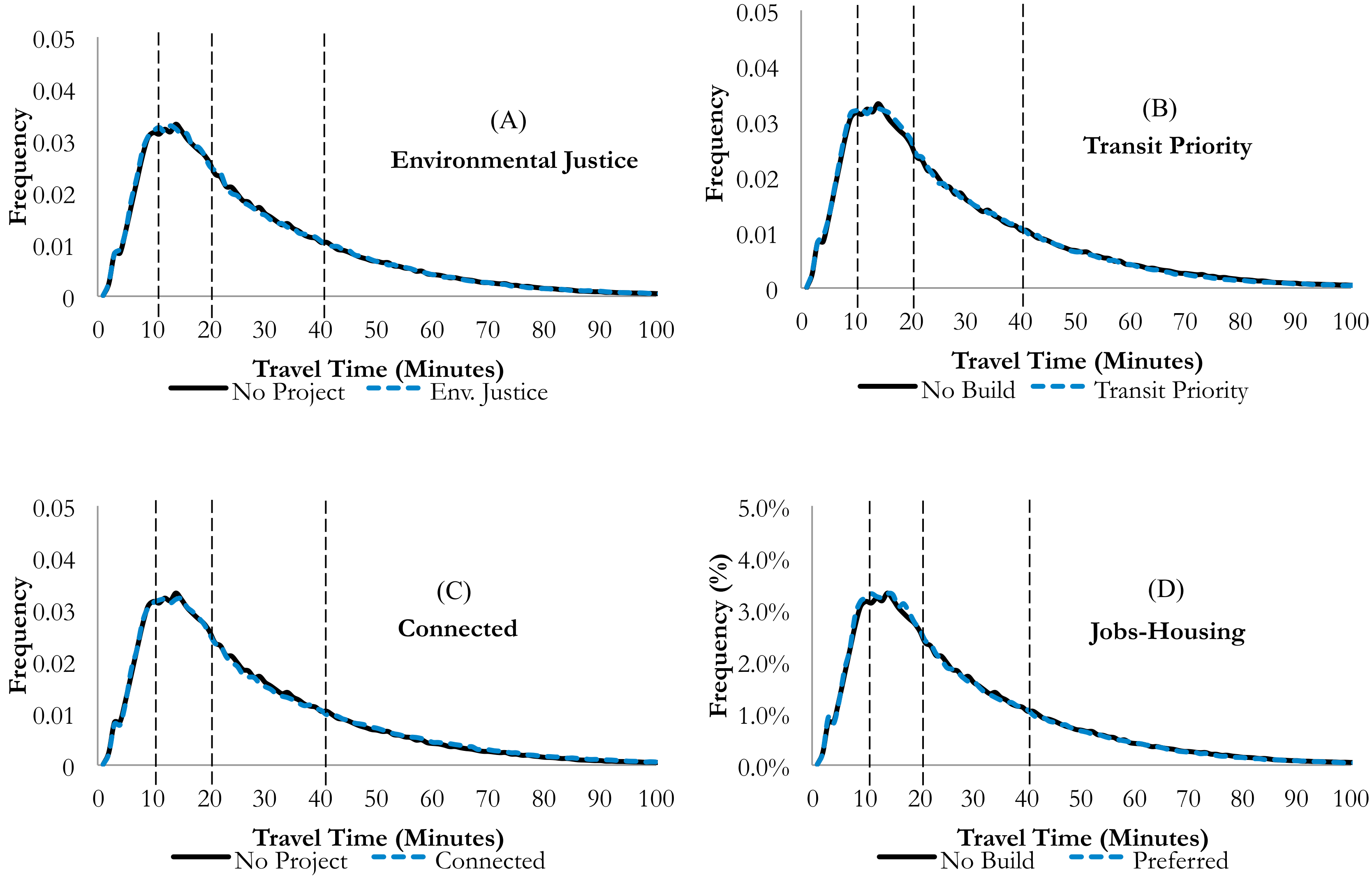

Figure 5.5 (A-D) Aggregate Commute Travel Time Densities (High Income). Environmental Justice Scenario (A), Transit Priority Scenario (B), Connected Scenario (C), Jobs-Housing Scenario (D).

Figure 5.5. (A) through (D) show the Aggregate Density comparisons of the commute travel time distributions for high income commuters. When compared to the distributions for low income travel times, we see that the travel time distributions of high income commuters have greater spreads (variance), indicating that high income commuters generally experience longer travel times. This is consistent with the reality that higher income commuters tend to live farther from employment districts, therefore experience longer traveler times (White, 1986).

As we saw for the scenario comparisons for low income commuters, the (slight) left-ward shift of the dashed curve indicates a general reduction in travel times for high income commuters. However, there is very little visual change in any of these distributions relative to the No-Project scenario.

The travel time frequency bins for high income commuters are presented in Table 5.6. As we saw for low income commuters, the travel time bins show more significant differences for the 40+ travel time group, although only slightly so. Particularly, we observe slight reductions in the shares for very long travel times for the Transit Priority, Environmental Justice, and Jobs-Housing scenarios, and a slight increase in the share of very longer travel times for the Connected scenario. In comparison with the results for low income commuters, we observe much less of a reduction in travel times of 40+ minutes, for all scenarios. It seems that high income commuters are much less affected by the transportation and land use changes of the different scenarios.

Table 5.6 Travel Time Group Results (High Income)

High Income Travel Time Groupings					
	No-Project	Transit Priority	Env. Justice	Connected	Jobs-Housing
0-10 Minutes	16.0%	16.5%	16.5%	16.0%	16.5%
10-20 Minutes	30.1%	30.6%	30.2%	30.0%	30.9%
20-40 Minutes	32.3%	32.4%	32.0%	31.2%	31.9%
>40 Minutes	21.6%	20.5%	21.4%	22.8%	20.7%

Individual Difference Density Comparison

Figure 5.6 *(*A) through (D) show the results for the commute travel times individual difference density comparison for the four Project scenarios. In this case, any data point to the right of the origin (zero on the x-axis) represents a positive change or increase in commute travel time, while a data point to the left of the origin represents a negative change or reduction in commute travel time. On other words, the share of the distribution to the right of the origin represents the "losers" [37] and the share of the distribution to the left represents the "winners". For the Transit Priority, Environmental Justice, and Connected scenarios, we observe that the black curve, representing low income commuters, falls primarily to the left of the gray curve. This indicates that low income commuters are more likely to experience reductions in travel time, relative to

[37] Note that we consider individuals who experience no change in travel time as "losers."

the high income commuters. However, the visual comparison is less clear for the Jobs-Housing scenario.

We can evaluate more clearly the impacts on the income classes by calculating the share of individuals who experience increases in travel times ("losers"). These are presented in Table 5.7. For low income commuters, we see that they are least likely to experience an increase in commute travel time for the Environmental Justice scenario, with 17.55% losers for Environmental Justice vs. 19.18%, 25.86%, and 23.23% for the Transit Priority, Connected, and Jobs-Housing scenarios, respectively. For High income commuters, they are more likely to experience an increase in commute travel time for the Connected scenario, relative to all other scenarios, with 30.48% for the Connected scenario vs. 25.53%, 25.53%, and 25.47% for the Transit Priority, Connected, and Jobs-Housing scenarios, respectively. When we compare across the income classes, we see that the high income commuter are more likely than low income commuters to experience increases in travel time, for all scenarios.

Table 5.7 Share of Commuters who Experience an Increase in Commute Travel Time

	Experienced an Increase in Travel Time (Losers)	
	Low Income	High Income
Transit Priority	19.18%	25.53%
Environmental Justice	17.55%	23.53%
Connected	25.86%	30.48%
Jobs-Housing	23.23%	25.47%

Summary of Travel Time Results

The distributional comparisons reveal additional useful information about the travel time related impacts on the two income classes, beyond what is indicated by the average measures used in the MTC equity analysis. The Aggregate Density frequency bin comparisons show that there are more distinct decreases in longer travel time frequencies for all scenarios, for both income classes. This is with the exception of the Connected scenario for high income commuters, where there is a slight increase in the share of longer trips. When we compare the impacts for low income commuters relative to high income commuters, we observe that they are more affected by the scenario changes, relative to high income commuters. The Individual Difference density comparisons reveal that the share of low income commuters experiencing an increase in travel time is at least 17.55% for all cases, as compared to 23.5% for high income commuters. It is important to note that this level of insight is not possible using average measures, as is typical of equity analyses done in practice. For example, MTC's results indicate that on average all commuters gain in travel time savings. Overall, our evaluation of commute travel time distributions show that the low income commuters are left slightly better off after the two scenarios, based on the calculated shares of "losers". This is opposite of MTC's findings, where higher income commuters are better off, relative to the low income commuters.

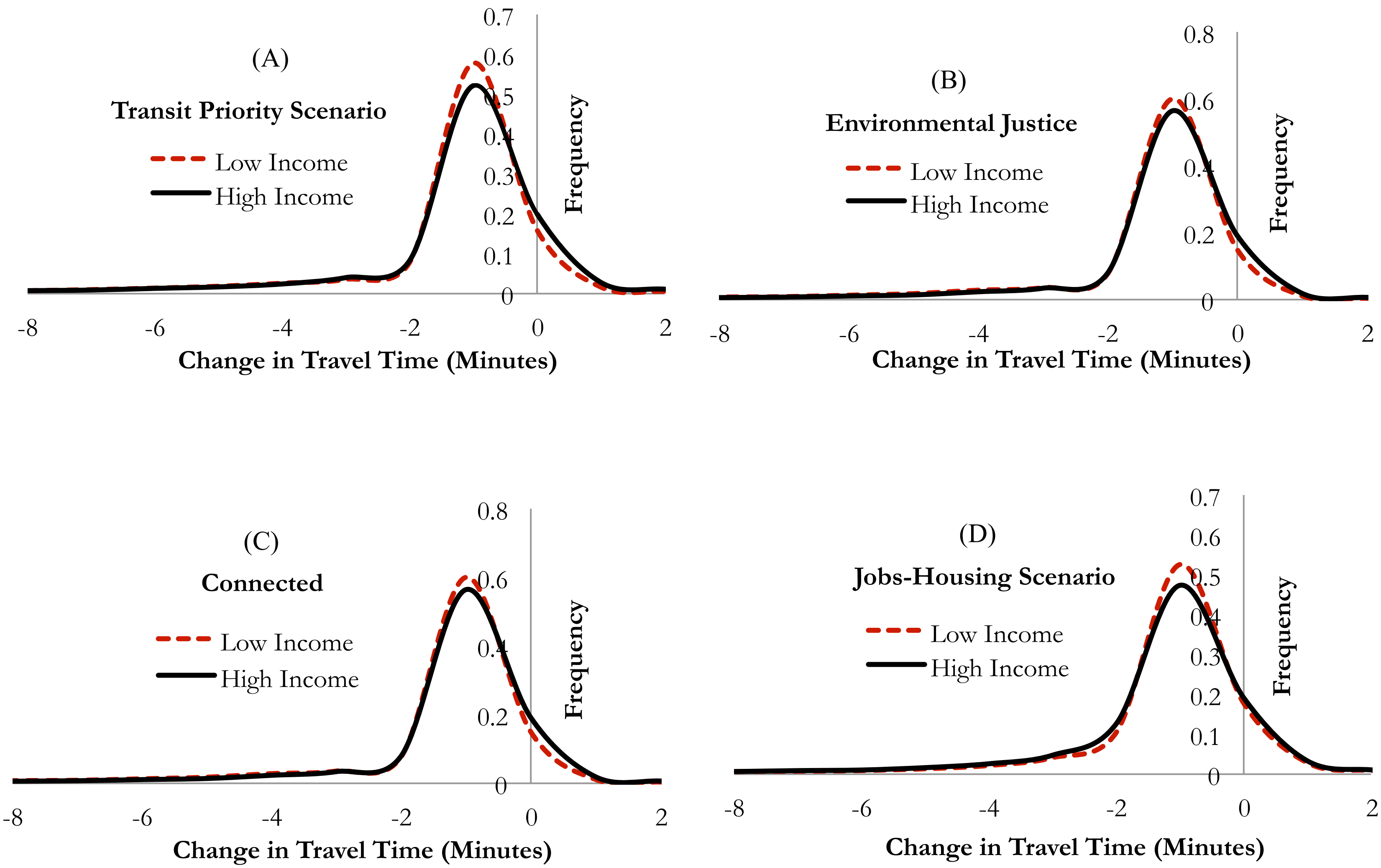

Figure 5.6 (A-D) Individual difference Density Comparisons (Commute Travel Time) Transit Priority Scenario (A)

Results for Logsum Accessibility/Consumer Surplus Measure

SF Bay Area Case Study Equity Analysis Results (Averages)

Table 5.8 presents the average difference in accessibility experienced daily and annually for low income and high income households. Recall from Section 3.3.3 that consumer surplus refers to the total value that individuals place on goods and services (Just et al., 2004). The calculation of the logsum consumer surplus measure calls for the use of heterogeneous marginal utilities of income, representing that individuals with different income levels have different willingness-to-pay for goods and services. Because the use of heterogeneous marginal utilities of income results in inconsistent scales when comparing consumer surplus measures across income groups, we use an average marginal utility of income for all individuals. If these were true measures of consumer surplus (using heterogeneous marginal utility of income), we would observe that the gains for higher income commuters would be greater that the gains for lower income commuters.

These values (in Table 5.8) (which are calculated at the household level) are calculated by measuring the difference in logsum accessibility due to each scenario relative to the No-Project scenario. The groups are segmented income classes and the differences are averaged within each income class. These evaluation results demonstrate the outcomes likely to result using the existing practice of applying average measures. The results show that on average, households will benefit in the case of all scenarios, although high income households benefit more so than low income households. Further, there are higher gains in accessibility due to the Jobs-Housing scenario, relative to all other scenarios. We also include ratios of high income to low income consumer surplus in Table 5.8. These show that on average, the high income commuter benefits are almost two times as much as the benefits to low income commuters. Further, these ratios show that the scenarios all result in very similar relative impacts.

Table 5.8 Average Difference in Logsum Accessibility/ Consumer Surplus (in unit of dollars)

Scenarios	**Average (Daily) Change in Consumer Surplus ($)**		**Average (Annual) Change in Consumer Surplus ($)**		**High/Low Inc. Ratio**
	Low Income	High Income	Low Income	High Income	
No-Project	--	--	--	--	--
Transit Priority	$0.98	$1.61	$254.80	$418.60	1.64
Environmental Justice	$0.83	$1.44	$215.80	$374.40	1.73
Connected	$1.11	$1.93	$288.60	$501.80	1.74
Jobs-Housing	$1.26	$2.19	$327.60	$569.40	1.74

SF Bay Area Case Study Equity Analysis Results (Distributional Comparisons)

Figure 5.7 (A) through (D) show the Individual Difference Density comparisons of accessibility, for the four Project scenarios. Any data point to the right of the origin represents an increase or positive change in accessibility, and point to left of the origin represents decrease or negative change in accessibility. Given that an increase in the accessibility value is the desired result, the share of the distribution to the right of the origin represents the "Winners", while the share of the distribution to the left of the origin represents the "losers". For all scenarios, we see that the curve for low income commuters falls to the left of the curve for high income commuters, indicating that low income households are much more likely to experience reductions in accessibility, relative to high income households. Further, the Transit Priority scenario distribution is bi-modal for low income commuters. The visual interpretation is that there are high frequencies of households experiencing small positive changes and small negative changes in accessibly. From the calculated shares of "losers" presented in Table 5.9, we see again that for all scenarios, low income households are most likely to experience a decrease in accessibility. In the most extreme case (the Transit Priority scenario), as many as 33.3% of low income commuters experience a loss in accessibility/ consumer surplus, compared to 13.4% for high income commuters. Here, we also calculate the average amount of loss in consumer surplus (in dollars) to be experienced by low income and high income losers (shown in Table 5.10). These are the average daily amounts of loss for households that experience a loss in consumer surplus (losers), for each income class and scenario. We see that regarding order of magnitude, low income households lose more in consumer surplus, for all scenarios, on a daily basis.

Table 5.9 Share of Households Who Experience a Decrease in Accessibility

	Experienced a Decrease in Accessibility (Losers)			
	Transit Priority	Jobs-Housing	Environmental Justice	Connected
Low Income	33.3%	19.3%	25.1%	16.7%
High Income	13.4%	6.0%	10.1%	7.7%

Table 5.10 Average Daily loss in Consumer Surplus for "losers"

	(Daily) Amount of Loss ($)			
	Transit Priority	Jobs-Housing	Environmental Justice	Connected
Low Income	-$1.76	-$3.54	-$2.04	-$4.14
High Income	-$1.38	-$3.34	-$1.50	-$3.02

Overall, the Individual Difference Density comparisons for the Accessibility/consumer surplus indicator reveal that as much as 33% of low income households will experience decreases in accessibility relative to 13.4% of high income households. Further, we observe the trend that the lowest income commuters are most likely to experience reductions in accessibility. A more thorough investigation of the travel-related conditions for low income and high groups is necessary to better understand the reasons for these results.

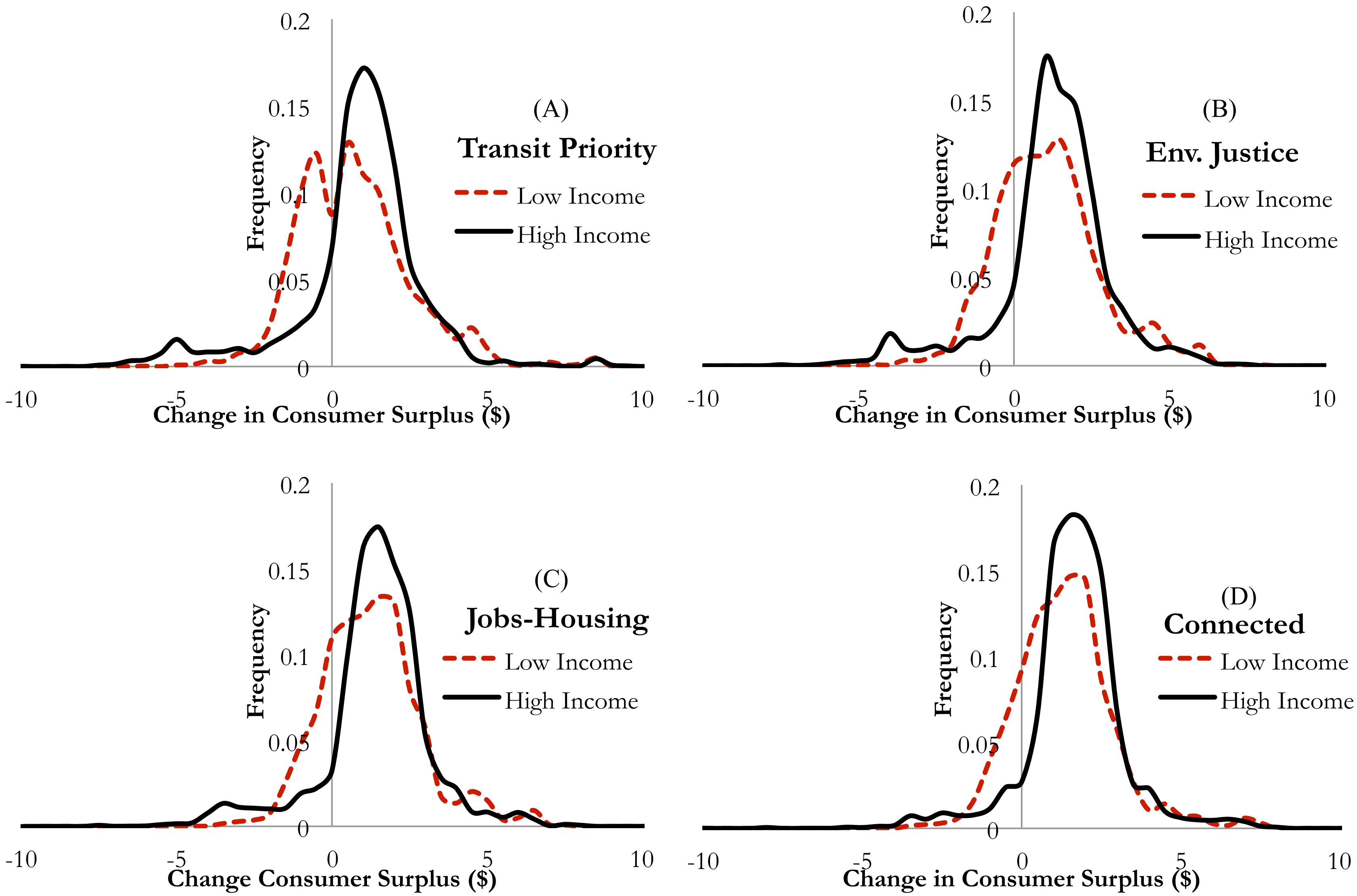

Figure 5.7 (A-D) Individual difference Density Comparisons (Logsum Accessibility/Consumer Surplus) Transit Priority Scenario (A)

Discussion of Comparison Results

These results provide important insights in three key areas. These are regarding the choice of unit of segmentation, the use of distributional measures compared to average measures, and the choice of equity indicator(s).

Our results provide strong support the use of individuals in population segmentation. This allows for greater accuracy in measuring the equity impacts of on the population segments. This is evidenced in the comparison of our average commute travel time results and MTC's results. Our average commute travel time measures show that for all Project scenarios the disadvantaged group (low income commuters) will on average experience a greater reduction in travel times than the comparison group (high income commuters). MTC's commute travel time results show the opposite, where the disadvantaged group (communities with at least 30% or more low income households) experience much smaller reductions in travel time than the comparison group (communities with less than 30% low income households). As highlighted throughout this chapter, the key methodological differences relevant here are with MTC's use of zones as units of analysis instead of individuals, as well as the definitions for disadvantaged and comparison groups. In our case, we define the disadvantaged group as low income individuals (individuals living in households earning \$30,000 or less annually), while the comparison group is high income individuals (individuals living in households earning \$100,000 or more annually). MTC defines the disadvantaged group as zones with 30% or more of households earning \$50,000 or less, while the comparison group includes zones with less that 30% of households earning \$50,000 or less. Although further investigation is needed to measure the bias associated with zone-based population segmentation, we attribute this difference in results to the fact that MTC's Communities of Concern only captures a portion of the intended target (low income) group. In fact, only about 40-55% of the target group is captured using the zone-based Communities on Concern (MTC, 2009, MTC, 2013a), whereas 100% of the target group can be capture using the individual-based approach. These results provide clear support for more disaggregate data representation in travel demand modeling and transportation equity analysis.

These results further show support for distributional measures over average measures. Particularly in the case of the Individual Difference density comparisons, we are able to evaluate correlations between socio-demographics (as well as other data dimensions) and transportation impacts on individuals. That is, this comparison reveals who the "winners" and "losers" are for the difference population segments. For both the travel time and accessibility/consumer surplus indicators we find clear relationships between income level and losing (or winning) as a result of the scenario. For the travel time indicators, the Individual Difference Density comparisons show that higher income groups are more likely to be losers, while this comparison for the accessibility/ consumer surplus indicator shows that low income households are more likely to be losers.

Finally, these results support the use of the logsum accessibility/ consumer surplus measure in transportation equity analysis. By design, this accessibility/ consumer surplus measure is more comprehensive than the travel time measure. In addition to travel times, the accessibility/ consumer surplus measure captures changes in travel costs and mandatory opportunities. The results show a difference in outcome between the travel time and accessibility/ consumer surplus indicators. The results for the travel time indicator show that low income commuters benefit more than high income commuters, both in terms of overall reductions in travel time and a smaller share of low income losers. In contrast, the accessibility/ consumer surplus results show that high income commuters benefit more than low income commuters. We attribute this difference to the fact that the travel time measure only captures a portion of the impacts of transportation plans, while the logsum accessibility/ consumer surplus measure is better are capturing more of the impacts, both transportation and land-use related.

5.4.4 Step 4: Equity Criteria and Scenario Ranking

Here we present the results of applying three different equity standards for ranking the four Project scenarios. It is necessary to translate these theoretical concepts into numerical criteria in order to apply the standards in ranking the scenarios. Of the equity standards presented in Table 3.10, these three are selected for demonstration because they are the most straight-forward in identifying the numerical ranking criteria, given the data available in this case study. We evaluate these criteria using the logsum accessibility/consumer surplus indicator. It is important to note that our contribution here is not with defining the best criteria for ranking scenarios, but to demonstrate the relevance of adopting some equity criteria, by which to rank the scenarios.

The three equity standards applied here are as follows:

Equality — Providing an equal level of benefits among all groups of interest. Note that given the different levels of need and value that individuals place on these benefits, equality of benefits may be achieved without the actual amount of benefits being equal (Miller, 1979; Forkenbrock, 2001; Rosenbloom, 2009).

Proportionality — Distributing benefits in proportion to the share that a group represents of the total population (Young, 1995; Forkenbrook and Sheeley 2004, Martens, et al 2011).

Rawls-Utilitarian — Providing a distribution that produces the greatest utility or level of satisfaction, for the most disadvantaged group (Rawls, 1972).

Equality

In order to implement the Equality standard for ranking scenarios, we adopt a simple criterion. Based on the weighted average daily benefit accrued to each income class, the Equality standard dictates that we rank the scenario with the smallest difference between the two income classes. The results are presented in Table 5.11. By this criterion we select the Transit Priority scenario as the top scenario. It is interesting to note that both the Jobs-Housing and Connected scenarios result in greater benefits for that the priorities scenario both income groups. This shows that the Equality criteria does not account for level of benefits for the income groups, but only the difference in these benefits across income groups.

Table 5.11 Equality Standard Results

	Average Daily Benefits per Household ($)			
	Transit Priority	Jobs-Housing	Environmental Justice	Connected
Low Income	$3.80	$3.95	$2.91	$4.11
High Income	$3.93	$4.88	$3.37	$4.43
High ($) – Low ($)	$0.13	$0.92	$0.46	$0.32

Proportionality

The Proportionality standard dictates that the equitable scenario is the one in which the share of benefits received is proportional to the share that a group represents in the full population. Table 5.12 through Table 5.15 show the shares of each income group in the population, compared their shares in aggregate consumer surplus. The tables also include the absolute difference in the population and benefit shares for each income group. This standard dictates that the scenario with the smallest difference between the shares is ranked as most equitable. Note that we present a separate scenario ranking for the two income classes. This is because the difference in the population and benefit shares differs between the income groups (for each scenario); however, the Proportionality criteria do not point to how the overall benefit (for both income groups) should be calculated. In this case, we rank the Connected scenario as most equitable for low income traveler and Transit Priority scenario as most equity able for high income commuters. Similar to the Equality criteria example above, this support the need for a multi-criteria equity standard for ranking the planning scenarios. It is also interesting the note that the sign of the difference (between the population benefit shares) is not relevant for ranking the scenarios using the Proportionality criteria. This is in contrast to some other equity standards (e.g. the Restorative Justice equity standard), where a greater share in benefits for the low income group would be considered more equitable.

Table 5.12 Proportionality Results for the Transit Priority Scenario

	Share in Population	**Share of Benefits**	**|Population % - Benefits%|**
Low Income	28.60%	23.70%	4.90%
High Income	23.40%	25.95%	2.55%

Table 5.13 Proportionality Results for the Jobs-Housing Scenario

	Share in Population	**Share of Benefits**	**|Population % - Benefits%|**
Low Income	28.60%	23.24%	5.36%
High Income	23.40%	27.21%	3.81%

Table 5.14 Proportionality Results for the Environmental Scenario

	Share in Population	Share of Benefits	|Population % - Benefits%|
Low Income	28.60%	23.79%	4.81%
High Income	23.40%	27.02%	3.62%

Table 5.15 Proportionality Results for the Connected Scenario

	Share in Population	Share of Benefits	|Population % - Benefits%|
Low Income	28.60%	24.54%	4.06%
High Income	23.40%	26.64%	3.24%

Rawls-Utilitarian

The Rawls-Utilitarian standard defines the more equitable scenario as the one in which the greatest level of utility or benefit is accrued to the most disadvantage group. Here we define the low income group as the most disadvantaged group. Based on these criteria we select the top scenario as the one in which the low income group accrues the highest level of benefit, which is the Connected scenario. Interestingly, the high income group also accrues the highest level of benefits from the Connected scenario, although this is not considered in this equity criteria. These results are shown in Table 5.16.

Table 5.16 Rawls-Utilitarian Results

	Total Annual Benefits			
	Transit Priority	Jobs-Housing	Environmental Justice	Connected
Low Income	$3.80	$3.95	$2.91	$4.11
High Income	$3.93	$4.88	$3.37	$4.43

Summary of Scenario Ranking Results

In summary, this ranking process requires that a numerical protocol (equity criteria) be developed and applied for the equity standard that is adopted. This is because the standards found in the literature are theoretical concepts and few if any have been applied in practice. For example, in applying the Equality standard, it is first necessary to define the benefit(s) to be evaluated, and then define the protocol for judging equality of these benefits across the population segments. Overall we find that scenario ranking vary based on the definition. For the Equality standards, the Transit Priority scenario was ranked as most equitable; for the

Proportionality standard the Connected and Transit Priority Scenario are ranked as most equitable, for low and high income commuters respectively; and based on the Rawls-Utilitarian standard, the Connected scenario was ranked as most equitable. Therefore it is critical that an equity standard be explicitly adopted and applied for the scenario analysis. It is also clear that some standards may call for some multi-criteria that accounts for the varying impacts across population segments. For example, the Proportionality standard lends itself to a separate ranking for the low income and high income segments. In this case, it is important to take the next step toward defining criteria that weights these impacts and produces a single scenario ranking.

5.5 Extensions and Considerations

The Proposed Equity Analysis Process is a flexible methodology and can be adapted to include a number of additional important extensions. These include the options for using a multi-criteria definition of population segmentation and additional equity indicators. Further, there are additions that may significantly improve the evaluation results. These are model data validation for population segments and statistical comparison of the equity outcome distributions. Here we discuss the usefulness of these extensions and considerations, and give examples where relevant.

5.5.1 Model Data Validation

The degree to which equity analysis results will reflect real world transportation impacts is closely tied the travel model input data and how well this data represents real world population characteristics and travel behavior data. In Section 5.3.2 (and Appendix B), we describe in some detail the basic population characteristics and travel behaviors from MTC's activity-based travel model, although we do not take the additional step of verifying that the data are representative of real world conditions. Further, it is important to verify that the model data are representative of differences across population segments. Although data validation is standard practice in the initial development of this large scale travel models, this is not necessarily done across all segmentation variables of interest relevant for equity analyses. Therefore, data validation across population segments is an important initial step for ensuring that equity analyses reflect realistic impacts for the defined population segments.

There are a number of data validation approaches. This could involve a simple comparison to verify that the model data matches the real world data, within some defined margins of error. An example comparing mode-share for work tours is illustrated in Figure 5.8. Bay Area Travel Survey Data for the year 2000 is used to represent the real world data, and MTC's Base Case 2000 data is used to represent the model data. Here we see that the general relative order of usage is preserved. The largest mode share is the auto mode, while the smallest is for walk/bike modes. However, there are some small differences between the model data and the real world data. For the transit and walk/bike mode shares, the model data shows slightly higher shares. The logical question here is whether these differences are statistically significant. In this case, this can be addressed this using simple t-tests. In other cases where we need to test the equality of two distributions (e.g. the distribution of travel distances), a non-parametric test of distributions that is appropriate for empirical distributions would need to be employed.

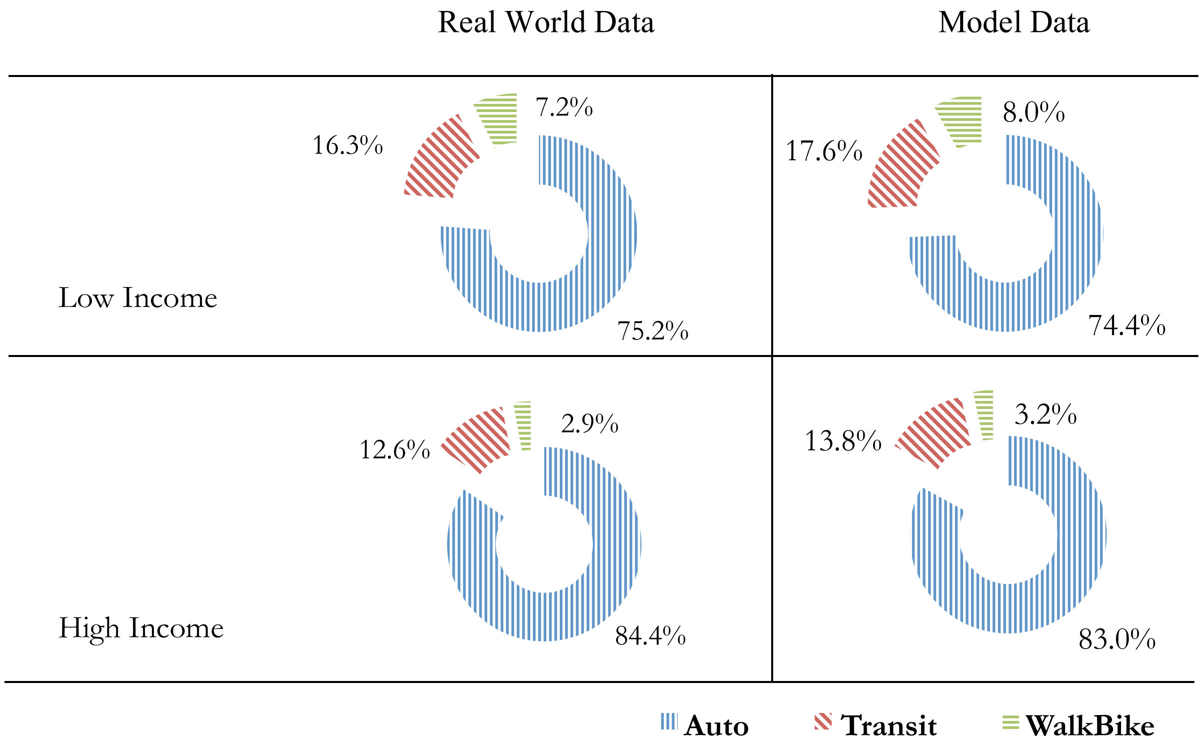

Figure 5.8 Real World vs. Model Data Work Tour Mode-Shares

It is also important to mention the significance of model calibration in verifying the representativeness of the travel model data, as the data validation is only part of the task of ensuring model data representativeness. Model calibration is common for mathematical models of complex outcomes where unknown parameters are to be estimated. This involves adjusting the model parameters such that the model predictions match observed data. The challenge here is regarding whether the model's sensitivity to individual preferences and overall travel behavior is preserved through the calibration process. For example, the addition of an alternative specific constant for low income transit riders in a mode choice model may certainly improve the accuracy of the mode share predicted by the model in the calibration year (providing a closer match to the observed mode share). However, this does not necessarily indicate an improvement in the model's sensitivity to mode choice preferences in the population, nor does it ensure the models ability to forecast mode share over time. For this reasoning, the influence of model calibration on data representativeness is a critical question for future work or applying travel demand models for equity analysis.

5.5.2 Population Segmentation and Additional Equity Indicators

In the results presented in this chapter, we use a single variable for population segmentation: income. However, the extension using additional variables is trivial. As is done in MTC's latest equity analysis, it is certainly possible to adopt multiple variables of population segmentation within our proposed equity analysis framework. For example, our description of the population data indicates a relationship between household size and income level. In this case it is desirable to segment groups using both income and household size. Regarding definitions of segmentation, the literature on transportation disadvantage points to a number of important variables. These include income level, auto ownership, and education level, walk accessibility (to activities), age, and political engagement (Currie et al., 2010). In some cases, the availability of segmentation variables can be constrained by variables available from the travel model. Otherwise, there is nothing restricting the application of multiply segmentation variables using the Proposed Equity Analysis Framework.

The importance of using multiple indicators is demonstrated from the current Bay Area case study, as a project may be equitable along one dimension and inequitable along another. Our proposed analysis process can be extended to evaluate any number of equity indicators. Further (as with population segmentation), the variables available for calculating equity indicators are constrained by the model can output available, particularly with the use of individuals as the unit of segmentation. However, activity-based travel models are able to generate a range of population, travel behavior, travel network, and spatial data from which numerous equity indicators can be calculated.

5.5.3 Statistical Comparison of Distributions

Once the distributions of the equity indicators have been generated, an important next step is to test that the distributional differences are statistically significant. There are actually two dimensions of change relevant here. The first dimension is regarding the changes across scenarios; are the changes associated with each project scenario, relative to the No-Project scenario, significant? The second dimension is regarding the changes across population segments; are the changes experienced by the different population segments significant? In both cases, we want to verify that the distributional differences we observe are not due to model error.

The first dimension falls under a much larger discussion about error and uncertainly in travel models. This is especially important in the context of activity-based travel models where simulation error is present. Because of the micro-simulation used, the results will vary stochastically. That is, each time the random number generator produces a seed value for the Monte Carlo simulation, the choice assignments for all travel choice dimensions will change. Although the error can be significantly reduced by increasing the sample size (Castiglione et al., 2003; Walker, 2006), there will always be some error present. In addition, there are other possible sources of error, including input data, model structure, and parameter estimation. A fuller discussion of error and uncertainty of travel model outcomes from a policy perspective can be found in (Walker et al., 2005). Although there are approaches to measuring uncertainty from travel demand models, this extends beyond the scope of the current research. In our case, we assume that the level of uncertainly is such that meaningful results are still generated from the travel model.

The second dimension focuses on testing whether distributional differences across population segments are statistically significant. Typically, there are a number of statistical hypothesis tests appropriate for testing the significance of scenario analysis results. Tests such as the Kolmogorov-Simirnov two sample tests and the Karl Pearson Chi-Squared goodness-of-fit test would generally be appropriate for testing the difference between two of more empirical distributions. However, the presence of simulation error in results from activity-based travel demand models presents some challenges regarding the application of these frequentist statistical tests. It is unclear whether currently available tests (such as the Kolmogorov-Simirnov and Karl

Pearson Chi Squared test) are able to account for simulation error. This challenge falls under the broader subject of statistical tests for simulation data, and is an important area of future work for testing the differences between distributions that are generated from activity-based travel demand model data.

5.6 Conclusion

We have presented a real world application of the proposed equity analysis process discussed in Chapter 3. We use the activity-based travel modeling system and transportation and land-use scenarios developed by the Metropolitan Transportation Commission (the Metropolitan Planning Organization for the nine-county San Francisco Bay area). In this case study we evaluate the equity impacts of four "Project" scenarios for low and high income commuters, using commute travel time and mandatory logsum accessibility/consumer surplus as equity indicators.

There are four primary takeaways from this chapter. First is regarding the unit of population segmentation. The case study results show a significant difference in equity outcome when using individual-level population segmentation, compared to using the zonal segmentation approach. In fact we find opposite results. We hypothesize that this difference is due to the fact that the zone-based approach only captures a portion of the target (40% in MTC's case), while the individual-level segmentation approach is able to capture 100% of the target group. Second is regarding the equity indicators evaluated. The commute travel time measure results suggests that low income commuters are better off than high income commuters, while the mandatory logsum accessibility/ consumer surplus measure results suggest that low income commuters are worse off than high income commuters. The logsum measure results further show that low income households are most likely to be "losers" relative to high income households. Although further investigation is warranted to understand the reasons for these results, we hypothesize that this difference in results is due to the fact that the logsum accessibility/consumer surplus measure by design is able to capture transportation and land-use related factors. In comparison, the travel time measure only captures one dimension of transportation user affects. In spite of the concerns discussed in Section 3.4.3, the logsum measure has a number of desirable qualities for equity analysis. This measure is a more comprehensive measure of transportation user benefits. Third is regarding the use of distributional comparisons for transportation equity analysis. Our results show that they can provide a richer picture of how groups are affected by transportation plans. The Individual Difference Densities can be used to identify the winners and losers resulting from the scenarios. It is also important to note the consistency of our results in the presence of strict restrictions on the calculations for the Individual Difference Densities. Both our average commute travel time measure and Individual Difference Densities for commute travel time indicate that low income commuters are better off, relative to high income commuters. This result holds even though mode, location, and time-of-day choices are held constant for the Individual Difference Densities calculation. No constraints are made on calculating the average measures. The average and distributional measures for accessibility/ consumer surplus results are also consistent. Finally, we make the case that scenario ranking, using an adopted equity standard, plays an important role in the analysis process. The results support our recommendation that transportation practitioners should explicitly adopt and apply equity criteria in determining the extent to which transportation scenarios are equitable.

In summary, the individual-level segmentation approach is preferred to the zonal approach, and results on the relative transportation effects of low income and high income commuters vary based on the equity indicator used. Further, distributional comparisons provide a much richer picture of how population segments are affected by transportation plans relative to average measure. Finally, the use of equity criteria for ranking transportation scenarios is an important and powerful step in transportation equity analysis.

Chapter 6 . Conclusions

6.1. Introduction

Although the transportation system plays an integral role in quality of life for all members of society, all transportation benefits (or costs) are not created equal. That is, transportation changes will indeed result in a distribution of transportation experiences that is a reflection of the heterogeneity among us. In spite of this, existing practices for regional transportation equity analysis fail to effectively evaluate the distribution of transportation outcomes across different segments of society, because they largely ignore these differences in transportation experiences at the individual level.

This dissertation endeavors to advance the practices for regional transportation equity analysis and overcome the existing shortcomings. We have presented an analytical framework for regional transportation equity analysis that leverages to power of activity-based travel demand models and distributional analysis (among other tools) to identify the "winners" and "losers" resulting from transportation plans. We started by developing a guiding framework, which outlines the important components of transportation equity analysis. We then presented our proposed process for equity analysis of regional transportation plans, emphasizing individual level population segmentation, distributional comparisons of the individual level equity indicators, and scenario ranking using equity standards. We gave two demonstrations usefulness of distributional comparisons, using hypothetical and real world settings. We concluded with a full scale, real world application of our proposed equity analysis approach, using the Metropolitan Transportation Commission's regional activity-based travel model and transportation and land-use scenarios for the San Francisco Bay Area. In this final chapter, we summarize the overall takeaways from this dissertation and discuss next steps and research directions.

The remainder of this chapter is organized as follows: in Section 6.2 we revisit the guiding framework for equity analysis that was introduced in Chapter 3 and discuss the efforts of this dissertation relative to this three-part framework. In Section 6.3 we summarize the major findings from each of the preceding chapters in this dissertation. In Section 6.4 we discuss important next steps and research directions, and in Section 6.5 we give concluding remarks.

6.2. Revisiting the Guiding Framework for Transportation Equity Analysis

The framework presented in Chapter 2 outlined three key components of transportation equity analysis: priorities, model, and indicators. The framework is illustrated in Figure 6.1. The first component emphasizes the importance of identifying community priorities. This involves accessing what the needs are for different communities. Although the Environmental Justice literature suggests certain areas of investigation, such as air quality, travel times, and vehicle-miles-travels (Forkenbrock and Weisbrod, 2001; Sanchez etal., 2007; Burt et al., 2010), priorities will likely vary for different groups. The second component of the analysis is the model used to measure the expected changes due to the transportation plan. The challenge here is with selecting a modeling tool that is appropriate for measuring the desired transportation (and/or land-use) changes. In this case, it is necessary that the model be capable of representing real world travel-related behaviors at the individual level. The third component deals with the selection and evaluation of equity indicators. These are the measures of transportation benefits (or costs) to be evaluated. The challenge here is in selecting indicators that reflect communities' transportation priorities, as indicated by the black dashed curve. Further, the approach taken for comparing these indicators across population segments is critical. As is emphasized through this dissertation, the use of aggregate level comparisons (average equity indicators) can result in misleading equity outcomes. Finally, the gray dashed curve emphasizes the iterative nature of equity analysis. That is, the results from evaluating the indicators may point to important changes in the model structure. For example as will be discussed later in this chapter, our analyses point to the inclusion of more long-term travel and land-use related equity indicators as an important next step, which has implications for the population synthesis and individual and household evolution over the planning horizon.

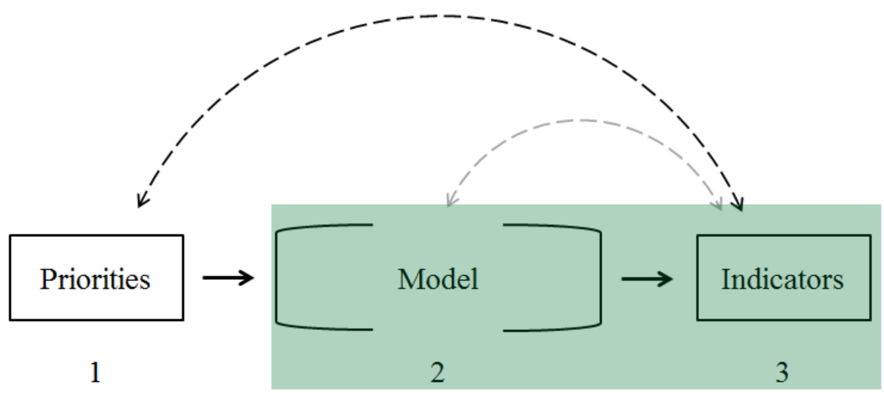

Figure 6.1 Equity Analysis Framework and Dissertation Emphasis

As indicated by the shaded region of the equity analysis framework in Figure 6.1, the methods presented in this dissertation primarily address the second and third components of the framework. Regarding the model, this dissertation makes a clear case for applying disaggregate data from activity-based models for regional transportation equity analysis. Regarding indicators, we demonstrated the power of distributional analysis, which provides a means of identifying the winners and losers resulting from transportation plans.

6.3. Summary of Findings

In Chapter 2, after presenting the guiding framework for transportation equity analysis (Figure 6.1), we reviewed the literature supporting the components of this framework and described the existing practice for regional transportation equity analysis. Here we first review the broader research needs from the literature regarding our guiding equity analysis framework. We then review the more specific research needs regarding the public practice on regional scale transportation equity analysis using travel demand models. We address some of these needs in this dissertation.

Regarding broader research needs relating to our guiding framework for transportation equity analysis, first is on validating the use of activity-based travel demand models for transportation equity analysis. There is only one case found in the literature where the ability of these models to represent the differences across population segments has been investigated (Bills et al., 2012). For this dissertation work, we accepted that these models are sufficient and provide for meaningful comparisons a cross population segments. However, this is an important research area, given that the representation of longer term population behavior (e.g. individual and household change or growth over time), and land-use behavior (e.g. gentrification and displacement) have yet to be accomplished together in practice. Second is regarding distributional comparison methods for transportation equity analysis. There is a need to develop more distributional comparison tools capable of evaluating individual level equity. There is one known approach to evaluating overall differences in distributions: Relative Distribution methods. However, these methods operate at the aggregate distribution level, as opposed to the individual level. Further, relative distribution methods are very mathematically complex and difficult for practitioners as well as academics to interpret. Thus, there is a need to develop distributional comparison methods that are more readily usable in practice. The third takeaway is regarding the consideration of long-term transportation and land-use related behaviors. Some effects of transportation changes in land-use impacts such as segregation, gentrification, and displacement are well investigated in the literature (Kennedy and Leonard, 2001; Sanchez et al., 2003; Sanchez, 2004; Kahn, 2007); however, such impacts have yet to be full captured for in equity analysis of long-range transportation plans.

Regarding more specific research needs relating to the existing practice for equity analysis of regional transportation plans, three critical shortcomings were found. First, the use of zones as units of segmentation can be problematic and result in aggregation bias. Second, the equity measures and indicators used in practice are weakly linked to transportation costs and benefits. For example, travel time is a very common equity indicator used in practice. However, it only captures one dimension of the benefits (or costs) associated with possible transportation and land-use investments (e.g. accessibility, user costs, and environmental factors). Finally, the use of average measures of equity indicators can be misleading and uninformative.

In Chapter 3 we proposed a process for regional transportation equity analysis that addresses the existing shortcomings relating to equity analysis. We discuss considerations and improvements to transportation equity analysis concerning population segmentation, equity indicators, distributional comparisons, and scenario ranking. The segmentation of the population into target and comparison groups involves the selection of one or more variables of segmentation, a unit of segmentation, and definitions of segmentation. The choice of variable of segmentation is closely tied to the equity dimension(s) adopted by the planning agency. For example, income is associated with vertical equity, while location is associated with horizontal equity. It is desirable for the unit of segmentation to be as disaggregate as possible, in order to overcome issues with aggregate bias. Given the capabilities of activity-based travel models, we recommend individuals or households as the unit of segmentation. The threshold for defining the target and comparison groups (e.g. defining the target group for low income households as those earning less than $30k annually), are ideally selected based on established definitions of transportation disadvantage. Regarding the selection of equity indicators, any number of equity indicators can be generated from the travel model output. However, consideration for how well the indicator(s) represents transportation impacts (costs or benefits) is critical. It is important to verify that the indicator(s) represents benefits (or costs) to individuals, and are not simply transportation system performance measures. Further, it is important to identify potential confounding factors associated with the indicators of these costs and/or benefits. For example, travel time measures can be confounded by travel frequency. Therefore if the travel frequency of different population segments are not controlled for when comparing travel time measures across population segments, this could result in biased measurements. Regarding distributional comparisons, we emphasize the importance of evaluating the individual-level changes in the equity analyses. A comparison of aggregate densities can provide useful information on the overall differences in distributions due to a planning scenario (e.g. a shift toward smaller or larger values). However, comparisons of Individual Difference Densities are able to reveal the share of the population segments expected to gain (winners) or be made worse off (losers) by a planning scenario. As a final step in the analysis process, we emphasize the importance of ranking the planning scenarios using explicit equity criteria. This is a step that is largely overlooked in practice.

In Chapter 4 we demonstrate the advantages of distributional comparisons, relative to average measures. We employ hypothetical transportation scenarios and develop two mode choice models, using synthetic and empirical travel data. The synthetic data are generated from a hypothetical setting, while the empirical data is taken from the 2000 Bay Area Travel Survey dataset. In these controlled settings, we explore the relationships between the characteristics and travel behavior of the population segments and the distributional outcomes due to the (hypothetical) scenarios. Overall, we find the distributional comparisons are capable of providing a fuller picture of individual travel experiences due to transportation investments. Not only do the Individual Difference Density comparisons reveal how individuals are affected by the scenarios (in terms of which individuals benefit and which individuals do not benefit), but they provide a means of reverse-engineering the scenario impacts and determining specifically what factors led to various transportation (equity) outcomes. This level of analysis is otherwise limited using average comparison measures.

The San Francisco Bay Area case study presented in Chapter 5 provided a number of key insights with respect to applying our proposed equity analysis process and the MTC activity-based travel model for regional transportation equity analysis. In this case study, we evaluate the equity impacts of four transportation and land-use scenarios for low income commuters, relative to high income commuters. We use commute travel time and mandatory logsum accessibility/consumer surplus as equity indicators, we segment the population at the individual level, and we calculate individual level measures of the indicators. We use two types of distributional comparisons to evaluate equity impacts on low and high income commuters: the Aggregate Density comparison and the Individual Difference Density comparison. The Aggregate Density comparison is done using the commute travel time measure, while the Individual Difference Density comparison is done for both the commute travel time and logsum accessibility/ consumer surplus measures. The Aggregate Density comparison is not done using the logsum measure because they would treat the individual utility-based values as if they were on an equal scale, and this is inappropriate. Our travel time results from the Aggregate Density comparison show that for all Project scenarios, low income commuters will overall experience a greater reduction in travel times than the comparison group (high income commuters). Further, the Individual Difference Density comparison shows that the share of low income commuters who do experience an increase in travel time (losers) is smaller than for high income commuters. The logsum accessibility/ consumer surplus results show the opposite; lower income households are more likely to experience losses due to the planning scenarios. We hypothesize that this difference between the travel time and accessibility/ consumer surplus results is due to the fact that the travel time measure only captures a portion of the impacts of transportation plans' impacts, while the logsum accessibility/ consumer surplus measure by design captures more of the impacts (both transportation and land-use related). When we look at travel time only, the low income group is better off, in comparison to the high income group. However, when we add impacts due to the change in employment (and other mandatory) opportunities, the low income group is worse off. Regarding scenario ranking, we develop ranking criteria using three different (theoretical) equity standards: Equality, Proportionality, and Rawls-Utilitarianism. Application of these equity standards result in all different rankings for the planning scenarios. This demonstrates the importance of adopting equity criteria (which represent the equity goals for the transportation plan) and applying these criteria in determining the most equitable planning scenario. A transportation plan can be considered equitable based one standard, but inequitable based on another.

6.4. Research Directions

While this dissertation takes a number of important steps toward advancing transportation equity analysis, process in the follows areas is critical for further understanding the potential of using activity-based travel demand models for equity analysis, and uncovering the full range of equity outcomes possible from transportation-related improvements. We use our guiding equity analysis framework to outline these research directions.

Priorities

In our analysis, we assume that the transportation priorities are reductions in commute travel time and increases in mandatory accessibility. However, there is a need to investigate (though qualitative and quantitative approaches) the transportation needs of various population segments. There is a large body of literature around travel behavior differences by ethnicity, income level, gender, etc., but this has yet to be applied in the equity analysis realm to identify transportation needs and constraints. This is also related to the question of what equity standard(s) to adopt. In this dissertation we establish that the selection of an equity standard is key; however, we do not provide a process for selecting the equity standard that is most desirable. There is considerable effort in this area, although to date, no consensus has been reached. Further, there is need to identify more robust equity criteria for scenario ranking based on the adopted equity standard(s). In our analysis, we demonstrate the scenario ranking using simplistic criteria, based on a single indicator. In the case of multiple indicators, it would be important to incorporate these indicators in the form a multi-criteria for scenario ranking.

Model

There are a number of research directions concerning the model to be used for scenario modeling. The first is regarding uncertainty in the model. There are a number of sources for error and uncertainty in large scale travel models, which will influence the model results. In our analysis we assumed that this influence was insignificant; however, there is a critical need to explore the magnitude of this influence. Second is regarding changes to the model structure to account for longer-term behaviors. This includes individual and household changes over time. The basic idea is that over time, individuals grow and evolve in terms their age, income level, preferences, etc., while households change and evolve in similar ways (e.g. household structure), and the model should be adapted to account for these effects. Third and also relating to long-term travel behavior is the need to model land-use related changes, such as gentrification and displacement, as mentioned earlier. Fourth is regarding how traveler purpose and activities are represented in the model. Currently, travel purposes are not modeled from a behavioral perspective: they are simply assigned to individual (and joint) travel records. In cases where we are interested in understanding the influence of transportation investments of health related activities, it would be useful to be able to forecast the change in these activities as a function of the transportation changes, and additionally how these vary by population segment.

Indicators

In this dissertation, we discuss important considerations for selecting equity indicators, as well as how to compare them across groups. However, we do not address the question of what equity indicators are best, and under what conditions. This is a fundamental question for transportation equity analysis that has yet to be addressed. Further, we have only scratched the surface with developing useful distributional comparison methods and meaningful summary measures based on these distributions. First, there are the issues of tracking individuals represented in the travel models across scenarios. Currently, new realizations for transportation-related choices are drawn each time the model is run, which makes it impossible to compare individuals and households across scenarios. In our case, we place a number of constraints on the calculations of equity indicators (for individuals and households) in order to make comparisons across scenarios, but further exploration regarding how to accurately monitor individual agents across different scenario runs is critical for distributional evaluation using the Individual Difference Density comparison approach. The second research need with respect to evaluating indicators is for more exploration into what population, travel behavior, and land-use related factors are associated with being a “winner” or “loser”. In our analysis, we gave some hypotheses for our results, but a much more in-depth analysis is an important next step. Specifically, it is important to investigate the underlying causes for our results (why is it that our average travel time results were opposite of MTC’s results, and why is it that our travel time and accessibility/ consumer surplus measures produced opposite results?). Further, it is important to understand how the losers can be compensated for their losses. Finally, an important next step is to apply our proposed equity analysis process to a range of transportation and land-use improvements in order to determine the types of improvements that are more equitable, and what factors can be adjusted in order to provide a more equitable outcome overall.

6.5. Conclusion

We have developed and demonstrated an approach to regional transportation equity analysis that addresses shortcomings of the existing practice and ultimately brings us closer to measuring and understanding the full of range equity outcomes associated with transportation plans. Other primary contributions are in providing a guiding framework for the important components of transportation equity analysis, making the case for disaggregate level population segmentation, evaluating the usefulness of an accessibility measure relative to a travel time (mobility) measure, demonstrating the usefulness of distributional comparison methods in equity analysis, and demonstrating the significance of equity criteria for scenario ranking. We have laid out a framework for using activity-based travel demand models to evaluate individual-level equity impacts and reveal the "winners" and "losers" resulting from transportation plans. In addition, this work serves to link equity analysis methods from the academic literature to equity analysis in practice. While we have made significant process, there are a number of key next steps and research directions. Among other improvements, these include the need to explore best practices for adopting equity standards and developing scenario ranking criteria based on these standards, the need to determine the influence of model-related uncertainty on equity analysis results, the need to explore how travel models can be adapted to represent longer-term travel and land-use related behavior, the need to evaluate the most desirable equity indicators for representing the costs and benefits of transportation plans, and finally the need to apply our proposed methods to a range of transportation-related improvements in order to explore which types of improvements are most (and least) equitable.

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Appendix A : Conceptual Evaluation Data Descriptions and Model Choice Model Estimation Results

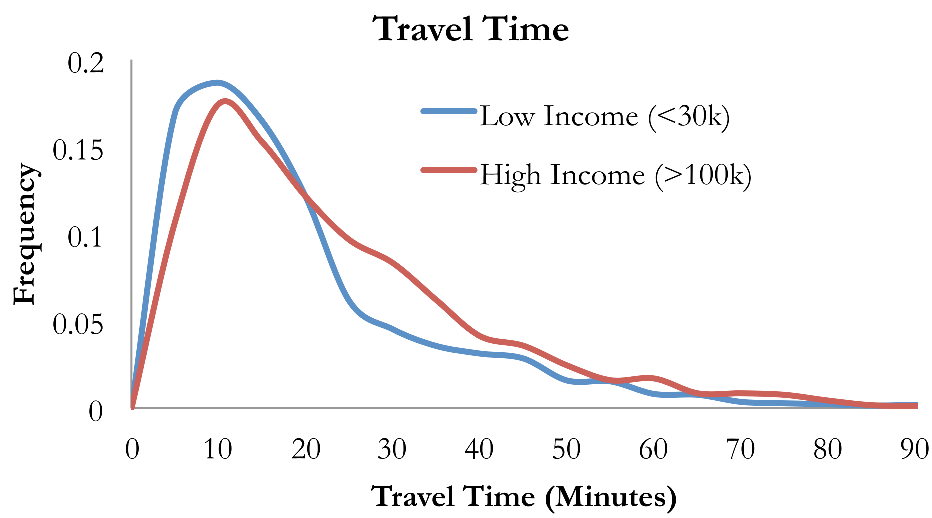

Figure A. 1 Distributions of Travel Times for Low Income and High Income Workers

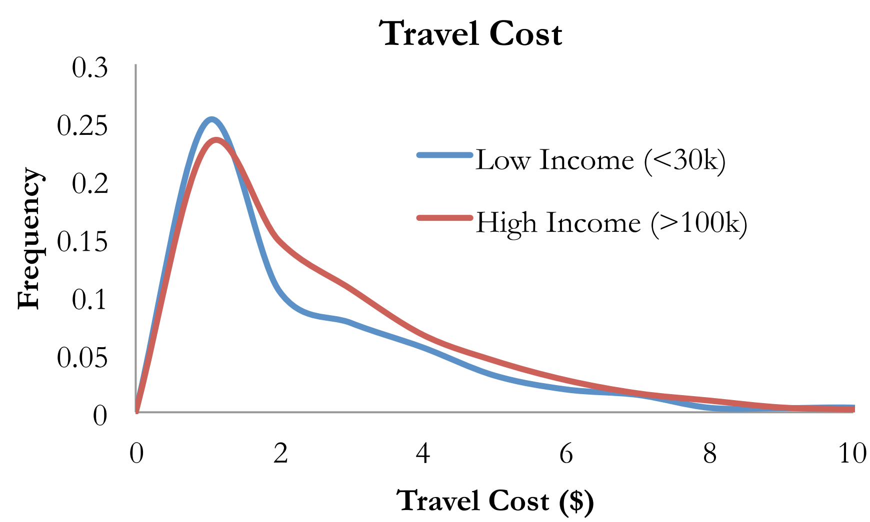

Figure A. 2 Distributions of Travel Costs for Low Income and High Income Workers

Table A. 1 Mode Choice Model Estimation Results

Parameter Name	Estimate
Alternative Specific Constants	
Auto Modes	
Shared-Ride 2	-1.7090
Shared-Ride 3	-2.5825
Active Modes	
Walk	-0.2205
Bike	-1.6223
Transit Modes	
Walk-Transit	0.2987*
Drive-Transit	-1.0560
In-Vehicle Travel Times	
Auto and Transit	-0.0245
Bike	-0.0785*
Walk	-0.0551
Transit Wait Times	
Initial Wait	-0.0365
Transfer	-0.0349
Costs	
Travel Cost	-0.2494
Parking Cost	-0.0416
Income Categories	
Active Modes	
Low Income	0.7076
Low-Medium Income	0.4533
Medium-High Income	0.5112
Transit Modes	
Low Income	0.2331
Low-Medium Income	0.1314
Medium-High Income	0.0003*
Tour Stops (Greater than 1)	
Active Modes	-0.8113
Transit Modes	-0.2292
Nest Coefficients	
Active Modes	1.2633
Transit Modes	1.4365

*Not significant at the 5% confidence level

Appendix B : Bay Area Case Study Data Description

Here we present a data description of the basic population (exogenous) and travel (endogenous) characteristics exhibited in the data used for the Bay Area case study in Chapter 5. As this general picture does not vary significantly across the MTC planning scenarios, we describe only the "No-Project" scenario data here. This data description serves to support the discussion of the case study results, as the equity impacts on population segments will be a reflection of the basic population and travel characteristics of these segments, as well as the expected transportation and land-use changes.

Population Data

There are a total of 4,357,430 individuals, living in 1,640,662 households in the data sample, which represents a 50% sample of all households in the region. The low income class represents the largest share of households, although only slightly so, with low income households representing 28.6% of the population and medium income, medium-high income, and high income classes representing 24.5%, 23.5%, and 23.4%, respectively. These income shares are illustrated in Figure B.1A.

In the person file, individuals are classified into person types. These person-types are as follows:

- Child – too young for school
- Student – non-driving age
- Student – driving age
- University Student
- Non-Worker
- Part-time Worker
- Full-time Worker
- Retired

The distributions of person-types by income class are shown in Figure B.1B. There are some interesting differences in the distribution of person-types across income classes. Overall, the highest share of individuals is full-time workers, for all income classes except the low income class. For the low income class, the highest person-type share is retirees (23.0%), with the next highest person-type shares being non-workers (18.54%) and full-time workers (17.9%). In contrast, 34.2% of medium income individuals, 43.6% of medium-high income individuals, and 48.6% of high income individuals are full-time workers. Relative to the higher income classes, low income individuals are most likely to be university students, non-workers, part-time workers, and retirees.

Each household's residential choice is represented as a travel analysis zone in the region. There is a total of 1454 travel analysis in MTC's zonal system. To give an idea of residential choices for low income and high income households, we map the share of low income and high income households for all zones in the Bay Area. These maps for low and high income communities are shown in Figure B.2 and Figure B.3, respectively. These maps show high concentrations of low income households primarily in the inner north, east and south bay areas which tend to have higher transit network densities, although there are certainly some low income households residing in less transit accessible areas. Higher income households are more concentrated in the outer south and east bay areas.

The size of households can generally be described in terms of the total number of household members, the number of workers, minors (children ages 0 to 17), and seniors (ages 65 and older). The total number of household members in the dataset ranges from one to 25 members, although this range is truncated at 6 household members in Figure B.4A for simplification purposes[38]. Regarding household sizes across income classes, lower income levels are associated with smaller households, while higher income levels are associated with larger households. For low income households, 77.4% are 1 and 2 person households, while 60.8% of medium income household, 48.1% of medium-high income households, and 39.2% of the high income households are 1 and 2 person households. Regarding the number of household workers, low income households are also more likely to have zero or 1 workers in the household, with 89.6%[39] of low income households and 66.6%[40] of medium income households having 0 or 1 workers. This is in contrast to the higher income classes, which are much more likely to have 1 or more workers in the household. Regarding the number of household minors, the large majority of households have no minors. Low income households are most likely to have zeros minors (76.6%), which high income households are least likely to have zeros minors (61.2%). Similarly, the large majority of households have zeros seniors; however, low income households are least likely to have zeros seniors while high income households are most likely to have zeros seniors. That is, the share of households with zero seniors ranges from 54.6% for low income households, to 76.7% for high income households.

Overall, it seems that the lower income individuals are characterized as mostly retirees, non-workers, part-time workers, or university students, while higher income individuals are most likely to be full-time workers than any other person type. Low income household tend to live closer to transit rich areas, relative to high income households. Further, low income households are characterized as smaller households with zeros or few workers, few minors, and are more likely to have seniors, relative to all other income classes. On the other hand, high income households are characterized as larger households, with one or more workers, more minors and fewer seniors, relative to all other households.

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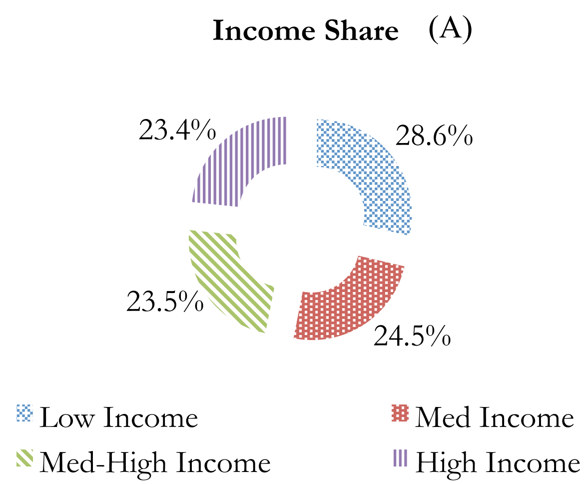
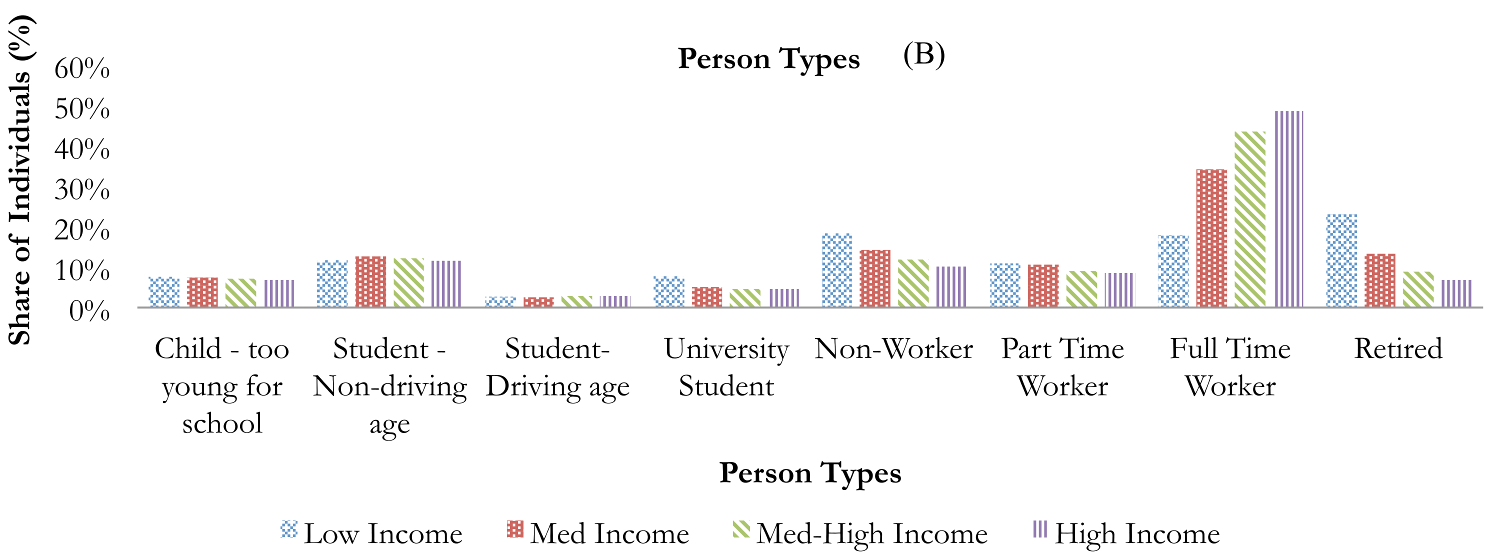
[38] Only 2.6% of household have more than 6 members.
[39] That is, 49.4% of low income households are 0 worker households and 40.2% and 1 worker households.
[40] That is, 17.2% of medium income households are 0 worker households and 49.4% and 1 worker households.


Income Share (A)
23.4%
28.6%
23.5%
24.5%
Low Income
Med Income
Med-High Income
High Income


Person Types (B)
Share of Individuals (%)
60%
50%
40%
30%
20%
10%
0%
Child - too young for school
Student - Non-driving age
Student- Driving age
University Student
Non-Worker
Part Time Worker
Full Time Worker
Retired
Person Types
Low Income
Med Income
Med-High Income
High Income

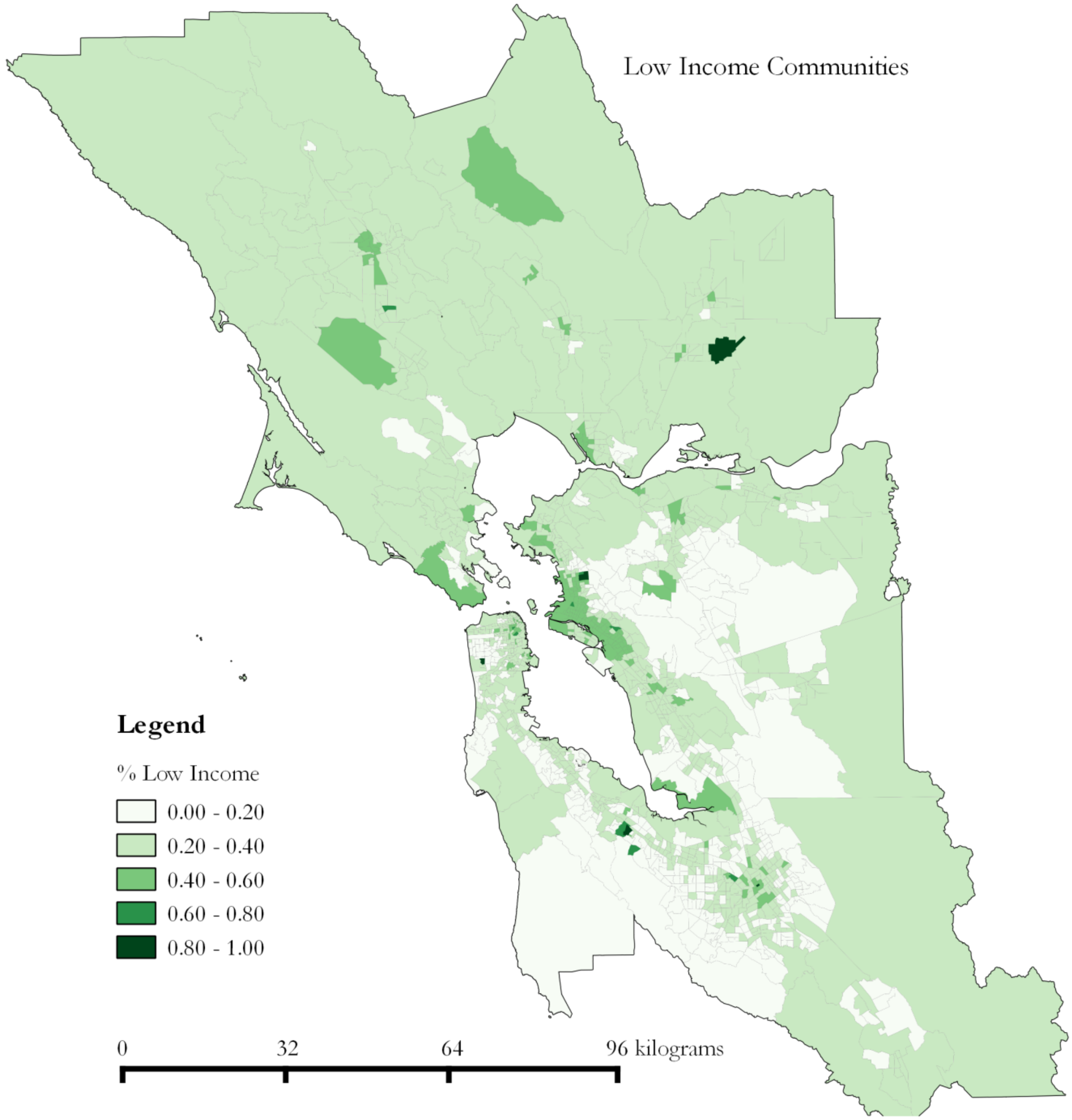


Figure B.2 Low Income Community (Earning $30k or less) Residential Locations

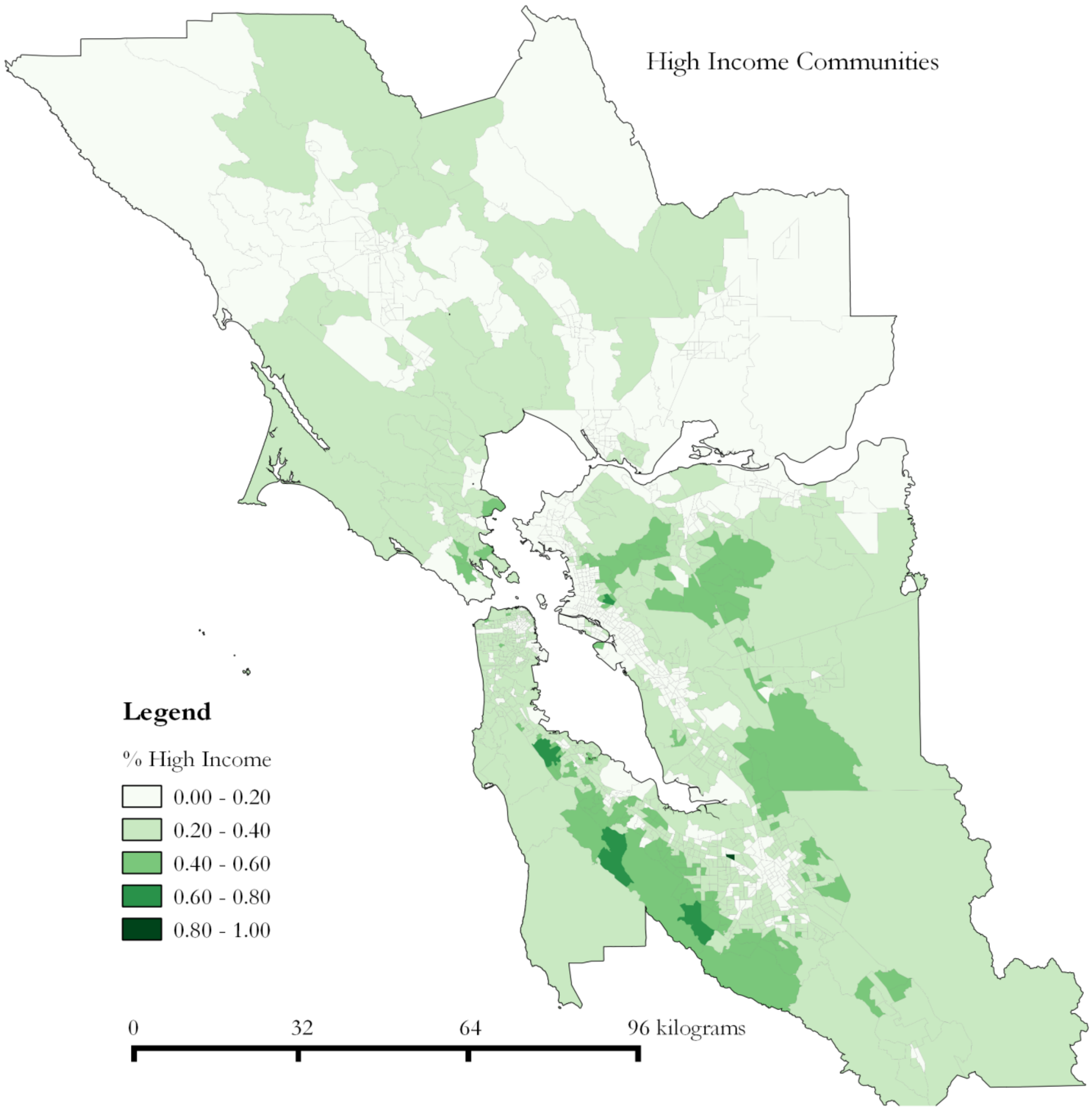


Figure B.3 High Income Community (Earning $100k or more) Residential Locations


Household Size (A)
Share of Households (%)
80%
30%
-20%
1
2
3
4
5
6
Number of Household Members
Low Income
Med Income
Med-High Income
High Income
Household Workers (B)
Share of Households (%)
80%
30%
-20%
0
1
2
3
4
Number of Household Workers
Low Income
Med Income
Med-High Income
High Income
Household Minors (C)
Share of Households (%)
80%
30%
-20%
0
1
2
3
4
Number of Household Minors
Low Income
Med Income
Med-High Income
High Income
Household Seniors (D)
Share of Households (%)
80%
60%
40%
20%
0%
0
1
2
Number of Household Seniors
Low Income
Med Income
Med-High Income
High Income

Travel Behavior Data

Regarding household tour frequency (as illustrated in Figure B.5A), it is clear that the low income households are much more likely to take one mandatory tour daily, while high income households are more likely to take two or more mandatory tours daily. That is 80.9% of low income households only take one tour daily, compared to 62.6% of medium income households, 48.9% of medium-high income households, and 39.9% of high income households. The non-mandatory tour frequencies are illustrated in Figure B.5B. Similarly, low income households are more likely to take one non-mandatory tour, although less so compared to that case of mandatory tours. That is, 67.3% of low income households, 56.5% of medium income households, 52.9% of medium-high income households, and 48.1% of high income households take one non-mandatory tour.

The number of individual tours range from one to two tours per day for mandatory tours, and from one to 5[41] non-mandatory tours per day. As shown in Figure B.6A, there is very little difference in mandatory tours across income classes. For all income classes, approximately 94% of individuals take one mandatory tour per day. Although, there is a slight trend suggesting that lower income individuals are more likely to take two mandatory tours a day; with 5.8% of low income individuals taking two mandatory tours per day, compared to 5.6%, 5.5%, and 5.7% for medium income, medium-high income, and high income individuals, respectively. Regarding non-mandatory tours, while the tendency overall is towards one or two tours, lower income individuals are relatively more likely to take one tour daily, while higher income individuals are relatively more likely to take 2 or more tours daily.

Regarding stop frequency for mandatory tours (as shown is Figure B.5C), there doesn't seem to be any interesting differences across income classes. Generally, there are few stops taken, with approximately 63% of all tours having zero stops, and 22% of tours having one stop, for all income classes. For non-mandatory tour stops (shown in Figure B.5D), there seems to be a slight trend. That is, for low income households, 36.3% of non-mandatory tours involve one or more stops, compared to 34.6% for medium income households, 33.3% for medium-high income households, and 32.1% for high income households.

Figure B.7 shows the tour mode shares for mandatory and non-mandatory tours. Note that for the purpose of simplicity, the travel modes have been grouped into auto, transit, and "walkBike" modes, where auto includes single and shared occupancy auto modes, transit includes all walk-transit and drive-transit modes, and walkBike includes walk and bike modes. We observe some interesting differences across tours types as well as income classes. For mandatory tours, lower income groups are more likely to travel by and transit and walkBike modes, while higher income groups are more likely to travel by automobile. That is, 17.5% and 13.8% of low income tours are made by transit and walkBike modes, respectively. This is compared to 14.2% and 6.8% of high income tours made by transit and walkBike modes, respectively. We observe a similar trend for non-mandatory tour mode shares. However, the transit mode shares are much smaller for

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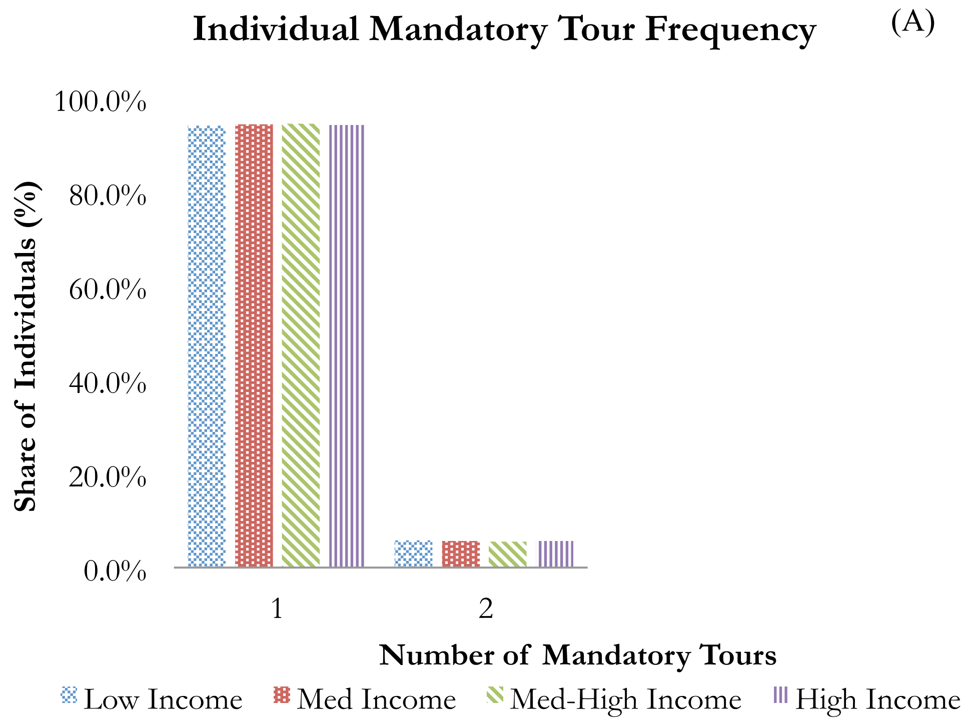
[41]The Figure B.6B is truncated at four tours per day, for simplicity purposes. Less that 0.5% of individuals will make more than four non-mandatory tours per day.

non-mandatory mode, relative to mandatory tours, while walkBike mode share are slightly higher.

Regarding household automobile ownership, the number of automobiles among household range from zero to four-plus automobiles. There are some observable differences in household auto ownership, by income class. As shown in Figure B.8, low income households are significantly more likely to own zero or one automobiles, relative to other income classes. Further, the higher income households are more likely to own two or more automobiles, relative to low income households.

Overall, we characterize the travel behavior of the lower income class by fewer tours (for mandatory and non-mandatory tour types). Further, lower income households are more likely to own zero or one automobiles, and have a higher tendency toward transit, walk, and bike modes. Higher income households have relatively higher trips frequencies, although the majority of higher income households stay within one to two mandatory and non-mandatory tours daily. In contrast, higher income households are much more likely to travel by auto models, relative to lower income households.

Figure B.5 A-D. Tour and Stop Frequency. (A) Mandatory Tour Frequency; (B) Non-Mandatory Tour Frequency; (C) Mandatory Tour Stop Frequency; (D) Non-Mandatory Tour Stop Frequency



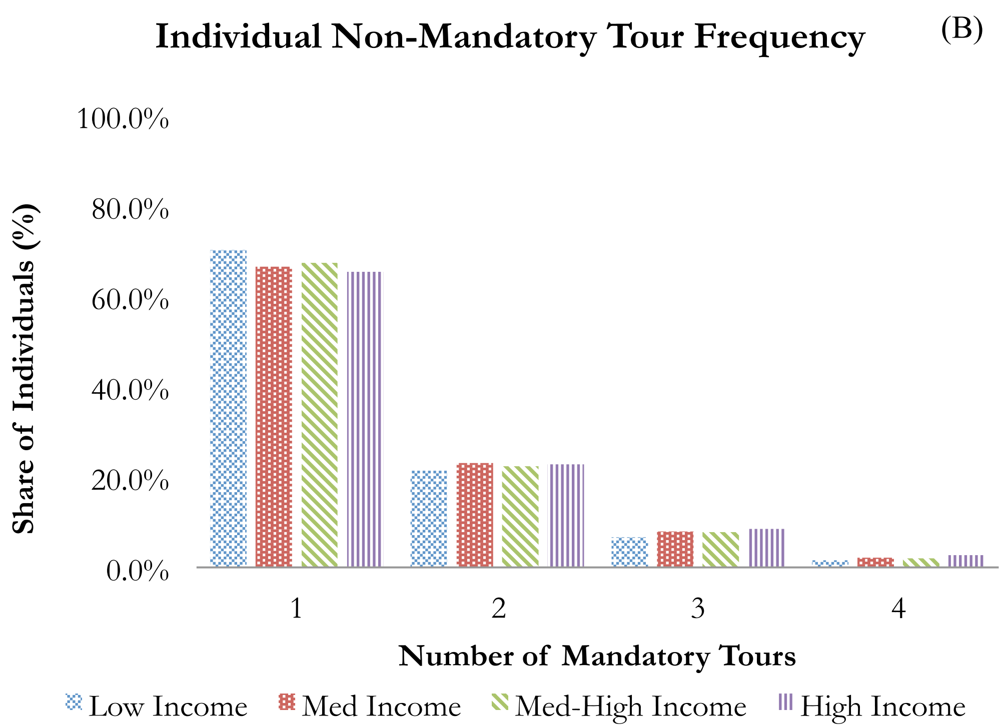


Figure B.6 A and B Individual Tour Frequencies for Mandatory (A) and Non-Mandatory (B) Tours

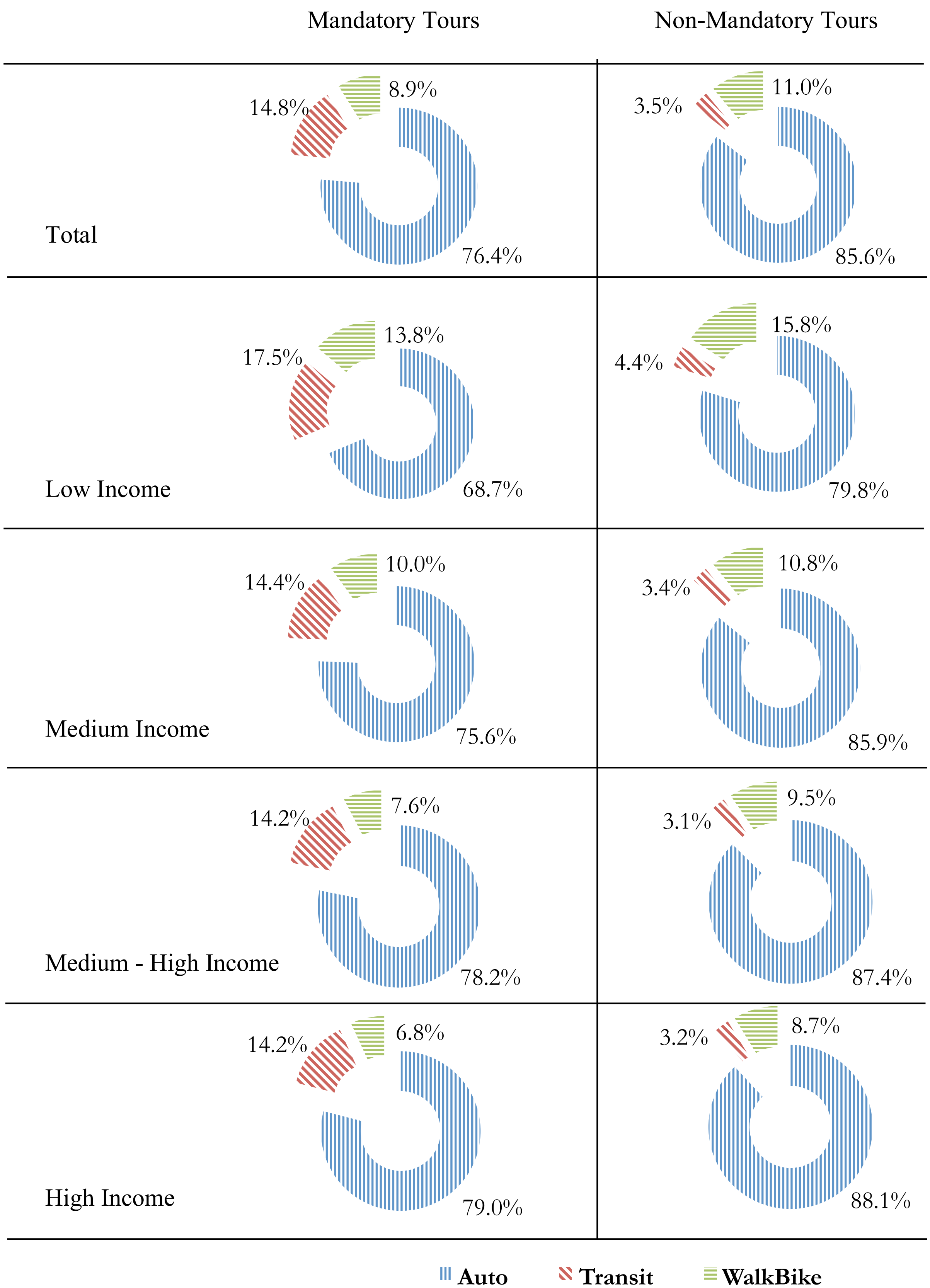


Figure B.7 Mode Shares for Mandatory and Non-Mandatory Tours

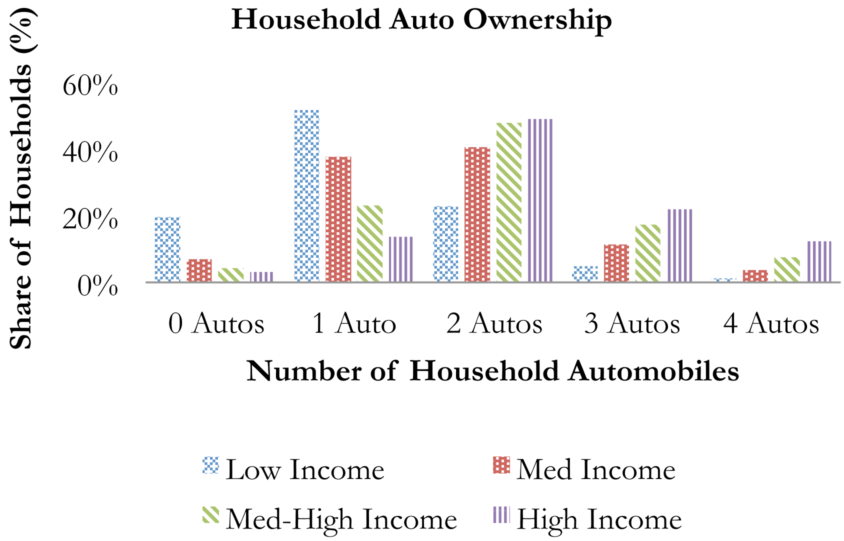


Figure B.8 Household Auto Ownership

Appendix C : MTC Communities of Concern Descriptive Statistics

	Communities of Concern			Remainder of Region			Regional Totals	
Population Subgroup	#	CoC %	% of Regional Total in CoCs	#	Remainder of Region %	% of Regional Total in Remainder of Region	#	%
Minority Population	1,124,851	81%	30%	2,660,518	48%	70%	3,785,369	54%
Low-Income Population	611,176	45%	40%	933,176	17%	60%	1,544,352	23%
Limited English Proficiency Population	269,569	21%	44%	344,137	7%	56%	613,706	9%
Zero-Vehicle Households	94,774	21%	40%	139,300	7%	60%	234,074	9%
Population 75+	71,709	5%	18%	337,516	6%	82%	409,225	6%
Population with a Disability	318,406	24%	29%	788,427	16%	71%	1,106,833	18%
Single-Parent Families	70,095	25%	31%	155,164	12%	69%	225,259	14%
Rent-Burdened Households	84,637	19%	35%	155,826	8%	65%	240,463	10%
All Persons	1,380,393	--	20%	5,570,371	--	80%	6,950,764	100%

Figure C. 1 MTC Communities of Concern Statistics (MTC, 2013a)