Title: Looking Beyond the Mean for Equity Analysis: Examining Distributional Impacts of Transportation Improvements

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Abstract

Activity-based travel demand models can be useful tools for understanding the individual level equity impacts of transportation improvements, because of their use of micro-simulation and ability to generate population and travel-related data at disaggregate (individual and household) levels. In this paper we first present a framework for equity analysis of transportation improvements, using activity-based travel demand models, distributional comparison measures, and incorporating equity standards. We then present two conceptual demonstrations of the advantages of distributional comparisons, relative to average measures. The first demonstration uses a synthetic data set and simple binary mode choice model and the second demonstration uses an empirical data set (the 2000 Bay Area Travel Survey) and more sophisticated (activity-based) mode choice model. These demonstrations show that distributional comparisons are capable of clearly revealing the winners and losers that result from transportation improvements, in comparison with average measures. The use of these results will likely result in different conclusions on transportation investments.

Introduction

Addressing inequities across all areas of society is critical for public policy development and implementation. 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 worlds other developed nations and rising (Tomaskovic-Devey and Lin, 2011), evidence of inequities can be found in numerous areas of society.

These 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.

Activity-based travel demand models are particularly useful for equity analysis of large-scale transportation improvements, 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.

Even with the advances of activity-based travel models and the growing use of them in practice (Dong et al., 2006), a number of challenges remain with applying these models for transportation equity analysis. The critical issues addressed in this paper lie with the analysis approaches taken to analyze equity outcomes of transportation infrastructure and policy improvements. These 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.

In this paper we first present a framework for equity analysis of long-range transportation plans, using activity-based travel demand model, distributional comparison measures, and incorporating equity standards. In addition, we give two conceptual demonstrations of the advantages of distributional comparisons, relative to average measures. The first demonstration uses a synthetic data set and simple binary mode choice model and the second demonstration uses an empirical data set (the 2000 Bay Area Travel Survey) and a more sophisticated nested mode choice model. These demonstrations show that distributional comparisons are capable of revealing the winners and losers that result from different transportation improvements; an analysis that is not possible using average measures. Further, distributional comparisons provide a framework for evaluating what population characteristics and conditions lead to certain distributional transportation outcomes. Ultimately, the use of these results from distributional measures will likely result in different transportation decisions, compared to the use of average measures.

Background

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 organize these various definitions and provide a clearer understanding of what is meant by *transportation equity* in this paper, we have structured the definitions in terms of a general equity concept, equity dimensions, and equity standards.

Concept: Transportation Equity 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. Improvements in 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: 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. These standards include pareto, egalitarianism, utilitarianism, restorative justice, etc.

The Existing Practice for Transportation Equity Analysis

In practice, the literature points to two high-level approaches to equity analysis. The first approach, which we refer to as the *modeling approach*, analyzes equity impacts using regional travel demand models, and second approach, which we refer to as the *non-modeling approach* does not apply travel demand models to evaluate equity outcomes.

The *non-modeling approach*, which tends to be most common among planning organizations (Amekudzi 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.) (MTC 2001, Rodier et al. 2009).

Our focus in this study is on the *modeling approach* to equity analyses, where transportation (and land-use) scenarios are modeled using a regional travel demand model. This is to measure the expected impacts of transportation (and land use) improvements on defined population segments and to compare these impacts (costs and/or benefits) across the segments in order to judge whether the distributions of impacts is equitable. This approach 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 (which simulate the expected changes after some transportation improvement has been made).

Critiquing the Existing Equity Analysis Process

There are three critical issues with the existing modeling approach practice for equity analysis. These issues are regarding the unit of analysis used for segmenting the population and the method of comparing equity indicators.

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 used for segmentation (e.g. income, ethnicity, etc.) can vary, these are generally selected to capture zones with high concentrations low income and minority households. Further, the units of segmentation used are aggregate spatial units, such as travel analysis zones (TAZs) or census tracts. As an example, if the communities of concern represent the target group, it is common to use all other zones in the regional together as the comparison group. The issue here is the use of zones as the unit of analysis. The use of zones can lead to a high degree of aggregation bias in evaluating the impacts on population segments. When using zones, in most cases there will be some share of the target group residing in comparison group locations and visa versa. Therefore it is impossible to isolate the impacts for the different groups. Activity-based travel models are capable of measuring disaggregate impacts, which would alleviate issues with aggregation bias.

The approach taken to compute the equity indicator(s) can also be problematic. The common approach is to calculate the mean value of the equity indicator and compare across the population segments, from the base-case scenario to some project scenario. The concern is that the use of the mean may mask important individual level outcomes. For example, the mean 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% either stay the same or are made to be worse off.

Proposal Equity Analysis Approach

We propose an equity analysis framework that makes use of disaggregate level data from activity-based travel demand models. In particular, this framework outlines the steps for post processing the scenario output from activity-based travel models, rather than changes to the full modeling process. This proposed framework is summarized in Table *1*. A general comparison of the existing vs. the proposed equity analysis processes is presented in the Table *2*. The third column in this table describes the improvements that the proposed equity analysis process makes, relative to the existing equity analysis practice. While there are a number of key improvements of this proposed approach over the existing approach, this paper focuses specifically on the benefits of individual level group segmentation and distributional analysis for transportation equity analysis.

Table 1 Summary of Proposed Framework for Transportation Equity Analysis

Steps	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:	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 to the target and comparison groups.
Step 4. Rank via Equity Criteria:	Select and evaluate the equity criteria by which the scenarios should be ranked, and rank the scenarios based on these criteria.

Table 2 Existing vs. Proposed Equity Analysis Process

Existing	Proposed	Improvements
Segment population and identify indicators	Segment population and identify indicators	The population is segmented using individuals or households as the units of analysis, rather than zones.
Calculate indicators	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	Compare changes in indicators across groups	Distributional comparison measures are used, rather than average measures.
	Rank scenarios using equity criteria	This is included as an important final step, in order to select a scenario that best meets the transportation equity goals for the region.

Distributional Comparison Measures

As mentioned earlier, the mean of any indicator will likely mask important information about the distribution of impacts, resulting in misleading equity analysis results. Alternatively, we propose the use of distributional comparisons, where distributions of the selected indicator(s) are generated and analyzed for the different population segments. Below, we describe two types of distributional comparisons: one of the aggregate densities and one of individual differences.

The first comparison is of the aggregate density of the equity indicator measured for each scenario being compared (e.g. before and after some transportation improvement(s)). This *Aggregate Density* comparison is illustrated in Figure 1. 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 2.

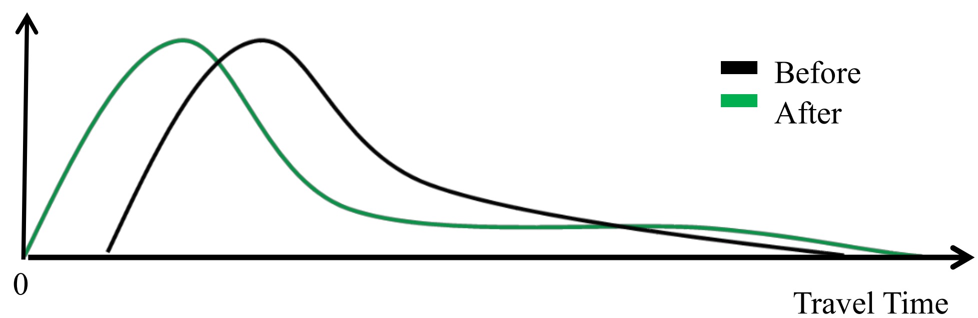

Figure 1 (Hypothetical) Aggregate Density Comparison

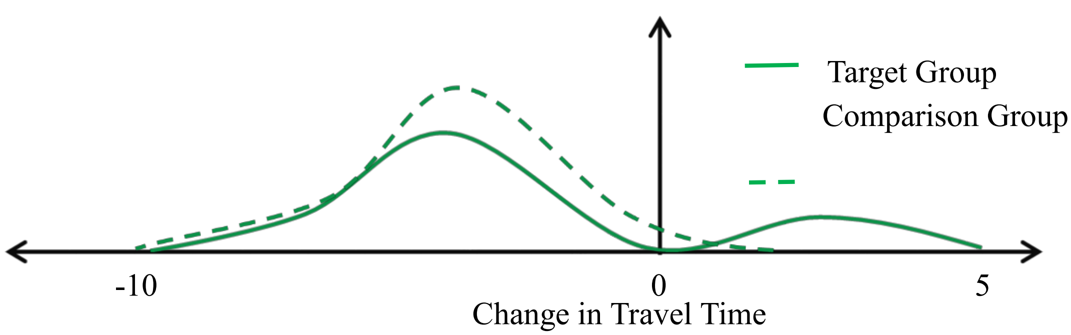

Figure 2 (Hypothetical) Individual Difference Density Comparison

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 each segment likely to experience positive or negative changes: *winners and losers*. Figure *2* gives a hypothetical example of the Individual Difference Density comparison, using the individual level changes in travel time for a target group vs. a 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 case, a significant share of the target group experiences losses in travel time, while very few in the comparison group experience gains. This type of finding is not possible using the Aggregate Density comparison. A graphical analysis of this individual level comparison provides a meaningful picture of how population segments will be affected. This type of analysis also lends itself nicely to cases where the impacts of several groups need to be compared. 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.

Demonstration Methodology

Description

The task of generating distributional equity measures using a large scale travel model and a fully representative population 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 seem impossible to disentangle. For this reason, we start by reducing much of this complexity to a simplified case for our first demonstration. We synthesize a sample population 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 impacts on 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.

Indicator

We use the logsum accessibility/consumer surplus measure as the equity indicator. 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 gives meaningful representations of transportation benefits. In this case, the logsum measure is comprehensive and captures all changes in utility due to the policy change.

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:

$$Logsum_n = E\left[max_j(V_{nj} + \varepsilon_{nj})\right] = \left[ln\left(\sum_j exp(V_{nj})\right) + C\right] \quad (1)$$

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[1]. While the logsum can be a useful measure of transportation accessibility, it is also mathematically equivalent to a measure of consumer surplus (Train, 2003).

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 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 and new utility levels) (Just et al., 2004).

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

$$\mathrm{CS_n} = \left(\frac{1}{\alpha_\mathrm{n}}\right)\left[\ln\left(\sum_\mathrm{j} \exp(\mathrm{V_{nj}})\right) + \mathrm{C}\right] \quad (2)$$

where the difference here relative to equation (1) is that the expression is divided by the marginal utility of income α_n, which converts the measure to monetary units.

Demonstration 1: Synthetic Data

Ultimately, we exploit the variation across traveler characteristics and experiences 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 of the sample along three dimensions: population, location, and transportation. Each individual is assigned one population variable (income level), a 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) that make up the sample 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,

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

share of income groups, availability of travel modes, and mean distance to the CBD. The total sample size is 1500.

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. The auto travel costs are calculated from the travel distances using a fixed 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.

Model

Using a discrete choice framework, we select parameters and develop binary mode choice utilities using the synthetic data variables (travel times, cost, and income) to simulate 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).

Scenario

We develop hypothetical policies to demonstrate cases where the policy results in 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 an efficient relocation of transit services, 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. For Neighborhood 1, bus riders experience a 50% reduction travel time. Further, because the bus frequencies for Neighborhoods 2 and 3 are drastically reduced, this 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 (low income travelers from 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 show the distributional changes resulting from a (controlled) transportation investment scenario.

Analysis and Results

First, we calculate the average change in the logsum measure, due to the scenario. These values are given Table 3. These values indicate that all travelers are winners and experience positive gains. Also, high income travelers experience slightly higher gains in this case.

Table 3 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 plot the Individual Difference Densities for high and low income travelers. 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 **Error! Reference source not found.**.

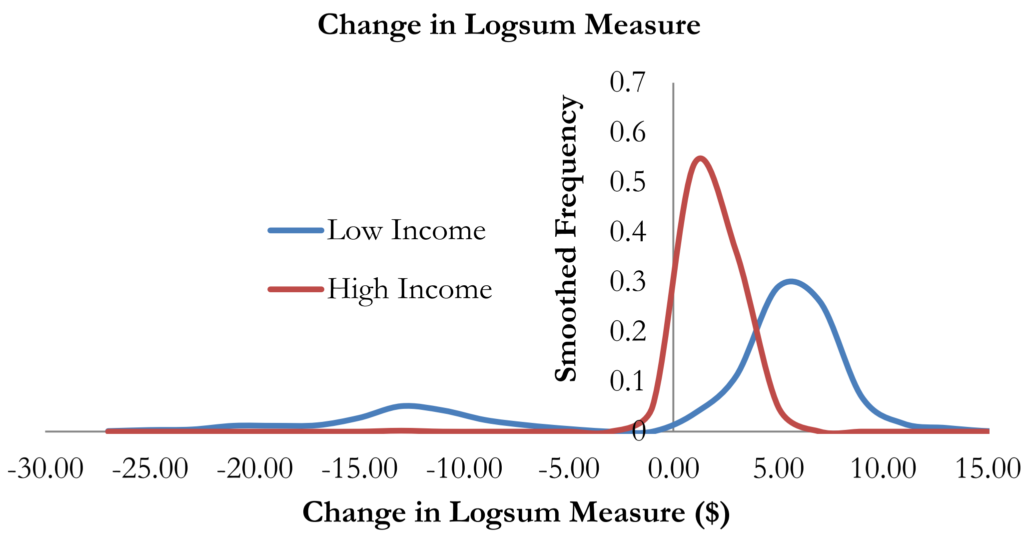

Figure 3 Individual Difference Density Comparison for a Hypothetical Setting

These results show that most travelers experience an increase in consumer surplus (winners). It is also clear that many low income travelers are more likely to experience higher gains, relative to high income travelers. However, it is also the case that some low income travelers are more likely to experience loses in consumer surplus (losers). It is important to note that this clear distinction between winners and losers is not possible without mode constraints (low income travelers from Neighborhood 2 only have access to bus). Varying changes to travel time and costs, even across modes, locations, and income groups, will result in winners or losers for a particular group, but not both.

This distributional comparison is not only useful for visually comparing and identifying winners and losers across population segments, but it can also be used to calculate measures of the shares of winners and losers for each population segment. As shown in Table *4*, we find that approximately 21% of low income travelers experience a reduction in consumer surplus, relative to less than 2% for high income travelers. We can further calculate the amount of loss experienced for each group. The low income travelers experience a loss of approximately $14.00 per person, relative to $0.45 for high income travelers, which represents a considerable disparity in transportation impacts.

Table 4 Share of Workers Who Experienced a Reduction in Consumer Surplus (Losers) and Magnitudes of Loss

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

Demonstration 2: Empirical Data

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 mode choice model that is estimated from empirical data, and using more realistic 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.

Data: 2000 Bay Area Travel Survey

The 2000 Bay Area Travel Survey (BATS) 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, household size, number of workers, number of children, number of 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 travelers (earning less than $30,000 annually) and 30% are made by high income travelers (earning more than $100,000 annually).

Mode Choice Model

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 three auto mode alternatives (drive alone, shared-ride 2, and shared-ride 3); the second nest includes two transit mode alternatives (drive-transit and walk-transit); and the third nest includes two active mode alternatives (walk and bike). Note that the auto modes are distinguished by occupancy level: single occupancy (Drive-Alone), double occupancy (Shared-Ride 2), and three or more occupants (Shared-Ride 3). Also, the transit modes are distinguished by access mode: drive-to-transit or walk-to-transit. 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

Setting and Planning Scenarios

As previously mentioned, 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 travelers are scattered across the region, in contrast to the previous example where all travelers lived in three neighborhoods and all traveled to the same employment destination. As with MTC's model and other mode choice models used in practice, the mode 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 interesting differences across income groups. The low income group is more likely to take Transit and Walk/Bike modes, relative to the high income group. This is shown in Figure 4.

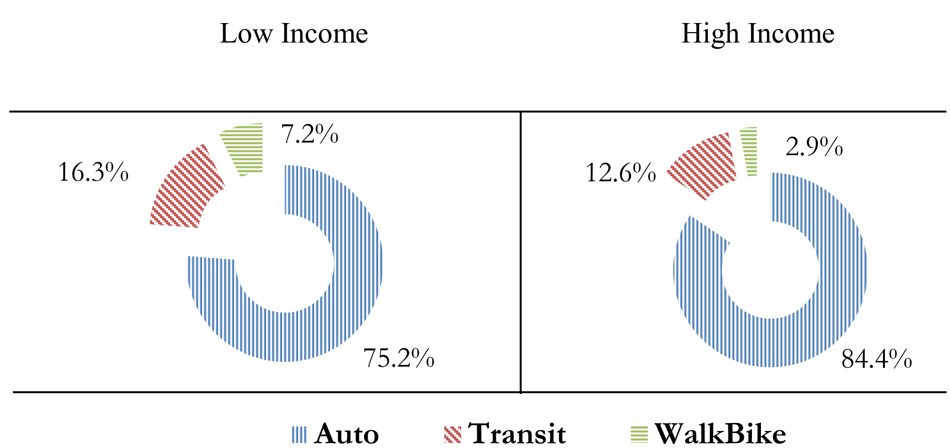

Figure 4 Mode Shares for Low Income and High Income Workers

Table 5 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

Results

Travel Cost Scenario

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 travelers are given in Table 6. Here we find that the average effects for income groups are similar: a small but positive change. Higher income travelers experience a (slightly) greater positive impact on average.

Table 6 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 seem to be consistent with the finding from the average measures. In **Error! Reference source not found.**, we see that relative positions of the curves for low income and high income travelers indicate that high income travelers are likely to experience higher gains, relative to low income travelers.

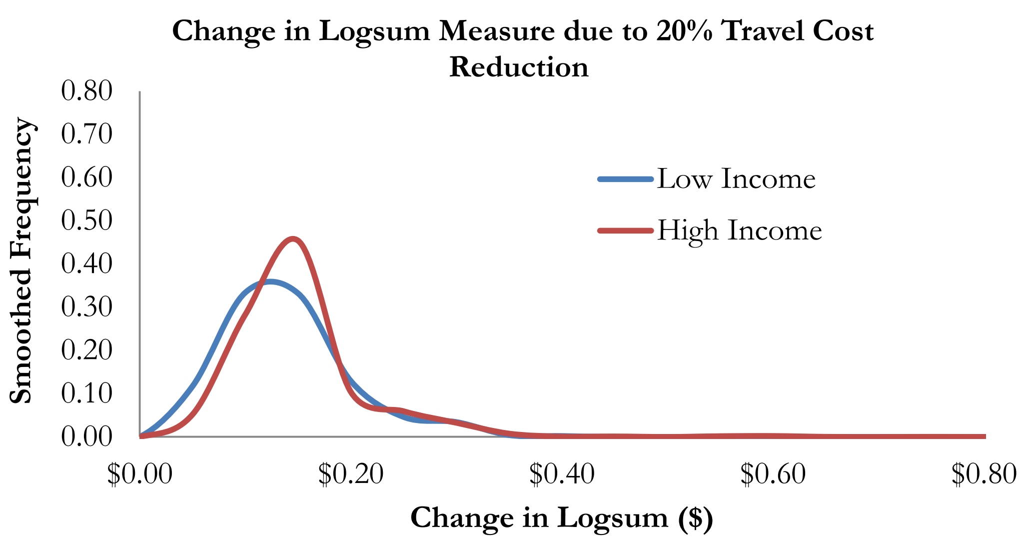

Figure 5 Individual Difference Comparison for Scenario 1 (20% Travel Cost Reduction for auto and transit modes)

Travel Time Scenario
For the second scenario, there is a uniform 20% reduction in travel times for all *travel modes*. For the active modes, this represents (for example) improvements in walking and biking infrastructure that enhance connectivity (i.e. bike trails, and pedestrian overpasses). The results from the average change in the logsum measure for low and high income *travelers* are given in Table 7, and the Individual Difference Density comparison results are given in Figure 6. As with the first scenario, we find positive average changes in the logsum measures for both low and high income *travelers*. However in this case, low income *travelers* experience a higher average benefit relative to high income travelers. Further, the magnitudes of the average changes are almost two times greater than those resulting from the travel cost scenario.

The Individual Difference Density comparison for this scenario produces more interesting results. In Figure 6 (A), we see that the scenario results for overall travel time reductions produce a bi-modal shape. In the first and taller peak (ranging approximately from \$0.00 to \$0.20), the curve for high income travelers is positioned above the curve for low income travelers, indicating that the higher income travelers are more likely to experience smaller gains. For the second peak area (ranging approximately from \$0.20 to \$0.50), the low income curve is positioned above the high income curve, indicating that lower income *travelers* are more likely to experience higher gains.

An important question here is why the travel time scenario results in a bi-modal shape, while the travel cost scenario produces a uni-modal shape. In contrast to the travel cost reductions 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 modes are assumed to have no travel costs.

To further understand the underlying causes for this shape (due to the overall travel time reduction), we generate three additional scenarios where we improve the travel times for modes separately. That is, we reduce auto, transit, and active travel times, one at a time. These scenario results are shown in the Figure 6 (B-D). Interestingly, we find that the greatest difference between the impacts to high and low income travelers comes from the reduction in active (walk and bike) travel times. This indicates that low income travelers are more likely to derive higher consumer surplus gains from improvements for active modes. While these results help us to tease out the influence on the overall bi-modal shape, is it not completely clear from the data why we find this result. There are certainly a number of complex relationships at play; specifically regarding mode availability, origin-destination pairs, and income level.

Table 7. Average Change in Consumer Surplus due to Scenario 2 (20% Travel Time Reduction)

	Average Change in Logsum Consumer Surplus	
	Low Income	*High Income*
Overall Travel Time Reduction	\$0.27	\$0.23
Auto Travel Time Reduction	\$0.13	\$0.16
Transit Travel Time Reduction	\$0.05	\$0.04
Active Travel Times Reduction	\$0.10	\$0.04

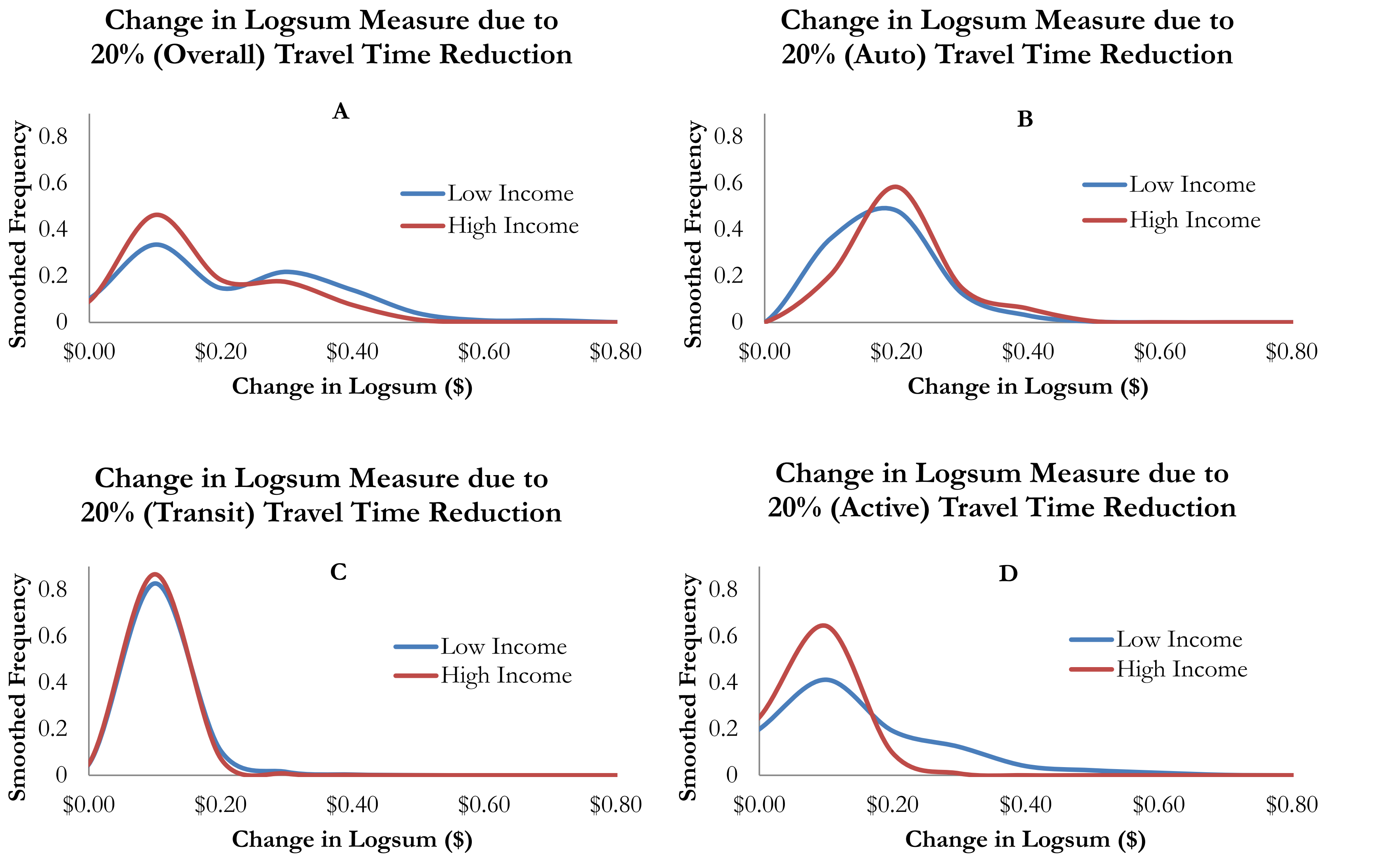

Figure 6 (A) Individual Difference Comparison for a 20% overall reduction in travel times. (B) Individual Difference Comparison for a 20% reduction in auto travel times. (C) Individual Difference Comparison for a 20% reduction in transit travel times. (D) Individual Difference Comparison for a 20% reduction in active (walk and bike) travel times. The bin size is $0.10

Conclusions

We have presented an approach for equity analysis of transportation improvements and demonstrated distributional comparisons of transportation impacts, using disaggregate (synthetic and empirical) travel data.

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 target 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 and evaluate equity criteria (based on the chosen equity objectives) and rank the planning scenarios based on the degree to which they meet the equity criteria.

In the second part of the paper, we focus on third step in the framework and provide demonstrations of what is means to process and evaluate distributional comparisons. Our first demonstration using synthetic data points to two data variables that strongly influence the distributional disparities between population segments. These 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. Our second demonstration using empirical data shows mode shares of low income and high income travelers can influence the distributional outcomes. The shapes of the Individual Difference Densities are reflective of which modes generate the greatest value for the different groups. While high income travelers derive much more of their utility gains from auto and transit modes, low income travelers 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 meaningful picture of individual travel experiences due to transportation investments. Further, they provide a means of analyzing these scenario impacts to identify the winners and losers, as well as determining specifically what factors lead to these transportation (equity) outcomes. This level of analysis is otherwise limited using average measures. It is likely that the use of distributional comparison for equity analysis would result in different conclusions around which transportation improvements are more equitable, as compared to using average measures.

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