# Anticipating Welfare Impacts via Travel Demand Forecasting Models: Comparison of Aggregate and Activity-Based Approaches for the Austin, Texas Region

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## ABSTRACT

A great disparity exists between the direction of travel demand forecasting by researchers, and the travel demand models used by transportation planning organizations. Activity-based models of travel demand have become increasingly studied in the academic realm and vast developments have been made over the past many years. However, travel demand forecasting tools used in practice by transportation planning organizations, and the like, have lagged behind, relying on the tried and true traditional, aggregate 4-step approach to travel demand modeling. Many reasons for such a paradox are possible, but one cause is that there is little work that directly relates these two approaches from a model performance perspective. The aim of this research is to provide just such a comparison, particularly relating to calculations of traveler welfare. A traditional, aggregate model and an activity-based microsimulation model of travel demand were developed in parallel using the same data for Austin, Texas. The models were applied for both a base scenario and several policy scenarios to test model performance and sensitivity to inputs. The spatial distribution of traveler welfare implied by these scenarios illuminates a variety of key differences in the ways these two models perform, and some evidence suggests that the activity-based model may boast a greater sensitivity to inputs. Additional outputs are produced to demonstrate the level of segmentation that can be attained in the generated outputs using microsimulation methods. The analysis performed in this research serves as a comparison of these two competing approaches to travel demand forecasting and offers some insight into the benefits of the activity-based approach from a practical standpoint.

## INTRODUCTION

Travel demand forecasting has been used widely for over 40 years. The earliest models of travel demand were intended to provide a tool to inform future infrastructure investments. Since that time, however, the focus for policy decisions has shifted from such long-term capital investments to shorter-term policies such as congestion management, promotion of alternative transport modes, and demand management (Bhat and Koppelman, 1999). This is due in part to the onset of environmental and transportation legislation like the 1990 Clean Air Act Amendment and the Intermodal Surface Transportation Efficiency Act (ISTEA), but also due to rising financial costs of such investments as practical space limits are reached. As policy decisions have changed, the questions posed to our travel demand forecasting models have changed, and behavioral travel theory has become an increasingly important component of the models.

The aggregate approach to travel demand involves a 4-step process. While not void of any behavioral theory, traditional aggregate models offer relatively few opportunities to incorporate behavioral mechanisms. The basic unit of these models is the trip, which ignores interactions among trips that are part trip chains. Moreover, the approach fails to recognize interactions that occur between different tours; hence, scheduling of trips is not considered. Finally, the trip-based method fails to recognize that travel is in fact a derived demand from the demand for activities themselves. In addition to a focus on trips, there is also a substantial amount of aggregation that generally occurs in traditional models. Vovsha et al. (2004) discuss these three types of aggregation: spatial, demographic, and temporal.

Limitations in the traditional, aggregate approach have led to the emergence of more sophisticated travel forecasting methods. Activity-based models of travel demand generally incorporate several attributes that manifest in added behavioral realism relative to their traditional counterpart. First, the consideration of activities as opposed to trips necessitates a tour-based approach to capture interactions and interdependencies between activities/trips as part of the same tour. Second, an activity-based approach can depict tour inter-relationships (i.e., relationships between different tours across the day). Third, interdependencies across individuals of the same household are introduced. And finally, the activity-based approach introduces an explicit hierarchy of activities/trips, although this hierarchy is not yet fully understood, and specification of different hierarchical structures will affect model estimation (Guo and Bhat, 2001). Regardless, this hierarchy is an important component in the sequencing and scheduling of travel for an individual's daily pattern.

There have been substantial advances in activity-based theory over the past 20 years, and the theoretical basis for moving from the more traditional, aggregate models to activity-based models seems rather clear; yet the use of aggregate models in practice remains widespread. One major reason for this could be that the literature offers next to nothing in terms of comparing the performance of these two different approaches; hence, planning organizations may be reluctant to invest in such costly approaches. Outside of work by the authors (Lemp et al. [2007]), only a couple reasonably relevant comparisons of models similar to these appears to have been presented or published. Walker's (2005) modeling of Las Vegas, Nevada provides a direct comparison of a microsimulation model with a rather traditional model. However, the basis for comparison was a trip-based microsimulation approach (not activity-based). Griesenbeck and Garry (2007) compare the specification of Sacramento's past, trip-based model to a newer, activity-based model on the basis of inputs and outputs, run times, effort required, and the process of model validation. They also test the sensitivity of the models to key demographics, but no other results were available or discussed. In contrast, this paper presents a direct comparison of traditional and activity-based microsimulation approaches, with an emphasis on results. Moreover, this work's focus on welfare measures under such model settings is highly unusual. Thus, this paper represents a continuation of previous work by the authors, but with a focus on welfare measures and their distribution across classes of the population (as opposed to system-level measures, such as total travel time, VMT, and speeds).

The remainder of this paper discusses the specification, application, and results related to changes in traveler welfare for two separate models of travel demand; one a traditional, aggregate type model and the other an activity-based microsimulation model. Earlier versions of the models and results are presented by McWethy (2006) and Lemp et al.

(2007), and those are focused on system-level comparisons. In contrast, this paper emphasizes traveler welfare computation methods and results, for both model systems. Welfare calculations at the level of individuals and within relatively narrow population segments illustrate how microsimulation techniques can better address a variety of important policy questions than their aggregate counterparts.

The two models were developed specifically for the purposes of providing a comparison between results. The models use the same datasets for calibration and contain some similar features to facilitate model comparison (e.g., population synthesis, auto availability, and traffic assignment). In addition, the models are both applied using the TransCAD GIS software package. Even with these shared attributes of the two models, certain questions remain difficult to answer regarding the two modeling paradigms. For instance, it would be difficult to suggest either model performs better than the other or that differences in model results are due to one factor or another. In fact, such questions may never be fully answered in such a context (except possibly in highly idealized and tightly constrained settings with simulated data). The purpose this paper is to highlight differences in model complexity, identify the types of results that can be achieved, and offer a sense of how the two models perform.

## DEMAND MODEL DESCRIPTION

The methodology used in estimation of the aggregate and activity-based models of travel demand was carefully structured to provide the most consistent basis for comparison of results and model sensitivities. Because of this, the two models share several features, including population synthesis and auto availability modules. However, the models are really quite distinct. This section describes the models rather briefly. More details on model components, assumptions, limitations, and estimation results can be found in Lemp (2007).

### Austin Data Sources and Details

Data used for model estimation for both models come from the 1996-1997 Austin Travel Survey (ATS), as provided by the Capital Area Metropolitan Planning Organization (CAMPO). After data cleaning, the data contained 1,609 households, 3,960 persons, 15,695 trips, 5,182 home-based tours, and 407 work-based tours. In addition to its travel survey, CAMPO provided a coded network for the region, zone to zone travel times, distances, and costs (for transit skims), zonal land use data, and truck/commercial vehicle and external-zone[1] trip tables.

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[1] These external-zone trips include at least one trip end in one of the region's 43 external zones. In the ATS trip data, external trips account for about 1.4% of all trips, though other external trips are considered in the trip tables as well. These external trip tables include external to external (i.e., trips passing through the region), external to local (i.e., trips produced outside the region that are destined for an internal zone), and local to external trips.

The other source of data was the 2000 Census and the corresponding Public-Use Microdata Sample (PUMS) found at the Census website (www.census.gov). This data was used in the population synthesis procedure for the creation of the base population of households and persons.

**Population Synthesis and Auto Availability**

While the population synthesis procedure is an important one, it is not discussed in detail here due to space constraints. For a detailed discussion of the procedure, the reader is referred to McWethy (2006) and Lemp (2007). However, it is important to note that while population synthesis is unnecessary for the aggregate model, the same procedure was used, and synthesized households were aggregated by type (across the 24 classes) for each TAZ. In doing so, consistent inputs were generated for both models providing a more uniform basis for comparison between the two.

Since our population synthesis procedure does not control for the number of automobiles in a household, an auto availability sub-model was calibrated specifically for use in both TDMs. The model is structured in a discrete choice framework using an ordered-probit structure with four alternatives (0, 1, 2, or 3+ autos), and controls for several household attributes and household location characteristics.

**Traditional Model Specifications**

The traditional TDM employed here relies on techniques used in several existing TDMs for the Austin region (CAMPO, 2000; Smart Mobility, 2003; Gupta, 2004; Kalmanje and Kockelman, 2004; and Kalmanje, 2005), all based on data in the 1996-1997 ATS, as well as many standard techniques outlined by Martin and McGuckin (1998). All components were estimated to facilitate comparison with the activity-based model, while maintaining a rather traditional (though not highly simplistic) structure. In addition, each model is segmented by trip type (home-based work [HBW], home-based non-work [HBNW], non-home-based work [NHBW], and non-home-based non-work [NHBNW]).The model uses reasonably standard and streamlined approaches: regression models for trip generation; multinomial logit models for destination, mode, and time-of-day (TOD) choice; and constant vehicle-occupancy assumptions.

Trip production models (segmented by trip type) were estimated using ordinary least squares (OLS) methods. While home-based (HB) trip productions[2] are modeled at the household level, non-home based (NHB) trip productions[3] are modeled at the TAZ level since they do not have either of their trip ends based at the household (by definition).

As is relatively common in destination choice models, a logsum (expected maximum utility

[2] Home-based trip productions refer to one-way trips where either end (origin or destination) of the trip is the home zone. In the destination choice model, the attraction zone for each trip production is found. Following destination and mode/TOD choice, HB trip production/attraction tables are converted to origin/destination tables by applying factors.

[3] Non-home based trip productions (unlike home-based) are synonymous with trip origins.

or minimum cost) formulation across modes and times of day (TODs) was used to estimate (and then apply) multinomial logit models of destination choice (segmented by trip type). The logsum from origin *i* to destination *j* for trip purpose *p* is computed as shown in equation 1, across all modes *m* and time periods *t*. Here, there are four modes and four time periods, which yield 16 terms in the logsum formula.

$$LOGSUM_{ijp} = \ln\left(\sum_{m,t \in C} \exp\left[U_{ijmpt}\right]\right) \tag{1}$$

where $U_{ijmpt}$ is the systematic (non-random) utility associated with mode *m* during time period *t* from zone *i* to zone *j* for trip purpose *p*.

For mode and TOD choice, joint multinomial logit models were estimated for each of the four trip types. Here the mode alternatives include drive alone (single occupancy) auto, shared ride (occupancy greater than 1) auto, transit, and walk/bike. The four TOD alternatives include AM peak (6am – 9am), midday/evening (9am – 3pm and 7pm – 9pm), PM peak (3pm – 7pm), and overnight (9pm – 6am). Because of the unreasonable values of travel time implied by the models (less than $2/hour and sometimes negative[4]), and the desire for time-sensitive travel patterns (in mode, route, and destination choices), values of travel time were assumed to be $9 per hour per person for work trips and $4.50 per hour per person for non-work trips. In addition, marginally relevant vehicle operating costs (for purposes of mode choice) of $0.10 per mile were assumed, which approximate past gasoline costs[5].

**Activity-Based Model Specifications**

The activity-based model was originally structured much like the MORPC model (PB Consult, 2005), though several simplifications were made. However, they do provide several important improvements on the model structure used for previous versions of this multi-year work, as presented by McWethy (2006) and Lemp et al. (2007). The current model structure, as shown in Figure 1, is discussed here now.

*Travel Generation Modules*

The notion that persons are assigned an overall daily pattern of activity is widely used in discrete choice models of activity-based travel demand (e.g., the Portland model [Bowman et al., 1998; Bowman, 1998], the MORPC model [PB Consult, 2005], the SACOG model [Bowman and Bradley, 2006], and several others [Vovsha et al., 2004]). Here MNL models were estimated for primary activity pattern (PAP) choice. PAP alternatives include

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[4] Both mode and nested mode-TOD models resulted in estimates of VOTTs that were generally very low, across trip purposes (typically less than $2/hour and sometimes negative). This may be due to travelers having a poor perception of actual travel costs and times, across modes, for their intended trips, and/or CAMPO's cost and time assumptions not matching travelers' realities. Prior analyses of ATS and CAMPO data suggest the same problem (see, e.g., Gulipalli [2005] and Gupta [2004]).

[5] Such travel costs may be actual or perceived. Actual costs may be $2 per gallon for a 20 mi/gal fleet fuel economy average, or $4 per gallon for a 40 mi/gal fleet. In practice, however, many travelers undervalue marginal gasoline costs, so per-gallon costs may be lower or fuel economies higher.

work patterns (1 or 2+ work tours), a school pattern, university pattern, work and university pattern (i.e., 1 or more work tour and 1 or more university tour), non-mandatory pattern (i.e., no work, school, or university activities), and stay-at-home pattern. Similar to the MORPC model, maintenance activities (e.g.., shopping, escorting, and banking) are modeled at the household level and allocated to household members, while discretionary activities (e.g., eating out and exercise) are modeled at the level of individuals. Finally, work-based sub-tour generation, based at the primary work location, is modeled in an MNL framework.

*Tour Primary Activity Models*

Each tour has an associated primary activity. MNL models of primary destination choice (for each tour segmented by tour type) determine the location of each primary activity. Measures of accessibility are lower-level mode choice logsums, constructed similar to the logsums implemented in the aggregate model's destination choice specification. However, the logsums do not consider the time-of-day element in the same way. Instead, representative time-of-day periods were selected for departure time and return times for each activity purpose, similar to the construction of the MORPC activity-based model.

Time-of-day is modeled in two sub-models: tour departure time and duration models (both segmented by travel purpose). These models represent a substantial departure from the tour TOD models employed by MORPC. In particular, the aggregate units of time considered for our model are six TOD periods: early morning (EM, before 6am), AM peak (AM, 6am-9am), midday (MD, 9am-3pm), PM Peak (PM, 3pm-7pm), evening (EV, 7pm-9pm), and late night (LN, after 9pm).

These models both employ MNL structure. Since an individual may undertake multiple tours, careful consideration was necessary in both the estimation and application of these models to ensure consistency in an individual's overall scheduling of tours (i.e., temporal constraints limit the feasible scheduling alternative choice sets). To this end, a hierarchy was implemented among tours for an individual for the sequencing in which tours are scheduled. Once the first tour is scheduled, the choice set for subsequent tours is limited to the representative set of feasible options. In addition, it was useful to control for variables reflecting the presence of subsequent tours.

As with the aggregate model of mode choice, the tour-based mode choice model, considers fixed values of travel time, though travel times and costs are bi-directional here (instead of uni-directional). In addition, the same choice alternatives are considered, although the mode alternatives are specific to the entire tour, not individual trips. To economize on models, the tour mode choice model does not employ full segmentation by primary activity purpose, but does use control variables specific to the primary activity, and the models use a MNL structure.

*Tour Secondary Activity Models*

A tour stop frequency MNL model determines the number of secondary activities on a tour: no stops, 1+ stops on the first half-tour, 1+ stops on the second half-tour, or 1+ stops on both half-tours. The model is conditional upon the tour mode chosen, tour departure time, and tour duration, and is segmented across tour travel purposes. The purpose of stops is not modeled, however.

If the stop frequency choice model application produces additional tour stops beyond the primary stop, the stop destination, TOD, and mode choice models are activated. For stop destination choice, generalized cost measures specific to the tour mode are used. Separate measures are used from the trip origin and to the tour's ending destination (tour primary destination [if stop is on first half-tour] or the tour anchor [if stop is on the second half-tour]). Here, the trip origin is the actual origin of the trip, which may be different from the origin location of the half-tour if multiple stops exist for the same half-tour. In addition, if there are multiple stops on the same half-tour, coefficients for the generalized cost to the tour's ending destination are allowed to vary. The models take a MNL structure, segmented by tour type.

Stop TOD choice is performed in a rather unique way. Two choice alternatives are permitted: (1) the choice of the same TOD as the previous trip, and (2) the choice of the TOD immediately following that TOD, which is only available if global and individual time constraints allow. These constraints tend to be very different systematically for stops on the first half-tour versus the second half-tour. For this reason, segmentation across half-tours was considered in these models using MNL techniques.

Trip mode choice is the final stage in this activity-based paradigm, and is applied to all trips. In general, mode tends to be consistent/unchanging across trips in a given tour (about 89% of modeled trips share the same mode as the tour mode); thus, tour mode choice has substantial predictive power for trip mode choice. Like the other mode choice models discussed in this paper, the trip mode choice model was structured as a MNL model.

**Traffic Assignment and Model Feedback**

The traffic assignment routine for both the aggregate and activity-based models is the same and is based on trips (as opposed to tours). The routine considers four TODs (AM and PM peaks, midday/evening, and overnight)[6], and typical deterministic user equilibrium (DUE) assignment routines were implemented using TransCAD GIS. Before traffic assignment is implemented, fixed truck and external trips provided by CAMPO were added onto modeled trip tables[7]. While this procedure is not ideal, it is not uncommon and provides a simple way for dealing with travel of these types.

In model application, full feedback (from network assignment to trip patterning) is an important component to ensure consistency between input and output travel times. In the aggregate model, output travel times are used in the upper level destination choice models.

[6] Midday and evening trip tables and late night and early morning trip tables from the activity-based model were aggregated prior to assignment to be consistent with the TOD periods of the aggregate model.
[7] Truck and external trip VMT accounted for approximately 2.5 and 2.8 million VMT daily, respectively. This represents about 15-20% of all daily VMT for the region.

In the activity-based model, travel times are introduced at the point of primary tour destination choice. To facilitate convergence, a method of successive averages (MSA) was utilized here (Boyce et al., 1994). The aggregate model was run to reach full convergence in each TOD while the activity-based model runs completed four iterations since each iteration requires a great amount of time for model application. In general, however, four iterations were enough to reach reasonable levels of convergence[8], though it was not required.

## WELFARE CALCULATIONS

For the *aggregate model*, normalized differences in logsums of systematic utilities are the basis for welfare change estimates relative to the base scenario. As indicated by Ben-Akiva and Lerman (1985), when divided by the marginal utility of money, these logsum differences provide a measure of consumer surplus (CS). The differences in destination choice logsums for the aggregate model provide a fairly complete evaluation of welfare, since mode and TOD choices are nested in the destination choice model. The consumer surplus can then be expressed as the normalized difference in the expected maximum utilities before and after a policy change, which causes a change in network performance:

$$CS_{iph} = \frac{1}{\gamma_p}\left[\ln\left(\sum_{j\in C}\exp(V_{ijph}{}^{A})\right) - \ln\left(\sum_{j\in C}\exp(V_{ijph}{}^{B})\right)\right] \qquad (2)$$

where $CS_{iph}$ is the expected change in the monetized value of maximum utility across alternatives. This change in consumer surplus (or compensating variation) is for trips originating at origin $i$ engaged in trip purpose $p$ by household of type $h$, and $B$ and $A$ denote the before and after travel conditions. $V_{ijph}$ is the systematic destination choice utility, $C$ is the choice set of all zones, and $\gamma_p$ is the marginal utility of money.

As shown by Kalmanje (2005), the marginal utility of money from such nested model structures can be expressed as follows:

$$\gamma_p = \beta_{(ls)p}\beta_{cp} \qquad (3)$$

where $\beta_{(ls)p}$ is the logsum coefficient from the destination choice model for trip purpose $p$, and $\beta_{cp}$ is the cost coefficient from the mode choice model. Hence, the marginal utility of money varies only by trip purpose, as shown in Table 1 (for the aggregate model).

Changes in consumer surplus (CS) are computed at the trip level using Equation 2, but these are most interesting at the level of individuals. Therefore, average trip making per person by purpose provided a weighted sum of welfare impacts. On average, each

[8] For convergence criteria, the TransCAD gap convergence formula was used based on differences in link flows from one iteration to the next. TransCAD suggests the use of a convergence level of 0.01 or less. Here, reasonable levels of convergence is used to suggest values not greater than 0.02.

Austinite makes 0.828 HBW trips, 1.92 HBNW trips, 0.491 NHBW trips, and 0.749 NHBNW trips on a typical weekday. These values are applied at the zonal level to develop an average welfare impact per person living in that zone. However, NHB trips are not made from the home zone, so NHB welfare effects were averaged over all zones (similar to Gulipalli [2005]), as shown in equation 4, and added to each zone's computed HB trip-making consumer surplus.

$$CS_{NHB} = \frac{1}{n}\sum_{i \in C}^{n} CS_{i,NHB} \tag{4}$$

where $n$ is the total number of zones.

Since the *activity-based model* does not contain an obvious or econometrically meaningful nesting structure, calculating welfare effects is less clear. However, the tour-mode choice and destination choice models display such a nesting structure. Therefore, CS changes are defined specifically by the tour unit, ignoring the welfare changes that occur at the trip level. As in the aggregate model, the tour destination choice model represents the upper level of a nest with tour mode choice embedded in the lower level. A similar welfare measure can then be formulated (equation 5), but at the tour level (instead of the trip level). In addition, such welfare effects are not only specific to each origin and tour purpose, but also to individuals - of known person type and PAP.

$$CS_{indp} = \frac{1}{\gamma_p}\left[\ln\left(\sum_{j \in C} \exp(V_{ijndp}{}^{A})\right) - \ln\left(\sum_{j \in C} \exp(V_{ijndp}{}^{B})\right)\right] \tag{5}$$

where $CS_{indp}$ is the change in CS for individual $n$ choosing PAP $d$ with tour type $p$ from origin (home) zone $i$, $B$ and $A$ again represent the before and after systematic utilities, $V_{ijndp}$ is the systematic utility from origin $i$ to destination $j$ for tour type $p$ by individual $n$ choosing PAP $d$, $C$ is again the choice set of all destination zones $j$, and $\gamma_p$ is (as before) the marginal utility of money for tour type $p$.

The marginal utility of money is formulated much like equation 3, except that it now refers to each of the seven tour types (as shown in Table 1), instead of trips.

Here, unlike the aggregate model calculations, one must compute welfare impacts for each person individually (instead of an average person), since tour mode choice includes household and individual characteristics. In addition, there are probabilities associated with each person choosing different PAPs and numbers of tours. Instead of computing welfare effects for each tour combination possibility, the chosen PAP and number of tours of each type for each individual from the base scenario are considered. Essentially, this means that travel generation and trip chaining decisions (into tours) are held constant. While individuals certainly have opportunities to shift their travel patterns from one scenario to another, trip and tour generation will be less affected than trip-level behaviors in the model, since the upstream travel generation models are insensitive to network performance. Of course, the same holds for welfare calculations in the aggregate model, and this is a characteristic of nearly all models of travel demand.

For comparison purposes, zonal level welfare values were computed for the activity-based model, similar to the aggregate calculations. This was done by averaging the consumer surplus for each (synthetic) individual residing in a given zone. Since the systematic utility calculations for the aggregate model are disaggregated by household type (i.e., those with and without a surplus in autos), zonal level calculations of welfare changes for each household type must be performed individually. For comparison purposes, activity-based model calculations are also disaggregated by the same auto surplus variable. Due to space constraints and because the results are largely similar, this paper presents only the results for households without a surplus in autos.

## SCENARIO DEVELOPMENT

This section provides a synopsis of the scenarios considered in model application. The traditional and tour-based TDMs described in the previous section were applied to four different scenarios in order to better understand model sensitivities to network changes and job distributions. While each scenario is interesting, the main objective of this work is to compare how these two modeling approaches perform. In particular, it is of interest to understand what (if any) benefits can be had through activity-based modeling.

The first scenario is the base scenario, which provides a status quo representation of the region, as well as a basis for comparison. In the second scenario, capacity of freeways is expanded, to represent a reasonable system expansion project. Capacities for the region’s two main north-south corridors (IH-35 and Loop 1) were modified, by simply adding a lane in each direction of each corridor. Total lane miles added to the network are over 200 in this scenario, which represents a capacity increase of about 37% for these two corridors, or roughly 9% of the region’s coded transportation network (not including centroid connectors).

The third scenario is a centralized employment scenario where the location of jobs is concentrated in the region’s most central and densely developed zones. For zones classified (by CAMPO) as rural (506 zones, about 47% of total), half of the basic, retail and service jobs were removed and for zones classified as suburban (342 zones), 30% of such jobs were removed. All removed jobs were then distributed among the zones classified as urban (201 zones) and CBD (25 zones) in proportion to these more central zones employment totals, resulting in a 58% increase in their (total) employment.

The last scenario is one in which fixed tolls are introduced along key transportation corridors. To provide some consistency with the expanded capacity scenario, the selected corridors for tolls were IH-35 and Loop 1. Since IH-35 is not so congested outside of Austin, tolls were not applied to its entire length. Instead, they were applied to a shorter segment near central Austin (about 20 centerline miles). For Loop 1, the same section used in the expanded capacity scenario is used here, since it is largely congested. Tolls for these corridors were set at $0.10 per mile.

## RESULTS

While the system-level results of these analyses would provide some interesting insight, such analyses have been provided in previous literature (see McWethy, 2006; Lemp et al., 2007; and Lemp, 2007). The results presented in this section emphasize the distribution of net benefits and costs (due to scenario shifts) across the region's households and travelers. Here, traveler welfare is measured as the change in consumer surplus from the base scenario to each other scenario. While the aggregate model welfare calculations are simpler and more comprehensive, the aggregate nature of the model's outputs does not allow for detailed benefit analysis of user groups. The activity-based model, on the other hand, offers many more opportunities for benefit analysis of different user groups, but the welfare calculations are rather cumbersome and require some simplifications. Since the calculation of welfare for the activity-based model ignores changes in consumer surplus at the trip level, welfare analyses are not directly comparable across the two modeling approaches. However, it is theorized that such trip-level effects in the activity-based model may be rather small in comparison to the relatively more important tour-level effects.

### Welfare Results

Figure 2A shows the spatial distribution of welfare change predictions for the aggregate model under the expanded capacity scenario. One key feature we see is that for each origin zone, the consumer surplus is positive. In other words, everyone benefits. In general, this seems reasonable since link travel times should be reduced in most cases under the expanded capacity scenario. The spatial variation in the consumer surplus indicates that persons gaining the most tend to be along (and especially to the ends) the expanded capacity corridors. Those gaining the least tend to be zones on the periphery (especially in the east) of the region, and the central zones since these zones are already quite near many job centers.

Figure 2B shows the spatial distribution of consumer surplus changes under the expanded capacity scenario, as predicted by the activity-based model. The spatial distributions of benefits are very similar to those of the aggregate model, but levels of consumer surplus for the activity-based model tend to be smaller in magnitude (median values of $0.12 per person – versus $0.27 per person for the aggregate model). If the additional "trip-level" benefits (as opposed to "tour-level" only) were realized in the welfare calculation for the activity-based model, the overall benefits would be greater, though they would probably still be lower than the aggregate model's predictions.

Of course, such a policy is not costless; someone will be paying for the capacity expansion, so true net benefits may not be positive. Litman (2002) suggests that capacity expansion for freeways in built-up areas costs between $5 million and $10 million per lane mile of added freeway. If it is assumed that the entire length (16 centerline-miles) of Loop 1 is located in built-up areas, 30 (of the 85) centerline miles of IH-35's capacity expansion lie in built-up areas, and the freeways cost $5 million/lane-mile in built-up areas of Austin, Texas and $3 million per lane mile elsewhere, the total cost of the capacity expansion project would be $790 million. If average welfare change per person is applied at the zonal level to each individual in the region, the total daily benefit estimated from the aggregate model is about $285,000 per day (or $104 million yearly). If the lifetime of the new lanes is roughly 20 years, the aggregate model predicts total benefits in the amount of $1.3 billion (assuming an annual discount rate of 5%) or $885 million (with a 10% discount rate). This amounts to net benefits ranging from about $100 million to over $500 million depending on the discount rate. Not surprisingly, calculation of total daily benefit using the activity-based model yields a smaller total ($173,000 daily or $63 million yearly). Discounting at 5% per year, total benefits for this scenario, after subtracting capital improvement costs, are negative (net loss of $4 million). Of course, if trip-level benefits (described above) were included in these welfare calculations, net benefits may be experienced. Moreover, the addition of new residents and travelers to the region over the coming 20 years will increase travel times, but also make delay costs more severe, thus improving the net present value of such an investment.

One main feature of the consumer surplus changes, as predicted by both models for the centralized employment scenario (Figure 3), is their organized and concentric nature, ringing central Austin. The biggest gainers are concentrated in the city center, as expected, since this is the location to where most employment was moved. The biggest losers tend to be on the periphery of the region, especially to the north. However, the aggregate model (Figure 3A) predicts almost no losers (i.e., welfare gains are positive for almost all zones). The implication of this is that Austin apparently does not have enough employment in central zones, and centralizing employment could be a good thing for everyone in the region. This result seems rather peculiar since there is already much congestion to and from Austin's downtown in the AM and PM peak periods. In contrast, the activity-based model predictions (Figure 3B) are somewhat more modest (and reasonable)[9]. It is expected that the centralized employment scenario would generate both winners and losers, but the aggregate model predicts almost all winners. The activity-based model predicts both winners and losers, with about an equal number of both. It seems that the welfare predictions of the activity-based model for this scenario are more reasonable.

Like the other two scenarios, both models predict similar spatial trends in welfare for the tolling scenario (Figure 4). Not surprisingly, the biggest losers tend to be located nearest to the tolled corridors, and to their south. Those zones with residents that lose the least tend to be on the fringes of the region, farthest from the toll ways. Though almost all are predicted to lose under this scenario, net benefits can be calculated as the sum of welfare change for each person in the region plus the revenue generated from the tolls.

[9] For households without auto surplus, the aggregate model's 95$^{th}$ percentile zonal winnings per person were $0.936 per day, and the 99$^{th}$ percentile winnings were $1.00 per day. The comparable winnings predicted by the activity-based model were $0.579 per person per day at the 95$^{th}$ percentile and $0.763 per person per day at the 99$^{th}$ percentile.

For the aggregate model predictions, the tolls cost the region's population roughly \$163,000 per day, but they generate about \$269,000 per day, for a yearly ***net*** benefit just over \$38 million. If a lane-mile costs \$5 million, and one discounts future toll earnings (assuming no population/travel demand growth), Austin may be able to build over 90 new freeway lanes-miles from such toll revenues, expanding capacity in the most congested corridors of Austin, reducing travel times and possibly converting all travelers' welfare losses into gains[10]. Alternatively, one might consider returning all congestion-based toll revenues to travelers in the form of travel budgets or "credits", as proposed in Kockelman and Kalmanje (2005); this can have great benefits in terms of offsetting any toll-related welfare losses, particularly among lower-income households (Kalmanje and Kockelman, 2004). The activity-based model predicts welfare losses of about \$132,000 per day, but daily revenues at around \$241,000. Over the course of a year, net benefits total nearly \$40 million, nearly the same prediction as in the aggregate model. Of course, when factoring in the fact that trip-level welfare changes are neglected in the activity-based model, net benefits would likely total something less than predicted here. Thus, the aggregate model predictions of total welfare change are likely higher than those from the activity-based model predictions.

To reiterate, the comparisons of welfare across the two modeling approaches are imperfect, since welfare measures are computed differently. The aggregate welfare computations are rather comprehensive across all travel, while the activity-based welfare calculations are constrained to the home-based tour level (for reasons described previously). Nevertheless, the analyses provide some interesting insights into how these two models spatially predict welfare change under different scenarios. If it is assumed that the exact welfare changes for the activity-based model are not dramatically different from our calculations, it is possible to draw some more definitive conclusions across these modeling paradigms. In the case of capacity expansion, one would probably see greater benefits overall, though these additional benefits would likely remain less than those predicted by the aggregate model. In the case of centralized employment, calculated benefits were close to zero, so there is no reason to think that the overall welfare would change much if other forces were allowed to play a role. And in the case of tolling, there are likely to be even fewer benefits, since overall traveler welfare fell in all cases. Thus, in each scenario, it seems that the welfare predictions of the aggregate model are greater than those of the activity-based model. In at least one case, that of centralized employment, the aggregate model predictions appear to be too high. This may indicate that the other scenario's aggregate model predictions are high as well.

While is difficult to establish the exact causes for the discrepancies between the two models' welfare predictions, one possible reason may be the great amount of aggregation that occurs in the trip-based model. After trip generation, almost all characteristics are lost about the individual/household producing the trip: only trip-type information is retained. In

[10] In the longer term, induced demand may take over, congesting such highways again. Nevertheless, these induced effects are arguably the result of other benefits, such as better home alternatives or shopping centers at greater distances.

contrast, there several more types of travel in the activity-based model, and all household, individual traveler, and PAP attributes are retained, thus avoiding aggregation errors. This situation is similar to averaging over individuals before evaluating a function, versus evaluating the function for each individual and then averaging. Thus, the activity-based method is arguably more accurate.

While the spatial distribution of welfare change is an important consideration in policy analysis, welfare change of different population segments is also of great interest. The microsimulation approach used for the activity-based model permits these sorts of illuminating – and often equity-driven – investigations, while the aggregate model does not, in general.

**Welfare by Traveler Groups**

Since one can compute consumer surplus changes for each individual in the activity-based model, it is possible to not only investigate welfare spatial distribution but also its demographic distribution. For instance, populations can be segmented by income (and neighborhood), and equity-focused analyses can be performed. Castiglione et al. (2006) indicated that this is an area of growing concern for planners in the United States. Here, just such an analysis is provided for the activity-based results.

The analysis discussed here is limited to three segments of the population: older individuals (over age 64), non-workers, and low income individuals (from households with income less than $25,000), along with combinations of such attributes. The same welfare measure (as defined previously for the activity-based model) is used, and average welfare changes are computed for each traveler type. Table 2 shows the welfare change for each of the population types under each of the three alternative scenarios.

Under the expanded capacity scenario, all three types examined here demonstrate lesser benefits in comparison to the average person. This is not so surprising since all three are expected to generate less travel in general than the population as a whole (and less travel allows for fewer benefits). When combinations of the population types are analyzed, the non-worker type tends to dominate the calculations. This indicates that being a non-worker is a more meaningful indicator of expected welfare effects than is income or age, and may be a consequence of the model structure itself (travel generation is segmented by person type [e.g., non-workers versus all others] at the start of the model) since similar trends are apparent for the other two scenarios. Under the centralized employment scenario, all three segments of the population are better off than the average, while under the tolling scenario, only low income individuals are better off. This is a peculiar finding since one would expect low income individuals to be less willing (and able) to pay tolls, and consequently, worse off. However, the model specifications for value of travel time do not vary by income level; thus, the model does not differentiate individuals on the basis of willingness to pay tolls (which is a model weakness). In the welfare calculations, income level is only recognized explicitly in its effect on the systematic utilities of tour mode choice, and implicitly through its effect on auto ownership (which also has an effect on the systematic tour mode utilities). As income rises, the systematic utility of transit mode decreases and, in general, auto ownership level increases. As auto ownership levels increase, systematic utilities of shared ride, transit, and walk/bike modes decrease. And therefore, lower income households will generally not be as negatively affected by tolls as would higher income households, which is an unfortunate consequence of the activity-based model specifications.

## CONCLUSIONS

The purpose of this research was to provide an objective comparison between welfare calculations of a traditional, aggregate model of travel demand and a microscopic tour-/activity-based model of travel demand. For the expanded capacity scenario, the aggregate model predicted considerable benefits ($500 million benefit over 20 years), even after accounting for the cost of such a capacity expansion project. In contrast, the activity-based model predicted more modest user benefits, which resulted in a small net loss ($4 million over 20 years) after accounting for costs. Both models predicted travel enhancements under the centralized employment scenario (though the enhancements were much greater for the aggregate model). And both predicted almost identical welfare impacts of the tolling scenario, where tolling revenues were predicted to offset added travel costs by roughly $40 million per year. While these results are quite interesting, the focus of this study was in identifying what (if any) gains are realized by moving to activity-based, microsimulation approaches for travel demand forecasting (as opposed to traditional, aggregate methods). Based on these welfare analyses, it is not so clear that the activity-based model performed "better" or was more sensitive to the inputs, though the microsimulation technique is quite useful in analysis of population segments, as demonstrated in this work. The aggregate model welfare can only really be segmented across zones. As we become more concerned with equity analyses of transport policies, this sort of welfare analysis could prove critical. Of course, microsimulation methods also can be used with a trip-based approach.

At least in one case (the centralized employment scenario), the results did indicate, that the welfare calculations of the aggregate model were quite different than what one would expect. Moreover, if one accounts for the fact that trip-level welfare changes in the activity-based model were ignored, it seems that the overall welfare changes suggested by the aggregate model are greater for each scenario than the activity-based model. This could be a result of the model specifications used for the two particular models studied here, or it could be a consequence of the activity-based or microsimulation modeling paradigm.

Of course, there is no questioning that the estimation, calibration, and implementation of an activity-based microsimulation approach is a *much* more computationally and time-consuming endeavor than its aggregate counterpart. Here, the activity-based model required the estimation of 621 parameters across 43 models, while aggregate model required just 132 parameters across 13 models. Moreover, data structuring was a real issue. The travel survey data were provided in a trip-based form, which had to be converted to a tour-based form, and the creation of the interdependent variables (e.g., time-of-day and mode specific variables) was quite time consuming. In addition, model running times are also quite long for the activity-based model relative to the aggregate model. In this experience, the aggregate model required about 15 minutes to complete a single run (not including any feedback). Somewhat dramatically, a single run of the activity-based model was approximately 40 times longer (10-11 hours).

In summary, this study examined two separate approaches for travel demand forecasting. While there are many limitations to the modeling methodologies and analyses, this investigation has illustrated many of the key differences between the two approaches and has highlighted important advantages and disadvantages. From a planning perspective, this research could prove to be helpful in the choice of modeling approach. If any planning agencies fear that a new (activity-based) model will produce very different results from past model runs, the analysis provided here should temper such reservations: for this Austin case study, both model systems yield similar implications overall. Of course, the activity-based model system offers several advantages, and it appears that top MPOs can and should ultimately make the leap to activity-based models.

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**Figure 1: The Activity-Based Model System**

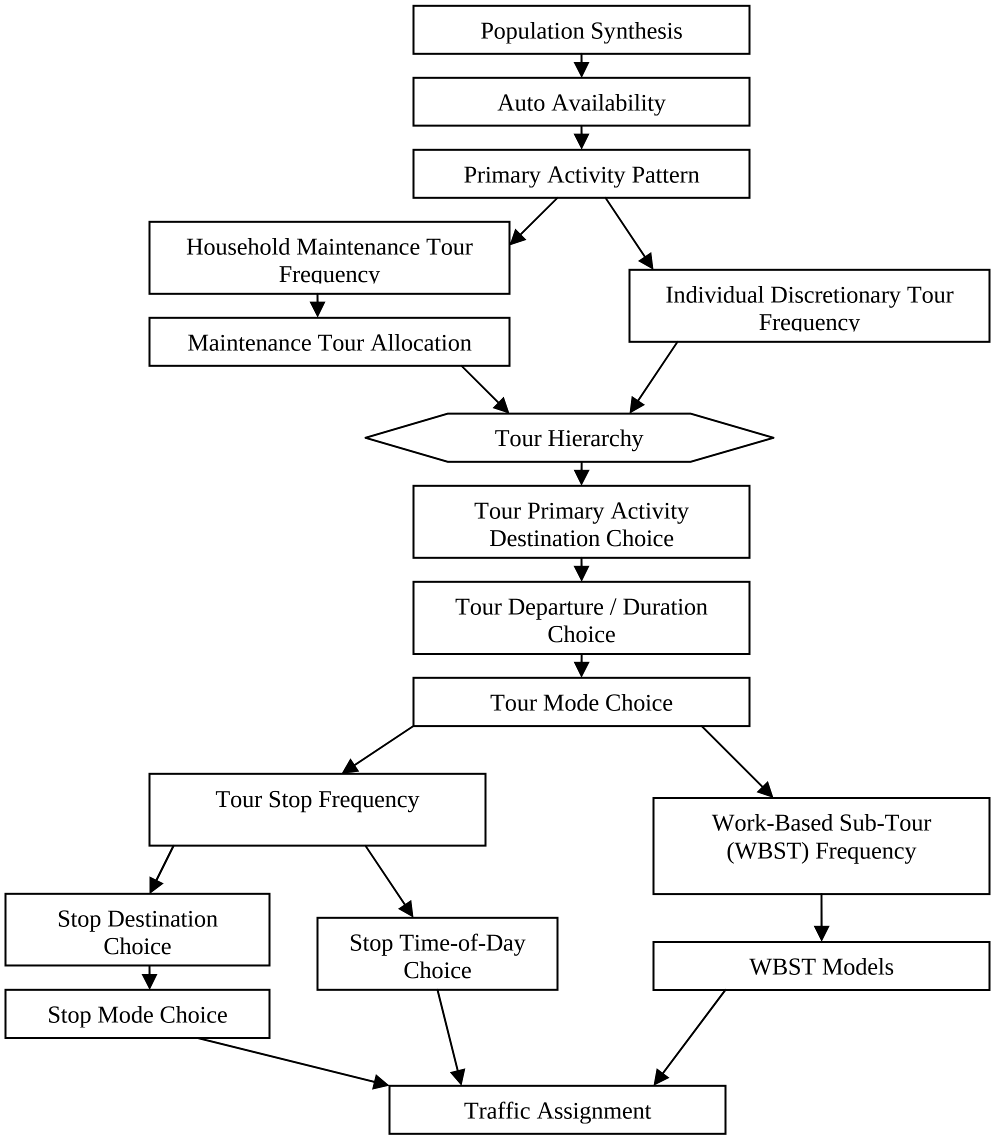

**Figure 2: Consumer Surplus ($/person) for Members of Households without Auto Surplus under Expanded Capacity Scenario**

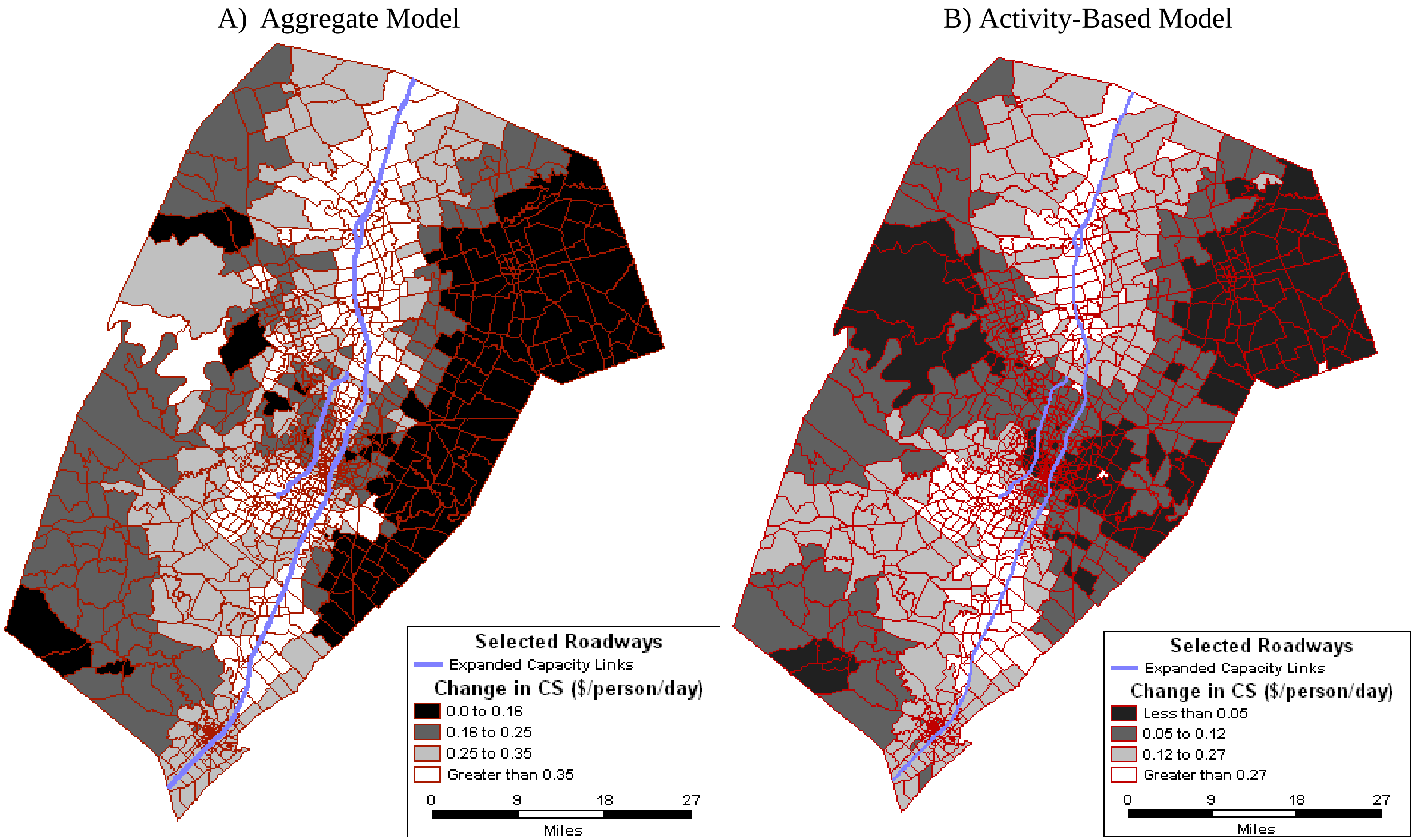

**Figure 3: Consumer Surplus ($/person) for Members of Households without Auto Surplus under Centralized Employment Scenario**

A) Aggregate Model

B) Activity-Based Model

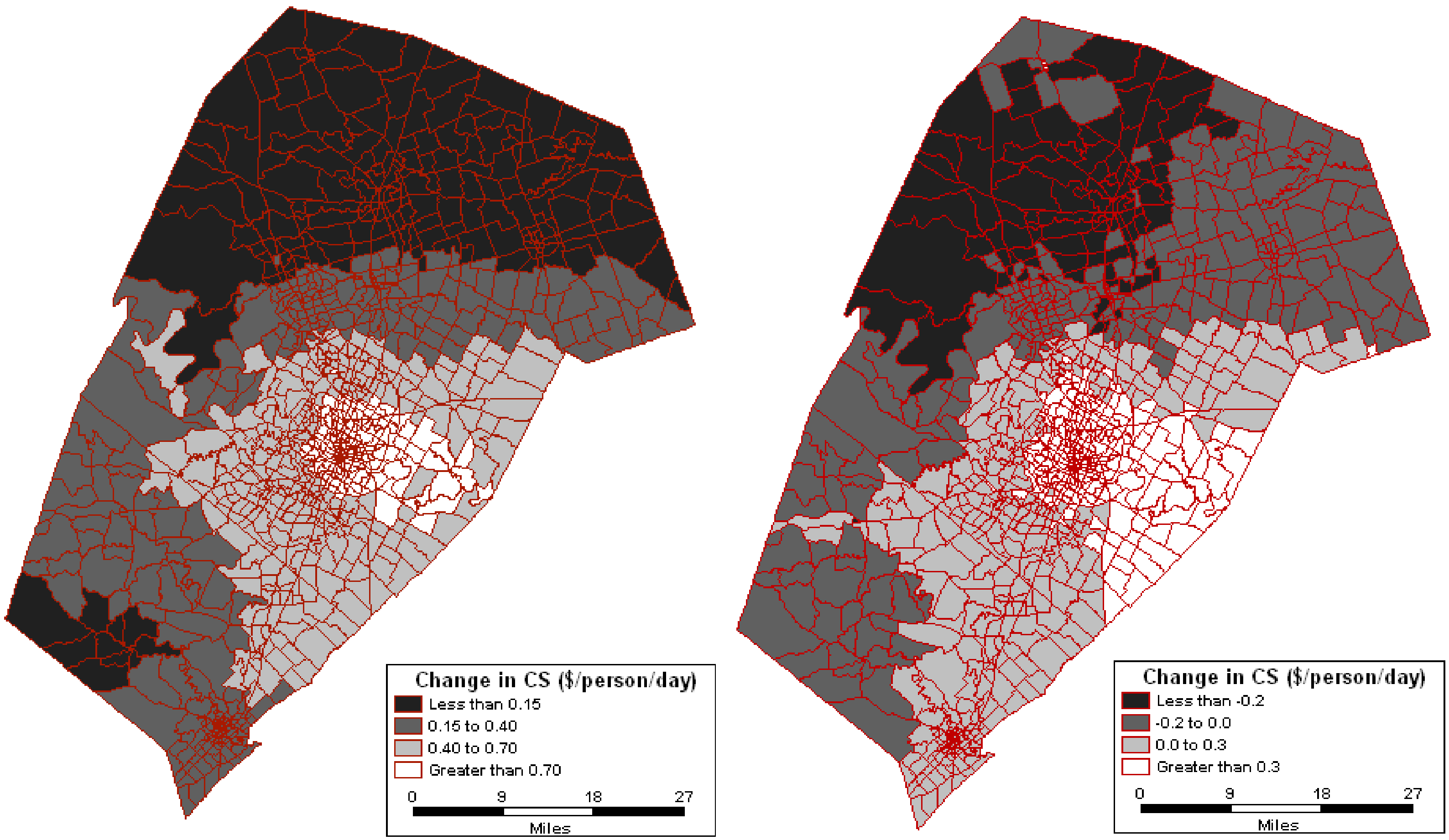

**Figure 4: Consumer Surplus ($/person) for Members of Households without Auto Surplus under Tolling Scenario**

A) Aggregate Model

B) Activity-Based Model

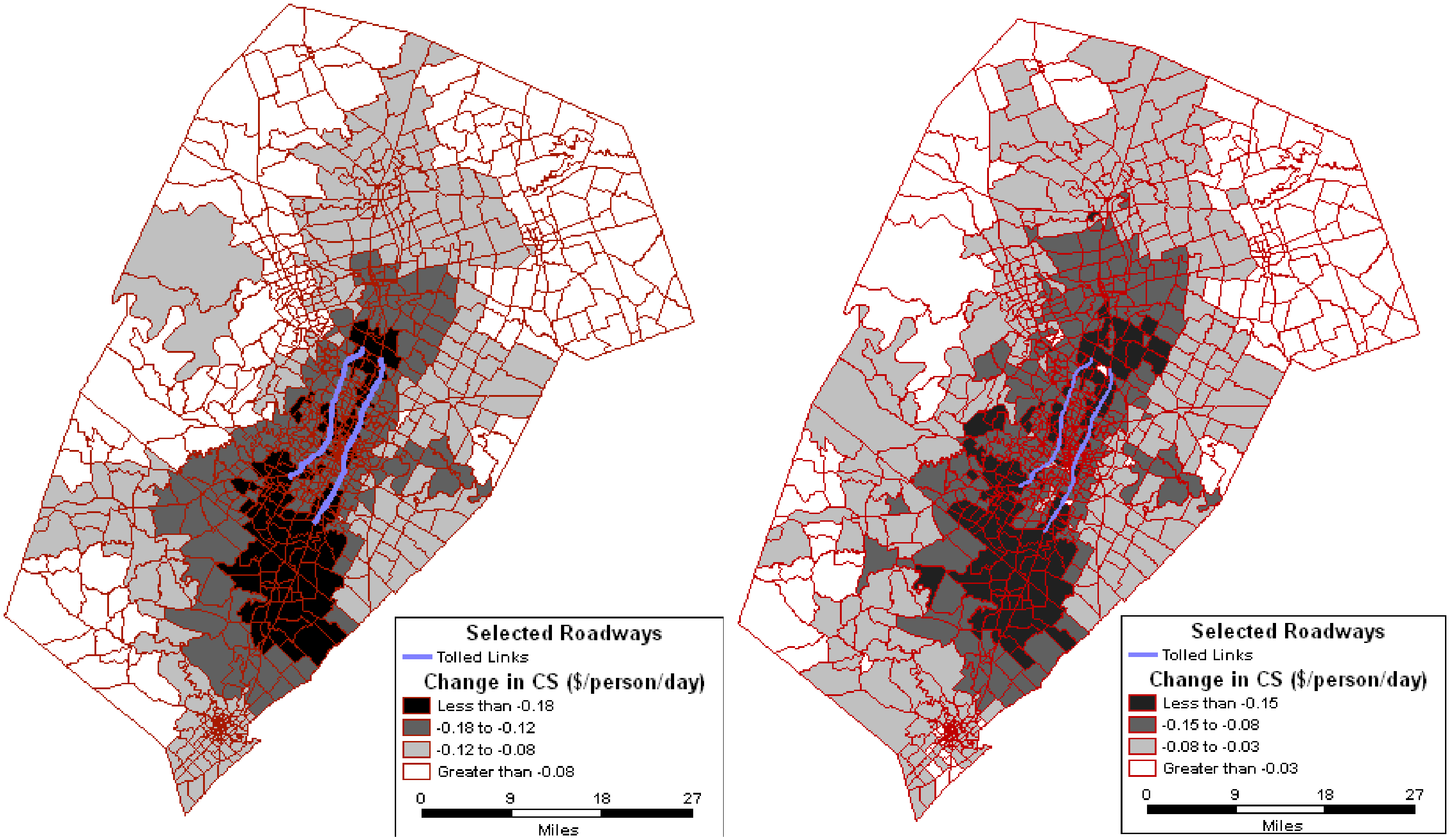

**Table 1: Marginal Utilities of Money by Trip/Tour Purpose/Type**

| Aggregate Model | | | |
|---|---|---|---|
| Trip Purpose | Logsum Coefficient from Destination Choice Model | Cost Coefficient from Mode/TOD Choice Model | Marginal Utility of Money, $\gamma_p$ (utility/$) |
| HBW | -1.669 | -0.191 | 0.318 |
| HBNW | -1.958 | -0.639 | 1.250 |
| NHBW | -6.379 | -0.091 | 0.578 |
| NHBNW | -4.542 | -0.257 | 1.169 |
| | | | |
| Activity-Based Model | | | |
| Tour Type | Logsum Coefficient from Tour Destination Choice Model | Cost Coefficient from Tour Mode Choice Model | Marginal Utility of Money, $\gamma_p$ (utility/$) |
| Work | -1.995 | -0.112 | 0.223 |
| School | -3.089 | -0.252 | 0.716 |
| University | -1.002 | -0.301 | 0.301 |
| Shopping | -2.254 | -0.295 | 0.666 |
| Escorting | -2.708 | -0.253 | 0.685 |
| Other Maintenance | -4.435 | -0.112 | 0.497 |
| Discretionary | -2.593 | -0.216 | 0.559 |

**Table 2: Activity-Based Model Predictions of Welfare Changes for Population Segments under Alternative Scenarios**

| Segment | Number of Individuals | Change in Consumer Surplus ($/person/day) | | |
|---|---|---|---|---|
| | | Expanded Capacity Scenario | Centralized Employment Scenario | Tolling Scenario |
| Entire Population | 1,059,008 | 0.1632 | 0.2072 | -0.1245 |
| Over Age 64 | 82,416 | 0.1253 | 0.2651 | -0.1341 |
| Non-Workers | 119,337 | 0.0356 | 0.2397 | -0.1378 |
| Low Income (HH income < $25,000) | 204,485 | 0.1218 | 0.2937 | -0.1135 |
| Over Age 64 & Non-Worker | 13,088 | 0.0340 | 0.2513 | -0.1415 |
| Over Age 64 & Low Income | 24,218 | 0.1053 | 0.2815 | -0.1178 |
| Non-Worker & Low Income | 29,204 | 0.0344 | 0.2259 | -0.1261 |
| Over Age 64, Non-Worker, & Low Income | 4,212 | 0.0332 | 0.2360 | -0.1344 |