Draft Final Report

Benefit Cost Analysis Using Activity-Based Models

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1.0 Introduction

1.1 Research Problem Statement

Benefit-cost analysis is a critical element of planning analysis for transportation investments and activity-based models open new opportunities to improve this process using disaggregated data. These disaggregated data address the aggregation bias inherent in current benefit-cost analysis (BCA) based on aggregate trip models. Aggregation bias refers to the assumption that group characteristics are shared by all members of that group. Trip-based models use aggregations of households that share attribute values to make forecasts, the idea being that all households of the same type behave similarly. For example, a trip-based model may use a common rate to predict the number of trips made by all households of a particular size, independent of household location, income or other influences on travel demand. BCAs of policy and investment alternatives by transportation planning agencies that use trip-based model outputs inherit these biases, resulting in distorted estimates of changes in consumer welfare. Activity-based models (ABMs) function at the disaggregate level of individual persons and households, and provide estimates of travel demand that are less subject to aggregation bias. ABMs incorporate more information about how individuals and household make travel-related choices and tradeoffs such as whether to travel to participate in activities, the scheduling of these activities. ABMs also produce more detailed outputs that can be used to evaluate the overall efficiency as well as the distributional implications of transportation investments. As a result, activity-based models can potentially be used to provide better estimates of differences in consumer welfare between policy and investment alternatives.

Recent research points to the use of expected utility measures of consumer welfare, because expected utility measures include more information about individual traveler preferences and the network performance, and they can provide more comprehensive and less biased measures of consumer welfare. However, there are numerous theoretical and practical challenges to using current ABMs to produce comprehensive measures of expected welfare. Adaptation of traditional rule-of-half based measures of consumer surplus to the disaggregate ABM framework provides an advanced yet still practical means of supporting benefit-cost analysis.

The San Diego Association of Governments (SANDAG) invested in the development of a benefit-cost analysis tool that uses outputs from SANDAG's CT-RAMP activity-based model. The tool uses ABM outputs to estimate impacts on consumer surplus reflective of a wide range of potential benefit types, such as mobility benefits, emissions reductions, accident reductions, increases in physical activity, and improved network reliability. However, the initial tool development revealed a number of methodological and practical challenges to using ABMs to support benefit-cost analysis. The research effort carried out for this project systematically investigated such challenges and implemented and test improvements to ABM-based BCA methods by means of a newly developed software tool (BCA4ABM). The tool was used with the SANDAG AB model, and also with the Tampa

AB model, which uses different AB model software (DaySim instead of CT-RAMP) and different network software (Cube instead of TransCAD). Finally, the new tool and the associated evaluation methods were subjected to a set of systematic sensitivity tests, providing more evidence as to their usefulness in different policy settings.

1.2 Project Objectives

Public agencies must appraise the effects of different investments and policies in order to make informed choices. Determining which investments and policies most effectively support agency goals is increasingly complex, due to constrained budgets and programming capacity, changes in transportation technologies, maturation of urban transportation systems leading to the desire to evaluate more nuanced policies, and advancements in technical analyses.

Both the private and public sectors use benefit-cost analysis, user benefit assessment, and other welfare analysis methods to provide critical information about the performance of projects and policies. In the public sector, there has been a focus on the overall costs and user benefits of the policy and investment choices and, increasingly, an interest in understanding the allocation of costs and benefits to different segments of the population.

Welfare analyses are typically based upon measures of consumer surplus extracted, either directly or indirectly, from econometric forecasting models. In the past 15 years, many large regional metropolitan planning agencies in the US have implemented activity-based travel demand forecasting models (ABMs) because they provide more comprehensive representations of individual and household travel choices as a result of functioning at a disaggregate level. This disaggregation also provides the ability to support more detailed and less biased analyses. Concurrent with the adoption of ABMs, benefit-cost analyses have evolved, with traditional rule-of-half-based methods being applied to value a wider range of effects and innovative expected utility-based methods being used to capture effects more comprehensively and consistently. However, there are virtually no examples of either approach being used in practice to quantify welfare impacts using the detailed information provided by ABMs.

The research described in the following chapters was designed to achieve two complementary objectives: to refine recently established methods and tools for calculating rule-of-half based consumer surplus measures using ABMs for benefit-cost analysis, and to develop new methods for calculating expected welfare measures using ABMs. The project aimed to develop practical methods for estimating changes in consumer surplus using DaySim and CT-RAMP, which are the ABM systems adopted by several large US metropolitan planning agencies. These methods were designed to exploit the detailed disaggregate nature of ABMs to provide more precise estimates of changes in consumer surplus, and to provide the ability to analyze the impacts of these changes on different populations. Critically, these consumer surplus estimation methods were implemented in software code that can be used by the participating public agencies and can be readily adapted for use by other agencies.

1.3 Contents of Report

Chapter 2 of this report provides practical background for the remaining chapters. Section 2.1 describes the existing state of the practice for using BCA with travel demand models. Section 2.2 describes the current SANDAG BCA tool, and Section 2.3 discusses the concerns and objectives of SANDAG and Florida DOT District 7 as potential users of new methods developed in this research.

Chapter 3 provides theoretical background on consumer surplus and expected welfare measures, comparing "rule of a half" generalized cost-based and logsum-based methods. After a series of sections on theory and practical pros and cons, Section 3.7 discusses how the different benefit measures can be derived from the specific DaySim ABM used in Tampa and the CT-RAMP ABM used in San Diego.

Chapter 4 discusses methods for evaluating health related benefits of walking and cycling, recommending a specific method for this project—the HEAT method developed by the World Health Organization.

Chapter 5 describes the methods and results of a series of exploratory comparisons of generalized cost-based and logsum-based "rule of a half" methods, carried out using the Tampa ABM in a series of controlled scenarios with systematic, region-wide changes in travel time and travel cost.

Chapter 6 describes a series of sensitivity tests that were run using the Tampa and San Diego model systems. The tests include an infrastructure scenario, a land use scenario, and a toll pricing scenario, as well as tests to gauge the sensitivity of the results to random variation in the ABM simulation.

Chapter 7 presents a brief summary of the project objectives and findings, as well as recommendations for practice and recommendations for further research.

Chapter 8 is a list of references.

Finally, Appendix A describes the implementation of the various benefit evaluation methods in a flexible new software tool named BCA4ABM, which was used to compute most of the results presented in Chapter 6. The structure and capabilities of the software tool are presented, and examples are provided of the various configuration and input files.

2.0 Practical Background

2.1 Travel Modeling and Benefit-Cost Analysis in Practice

There is an extensive history of application of benefit-cost analysis methods in the evaluation of transportation investments. The practice has been largely limited, however, to fairly aggregate treatments of consumer surpluses in the assessment of large-scale investments in physical infrastructure. In part this is a result of the coarse nature of the data that is available regarding ex-ante and ex-post performance of investments in transportation assets.

The practices involved in the evaluation of transportation investments can vary considerably from one setting to another. Over the years, professional associations and government agencies have adopted guidelines and rules for benefit-cost analysis in an attempt to standardize the methods and approaches that analysts employ. The ASSHTO User and Non-User Benefit Analysis for Highways, 3rd Edition is a comprehensive guide to the application of user benefit analysis for the evaluation of highway investments. A companion guidebook for transit analysis is the Transit Cooperative Research Program Report 78, Estimating the Benefits and Costs of Public Transit Projects.

These guidebooks set out the basic steps and methods for appropriately measuring the benefits to transportation users from changes in transportation supply conditions - including defining the Base Case vs. the Project Alternative, correctly measuring user benefits (the user benefit formulae), measuring project performance over time (the concept of present value), discounting benefits and costs, and performing benefit–cost analysis and project selection. At the heart of these methods is the user benefit formulae, or the "rule of a half" measurement of the change in consumer surplus; which is presented and explained in detail in Chapter 3. In brief, the "rule of a half" incorporates the expected benefits accruing to existing trips (trips made in both the "base" and a "build" scenarios), as well as accounting for any new generated (or suppressed) trips by assuming that those trips receive only half of the benefit that is gained (or lost) by comparable existing trips (i.e. between the same origin and destination by the same mode during the same time period).

Advances in travel modeling over the last few decades have provided a sound basis for evaluating the performance implications of many kinds of transportation investments without resorting to expensive, complicated, and time-consuming data collection exercises. Models also have the advantage of making it possible to ask prospective questions regarding the merits of large-scale investments in transportation systems. In this modeling setting the basic user benefit calculation can be made more detailed to recognize the major sources of user benefits: the savings in travel time, operating costs, unreliability, and accident costs, and the consumer surplus that such savings generates. The user benefit calculation also incorporates induced traffic demand by incorporating traffic volumes with and without the project. The representation of traveler time and money costs in terms of generalized time or generalized costs, and the inclusion of both income and travel time as variables in mode choice, allows for the application of the Rule of a Half in a manner that permits integration across a number of different benefit metrics and classes of transportation users that exhibit a range of preferences.

General Description of User Benefits

The primary benefits from transportation improvements are reductions in the costs of inputs into the movement of individuals and goods. Reducing these costs yields benefits. The benefits included in a state of the practice user benefit tool (such as the PSRC User-Benefit Tool described in the Project Task 1.2 memo) include those listed below. The field of economic analysis in general, and benefit-cost analysis in particular, has amassed an extensive literature regarding the costs associated with the consumption of various economic resources, including travelers' time, vehicle use, clean air and safe traveling. Where possible, economists try to establish such values by observing consumption behavior directly in markets, thereby revealing relative values of benefit and cost elements. This is not always possible, and, as a result, a range of advanced techniques has been established to develop estimates of costs of resources where no suitable market activity affords observations.

In practice, benefit-cost accounting makes use of this accumulated knowledge by representing unit costs for various resources as input parameters. As with any set of assumptions, the outcome of the analysis can be substantially influenced by the particular values that are employed.

- **Travel Time Savings:** Travel time costs are written to so-called "skim matrices" of measures of the travel time impedances of the various inter-zonal paths in the network assignment process. Travel time costs are skimmed independently for each class of user assigned to the network and for each time of day assignment period. Travel times must be converted to monetary costs by multiplying by an assumed value of travel time (VOT). There have been many studies of travel-time savings that have established that the value of travel time saved (VOT) is closely linked to the wage rate of passengers in autos and transit vehicles, and the wages paid to drivers plus the time cost of cargo inventory for commercial vehicles. There is also variability around these mean values due to user travel time cost perceptions idiosyncratic to particular trip circumstances.
- **Vehicle Operating and Ownership Costs**. There is an extensive literature, for vehicles of all types, which can be used to relate changes in network performance characteristics to vehicle cost savings. In its most basic form vehicle operating costs may be represented as a constant per mile value in travel models. These money costs are treated as any other monetary price variable in the consumer surplus calculations.
- **Toll Costs, Parking Costs, and Transit Fares:** Toll costs, parking costs, and transit fares are all out-of-pocket costs associated with driving a vehicle or patronizing transit services. Toll costs are typically assigned to specific road links in a network, transit fares accumulate over the segments of a transit path and parking costs are associated with vehicle trip destinations. Each in turn can be aggregated to origin-destination pairs and regarded as part of a trip "price", just the same as time costs and vehicle operating costs.

- **Improved Travel Time Reliability:** Standard travel models represent an expected travel condition during atypical weekday yet the true conditions vary considerably from day to day. The variable performance of a transportation network contributes to personal or firm scheduling costs and the costs associated with failing to meet timelines. A high degree of performance variation implies there is a high risk of experiencing particularly onerous conditions; low variation implies lower risks. This risk can be translated into a "certainty equivalent" or willingness-to-pay for the risk reduction. This is implemented in the BCA tool by correlating speed variances with average speeds that are produced by the PSRC regional travel demand model. The "certainty-equivalent" value concept says that variability in highway performance can be reduced to a single indicator equal to the certainty-equivalent value of the performance variability. This yields a specific relationship between freeway link volumes and link speeds with and without an unreliability penalty. The certainty equivalent can be expressed as time and value just as other measures of time are valued, yielding standard consumer surpluses. (Alternative methods for valuing reliability benefits are presented in later chapters.)
- **Accidents, vehicle emissions, toll revenues, and transit operating revenues:** In addition to the various costs to users that constitute the consumer surplus measures that are part of a user-benefit tool, there are other costs that are typically treated as accounting entities. Each of these categories of costs can vary under alternate investment or policy scenarios but the costs may not strictly be associated with transportation system users. As such, the accounting of these costs or benefits will not involve consumer surplus calculations but rather the summing or transformation of a cost until associated with an accounting of some measure of transportation system performance. For example, vehicle emissions can be treated as a function of vehicle speeds and an emission rate for different vehicle types operating under different speed conditions. The sum of these emissions will vary across scenario but the costs themselves not a price that is experienced by any specific user of set of users. Rather these costs are social costs, which may manifest in other aspects of the economy, such as the costs of health care or foregone earnings or leisure benefits due to compromised wellness.

Meaningful User Benefit Analysis Relies on Segmentation of Demand

If all users of the transportation system had identical preferences (values of time) and choices, and if quantity demanded did not change with prices, then a simple summing of costs for the "Base" and "Build" scenarios would be sufficient to allow for a representation of the user benefits associated with the "Build" scenario relative to the "Base" scenario. Unfortunately, such an unrealistic representation of transportation demand is often employed in user benefit analysis. The result is a violation of the underlying principles of welfare analysis specifically, and microeconomics in general. Just as market segmentation improves behavioral realism in travel modeling, the same produces meaningful representations of the welfare gains to individual users and groups of users.

With traditional aggregate zone-based travel demand models, the segmentation of demand and proper treatment of preferences in welfare analysis based on travel modeling can require performing millions of consumer surplus calculations (Origin-Destination zone pairs, user classes, times of day, benefit types) with data extracted from many sparsely populated model output matrices. As models tend toward using more spatial detail in zone systems and networks and more user classes in assignment, the increasing number of computations required becomes a practical impediment. In this regard, the transition to activity-based modeling (ABM) opens up new possibilities. Activity-based models write out the various trip-related costs directly to lists of trips, persons, or households. Values of time can be sampled from distributions that are specific to households, individuals, or even individual trips and employed in the basic user benefit formulae—thereby introducing a stochastic aspect to the user benefit computation.

2.2 Overview of the Current SANDAG BCA Tool

The starting point for the research carried out in this project was a Benefit-Cost Analysis (BCA) tool that was developed for use by the San Diego Association of Governments (SANDAG) for use with the outputs of their activity-based model (ABM), which uses the CT-RAMP demand model software along with the TransCAD network software. The key inputs and outputs for that tool are summarized in Table 1 through Table 9. The key inputs are individual household and trip records from the ABM, which simulates individual households and persons and their travel for an entire day, and link records from the network traffic assignment, which finds the optimal routes through the network for autos, trucks and buses and thus determines traffic flows and congestion on each link in the network during each period of the day (AM peak, midday, PM peak, evening, night/early AM).

The key outputs for this project are those in Table 1 through Table 9 that are derived from the ABM trip records—including travel time costs (by auto, transit, walk or bike), travel monetary costs (for fuel, tolls, parking and transit fares), and physical activity benefits related to the reduced risk of mortality from walking and biking. Other benefits and costs related to truck travel, accidents, reliability and emissions, are based mainly on the link-level output records, and usually cannot be related back to specific households, persons or trips.

In the context of the existing methods implemented for SANDAG, potential objectives of this research included:

- Transferring the existing BCA tool and methods to another region (Tampa) that uses different network and ABM software. Tampa uses Cube instead of TransCAD for network modeling and DaySim instead of CT-RAMP for the ABM demand model, Tampa also uses different database structures (the original SANDAG BCA tool is highly customized to the particular SQL database structure that SANDAG uses to store model inputs and outputs).
- Testing methods of including additional aspects of expected welfare in the benefits measures that may not be captured by changes in travel times and costs. For

example, measures may be based on utility (logsum) values from particular AB sub-models of interest.

- Testing possible methods of distributing network link-based benefit measures (those to the right of Table 2.1) to individual trips output from the AB model. This would allow those benefits to also be segmented according to sub-populations of interest, such as income groups and residence areas.
- Incorporating any other important benefit measures that can be added in a straightforward way. For example, this could include noise impacts. Regional economic development benefit measurement, however, would require an additional layer of analysis, and such benefits are often conflated with capitalization of travel benefits, and raise the risk of double counting.

Table 1: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Residential Mobility

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Residential mobility (travel time)	No	Yes	No	No	No

Table 2: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Residential Monetary Travel Costs

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Residential monetary travel costs	No	Yes	No	No	No

Table 3: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Physical Activity

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Physical activity (walk and bike)	No	Yes	No	No	No

Table 4: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Residential Vehicle Ownership Cost

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Residential vehicle ownership cost	Yes	No	No	No	No

Table 5: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Truck Mobility

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Truck mobility (travel time)	No	No	No	Yes	Yes

Table 6: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Truck Operating Costs

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Truck operating costs	No	No	No	Yes	Yes

Table 7: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Accidents

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Accidents (based on VMT on links)	No	No	Yes	Yes	Yes

Table 8: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Reliability

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Reliability (link-based measures)	No	No	Yes	Yes	Yes

Table 9: Input and Output for the Current SANDAG Benefit-Cost Analysis Tool—Emissions

Output	Input: Households with vehicle ownership from AB model	Input: Trips by mode with travel times, costs and distance from AB model	Input: Car flows on each link from network model	Input: Truck flows on each link from network model	Input: Congestion and speeds on each link from network model
Emissions (via emissions model)	No	No	Yes	Yes	Yes

Other inputs not shown in Table 1 through Table 9 include parameters related to values of time, temporal discount rates, and other assumptions, as well as matrix-based inputs related to additional travel markets, such as external trips.

2.3 Agency Objectives: SANDAG and FDOT District 7

Task 1.1 of the project research scope was to determine the objectives of the relevant planning agencies in the context of performing BCA with their travel demand models. During the summer of 2015, meetings were held with key staff from SANDAG and from Florida DOT District 7 (including Tampa). The existing SANDAG tool was summarized for the agency staff (using a format similar to Table 1 through Table 9) and the research objectives of the project were described. The agency staff were asked about their priorities and needs related to the research objectives.

Many of the views stated regarding the use of cost-benefit analysis with activity-based models were the same for the representatives of the two agencies. Those included:

- Both agencies stated that it is very important to look at the **distributional effects** of transportation policy costs and benefits across different population segments and geographic segments. The population segmentation may be by income groups, car ownership groups, or other factors. The geographic segmentation may be by types of areas (e.g. inner-city versus suburban), but there may also be cases of ethnic groups of interest that tend to be concentrated geographically.
- Both agencies have constituencies who are very interested in the benefits of **active transportation** (walking and biking), and are interested in how those benefits are determined in the models and then translated into monetary values. In additional to the health benefits of increased exercise, the measures should ideally also look for evidence of likely changes in accident rates for pedestrians and cyclists.
- Both agencies are interested in including **travel and activity benefits other than changes in travel time and travel cost,** such as being able to reach more attractive destinations and/or participate in a wider variety of activities, and are curious as to how that can be done using the activity-based model outputs. (That that is one of the key research focuses of this project.)
- Both agencies agreed that calculating **changes in localized environmental effects**, such as pollution dispersion or noise impacts near new or changed infrastructure, is beyond the scope of what they expect from a benefit-cost tool of this sort.

- Neither agency identified any new type of cost or benefit that needs to be added to the list that is currently considered in the existing SANDAG tool (see Table 1 through Table 9). Thus, our research focused on testing improved ways to calculate the measures that are already included in the SANDAG tool.

There were also some differences with regard to the two agencies:

- SANDAG has been using its current activity-based model for a number of years, and already has some experience in using the initial BCA tool created by RSG as part of a recent economic evaluation project. In contrast, FDOT District 7 has just begun to use its new AB model, and has not yet had access to a BCA tool that takes advantage of the disaggregate AB model output. Thus, one of FDOT's key objectives for the project was to get a BCA tool in place and to get some guidance and experience in using it. (FDOT is contributing supplemental project budget towards this objective.)
- While SANDAG has already implemented the California-specific EMFAC emissions model post-processor and used it with the existing BCA tool, the Tampa region is currently in attainment for all major air pollutants, so has not been required to forecast emissions. This situation may change in the near future, however, so FDOT District 7 may need to start applying the EPA MOVES emission model in the future.
- SANDAG (with RSG) carried out a concurrent Federal research project—the SHRP 2 C04 implementation project (Strategic Highway Research Program, 2013)—to better model the effects of reliability and tolling on congestion in the San Diego region. The data and model improvements for that study provided an alternative way to calculate reliability-related benefits and costs for use in the BCA tool, as described in later chapters.

In summary, both SANDAG and FDOT District 7 expressed keen interest in this research and in implementing any improved BCA tools and methods that result from the project.

3.0 Consumer Surplus and Expected Welfare Measures: "Rule of a Half" and Logsum-Based Approaches

3.1 Introduction

Transportation pricing and investment decisions are an important context in which to evaluate alternative benefit-cost analysis (BCA) methodologies. The reason is that passenger transportation, in particular, involves settings where the affected user- and non-user communities are heterogeneous. Users vary in their endowments of wealth, income levels, preferences, and uses of transportation services. Additionally, there are a variety of transportation modes that differ not only in their technology, but also the commitment of out-of-pocket and time resources, and exposure to health and other risks.

The result is that there are behavioral variations observed among users in the context of any given portfolio of alternative modes, paths, trip purpose, etc. This poses a challenge in aggregating and comparing the comparative virtues of investment and pricing policy alternatives. It also spotlights the sensitive interpersonal variations in the value or benefit conferred by a particular project or policy alternative. These distributional impacts form the basis for so-called environmental justice (EJ) analysis of transport improvements.

The balancing of benefits and costs occurs continuously in the provision by the private market of most goods and services. In the private market place, however, there are typically many alternative providers of any given good or service. The disciplining effect of competition and profit motivation result not only in natural pressures to select the most cost-effective alternatives, but also provide goods and services that are highly differentiated. The incentive to address varied tastes and abilities to pay is thus inherent in private motivations. In contrast, the public sector plays a highly visible, and often singular, role in investment and operation of certain passenger transport activities—especially in urban travel settings. The result is a need for a transparent administrative process that reveals the genesis of choices and tallying of the consequences of those choices on heterogeneously situated users. The public sector project and project portfolio selection process can be influenced by decision-maker preferences that are not explicit *ex ante*, and travel model data can reduce the arbitrariness of decisions.

The regional travel demand modeling process is the primary mechanism for creating the data on which public policy makers rely in evaluating project and policy alternatives. These models vary in design and complexity, but in general terms aim to emulate user behavior and system performance by modeling users' mode, path, distribution, and other choice dimensions in a network context. The various choice modules are assembled in an order presumed to represent the logical order of user decision-making. Elaborations of a module, such as the mode choice step or module, may comprise several nested choice representations.

Regional travel demand models use binomial or multinomial statistical representations—typically based on assumptions of logistic distributions because of their attractive mathematical properties. The basic, underlying economic concept is that users make choices that yield the greatest utility to them. Utility is a fundamental economic construct that measures well-being in units of "utils". Heterogeneity in taste or preference is introduced as differentially-weighted conversions of "utils" to monetary value, correlates for tastes and preferences (such as income trip purpose, sex, etc.) or randomness in the coefficients that weight the dimensions of transportation performance that exogenously mediate choice behavior.

The coefficients of the choice models are derived from survey-based observation of actual choice-making (revealed preference), or simulated choice-making (stated preference). They are typically estimated using discrete choice models under the assumption that the errors are distributed by one of the family of Generalized Extreme Value (GEV) distributions, of which the logit model is a special case. The class of models of this type are often referred to as random utility models, although they are not unique in introducing randomness to utility specifications.

3.2 Utility Theory and Consumer Surplus

Utility theory is at the core of the consumer surplus concept and the various alternative means of means of measuring it empirically. Utility is a non-monetary measure of well-being. It is assumed that travelers behave so as to maximize utility in making mode and other travel choice decisions. For the purposes of this report, we denote utility associated with travel as in Equation 1 for a user n and selected travel mode m.

Equation 1: Utility Term

$$U_{n,m} = \text{utility to user } n, \text{ in utils, of travel by mode } m$$

Consumer surplus, in contrast to utility, is a monetary concept. Utility is monetized by applying a factor that converts "utils" to money by assuming a constant relationship (for a given user) on the margin between an increment of utility and an increment of income. Coupled with utility maximizing behavior across the choices of travel modes available, this conversion yields consumer surplus (CS) as expressed in Equation 2.

Equation 2: Consumer Surplus

$$CS_n = \left(\frac{1}{\alpha_n}\right)\max\left(U_{n,m}\right)\forall_m = \text{consumer surplus for user } n, \text{ in monetary value, where}$$

$$\left(\frac{1}{\alpha_n}\right) = \frac{dY_n}{dU_n} = \text{marginal monetary value of utility for user } n, \text{ and}$$

$$Y_n = \text{income of user } n$$

This expression of consumer surplus is, of course, for a particular user, n, and a particular set of modal alternatives, m, with given service characteristics. The consumer surplus will also be particular to the type of travel, time of day, a path or OD pair, and other dimensions not formally portrayed here to simplify the notation. A change in a network or modal performance characteristics will yield a change in user behavior and thus in the consumer surplus for user n. Computation of the "delta" consumer surplus between conditions A and B is usually what is sought in transportation project and policy evaluations, as in Equation 3.

Equation 3: Change in Consumer Surplus Between Conditions A and B

$$\Delta CS_n = \left[\left(\frac{1}{\alpha_n}\right)\max\left(U_{n,m}\right)\forall_m\right]_B - \left[\left(\frac{1}{\alpha_n}\right)\max\left(U_{n,m}\right)\forall_m\right]_A$$

To operationalize the measurement of ΔCS, we need to devise an approximation to the utility function. This approximation needs to be able to be a function of measurable quantities, such as modal service dimensions, user characteristics and coefficients, forming a "representative utility" denoted as V. The representation will be imperfect because there are also unobservable characteristics of utility that are not accommodated by V. These ε are assumed to be randomly distributed by a realistic, but convenient distributional form.

Because the approximation of utility is stochastic, consumer surplus measures are now expected, rather than deterministic values. With the assumption of a logistic distributional for the error terms, a working representation of the expectation of CS and ΔCS can be measured, as in Equation 4. The expectation of the error terms, like the error terms themselves, is unobservable. However, in computing the expectation of ΔCS, the constant C is subtracted from itself and removed from the computation.

Equation 4: Consumer Surplus Expressed in the Form of Logit Model Equations

$$U_{n,m} = V_{n,m} + \varepsilon_{n,m}$$

$$E\left(CS_n\right) = \left(\frac{1}{\alpha_n}\right)E\left[\max\left(V_{n,m} + \varepsilon_{n,m}\right)\forall_m\right]$$

$$= \left(\frac{1}{\alpha_n}\right)\ln\left(\sum_m e^{V_{n,m}}\right) + C$$

$$\Delta E\left(CS_n\right) = \left(\frac{1}{\alpha_n}\right)\left[\ln\left(\sum_m e^{V_{n,m}}\right)_B - \ln\left(\sum_m e^{V_{n,m}}\right)_A\right]$$

Conveniently, under the statistical assumption the expected value of consumer surplus, E(CS), and the change in expected value of consumer surplus, ΔE(CS), computations are functions of the natural log of the sum over modes of the exponentiation of the representative utility, V, by mode for each user. (See Williams (1977) and Small and Rosen (1981) for the derivation. It depends on the assumptions that each εn,m is Independent and identically distributed (iid) and utility is linear in income. This means that αn is assumed constant with respect to income for individual n.) These so-called log-sums are the denominators of choice probability models that assume the logistic distribution. The mode choice model in Equation 5 is a source for this log-sum and thus a potential means of measuring the delta consumer surplus resulting from a change in conditions from A to B.

The probability p of user n selecting mode m is a function of the representative utility, V, of all modes.

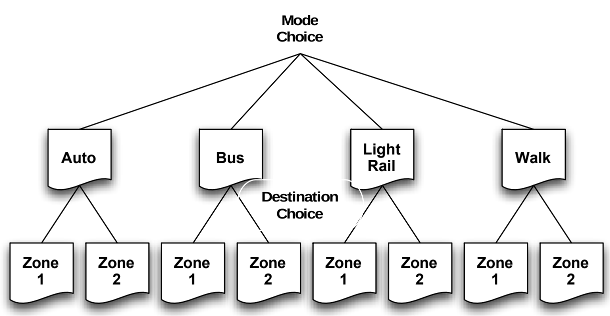
Equation 5: Logit Model Probability as a Function of Utilities

$$p_{n,m} = \frac{e^{V_{n,m}}}{\sum_{m} e^{V_{n,m}}}$$

It is important to note that because "utils" have no natural units, and the utility of each alternative can only be measured relative to other alternatives, logsums such as those introduced in Equation 4 have no natural "zero" point—thus the appearance of the arbitrary constant C in the equation. As can be seen in subsequent chapters, this fact has important implications for the use of logsum-based measures in benefit calculations.

Simple choice models like those of Equation 5 can be elaborated by nesting it with one or more other choice dimensions. For example, one may wish to model the user's choice of mode and the choice of destination together in a consistent manner, as in Figure 1. As Daly (2001) and others have demonstrated, if the error terms are distributed GEV and the nests are non-overlapping, there can be correlations among the choices within a nest and the log-sum is still a useful measure of consumer surplus.

Figure 1: Two-level Nested Choice Model



To operationalize consumer surplus measurement using the log-sum approach, the representative utility, V, must first be specified. The representative utility takes the general form of Equation 6. The explanatory variables can be continuous or discrete. Their coefficients are measured using estimation methods particular to the manner in which the sample of revealed or stated behavior was drawn. Typically, this involves estimating Equation 5 using maximum likelihood techniques across the sample of N users.

Equation 6: Utility as a Function of Mode Attributes and Socioeconomic Attributes

$$V_{n,m} = \beta_{1,m} X_{n,m}^{Time} + \beta_{2,m} X_{n,m}^{\mathrm{Cost}} + \ldots + \varphi_{1,m} Z_{n}^{Wage} + \varphi_{2,m} Z_{n}^{Age} + \ldots + \varepsilon_{n,m} \text{ where}$$

$X_{n,m}^{i} =$ attribute i of mode m as experienced by user n, and

$\varphi_{n,m}^{j} =$ socioeconomic attribute j of user n

To measure consumer surplus, α_n must be derived. The negative of the coefficient on the travel cost variable in Equation 6 is typically used to measure α_n. This coefficient should be negative to reflect the negative effect of additional cost on representative utility. The negative of this coefficient is thus the marginal utility of one monetary unit (e.g., a dollar); by normalizing this value with respect to the users' wage, a user-specific α_n can be obtained. The value of $\Delta E(CS)$ can then be calculated from Equation 5 for each user.

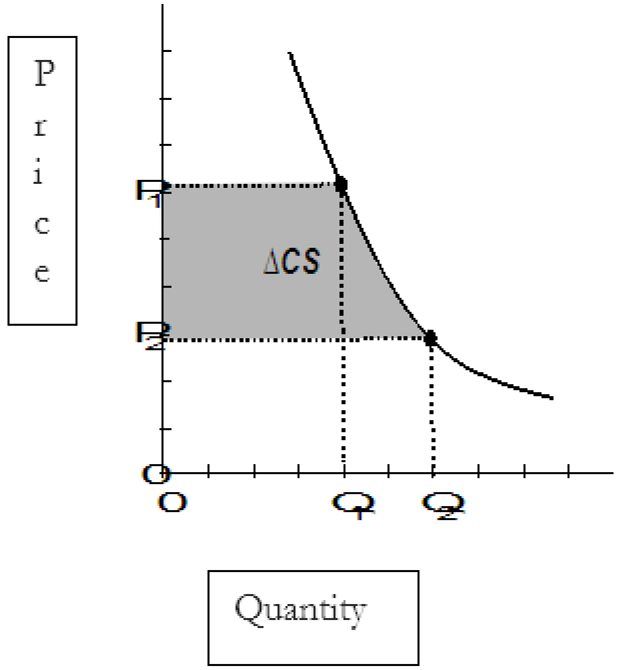
In a project evaluation setting, the $\Delta E(CS)$ of each user is aggregated. This step is controversial. Despite the ability to develop of measure of α_n that is idiosyncratic to each user, deriving the average $\Delta E(CS)$ by weighting each user equally implies cardinality of utility and a position on the distributional impacts of the project or policy. In the simplified example given here, we have abstracted from the fact that travel behavior is differentiated by trip purpose, time of day, destination and other characteristics of interest in addition to the mode used.

3.3 Logsum Versus Marshallian Consumer Surplus Measurement

The concept and application of consumer surplus long predates the innovations by Cochrane, Neuberger (1971), McFadden (1978) and others beginning in the 1970s that linked discrete choice modeling to utility theory and ultimately to the log-sum measurement technique. Dupuit (1844) seems to have conceived of the concept of consumer surplus in project settings, and Marshall (1920) defined consumer surplus as the excess over and above its market price that users individually and in the aggregate would willingly pay before they would choose not to consume. The terms consumer surplus and excess willingness-to-pay are conflated today.

Recognizing that the absolute value of consumer surplus is unknowable, economists adopted the Marshallian consumer surplus concept to measure the changes in consumer surplus due to changes in prices arising from project or policy changes. Specifically, it is used to measure the change in consumer surplus associated with a change in price from P1 to P2 and quantity from Q1 to Q2 as in Figure 2. The ΔCS is thus measured as in Equation 7, and referred to commonly as the "***rule-of-a-half*** method.

Figure 2: Computation of ∆CS in Marshallian Demand Context



Equation 7: The "Rule of a Half" Formula for Change in Consumer Surplus

$$DCS = \frac{(Q_1 + Q_2)(P_1 - P_2)}{2}$$

In modern passenger transportation analysis, the "price" is conventionally replaced with the generalized cost (GC) of travel. The generalized cost of travel is computed from multiplying the vector of W performance elements of trip making (such as in-vehicle travel time, waiting and walking time, mode transfers and transfer delay, vehicle operating, etc.) by a vector of monetizing coefficients, per Equation 8.

Equation 8: Generalized Cost as a Function of Travel Attributes and Monetizing Weights

$$GC_{n,m} = c_{1,m}X_{1,m} + c_{2,m}X_{2,m} + \ldots + c_{W,m}X_{W,m}, \text{ where}$$
$$X_{w,m} = \text{travel performance dimensions by mode, and}$$
$$c_{w,m} = \text{monetizing weights}$$

Generalized costs are obtained from the logistic mode choice model of the representative utility, per Equation 9, since all of the same travel performance dimensions will be in V. Note also from Equation 9 that generalized time (GT) can be derived analogously from the representative utility specification.

Equation 9: Generalized Cost and Generalized Time as a Function of Utility and Coefficients

$$GC_{n,m} = \frac{V_{n,m}}{b_{2,m}} = \text{generalized cost of using mode, } m, \text{ by user } n, \text{ where}$$

$$b_{2,m} = \text{the coefficient on cost in } V_{n,m}$$

$$GT_{n,m} = \frac{V_{n,m}}{b_{1,m}} = \text{generalized time of using mode, } m, \text{ by user } n, \text{ where}$$

$$b_{1,m} = \text{the coefficient on travel time in } V_{n,m}$$

Conceptually, therefore, the Marshallian ΔCS can be reported at the same (user) resolution as the log-sum ΔCS computation. In this sense, the two methods have the potential to provide the same information regarding the ΔCS computation. The Marshallian and log-sum approaches also face the same aggregation and distributional impact controversies as the log-sum approach. The choice of GC versus GT characterizations of price (or impedance) is primarily for consistency with a regional model's traffic assignment approach (whether based on GC or time only) and a preference for application of time values in post-processing from stated preference (SP) exercises or other exogenous sources.

3.4 Theoretical Issues with the Marshallian Versus Logsum Methods

The major theoretical issues with the representation of the "rule of a half" computation of ΔCS represented by Figure 2 and Equation 7 is whether the demand curve represented is the correct.

The first issue relates to the fact that Marshallian demand curves conflate two factors that influence consumer choice in reaction to a price change—i.e., a substitution effect relative to other goods, and an income effect that arises from the change (up or down) in income as a result of the change in price. This is because there is no shifting of the demand curve (as would occur with an implicit net income change) in the typical application of the Marshallian approach.

- If the change in spending on the good in question is large relative to income, the ΔCS (change in the area under the demand curve) does not really measure the change in willingness-to-pay. This is because it is argued that it should be measured as the so-called compensating variation (CV) that consumers would need to return to them to their previous level of utility. Thus, Marshallian demand curves are said to be uncompensated demand curves.
- If, however, the change in spending is small relative to income, then the compensating variation would, in fact, be well measured by the uncompensated, Marshallian demand curve.

Since, in most settings, projects and policies change network-wide prices of travel relatively little, relative to income, the uncompensated nature of Marshallian demand curves may not be empirically relevant. Additionally:

- The log-sum method itself generally relies on a random utility model that also yields a (probabilistic) Marshallian demand curve. Thus, log-sum computations of ΔCS are not inherently superior to the convention of Equation 7. McFadden (1981) proposed adding a term to the representative utility relationship that neutralized the income effect in the setting of a GEV model by adding a term equal to the user's income (Y) minus the new price (P), as in Equation 8 as an approximation to the CV (Hicksian) demand curve (see Hicks (1956)).
- However, there are also those who, like Johansson (1993) believe that the appropriate CS measure uses a demand curve that adjusted by the maximum amount a consumer is willing to pay to prevent a price increase (or receive to enjoy decrease). This is called the equivalence variation (EV) demand curve.

Equation 10: Equivalence Variation Utility Function

$$V_n = V\left(\delta\left(Y_n - P_n\right), \beta X_n, \phi Z, \varepsilon_n\right)$$

The bottom line in the demand curve debate is that the CV variant uses the old utility level and the new prices, the EV uses the new utility level and the old prices, and the Marshallian method lies in between.

A more fundamental issue in this debate is whether the critical assumption that the marginal utility of income (α_n) is constant with respect to income. If not, then α_n becomes a more complex function of the change in attributes, and the logistic measurement of representative utility (that affects all three CS computation methods) is inaccurately measured if this effect is not accommodated (Dalvab et al. (2008)).

Theory, in our view, is not dispositive of this debate. If project or policy changes are small in overall impact on generalized costs of travel (and, thus, the estimate of representative utility), then the method chosen to compute ΔCS is not terribly relevant. Indeed, several authors who have employed Marshallian and log-sum methods find little difference between the two approaches (de Jong et al. (2005); Kohli et al. (2006)). The methodological approach has to be settled on other bases.

3.5 Practical Virtues and Issues: The Marshallian "Rule of a Half" Method

The primary virtues of the Marshallian approach, in our view, include the following.

- The Rule-of-the-Half computation is in wide use. This aids in comparative and reference analysis of prior benefit-cost analyses of similar project or policy improvements.
- Its fundamental computations are more transparent than in the case of log-sum approaches. It is easier to motivate lay audiences to embrace benefit-cost analysis as a result.

- The use of generalized cost specifications in the Rule-of-the-Half computations creates a natural link to random utility models if available in the region of analysis, but the method can also be used when sophisticated regional models are not available.
- It can be applied at the link level when the choice process occurs at that level (as in managed lanes). This is true to the extent that most of the performance elements in the GC specification are link-specific and value of time distributions are knowable by link or invariant by link.
- The results obtained by use of this method, done accurately, are not likely to be order-of-magnitude different relative to other approaches.

The primary issues in the use of this approach include the following:

- Without special tools to automate the process, it can be cumbersome to properly apply the method, especially when substitution across mode or time of day, for example, occurs in the project case.
- Regional models do not typically properly script computation of ΔCS in the Rule-of-the-Half manner as part of their reported output.
- There may be circumstances where the demand-curve linearization implicit in the Rule-of-the-Half computation is material.
- It is not easy to correct for the uncompensated nature of demand while maintaining the transparency of the approach.
- It is difficult to accommodate a new mode as the project case in a ΔCS computation without introducing arbitrary bounding assumptions.
- Doing ΔCS analysis by user segment is perfectly possible, but is laborious without automated tools.

3.6 Practical Virtues and Issues: The Logsum Approach

The primary virtues of the log-sum approach, in our view, include the following.

- Modern random utility-based regional models essentially have built-in capability for producing log-sums to support ΔCS computation since they are needed internally to measure demand.
- Implemented properly, even behaviors with complex nesting can yield log-sum computations to facilitate ΔCS computation.
- Population segmentation of ΔCS is relatively straightforward, which is an aid to EJ and other distributional considerations.
- The typical random utility model does not address the uncompensated demand relationship issue in a satisfactory way (if at all), but approximations to CV and EV compensation approaches have been developed experimentally.

The primary issues with the log-sum approach, in our view, include the following.

- The log-sum concept is opaque to all but non-lay audiences, possibly making the ΔCS computation dismissible as "black box" results.

- Only regional entities with considerable staff and other resources can hope to implement ΔCS modeling. This leaves other entities with a need for simpler tools.
- Even in regions with considerable resources, the development of reliable parameters for the representative utility relationships has proved challenging. (This is then, of course, also a barrier to applying Rule-of-the-Half computations reliably since GC modeling relies on representative utility specifications.)
- The practice of parameterization and monetization in the random utility model context should theoretically be straightforward, but one observes exogenous application of values of time from SP or other regional implementations. This may suggest that the complexity of the models can outstrip the data available for model fitting.
- As observed by Kohli (2006), log-sums calculated from models which are subsequently pivoted on a base matrix, are inconsistent with the matrices used in assignment.

3.7 Implementing Both Approaches with the Tampa and SANDAG Model Systems

As mentioned previously, Florida DOT uses the DaySim ABM (Bradley, et al. 2009) in the Tampa region, while SANDAG uses the CT-RAMP ABM (SANDAG 2015) in San Diego. In this section, we summarize how these two ABM systems are structured and implemented, and discuss means of deriving measures of consumer surplus and expected welfare from both. A key consideration is to develop methods that are, to the extent possible, ABM platform-independent, so that they may be applied in San Diego and Tampa, as well as in other regions using the CT-RAMP, DaySim, or other ABM systems.

Relevant Similarities and Differences Between the San Diego and Tampa Models

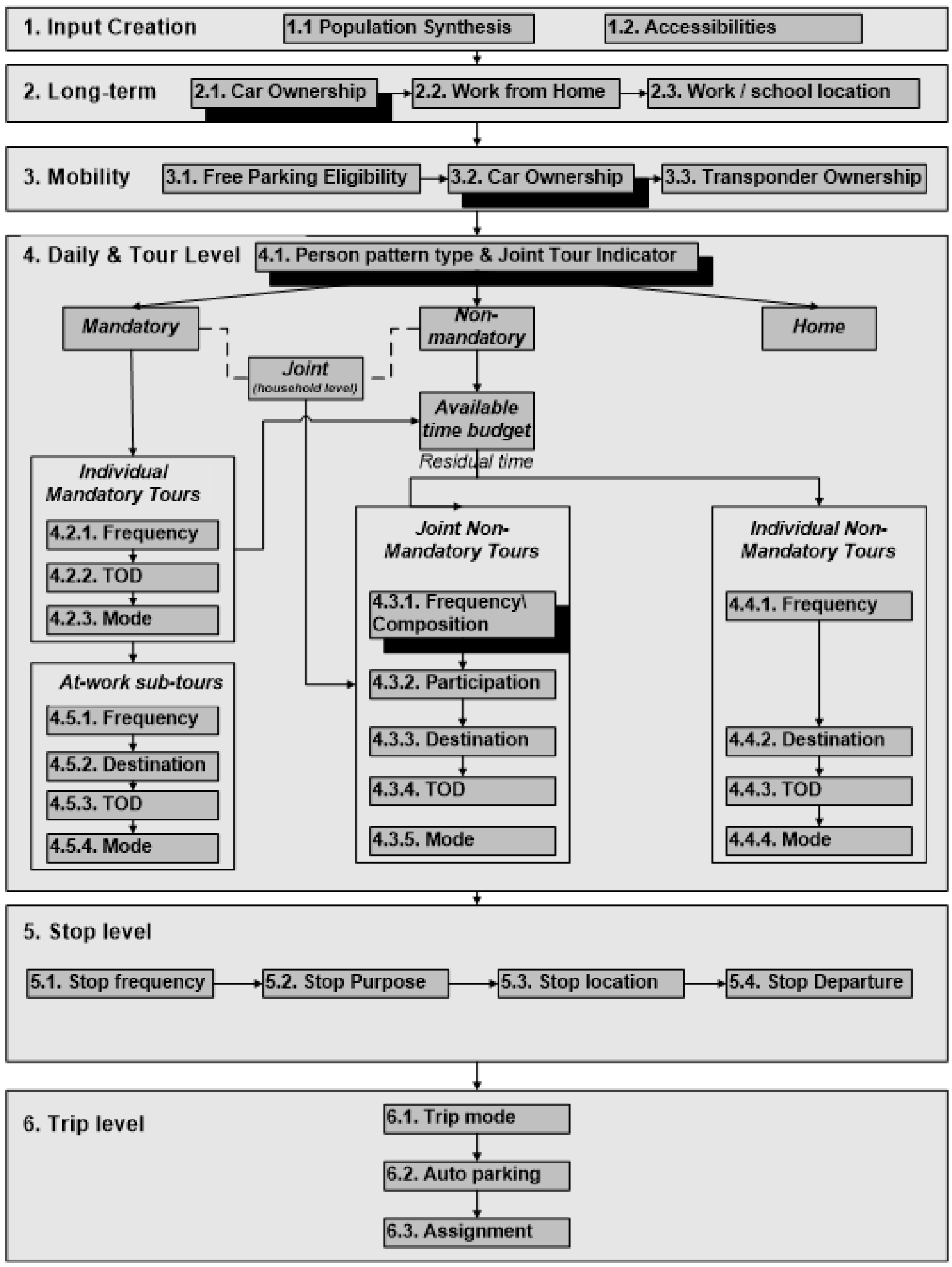
Overall, the two model systems contain far more similarities than differences with regard to the way that travel times and costs are used at various levels of the model system. Given that CT-RAMP and DaySim account for the large majority of ABM implementations for US MPO's, and that the "TourCast" (Cambridge Systematics) ABM system structure is also quite similar, an approach that works with these two model systems is likely to be transferable to most AB models in national use.

CT-RAMP and DaySim (as well as TourCast, and other earlier models such as SFCTA's SF-CHAMP and DRCOG's Focus) use the same general structure of models, which can be seen in Figure 3 and Figure 4:

- ***Longer term models***, including usual work and school locations and auto ownership
- ***Day-level models***, which include models of tour generation (and perhaps some elements of additional activity generation scheduling)
- ***Tour level models***, which predict tour primary destination location, tour main mode, and tour arrival and departure time periods.
- ***Trip-level models,*** which include models of intermediate stop generation and location, and trip mode choice (and in some cases, trip time of day choice)

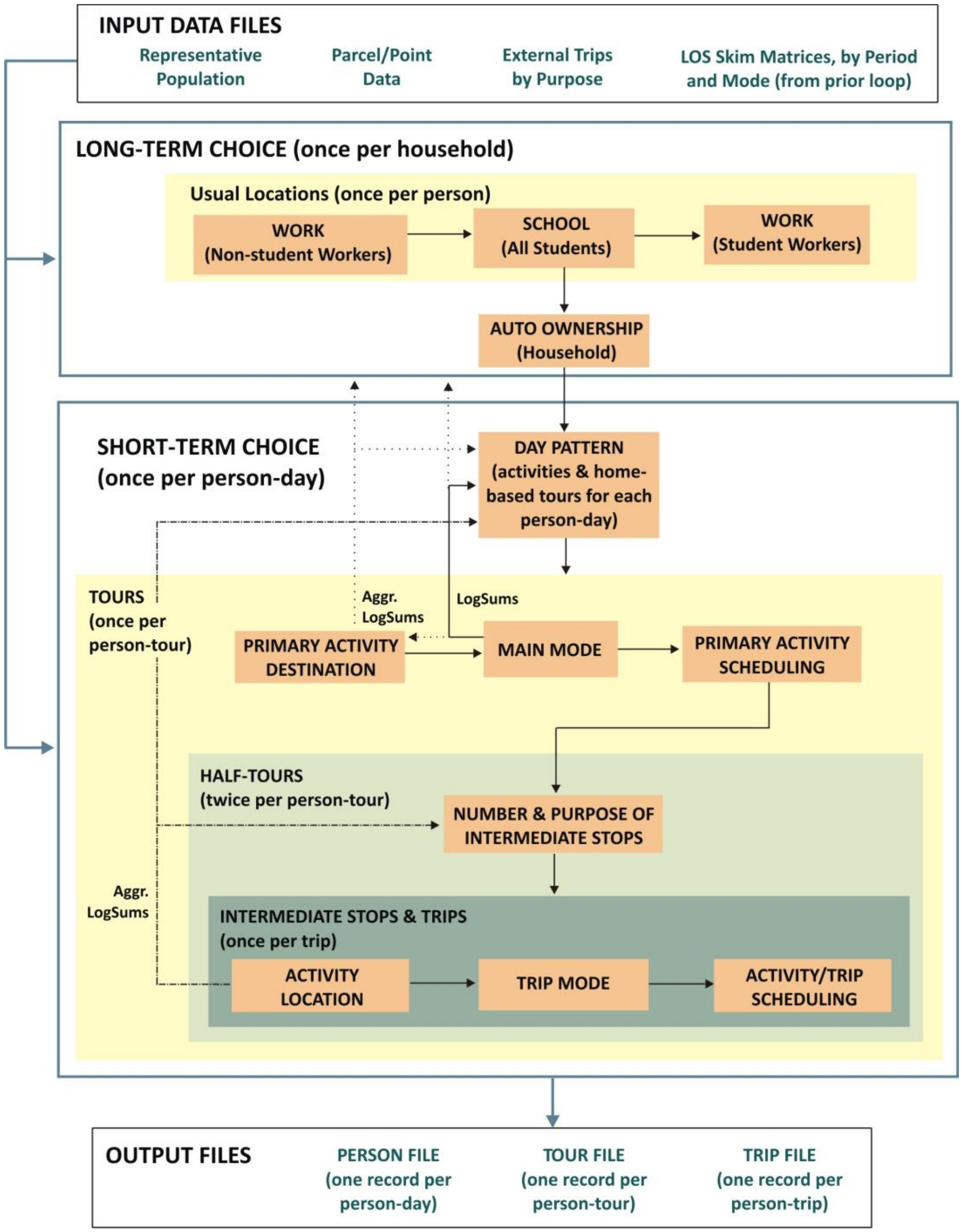
Both CT-RAMP and DaySim write output records at all of these levels: person and household records, person-day and household-day records, tour records and trip records. Although the current SANDAG BCA tool uses only trip-level output records (for travel time and cost) and household-level output records (for auto ownership costs), it is possible to use output records from any of these levels, such as the person-day level to calculate the amount of time each person spends walking and biking to calculate physical activity health benefits.

Figure 3: CT-RAMP Model Structure used in San Diego



Source: SANDAG (2015), Page 12.

Figure 4: DaySim Model Structure Used in Tampa



Source: Bradley, et al. (2009). Page 9.

Another key similarity in the two model systems is the way in which logsums are used to pass accessibility and utility information between models at different levels in the system. (As described earlier in this chapter and in Equation 4, a "logsum" is the expected total utility across a set of available choice alternatives—i.e. across all modes in a mode choice model.). Some important similarities in this regard include

- Both model systems use logsums from the tour mode choice models as key variables in the attractiveness of alternative locations in the tour destination choice models, usual work location model and usual school location models. The mode choice logsums between home and the usual work and school locations with a car versus the analogous logsums without a car are also used in the auto ownership models. In both model systems, the mode choice logsums are calculated for assumed time of day combinations rather than for every possible time of day combination, in order to reduce computation time. In every other way, these logsums are "fully disaggregate" in both model systems, meaning that they are calculated using the full set of household-, person- and tour-specific variables in the mode choice models.
- Both model systems use somewhat more aggregate mode/destination logsums as accessibility measures in the day-level and longer term choice models. These logsums measure the composite utility from an origin zone across all possible destination zones and across all available modes to each destination. They are analogous to the fully disaggregate logsum that could be calculated at the tour level from the tour destination choice models, but they are pre-calculated using slightly simpler and more aggregate models of mode and destination choice. The "aggregate accessibility logsums" are segmented by destination activity purpose and by auto sufficiency segment for the SANDAG CT-RAMP model, and are segmented by destination activity purpose, auto sufficiency segment, value of time segment, and residence distance to transit segment for the Tampa DaySim model. Both model systems pre-calculate these measures for each residence zone at the start of each run and write the values to a file for further use. In addition to the computational efficiency of pre-calculating these more aggregate logsums, there is the added benefit that they are calculated across all possible destination zones, while the tour destination choice models are only run for a randomly sampled subset of possible destinations, which adds some degree of random variability to the disaggregate logsum measure from those models. Also, the aggregate logsum measures are calculated for every household and person in the synthetic population, regardless of whether or not a person is predicted to make any trips during the simulated travel day, so they are available for all persons in all scenarios, regardless of how many tours and trips are generated or suppressed between scenarios.

There are also some differences to note between the two model systems:

- The CT-RAMP system uses a series of interrelated tour generation and scheduling models at the day level, with separate models for mandatory (work and school), joint non-mandatory and individual non-mandatory tours (see Figure 3). By contrast, the DaySim model has a single "Day Pattern" model at the day level (see Figure 4), which simultaneously generates tours for all seven activity purpose types. This difference has some implications in terms of possible logsum measures, as the DaySim structure could produce a single "day pattern logsum", while the CT-RAMP structure would produce a number of logsums from the conditionally-related models. Without extensive testing, it would not be clear how this difference would impact possible use in BCA analysis, but it would make it difficult to recommend a day-level measure that would be consistent across ABM platforms.

- At the intermediate stop/trip level, below tour level, the two model structures are very similar, but have some differences in the way that mode times and costs are used in the intermediate stop generation and location models. These differences could be investigated further if there were a desire to use intermediate stop utility logsums as benefit measures.
- At both the tour and trip levels, the two model systems predict mode and departure time in different sequences. We do not expect that this will introduce any appreciable differences in utility logsum definitions at the tour destination level, as those are calculated in both systems for specific assumed times of day, for reasons of computational efficiency.

Past Use of the CT-RAMP and DaySim Models in Benefit-Cost Analysis

In addition to being used for the initial version of the SANDAG BCA tool described in Section 2.2, the CT-RAMP model has been used to provide input to the SUMMIT benefit-cost tool used for New Starts transit project appraisal. The New Starts process requires the use of fixed trip tables, looking only at changes in mode choice and assuming no changes in trip generation or distribution. This means that only the tour mode choice models of CT-RAMP need to be run, along with the lower Stop and Trip level models. The changes in tour mode choice model logsums under different scenarios are used by SUMMIT to evaluate changes in consumer surplus.

While focusing only on tour mode choice logsums may be appropriate for the New Starts evaluation process, it is much less suitable for more general cost-benefit analysis of regional plans or projects. There are two main reasons for this, regardless of whether the CT-RAMP or DaySim model structure were to be used:

- A change in tour mode may make intermediate stops more attractive or less attractive for that tour. Unless many destinations are within convenient walking distance of each other, it will generally be more convenient to make multi-stop trip chains by auto than by transit. This will not be reflected in the mode choice model logsum unless the mode choice model itself includes some inclusive logsum variable reflecting the intermediate stop accessibility by each mode, given the tour origin and destination.
- More importantly, changes in the mode choice logsum do not reflect changes in higher level choices that may also occur due to policy changes, particularly changes in destination choice or changes in tour generation and tour pattern types. If the higher level models contain logsum variables that adequately reflect changes in utility from the lower level choices, then it should be better, in theory, to use logsums from higher up in the model structure.

One of the most advanced uses of an activity-based model for evaluation of consumer surplus was done using one of the earliest implementations of the DaySim family of models in Portland, and is described in Dong, Ben-Akiva, Bowman and Walker (2006). That model system had a structure similar to the Tampa system, with a single Day Pattern model at the day level, but it did not include upper level models of usual work and school location.

The Dong, et al (2006). paper includes a useful discussion of the "scale" and "level" properties of logsum measures and their importance for use in economic evaluation. These properties are related to the fact that choice model logsums are in units of "utils", which have no physical meaning and are determined mainly as a function of the amount of unexplained variance in the data used for model estimation. As a result, logsum values have no natural "zero point" level—one can add or subtract any arbitrary value from them without affecting the performance of the model. Fortunately, all economic evaluation tools are used to <u>compare</u> different scenarios, which means that one analyzes the <u>difference</u> in logsums across scenarios rather than the value of a single logsum. When subtracting one logsum value from another, the level issue disappears, because any arbitrary offset to the logsums will cancel out in the subtraction. **An issue <u>does</u> arise**, however, when tours and trips are generated or suppressed across scenarios, in which case the question becomes what logsum value to assume for a tour or trip for a scenario in which that tour or trips was not made. This is a similar issue as that dealt with by the "rule of a half", and one which is discussed extensively in the remaining chapters.

The "scale" issue can also be problematic, because one wishes to translate logsum differences into useful units such as minutes of travel time or dollars of travel cost, but that is not always straightforward in practice. If the logsum is from a model that uses travel time or travel cost as explicit variables, then the translation is as simple as dividing the logsum by the cost or time coefficient. For example, if the difference in logsum values is 0.10 utils, and the travel time coefficient is -0.02 utils per minute, then the logsum difference is equivalent to 5 minutes. Tour mode choice models have time and cost coefficients, so this simple transformation is possible for tour mode choice. Tour destination choice models that have mode choice logsum variables also allow for this simple scaling. However, models above the tour pattern, such as day activity pattern models with more complicated nesting structures, do not allow for simple scaling. In Dong, et al (2006). the authors generated accessibility benefit/cost measures from the day pattern model logsums, and compared those to measures generated from the lower-level tour mode/destination choice models. While that research was an early example that did not address some of the technical issues that will be addressed in this project, it nevertheless demonstrated the feasibility of using various types of model logsums as benefit measures, and also provided evidence that those measures reflect reasonable differences along key segmentation variables such as income, auto ownership and urban versus suburban residence.

Possible Uses of CT-RAMP and DaySim Logsum Measures for this Project

The most promising possibilities include

- Use ***tour mode choice logsums*** only. This is the previously used method, described above for the New Starts SUMMIT approach

- Use ***tour destination choice logsums*** only, instead of tour mode choice logsums. Because the tour mode choice models are fully nested under the tour mode destination choice models, the tour destination choice models have the advantage of incorporating the tour mode choice logsum, while also capturing changes in destination choice utility. A potential drawback of using tour destination choice logsums is that these models use sampling of alternative destinations in application, so may be subject to variation due to random simulation error. (Although the model systems are coded to use the same destination choice set for any given person and tour across different scenarios, there are different choice sets for each person and tour. However, since millions of tours are simulated per scenario, the large sample size may mitigate the effect of random simulation error. This issue is investigated further in the sensitivity tests reported in Chapter 7.)
- Use ***intermediate stop location model*** logsums, in addition to the tour destination choice or mode choice logsums suggested above. This would add any additional accessibility benefit to make intermediate stops. If this logsum were calculated and used in the intermediate stop generation model, then the logsum from the stop generation model could be used instead of the logsum from the stop location model. That does not seem to be the case in either DaySim or CT-RAMP, however, so the stop location model seems to be a better candidate, although it would require weighting the stop location logsum by the simulated (or expected) number of stops before adding to tour level logsum measures. (The intermediate stop location models also use sampling of alternatives, so are subject to the same type of random simulation error as described above for the tour destination models.)
- Use ***day pattern model*** logsum, instead of tour-level model logsums. As mentioned above, this option would be simpler for the DaySim structure than for the CT-RAMP structure, because it uses a simpler, more “centralized” structure to generate tours for all activity purposes. The DaySim model uses disaggregate mode choice logums for work and school, conditional on the usual work and school locations, and uses aggregate mode/destination logsums for all other purposes. So, in theory, this model incorporates accessibility effects for all tours and tour purposes, although it may be necessary to also add logsums from the longer term models (usual work location, usual school location, auto ownership) in order to capture all changes in utility.
- Use ***aggregate accessibility (mode/destination) logsums*** directly as a measure of the utility of making a tour, and weight them by the number of tours predicted for each purpose. Compared to the preceding approach (day pattern model logsums), this approach has the advantage that it would be feasible to implement consistently for both model systems, but has the disadvantage that it would not fully capture the utility of making more tours or fewer tours, as the day pattern model also includes the utility of not traveling. The Dong, et al. (2006) paper offers an early comparison of the results of using these two types of approaches.

All of these measures were tested as some point in this project, although the research results presented in later chapters of this report focus mainly on the use of tour destination choice logsums and aggregate accessibility logsums, as those appeared to be the most promising for practical use.

Use of Income-Neutral Utility Measures

Just as the current SANDAG BCA tool uses a single value of time (VOT) for all persons, as recommended by US DOT guidance in the interest of equity, it may also be desirable to remove variations due to VOT from any logsum-based measures that are used. In practice, this requirement could cause substantial increases in model run time, as it would require a calculating a second version of any logsums that are to be used in BCA, since the original versions that use VOT would still be required for the model probability equations. As described above, however, both DaySim and CT-RAMP also use accessibility logsums, and it is relatively easy to generate and use income-neutral versions of those simpler logsums, requiring little or no additional run-time for those calculations.

In both model systems, there are several other types of income-specific variables in addition to VOT-related variables, so it would be possible to go a step further and remove any income-related variations in the utilities—e.g. by calculating versions of all logsums using a single median income value. This could require even a greater increase in model run times, as it would potentially impact a wider range of calculations.

The treatment of income in the various methods of benefit calculation is an important consideration in the analysis reported in the following chapters.

4.0 Methods for Evaluating Health Benefits of Active Transportation

4.1 Counting Active Transport Benefits

Both SANDAG and Florida DOT are interested in enhancing the evaluation of the health benefits of walking and cycling for benefit-cost analysis. In this section, we present some recent research and the method selected for implementation the BCA tool for this project.

Litman (2015) provides a lengthy list of potential benefits related to "active transportation". These include mobility benefits, usually ascribed to removing barriers to walking or cycling through infrastructure improvements that would actually improve travel time or perceived utility, such as an off-street path that provides a feeling of safety. Other potential benefits include reduced congestion attendant reduced auto trips on roads, accident reduction, and health benefits of exercise. Others argue for benefits such as increased livability and increased property values due to accessibility. However, measuring such benefits raises risks of arbitrariness and double counting of primary user benefits.

Of those benefits that can be modeled regionally using a travel demand modeling system, the mode shift away from auto usage, which implies reductions congestion (lost travel time), in pollution emissions and motor vehicles accidents, is covered in the general treatment of user benefits from those particular sources. Property value changes, often modeled through hedonic regressions, are maybe be captured somewhat by changes in accessibility benefits measured through the accessibility logsums (although they are not included in most benefit-cost analysis frameworks, mainly due to a risk of double-counting). This leaves health benefits derived from active transport modes as deserving separate treatment. In the remainder of this section, we focus on the safety and health benefits, which seem to be the most appropriate active transportation metrics for regional modeling and are analyzed somewhat distinctly from other modes.

The consensus of the literature indicates that active transportation benefits should be tabulated to reflect the number of new walking and cycling users, however defined. This can be measured at the facility level as the number of new users of, say, an off-street trail. Region-wide, this could be measured as the number of persons who switch to becoming regular bicycle or walking commuters. In either case, the so-called "rule of half" should not be used, which is consistent with the treatment of benefits derived from improved levels of health and safety (United Kingdom Department for Transport, 2014a).

Safety

The literature on accident reduction as a result of infrastructure investments in bicycle and pedestrian environments is based on various design improvements to intersections and other design treatments, which makes it somewhat difficult to model regionally. Safety benefits for active transport modes are related to changes in accident frequencies. The loss of life and personal injury monetization is similar to other modes; however, quantifying how many accidents of various levels of severity due to a particular infrastructure treatment is difficult.

NCHRP Report 552: Guidelines for Analysis of Investments in Bicycle Facilities (2006) is inconclusive in making any recommendations for evaluating safety with respect to bicycling. The guidance documents created by the United Kingdom Department for Transport (2014a) and New Zealand Transport Agency (2013) go so far as to acknowledge studies that show a non-linear decreasing relationship between the volume of cyclists and pedestrians and accidents. NZ Transport cites "safety in numbers" as drivers become more aware with higher volumes of walkers and cyclists. UK TAG A4.1 provides a useful description of the non-linear relationships between cycling demand and the number of accidents:

I= aE^b

Where I = injury measure; E = measure of walking and cycling; a = a constant; b = a constant found to be approximately 0.4. This implies that a doubling of cycling would lead to only at 32% increase in cycling accidents (2^0.4=1.32), although for very small volumes a linear response might be more appropriate, subject to further research. Accident severity is assumed to come from lookup tables, by mode.

Overall, the literature on accidents for walking and cycling do not provide a clear method for valuing benefits, but do indicate that the disbenefits related to increased accidents are heavily outweighed by the benefits of improved health and reduced risk of mortality and morbidity. This is especially true as walking and cycling rates reach high levels and "safety in numbers" effects occur, in which case increases in walking and cycling may not lead to any increases in accidents. (For example, the European countries with the highest rates of cycling also tend to have the lowest accident rates.)

Health

Approaches to modeling the impacts of bicycling and walking on health have evolved in recent years. Earlier approaches, such as described in NCHRP 552 (2006), estimated benefits based on avoided costs for medical care and workers' compensation. Avoided costs to treat diseases due to lack of physical activity were estimated at $19 to $1175 per capita for ten different studies. There are a variety of ways in which these benefits are counted, including what diseases are considered and what insurance actually pays versus the value of the treatment. In addition, it is not clear what level of physical activity is required to achieve these benefit levels. The report recommends using the median value of ten studies of $146 to derive an aggregate health benefit based on assumed usage rates. For example, the NCHRP 552 method was used in the TIGER V grant application for the Atlanta Beltline Community Connector project (HDR, May 2013).

New Zealand Transport (2008) estimated health benefits per person for new users of a facility of NZ$2.60 per kilometer of treatment, based on an average-length pedestrian trip, or NZ$1.30 per kilometer for a bicycle trip, using 2008 NZ dollars, although the basis for these calculations is not transparent.

More recently, a series of studies and meta-analyses by the World Health Organization (WHO) in Europe have resulted the development of a Health Economic Assessment Tool (HEAT), which appears to be the most comprehensive and scientifically transparent treatment of active transport benefits to date (WHO 2014). HEAT is a software tool, which has been adopted by the English and Swedish departments of transport as the recommended methodological approach for estimating the health impact of walking and cycling. WHO commissioned an international panel of experts and review numerous epidemiological studies as part of their work. From this work, several important conclusions and assumptions have emerged:

- **Mortality vs. Morbidity** -- Morbidity, the incidence of disease is difficult to quantify due to a large variety of factors such as which diseases to consider, uncertain causality, and incomplete data on outcomes. Due to such ambiguities, HEAT focuses on all-cause mortality rates. This also permits inclusion of the negative effects of increased exposure to air pollution and potential traffic accidents. A study that compared the relative risks of mortality among cyclists and non-cyclists to have the greatest potential for a more uniform approach.
- **Measurement Method** -- HEAT uses a dose-response method of assessing changes in mortality, which obviates the need for obtaining baseline measures of physical fitness.
- **Age** – Mortality rates differ significantly by age, which should be taken into account if a model can produce these. Most studies do not involve children. The primary endpoints that active living tends to mitigate are coronary artery disease related deaths, and these are not usually realized until later in life, and may be too late to stave off in old age if a person has been sedentary up to that point.
- **Gender** – Epidemiological studies do not find significant differences between the sexes when it comes to all-cause mortality that would warrant different risk profiles. There may be some differences, however, in terms of active transportation habits. This study says that women more often walk and bicycle than men, and that studies should take these differences into account.
- **Timing** – Epidemiological studies show that the health benefits of activities take time to build up and should be based on habitual behavior, not just occasional. They suggest using a 5-year lag to represent this building up period for newly modified behavior.
- **Substitution Effects** – It is possible that some people may be substituting biking for walking or vice versa, which may have offsetting health impacts. Another example is the substitution of travel time for activity time, such as people spending more time traveling (e.g., biking instead of driving) and spending less time in an active leisure activity (e.g., jogging), which again may offset to some extent. Modeling should seek to identify these substitution effects.
- **Seasonality** – It is recommended that seasonality be taken into consideration as local weather and cultural conditions dictate, although no guidance is given for changes in exposure by season.
- **Life tables** – Life tables, which show mortality rates over time, include changing rates as people become more active, and may provide more accurate estimates of health effects for persons of different ages. The makers of HEAT, however, concluded that inclusion of life tables in the software would add more complexity than would be worth the small increment in accuracy.
- **Valuation** -- For transport planners, the standard metric is value of a statistical life (VSL), which is based on willingness to pay to reduce risk of death. This is what is used in HEAT. Values for VSL vary by country and study. A review by the Organization for Economic Cooperation and Development (OECD) obtained an average estimate of US $3.6 million obtained for 27 EU countries, varying from $1.8 to $5.4 million (2005 dollars). HEAT uses

€1.57 million per person. Discount factors are applied just as with other transport benefits. Note that health policy experts tend to prefer other measures, namely quality-adjusted life years (QALY) or disability adjusted life years (DALY).

4.2 The HEAT Methodology as Applied in the BCA Tool

The HEAT tool is designed to answer the following question: If x people cycle or walk for y minutes on most days, what is the economic value of the health benefits that occur as a result of the reduction in mortality due to their physical activity?

The evidence from a couple of cohort studies in Copenhagen is that regular commuter cyclists have a relative risk of 0.72 of all-cause mortality (95% CI: .57-.91) compared with non-cyclists, controlling for age, sex, smoking habits and leisure-time physical activity. Later meta-studies assumed a linear dose-response rate, with an assumed average intensity of 6.8 METS (metabolic equivalent task) per week, or about 100 minutes. 150 minutes per week is recommended by fitness experts (30 minutes, 5 times per week). An international advisory group recommended a linear-dose response curve based on a relative risk of 0.90 (CI 0.87-0.94) for cycling and applying a constant absolute risk reduction. For walking, the relative risk estimate was 0.78 (CI 95%: 0.64-0.98) for a walking exposure of 29 minutes, 7 days a week, and the advisory group recommended a linear dose-response curve, based on a relative risk of 0.89 (CI 0.83-0.96).

For cyclists, this function assumes that the average active cyclist receives a protective benefit of 10% (1 - .90) where 0.90 is the relative risk in any given year. This means that cyclists are 10% less likely to die than a non-cyclist from any cause. This average is based on 100 minutes per week for 52 weeks a year, or 87 hours per year. If the user enters a number less than 100, say 29, then the protective benefit is 29/87 = 1/3 of 10% for a 3.3% protective benefit. If the user enters a larger number of hours per week, say 174 (2 x 87), the resulting protective benefit is 20%. Consistent with literature on risk reduction, the benefits are capped at 45% for cyclists and 30% for walking. The values used in the HEAT tool are shown in Table 10 (CI = confidence interval.)

Table 10: Summary of Basic Values for HEAT

Mode Capped at	Applicable Age Range	Relative Risk	Volume	Benefits Capped at
Walking	20-74 years	0.89 (CI 0.83–0.96)	168 min/week	30% (458 minutes)
Cycling	20-64 years	0.90 (CI 0.87–0.94)	100 min/week	45% (450 minutes)

HEAT uses population-level mortality data to estimate the number of adults who would normally be expected to die in any given year in the target population. Next, it calculates the reduction in expected deaths in this population using the functions described above, and assuming user inputs on level of cycling or walking. HEAT produces an estimate of economic savings from the calculated reduction in deaths as well as discounted and average savings.

Interestingly, the documentation does not address the combined effects of walking and bicycling. It would stand to reason that the maximum benefit of the two effects should be considered for capping benefits; however, it is not clear whether the combined effect of biking and walking is additive. Other literature (see below) provides some clarity by converting walking and cycling time into METs.

Based on the documentation, HEAT is applied to analyze the benefits of either walking or bicycling, but not necessarily both at the same time. If applied separately, this could lead to an overstatement of benefits. Required inputs to HEAT include:

Default values, derived from literature and expert consensus, for the following items are given in HEAT, but may be replaced with local data:

- Mortality rates (e.g., WHO European Detailed Mortality Database, or local mortality rates)
- VSL (values of a statistical life) adopted from local values
- Period of time over which average benefits are to be calculated
- Discount rate (default is 5%)

In addition, the user needs to input the average time/distance/trips walking or cycling per person per day and the number of people benefiting (walking or cycling by the prescribed average amounts). This information can be derived directly from the ABM outputs, which provide a list of trips for a "representative" weekday's travel for each person, from which the total time spent walking and cycling can be calculated for each person in the synthetic population.

Future Developments

As the health benefits of active transportation and land use changes is a topic currently receiving a great deal of research attention, we expect that the recommended methods of evaluating such benefits in the BCA context may evolve substantially in the coming years. One promising research area is the evolution of the Integrated Transport and Health Impact Modeling Tool (ITHIM) (CEDAR 2016), which is currently under development to be used a more disaggregate level that will be compatible with outputs from an AB model.

5.0 Initial Comparisons of Rule of a Half and Logsum-Based Measures

5.1 Analysis Approach

Our initial analysis approach was to study the properties of alternative rule-of-half and logsum-based benefit measures in a controlled setting, using only variations in travel times and costs, for which the rule-of-a-half approach should capture most or all of the benefits and we can expect logsum-based measures to have comparable values.

To generate data for the analysis, we used the Tampa ABM model, with inputs for the 2010 base year. The base year inputs to the DaySim ABM include:

- **Land use data** for just over 1 million parcels in the region, with the number of resident households, employment by type, school enrollment by type, distance from the nearest transit stop, and various buffered inputs for each parcel.
- A **synthetic population** for the Tampa Bay region, with roughly 1.3 million households and 3.1 million person records, with each household located on a specific parcel
- Zone-to-zone **travel time and cost matrices** for just over 3,000 zones in the region, with the following variables:
  - Walk time
  - Bike time
  - SOV auto distance
  - SOV auto in-vehicle time
  - SOV auto toll
  - HOV auto distance
  - HOV auto in-vehicle time
  - HOV auto toll
  - Transit in-vehicle time
  - Transit first wait time
  - Transit transfer and extra wait time
  - Transit number of transfers
  - Transit fare
  - Park-and ride auto in-vehicle time
  - Park-and ride transit in-vehicle time
  - Park-and ride first wait time
  - Park-and ride transit transfer and extra wait time
  - Park-and ride transit number of transfers
  - Park-and ride transit fare
- The auto and transit matrices are for four time periods:
  - AM peak (6:00-8:59 AM)
  - Midday (9:00 AM-3:59 PM)
  - PM peak (4:00 PM-6:59 PM)

- Evening/Night (7:00 PM-5:59 AM)

The DaySim model was run nine times with just one iteration through the synthetic population (no global feedback from traffic assignment). The zone-to-zone travel time and cost matrices (and the auto operating cost per mile assumption) were varied systematically across the nine runs

1. **Base**: All time and cost matrices used as-is.
2. **Cost-0.50**: The auto toll and transit fare matrices and auto cost per mile were factored by 0.50 (a 50% reduction for all zone pairs)
3. **Cost-0.75**: The auto toll and transit fare matrices and auto cost per mile were factored by 0.75 (a 25% reduction for all zone pairs)
4. **Cost-1.25**: The auto toll and transit fare matrices and auto cost per mile were factored by 1.25 (a 25% increase for all zone pairs)
5. **Cost-1.50**: The auto toll and transit fare matrices and auto cost per mile were factored by 1.50 (a 50% increase for all zone pairs)
6. **Time-0.50**: All auto, transit and park and ride travel time matrices were factored by 0.50 (a 50% reduction for all zone pairs)
7. **Time-0.75**: All auto, transit and park and ride travel time matrices were factored by 0.75 (a 25% reduction for all zone pairs)
8. **Time-1.25**: All auto, transit and park and ride travel time matrices were factored by 1.25 (a 25% increase for all zone pairs)
9. **Time-1.50**: All auto, transit and park and ride travel time matrices were factored by 1.50 (a 50% increase for all zone pairs)

For each of these runs, several output variables were written out for each simulated trip and tour:

- Auto in-vehicle time
- Transit in-vehicle time
- Transit walk access/egress time
- Transit wait time
- Bike time
- Walk time (on non-transit trips)
- Auto toll cost
- Auto operating cost
- Auto parking cost
- Transit fare
- Tour destination choice logsum
- Tour mode choice logsum
- Tour time of day choice logsum
- Intermediate stop generation logsum
- Intermediate stop location logsum
- Trip mode choice logsum
- Tour-specific value of time ($/hour)

Each of the runs 2-9 was compared to the Base scenario run 1. In terms of the "rule of a half" calculation, the "base" case demand and costs (Q1 * P1) are read directly from the base case trip output file, and the "build" case demand and costs (Q2 * P2) are read directly from the relevant trip output file for the run that is being compared to the base. Because the travel times and costs were factored in such a controlled manner, we also know what the times and costs would have been for each base case trip had it been made in one of the build scenarios (Q1 * P2), as well as what the times and costs would have been for each build scenario trips had it been made in the base scenario (Q2 * P1). For example, if a trip that had an auto time of 20 minutes in the base scenario had been made in the "Time-1.50" scenario, it would have had an auto time of 30 minutes (20 * 1.5).

With these inputs, we can calculate the rule of a half benefits for each of the time and money costs separately for each trip, and add them together across all trips and tours in the synthetic population.

For the logsum values, it is not possible to use the fully disaggregate calculation of the rule of a half, because the same trips are not made in each of the scenarios, and we cannot use the simple factoring approach to determine what the logsum for a particular tour or trip would have been if it had been in one of the other scenarios. That would require applying the ABM to that same set of tours, holding certain tour characteristics predicted from the other run constant, such as tour purpose. That type of calculation would not be very feasible in practice, as it would require programming a new mode of running the ABM software, and would nearly double the model run time required to generate inputs for the BCA process. (ABM run times can already be quite long).

As mentioned in Chapter 3, logsums have no absolute zero point – the offset from 0 is arbitrary depending on how the relevant choice model is specified. Thus, we cannot simply sum the logsum values across the population and subtract one from the other, because any tours that are generated in one scenario relative to the other will receive the full, non-normalized value of the logsum. For example, if the logsums have a mean value of 4.0 in the base scenario, then any new tours and trips generated in the build scenario will tend to give a positive difference between the build and base total logsums, but if those logsums have a mean value of -4.0 in the base scenario, then any new tours and trips generated in the build scenario will tend to give a negative difference between the build and base total logsums. Because the mean value is essentially arbitrary (subject to the constant C in Equation 4 in Chapter 3), it is best to adjust the logsums so that they have a mean value of 0 in the base scenario.

In practice, this adjustment can be done by normalizing each logsum value by subtracting the mean observed value. In this test, the logsums were accumulated by tour purpose, and the mean logsum by tour purpose was used to normalize the logsums in the benefit calculations. (Tour purpose is a key variable to use, as most ABMs, including DaySim and CT-RAMP, have different tour destination choice and tour mode choice models for different tour purposes.)

So, for each tour purpose, the logsums are added across all tours in the output trip list, and divided by the number of tours made for the purpose:

MeanLogsum(base) = TotalLogsums(base) / NTours(base)

MeanLogsum(build) = TotalLogsums(build) / NTours(build)

Then, instead of using *TotalLogsums(build) – TotalLogsums(base)* as the measure of benefits, it is adjusted by the difference in the number of tours times the mean logsum in the base case:

*TotalLogsums(build) – TotalLogsums(base) - (NTours(build) – NTours(base)) * MeanLogsum(base),*

…which is equal to…

*(MeanLogsum(build) * NTours(build)) - (MeanLogsum(base) * NTours(base)) - (NTours(build) – NTours(base)) * MeanLogsum(base),*

…which further simplifies to…

*NTours(build) * (MeanLogsum(build) – MeanLogsum(base)),*

… which is simply the number of tours in the build case times the difference in average logsums between the two scenarios.

Following the logic of the "rule of a half", a further adjustment can be made in which the difference in the number of tours generated between scenarios only receives half of the difference in average logsums. The logic is that that the alternative to making a tour (such as staying at home) also has some non-zero utility, and that is not captured in tour-level or trip-level model logsum (although it could be captured in a higher-level tour generation logsums). So, the more conservative measure is:

*½ * (NTours(build) + NTours(base)) * (MeanLogsum(build) – MeanLogsum(base))*

This is the "rule of a half" form of ½ * (Q2 + Q1) * (P2 – P1), where in this case, Q is the number of tours and P is the average logsum value across the tours.

5.2 Analysis Results

In our preliminary tests to compare logsum-based measures to more traditional rule of a half-based measures under the nine scenarios, it was found that only the tour destination choice logsum—the "highest" level of the logsums tested—gave results that were consistently comparable to rule of a half-based measures. This finding makes sense, as one common response to changing travel times and costs is to change destination rather than mode. Because the tour destination choice model is "above" the tour mode choice model in the DaySim and CT-RAMP ABM structures, and includes a mode choice logsum variable, the destination choice logsum incorporates both mode effects and destination effects. For example, a reduction in auto travel times may cause a traveler to still use auto and to visit a more distant destination that offers higher value (e.g. a better supermarket or mall for shopping). The mode choice logsum would show a disbenefit due to the longer total travel time (faster speed but longer distance), while the destination choice logsum would show that the disbenefit in travel time is more than compensated by the greater attractiveness of the destination.

The logsums for intermediate stop location choice were also investigated, but did not show any consistent relationships to the rule of half measures. Thus, the tour destination choice logsums are the focus of the results presented below.

Figure 5 to Figure 11 show the benefit measures for each of the seven tour purposes distinguished in the DaySim ABM for Tampa Bay, with Figure 12 showing the totals across all seven purposes combined. The benefits are in 2010 dollars for a single weekday, summed across the full synthetic population. For each of the nine scenarios, four benefit measures are shown:

- **ROH-ExtVOT-** This is the rule of a half measure based only on changes in travel times and costs. The values of time used for the benefit calculation are assumed external to the model rather than using the value of time directly from the AB models, and are as follows:
  - Work tours: All times valued at $20/hour
  - Other tours: All times valued at $10 hour
- **ROH-ModVOT-** This is the rule of a half measure based only on changes in travel times and costs, but with times converted to monetary values using the tour-specific VOT from the ABM rather than external values. (The value of time in the Tampa DaySim is a function of tour purpose, household income, auto occupancy for car trips, plus a random component that is log-normally distributed.)
- **ADJ-Tour dest_ls:** This is the adjusted measure based on the average tour destination choice logsums by tour purpose. As described above, it is equal to the number of tours in the build scenario times the difference in average logsums between the base and build scenarios.
- **ROH-Tour dest_ls:** As described above, this is a somewhat more conservative measure that applies the rule of a half logic to only allocate half of the difference in average logsums between the two scenarios to the difference in tours between the two scenarios.

When looking at the results across Figure 5 to Figure 12, some clear trends in the results are evident:

- As expected, all of the results show positive benefits when travel costs or times decrease compared to the base, and negative benefits when travel costs or times increase. This is true for both the rule of half-base measures and the tour destination choice logsum-based measures. (It was not always true when tour mode choice logsum-based measures were used in early tests, due to that fact that mode choice logsums do not capture destination-shifting effects, as discussed earlier in this chapter.
- For all of the types of measures, the magnitude of the (dis)benefits for the scenarios with changes in travel times are larger than for the scenarios with changes in travel costs. This is true because the monetized value of travel time is substantially larger than the actual monetary cost (tolls, fuel, fares) for most trips, and thus each percent change relative to the base case is larger for monetized travel time than for travel cost.
- For the cost change scenarios, it makes no difference whether the model value of time (ModVOT) or an externally assumed value of time (ExtVOT) is used in the calculations, because all of the scenario changes are to travel cost, and none are for travel times.
- For the time change scenarios, the (dis)benefits calculated using the ABM tour-specific model value of time (ModVOT) are always slightly higher than those calculated using the externally assumed values of time (ModVOT). One could calibrate the two measures to produce the same values by slightly adjusting the externally assumed values of time. However, the results shown in the charts are for the <u>total</u> population, and not for particular market segments. If one were to segment the results by income, for example, the ROH-ModVOT values would increase substantially with income, because the VOT used in the models increases with

income. The externally assumed VOT do not vary with income, and thus provide income-neutral ROH benefit measures, which are often desired on equity grounds.

- There are only slight differences between the ADJ-tour dest_ls and ROH-tour dest_ls in all cases. The difference between these two measures arises solely from differences in the number of tours generated in the two scenarios, and the results show that the (dis)benefits accruing to existing travel (tours made in both scenarios) are much more substantial than the (dis)benefits accruing to generated or suppressed tours. This is true even in very "drastic" scenarios in which all travel times or costs in the region change by 50%. With such small differences, it is reasonable to focus only on one of these two measures in further analyses. As the ROH-tour dest_ls measure is the more conservative of the two, that measure will be used in further analyses.
- Comparing the two measures most relevant for practical BCA (ROH-ExtVOT and ROH-tour dest_ls), the two are very close for the cost change scenarios for all of the travel purposes and across the purposes combined. (The largest differences are for the Shopping purpose.) For the time change scenarios, the logsum-based ROH measure is substantially smaller than the generalized cost-based ROH measure for the School purpose, and slightly smaller for the Work purpose, but the logsum-based measure is somewhat higher than the generalized cost-based measure for all other travel purposes. When adding across all purposes (Figure 12), the logsum-based measure is slightly higher than the generalized-cost based measure. One reason why the logsum-based measure is relatively higher for the purposes other than work and school is that work and school destinations are more constrained--particularly in the short term, while there is typically more flexibility in choosing destinations for the other tour purposes, and thus more potential for obtaining destination-switching benefits that are not reflected in travel time and cost changes.

Figure 5: Comparison of Benefit Measures for Work Tours

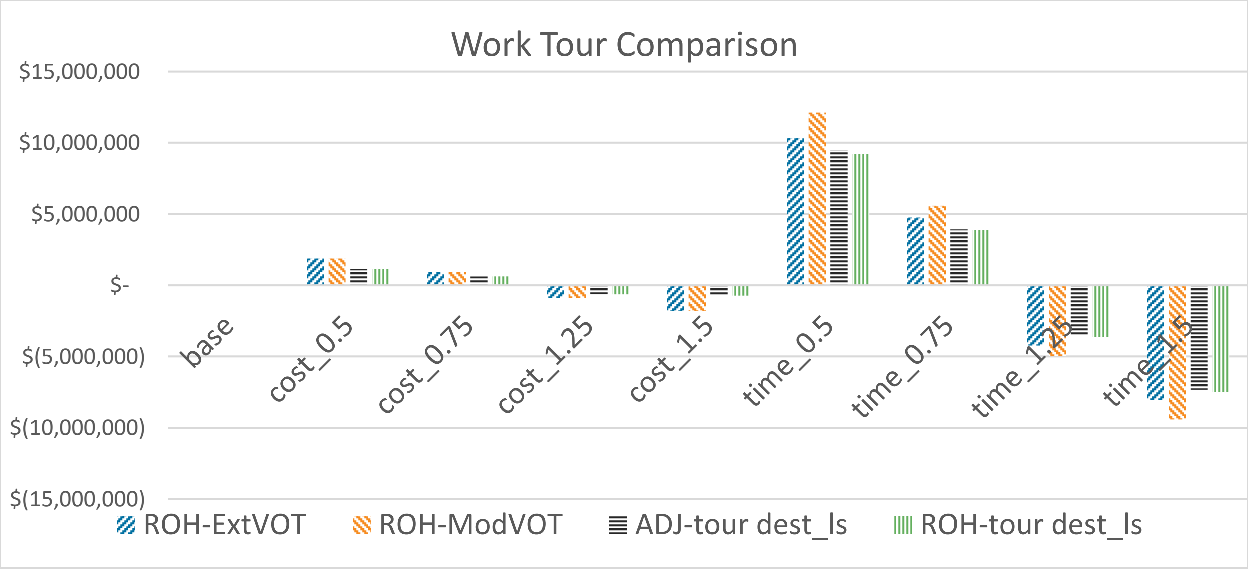


Figure 6: Comparison of Benefit Measures for School Tours

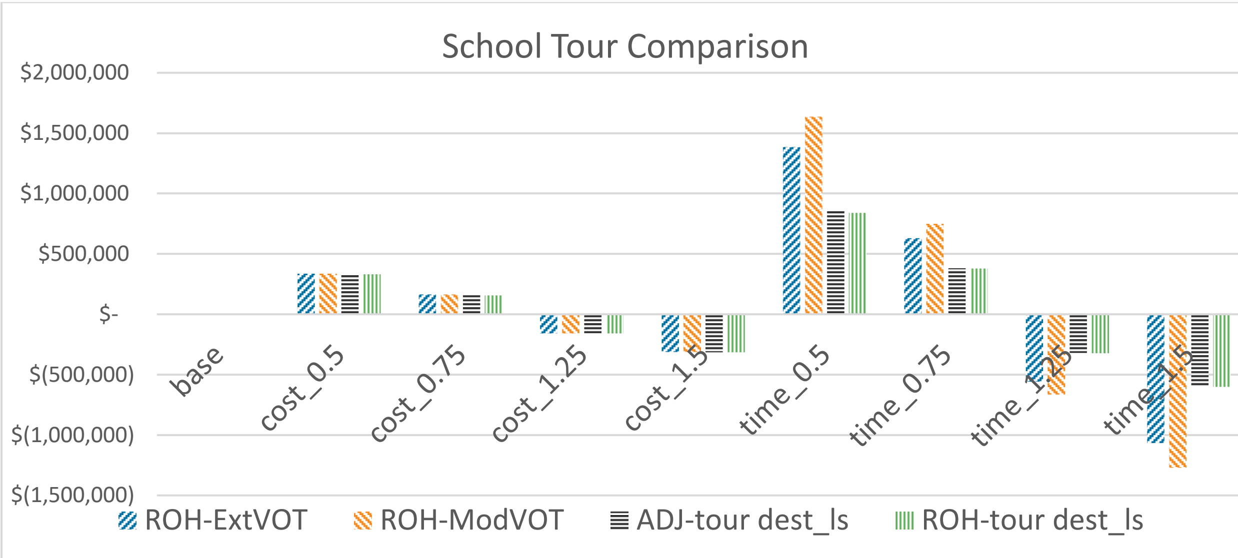


Figure 7: Comparison of Benefit Measures for Escort Tours

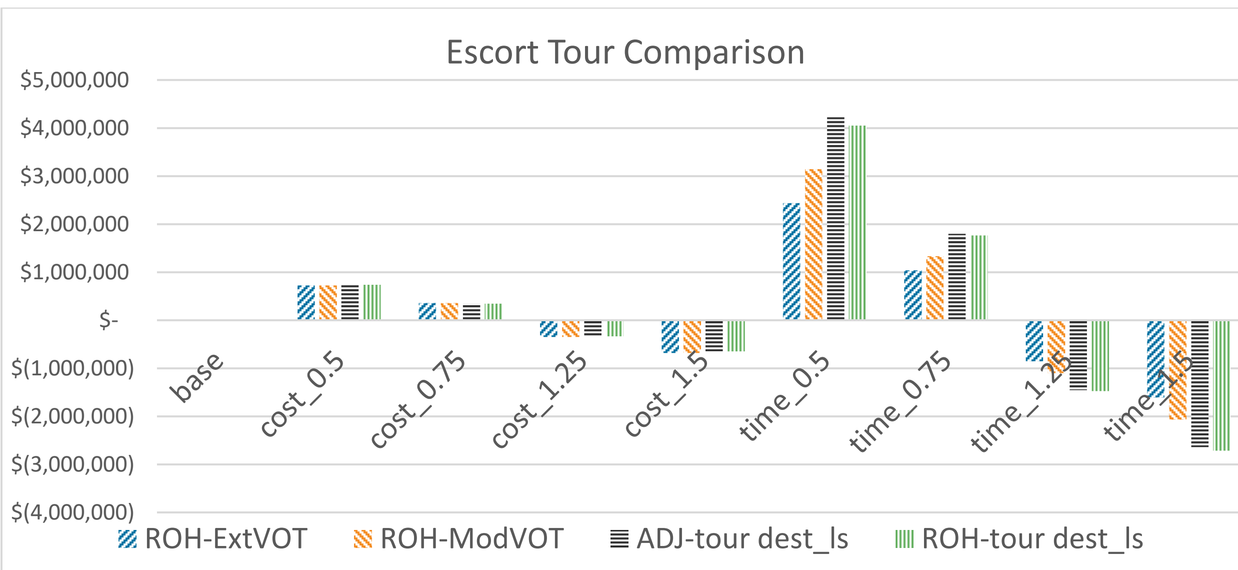


Figure 8: Comparison of Benefit Measures for Personal Business/Errand Tours

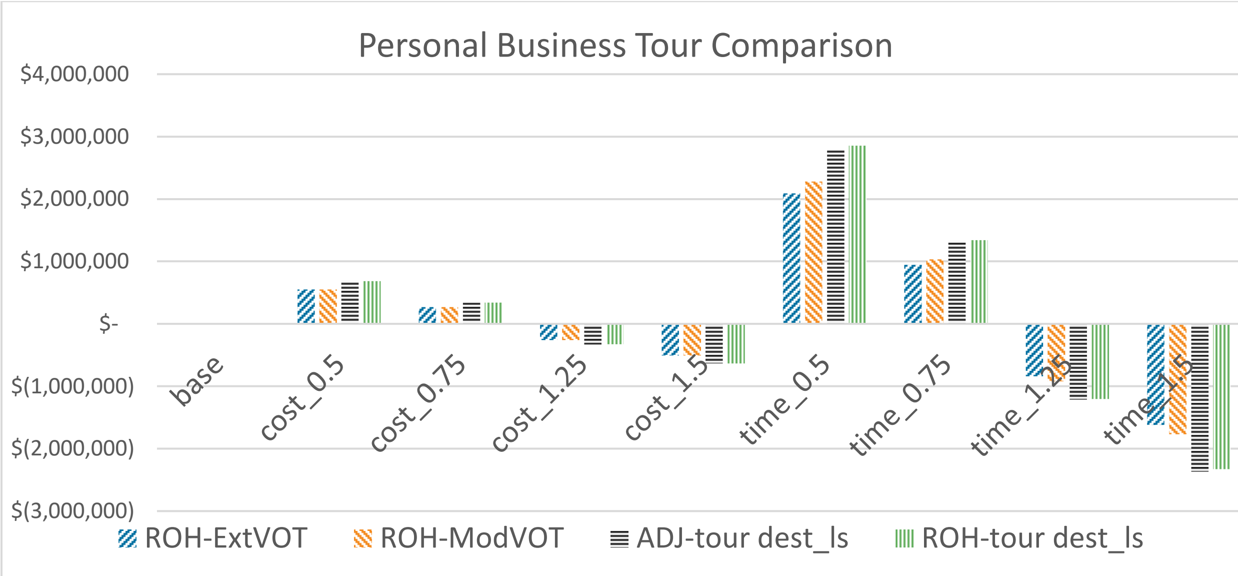


Figure 9: Comparison of Benefit Measures for Shopping Tours

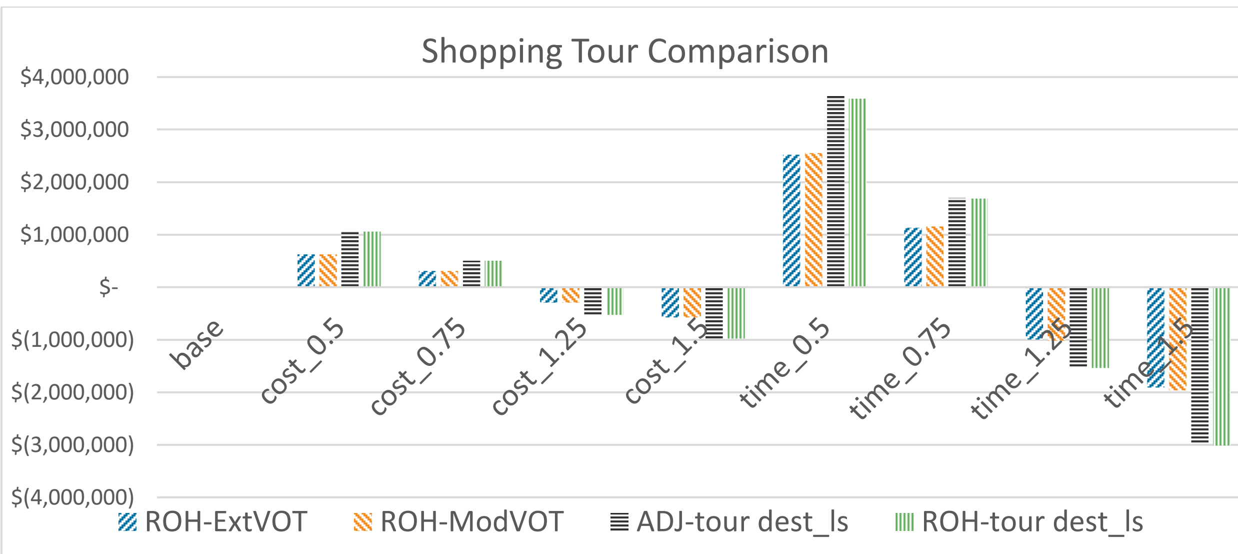


Figure 10: Comparison of Benefit Measures for Meal Tours

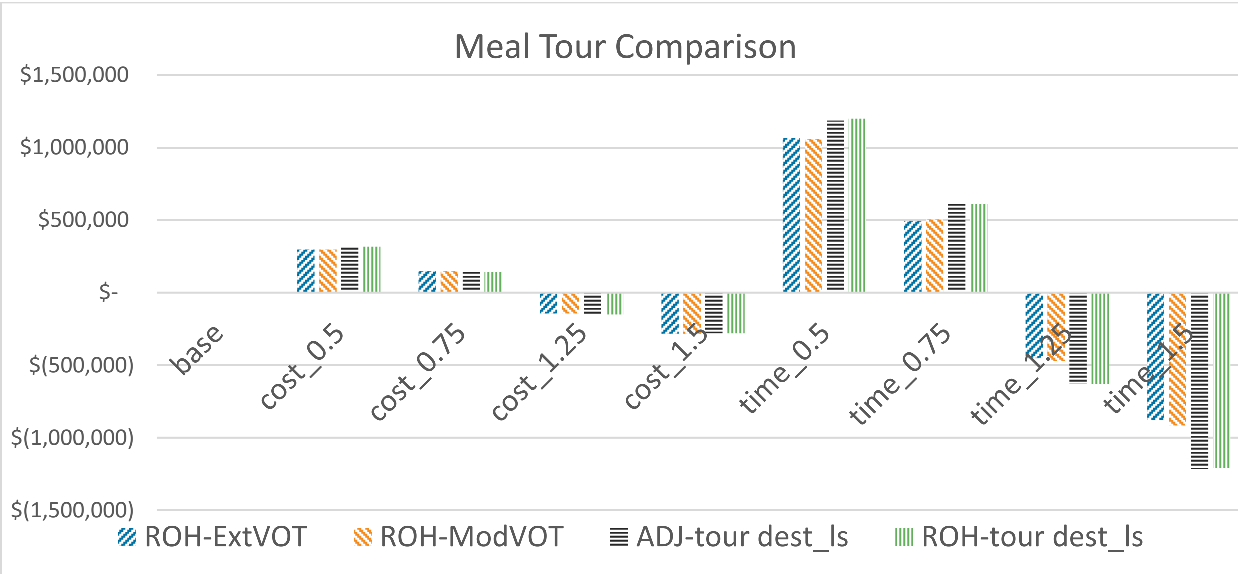


Figure 11: Comparison of Benefit Measures for Social and Recreation Tours

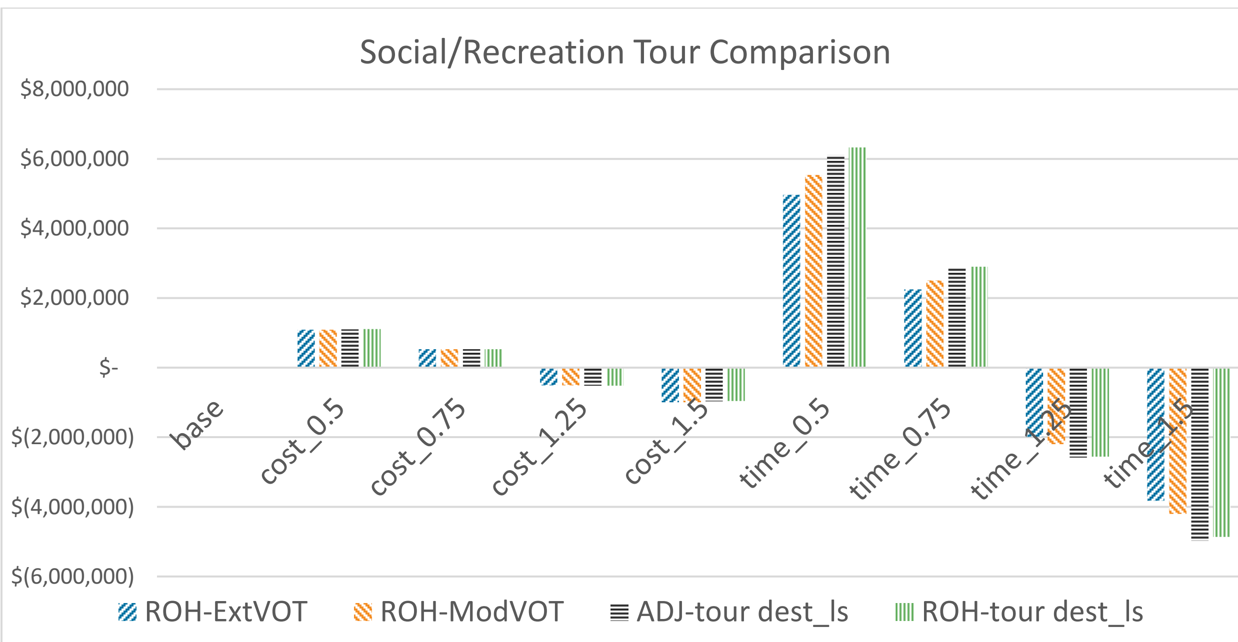
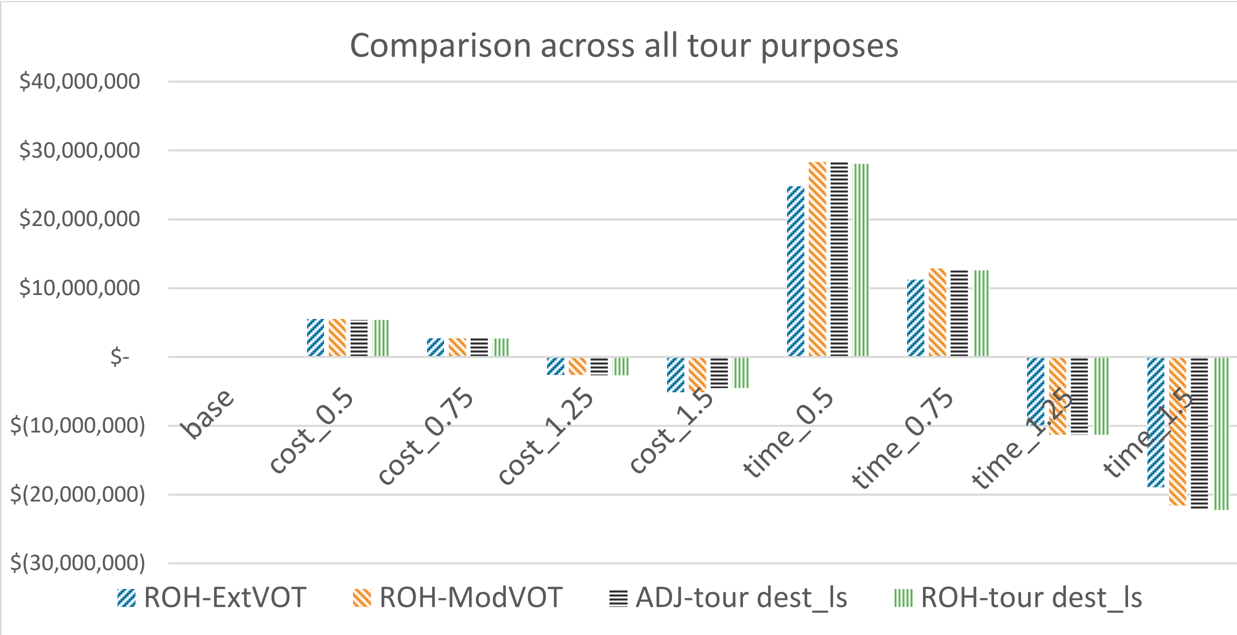


Figure 12: Comparison of Benefit Measures for All Tour Purposes Combined



Sensitivity to Income Changes

The Tampa Bay DaySim model was also run for four additional scenarios that did not involve changing travel times or costs, but changed household incomes in the synthetic population instead. These scenarios are:

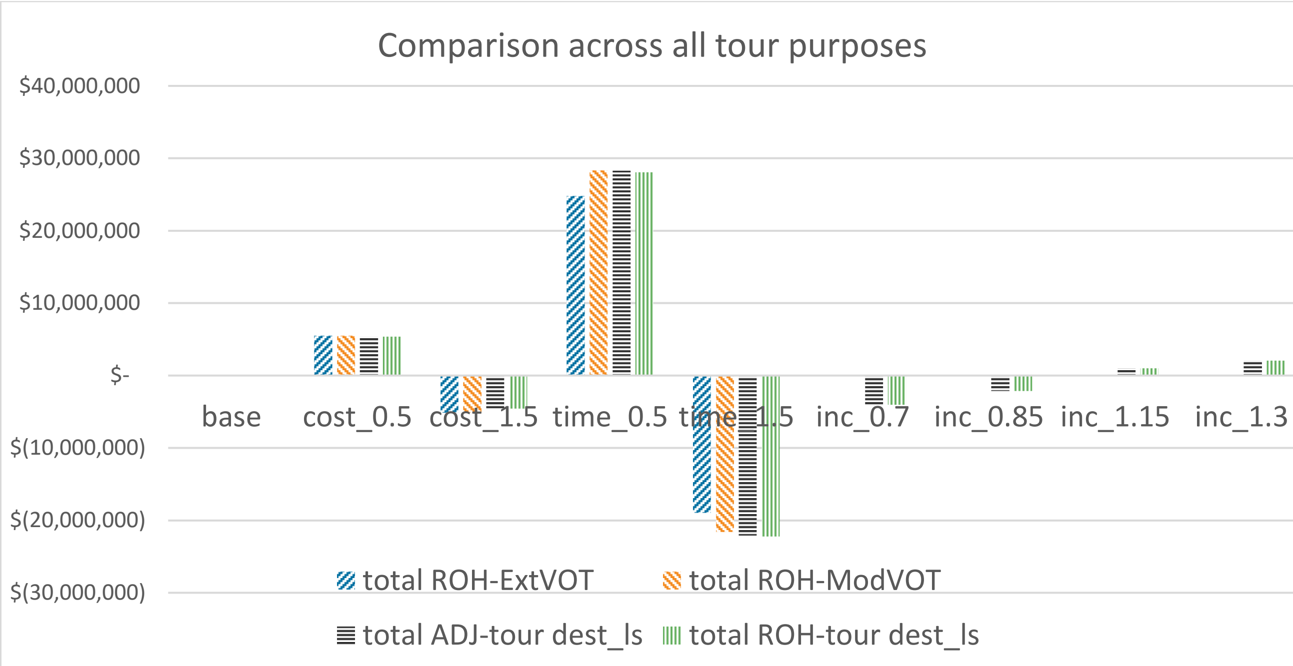
1. **Inc_0.7**: The income for every household was factored by 0.70 (a 30% reduction versus the base)
2. **Inc_0.85**: The income for every household was factored by 0.85 (a 15% reduction versus the base)
3. **Inc_1.15**: The income for every household was factored by 1.15 (a 15% increase versus the base)
4. **Inc_1.3**: The income for every household was factored by 1.30 (a 30% increase versus the base)

The results are shown in Figure 13, alongside the most extreme of the cost and time shift scenarios, included for comparative purposes. Some results are:

- The generalized cost-based ROH measures are 0 in all cases, because travel times and costs do not change relative to the base scenario, and the generalized cost-based ROH measure is only sensitive to changes in travel time or cost.
- The logsum-based measures change somewhat, because those with higher incomes tend to make more tours and trips, and have higher values of time. However, the logsum-based measures are much smaller than those related to the time and cost change scenarios.
- The disbenefits of decreasing income are somewhat larger than the benefits of increasing income. This is because several of the income relationships in the DaySim models are non-

linear, with larger effects per dollar of income in the lower income ranges than in the higher income ranges.

Figure 13: Comparison of Benefit Measures for All Tour Purposes Combined



In summary, a potential advantage of using logsum-based benefit measures over generalized-cost based measures is that they are able to capture some of the benefits of activity participation other than those reflected in travel time and cost changes, and thus are sensitive to changes in income that influence activity and travel patterns. The same point would apply to changes in other socio-economic variables such as employment status and student status.

5.3 Recommendations for the BCA Tool and Sensitivity Tests

Based on the analyses and findings reported in the previous sections, a number of decisions were made for the final phases of the project:

- For the BCA tool, two alternative benefit measures should be implemented:
  - A generalized-cost based ROH measure using externally assumed values of time. This measure should be based on disaggregate measures of travel time and cost changes, determining what the travel times and costs of each trip would have been if that trip would have been made in the alternate scenario.
  - A logsum-based ROH measure using the logsum from the tour destination choice model in each scenario. Because disaggregate calculation of the logsum for each tour under the alternate scenario was deemed infeasible for practical application, the ROH calculations should be done using aggregate averages by tour purpose.

- It would be possible to have the BCA tool generate generalized cost-based ROH measures using the trip-specific values of time (VOT) that are used in the DaySim models. However, such measures would generally not be acceptable on equity grounds, as the monetary benefit assigned to travel time changes would be highly income-dependent. Instead, it may be more informative to vary how the value of time is set in the ABM as a function of income, as part of the sensitivity tests.
- There may be some level of aggregation bias in the calculation of the logsum-based ROH. It would be interesting to see how such measures change if a different level of aggregation is used (for example, aggregating by tour purpose/mode combination, rather than simply tour purpose).

6.0 Sensitivity Tests of the Software Tool and Alternative Benefit Measures

6.1 Analysis Approach

The original project scope specified four types of sensitivity tests:

- Sensitivity to a significant infrastructure change
- Sensitivity to a significant land use change
- Sensitivity to the type of benefit measure – generalized cost-based or logsum-based
- Sensitivity to random variation in the ABM simulation, in general and in value of time distributions

Rather than treat these as four separate types of tests, it is more informative to perform the tests in combination. The two types of benefit measures—generalized cost-based rule of half and logsum-based rule of half—will be compared in every scenario. Also, the infrastructure change and land use change scenarios will be assessed under different ABM settings that determine random variation during the simulation. Carrying out these tests also allowed us a chance to test and independently verify the computations in the software tool created for this project, BCA4ABM, which is document in Appendix A.

Twelve different model runs were set up for the Tampa Bay model system, as shown in Table 11 through Table 13. The entry in **bold text** in each row indicates what has changed relative to the "base" run that it is compared against, which is listed in the last column to the right.

- **Run 1A**: The Base run uses all the 2010 base year inputs for the Tampa Bay regional model, as described in Section 5.1.
- **Run 1B**: Uses all the same inputs as Run 1A, but uses a different random seed, which produces an entirely different sequence of random numbers used to simulate choices in the ABM.
- **Run 1C**: Again, uses all the same inputs as Run 1A, but does not use a random component in setting the VOT for each tour. Thus, the VOT is based only on tour purpose and household income, and has less variability.
- **Run 1D**: The same as run 1C, but also removes the effect of household income on VOT – so the VOT for each tour is based only on the tour purpose.
- **Runs 2A, 2B, 2C and 2D**: The same as runs 1A, 1B, 1C and 1D respectively, but changing the road network in Cube to reflect the "New lanes" infrastructure scenario, as described below.
- **Runs 3A, 3B, 3C and 3D**: The same as runs 1A, 1B, 1C and 1D respectively, but changing the input synthetic population and parcel land use file to reflect the "More infill" land use scenario, as described below

Table 11: Runs for Sensitivity Tests Related to Random Variation and Value of Time (1 Series)

Run	Random Seed	Random in VOT	Income in VOT	Network Scenario	Land-Use Scenario	Compare to run…
1A	1234	True	True	Base	Base	n/a
1B	**4321**	True	True	Base	Base	1A
1C	1234	**False**	True	Base	Base	1A
1D	1234	**False**	**False**	Base	Base	1A

Table 12: Runs for Sensitivity Tests Related to Infrastructure Changes (2 Series)

Run	Random Seed	Random in VOT	Income in VOT	Network Scenario	Land-Use Scenario	Compare to run…
2A	1234	True	True	**New Lanes**	Base	1A
2B	**4321**	True	True	**New Lanes**	Base	1B
2C	1234	**False**	True	**New Lanes**	Base	1C
2D	1234	False	**False**	**New Lanes**	Base	1D

Table 13: Runs for Sensitivity Tests Related to Land Use Changes (3 Series)

Run	Random Seed	Random in VOT	Income in VOT	Network Scenario	Land-Use Scenario	Compare to run…
3A	1234	True	True	Base	**More Infill**	1A
3B	**4321**	True	True	Base	**More Infill**	1B
3C	1234	**False**	True	Base	**More Infill**	1C
3D	1234	False	**False**	Base	**More Infill**	1D

The procedure for running the sensitivity tests was as follows:

- Prepare all input files for each of the 12 ABM runs. This includes
  - Creating the new Cube network input file for the “New lanes” infrastructure scenario.
  - Creating the new DaySim input parcel and synthetic population files for the “More infill” land use scenario.
  - Customizing the DaySim configuration files for each run to use the appropriate random seed and VOT settings, and the appropriate input files, and scenario-specific output directories.
  - Customizing the Cube scripts for each run to use the appropriate network files, and the appropriate input and output directories.
- Do a full integrated Cube/DaySim run for each of the 12 runs, with 3 global iterations to feed the trips from DaySim into Cube traffic assignment and then feed the resulting travel time and cost matrices back into DaySim.

- For each of the 11 scenario comparisons, run DaySim two times in "BCASkimAttachmentMode"—once to attach the "build" scenario travel times and costs to the "base" scenario trips, and then again to attach the "base" scenario travel times and costs to the "build" scenario trips. (This new way of running the AB model was programmed for this project to provide needed input for the BCA4ABM tool. It runs quite fast, attaching new times and costs to a trip file with over 10 million trips in less than 15 minutes. A similar process is also available for the CT-RAMP model, and was used for the San Diego region test described later in this chapter.)
- For each of the 11 scenario comparisons, run the BCA4ABM software tool to generate BCA outputs for the specific pair of runs.
- The ABM model outputs were also analyzed using a computer program written to provide an independent check on the outputs of the BCA4ABM tool, and all common calculations produced identical results. (The computer program also generated other diagnostic outputs, some of which are reported later in this chapter.)

A major difference between these tests and the more controlled set of runs described early in Chapter 5 is that these runs were done using the full Tampa ABM system integrated with Cube, with global feedback between the AB demand model and the traffic assignment. Performing these runs in the standard modeling environment for the Tampa ABM helps ensure that the BCA tool will be applicable in practice for users of the Tampa model.

The specification infrastructure and land use scenarios are described below. Note that neither of these scenarios are actually being considered by the regional government agencies at this time – in fact they were intentionally specified to <u>not</u> represent current regional plans. Instead, they were designed to be fairly straightforward to implement and interpret, while still representing of the <u>types</u> of scenarios that many agencies are interested in implementing.

The "New Lanes" Infrastructure Scenario

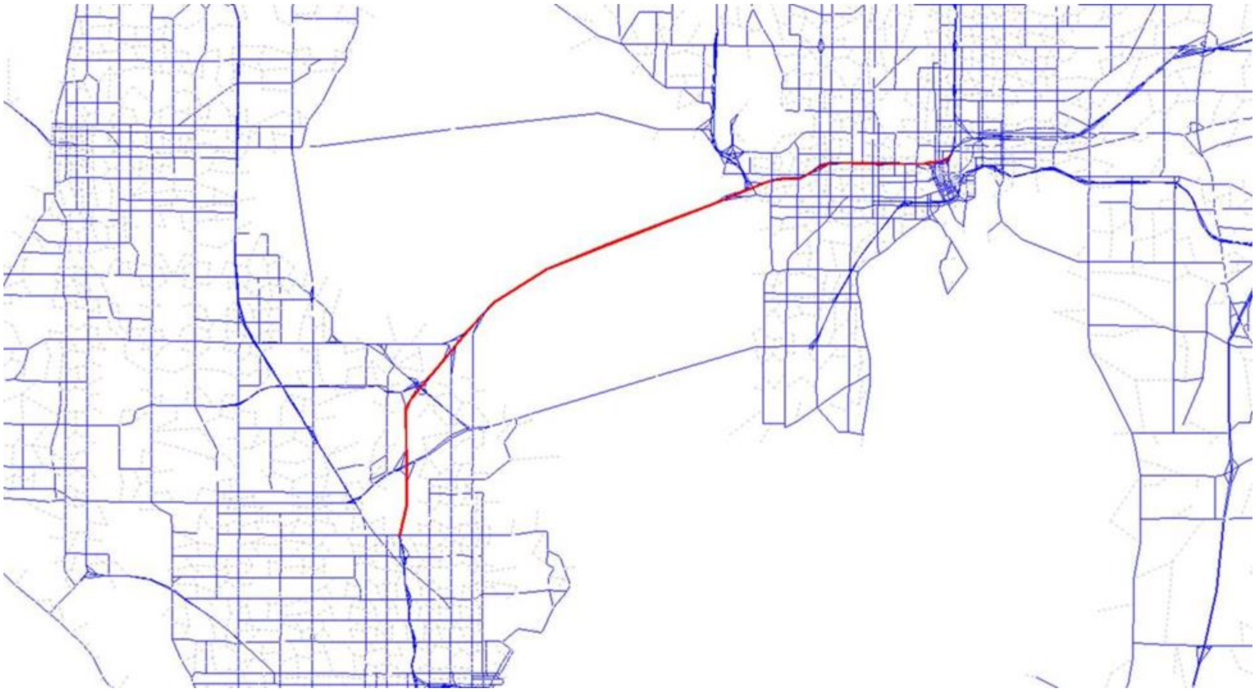
To define the infrastructure scenario, a corridor along Interstate 275, which includes the Howard Frankland Bridge, was selected. The selected corridor starts from Interstate 4 and goes to 62nd Avenue North in Pinellas Park. The infrastructure scenario adds a new lane in both directions of the selected corridor. The Howard Frankland bridge had four lanes in each direction, while for the entire corridor, number of lanes ranges from 3 to 4. For the purpose of coding the infrastructure scenario, a link flag attribute (BCATestFlag) was added to the base network, which took on a value of "1", if the link belonged to the selected corridor and "0" otherwise. This was done by manually locating the links on Cube network with help from Google Maps and then updating the BCATestFlag attribute in the link attribute table. The BCATestFlag attribute holds true for 84 links out of 32,465 total links in the highway network. Next, a computation set was defined using the attribute calculation utility of the Cube software. The computation set applies the following equation to each link in the subset of links defined by the conditional expression.

Equation: Number_of_Lanes = Number_of_Lanes + 1

Conditional Expression: BCATestFlag == 1

The number of lanes attribute was increased by one for all the links where the BCATestFlag attribute was true. This resulted in the number of lanes on the Howard Frankland bridge increasing from 4 to 5 in both directions. Overall, the number of lanes in the selected corridor ranges from 4 to 5 in the “new lanes” infrastructure scenario. Figure 14 highlights the selected corridor in red.

Figure 14: Selected Corridor for Infrastructure Scenario



Note that it would also be possible to model the removal of a lane or the downgrading of a facility (e.g. from freeway to boulevard). Other types of network changes that would be possible to model include changing speed limits, introducing tolls or changing toll levels on specific links, adding or converting HOV-only lanes, designating lanes as trucks-only, or restricting trucks from using certain lanes. More detailed infrastructure changes, such as changing the configuration and/or signal timings of specific intersections or ramps, are more difficult to simulate accurately with static traffic assignment and would best be carried out using mesoscopic or microscopic traffic simulation models. The BCA methods described in this report could also be used with AB models integrated with more detailed traffic simulation methods (e.g. dynamic traffic assignment), once those methods come into more widespread use.

The “More Infill” Land Use Scenario

This scenario is designed to simulate the effects of infill housing development that would allow households to move closer to the highest concentrations of employment and transit services in downtown areas. The housing could be in higher density residential and/or mixed used development. The steps followed to create this scenario were:

- 100 contiguous zones were selected in downtown Tampa that have a high accessibility to both employment and transit stops in the buffered parcel data. (These are zones 372-471).

- Another 100 contiguous zones were selected in downtown St. Petersburg that also have a high accessibility to both employment and transit stops in the buffered parcel data. (These are zones 1603-1702).
- Each of these areas has roughly 45,000 resident households in the 2010 synthetic population.
- Each of the households living in the two areas was classified according to the combination of household size (1,2,3,4+), number of workers (0,1,2+), and income (5 groups).
- For each household originally living in in one of the two “infill” areas, a household was selected at random from any zones outside of the infill areas that has the same combination of characteristics (household size, workers, and income categories), and that household was moved them onto the same parcel as the original household. This means that every parcel in the infill areas keeps the same types of households, but now has twice as many of them. In total, there are roughly 90,000 households moved into these areas, meaning that the zones outside of the two areas lose about 5% of their households, on average, although there is random variation across the zones. (Zones with a distribution of household types most similar to the households already living in the infill areas are somewhat more likely to have households move into the infill areas.)
- In addition to changing the residence location of certain households in the synthetic household file, the parcel database was updated to reflect the changed number of households living on each parcel and within the buffer areas around each parcel.

Note that the location of income and transit services was not changed in this scenario. In a more realistic scenario, one might expect that the number of jobs of certain types and transit stops and/or frequencies would also increase in these areas in response to the doubling of the local population. As transit is not capacity-constrained in the model, this will not adversely affect the transit level of service. Since work location is balanced to the available jobs, however, it may be the case that the home-to-work distances will not decrease as much as they would if jobs were also moved into the infill areas. (The distances will still decrease overall, however, because these areas already have many more jobs than residents in the base scenario.)

6.2 Sensitivity Test Results for Tampa

In this section, we explore the results of the sensitivity test runs. The first set of charts show the overall tour generation, travel distance and mode shares for the 12 different runs. In the charts, the runs 1A is the base, with 1B changing only the random number sequence used for the simulation, run 1C only removing random variation in the values of time (VOT) used by the model, and run 1D the same as 1C, but also removing any income variation in VOT, so VOT various only by tour purpose—work versus non-work. Runs 2A-2D are done by repeating runs 1A-1D, but with the “New Lanes” infrastructure scenario in the network inputs. Runs 3A-3D are done by again repeating runs 1A-1D, but with the “More Infill” land use scenario in the parcel and synthetic population inputs.

Figure 15 shows that the region-wide average number of tours made person day remains almost exactly the same at about 1.4 tours/day for all 12 runs. The tour rates across the runs vary by less than 1% for all purposes and in total. Although some tours may be generated or suppressed in particular areas, the region-wide averages are barely influenced at all. Although not shown here, the same is true for the number of trips per tour (about 2.6 trips per tour, on average) and the number of trips per person-day (about 3.6 trips/day). The low sensitivity in tour and trip generation on a region-wide basis makes sense, as both the infrastructure and land use scenarios are fairly restricted in their geographic scope and their effects on region-wide accessibility. The implication for the results below is that the benefit measures will not tend to be very sensitive to assumptions regarding generated or suppressed tours.

Figure 15: Average Tours per Person-Day in the 12 Tampa Model Runs

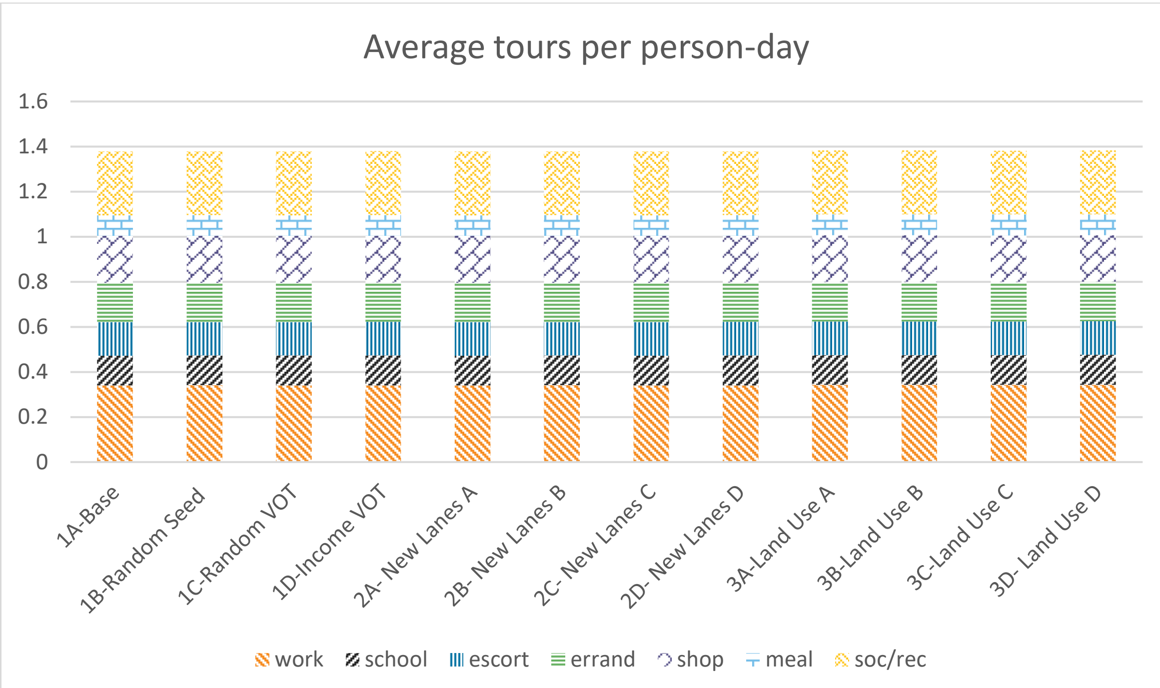
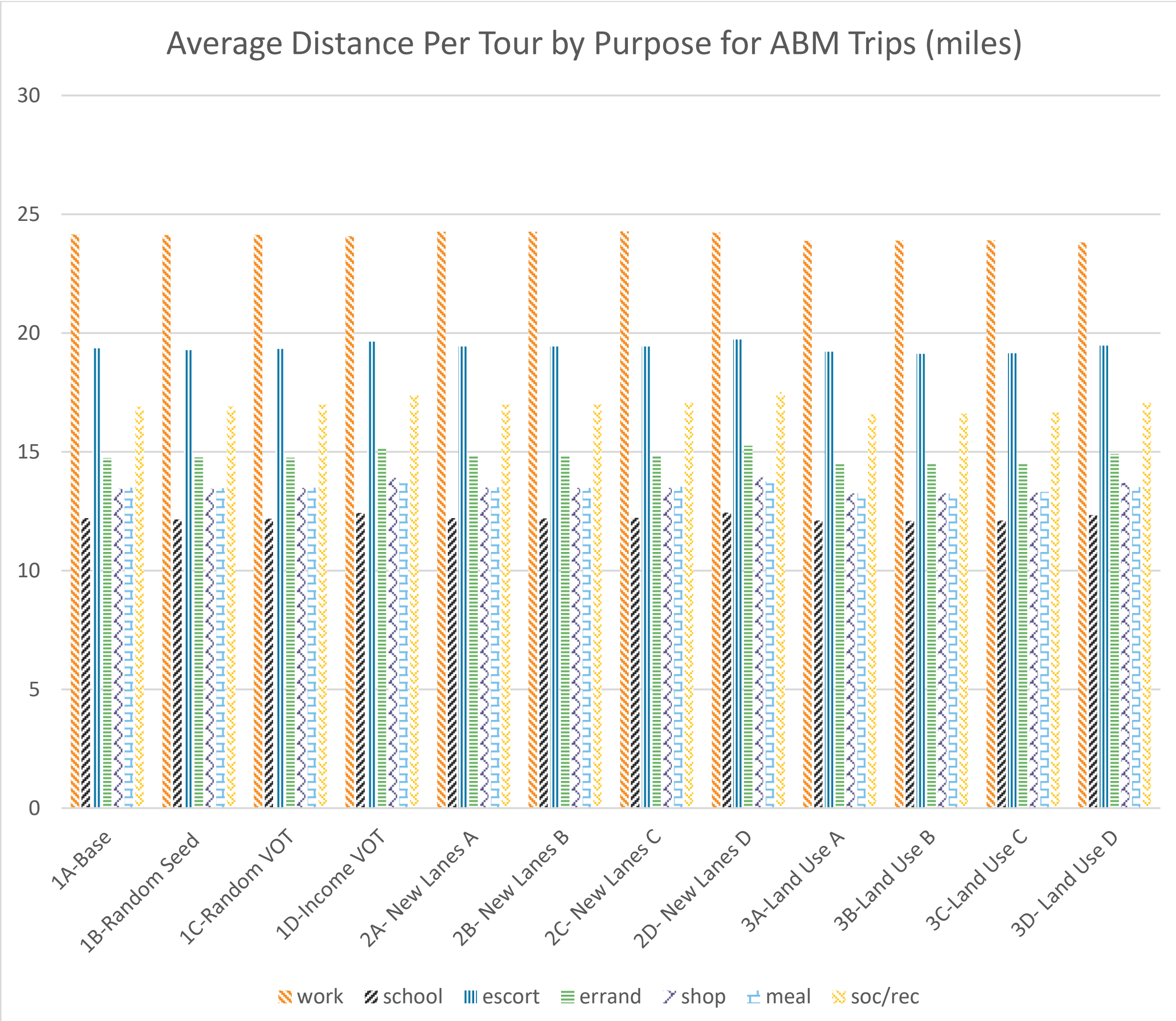


Figure 16 illustrates that destination shifting effects are also fairly limited on a region-wide level, as the average distance traveled per tour (round trip, including all trips on the tour) does not vary substantially per tour. In the Land Use runs, the distance may by up to 1% shorter on average for some tour purposes due to more people living in compact downtown areas, but overall the travel distances change very little. (There will also tend to be some offsetting effects in the models, as some people who live outside the downtown areas choose to travel longer distances due to slightly less traffic congestion resulting from the fact that some households have moved out of those zones.

Figure 16: Average Total Roundtrip Distance per Tour in the 12 Tampa Model Runs



The largest shifts across the 12 runs are in mode choice. Figure 17 shows the tour mode share of the trips produced by the ABM, while Figure 18 shows the change in mode share for each of 11 runs when compared to the corresponding "base" run (shown in the right-hand column of Table 11 through Table 13).

If one looks very closely at Figure 17, the most pronounced changes are somewhat higher walk and bike mode shares in the Land Use (3A-3D) scenarios than in the other scenarios. This is seen more clearly in Figure 18 looking at the change in mode shares by scenario. There are a few interesting things to note in this figure:

- When simply changing the random seed (run 1B vs 1A), none of the mode shares change by even one half of one percent, so almost no change in region-wide results.
- When removing the random variation in VOT (run 1C vs 1A), walk and transit trips are reduced by roughly 4%, while trips by the bike and auto modes increase to compensate. This is because those people with the lowest VOT tend to be the ones who choose the slowest

modes—walk and transit, and removing the random component narrows the VOT distribution used by the models, so that there are fewer people with VOT in the lower ranges that will choose the slower modes. This is even more pronounced when the income-based variation is also removed from VOT (1D vs. 1A), where walk trips are 7% lower and bike trips 5% lower, and transit trips lower as well. These runs show that mode choice is sensitive to the VOT distribution used in the models, so in practice it would be important to re-calibrate the mode choice models if one were to change the VOT distribution that is used. For this project, the important question is whether or not the sensitivity of the models and benefit calculations varies a great deal depending on which run (1A, 1B, 1C or 1D) is used as the base scenario.

- It is interesting that the trips by mode change by less than 1% region-wide in all of the New Lanes infrastructure scenario runs, when compared to the corresponding base run (2A vs 1A, 2B vs 1B, etc.). One would perhaps expect to see auto mode shares increase at least by a noticeable amount when adding lanes to one of the most congested freeways in the region. In the Tampa region, however, there may not be many non-auto trips across the Bay in the base scenario, so not a great potential for increased auto mode share if travel times are reduced.
- The most pronounced and consistent change is that the number of walk trips increase by about 8% and the number of bike and transit trips increases by about 4-6% in the Land Use scenario runs when compared to the corresponding base runs (3A vs. 1A, 3B vs. 1B, etc.). This region-wide change is quite substantial when taking into account that only about 6% of the region's population change residence location in this scenario, indicating a major mode shift for those households who are relocated to the downtown areas.
- The fact that there is no major variation for the changes seen across the four infrastructure scenario runs (2A-2D) and across the four land use scenario runs (3A-3D) suggests that the sensitivity of the models is not greatly influenced by the random seed or the particular VOT settings that vary across the A, B, C and D runs.

Figure 17: Region-Wide Tour Mode Shares in the 12 Tampa Model Runs

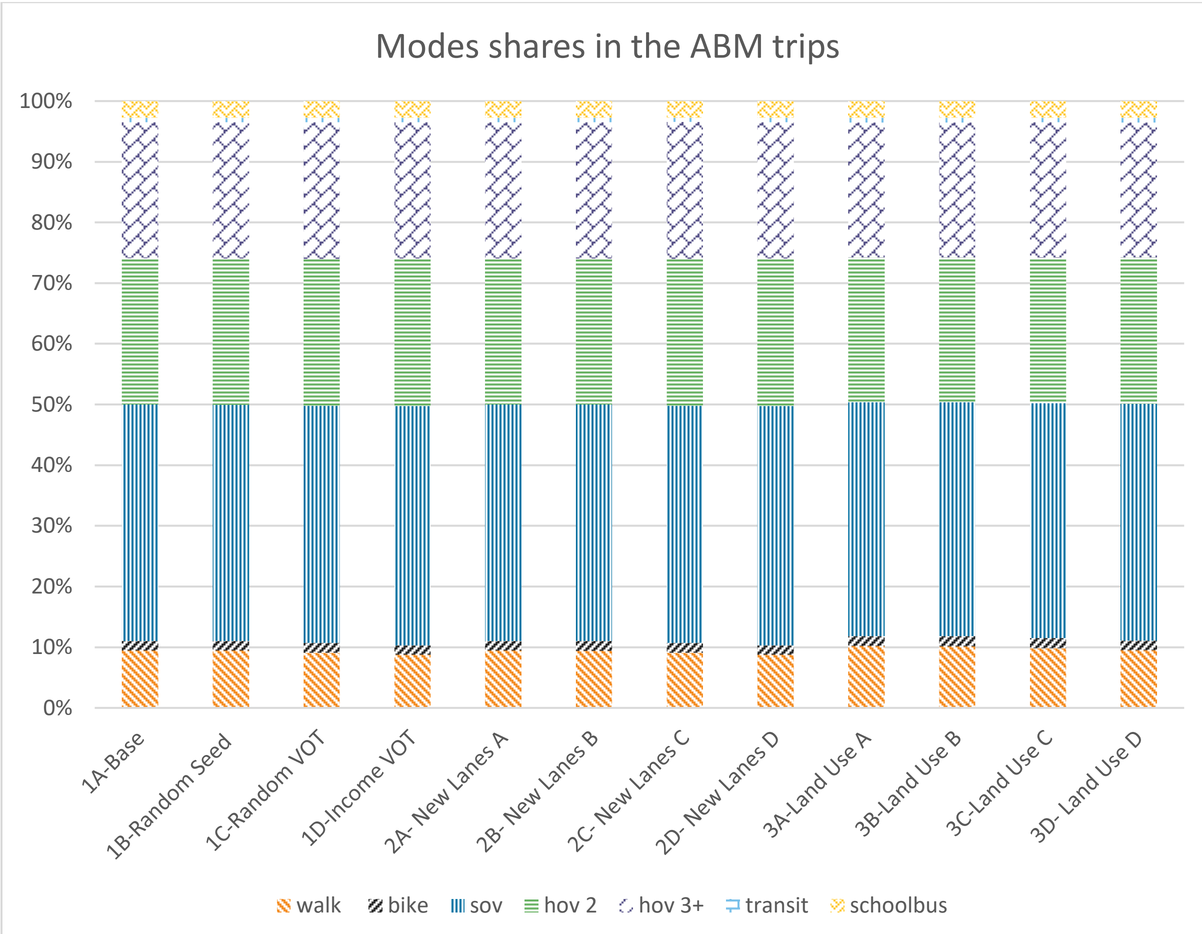
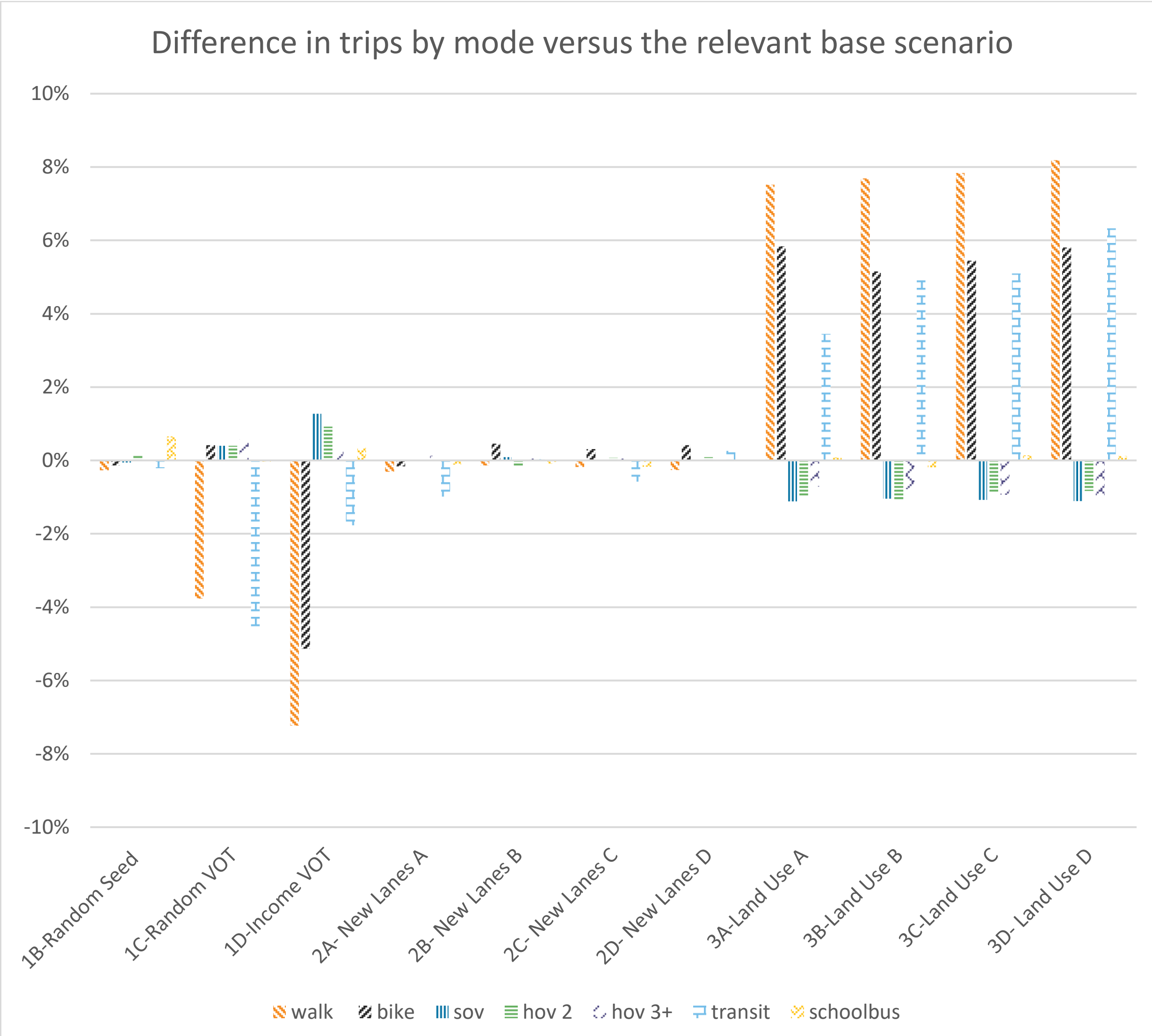


Figure 18: Change in Region-Wide Trips by Tour Mode in 11 Tampa Model Runs Compared to a Base

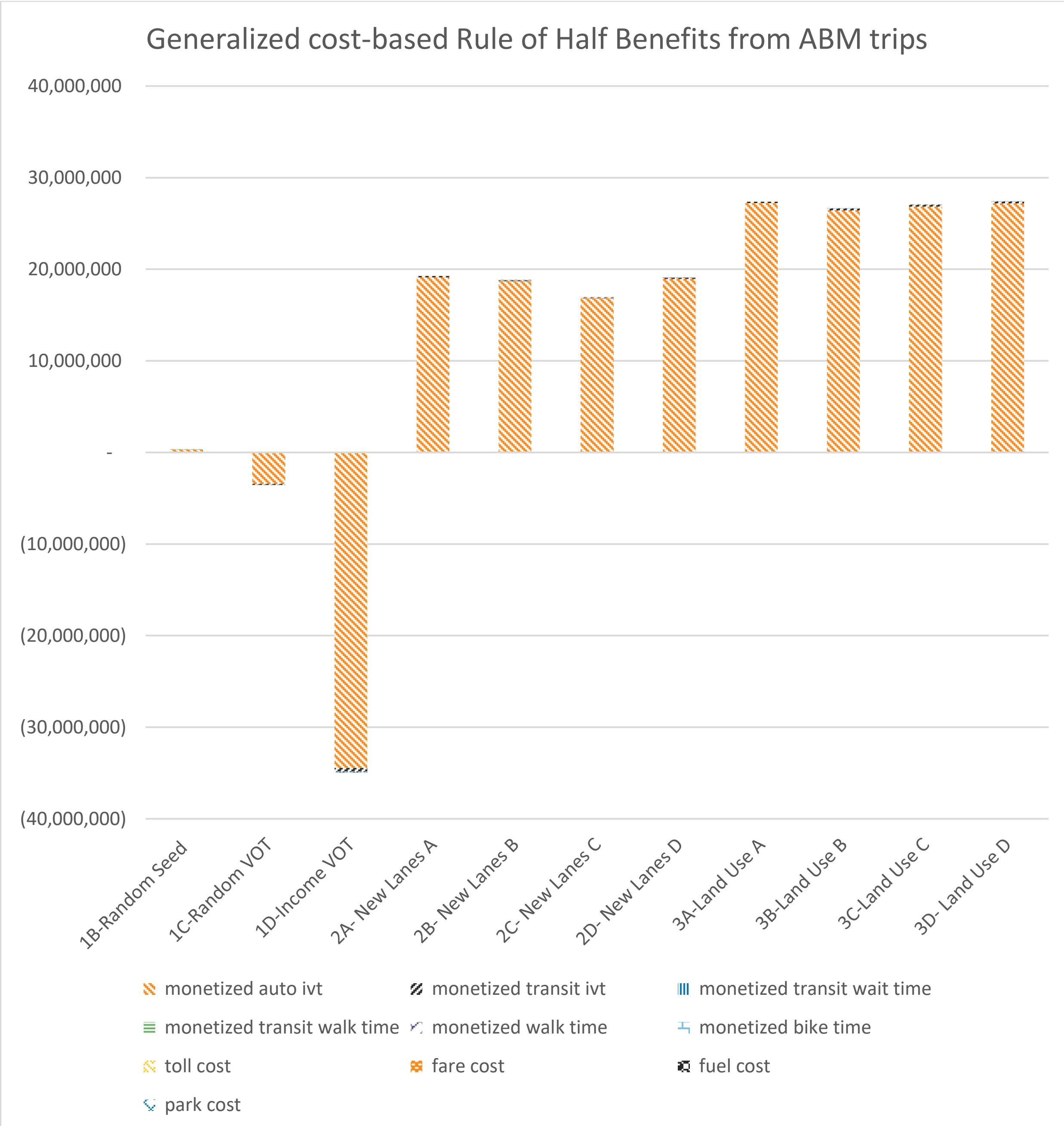


Next, we look at the Rule of a Half-based benefits that were generated using the BCA4ABM tool for the 11 comparisons (and verified by running the same model outputs through an independently created computer calculation program and obtaining identical results). Figure 19 looks at the "traditional" generalized cost-based ROH measures, adding up 10 different time and cost components—6 time components (auto in-vehicle, transit in-vehicle, transit wait, transit walk access/egress, bike, and (non-transit) walk time), and 4 cost components (auto tolls, auto fuel, auto parking and transit fare). In this case, the time benefits were monetized using assumed VOT of \$10/hour for Work in-vehicle time, \$15/hour for Work out-of-vehicle time, \$6/hour for Non-work in-vehicle time, and \$9/hour for Non-work out-of-vehicle time (see the BCA4ABM settings in Figure 30 in Appendix A). The per-day values are annualized using a factor of 365 days per year and then discounted using an assumed discount rate of 0.75 out to an arbitrary evaluation year. These are the same values that were used in the SANDAG BCA tool (except for the discount rate, which varies according to the specific evaluation year). Some things to note about the results:

- In all cases, auto in-vehicle time dominates the value in the calculation. This is in large part an artifact of the way that the generalized cost-based ROH calculations are done. They are only non-zero if the zone-to-zone travel time and cost matrices change between the scenarios. The walk and bike skims used in the models are constant and not influenced by traffic congestion, so the ROH-based benefits for walk and bike time are always 0, even though there may be a substantial change in the number of walk and bike trips, as seen in Figure 18. Transit skims and paths may change somewhat between scenarios due to a changed prediction of traffic volumes and speeds on specific links, but there are relatively few transit trips in any scenarios, so a small contribution to benefits for any of the transit-related variables. Because highway assignment is the main thing that changes between iterations of the model system, it is thus the main source of differences across the runs. This, plus the fact that most trips are by auto, lead to the situation that auto in-vehicle time changes dominate the generalized cost-based ROH benefit calculations.
- There is virtually no net benefit or cost from simply changing the random seed (1B). For sake of comparison, the net benefit is only about 2% of the net benefit found for the New Lanes scenario (2A-2D).
- There is a modest negative benefit (higher auto travel time) from eliminating the random component from the simulated VOT distribution, so that VOT only varied by tour purpose, auto occupancy, and income (1C). The apparent negative benefit comes from the reduction in walk and transit trips and slight increase in auto trips and resulting slight increase in congestion and travel times. This negative benefit is much more pronounced when also removing any income variation from the VOT distribution (1D), leading to much less variation in simulated VOT across the population. The disbenefit relative to the base scenario (1A) is due to a larger shift toward auto trips (see Figure 9) and resulting increase in auto congestion and travel times.
- The infrastructure scenario has a positive benefit of around $20 million in all four comparisons (2A vs 1A, 2B vs 1B, etc.), while the land use scenario has a positive benefit of around $28 million in all four comparisons (3A vs 1A, 3B vs 1B, etc.). This indicates that the generalized cost-based benefit calculation is not very sensitive to the underlying random seed or VOT distribution.
- An annual benefit of only $20 million seems quite low for a hypothetical infrastructure project that could cost billions in reality. This is due mainly to the fact that overall auto times in the model and traffic assignment do not appear to go down very much in response to adding a lane in each direction, and thus the resulting changes in mode choice, destination choice and tour generation are negligible, as seen in the various figures above. As discussed further below, we suspect that the Tampa model may not be reflecting the true benefits of this scenario very accurately.
- An annual benefit of only $28 million also seems quite low for a land use scenario that relocates almost 90,000 households to a more accessible area, Here, the problem is likely not due to the Tampa model in particular, but to the generalized cost-based ROH method that

does not capture such accessibility benefits. The benefits that are captured are due to small decreases in traffic congestion and auto travel times outside the downtown areas resulting from the fact that about 7% of their households have moved into the downtown areas and thus take trips off the roads in most of the region (presumably increasing traffic congestion somewhat in the downtown areas, which will offset the region-wide benefits to some extent).

Figure 19: Generalized Cost-Based Rule of a Half Benefits from the ABM Trips (annual $)



One of the key objectives of the sensitivity tests is to compare different measures of consumer surplus and expected welfare, in the form of generalized cost-based versus various logsum-based benefit measures. In Figure 20, we compare four different benefit measures in terms of the total annualized benefit for each of the 11 run comparisons:

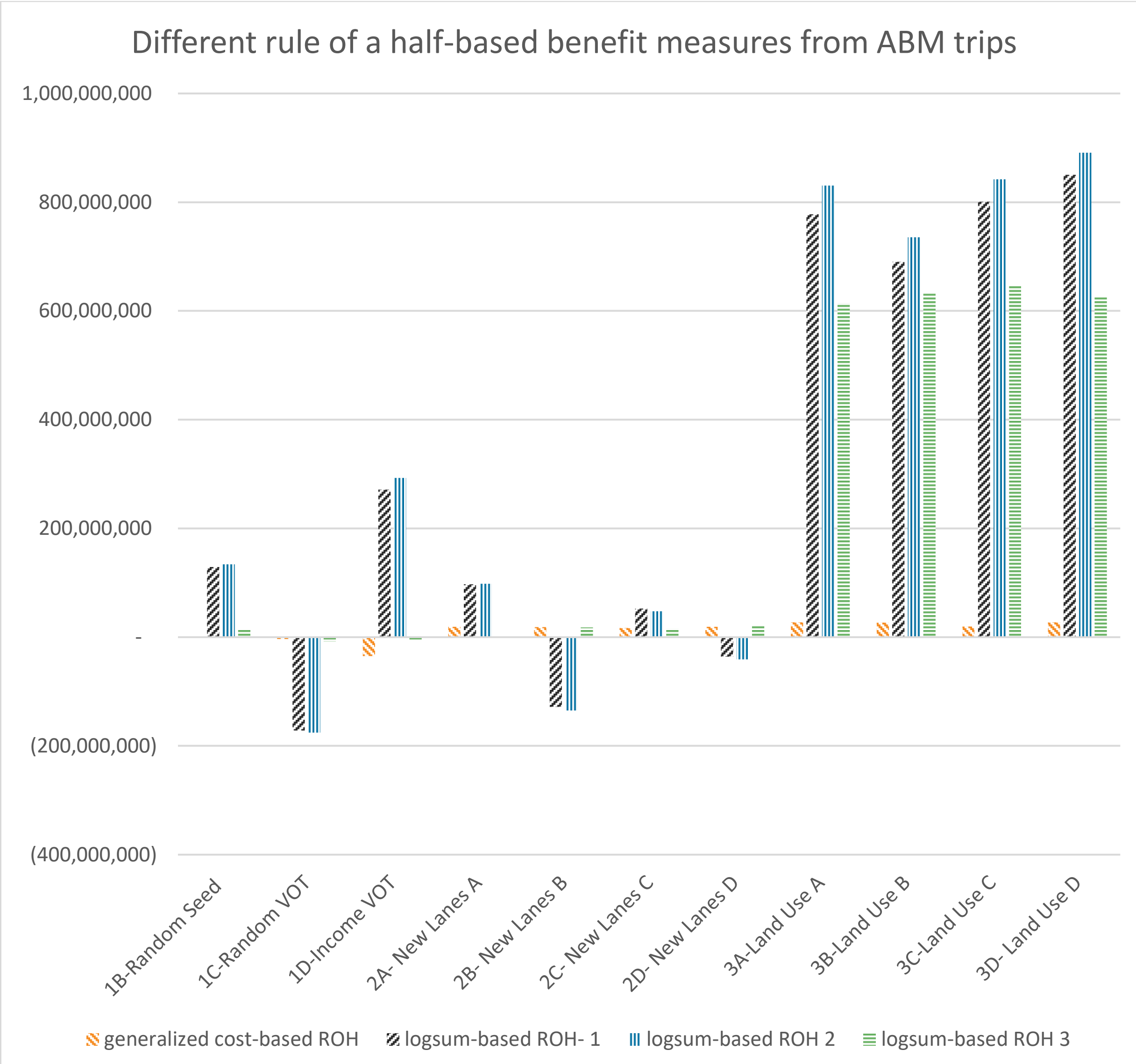
Generalized cost-based ROH- : This is the conventional rule of a half measure, which was already discussed and shown above in Figure 19. It is an output of the BCA4ABM tool.

Logsum-based ROH-2 : This is based on the tour destination choice logsums, using the "rule of a half" formulation introduced in Chapter 5, in which the logsums are normalized by subtracting the average base scenario logsum value after aggregation by tour purpose. The logsum is also divided by a purpose-specific travel time coefficient to convert to equivalent minutes of travel time, and then multiplied by an externally assumed value of time to convert to dollars. This is the same measure as the "ROH-tour dest ls" measure that was tested against the generalized cost-based ROH in the controlled sensitivity analyses reported in Chapter 5. As described in Appendix A, this formulation was programmed into the BCA4ABM tool, and it is one of the standard outputs.

Logsum-based ROH-1 : This is analogous to Logsum-based ROH-2 above, based on the tour destination choice logsums, but this time normalizing the logsum values using average logsums aggregated by <u>both</u> tour mode <u>and</u> tour purpose, rather than just by tour purpose. This measure is currently <u>not</u> an output of the BCA4ABM tool, but was calculated and reported by a separate calculation program in order to assess the level of aggregation bias that may be introduced by averaging the logsums only by tour purpose. (The ideal would be to use fully disaggregate logums, but it is currently not practical to calculate the logsums for every tour under the alternate scenario.)

Logsum-based ROH-3: . This is a measure that uses the person-level destination choice accessibility logsum for the calculations, in place of the tour-specific destination choice logsum that is used for ROH-1 and ROH-2. In contrast to using the tour-level destination choice logsums, it is possible to use a fully disaggregate approach to generate this benefit measure instead of using an aggregate averaging approach to normalize the logsum values. This is possible because these simpler accessibility logsums are calculated and can be written out by DaySim (and CT-RAMP) for every person and tour purpose, regardless of whether or not that person is simulated to make any tours or trips for the purpose. For each trip that is made, this measure uses the difference in the person-level accessibility logsums for the tour purpose calculated by the ABM under the two scenarios. This measure is currently NOT an output of the BCA4ABM tool, but was calculated and reported by a separate calculation program in order to compare against the tour destination choice logsum-based measures.

Figure 20: Comparison of Different Rule of a Half-Based Measures for ABM Trips (annual $)



Some important findings in Figure 20 are:

- In general, the logsum-based measures are much larger than the generalized-cost based measures. In fact, the generalized cost-based ROH measures are small enough in comparison that they are barely visible in Figure 20, because the scale is much larger than when they were previously shown in Figure 19. For the Land Use scenario runs, for example, the logsum-based benefits are all above $600 million when annualized, compared to just under $30 million for the generalized-cost based ROH—a difference of a factor of 20 or more. For the other runs, the differences are not as large, but are still substantial.
- The logsum-based ROH-1 and ROH-2 measures are based on tour destination choice logsums, and these use tour-specific VOT, while the accessibility logsums used for ROH3 use the same VOT for all scenarios, varying only by tour purpose, with no random component or income effect. This is a likely reason why there is more variability in the ROH-1 and ROH-2

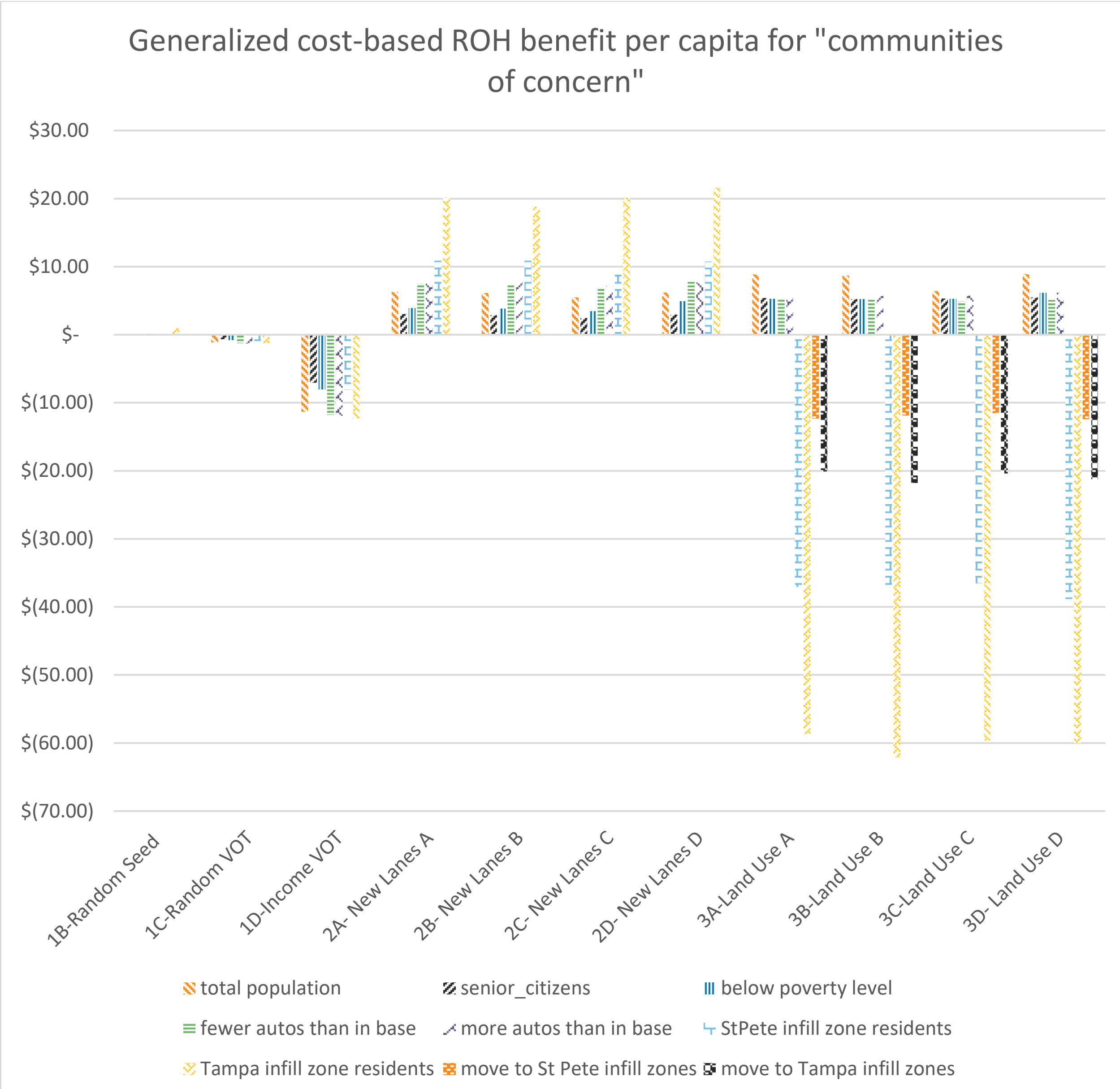
values than the ROH-3 values, particularly for the first 7 runs (1B-2D), where the benefit measures for the ROH-3 measure are much smaller and more in line with the generalized cost-based result. Another reason that the accessibility logsum-based measures show less random variability than the tour-level logsum-based measures is that the accessibility logsums are always calculated across all destination zones in the region, while the tour-based destination choice models use random sampling of (typically 50 to 100) alternative destination locations in order to reduce model run time.

- In all cases, the ROH-1 measure (destination choice logsum averaged by tour mode and purpose) is similar in direction and magnitude to the ROH-2 measure (destination choice logsum averaged only by tour purpose), but the ROH-1 measure is consistently about 6% smaller in magnitude than the ROH-2 measure. This result suggests that there is some aggregation bias that is reduced in the ROH-1 measure, but the magnitude of the bias is not very large, particularly when compared to the differences between these two measures and the generalized cost-based and accessibility logsum-based measures.
- The results for the tour destination choice logsum based ROH-1 and ROH-2 show inconsistent results for the four infrastructure scenario runs (2A to 2B), with positive benefits in two cases and negative benefits in two cases, even though the generalized-cost based measure showed consistent (but very low) results across the four runs. This finding is unexpected, particularly since the generalized cost-based and tour destination choice logsum-based measures gave such consistent results in the more controlled tests reported in Chapter 5. This finding raises some suspicion about the stability of how the New Lanes scenario is being simulated in the Tampa ABM. One possibility is that the traffic assignment is not being run to a sufficient level of convergence and/or that the DaySim model and the Cube traffic assignment are not being given enough global iterations to arrive at a stable solution. If the assignment model and the integrated model system are not reaching a converged, stable final outcome, then this can introduce randomness and unexpected variation in the results. (In a recent review for FHWA, Caliper Corporation (2015) reported that very few MPO models are run to an acceptable level of convergence, either within the traffic assignment stage or in the iteration between traffic assignment and the demand model.) If there were an issue with model convergence, it would likely affect all of the benefit measures in a similar way, but it could be a source of unexpected variation across the different model runs. This possibility could be tested empirically in further research by performing some of the same runs with the Tampa model to a tighter level of convergence.
- A final point of note is that all three logsum measures give fairly consistent results for all four runs for the Land Use scenario. We noted above that the generalized cost-based measure is likely to give a gross underestimate of the welfare benefits of such a major land use shift, so the logsum-based measures appear both internally consistent and more reasonable. (When divided by the size of the population, the benefit of about $750 million per year is equal to about $270 dollars per capita per year, or less than one dollar per capita per day, which does not seem too extreme for a scenario in which 6% of the population relocate to two areas of the region with the highest accessibility to jobs and businesses and transit service.)

The BCA4ABM tool also outputs separate benefit calculations for specific "communities of concern" (COC), which are subpopulations defined by the user as a function of household and person characteristics. This feature allows the tool to be used for equity/environmental justice analysis. COC's can be based on person characteristics such as age, gender and employment status, and on household characteristics such as income, auto ownership and residence location. They can also be based on a comparison of household characteristics in the base and build scenarios, to isolate those who change between scenarios. (It is simple in the BCA4ABM tool to modify the definition of the COC's, as shown in Appendix A.) In Figure 21 we show the generalized cost-based annual benefit per capita for the following groups, which are not mutually exclusive (meaning that the COC membership is defined independently for each one, and may be overlapping):

- **Senior citizens**: All persons age 65 or older
- **Below poverty level**: Persons in households with income below the official poverty level, which is a function of household size
- **Fewer autos than in base**: Persons in households which the model predicts will "give up" one or more autos in the build scenario, as compared to the base scenario.
- **More autos than in base**: Persons in households which the model predicts will "add" one or more autos in the build scenario, as compared to the base scenario.
- **St. Pete infill zone residents**: Persons in households living in the 100 zones designated as infill zones in downtown St. Petersburg in the land use scenario.
- **Tampa infill zone residents**: Persons in households living in the 100 zones designated as infill zones in downtown Tampa in the land use scenario.
- **Move to St. Pete infill zones**: Persons in households living outside of the infill zones in the base scenario, and living in one of the downtown St. Petersburg infill zones in the "build" scenario
- **Move to Tampa infill zones**: Persons in households living outside of the infill zones in the base scenario, and living in one of the downtown Tampa infill zones in the "build" scenario

Figure 21: Generalized Cost-Based ROH Annual Benefit Per capita for "Communities of Concern"



Findings from Figure 21 include:

- The per capita benefits for "senior citizens" and "below poverty level" are consistently about 30% below the average per capita benefits for the total population. This is because these population groups tend to make fewer trips than the average resident—particularly for work trips, which have the highest VOT for converting travel time benefits to monetary values.
- For the infrastructure scenario (2A-2D), those who live in the Tampa downtown area have per capita benefits about twice as high as the average, and those who live in St. Petersburg downtown area have per capita benefits about 50% higher than the average. This is presumably because the new lanes on I-275 would go through (or near) to both of these areas, and so these residents would realize more of the travel time benefit than the average

person in the region. Those households that would change auto ownership level in the "new lanes" scenario also have somewhat higher benefits than average. This makes sense because the greater effect that the build scenario has on a particular household in terms of travel times, the greater the effect it will have on their auto ownership decisions.

- For the land use scenario (3A-3D), the generalized cost-based measure has the opposite effect from what one would expect for the COC's related to residence location. Those living in the Tampa and St. Petersburg downtown infill areas have large negative (dis)benefits, even though the average per capita benefits in the region are positive. This is because there are now twice as many residents in the infill areas, which leads to more traffic congestion. This negative benefit is also true for those who have moved into the infill area between the two scenarios. (Although those new residents make more trips by walk, bike and transit, they still make most of their trips by auto, and add to downtown congestion.) The negative benefit measure for those who actually receive the most actual benefit from the land use scenario highlights the weakness of the traditional generalized cost-based ROH measure. It keeps the trip modes and destinations constant in each scenario when evaluating the benefits, and asks "how would the generalized cost have changed if using the same mode to the same destination in the alternative scenario?". Most of the actual benefit for the land use scenario is from the people who move into those areas being able to reach attractive destinations with shorter trips, and sometimes by different modes, and those benefits are not captured with the traditional method—only the negative benefits of increased auto travel times in the infill areas. ***This is a key finding from this analysis***.
- The consistency of the COC benefits across the four infrastructure scenario tests (2A-2D) and the four land use scenario runs (3A-3C) indicates that the traditional generalized cost-based ROH measure is not very sensitive to random and VOT-based variations in the base scenario (A, B, C and D runs), even when calculated across smaller subpopulations.

Figure 22 shows a similar breakdown by community of concern as used in Figure 21, but this time using the tour destination choice logsum-based ROH measure, with aggregation of average logsums by tour purpose, which is output by the BCA4ABM tool. For all of the comparisons from 1B to 2D, the logsum-based benefits for those in households that add or subtract autos between runs are much larger than for any other groups. This is because of the large increase in accessibility gained by adding a car or lost by subtracting a car. The models in the ABM capture those changes in accessibility, but do not directly measure the changes in auto ownership costs that one has to pay to receive the benefits of adding an auto (or vice versa). In the BCA4ABM tool, there is a separate calculation of household auto ownership cost (dis) benefits (presented below in Figure 24) which offsets the logsum-based benefit for the most part. But if one uses generalized cost-based ROH measures instead, the BCA4ABM tool will still include the cost changes of adding or subtracting autos without including the full accessibility (dis) benefit of adding or subtracting an auto. This potential inconsistency of fully including auto ownership costs while potentially underrepresenting the accessibility benefits of auto ownership using the generalized cost-based ROH measure is ***another important finding*** of this analysis.

In Figure 22, the accessibility benefits of adding an auto are still very high in the land use scenarios (3A-3D), but the disbenefits of subtracting an auto are not as great as in the other scenarios. This is because many of those households that are simulated to give up an auto in the infill scenarios are households that move into the downtown infill zones, and those zones have the highest accessibility by non-auto modes. Those households that move into the infill zones have the highest benefits overall in the land use scenario runs (3A-3D). In Figure 21, those same households were shown to have slightly negative benefits using the generalized cost-based measure, due to somewhat greater auto congestion. The logsum-based measure captures the positive accessibility benefits of moving into the downtown (for which many of those households would presumably have to pay increased housing costs, so many of the true benefits would be captured in the real estate market).

Figure 22: Destination Logsum-Based ROH Annual Benefit per capita for "Communities of Concern"

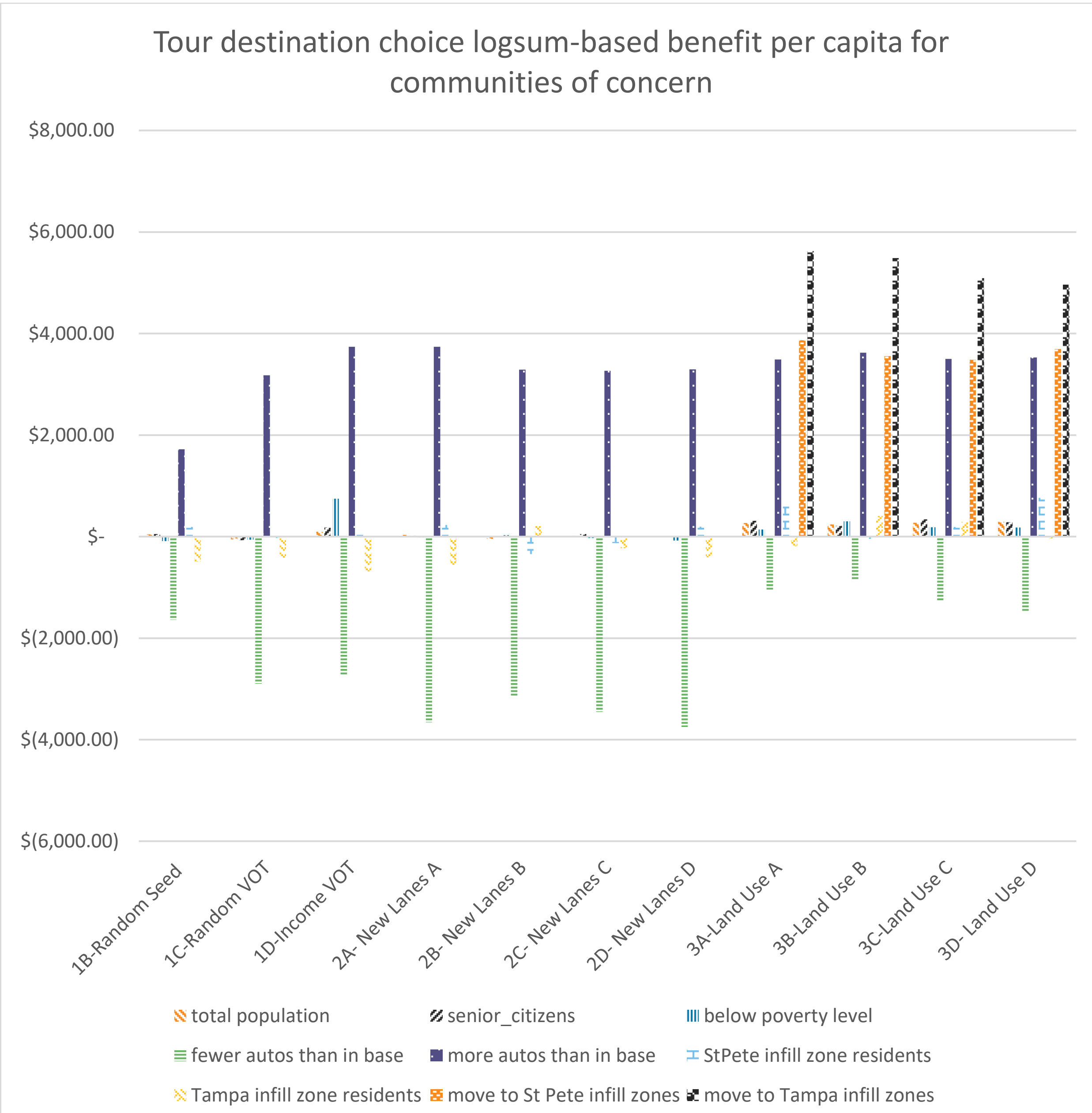
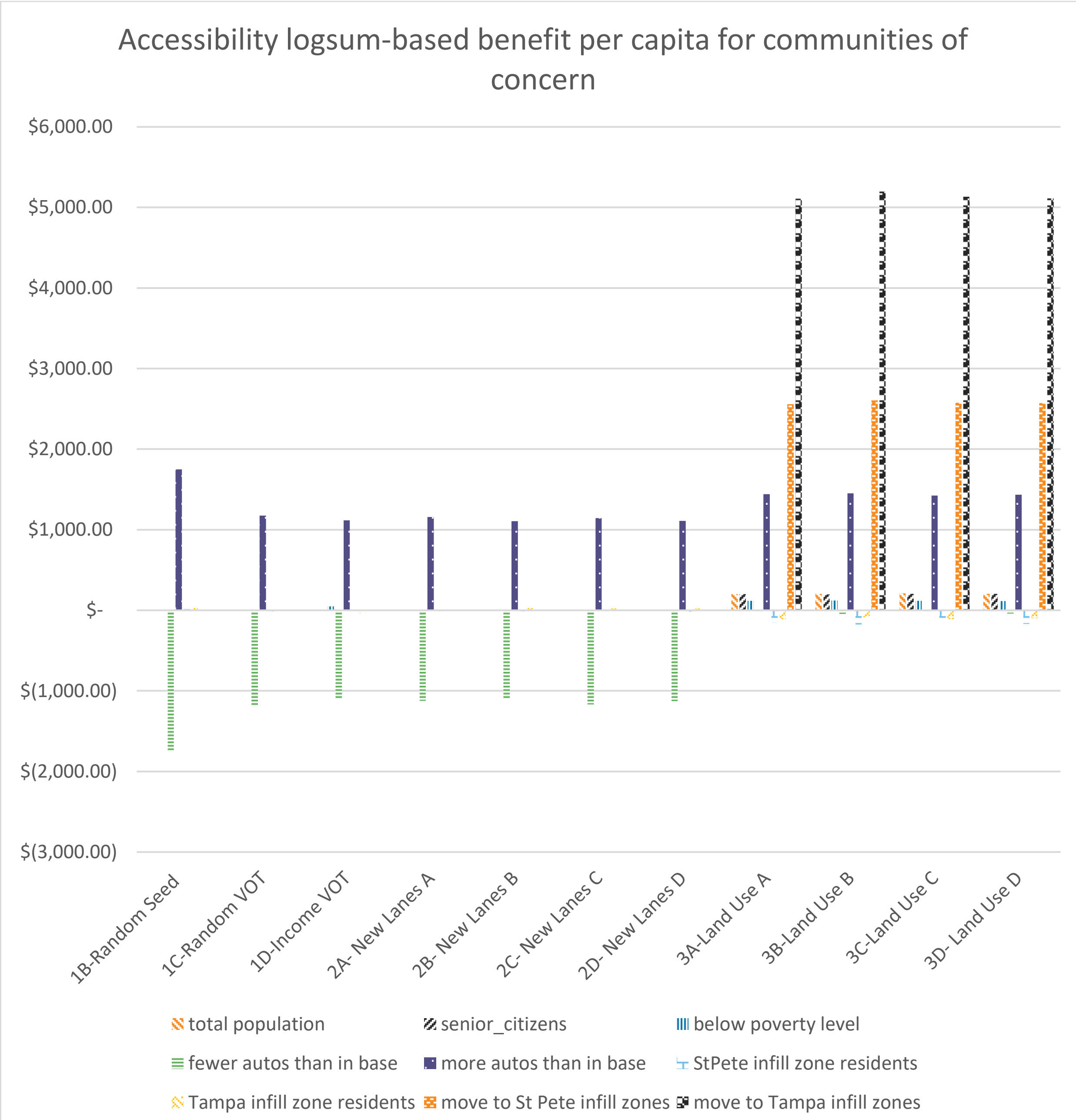


Figure 23 is analogous to Figure 21 and Figure 22, but shows the per capita (dis)benefits calculated using the accessibility logsums from the simpler mode/destination choice models used in the Tampa ABM. The results look much the same as when using the tour destination logsum-based measure (Figure 22), but with the magnitude of the results somewhat lover. For example, the benefit of adding an auto using the tour destination logsum-based measure is about $3,000 per capita in all scenarios, but only about $1,000 per capita using the accessibility logsum-based measure (. The BCA4ABM tool assumes an annual auto ownership cost of $2,000 per vehicle, which would be somewhat less than $1,000 per capita if spread across the people in the household that own the vehicle. By this comparison, the benefits of adding an auto in Figure 23 seem to be in the right range, while those in Figure 22 seem fairly high (and those in Figure 21 from the generalized cost-based measure too low).

The accessibility logsum based measures seem to be a good medium point between the traditional generalized cost-based measures and the tour destination choice logsum-based measures. Compared to the tour destination choice logsum-measures, they seem to be more stable and more comparable to the generalized cost-based measures, but to also capture the types of major changes in accessibility that are captured by the tour-level logsums. The accessibility logsum-based measures also have an advantage that they are calculated for every household and person in the ABM regardless of whether or not they make any simulated trips, and thus they can be used easily in ROH calculations at the fully disaggregate level, avoiding the aggregation bias that is introduced by averaging when using the tour destination choice logsums.

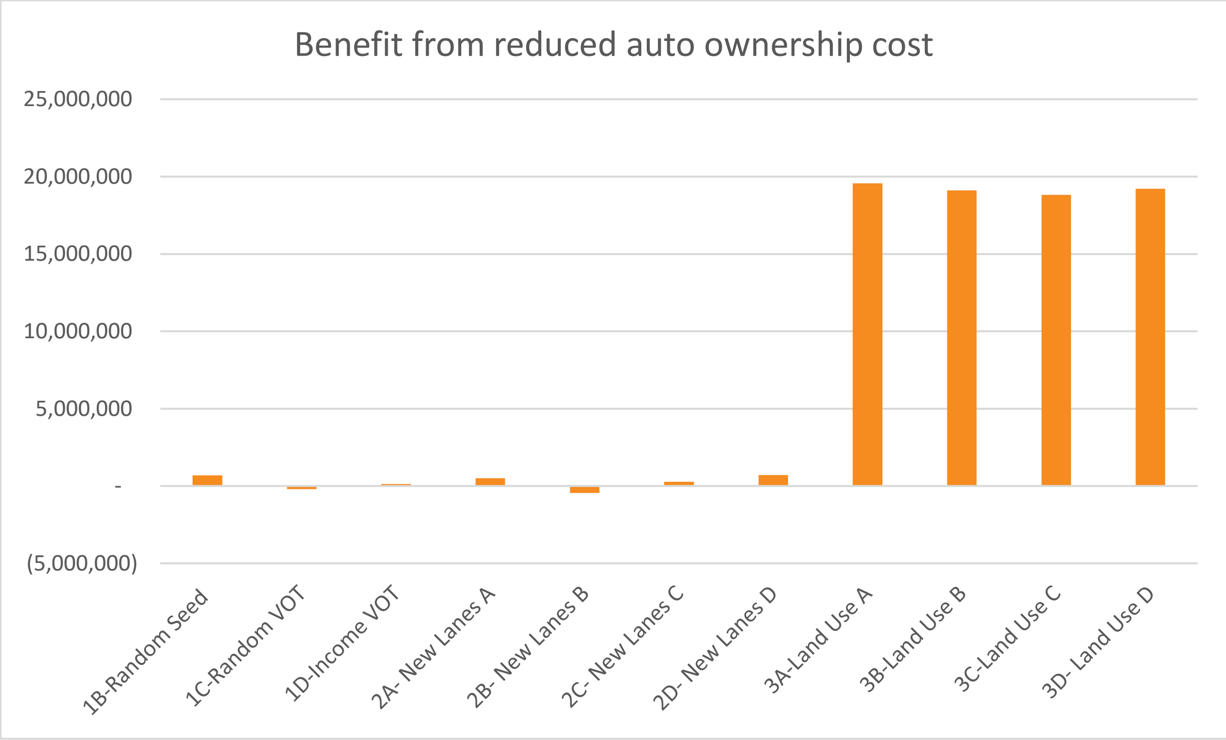
Figure 23: Accessibility Logsum-Based ROH Annual Benefit per capita for "Communities of Concern"



Auto Ownership Costs

As discussed in the preceding paragraphs, the BCA4ABM tool (and the SANDAG tool it is originally based on) include a separate calculation of (dis)benefits that arise from changes in auto ownership levels. Figure 24 shows the total benefit output by the BCA4ABM tool for the 11 comparisons. Only the land use scenario (3A-3D) shows a substantial change, with benefits of about $20 million. With the assumed auto ownership cost of $2,000 per auto, this result translates to a decrease of auto ownership by about 10,000 vehicles in the region. Given that about 80,000 households are simulated to move into the infill areas in the land use scenario, this reduction in auto ownership seems reasonable. As discussed above, the logsum-based measures of trip-level benefits tend to capture the increase in accessibility that buying an auto provides, while the more traditional generalized cost-based measures do not.

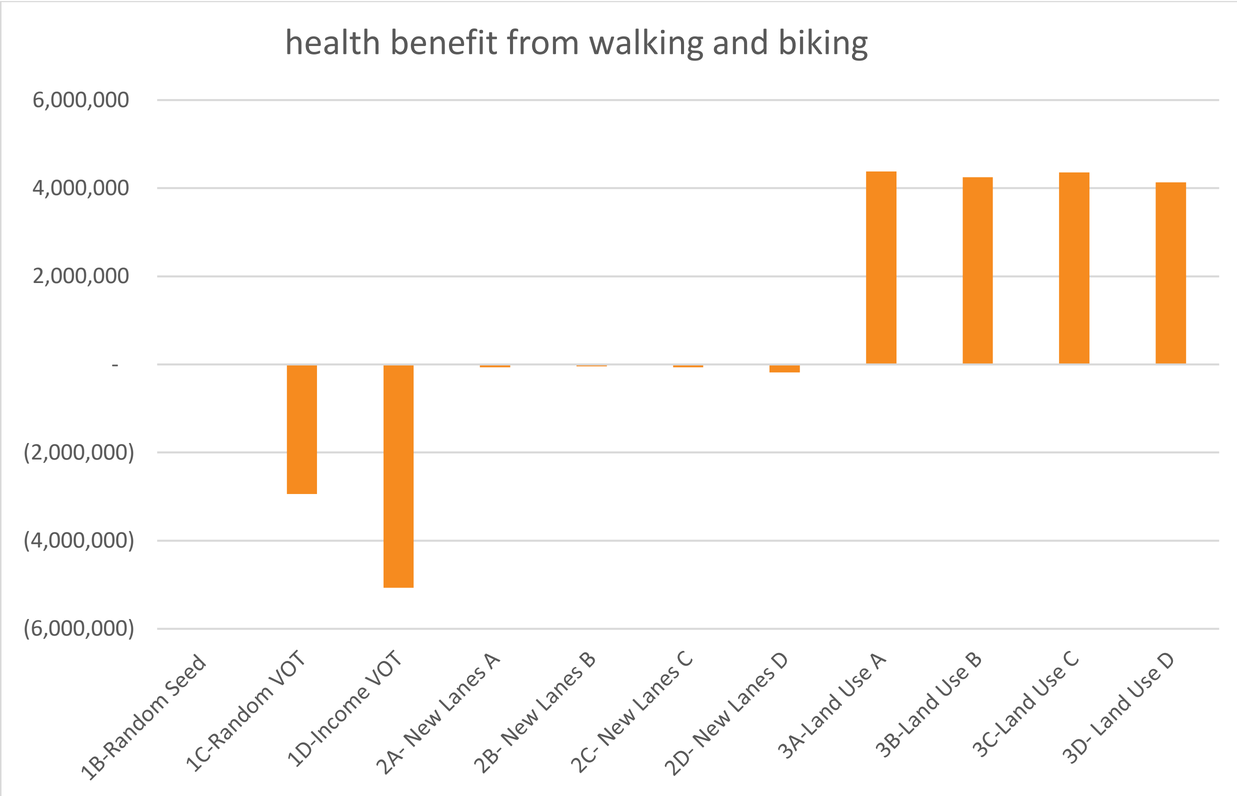
Figure 24: Total Benefits from Reduced Auto Ownership Costs



Health Benefits Due to Increased Walking and Biking

The BCA4ABM tool applies the equations from the World Health Organization HEAT methodology, described in Chapter 4, to calculate benefits related to a change in the risk of mortality due to a change in the time spent walking and biking each day. Because the relationship is non-linear, the time spent walking and biking is calculated from the ABM trip data for each person in the population, the health benefits are summed across all persons in the population, and then the difference in benefits between the build and base scenarios is calculated. The resulting health benefits from the 11 Tampa model comparisons are shown in Figure 25. As described above, the mode shares for walking and biking are sensitive to the VOT distribution used in the models, so there are fewer walk and bike trips in Runs 1C and 1D. The infrastructure scenario (runs 2A-2D) causes only a slight drop in walk and bike trips. The land use scenario (runs 3A and 3D) shows the highest benefit due to increases in walking and biking for the people moving into the infill areas. The total size of the benefit, at about $4 million per year, is smaller in magnitude than most of the other benefits calculated in the BCA tool, although it should be kept in mind that the Tampa region currently has fairly low walk and bike mode shares compared to many other US regions.

Figure 25: Total Health-Related Benefits from Increased Walking and Biking



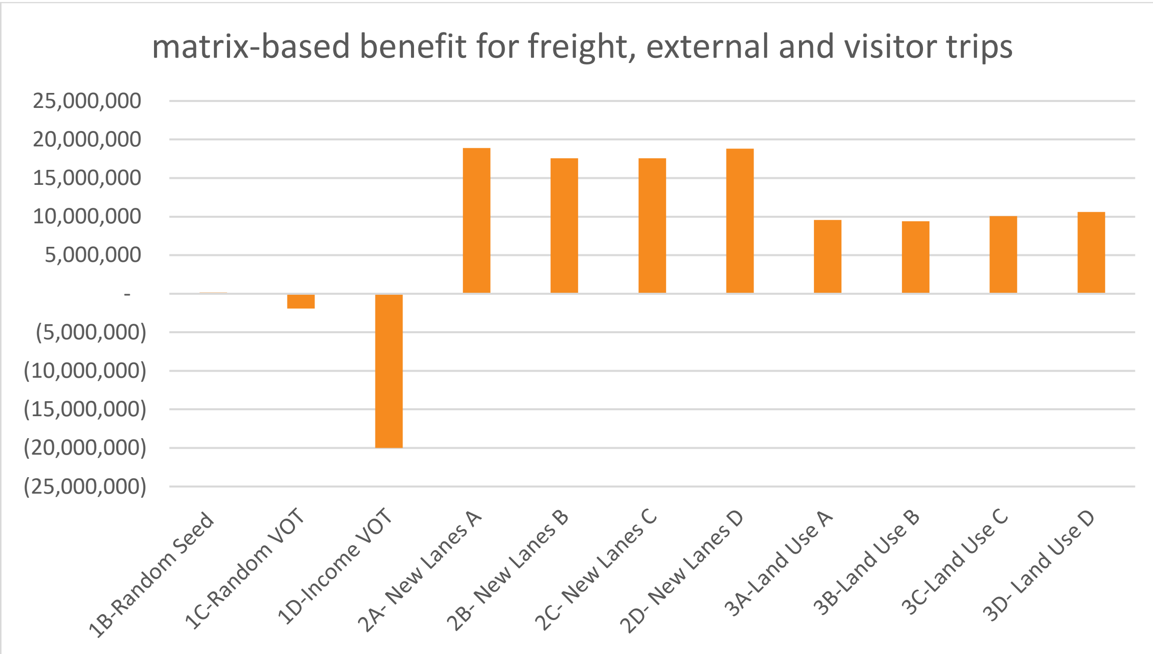
Aggregate Matrix Based Benefits for Other Travel Markets

Like all ABM systems, the Tampa Bay model has a number of market segments that are forecast using aggregate trip-based models rather than the DaySim ABM. These include:

- Trips made by commercial vehicles in three size classes (freight trips)
- Through trips on the highway network (X-X trips)
- Resident trips to destinations outside the region (I-X trips)
- Non-resident trips from outside the region to destinations within the region (X-I trips)
- Non-residents trips made completely within the region (visitor trips)
- Trips to and from the airport (special generator trips)

For these trips, the BCA4ABM tool uses the matrix-based version of the rule of a half to calculate benefits. The matrices with the number of trips for the base and build scenarios (Q1 and Q2) and the travel times and costs in the base and build scenarios (P1 and P2) are specified in the "aggregate data manifest", and the ROH equations are in the aggregate data expression file (as shown in Table 34 in Appendix A). For the Tampa runs, the benefits are due to changes in highway travel times, as there were no changes in toll costs in any of the scenarios run. Figure 26 shows an annual benefit of about $18 million for the infrastructure scenario (2A-2D), due to reduced travel times on the widened section of I-275, and an annual benefit of about $10 million for the land use scenario (3A-3D), due to reduced congestion outside of the downtown infill areas. Compared to resident trips from the ABM, a higher proportion of freight and external trips use the interstates and other main highways, so changes in the travel times on those facilities account for most of the benefits.

Figure 26: Matrix-Based ROH Benefits for Freight, External and Visitor Trips



Note that the BCA4ABM tool could be used with an aggregate zone-based “four step” model output or with aggregated ABM outputs, deriving generalized cost-based ROH benefits for all residents’ travel through the aggregate matrix-based calculations. However, this would lose the important advantages of being able to use logsum-based benefit measures and/or separate “community of concern” calculations that are possible with the disaggregate trip-level output from the ABM.

Link-Based Benefits—Accidents, Reliability, and Operating Cost

Additional benefit types are calculated in the BCA4ABM tool using the road link-level output files. The formulation currently used for accidents uses the daily (full-day) link-level outputs, while the formulations for travel time reliability and operating cost benefits use the time-of-day period specific link-level outputs, as they are sensitive to congestion and speeds during specific time periods.

Figure 27 shows the calculated change in accident costs from the 11 Tampa model comparisons. The daily link expression file (Table 35 in Appendix A) specifies the equations for costs due to fatalities, injuries and property damage, borrowing the simple mileage-based equations used in the SANDAG BCA tool. The runs with more compressed VOT (1C and 1D) and with adding lanes on the I-275 (2A-2D) have somewhat more auto trips compared to the respective base scenario, and thus a disbenefit due to an increase in accident-related costs. The land use scenario (3A-3D) generates fewer total auto trips and VMT, so shows a benefit due to decreased accident-related costs.

The magnitude of the accident-related benefits—over $100 million annualized—seems quite high compared to some of the other benefit measures. The results should be checked against those produced by the original SANDAG tool, to ensure that the equations were specified correctly. It is also recommended to use a more refined benefits formulation in which accident rates are a function of congestion levels and facility types as well as VMT.

Figure 27: Link-Based Benefits for Changes in Accidents

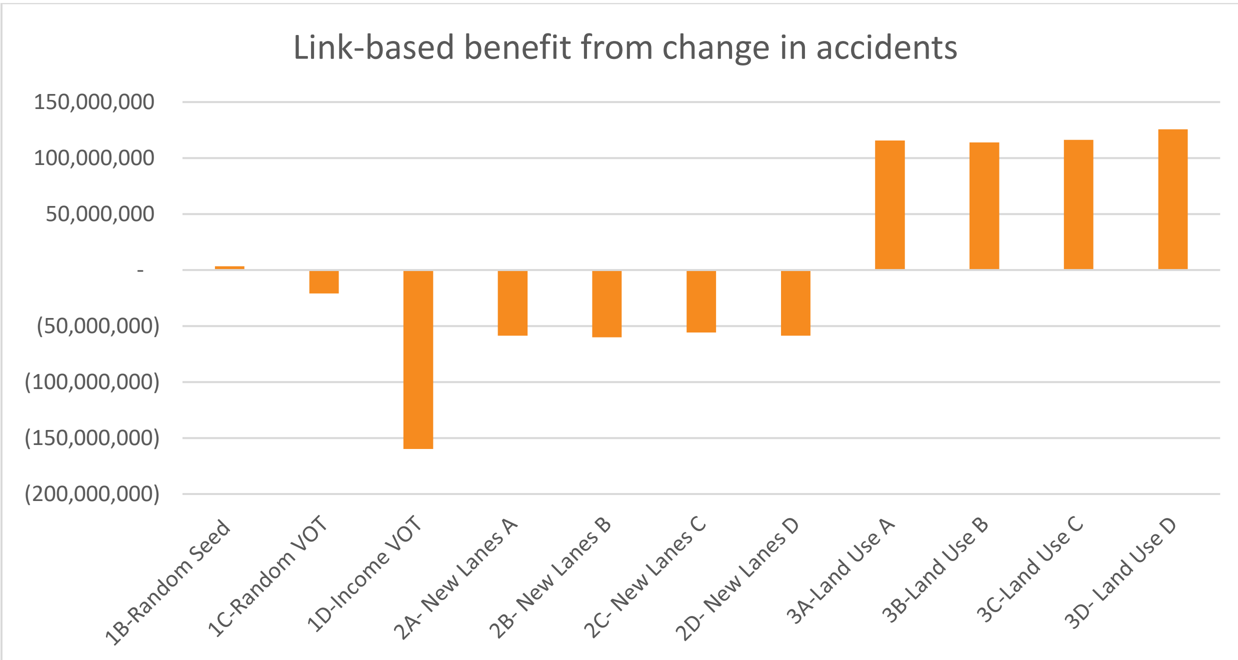


Figure 28 and Figure 29 show the benefits due to changes in highway travel time reliability and operating costs, respectively, with the equations specified in the "time period-specific link expression file" (Table 36 in Appendix A). Here, the BCA4ABM tool calculates benefits for autos and trucks separately. Figures 28 and 29 show similar patterns as Figure 27 —the "new lanes" scenario (2A-2D) has slight negative benefits due to an increase in auto and truck trips and miles, while the land use scenario (3A-3D) has more substantial positive benefits due to a decrease in auto trips and congestion outside of the infill areas.

Figure 28: Link-Based Benefits for Changes in Highway Travel Time Reliability

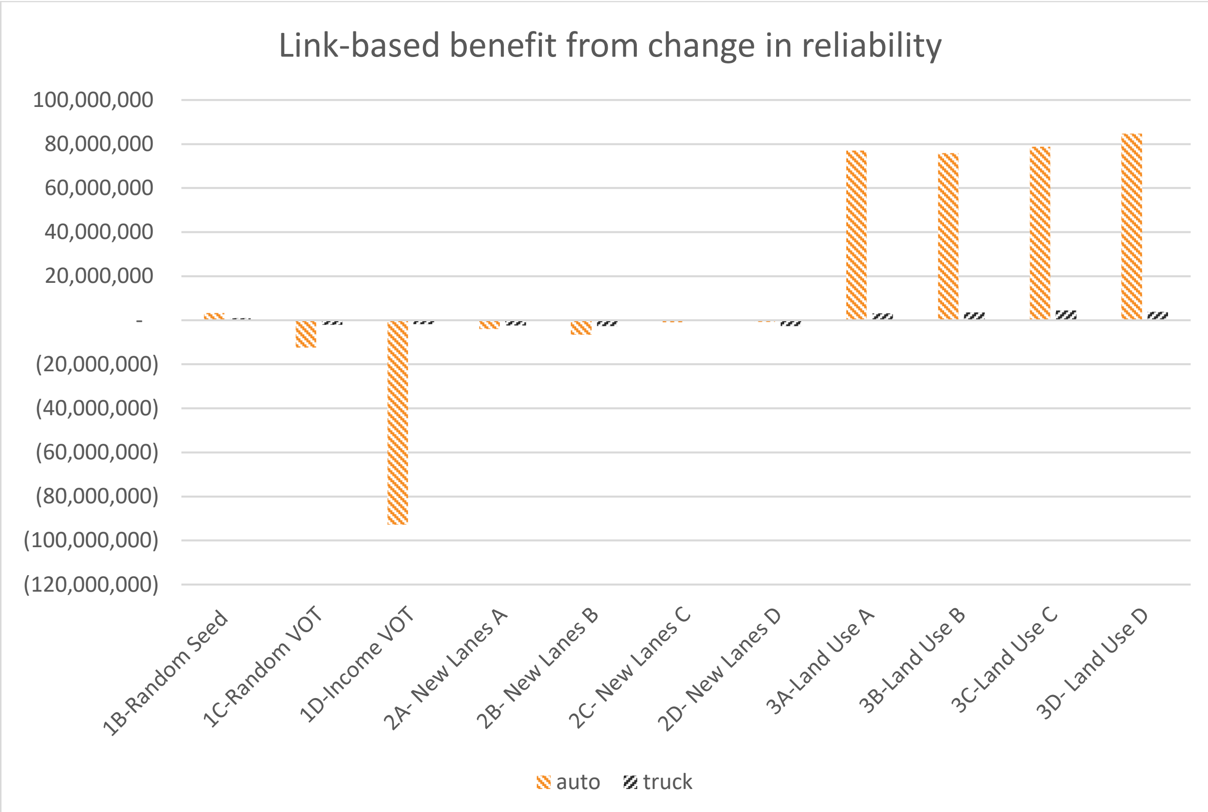
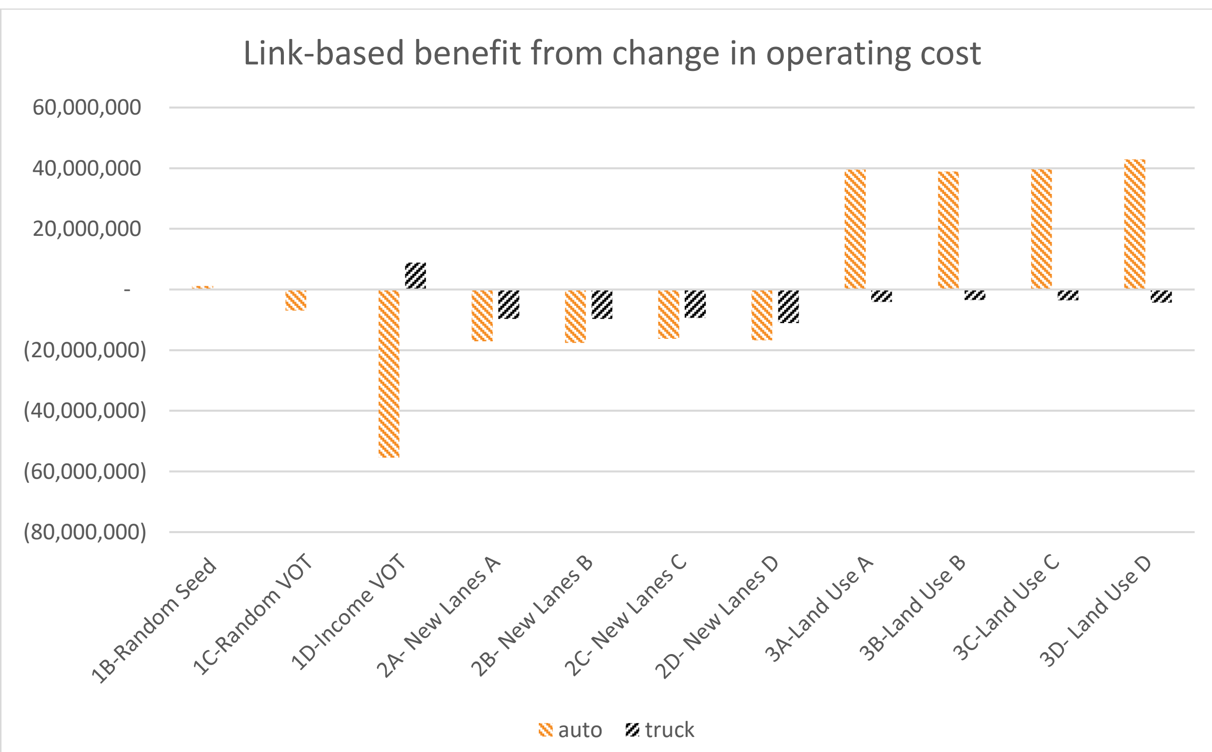


Figure 29: Link-Based Benefits for Changes in Vehicle Operating Costs



It is counter-intuitive that adding lanes to a congested highway would yield slightly negative travel time reliability benefits for both autos and trucks (Figure 28). This result, along with other counter-intuitive results for the infrastructure scenario mentioned previously in this chapter, indicate that the model feedback between the highway assignment model and the ABM may not have converged completely, or that other issues have distorted the model results.

It is also the case that if reliability is an important determinant of demand, then the generalized cost components in the trip-based rule of a half calculations would ideally include a reliability component of generalized cost as well. This is tested in the next section using an enhanced travel demand model formulation for SANDAG.

It is also somewhat counter-intuitive that truck operating costs increase for trucks for the land use scenario in Figure 29, while they decrease for autos. The likely explanation is that having households move from the outer areas to the downtown infill areas frees up auto capacity in the outer areas, which may cause some trucks to choose somewhat longer routes that avoid the downtown areas to save travel time.

Also, as was the case for the link-based accident benefits, the magnitude of the reliability and operating cost benefits in Figure 27 and Figure 28 seem quite high in comparison to other types of benefits, indicating that there may be a scaling issue in the link-based benefit calculations that warrants further investigation.

Note that auto operating costs have already been incorporated in the various ROH measures for the ABM trips, and also in the aggregate matrix-based ROH measures for the freight, external and visitor trips. Thus, including link-based benefits of operating cost changes as well would lead to double-counting. The user has the option of using the benefits from the ABM trips and aggregate matrices, or from the link-based calculations. Using the measures from the ABM trips has the advantage that the benefits can be segmented by "community of concern". Also, if one is using logsum-based benefit measures from the ABM, there is straightforward way to remove the effect of operating cost changes from the measure. For truck trips, there is a simpler decision to use either the aggregate matrix-based calculation or the link-based calculation.

It may also be possible to associate travel time reliability directly with the ABM trips, as demonstrated in the following section. In that case, there would also be double counting if also using the link-based measure of reliability benefit for resident auto trips, so the issue would be analogous to the one for operating cost. In that case, the best solution may be to use the link-based reliability measure only for trucks.

6.3 An Additional Sensitivity Test for San Diego

We wanted to test that the BCA4ABM tool would also run satisfactorily with the outputs from the SANDAG ABM. For this test, we took advantage of two scenarios that had already been run for the recent SHRP 2 C04 implementation project:

- A "base" run with all the standard base year inputs.
- A "build run" which doubled the toll price on the I-15 and SR-125 tolled facilities.

Thus, this comparison tests a pricing policy, which was not included in the Tampa sensitivity tests.

More importantly, in the C04 implementation project, a method was developed to predict travel time reliability (the standard deviation of travel time on a specific link during a specific period of the day), to use this measure in the traffic assignment process, and to produce zone-to-zone skim matrices of this reliability measure which are used in the travel demand models. That means that the level of travel time variability can be written to each trip record, and used directly in the generalized cost-based rule of half calculations (and will also influence the logsum-based benefit measures. One of the research objectives of this project is to look at the methodological benefits of being able to take benefits which are typically link-based, such as reliability, and distribute them to individual trips. This allows us to compare the link-based benefit measure to the trip-based benefit measure for reliability.

Table 14 and Table 15 show the results reported by the BCA4ABM tool comparing the SANDAG base scenario to the "build" scenario with tolls doubled on the I-15 and SR-125—the only major tolled facilities in the region. The total generalized cost ROH method shows an annualized disbenefit of roughly $4.5 million per year, which is only $1.42 on average for the roughly 3.2 million residents of the region. The value is fairly low because only a small percentage of region residents use the tolled lanes. Almost 90% of the disbenefit is due to increased toll costs. However, not all toll road users in the base case are predicted to pay the higher toll level. Some choose instead to use different routes on the adjacent facilities, where they add to the congestion levels on those facilities. This accounts for the other major source of disbenefits—an increase in auto in-vehicle times which causes a disbenefit of roughly $0.5 million, about 12% of the total disbenefit.

The tour destination choice logsum-based ROH measure was also calculated for the SANDAG tours, using the same aggregation method that was used for the Tampa runs. The total logsum-based ROH benefit is very similar to the generalized cost-based ROH measure, with a disbenefit of $4.2 million per year. The major change in the build scenario is a change in the travel cost on existing facilities, so it not surprising that the logsum-based and generalized cost-based measures give similar results, as the generalized cost-based measure is able to reflect changes in toll costs, and there is very little mode switching or destination switching in this scenario. A slight decline in auto ownership caused by the increase tolls yields an auto ownership cost benefit of $274,000, which is only about 140 fewer vehicles at an annual cost of 2,000 per vehicle. There is also a very slight shift toward walk and bike modes, yielding a tiny health benefit of only about 1 cent per capita.

The benefit measures calculated from the network link-level outputs are also shown in Table 14. There is a reduction in accident-related costs of about $15 million on the toll links, which is offset somewhat by an increase in accident-related costs of about $3.2 million on the other (non-tolled links). The ability to report the link-related benefits separately for the tolled and non-tolled links is another example of the flexibility in configuring the BCA4ABM tool. The toll facility prices are already set in the base case so that there is very little congestion on those links, so raising the tolls levels provides very little benefit on the toll links in terms of increasing reliability and reducing delay costs. However, the shift of autos to the adjacent non-tolled links causes additional delays for both trucks and autos, with disbenefits of around $2.2 million for autos and $0.8 million for trucks. The shift toward longer and slower auto routes on adjacent facilities also causes an increase in operating costs for auto, while trucks, which generally have high values of time, tend to stay on the toll facilities and gain a slight benefit in operating cost. Overall, the benefits calculated from the link-level outputs are in the expected direction, but the magnitudes are quite high when compared to the size of the (dis)benefits calculated from the ABM trip lists. This discrepancy in magnitudes was also noted in the Tampa model results described earlier, and is cause for further investigation and testing.

A new output for the SANDAG runs is a skim of the standard deviation of auto time ("auto ivt std dev"), which is skimmed from the network and used in the route choice and mode choice utilities in the assignment and the ABM, and thus attached to individual trips in the ABM output. This run demonstrates that it is possible to distribute reliability benefits from the link level to individual trips, where they could be further analyzed by communities of concern, etc. In this case, however, the monetized reliability benefit is positive and quite small (only about 2 cents per capita), and is somewhat similar to the delay benefit on the tolled links in the network link-based measures. The link-based measures also show a much larger disbenefit due to increased congestion on the non-tolled links, and this negative benefit does not appear to be captured by the trip-level standard deviation benefits. This is the first time that this new reliability skimming method has been tested and evaluated for SANDAG (as part of the SHRP 2 C04 implementation project), and it appears that further testing and comparisons under a wider range of scenario assumptions would be informative.

Table 14: Results for SANDAG BCA4ABM Run for Doubling Tolls on I-15 and SR-125

Benefits from ABM trip lists	Total	Per Capita
monetized auto ivt	$ (552,710)	$ (0.18)
monetized auto ivt std deviation	$ 60,683	$ 0.02
monetized transit ivt	$ (18,005)	$ (0.01)
monetized transit wait time	$ (7,173)	$ (0.00)
monetized transit walk time	$ (29,778)	$ (0.01)
monetized walk time	$ (72,232)	$ (0.02)
monetized bike time	$ 20,208	$ 0.01
fare cost	$ 1,095	$ 0.00
fuel cost	$ 14,680	$ 0.00
park cost	$ 0	$ 0.00
toll cost	$ (3,834,861)	$ (1.22)
total generalized cost ROH benefit	$ (4,478,777)	$ (1.42)
destination logsum ROH benefit	$ (4,225,784)	$ (1.34)
auto ownership cost benefit	$ 274,000	$ 0.09
health benefits due to walking and biking	$ 38,994	$ 0.01

Table 15: Results for SANDAG BCA4ABM Run for Doubling Tolls on I-15 and SR-125

Benefits from network link files	Total	Per Capita
crash cost- fatalities- toll links	$ 2,466,047	$ 0.78
crash cost- injuries- toll links	$ 6,165,116	$ 1.96
crash cost- property damage- toll links	$ 6,165,116	$ 1.96
total crash cost- toll links	$14,796,279	$ 4.71
crash cost- fatalities- non-toll links	$ (536,904)	$ (0.17)
crash cost- injuries- non-toll links	$ (1,342,259)	$ (0.43)
crash cost- property damage- non-toll links	$ (1,342,259)	$ (0.43)
total crash cost- non-toll links	$ (3,221,421)	$ (1.02)
auto delay cost - toll links	$ 24,669	$ 0.01
truck delay - toll links	$ 0	$ 0.00
auto delay cost - non-toll links	$ (2,256,232)	$ (0.72)
truck delay - non-toll links	$ (786,204)	$ (0.25)
auto operating cost	$ 3,871,995	$ 1.23
truck operating cost	$ (54,836)	$ (0.02)

7.0 Summary and Recommendations

7.1 Overview of Objectives and Progress

This project has two overarching objectives:

- Devise benefit-cost analysis (BCA) methods specifically for use with activity-based models (ABM), testing different ways to take advantage of the highly disaggregate (person-level) simulation and outputs of the ABM.
- Design, create and test a software tool that implements the ABM-specific BCA methods, in a way that is configurable for use by different agencies that use different ABM and network software.

The first objective was met in a number several different ways. Agency requirements and desires for an ABM-based BCA tool were discussed with staff at San Diego Association of Governments (SANDAG) and the Florida DOT Tampa Bay office (District 7). It was found that the overall scope of the pre-existing SANDAG BCA tool was sufficient (see Chapter 2), but that there was an interest in being able to obtain more inclusive, accurate, and/or informative benefit measures from the ABM outputs, particularly in terms of:

- Better capturing expected consumer welfare benefits beyond those that can be measured solely as a function of travel time and cost changes, including being able to visit a broader range of destinations and participate in a wider variety of activities;
- Better capturing health benefits related to walking and cycling;
- Better capturing travel time reliability benefits;
- Being able to obtain segment-specific benefit measures for particular "communities of concern", and to specify those segments flexibly in terms of household and person characteristics

A key focus of the research was to compare traditional generalized cost-based "rule of a half" (ROH) methods for calculating consumer surplus to more advanced methods that use the "logsums" from the ABM choice models to obtain more inclusive measures of expected welfare. The theoretical and practical aspects of these two alternative approaches were investigated, as well as the possibilities for implementing these approaches using the Tampa Bay and San Diego model systems (Chapter 3). Concurrently, the literature on evaluating health benefits of walking and cycling was reviewed (Chapter 4), and the HEAT method devised by the World Health Organization was selected for implementation in this project, due to its extensive research base and the ease of applying it at the individual person level that the ABM provides.

Exploratory research was carried out by running the Tampa Bay ABM under a highly controlled series of scenarios with region-wide percentage changes in travel time or cost. (Chapter 5). After testing a number of candidate logsums from different model components, the tour destination choice logsum was selected as the most promising basis for further investigation, due to the fact that it is the "highest level" logsum at the tour or trip level, and thus captures the welfare effects of destination choice, mode choice and time of day choice simultaneously. Because there may be generated or suppressed tours between scenarios, and because model logsums have no absolute scale (the "zero point" is arbitrary), it was necessary to develop an approach for using the logsums that would assign appropriate (dis)benefits to generated or suppressed tours. This was done using the same logic as the ROH approach, assigning one half of the difference in logsums between scenarios to the difference in the number of tours made.

Under the exploratory scenarios using the Tampa ABM, the traditional generalized cost-based ROH and the tour destination choice logsum-based ROH measure provided very comparable in terms of the magnitude and sensitivity for each tour purpose, and in total across tour purposes. This was a "best case" test for the generalized cost-based ROH approach, because all of the scenario changes were simple changes to travel times and costs which are captured by the traditional generalized cost-based approach. One would thus expect the generalized cost-based and logsum-based to result in similar benefit measures, which was the case. This finding does not ensure that the two methods will give similar results under different types of scenarios, and a wider range of scenarios was developed for further sensitivity testing.

While the exploratory tests of alternative methods were being carried out and refined, the BCA4ABM software tool was developed and tested (Chapter 6). The tool was coded using the same Python routines that are being used for the ActivitySim project, which is being funded through AMPO by several different MPO's to create the next generation of ABM software. The most positive aspects of the software tool are that it is easily configurable by the user, and that it runs fairly fast, even with the large data sets produced by ABMs. The tool was first coded to implement the same equations as the pre-existing SANDAG BCA tool, and then specific benefit measures were added and/or modified based on the findings of this project. The specific types of benefit measures that are produced by BCA4ABM are for the Tampa and San Diego implementations are:

- Based on the trip, person and household files output by the ABM:
  - Disaggregate generalized cost-based ROH benefits, in total and by component (auto in-vehicle time, transit in-vehicle time, transit wait time, transit walk access/egress time, other walk time, bike time, fuel cost, toll cost, parking cost, transit fare cost)
  - Destination choice logsum-based ROH benefits, in total and by tour purpose
  - Benefits due to change in auto ownership costs
  - Benefits due to health effects of changes in walking and cycling time
  - Separate segment-specific calculations of all of the above benefits for each user-specified "community of concern" (senior citizens, households below the poverty level, households living in specific areas, etc.)
- Based on trip, time and cost matrices for other market segments handled by zonal aggregate models in the network software (freight, externals, visitor trips, special generators):
  - Matrix generalized cost-based ROH benefits, in total and by component (in-vehicle time, toll cost, operating cost)
- Based on the link-level output from the network software, for time-period specific traffic assignments and/or daily traffic assignments:
  - Accident-related benefits for changes in fatalities, injuries and property damage.

- Travel time (un)reliability benefits for changes in the chance of delays, separately for autos and trucks.
- Operating cost benefits for changes in vehicle operating costs on the network, separately for autos and trucks.

All of these measures can be reconfigured by changing the variables used, the form of the equations, and/or the parameters assumed. This flexibility makes it possible to adapt the tool for use with different ABMs and network software packages, and to substitute or refine the particular measures that are used. The definition of the "communities of concern" can also be changed quite easily.

The final phase of the project was to apply the BCA4ABM tool in a series of sensitivity tests. The specific tests for the Tampa region were:

- An infrastructure-related test: The "new lanes" scenario was created by editing the Cube network file to add a lane in each direction to a long, congested stretch of I-275, stretching from St. Petersburg across the Frankland bridge and through central Tampa to the I-4.
- A land use-related test: The "more infill" scenario was created by editing the synthetic population and parcel land use file to simulate a doubling of population in two areas in downtown Tampa and downtown St. Petersburg that had the highest accessibility to jobs and transit in the base scenario. Each of these areas had roughly 40,000 households in the base scenario, so this scenario has about 80,000 households (about 6% of region households) moving from other areas into the downtown areas with the highest walk and transit accessibility.
- Tests of random simulation variability: The base scenario, the infrastructure scenario and the land use scenario were each run under four different configurations: (A) a base configuration, (B) changing only the random number sequence used for simulation, (C) removing the random component from the value of time (VOT) distribution used in the ABM, and (D) also removing the income component from the VOT distribution used in the ABM.

The outputs from the BCA4ABM tool for these model runs was verified by writing a separate computer program to perform independent calculations on the same model outputs. That program was also used to calculate a separate type of logsum-based ROH measure to compare against the two ROH measures implanted in the BCA4ABM tool. The third ROH measure uses accessibility logsums that are pre-calculated in the ABMs to use as accessibility measures for those living in specific zones in specific market segments (a function of tour purpose, income, car ownership, and proximity to transit). The accessibility logsums are generated by joint destination and mode choice models that are simpler and more consistent in form than the tour level destination choice logsums.

The findings from the runs are described in detail in Chapter 7. Some general conclusions based on the findings are:

- The land use scenario has very large positive benefits when using the logsum-based ROH measures, but has very small positive benefits when evaluated using the traditional generalized cost-based ROH measure. When the "community of "concern" calculations are done specifically for those households that move into the infill areas, the difference is even more pronounced. While those households gain the highest positive benefits using the logsum-based ROH measures, they are given a negative net benefit using the generalized based ROH measure. This is because the generalized cost-based measure only captures the effect of the increase in auto travel times in the downtown areas, but does not capture the welfare benefits of being able to shift to other modes and closer destinations when moving into the infill areas.

- The infrastructure scenario generally shows small positive benefits due to a decrease in peak hour congested travel times on the I-275 portion with added lanes. However, some of this travel time gain is offset by slight changes in destination choice to longer trips. Overall, the benefits of the infrastructure are not as large as one might expect, and show some unexpected variability—particularly for the logsum-based measures. Further useful tests in this direction may be to run additional iterations in traffic assignment and/or additional global iterations between the ABM and traffic assignment, to ensure that the full model system is reaching a stable final outcome in response to the change in highway capacity.
- The sensitivity tests to random variation and VOT variation show that the more that the VOT distribution is narrowed due to removing random variation and income-related variation, the fewer walk, bike and transit trips are predicted, since these modes are chosen more often in the simulation by those in the lowest VOT range. The logsum-based ROH measures are more sensitive to this mode switching than are the generalized cost-based measures.
- The sensitivity of the results for the infrastructure and land use model benefits across the four different base scenarios with different random seed and VOT specification is quite small for all of the measures, particularly in the land use scenario. This finding indicates that the benefit measures are not very sensitive to random simulation variation in the ABM forecasts, although the tour-level logsum-based measures seem more sensitive to such variation than the generalized cost-based measures or the simpler accessibility logsum-based measures.
- The results for the "community of concern" segmented benefit calculations illustrate that it is possible to generate separate benefit measures for a variety of different segments specified by household and person characteristics. Senior citizens and low income households generally have smaller benefits and disbenefits because they tend to make fewer trips than the average resident. Segmenting by residence area can be valuable in identifying who benefits the most (and the least) in specific scenarios.
- It is important to include the separate calculation for auto ownership cost benefits when logsum-based benefit measures are used, because higher levels of auto ownership provide benefits of higher accessibility, and the fixed cost of auto ownership is not incorporated in the logsum measure itself, so needs to be calculated separately.
- The health benefit measures for walking and cycling show significant benefits for the land use scenario that was tested, although the magnitude is not as large as most of the accessibility-based benefits.
- The benefits for the freight, external and visitor markets, calculated using matrix-based ROH formulations, seem reasonable in terms of both signs and magnitude in the Tampa test runs.
- The link-based benefit calculations for accidents, reliability and operating costs generally produce results in the expected direction and reasonable relative magnitudes, but the absolute magnitudes of the benefits seem quite high when compared to the other benefit measures

output by the BCA4ABM tool. Further testing and refinement of the link-based measures seems warranted.

7.2 Recommendations for Practice

The primary research focus of the project was to compared alternative measures for the ABM trips using traditional generalized cost methods and various logsum-based measures. Different sensitivity tests were performed to compare the methods, helping to clarify the pros and cons of using each method. Table 16 provides a summary of the properties of the three types of measures that were tested most thoroughly:

- The traditional generalized cost-based ROH method using changes in travel times and costs
- A logsum-based method applying the ROH logic to tour-level destination choice logsums
- A second logsum-based method applying the ROH logic to zone/market segment level destination/mode choice accessibility logsums.

Both of the logsum-based approaches capture several sources of accessibility benefits that generalized cost-based methods cannot capture well, including benefits of mode switching, destination switching, and auto ownership change. Of the two logsum-based methods, the simpler accessibility logsums appears more suitable for use in BCA, for a number of reasons:

- The existing ABM software platforms (DaySim, CT-RAMP, TourCast) pre-calculate these accessibility logsums in a way that is fairly consistent across platforms.
- The mode and destination choice equations used to calculate the simpler accessibility logsums are not as complex as those used in the tour-level models. (As a corresponding downside, the simpler measures may leave out some specific effects that the more detailed tour-level models include, such as time-period-specific effects.)
- The accessibility logsums are calculated for all residence zones and market segments, so values are available for all persons in the synthetic population in all scenarios, regardless of whether or not any tours or trips are simulated for a particular person in a particular scenario. This makes it simple to use a fully disaggregate implementation of the ROH methodology. For the tour-level logsums, on the other hand, it is not practical to calculate the logsums for all tours for both the base and build scenarios, so an aggregate ROH method must be used, and can introduce aggregation bias. (A question related to the accessibility logsums is how to scale them—i.e. to apply them for each trip, for each tour, etc. In this research, they were applied for each trip, but further sensitivity tests in this direction would be useful.)
- The accessibility logsums are calculated for different income/value of time classes for each residence zone, so it would be straightforward to use income-neutral logsum measures by simply using the logsums from the middle income group rather than each household's own income group. The tour level logsums approach, on the other hand, would require recalculation of all logsums using a different income, which would not be practical. (An income-neutral measure is often desirable in BCA analysis for reasons of social equity, so as not to value one individual's time more highly than another's, even though the first individual may be able and willing to pay more to save travel time.)

- The simpler accessibility logsums are calculated across all possible destination zones in the region, while the tour-level logsums are calculated only over a randomly-selected sample of destinations, which adds some random noise to the logsums. Additional random variation in the tour level logsums may come from the stochastic choices simulated in the higher level models in the ABM system, which is not the case for the accessibility logsums.

An additional benefit of the simpler accessibility logsums is that they are calculated for zone/market segment combinations rather than for individual households, and thus could also be applied as benefit measures for advanced 4-step zone-based model systems.

Regarding the treatment of income, we recommend that the value of time (VOT) be appropriately stratified or modified by income in the component AB models themselves, as recommended, for example, in the SHRP 2 C04 report (Strategic Highway Research Program, 2013). Including income effects on VOT and other utility components in the models is important for obtaining realistic predictions from the models. In the BCA process, however, one may wish to use income-neutral benefit measures for reasons of social equity. In that regard, the generalized cost-based or accessibility logsum-based approaches are the most amenable to obtaining income-neutral measures.

For further application of the BCA4ABM tool in the Tampa region, we recommend that the accessibility logsum measures be appended to the household-level record produced by the ABM and that the logsum-based ROH equations be modified to use these logsums rather than the tour destination choice logsums. For the first applications of the tool, we recommend that both the generalized cost-based ROH and accessibility logsum-based ROH measures be produced and compared to decide which one to use for particular applications. If sufficient experience and confidence using the logsum-based method is developed, then the calculations required for the generalized cost-based method can eventually be omitted.

We further recommend that the link-based benefit equations and outputs be further assessed and modified as necessary, particularly for the accident-related benefits. We also recommend that the operating cost benefits be derived and used from the ABM-based and matrix-based outputs for auto trips and truck trips, rather than using the link-based measures.

Table 16: Summary of the Properties of Alternative Benefit Measures for the ABM Trips

Properties	Traditional Generalized Cost-Based ROH	Tour Destination Choice Logsum-Based ROH	Simpler Accessibility Logsum-Based ROH
Ease of understanding the method	Relatively easy to understand	Models can be quite complex	Uses somewhat simpler models than tour destination choice
Captures changes in travel times and costs	Yes, in a straightforward way	Yes, in a more complex way	Yes, in a more complex way
Captures benefits of mode switching	Only insofar as it provides a savings in travel time and/or cost	Can include a wider range of utility components of the mode	Can include a wider range of utility components of the mode
Captures benefits of destination switching	Only insofar as it provides a savings in travel time and/or cost	Can include a wider range of attractiveness components of the destinations and activities	Can include a wider range of attractiveness components of the destinations and activities
Captures benefits of trip generation/suppression	Via the rule of a half approximation	Via the rule of a half approximation	Via the rule of a half approximation
Captures benefits of car ownership change	No	Yes, as it results in greater accessibility.	Yes, as it results in greater accessibility.
Need to assert travel times and costs for all modes, even when not available in a particular scenario	Yes. This can be a problematic aspect of the method.	No. Non-availability of modes is captured in the logsum.	No. Non-availability of modes is captured in the logsum.
Can apply ROH on a disaggregate level to avoid potential aggregation bias	Yes, but requires a step to append times and costs from one scenario to trips from another	Not practical. Would require rerunning the ABM models on trips from another scenario	Yes, relatively easy, as most ABMs produce these logsums for all persons for all scenarios
Can produce income-neutral benefit measures	Yes. Values of time are assumed externally.	Not practical. Would require calculating a 2nd version of the logsum with a different income value	Yes. The accessibility logsums are already segmented by income (via value of time)
Possible effects of random simulation variation on results	Low. Calculations are simple and non-random for each trip.	Higher. Individual tours are simulated with random variation in the choice set and the higher level choices	Low. The destination choice set includes all zones. Model structure is the same for all purposes and segments.

7.3 Recommendations for Further Research

While the research undertaken in this project has investigated alternative logsum-based benefit measures for using with ABMs, there is a great deal of further research that could be done. This could include:

- Testing a wider range of types of scenarios, with the Tampa and San Diego ABM systems, as well as other ABM's in other regions.
- Testing the effects of assignment convergence level and global system convergence level on the benefit results, particularly for scenarios with significant infrastructure changes. (This is an area which needs more testing for travel demand modeling in general—not just for benefit-cost analysis.)
- Testing the allocation of link-based benefits such as probable crash costs to trips or individuals by way of skims.
- Testing of these methods with advanced statewide models or other models with greater representation of long distance travel and freight.
- Testing of analogous disaggregate benefit methods for freight simulation models.
- Making more extensive use of the "community of concern" feature to learn more about the relative costs and benefits that tend to accrue to different segments of the population.
- Testing further scenarios with the SANDAG model to compared link-based travel time reliability measures to reliability measures that are skimmed and written to individual trip records. (It would also be interesting to test this approach with other ABMs, but those regions would first need to implement the SANDAG methods for calculating and skimming the link-level travel time variability measures.)
- Testing the methods in a wider variety of regions, including very large regions with very high transit and pedestrian mode shares, as well as smaller regions with very low non-auto shares.
- Several MPO's are interested in using the new, disaggregate version of the ITHIM model (CEDAR 2016) for evaluating the health benefits of active transportation and land use changes. As that method is implemented together with ABM systems, it will be interesting to compare the benefit outputs with those produced by the HEAT method implemented in the BCA4ABM tool. In such cases it may be better to use the ITHIM outputs directly, in a similar way as one can use the outputs of the EMFAC and MOVES emissions models directly to evaluate the health impacts of air pollutant emissions.

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Appendix A. Description of the BCA4ABM Software Tool

This chapter documents the details of BCA4ABM software tool, which was designed and written for this project to be a flexible, configurable tool that can be run with various ABM and network packages and data structures, and easily configured to use standard "Rule of Half" based benefit calculations and/or alternative benefit measures. The tool is also designed to support separate calculations for different demographic or socio-economic "communities of interest"

The first two sections of this chapter describe the structure of the tool. The last two sections provide details of configuration settings and an example implementation for the Tampa ABM model.

Overview

BCA4ABM[1] is an open software platform for performing travel demand model benefit-cost analysis. It is a general framework for aggregate (matrix), disaggregate, and link-based calculations and is implemented entirely with open source Python scientific computing libraries, most notably **pandas**[2] for data tables and **numpy**[3] for matrices. The various calculations in BCA4ABM are grouped into processor modules. The various steps in order of execution in the BCA4ABM tool are listed in Table 17.

Table 17: BCA4ABM Module Steps

Step	Description
initialize_output_store	Creates the HDF5-format data output file
demographics_processor	Disaggregate (ABM) person-level calculations
person_trips_processor	Disaggregate (ABM) trip-level calculations
auto_ownership_processor	Disaggregate (ABM) person- and household-level auto ownership calculations
physical_activity_processor	Disaggregate (ABM) person- and trip-level physical activity calculations
aggregate_trips_processor	Matrix-based calculations for aggregate (non-ABM) trip output
link_daily_processor	Link-based calculations on the daily link file
link_processor	Link-based calculations on the time period-specific link files
write_results	Writes measures to output files
print_results	Prints measures to the console

[1] Link to bca4abm, an open platform for performing Benefit-cost analysis comparing scenarios generated by travel demand models. It is a general framework for aggregate (matrix), disaggregate, and link-based calculations and is implemented entirely with open source Python scientific computing libraries, most notably pandas for data tables and numpy for matrices.
[2] Link to *pandas*, an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language
[3] Link to NumPy, the fundamental package for scientific computing with Python.

Directory Setup

The core BCA4ABM software is installed as a Python package and is imported as a library. The core BCA4ABM software is stored separately from the implementation-specific data. Each implementation expects all the input and configuration files to be inside a pre-defined directory structure. The tool is run using the batch file **run_bca.bat** inside the working directory. The user can enable or disable processors in a BCA run by editing the **run_bca.py** Python script file. Figure 30 shows the basic directory structure for a BCA4ABM implementation, followed by description of directory contents (Table 18 through Table 23).

Figure 30: BCA4ABM Directory Structure

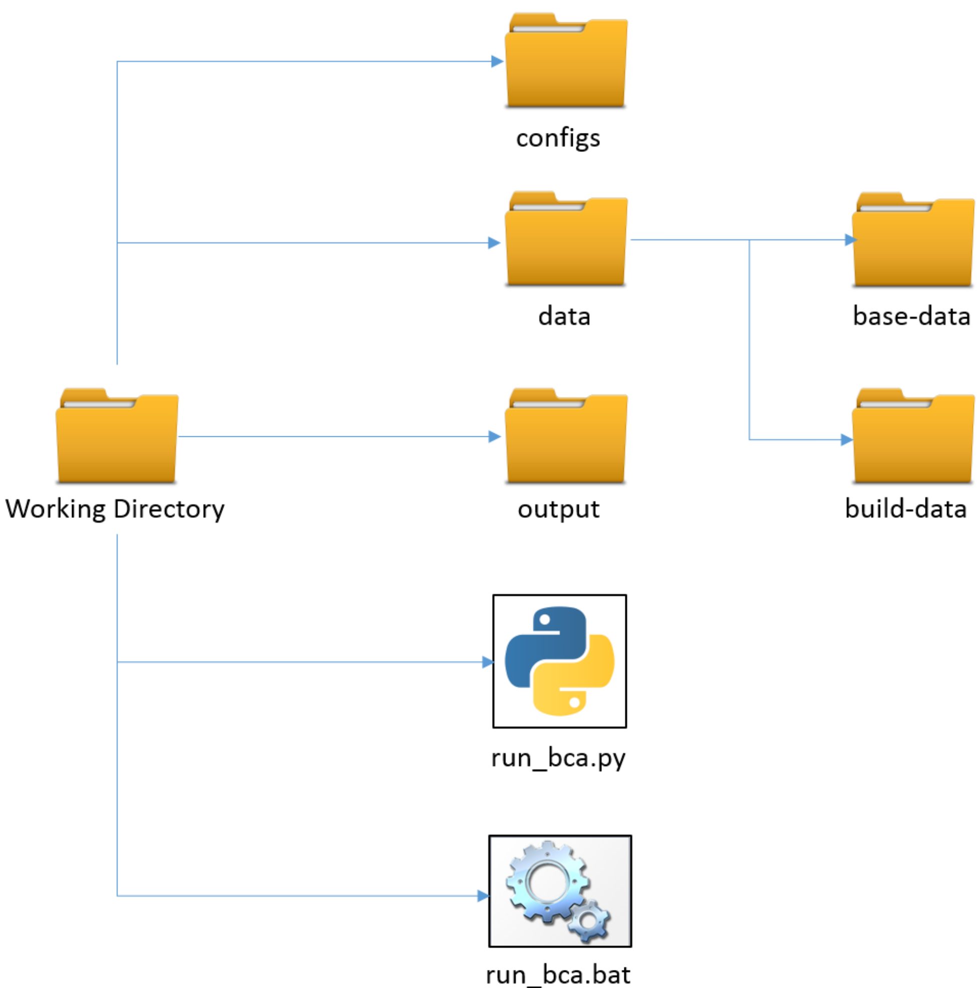

Table 18: Working Directory Contents

File	Description
run_bca.bat	Batch file for running BCA4ABM tool
run_bca.py	Main Python shell script for loading required libraries and calling BCA4ABM processors for benefits calculation
/configs	Sub-directory containing all the configuration files for BCA4ABM processors
/data	Sub-directory containing ABM disaggregate, aggregate, and link level input data
/output	Sub-directory to store outputs from all the processors

BCA4ABM requires model outputs for both a "base" and a "build" alternative. The required model outputs which are input to BCA4ABM need to be the same for both alternatives. The values in the model outputs can be different, but the files, the formats, the number of matrices, etc. all need to be the same.

All base and build alternative inputs are specified in the data folder. All model outputs are input to BCA4ABM in CSV (comma separated), TSV (tab separated) or OMX (open matrix[4]) format. Details of configuration and settings files are described in section 6.3. Structure of the input and output files from the Tampa implementation of BCA4ABM are described in section 6.4.

Table 19 and Table 20 list the files that are expected in the /CONFIGS and /DATA directories. Table 21 and Table 22 are examples of the files in the /BASE-DATA and /BUILD-DATA directories for the Tampa example. The specific link files are named in the "link_data_manifest.csv" file, and the matrix (. OMX) files are identified in the aggregate_data_manifest.csv file, which are both in the /DATA directory. Table 23 lists the types of output files that are produced in the /OUTPUT directory. Some of these are optional, as they are very detailed outputs of benefits at the person or trip level, and produce large output files.

[4] Link to the OMX Matrix file, a structured collection of two-dimensional array objects and associated metadata. OMX is built on top of the well-established HDF5 scientific data storage standard. An OMX file has a specific layout that is intended to ensure that complete and consistent information about the matrix data is stored and that the data can be retrieved correctly and efficiently.

Table 19: /configs Directory Contents

File	Description
aggregate_trips.csv	Python expressions file for aggregate trips processor
auto_ownership.csv	Python expressions file for auto ownership processor
demographics.csv	Python expressions file for disaggregate person processor
link.csv	Python expressions file for time period link-based calculations
link_daily.csv	Python expressions file daily link based calculations
person_trips.csv	Python expressions file for disaggregate trips calculations
physical_activity_person.csv	Python expressions file for disaggregate person physical activity calculations
physical_activity_trip.csv	Python expressions file for disaggregate trip physical activity calculations
settings.yaml	Configuration settings file

Table 20: /data Directory Contents

File	Description
aggregate_data_manifest.csv	Aggregate data input files manifest
base_households.csv	Base alternative households
basetrips_baselos.csv	Base alternative trips with base alternative trip level-of-service
basetrips_buildlos.csv	Base alternative trips with build alternative trip level-of-service
build_households.csv	Build alternative households
buildtrips_baselos.csv	Build alternative trips with base alternative trip level-of-service
buildtrips_buildlos.csv	Build alternative trips with build alternative trip level-of-service
link_data_manifest.csv	link time period tables to process in link processor. The daily like table is not specified since it is handled by a separate daily link processor
person.csv	Base and build alternative person records
/base-data	Base alternative aggregate data
/build-data	Build alternative aggregate data

Table 21: /base-data Directory Contents—Tampa Example

File	Description
HA_ DIR_LINK_DAILY.csv	Base alternative Daily time period link records
HA_ DIR_LINK_<TOD>.csv	Base alternative link records for all time periods <TOD>
VISIT_<TOD>_A10.omx	Base alternative Visitor trip file for all TOD
Truck_<TOD>_A10.omx	Base alternative Truck trip file for all TOD
CONGSKM_<TOD>_TRK.omx	Base alternative Truck – congested skims for all TOD
CONGSKM_<TOD>_IEEI.omx	Base alternative Internal-External congested skims for all TOD
CONGSKM_<TOD>_HOV_A10_UPD.omx	Base alternative HOV congested skims for all TOD
CONGSKM_<TOD>_A10_UPD.omx	Base alternative DA congested skims for all TOD
AIRP_<TOD>_A10.omx	Base alternative Airport trip files for all TOD

Table 22: /build-data Directory Contents—Tampa Example

File	Description
HA_ DIR_LINK_DAILY.csv	Build alternative Daily time period link records
HA_ DIR_LINK_<TOD>.csv	Build alternative link records for all time periods <TOD>
VISIT_<TOD>_A10.omx	Build alternative Visitor trip file for all TOD
Truck_<TOD>_A10.omx	Build alternative Truck trip file for all TOD
CONGSKM_<TOD>_TRK.omx	Build alternative Truck – congested skims for all TODs
CONGSKM_<TOD>_IEEI.omx	Build alternative Internal-External congested skims for all TOD
CONGSKM_<TOD>_HOV_A10_UPD.omx	Build alternative HOV congested skims for all TOD
CONGSKM_<TOD>_A10_UPD.omx	Build alternative DA congested skims for all TOD
AIRP_<TOD>_A10.omx	Build alternative Airport trip files for all TOD

Table 23: /output Directory Contents

File	Description
auto_ownership.csv	Auto ownership benefit results by person (optional detailed output)
bca_results.h5	HDF5 output database
coc_silos.csv	Size of communities of concern for separate benefit calculations and reporting
coc_results.csv	Benefit results by community of concern
link_benefits.csv	Link benefits by time period
link_daily_benefits.csv	Daily link benefits
persons_merged.csv	Benefit results by person (optional detailed output)
physical_activity.csv	Physical activity benefit results by person (optional detailed output)
summary_results.csv	All benefit measure results calculated by the tool
trips_with_demographics.csv	Benefit results by trip (optional detailed output)

Tool Configuration

BCA4ABM can be configured based on the requirements of the project and user. The tool is configured using the settings.yaml file, while individual processors can be configured using the expressions files of each processor. The BCA4ABM tool configuration steps can be grouped into two steps – settings for the model run and settings for benefit calculations on disaggregate trip lists files, assignment link output files and aggregate demand matrices. The following sub-sections describe each of these with examples.

The Main Settings File

The main settings file is used to configure the settings for the BCA4ABM run. The settings can be grouped as – global and local keys, run settings and table definitions.

Global and Local Keys

Global and Local keys are defined in the settings file to be accessed by all the processors. Local keys are accessed only by specific processors but are available globally. Table 24 lists the global keys with their descriptions.

Run Settings

The run settings include setting data dump flags to true or false which specifies if BCA4ABM should write out intermediate calculation CSV tables for debugging. Other general settings include tour purpose work code mappings.

Table 24: Global and Local Keys

Key	Description
DISCOUNT_RATE	Discount rate for all modules
ANNUALIZATION_FACTOR	Annualization factor for all modules
POVERTY_1, POVERTY_2, POVERTY_N	Poverty threshold for the demographic module
ANNUAL_COST_PER_VEHICLE	Annual cost per vehicle for the auto ownership module
WALK_FACTOR_AGE_UNDER_20, WALK_FACTOR_AGE_20_TO_74, WALK_FACTOR_AGE_75_PLUS	Walk factor coefficients for the physical activity model
WALK_DIVISOR_MINUTES_PER_DAY	Physical activity model settings for the physical activity module
WALK_MAX_RISK_REDUCTION	Physical activity model settings for the physical activity module
BIKE_FACTOR_AGE_UNDER_20, BIKE_FACTOR_AGE_20_TO_64, BIKE_FACTOR_AGE_65_PLUS	Bike factor coefficients for the physical activity model
BIKE_MAX_RISK_REDUCTION	Physical activity model settings for the physical activity module
TOTAL_MAX_RISK_REDUCTION	Physical activity model settings for the physical activity module
VALUE_OF_MORTALITY_RISK_PER_YEAR	Physical activity model settings for the physical activity module
TOLL_INCLUSION_FACTOR, FUEL_INCLUSION_FACTOR, PARK_INCLUSION_FACTOR, FARE_INCLUSION_FACTOR	Link calculation settings for the links module
RELIABILITY_RATIO, VALUE_OF_RELIABILITY_AUTO, VALUE_OF_RELIABILITY_TRUCK	Reliability coefficients for the links module
TIME_RATIO_FACTOR, TIME_RATIO_POWER, TIME_RATIO_UPPER_LIMIT, TTI50_POWER, TTI80_LOG_MULTIPLIER	Reliability constants for the links module
OPERATING_COST_PER_MILE_AUTO, OPERATING_COST_PER_MILE_TRUCK	Operating costs for the links module
CRASH_RATE_PDO, CRASH_RATE_INJURY, CRASH_RATE_FATAL	Crash model settings for the daily link module
CRASH_COST_PDO, CRASH_COST_INJURY, CRASH_COST_FATAL	Crash model settings for the daily link module

Key	Description
AOC_COST_COUNTING_FACTOR, TOLL_COST_COUNTING_FACTOR	Link calculation settings for the links module
WORK_IVT_VOT_MAP, WORK_WALK_VOT_MAP, WORK_WAIT_VOT_MAP, VOT_MAP, TOUR_PURPOSE_UTILS_PER_MIN_MAP	In-vehicle, walk, and wait time values-of-time by work and non-work for the person trips module

Table Definitions

Table definitions specify the mappings of internal table field names to external input file field names and the list of fields to load into memory for the BCA4ABM run. These need to be defined for all the base and build input files. Each table includes a mapping with the raw CSV/TSV table field name followed by the name to use in expressions file for each processor. All fields to be used in expressions must be in the mapping since the mapping defines which fields are loaded into memory. Unique person and household indexes are mandatory for household and person files. Trip files should include a tour ID, half-tour ID and half-tour-segment ID to form a unique index for each trip. Table 25 lists all table definitions. Section 6.4 presents examples of these definitions from the Tampa implementation.

Table 25: Table Definitions

Token	Description
base_households	Base alternative household file (CSV/TSV)
base_households_column_map	Table definition for base alternative household file
build_households	Build alternative household file (CSV/TSV)
build_households_column_map	Table definition for build alternative household file
persons	Base/Build alternative person file (CSV/TSV)
persons_column_map	Table definition for person file
basetrips	Basetrips_baselos trip file name
basetrips_column_map	Basetrips_baselos table definition
basetrips_buildlos	Basetrips_buildlos trip file name
basetrips_buildlos_column_map	Basetrips_buildlos table definition
buildtrips	Buildtrips_buildlos trip file name
buildtrips_column_map	Buildtrips_buildlos table definition
buildtrips_baselos	Buildtrips_baselos trip file name
buildtrips_baselos_column_map	Buildtrips_baselos table definition
aggregate_data_manifest_column_map	Table definition for aggregate data manifest

Token	Description
link_data_manifest_column_map	Table definition for link data manifest
link_table_column_map	Table definition of all link files
link_daily_file_name	Daily link file

Setting Up Benefit Calculations

BCA4ABM exposes most of its calculations in CSV files that contain numpy and pandas expression that operate on the input data tables and matrices. This avoid having to modify Python code when making changes to the model calculations. After configuring the settings file, the next step in setting up the tool is to configure expressions files to set up benefits calculations for each processor. The expression files corresponding to each processor are as follows:

1. Demographics processor: demographics.csv
2. Person trips processor: person_trips.csv
3. Auto ownership processor: auto_ownership.csv
4. Physical activity processor: physical_activity_trip.csv and physical_activity_person.csv
5. Aggregate trips processor: aggregate_trips.csv
6. Daily link processor: link_daily.csv
7. Time period link processor: link.csv

Here are the key conventions for writing expressions in BCA4ABM tool:

1. Each expression is applied to all rows in the table being operated on or to the entire matrix if a matrix calculation.
2. Expressions must be vectorized expressions and can use most numpy and pandas expressions.
3. Global constants are specified in UPPERCASE, are under user control, and come out of the settings file.
4. The target field in the expressions file will create a new pandas table field that can be referenced later in the expression file and will be saved in the output tables.
5. Specifying a target field with _underscore will create a temporary variable that is not saved to the pandas table.
6. Comments are specified with #.
7. When editing the CSV files in Excel, use single quote ' or space at the start of a cell to get Excel to accept the expression.
8. The reserved keywords listed below for table names are just for clarity; in all cases you can also refer to the active table as df.
9. All target fields specified in the expressions file will be aggregated and written out to the summary results file. Each summary result entry is named as follows: the two-digit processor abbreviation + the target field. For example: AO_base_auto_ownership_cost.

BCA4ABM has a few reserved keywords for table names and/or matrices, which should be used in the expressions. These are as follows:

1. aggregate_trips.csv references the fields in aggregate_data_manifest.csv as: base_trips, build_trips, base_ivt, build_ivt, vot, aoc_units, base_aoc, build_aoc, toll_units, base_toll, build_toll.
2. auto_ownership.csv, demographics.csv, physical_activity_person.csv refer to the person table as persons.
3. link.csv, link_daily.csv refer to the links table as links.
4. person_trips.csv refers to the trips table as trips.
5. physical_activity_trip.csv refers to the base and build trips as trips, base, build.

Section 6.4 presents examples of these expression files for the Tampa implementation.

Tampa Implementation of BCA4ABM

This sections presents the details of one of the BCA4ABM implementations for the Tampa ABM. In this implementation, the build alternative adds a lane in both directions along Interstate 275, including the Howard Frankland bridge. The base scenario is referred to as “1A”, the build scenario is “2A” and the BCA run is “1A_vs_2A”. The inputs section defines all the input and configuration files for this run. The outputs section defines all the outputs.

Inputs

As described in section 6.2 and 6.3, setting up a BCA4ABM run starts with preparing the directory structure and assembling the input data. Next, the settings file and expression files are configured based on the input data and project requirements. The inputs for the Tampa ABM came from the outputs of the DaySim and Cube-based Tampa model. The basetrips_buildlos and buildtrips_baselos files were generated by running DaySim in skim attachment mode. Skim attachment mode takes an output DaySim trip list and attaches network skim information from a different model run based on each trips’ attributes – origin, destination, mode, time period, etc. Table 26 to Table 29 detail all the input tables.

Data Tables

Table 26: Households Table Details for Base and Build Scenarios

Field	Description
hhno	Household ID
hhincome	HH income in dollars
hhsize	HH size
hhexpfac	HH expansion factor
hhveh	Number of autos in the household
hhtaz	Household TAZ

Table 27: Persons Table Details

Field	Description
pno	Person ID
hhno	Household ID
pptyp	Person type
pgend	Gender of the person
pagey	Person’s age in years

Table 28: Trips Table Details

Field	Description
hhno	Household ID
pno	Person ID
tour	Tour ID
half	Half tour ID
tseg	Half tour segment ID
pdpurp	Tour purpose
mode	Trip mode
autotime	Auto time
transittime	Transit time
transitwait	Transit wait time
transitwalk	Transit walk time
biketime	Bike time
walktime	Walk time
tollcost	Total toll cost
fuelcost	Total fuel cost
parkcost	Parking cost
farecost	Total transit fare
tourdest_ls	Tour destination logsum

Table 29: Links Table Details

Field	Description
distance	Link length in miles
dircode	Link direction
time	Free flow time
congtime	Congested travel time
area_type	Area type
facl_type	Facility type
num_lanes	Number of lanes
capacity	Capacity
twoway	Two-way indicator
vol_total	Total volume
trk_vol	Truck volume

Aggregate skims and trip matrices for base and build alternative files are inputted as OMX matrices. All the input skims and trip matrices are specified in the aggregate_data_manifest table. Aggregate data manifest specifies aggregate markets for which to apply the aggregate calculations defined in aggregate_trips.csv. Each row in the manifest contains a trip matrix, an in-vehicle time matrix, an auto operating cost matrix, and a toll matrix. Each matrix will be loaded for the base and build alternative from the base and build-data folders. These matrices plus the additional settings in each row for units, value-of-time, etc. are referenced in the expressions.

Configuration Settings

This sub-section presents the configuration settings for the 1A_vs_2A run. The global and local keys are presented for the demographics (Figure 31), auto ownership (Figure 32) physical activity (Figure 32), person trips (Figure 33), time-period link (Figure 34) and daily link (Figure 35) processors as specified in the settings.yaml file. Next, table definitions are presented for demographics data (Figure 36), trip data (Figure 37), aggregate and link data (Figure 38).

Figure 31: Keys—Demographic Processor

```
locals:
  DISCOUNT_RATE: 0.75
  ANNUALIZATION_FACTOR: 365

locals_demographics:
  POVERTY_1: 11770
  POVERTY_2: 15930
  POVERTY_N: 4160
```

Figure 32: Keys—Auto Ownership and Physical Activity Processor

```
locals_auto_ownership:
  ANNUAL_COST_PER_VEHICLE: 2000

locals_physical_activity:
  WALK_FACTOR_AGE_UNDER_20: 0
  WALK_FACTOR_AGE_20_TO_74: 0.11
  WALK_FACTOR_AGE_75_PLUS: 0
  WALK_DIVISOR_MINUTES_PER_DAY: 24
  WALK_MAX_RISK_REDUCTION: 0.3
  BIKE_FACTOR_AGE_UNDER_20: 0
  BIKE_FACTOR_AGE_20_TO_64: 0.1
  BIKE_FACTOR_AGE_65_PLUS: 0
  BIKE_DIVISOR_MINUTES_PER_DAY: 14.3
  BIKE_MAX_RISK_REDUCTION: 0.45
  TOTAL_MAX_RISK_REDUCTION: 0.45
  VALUE_OF_MORTALITY_RISK_PER_YEAR: 100000
```

Figure 33: Keys—Person Trips Processor

```
locals_person_trips:
  # map trips table tour_purpose to work/notwork boolean
  TOUR_PURPOSE_WORK_MAP:
    0: 0   # home
    1: 1   # work
    2: 0   # school
    3: 0   # escort
    4: 0   # chore
    5: 0   # shop
    6: 0   # meal
    7: 0   # social
  # work/nonwork in-vehicle-time value of time
  WORK_IVT_VOT_MAP:
      0: 6.0     # nonwork
      1: 10.0    # work
  # work/nonwork walk value of time
  WORK_WALK_VOT_MAP:
      0: 9.0     # nonwork
      1: 15.0    # work
  # work/nonwork wait value of time
  WORK_WAIT_VOT_MAP:
      0: 9.0     # nonwork
      1: 15.0    # work
  # work/nonwork value of time
  VOT_MAP:
      0: 10.0    # nonwork
      1: 20.0    # work
  TOUR_PURPOSE_UTILS_PER_MIN_MAP:
    0: 0.000   # home
    1: 0.003   # work
    2: 0.003   # school
    3: 0.015   # escort
    4: 0.015   # chore
    5: 0.015   # shop
    6: 0.015   # meal
    7: 0.015   # social
  TOLL_INCLUSION_FACTOR: 1
  FUEL_INCLUSION_FACTOR: 1
  PARK_INCLUSION_FACTOR: 1
  FARE_INCLUSION_FACTOR: 1
```

Figure 34: Keys—Time Period Link Processor

```
locals_link:
  # unreliability costs - inputs
  RELIABILITY_RATIO: 0.5
  VALUE_OF_RELIABILITY_AUTO: 10.00
  VALUE_OF_RELIABILITY_TRUCK: 40.00
  # unreliability costs - constants
  TIME_RATIO_FACTOR: 1.0274
  TIME_RATIO_POWER: 1.2204
  TIME_RATIO_UPPER_LIMIT: 3
  TTI50_POWER: 0.8601
  TTI80_LOG_MULTIPLIER: 2.1406
  # operating costs
  OPERATING_COST_PER_MILE_AUTO: 0.20
  OPERATING_COST_PER_MILE_TRUCK: 0.80
```

Figure 35: Keys—Daily Link Processor

```
locals_link_daily:
  # accident costs
  # Crash rates per vehicle-mile
  CRASH_RATE_PDO: 0.0001
  CRASH_RATE_INJURY: 0.00001
  CRASH_RATE_FATAL: 0.000001
  # Crash costs in Dollars
  CRASH_COST_PDO: 2500
  CRASH_COST_INJURY: 25000
  CRASH_COST_FATAL: 100000

locals_aggregate_trips:
  AOC_COST_COUNTING_FACTOR: 1.0
  TOLL_COST_COUNTING_FACTOR: 1.0
```

Figure 36: Demographic Table Definitions

```
### table definitions

base_households: base_households.tsv
base_households_column_map:
  hhno: hh_id
  hhincome: hh_income
  hhsize: hh_size
  hhexpfac: hh_expansion_factor
  hhvehs: base_vehicles
  hhtaz: base_hhtaz

build_households: build_households.tsv
build_households_column_map:
  hhno: hh_id
  hhvehs: build_vehicles
  hhtaz: build_hhtaz

persons: person.tsv
persons_column_map:
  pno: person_idx
  hhno: hh_id
  pptyp: person_type
  pgend: person_gender
  pagey: person_age
```

Figure 37: Example Trip Table Definition

```
basetrips: basetrips_baselos.tsv
basetrips_column_map:
  hhno: hh_id
  pno: person_idx
  tour: tour_idx
  half: half_tour_idx
  tseg: half_tour_seg_idx
  pdpurp: tour_purpose
  mode: trip_mode
  autotime: base_auto_time
  transittime: base_transit_time
  transitwait: base_transit_wait
  transitwalk: base_transit_walk
  biketime: base_bike_time
  walktime: base_walk_time
  tollcost: base_toll_cost
  fuelcost: base_fuel_cost
  parkcost: base_park_cost
  farecost: base_fare_cost
  tourdest_ls: base_ls
```

Figure 38: Aggregate Data and Link Table Definition

```
aggregate_data_manifest_column_map:
  description: description
  trip_file_name: trip_file_name
  trip_table_name: trip_table_name
  ivt_file_name: ivt_file_name
  ivt_table_name: ivt_table_name
  dollars_per_hour: vot
  aoc_file_name: aoc_file_name
  aoc_table_name: aoc_table_name
  aoc_dollars_per_unit: aoc_units
  toll_file_name: toll_file_name
  toll_table_name: toll_table_name
  toll_dollars_per_unit: toll_units

link_data_manifest_column_map:
  description: description
  link_file_name: link_file_name

link_table_column_map:
  distance: distance
  dircode: dircode
  time: time
  congtime: congested_time
  area_type: area_type
  facl_type: facility_type_code
  num_lanes: num_lanes
  capacity: capacity
  twoway: two_way
  vol_total: total_volume
  trk_vol: truck_volume

link_daily_file_name: ha_DIR_LINK_DAILY.csv
```

Expressions

Expression files from the 1A_vs_2A run are presented below. The details of how the expressions are coded were described in section 6.3. Expression files for following processors are presented here – demographics (Table 30), person-trips (Table 31), auto ownership (Table 32), physical activity (Table 33), aggregate trips (Table 34), daily link (Table 35) and time-period link data (Table 36).

Below is a snapshot of the demographics.csv expression file. Within the demographics expressions file are coded what are known as communities of interest (COI). COIs are special markets for whom a separate benefits calculation is of interest. BCA4ABM computes the person level benefits for the entire population and then separately for each COIs defined here. A COI is defined as target variable in the demographics expression file with a prefix – "coc_". COIs can be defined using any person or households level variables defined in the person and household column maps in the settings.yaml file. For example, the coc_downtownTampa COI (see below), represents persons living in downtown Tampa in the base scenario. This COI is defined as persons whose household zone in the base scenario is in Tampa downtown (defined as HHTAZ >= 372 & HHTAZ <= 471).

Table 30: Demographics Expression File

<table>
<tr><th>Target</th><th>Expression</th></tr>
<tr><td>_poverty_threshold</td><td>(persons.hh_size==1)*POVERTY_1 + (persons.hh_size>1)*POVERTY_2 + (persons.hh_size - 2).clip(lower=0)*POVERTY_N</td></tr>
<tr><td>coc_poverty</td><td>persons.hh_income <= _poverty_threshold</td></tr>
<tr><td>coc_senior_citizens</td><td>persons.person_age > 65</td></tr>
<tr><td>coc_downtownTampa</td><td>(persons.base_hhtaz>=372) & (persons.base_hhtaz<=471)</td></tr>
<tr><td>coc_downtownStPeter</td><td>(persons.base_hhtaz>=1603) & (persons.base_hhtaz<=1702)</td></tr>
<tr><td>coc_landuseTampa</td><td>((persons.build_hhtaz>=372) & (persons.build_hhtaz<=471)) & ((persons.base_hhtaz<372) | (persons.base_hhtaz>471))</td></tr>
<tr><td>coc_landuseStPeter</td><td>((persons.build_hhtaz>=1603) & (persons.build_hhtaz<=1702)) & ((persons.base_hhtaz<1603) | (persons.base_hhtaz>1702))</td></tr>
<tr><td>coc_autoMore</td><td>(persons.build_vehicles>persons.base_vehicles)</td></tr>
<tr><td>coc_autoFewer</td><td>(persons.build_vehicles<persons.base_vehicles)</td></tr>
</table>

Table 31: Person Trips Expression File

Description	Target	Expression
work tour indicator	_work	trips.tour_purpose.map(TOUR_PURPOSE_WORK_MAP)
monetized auto ivt	auto_time	-0.5 * trips.hh_expansion_factor * (trips.build_auto_time - trips.base_auto_time) * _work.map(WORK_IVT_VOT_MAP)/60.0 * DISCOUNT_RATE * ANNUALIZATION_FACTOR
monetized transit ivt	transit_time	-0.5 * trips.hh_expansion_factor * (trips.build_transit_time - trips.base_transit_time) * _work.map(WORK_IVT_VOT_MAP)/60.0 * DISCOUNT_RATE * ANNUALIZATION_FACTOR
monetized transit wait time	transit_wait_time	-0.5 * trips.hh_expansion_factor * (trips.build_transit_wait - trips.base_transit_wait) * _work.map(WORK_WAIT_VOT_MAP)/60.0 * DISCOUNT_RATE * ANNUALIZATION_FACTOR
monetized transit walk time	transit_walk_time	-0.5 * trips.hh_expansion_factor * (trips.build_transit_walk - trips.base_transit_walk) * _work.map(WORK_WALK_VOT_MAP)/60.0 * DISCOUNT_RATE * ANNUALIZATION_FACTOR
monetized bike time	bike_time	-0.5 * trips.hh_expansion_factor * (trips.build_bike_time - trips.base_bike_time) * _work.map(WORK_IVT_VOT_MAP)/60.0 * DISCOUNT_RATE * ANNUALIZATION_FACTOR
monetized walk time	walk_time	-0.5 * trips.hh_expansion_factor * (trips.build_walk_time - trips.base_walk_time) * _work.map(WORK_WALK_VOT_MAP)/60.0 * DISCOUNT_RATE * ANNUALIZATION_FACTOR
toll cost	toll	-0.5 * trips.hh_expansion_factor * (trips.build_toll_cost - trips.base_toll_cost) * TOLL_INCLUSION_FACTOR * DISCOUNT_RATE * ANNUALIZATION_FACTOR
fuel cost	fuel	-0.5 * trips.hh_expansion_factor * (trips.build_fuel_cost - trips.base_fuel_cost) * FUEL_INCLUSION_FACTOR * DISCOUNT_RATE * ANNUALIZATION_FACTOR
park cost	park	-0.5 * trips.hh_expansion_factor * (trips.build_park_cost - trips.base_park_cost) * PARK_INCLUSION_FACTOR * DISCOUNT_RATE * ANNUALIZATION_FACTOR
fare cost	fare	-0.5 * trips.hh_expansion_factor * (trips.build_fare_cost - trips.base_fare_cost) * FARE_INCLUSION_FACTOR * DISCOUNT_RATE * ANNUALIZATION_FACTOR
total monetized time	monetized_time_old_method	auto_time+transit_time+transit_wait_time+transit_walk_time+bike_time+walk_time

Description	Target	Expression
total cost	cost_old_method	toll+fuel+park+fare
total ROH benefit	total_old_method	monetized_time_old_method + cost_old_method

Table 32: Auto Ownership Expression File

Description	Target	Expression
base scenario auto ownership cost	base_auto_ownership_cost	persons.hh_expansion_factor * persons.base_vehicles * ANNUAL_COST_PER_VEHICLE / persons.hh_size
build scenario auto ownership cost	build_auto_ownership_cost	persons.hh_expansion_factor * persons.build_vehicles * ANNUAL_COST_PER_VEHICLE / persons.hh_size
auto ownership cost benefit	diff_auto_ownership_cost	build_auto_ownership_cost - base_auto_ownership_cost

Table 33: Physical Activity Expression File

Target	Expression
base_walk	(trips.base == 1) * (trips.base_transit_walk + trips.base_walk_time)
base_bike	(trips.base == 1) * trips.base_bike_time
build_walk	(trips.build == 1) * (trips.build_transit_walk + trips.build_walk_time)
build_bike	(trips.build == 1) * trips.build_bike_time

Table 34: Aggregate Trips Expression File

Description	Target	Expression
value of time	vot	vot
in vehicle time benefit	ivt_benefit	0.5 * ((base_trips + build_trips) * (base_ivt-build_ivt)).sum() * vot/60.0 * DISCOUNT_RATE * ANNUALIZATION_FACTOR
auto ownership cost benefit	aoc_benefit	0.5 * ((base_trips + build_trips) * aoc_units * AOC_COST_COUNTING_FACTOR * (base_aoc-build_aoc)).sum() * DISCOUNT_RATE * ANNUALIZATION_FACTOR
toll benefit	toll_benefit	0.5 * ((base_trips + build_trips) * toll_units * TOLL_COST_COUNTING_FACTOR * (base_toll-build_toll)).sum() * DISCOUNT_RATE * ANNUALIZATION_FACTOR
total aggregate trip benefit	total_benefit	ivt_benefit + aoc_benefit + toll_benefit

Table 35: Daily Link Expression File

Description	Target	Expression
total vehicle miles travelled	vmt_total	links.total_volume * links.distance
annualized crash cost property damage	crash_cost_pdo	vmt_total * CRASH_RATE_PDO * CRASH_COST_PDO * DISCOUNT_RATE * ANNUALIZATION_FACTOR
annualized crash cost injury	crash_cost_injury	vmt_total * CRASH_RATE_INJURY * CRASH_COST_INJURY * DISCOUNT_RATE * ANNUALIZATION_FACTOR
annualized crash cost fatalities	crash_cost_fatal	vmt_total * CRASH_RATE_FATAL * CRASH_COST_FATAL * DISCOUNT_RATE * ANNUALIZATION_FACTOR
total annualized crash cost	crash_cost_total	crash_cost_pdo + crash_cost_injury + crash_cost_fatal

Table 36: Time Period Link Expression File

Description	Target	Expression
number of autos	auto_volume	links.total_volume - links.truck_volume
auto vehicle-miles	vmt_auto	auto_volume * links.distance
truck vehicle-miles	vmt_truck	links.truck_volume * links.distance
auto operating cost	cost_op_auto	vmt_auto * OPERATING_COST_PER_MILE_AUTO * DISCOUNT_RATE * ANNUALIZATION_FACTOR
truck operating cost	cost_op_truck	vmt_truck * OPERATING_COST_PER_MILE_TRUCK * DISCOUNT_RATE * ANNUALIZATION_FACTOR
total auto and truck operating cost	cost_op_total	cost_op_auto + cost_op_truck
congested time ratio	time_ratio	links.congested_time / links.time
power function of congested time ratio	ttim2	(TIME_RATIO_FACTOR * (time_ratio ** TIME_RATIO_POWER)).clip(upper=TIME_RATIO_UPPER_LIMIT)
50% percentile time	tti50	ttim2 ** TTI50_POWER
80% percentile time	tti80	1 + log(ttim2) * TTI80_LOG_MULTIPLIER
delay per mile	dly_per_mile	tti50 + (tti80 - tti50) * RELIABILITY_RATIO
auto equivalent delay in hours	equiv_delay_auto	dly_per_mile * links.distance * auto_volume/60

Description	Target	Expression
truck equivalent delay in hours	equiv_delay_truck	dly_per_mile * links.distance * links.truck_volume/60
auto delay cost	cost_delay_auto	equiv_delay_auto * VALUE_OF_RELIABILITY_AUTO * DISCOUNT_RATE * ANNUALIZATION_FACTOR
truck delay cost	cost_delay_truck	equiv_delay_truck * VALUE_OF_RELIABILITY_TRUCK * DISCOUNT_RATE * ANNUALIZATION_FACTOR
total auto and truck cost	cost_delay_total	cost_delay_auto + cost_delay_truck

Outputs

Table 23 listed all the output files. BCA4ABM produces outputs at different level of analysis, including:

1. Summary outputs: all measures computed by BCA4ABM tool are summarized in a single output file. Table 37 to Table 42 list the measures from…
    a. ABM output-based results: Summary results at the household, person and trip level.
    b. Link-based results: Summary results from the daily and period-specific link files.
    c. Matrix-based results: Summary measures computed from the aggregate skims and trip files.
2. Community of interest: all person level benefits for each community of interest defined in the demographics expression file
3. HDF5 database: output database, which can be viewed with the OMX Viewer[5].

[5] Link to the OMX Viewer, which allows one to open and explore OMX files.

Table 37: Summary Results—Household Level

Target	Description
AO_base_auto_ownership_cost	base scenario auto ownership cost
AO_build_auto_ownership_cost	build scenario auto ownership cost
AO_diff_auto_ownership_cost	auto ownership cost benefit

Table 38: Summary Results—Person Level

Target	Description
PA_base_value_of_risk_reduction	base_walk/bike_health_benefit
PA_build_value_of_risk_reduction	build_walk/bike_health_benefit
PA_benefit_risk_reduction	difference in_walk/bike_health_benefits

Table 39: Summary Results—Trip Level

Target	Description
PT_auto_time	monetized auto ivt
PT_transit_time	monetized transit ivt
PT_transit_wait_time	monetized transit wait time
PT_transit_walk_time	monetized transit walk time
PT_walk_time	monetized walk time
PT_bike_time	monetized bike time
PT_toll	toll cost
PT_fare	fare cost
PT_fuel	fuel cost
PT_park	park cost
PT_monetized_time_old_method	total monetized time benefit
PT_cost_old_method	total direct cost benefit
PT_total_old_method	total rule of half benefit
PT_roh_benefit_work_avg	logsum-based rule of half_work
PT_roh_benefit_school_avg	logsum-based rule of half _school
PT_roh_benefit_escort_avg	logsum-based rule of half _escort
PT_roh_benefit_chore_avg	logsum-based rule of half _chore

Target	Description
PT_roh_benefit_shop_avg	logsum-based rule of half _shop
PT_roh_benefit_meal_avg	logsum-based rule of half _meal
PT_roh_benefit_social_avg	logsum-based rule of half _social
PT_roh_benefit_total_avg	logsum-based rule of half _total

Table 40: Summary Results—Daily Link-Based

Target	Description
LD_vmt_total	total vehicle miles travelled
LD_crash_cost_fatal	annualized crash cost fatalities
LD_crash_cost_injury	annualized crash cost injury
LD_crash_cost_pdo	annualized crash cost property damage
LD_crash_cost_total	total annualized crash cost

Table 41: Summary Results—Period-specific Link-Based

Target	Description
L_cost_delay_auto	auto delay cost
L_cost_delay_truck	truck delay cost
L_cost_delay_total	total auto and truck cost
L_cost_op_auto	auto operating cost
L_cost_op_truck	truck operating cost
L_cost_op_total	total auto and truck operating cost

Table 42: Summary Results—Aggregate Matrix-Based

Target	Description
AT_ivt_benefit	in vehicle time benefit
AT_aoc_benefit	auto ownership cost benefit
AT_toll_benefit	toll benefit
AT_total_benefit	total aggregate trip benefit