A Comparative Illustration of Trip- and Activity-Based Modeling Techniques

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1 January 1900

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List of Acronyms

ABM activity-based model
ACS American Community Survey
BRT bus rapid transit
CRT commuter rail transit
DAP daily activity pattern
PUMA Public Use Microdata Area
PUMS Public Use Microdata Sample
TAZ transportation analysis zone
TLFD trip length frequency distribution
UDOT Utah Department of Transportation
WFH work-from-home
WFRC Wasatch Front Regional Council

1 Introduction

Activity-based models (ABMs) have been championed by researchers and many practitioners as being theoretically superior to the trip-based models historically used in transportation planning efforts since the 1950s.

Despite the theoretical benefits, many agencies have delayed or declined to transition to an ABM citing additional data requirements, staff training, computational resources, and related concerns. There is also not a consensus that ABMs result in better infrastructure volume forecasts, the primary—or even sole—purpose of many regions' travel demand analysis efforts.

In this research, we investigate the quality and characteristics of travel analyses enabled by an ABM. We do this by applying an array of infrastructure and behavior scenarios to both an ABM and a trip-based model representing the Wasatch Front (Salt Lake City) region of Utah, USA. The results will compare the implications of each model and help inform agencies that are considering adopting an ABM.

The document proceeds in a typical fashion: Chapter 2 provides a discussion of the differences between trip-based models and ABMs, alongside a discussion of previous studies examining the theoretical and analytical benefits of each framework. Chapter 3 first describes the model frameworks used in this research, namely the regional trip-based model and an activity-based model constructed to support research activities in the region; this section also describes three scenarios designed to test the usefulness and applicability of the different model frameworks. Chapters 4–6 describe the findings from each scenario, alongside a discussion of their limitations and implications. Chapter 7 provides a series of recommendations and opportunities for future research.

2 Literature Review

Travel demand modeling in the modern sense has its origins in the 1950's, with the Chicago Area Transportation Study (Chicago Area Transportation Study 1959) being one of the first urban planning studies to use the now-ubiquitous "four-step" modeling framework (McNally 2007). Up to this point, most urban transportation planning used existing demand or uniform-growth travel forecasts to model travel demand, but the Chicago Study used a combination of trip generation, trip distribution, modal split, and network assignment models to more accurately represent travel behavior (Weiner 1997). Since then, there have been numerous studies iterating on the "four-step" (more appropriately termed "trip-based") framework, and trip-based models are now the primary tool used in forecasting travel demand across the United States (Park et al. 2020).

These trip-based models are not without problems, however. Rasouli and Timmermans (2014) give several shortcomings of trip-based models. First, they use several sub-models that are (implicitly or explicitly) assumed independent, and this can result in a lack of consistency or integrity between sub-models; for example, the assumed value of time in the mode choice model might be radically different than the assumed value of time in the tolling assignment model. Second, they are strongly aggregated in nature, which can cause significant aggregation bias with high and low values excluded. Finally, they lack "behavioral realism"—that is, they do not have a concept of individuals making decisions, which is what travel behavior actually is.

Jones (1979) proposed an alternative to the trip-based paradigm, namely an "activity-based" framework that models daily activity patterns at an individual rather than aggregate level. An activity-based model (ABM) places the focus on "activities" rather than "trips" as the basic unit of analysis, and predicts a sequence of activities for each individual and household, with information such as activity location, start time, and duration, using a high level of temporal and spatial granularity. "Trips" are then journeys from one activity to the next (Pinjari and Bhat 2011). By adopting this activity-centric framework, ABMs provide a more consistent and comprehensive representation of travel behavior. They take into account complex dependencies and interactions within the model as a whole and at an individual level. ABMs acknowledge that travel choices are not made in isolation, but rather influenced by the preceding activities. This means that e.g. if an individual takes transit to work, they will not be able to drive home. ABMs therefore present a more conceptually accurate model of actual travel behavior than traditional trip-based models.

Despite these advantages, many agencies have yet to adopt ABMs, and instead continue to use trip-based models (Miller 2023). While ABMs are superior in certain aspects, they also have disadvantages, such as requiring more detailed input data and greater computational resources. It is also not always clear if ABMs provide substantially better forecasts than their trip-based counterparts, nor if this tradeoff is worth it for every agency. This literature review presents an overview of both modeling frameworks, and discusses the advantages and disadvantages of using an ABM.

2.1 Overview of Model Types

Trip-based models are often referred to as "four-step" models due to their four fundamental sub-models: trip generation, trip distribution, mode choice, and network assignment (National Academies 2012, 28). They can be more complicated than this, possibly including integration with a land use forecast, iteration between mode and destination choice, etc., but the "four steps" are the central component of any of these models (McNally 2007).

In a typical trip-based model, travel demand is predicted based on aggregate population data, often delineated by each transportation analysis zone (TAZ). Each sub-model relies on this aggregate data; for example, the modal split sub-model will often use average TAZ income as an input (National Academies 2012, 14). The aggregate data is also often "disaggregated" and segmented along variables such as household size and vehicle ownership. Regardless of the segmentation variables used in the first three model steps, the resulting trip matrices by mode and time of day are then assigned to a transportation network (there are various algorithms for doing so, see Ortúzar and Willumsen (2011)).

Activity-based models differ significantly from this approach. Rather than using aggregate data, ABMs use data representing an actual or synthetic population, with individual person and household data (Vovsha, Bradley, and Bowman 2005). These models use an activity or tour scheduler to assign a daily activity pattern (DAP) of zero or more tours to each individual (*n.b.* a tour is a series of trips that begin and end at home). These DAPs are restricted temporally, spatially, and modally; i.e., each person has a logical and followable sequence of trips and activities (Bowman 1998). A "drive alone" trip from work to lunch, for example, cannot be made if transit was taken to work. ABMs output a list of tours and trips by person, time, location, and type, and these can then be assigned to a transportation network in a similar manner as in a trip-based model.

2.2 Comparison of Modeling Frameworks

In discussing the differences between ABMs and trip-based models, there are really two comparisons that need to be made: how the population data is structured, and how travel is organized. Trip-based models generally use aggregate population data while ABMs use a synthetic population, and trip-based models organize travel into trips while ABMs organize travel into activities and tours. The following sections will explain these aspects of travel demand modeling and discuss the claimed advantages and disadvantages of each model type.

2.2.1 Population Data

The aggregate population data used in trip-based models can vary in origin and level of detail, but the basic concept is the same: the study area is organized into generally small zones, and certain demographic and socioeconomic data is known or obtained for each zone (National Academies 2012, 14). This includes data such as number of households, average household income, population, number of workers, etc. Based on this information, the zone can be segmented along arbitrary variables. For example, since households with more workers and more vehicles tend to make more work trips, it is useful to estimate the distribution of households in each zone along these two variables. Then, average trip production rates are determined for each household category (e.g. for households with each number of workers by vehicles), and the total number of trips produced in a zone is calculated based on these rates (National Academies 2012, 37).

This approach is relatively straightforward: the required input data is usually easy to obtain, the trip generation models are often simple, and it is computationally inexpensive (National Academies 2012). However, the types of analyses possible are limited by the initial segmentation of the aggregate population data. An analysis based on parents'/adults' highest received education, for example, would require determining the number of households in each TAZ with each possible combination of education level. This can theoretically be done, but more detailed and varied analyses would require more levels of segmentation, greatly increasing the number of classifications needed. Aggregation at any point precludes that segmentation from use in subsequent model steps as well as in any post-hoc analysis. Since these segmentations need to be carried through each model step, trip rates, mode choice equations, etc. need to be estimated for every classification, and while relevant real-world data may exist, sample sizes approach zero very quickly, and so the estimates have little statistical value (Moeckel et al. 2020; National Academies 2012).

This becomes a particular issue in equity analysis because it is perhaps impossible to determine equitable distribution of "winners" and "losers" of a potential policy without using demographic variables in the trip generation and destination and mode choice steps (Bills and Walker 2017). Though many studies have shown that trip production and mode choice behavior differ by ethnic group even after controlling for income Bhat and Naumann (2013), including such variables in trip-based models is problematic. Does coding such a variable in a mode choice model represent discrimination? Or does doing so assert that present differences resulting from unequal opportunity will persist into the future planning years? Regardless the reasons for their exclusion, these variables consequently cannot be used in a post-hoc analysis of a transportation policy because the trip matrices do not contain the adequate segmentation.

An alternative approach to population data is to use a full synthetic population. A synthetic population takes demographic and socioeconomic data at various levels of detail to create a "population" with generally the same distribution as the study area (National Academies 2012, 93). The goal is to have a population that is functionally similar to the actual population, but without the privacy concerns of using real individual household data. Castiglione et al. (2006) argue that the major advantage with this approach is that the demographic and socioeconomic data is known at the person and household level, rather than the zone level, and this data remains available throughout the modeling process. This allows, for example, an equity analysis to determine the "winners" and "losers" of a proposed development without needing to encode demographic variables into each step of the model.

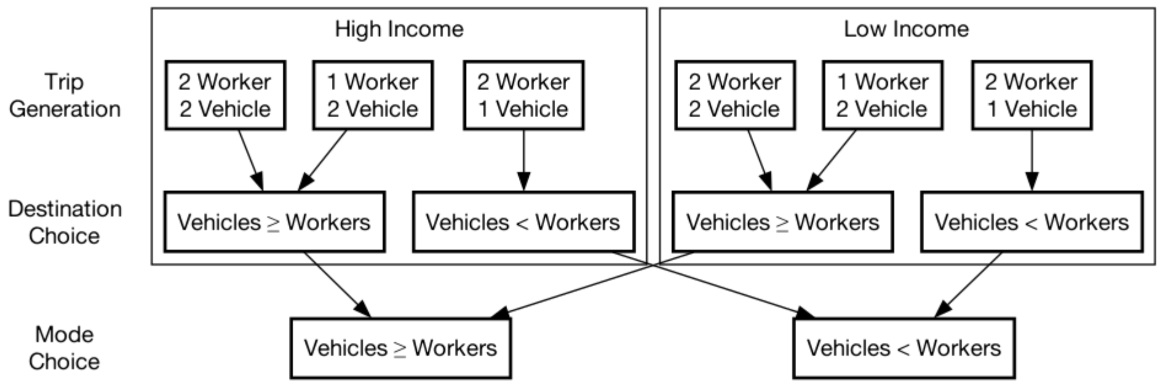
Bills and Walker (2017) used the 2000 Bay Area Travel Survey to create a synthetic population and compare the effects that certain scenarios had on high income and low income populations. With a 20% reduction in travel cost, they found that high income workers benefited more than low income workers. They did similar comparisons for scenarios involving reduced travel times for different mode choices and saw the effects each scenario had on the high and low income workers. These types of analysis, which are not possible with aggregate population data (**this is actually possible; a lot of trip-based models segment high/low income**), can be very valuable in transportation planning and policy making.

It is important to note that while many connect them only with ABMs, synthetic populations can be used in running trip-based models as well. Trip-based models using a synthetic population—often called trip-based microsimulation models—do exist (see Walker (2005) and Moeckel et al. (2020)), but these are relatively rare.

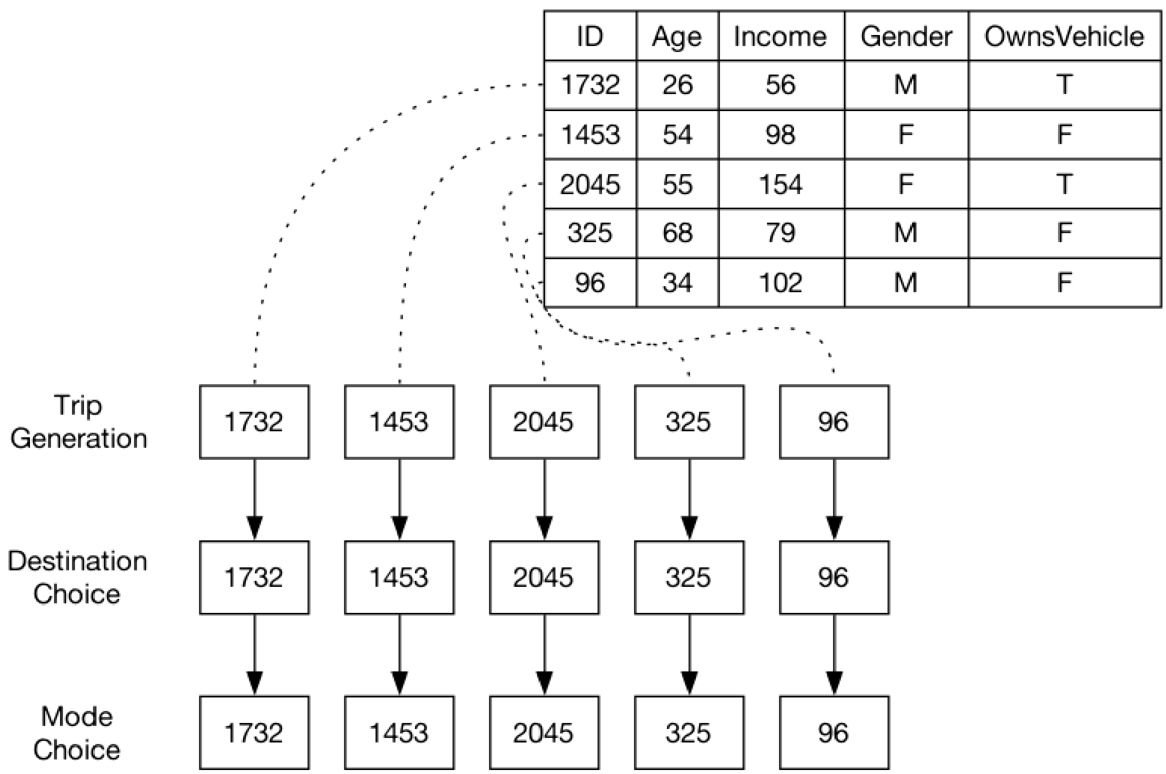
Figure 2.1 gives a visualization of an example "information pipeline" for a trip-based model using aggregate data and an ABM using a synthetic population. In the aggregate data model, it is impossible to know which trips are made by e.g. 2-worker, 1-vehicle, low-income households; it only describes which trips are made by households with fewer vehicles than workers. With a synthetic population, however, *individuals* are being modeled, and so each trip can be traced to a specific person. All information is known at each point in the model regardless of which data is used in previous steps.

2.2.2 Travel Behavior

The other primary difference between trip-based models and ABMs—and the main difference from trip-based microsimulation models—is that ABMs organize travel into "tours", a sequence of trips that begin and end at the home, rather than just trips. It should be noted that Miller (2023) argues that many current "activity-based" models ought to be labeled "tour-based" due to this focus on building tours. This is contrasted with "activity scheduling" models, in which activity participation is modeled explicitly and trips emerge as the means to get from one



(a) Trip-based



(b) Activity-based

Figure 2.1: Example "information pipeline" for a trip-based model and an ABM.

activity to the next. However, in practice there are few true "activity scheduling" models, and the term "activity-based" is used to refer to both activity scheduling and tour-based models.

In a typical trip-based model, trips are forecasted based on empirical trip rates, usually by trip purpose and by household type (for example, low-income, 1-vehicle households make a certain number of "home-based work" trips) (McNally 2007). These trips are then assigned an origin and destination, mode, and often a time of day (peak/off-peak, etc.), resulting in a list of trips between each zone by mode and purpose. A trip-based microsimulation model may use regression models rather than aggregate data for some of the model steps (Moeckel et al. 2020), but the end result is similar: a list of trips by person, noting mode and purpose. However, this trip list may be inconsistent, and the forecasted trips may not be physically possible to complete in any sequence, as there is no sense of "trip-chaining". The hope, though, is that over an area the inconsistencies would cancel out, leaving an overall accurate forecast.

ABMs, on the other hand, model *tours* rather than trips. This attempts to create consistency in trip origins/destinations, mode choice, and time of day: since each trip is a part of a "chain" (tour), the trips within a tour are dependent on each other (Rasouli and Timmermans 2014). The open-source ABM ActivitySim (Association of Metropolitan Planning Organizations 2023a), for example, has a tour-scheduling model that determines the number of "mandatory" (work, school, etc.) and "discretionary" tours each individual will make, and performs tour-level mode and destination choice for each tour. After the tour-level decisions are made, trip-level mode/destination choice is done for each trip in the tour, including the possible addition of subtours (see Vovsha, Bradley, and Bowman (2005), fig. 18.1).

Figures 2.2 and 2.3 show an example of the trips assigned to a network in the various model forms. Figure 2.2 depicts network assignment in a typical trip-based model where the total number of trips between each zone is given. With these results, the mode and purpose of each trip is known, but, with aggregate data, there is no way of telling who made which trips other than the segmentation in the previous steps (see Figure 2.1a). It is also not possible to construct a coherent daily list of trips for individuals.

Figure 2.3, on the other hand, depicts visual representations of an *individual's* travel made possible by the use of a synthetic population. Figure 2.3a depicts the trip list that could be given for an individual in a trip-based microsimulation model. Though each individual's trips are known, there is no guarantee of consistency between trips. For example, it could predict that the individual takes transit to work but then drives home or that the individual makes two recreational trips without ever making a return trip. The activity-based approach, depicted in Figure 2.3b, attempts to add this consistency by modeling tours, and only generating trips consistent with each tour.

In addition to intra-person dependencies, Rasouli and Timmermans (2014) note that ABMs can model dependencies between members of a household as well. A vehicle can't be used by multiple people in the same household at the same time to travel to different destinations. Because the people within the household will have travel patterns that depend on the patterns of others in the household, a policy affecting one person in the household can affect everyone

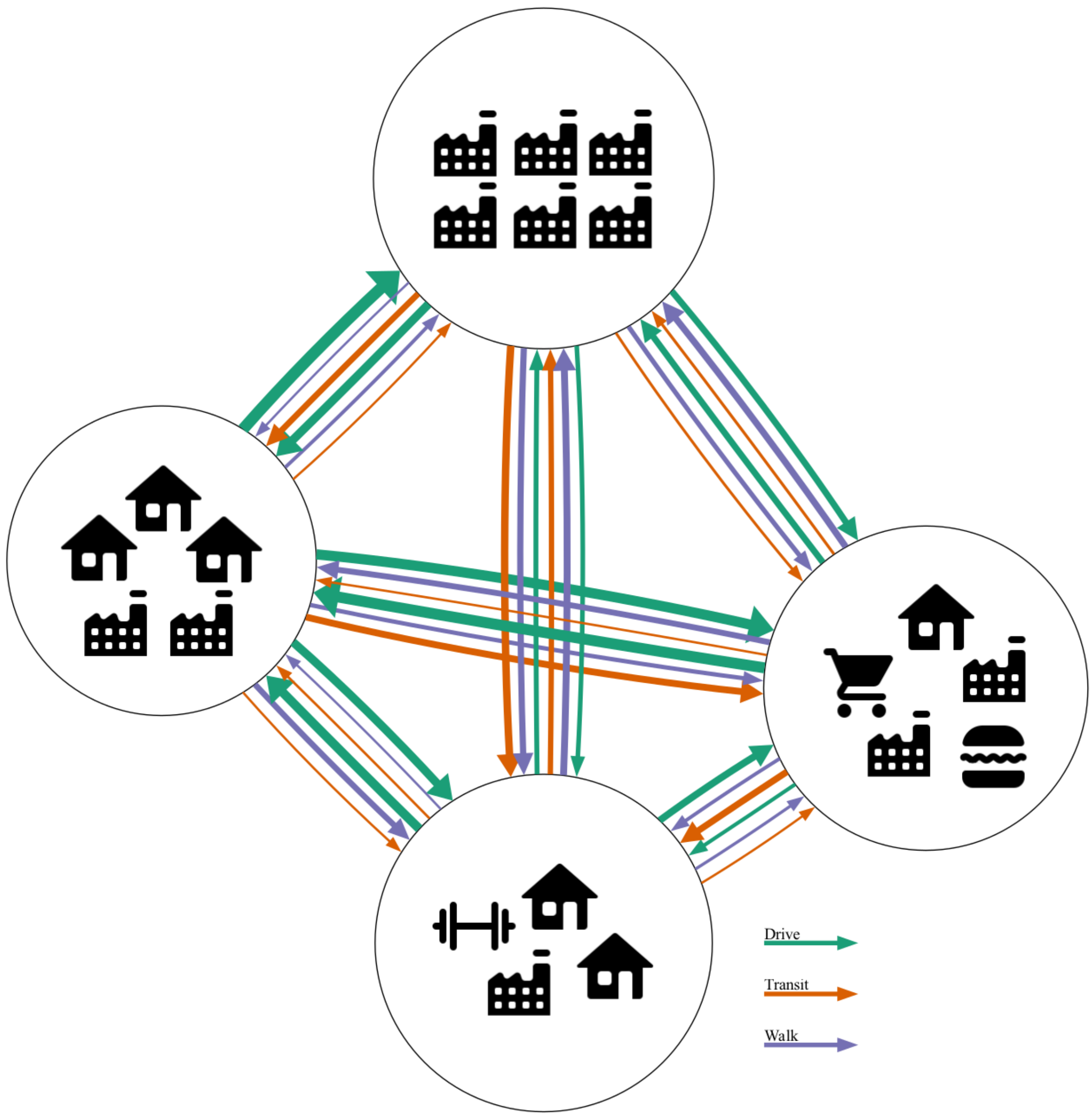
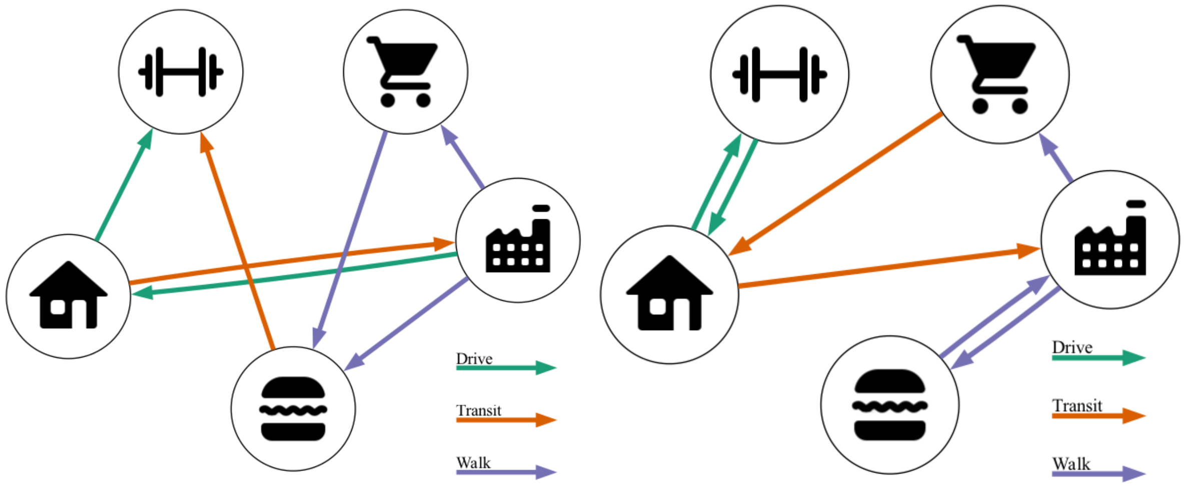


Figure 2.2: Example network assignment using aggregate data. There is little information on who is making which trips, and it is not known how trips are related to each other.



(a) Trip-based microsimulation

(b) Activity (tour)-based

Figure 2.3: Example network assignment using a synthetic population allows an individual's travel to be tracked. In the tour-based approach, an attempt is made to make the trips consistent with each other.

in the household no matter how directly the policy connects to them (Vovsha, Bradley, and Bowman 2005). These effects aren't possible to forecast in a trip-based model.

Another advantage of organizing travel into tours comes regarding accessibility analyses. Dong et al. (2006) note that when trip-based models are used to analyze accessibility, each zone must be analyzed independently of travel behavior. This approach only analyzes zones' proximity to each other and does not take into account individual travel patterns. They argue that this is a limited view of accessibility, and discuss the "activity-based accessibility measure" (ABA), which is evaluated based on all trips in a day rather than particular trips. As an example, if an individual doesn't live within a 20-minute drive of a grocery store, traditional measures might rate this as poor accessibility. However, if they travel to a park with a nearby grocery store as part of their DAP, then in reality the accessibility should be rated much higher. This proximity may even influence *which* park is chosen. Overall, they found that the ABA predicts more reasonable accessibility outcomes compared to traditional measures.

2.3 Lack of ABM Adoption

Though ABMs have many clear advantages over trip-based models, adoption among agencies has been relatively slow. Many ABMs are implemented in proprietary software, which creates difficulty in maintaining and iterating on the model, Miller (2023) argues. Even in an open-source model like ActivitySim (Association of Metropolitan Planning Organizations 2023a), Miller notes several disadvantages of ABMs:

- Computational inefficiency and complicated program design: ABMs take more time, more computing power, and more money to run. This is because the synthetic population needed to run an ABM uses much more data. In areas with thousands of TAZs and millions of people, a super computer is needed, and it will cost much more than what is spent to run trip-based models. If a city can see similar results using a trip-based model, they may decide not to invest in an ABM.
- Absence of a standard model system: The modeling systems are often designed with different approaches and for specific areas making it hard to transfer from one urban area to another. This also makes it difficult for agencies to determine which approach is the best and decide which to implement. In relation to this, Miller also states that the pressures of publishing unique and ground-breaking research in academia can deter researchers from converging towards best theories and methods.
- Lack of resources: Most of these models were developed in academic settings which often lack resources, and possibly desire, to put them into practice. This leaves it up to governments and consultants to put the models into practice, but they can be hesitant to promote software development and to invest in new systems.

For these reasons, as well as the inertia of current practices, the majority of agencies and organizations in the US remain using trip-based models for demand forecasting and policy analysis.

2.4 Research Gap

Although there has been much research on ABMs and their theoretical advantages, practical comparisons of the model frameworks have been limited. It is often taken as given that ABMs are unilaterally superior to traditional trip-based models due to their better theoretical foundation, but it is not clear if that better foundation always yields better results in terms of analytical flexibility or policy outcomes. Ferdous et al. (2012) compared the trip- and activity-based model frameworks of the Mid-Ohio Regional Planning Commission and found that the ABM performed slightly better at the region level, but about the same at the project level. This is not an overwhelming victory for ABMs, and so based on this an agency may reasonably decide that the increase in data, computational, training, and potentially financial requirements outweigh the potential gains of switching to an ABM.

Ferdous et al. (2012), however, mainly compared the *accuracy* of the two frameworks, but did not address the methodological differences between them. What types of data collection/synthesis are needed for each model type? Are there analyses that can only be done through (or that are made easier by) one of the model types? What would an agency need in order to transition from a trip-based model to an ABM? Are certain types of scenarios suited to one model type? Though some of these questions have been discussed (see e.g. Lemp, McWethy, and Kockelman 2007), a holistic methodological comparison is lacking. Additionally, the answers in the current literature are mainly theoretical, with little use to an agency considering the transition.

This research aims to answer these questions by providing a side-by-side comparison of a potential trip-based and activity-based modeling methodology. Several "proposed development" scenarios are run in each model, and the strengths and weaknesses of each approach are compared. It is important to note that this paper is not focused on model accuracy, as in any model type this can be adjusted dramatically through calibration efforts. Rather, the focus is on the methodological differences between the approaches, and the types of analyses that can be done with each model type.

3 Methodology

This paper seeks to compare methodological differences between trip- and activity-based modeling frameworks. The Wasatch Front Regional Council (WFRC) travel demand model is used as a representative trip-based model, and an ActivitySim implementation in the same study area is used as a representative activity-based model (ABM). Note that the focus is not on comparing model accuracy or performance, but rather on comparing the process of using each model, including the types of analyses that can be performed. There are therefore few direct comparisons of model outputs between each type. Instead, this research highlights the strengths and weaknesses of each model type in planning and policy analysis, and illustrates these differences.

The following sections discuss the specific models in more detail.

3.1 WFRC Model

The WFRC model is implemented in the CUBE software by Bentley (Bentley Systems n.d.), and is currently used by WFRC for modeling travel in the Salt Lake City, Utah area. WFRC provided the model directly, including land use forecasts and the current long-range transportation plan. The model is taken essentially as-is, with no changes other than those noted in Chapters 4–6.

The WFRC model, like many trip-based models, requires the following inputs:

- Land use data, including information about population, employment, and socioeconomic variables such as income, delineated by transportation analysis zone (TAZ). This is provided by WFRC directly, as an output of their land use forecasting model(s).
- Travel skims, detailing travel time, cost, etc. between each origin-destination pair of TAZs. The WFRC model uses an iterative process of assigning volumes to the transportation network and recalculating the skims, which are used in the mode and destination choice model steps.
- Transportation networks, including highway, transit, etc. networks which connect the TAZs to each other. These networks contain information such as link speed and capacity. Though the WFRC model assigns travel volumes to the network, this paper does not compare the model's network assignment results. However, the network volumes are still used to calculate the loaded network skims.

- Lookup tables, used in many model steps for information such as trip rates by household type. These are taken directly from the WFRC model without modification.
- Model constants and coefficients, which some model steps such as mode choice require for calibration. These are also taken directly from the WFRC model.

Like many trip-based models, the WFRC model follows the "four-step" approach and has main steps of trip generation, trip distribution, mode choice, and network assignment. The model also includes a disaggregation step at the beginning where the TAZ-level data is used via lookup tables to estimate the number of households by size, income group, number of workers, and auto ownership. The trip generation step uses lookup tables for each household type to determine the number of trips produced by purpose. Trip attractions are determined based on the number of jobs in each TAZ, with differing coefficients by job type. Trip distribution uses a gravity model of the form

$$T_{ij} = P_i \times \frac{A_j F_{ij}}{\sum_J A_j F_{ij}},$$

where T_{ij} is the number of trips from zone i to j, P_i is the productions at i, A_j is the attractions at j, F_{ij} is the cost term/function from i to j, and J is the set of all zones trips from i can be attracted to. Mode choice uses a choice model to assign a percentage of trips of each purpose to each mode. Network assignment is done via an iterative process to equalize travel time between potential routes.

The WFRC model outputs include trip tables by purpose, mode, and time of day, as well as loaded network skims.

3.2 ActivitySim

ActivitySim is an open-source ABM led by a consortium of transportation planning agencies. ActivitySim is highly configurable, and many agencies have their own bespoke implementation. This paper uses an ActivitySim implementation based on Gregory S. Macfarlane and Nathan J. Lant (2021), which is in turn based on the prototype configuration for the Metropolitan Transportation Commission serving the San Francisco area (Erhardt et al. 2011). The exact implementation is available on GitHub.

ActivitySim requires similar inputs to the WFRC model, though it does not assign traffic and so does not require any transportation networks. However, ActivitySim does require network skims for information on travel time, cost, etc. These skims are obtained from any network assignment process, though ActivitySim itself does not include network assignment. A discussion and comparison of network assignment processes is outside the scope of this project, so this ActivitySim implementation uses the travel skims output from the WFRC model directly.

ActivitySim additionally requires population data at an individual level, including information such as age, household income, and home location. Due to privacy concerns, real data is rarely used for this purpose, and a synthetic population representative of the study area is used instead. Section 3.2.1 discusses the population used in more detail.

ActivitySim, like all ABMs, simulates transportation decisions on an individual level. ActivitySim has a hierarchical decision tree, where long-term decisions (such as auto ownership and telecommute frequency) are made first, followed by daily and tour- and trip-level decisions such as scheduling and mode choice (see Figure 3.1). Each of these steps determines information that will be used in subsequent steps, and many steps can be turned on or off depending on what is needed for the model implementation.

The steps can broadly be categorized into five groups, as shown in Figure 3.1: aggregate, household/personal, daily, tour-level, and trip-level steps. The aggregate steps mainly involve determining impedance measures between each pair of zones (travel time, distance, cost, etc.). In this case, these impedances are supplied directly as network skims, output from the WFRC model.

The household/personal steps relate to long-term decisions that are unlikely to change quickly based on daily transportation conditions. These steps include determining remote work status, work/school location, auto ownership, transit pass ownership, and free parking availability at work. Much of this information can be supplied directly or explicitly modeled. This ActivitySim implementation does not supply any of this information directly, and explicitly models remote work status, work/school location, auto ownership, and free parking availability. Transit pass ownership is not modeled.

The daily decisions primarily concern an individual's DAP. ActivitySim contains a step to assign mandatory, non-mandatory, and joint tours based on personal and household information (joint tours combine both mandatory and non-mandatory activities). For example, full-time workers are more likely to make a mandatory tour than part-time workers, all else being equal.

Once a DAP is chosen, ActivitySim creates tours for each major activity in the day. Additionally, ActivitySim determines if an individual makes an "at-work" tour (e.g. leaving for lunch and returning to the workplace). Each tour is scheduled and assigned a primary mode, as well as a primary destination for non-mandatory and joint tours. The tours are then populated with trips, and ActivitySim assigns each trip a purpose, destination, time of day, and mode compatible with the tour-level assignment.

The final steps of ActivitySim are writing output trip matrices and other tables, including information on land use, persons, households, tours, and trips.

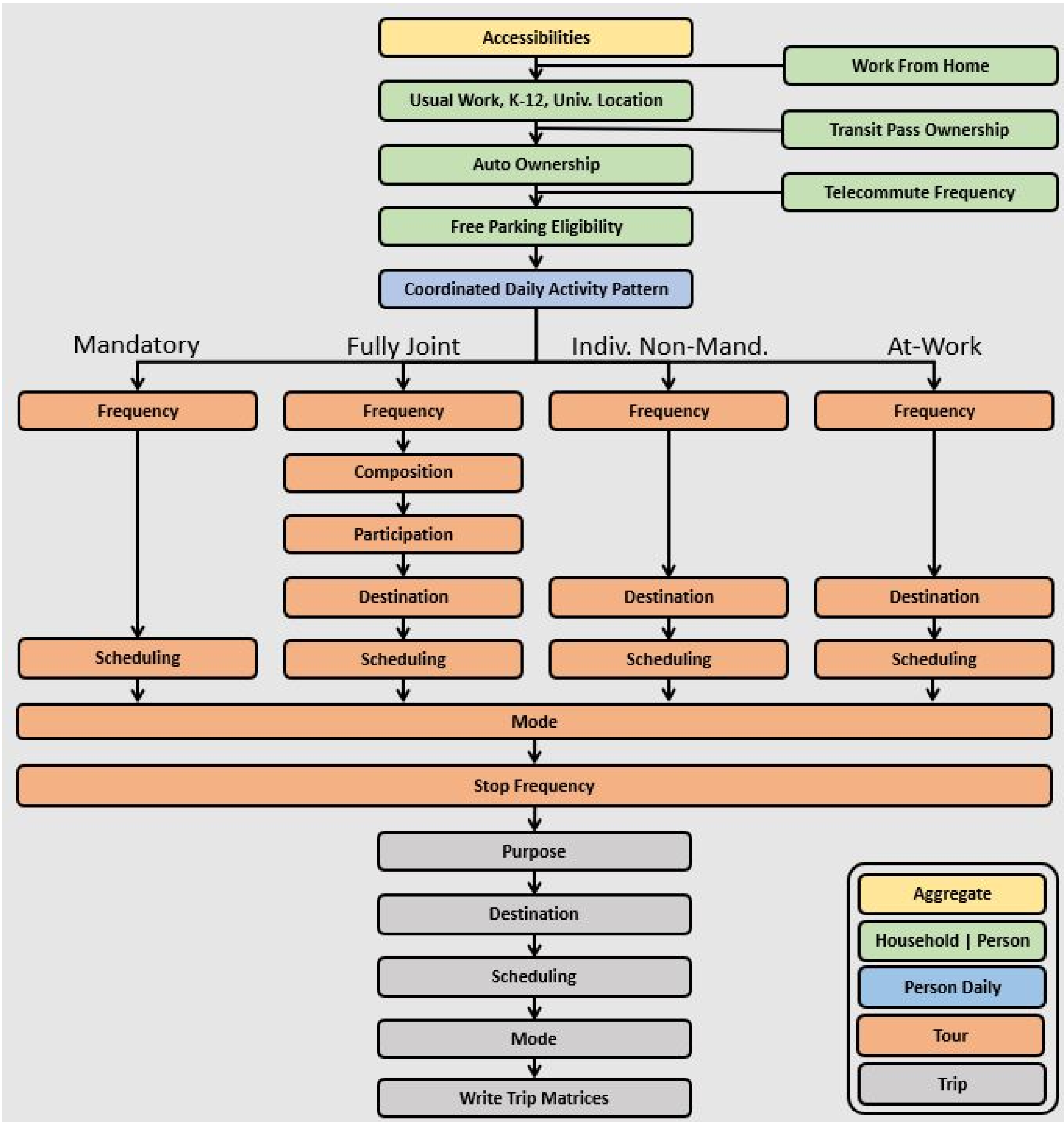


Figure 3.1: ActivitySim sub-model flowchart. Long-term decisions are made first, followed by more granular ones.

3.2.1 PopulationSim

This paper uses PopulationSim (Association of Metropolitan Planning Organizations 2023b) to create a synthetic population for ActivitySim. The synthetic population aims to be representative of the study area while maintaining privacy. PopulationSim takes as input a “seed” of individuals and households, and populates the area with copies of these to match given control totals.

The seed sample comes from the 2019 American Community Survey Public Use Microdata Sample (U.S. Census Bureau 2022), which contains a sample of actual (anonymized) individuals and households at the Public Use Microdata Area (PUMA) geography (PUMAs partition the United States into areas of around 100,000 people each (U.S. Census Bureau 2023)). The control totals come from two different sources: the U.S. Census and the WFRC model. Table 3.1 shows these controls as well as their geographic level and source. PopulationSim also allows setting different weights to each control, and Table 3.1 gives this information as well.

Table 3.1: PopulationSim Control Totals by Geography and Source

Control	Geography	Source	Weight
Population	Entire Region	Census	5,000
Number of Households	TAZ	WFRC Model	1,000,000,000
Household Size	Census Tract	Census	10,000
Persons by Age Group	Census Tract	Census	10,000
Households by Income Group	Census Tract	Census	500
Workers per Household	Census Tract	Census	1,000

Most of these controls come from Census data, with only the number of households per TAZ coming from the WFRC model data. Note also that there are many personal and household variables that are not accounted for in these controls, such as sex, vehicle ownership, internet access, etc. These variables are not controlled for and are dependent on which seed persons or households are copied in controlling for the other variables. However, this process is assumed to still give a representative enough estimate for the uncontrolled variables without needing to model them explicitly.

The outputs of PopulationSim include a persons and households table comprising the synthetic population, as well as summary tables.

3.3 Initial Model Comparison/Calibration

While this research does not directly compare the outputs of ActivitySim to those of the WFRC model, it is important to ensure similar performance between the two models for meaningful analyses. As such, a baseline scenario in both models is used in order to calibrate the ActivitySim implementation to the WFRC model. This baseline scenario uses the 2019 WFRC model as-is. For ActivitySim, the baseline scenario uses 2019 Census and WFRC data to create the synthetic population, and the choice models use land use data and network skims from the baseline WFRC scenario.

3.3.1 Verification of the Synthetic Population

The controls for PopulationSim mostly come from the Census, as can be seen in Table 3.1. However, the WFRC model contains TAZ-level data including population and median income. The WFRC model also has a disaggregation step that estimates the number of households by size and income group.
This section compares the output of PopulationSim to the WFRC model on each of these variables at the TAZ level.

Figure 3.2 shows the difference in TAZ population between PopulationSim and the WFRC data. It is worth noting that since the number of households was controlled at the TAZ level from the WFRC data with an extremely high weight, the number of households per TAZ in the synthetic population match exactly to the WFRC data. The average household size will therefore follow a similar error distribution to the one shown in Figure 3.2.

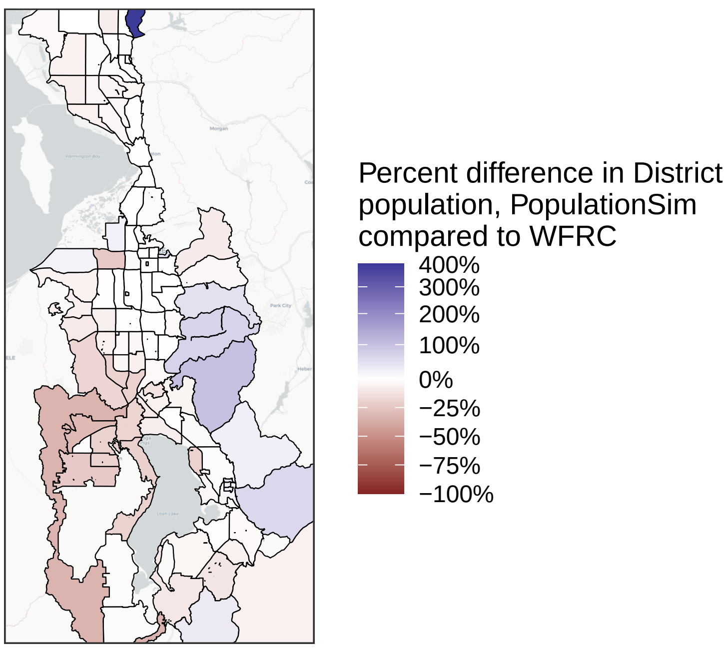


Figure 3.2: population comparison

The population per TAZ is similar to the WFRC data in most places, though there are some discrepancies especially near Herriman and Lehi. Since total population is a region-level control, but number of households is a TAZ-level control, this shows PopulationSim is predicting a smaller average household size in Herriman and Lehi than the WFRC data suggests.

Income is also an important factor in travel behavior (Zegras and Srinivasan 2007), and Figure 3.3 shows a TAZ-level comparison of median income between the synthetic population and the WFRC data. The synthetic population does have a lower median income than the WFRC data in many TAZs, but the error is in most cases fairly small, especially in more populated areas. However, both the WFRC model and ActivitySim use household income *groups* rather than individual household income to inform travel decisions. These groups are taken from the WFRC model (see Table 3.2), and the groups in PopulationSim and ActivitySim were adjusted to match. Figure 3.4 shows the difference in number of households by income group, and this figure shows a similar trend of PopulationSim over-predicting low-income households.

Table 3.2: income groups

Income Group	Income Range
1	$45,000
2	$45,000–$75,000
3	$75,000–$125,000
4	$125,000

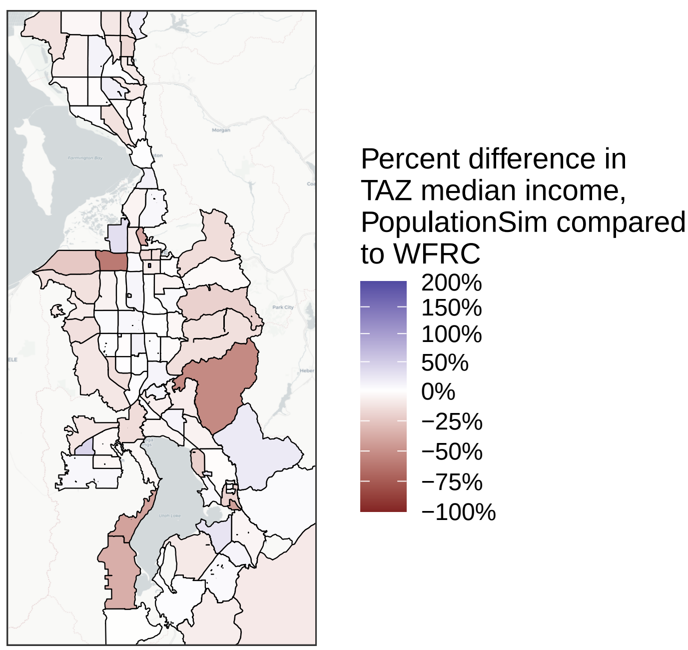


Figure 3.3: med inc

Income was not weighted very heavily as a control in PopulationSim (see Table 3.1), and this

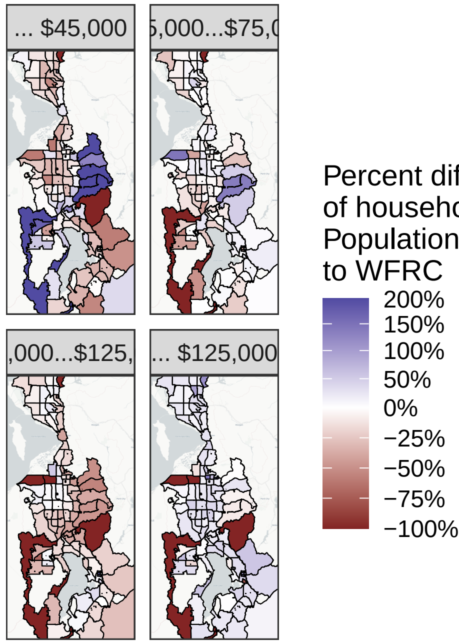


Figure 3.4: inc groups

is in part why there are discrepancies between the models. However, the overall distribution of income is similar between the models, as Figure 3.5 shows.

3.3.2 Verification and Calibration of ActivitySim

This section compares the outputs of both models to verify that trip patterns roughly agree between them. There are three comparisons of interest between the outputs of the two models: mode split, trip length frequency distribution, and remote work.

The initial baseline ActivitySim scenario predicted a mode split significantly different to that from the WFRC model, and so calibration efforts were needed. We adjusted the alternative-specific constants in ActivitySim's mode choice model to better match the mode split in the WFRC model. Table 3.3 compares the mode split of both models after several iterations of this calibration. Overall, the calibration resulted in a reasonably similar mode split between the two models, though there are still discrepancies (e.g. ActivitySim is predicting about twice as many transit trips as the WFRC model). However, further adjustment of the constants would cause their values to become unreasonably large, as ActivitySim's mode split begins converging at this point regardless of the calibration constant values (see Figure 3.6). This is likely due to the mode choice coefficients being unrepresentative of the study area. This ActivitySim configuration is ultimately based on the San Francisco area, and so coefficients on variables such as travel time and income are calibrated for that area (hence in part why there are so many more transit trips).

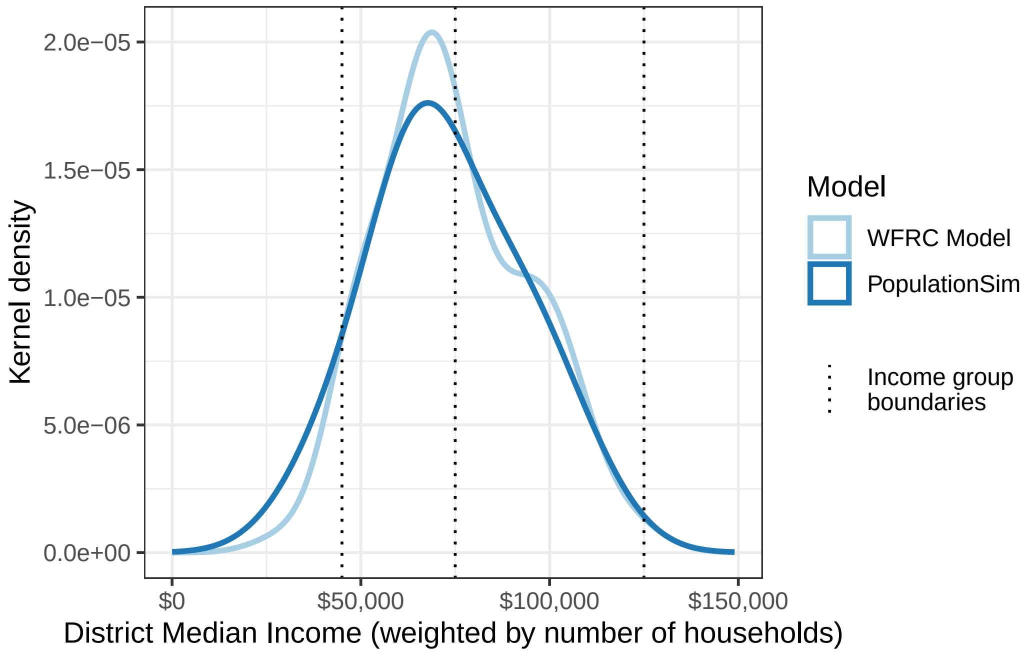


Figure 3.5: inc density

Table 3.3: mode split

Purpose	Mode	ActivitySim predicted trips	WFRC predicted trips	Error	% Error
Auto	Home-based Other	3253220	4096688	-843468	-20.6%
Non-motorized	Home-based Other	532274	510143	22131	4.3%
Transit	Home-based Other	67396	37346	30050	80.5%
Auto	Home-based Work	1524169	1586414	-62245	-3.9%
Non-motorized	Home-based Work	83119	76506	6613	8.6%
Transit	Home-based Work	62814	48752	14062	28.8%
Auto	Non–home-based	1839065	2224878	-385813	-17.3%
Non-motorized	Non–home-based	162979	146404	16575	11.3%
Transit	Non–home-based	30513	13453	17060	126.8%

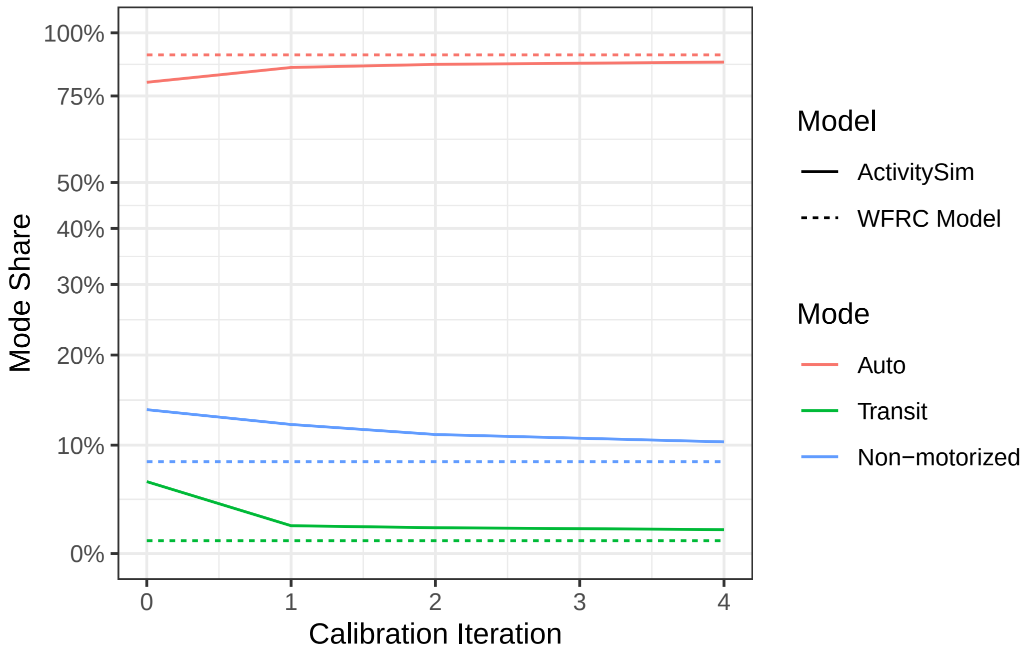


Figure 3.6: calibration plot

Figure 3.7 compares the trip length frequency distribution of the two models by mode and purpose. Both ActivitySim and the WFRC model contain destination choice models which can be adjusted to affect the distribution of trip length. However, as the figure shows, the two models have similar TLFDs, so no adjustment was necessary. The most significant discrepancies are with transit trips, again likely due to this configuration of ActivitySim being calibrated to San Francisco, making transit more attractive. Note that though these distributions match well enough for the purposes of this research, further calibration would be required to create a production-ready ActivitySim implementation.

The WFRC model has basic support for predicting telecommuting and work-from-home trips. This includes a lookup table of telecommute percentages based on job type and year. ActivitySim also has this functionality, and can additionally use individual- and household-level variables in its predictions. It is worth noting that both the WFRC model and ActivitySim make a distinction between "telecommuting", where an individual commutes to work some days and does not others, and "work-from-home" (or "home-based jobs" in the WFRC model), where an individual's workplace is always at their home.

The ActivitySim implementation discussed in Gregory S. Macfarlane and Nathan J. Lant (2021) does not include any submodels related to remote work. However, the example ActivitySim implementation for SEMGOG *does* include these submodels, and our ActivitySim implementation takes these submodels directly from the SEMCOG example. ***Some modifications to the remote work submodels were needed for compatibility, but only included....***

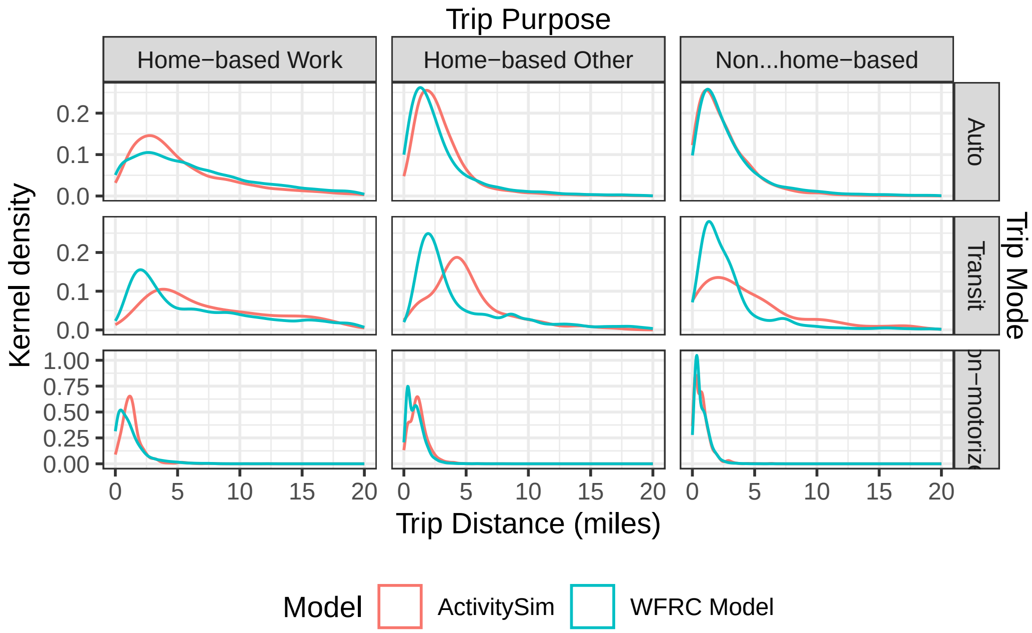


Figure 3.7: tlfd comparison

Both models treat "work-from-home"/"home-based jobs" similarly. The WFRC model's land use data contains employment by type in each TAZ, and it considers a "home-based job" as a separate job type, so these are not counted toward employment totals in trip generation and subsequent steps.
ActivitySim has a "work from home" submodel which assigns workers work-from-home status based on personal variables such as income, sex, and education (coefficients on these variables were left unchanged from the existing configuration, see Table 3.4). There is also a "target work-from-home percent" value that adjusts the model to reach the specified work-from-home proportion of all workers. Individuals with work-from-home status are then prohibited from making a mandatory tour. This target work-from-home percentage is set at 2.3%, based on a weighted average from the WFRC model data. We made no other adjustments to the ActivitySim work-from-home submodel.

The two models differ in their approach to telecommuting, however. The WFRC model has a lookup table of telecommuting shares based on job type (see Table 3.6), including predictions for future years. ActivitySim has a "telecommute frequency" submodel which assigns workers a telecommute status indicating the number of days they work remotely per week. Based on this status, ActivitySim adjusts the likelihood of making a mandatory tour. Telecommute status depends on personal variables similar to those in the work-from-home submodel by default. Notably, the telecommute frequency submodel also includes adjustments based on an individual's distance to work. No other changes were made to the existing variables in this submodel, and Table 3.5 shows the submodel coefficients.

Table 3.4: asim wfh model coeffs

Description	Coefficient
Constant for Working from home	0.438
Full time worker (1 if true)	-0.812
Female Worker	-0.347
Female worker with a Preschool Child in Household	0.573
Accessibility to workplaces of the home mgra	-0.140
Presence of Non Working Adult in the Household	-0.372
Education Level Bachelors or higher degree	0.285
Household income Less than 30K	-0.393
Age Group - Less than 35 years	-0.574
Age Group - 35 yrs to 45 yrs	0.000
Age Group - 45 yrs to 55 yrs	0.214
Age Group - 55 yrs to 65 yrs	0.452
Age Group - Older than 65yrs	0.584
ABM2 calibration - work from home	-0.016
Phase2 calibration temp	-0.628

In order to calibrate ActivitySim's telecommute frequency submodel to the WFRC data, however, we added additional job type variables to ActivitySim to match those given in Table 3.6. Because these are choice coefficients rather than target percentages, the values needed to be calibrated to match the WFRC targets. The calibration allowed ActivitySim to match these targets exactly, and the coefficients are given in Table 3.6.

Because both remote work submodels in ActivitySim are run before an individual's DAP is chosen, ActivitySim implicitly models a "rebound effect", where individuals working remotely on any given day may be more likely to make discretionary tours. However, because the WFRC model does not include this effect, the ActivitySim DAP model is left unchanged. Table 3.7 shows the coefficients of the DAP model for individuals who work remotely.

Table 3.5: asim tc model coeffs

Description	1_day_week	2_3_days_week	4_days_week
Retail	0.312	0.125	0.078
Food	-0.368	-0.148	-0.092
Manufacturing	0.038	0.015	0.010
not sure, unused	0.000	0.000	0.000
Office	1.782	0.712	0.445
Government and education	-0.560	-0.224	-0.140
Health	0.158	0.063	0.039
other	1.535	0.614	0.384
Agriculture	2.262	0.904	0.566
Mining	-2.030	-0.810	-0.511
Construction	0.816	0.326	0.204
Has children 0 to 5 years old	0.000	0.000	-0.864
Has children 6 to 12 years old	0.000	0.517	-0.810
One adult in hh	0.177	0.000	-0.043
2 or more adults in hh	0.000	0.000	0.000
female	0.000	0.000	0.000
Part-time worker	0.000	0.425	1.112
College student	0.000	0.600	0.000
Pays to park	0.457	0.000	0.000
Income 60-100k	0.560	0.389	0.000
Income 100-150k	0.644	0.193	0.000
Income 150k+	0.920	0.765	0.000
0 Autos	0.000	0.407	0.000
1 Auto	0.000	0.000	0.000
3+ Autos	0.000	-0.730	0.000
Distance to work	0.016	0.000	0.000
temp_calibration	-4.000	-4.250	-6.000

Table 3.6: wfrc telecommute data

Job Type	WFRC Telecommute %	ActivitySim Telecommute Utility Coefficients		
		1 day	2–3 days	4 days
Retail	2.70%	0.312	0.125	0.078
Food	1.87%	-0.368	-0.148	-0.092
Manufacturing	2.02%	0.038	0.015	0.010
Office	6.66%	1.782	0.712	0.445
Gov't/Education	1.67%	-0.560	-0.224	-0.140
Health	2.86%	0.158	0.063	0.039
Agriculture	6.93%	2.262	0.904	0.566
Mining	0.53%	-2.030	-0.810	-0.511
Construction	3.28%	0.816	0.326	0.204
Other	5.37%	1.535	0.614	0.384

Table 3.7: asim dap model remote work coeffs

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.62	16.5	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.88	17.0	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.32	18.6	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.21	19.4	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.44	17.0	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.46	20.2	1	0	3	1

3.4 Example Scenarios

There are three proposed scenarios to implement and run in each model for comparison. This is not a comprehensive list covering all potential scenario possibilities, but is taken to represent many of the types of scenarios an agency would analyze.

The first scenario involves a change in land use near the former state prison site in Draper, Utah. Current plans for this site involve new development known as "The Point", which will add high-density housing and commercial development to the area. This research scenario will be based on this development, but will include only the land use changes. The actual development plans also include expansion of transit, but this will not be a part of this scenario.

The second scenario centers around an augmentation of transit service along the Wasatch Front. The FrontRunner, a CRT line connecting Provo to Ogden, is slated for expansion. The expansion includes additional stations and increased travel speeds due to vehicle electrification. This scenario models these changes in accordance with the planned expansion of the service.

The third scenario addresses the growing trend of remote work. Given technological advancements and the notable surge in remote work during the COVID-19 pandemic, this scenario models a substantial increase in remote work based on projections from WFRC.

Each of these scenarios is based on the baseline 2019 scenario in the respective model, and ignores any additional expected growth or development beyond the specific changes of each scenario. For example, the increased WFH scenario uses WFH projections from 2050, but land use and socioeconomic data from 2019. These scenarios are therefore not realistic, but they serve as illustrative examples of the types of planning and development scenarios agencies may wish to analyze.

All three of these scenarios are coded in both the WFRC model and ActivitySim. The results (Chapters 4–6) describe the process of coding each scenario and analyzing them, as well as the analyses themselves.

4 Scenario 1: Change in Land Use

Near Draper, Utah there is a defunct prison site that is slated for redevelopment (see Figure 4.1). The 600-acre site will be developed into a multi-use residential and commercial area, with an emphasis on walkability and transit. This development is known as The Point, and is the basis for the first model scenario in this paper.

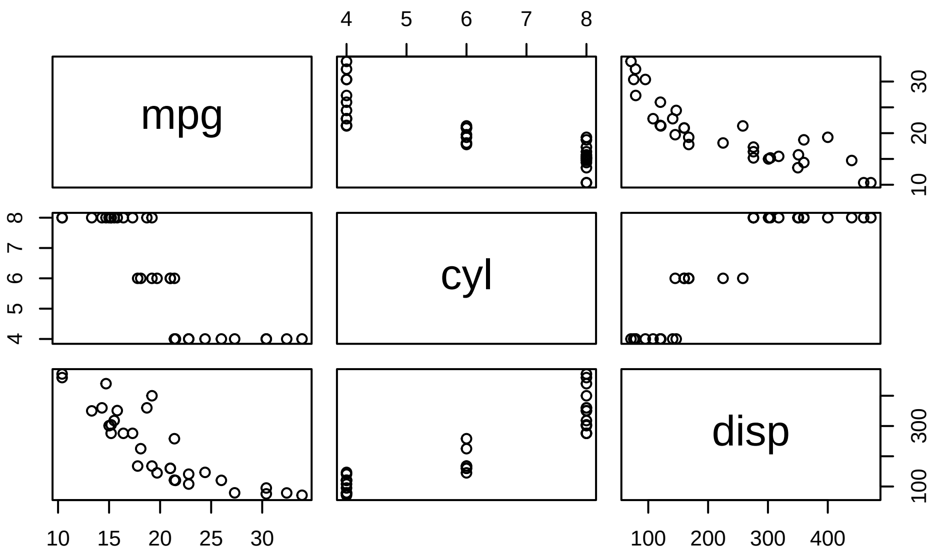


Figure 4.1: draper prison location

This scenario models the change in land use that a development such as The Point would create. Though the actual development plans for The Point include an expansion of transit services, only the additional households and jobs created from this development are modeled in this scenario. The data for the land use changes comes from the WFRC land use forecast, which is in turn based on projections from the Point of the Mountain State Land Authority (**state_land_authority_framework_2021?**). The development is expected to be fully completed by 2050, and so the 2050 WFRC land use and socioeconomic data projections are used for this site.

The site consists of 5 TAZs, as shown in Figure 4.2. Table 4.1 shows the households, population, and employment by type of these TAZs in both the baseline scenario and with the new land use. Notably, there were no households and relatively few jobs in these TAZs in the baseline scenario. No changes other than to the land use/socioeconomic data in these 5 TAZs was made relative to the baseline scenario.

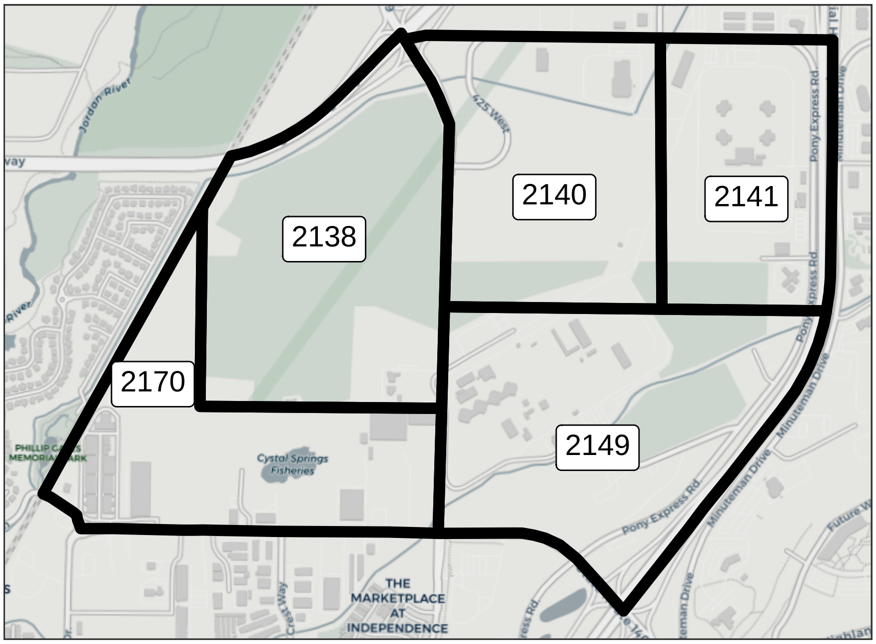


Figure 4.2: the point zones

Table 4.1: the point data

TAZ	TOTHH	HHPOP	RETEMP	INDEMP	OTHEMP	TOTEMP
2138	0	0	0	0	0	0
2140	0	0	0	0	0	0
2141	0	0	0	0	277	277
2149	0	0	0	0	796	796
2170	0	0	3	1359	71	433

TAZ	TOTHH	HHPOP	RETEMP	INDEMP	OTHEM
2138	7431	17811	4.33	0.0	76.
2140	0	0	610.33	4.0	7389.
2141	0	0	1449.33	0.0	5363.
2149	0	0	962.00	1.5	7372.
2170	0	0	7.00	357.3	106.

4.1 Scenario Creation

In the WFRC model, this change is trivial to implement. The model uses the land use/socioeconomic data directly, so the only adjustment needed is replacing the data for the specific TAZs with the 2050 data. As noted previously, all other TAZs have the same land use data as in the 2019 baseline scenario.

ActivitySim requires two changes for this scenario. The first is an update to the TAZ-level land use and socioeconomic data, which is identical to the process for the WFRC model. The second is an updated synthetic population. In order to keep consistency between model scenarios, a new population was created only for the 5 affected TAZs and joined to the existing synthetic population. There were no individuals or households in the affected zones in the existing synthetic population, so no individuals or households needed to be removed before joining the two populations.

Creating the new synthetic population followed a similar process as in the baseline scenario (Section 3.2.1), but used the new land use data as new TAZ-level controls. However, many of the controls for PopulationSim use tract-level data from the Census, and existing Census data for these controls is unrepresentative of the new development. Because of this, the Census tract covering the Gateway area in Salt Lake City (see **?@fig-gateway-tract**) is used to represent the new development patterns at The Point. The income distribution, etc. of this area will therefore match that of the Gateway area, though the TAZ-level controls and land use/socioeconomic data will match the WFRC projections for 2050.

? Note in realistic scenario you could use just the land use forecast as controls directly, rahter than the whole census shenanigans but we didn't do that since we wanted the models to be independent.

4.2 Scenario Analysis

In a trip-based model, it is relatively easy to calculate person-miles traveled from trips produced in the new development zones (see Figure 4.3), and where they are being attracted (see Figure 4.5a). However, those living in the new development make many more trips than only those produced in their home zone. In a trip-based model, this is modeled with "non–home-based" trips. However, it is difficult to know how best to distribute non–home-based trips, since by definition these trips do not have an origin or destination in the zone that generated them. ***cite something about how it's a problem***

By contrast, since an ABM models individuals explicitly, it is easy to follow the daily trips of any individual. **?@fig-lu-personmiles-abm** shows a similar plot of person-miles traveled, but of all trips made by individuals living in the new development zones. We can additionally make a distinction between trips produced in the individuals' home zones and those produced elsewhere. Note that in a trip-based model, a round-trip from home to work and back is regarded as two trips produced in the home zone. ActivitySim does not deal with productions and attractions in the same way, so for comparison between models we are counting a trip with an origin or destination in the home zone as produced by that zone (e.g. in Figures 4.4 and (**asim_lu_new_desire_map?**)).

Figure 4.5 shows desire line plots of trips generated by the new development zones. For home-based trips, it is easy to see where trips are produced and attracted to, and this is shown in

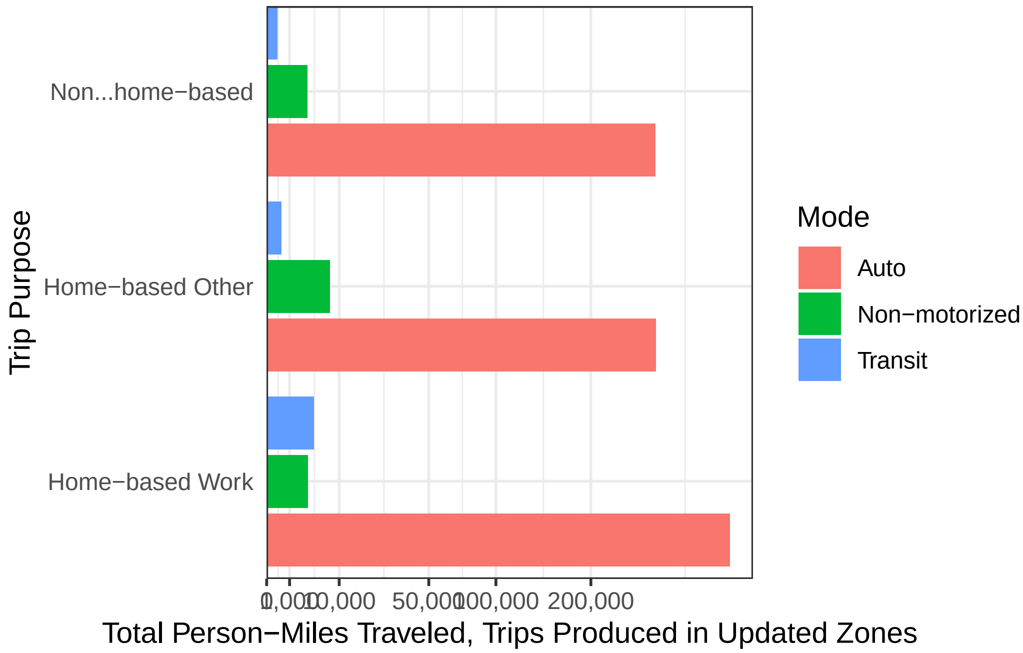


Figure 4.3: personmiles cube

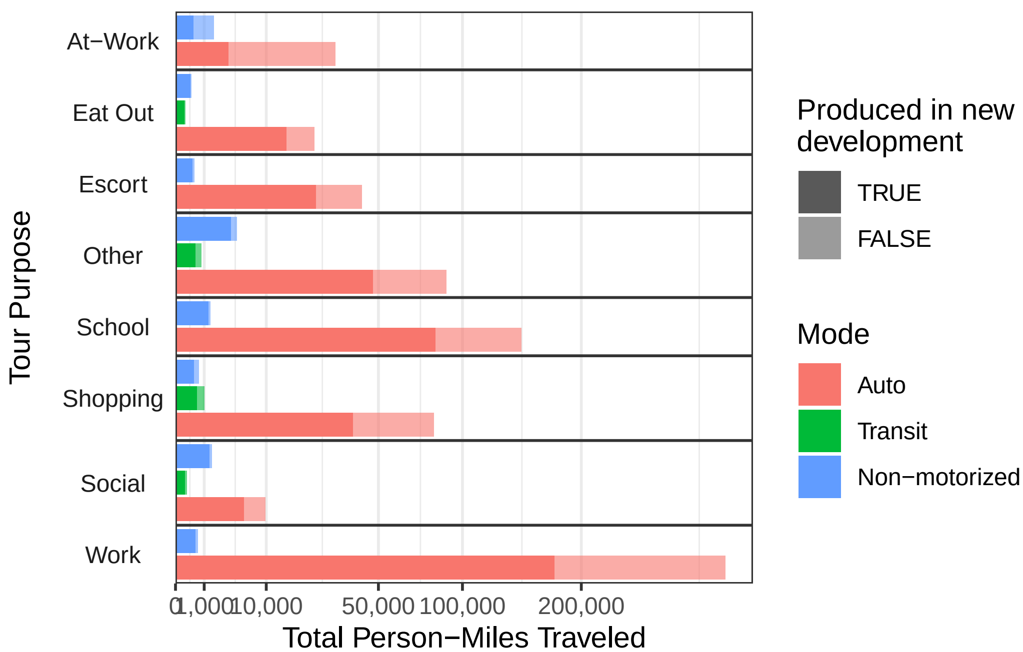
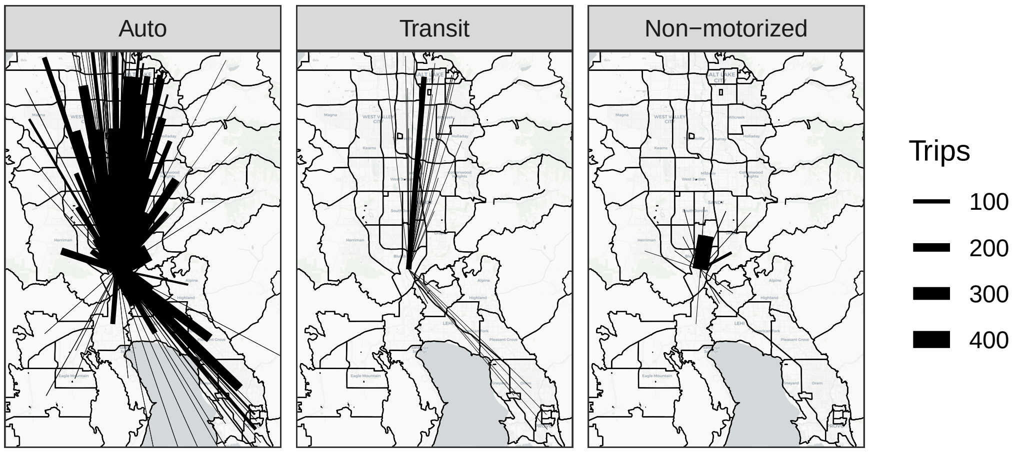


Figure 4.4: personmiles asim

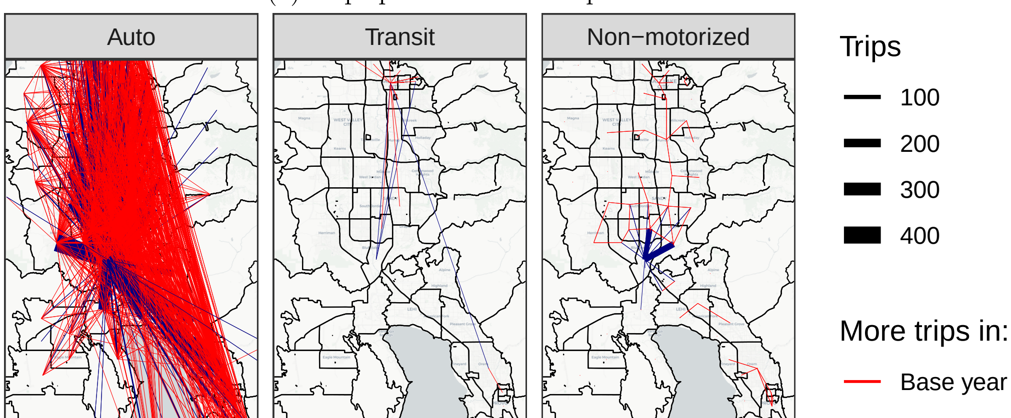
Figure 4.5a. However, the non–home-based trips are more difficult to analyze. Because non–home-based trips are relocated to zones other than where they were generated, it is impossible to filter to only those non–home-based trips generated by the new zones.

The best approach is to take the difference in non–home-based trips between the scenarios (Figure 4.5b), though this presents two problems. The first is that for real-world analyses, where land use changes are not isolated, it becomes impossible to tell which non–home-based trips are generated by which developments, as the trips are seen only in aggregate. The second problem is with the distribution of the non–home-based trips. Though the exact distribution process depends on the specific model used, Figure 4.5b shows inconsistencies with the approach in the WFRC model. Between the baseline scenario and the updated land use scenario, many pairs of zones saw an increase in the number of non–home-based trips between them, but other pairs saw a *decrease*. Additionally, all pairs of zones that saw an increase in non–home-based trips include a production or attraction to the new development zones. ***The WFRC model redistributes non–home-based trips as part of its network assignment step, which occurs*** **after** ***all trip matrices are created***. *it's either this or the only increase in nhb trips is from non-residents, which doesn't make much sense.* The only measure of the increase of non–home-based trips after redistribution is therefore in the highway network, reported as roadway volumes. This compounds with the first problem and makes it even more difficult to tell where the non–home-based trips are coming from.

As mentioned, an ABM allows for tracking of individuals explicitly, and so analyzing non–home-based trips is much more straightforward. **?@fig-lu-desire-abm** shows desire lines of all trips made by individuals living in the new development zones, colored by place of production. It is also easy to see how trips are related to each other, as each individual has a specific sequence of trips. The individual nature of an ABM avoids entirely the problems trip-based models have with non–home-based trips. In a complicated land use forecast, each development's full contribution to network congestion can be analyzed individually.



(a) Trips produced in the updated TAZs.



(b) Difference in non–home-based trips.

Figure 4.5: Desire lines of trips made in the WFRC model by mode. Note that the non–home-based trips are obtained by differencing the non–home-based trip matrix with the base year.

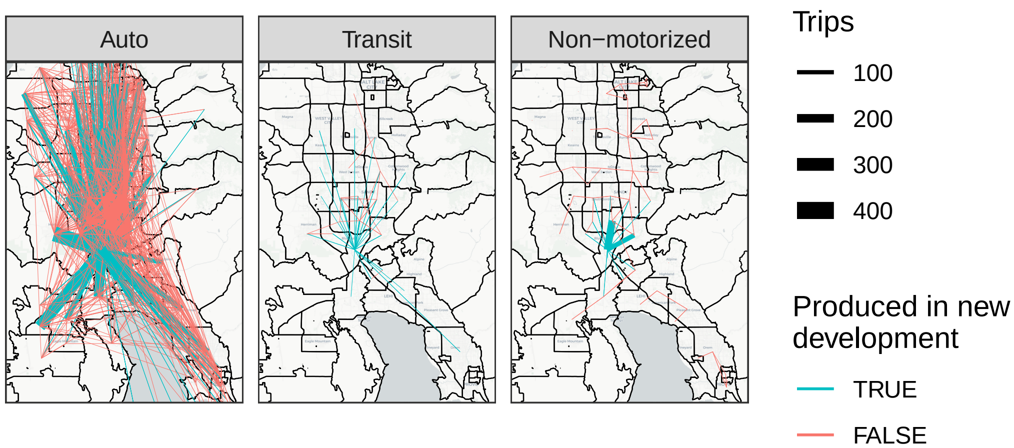


Figure 4.6: Desire lines of trips made in ActivitySim by mode.

5 Scenario 2: Increased Transit Service

The FrontRunner is a commuter rail line between Provo and Ogden, Utah, with several stops in-between. Currently, there is only one set of tracks for much of the line, and train crossings are only possible near stations. Because of this, headways are quite large, with trains running every half-hour in peak periods and hourly in off-peak periods. Additionally, trains occasionally need to wait for each other in order to cross paths.

There is a planned improvement to the FrontRunner that would "double-track" the entire route, allowing trains to pass each other at any point. This would allow for much smaller headways, which are currently planned at 15 and 30 minutes for peak and off-peak periods respectively (half of the current headways). The improvement would also partially electrify the FrontRunner, allowing for faster travel speeds, and extend the track farther south with additional stops.

This scenario models these planned improvements to the FrontRunner. The scenario adjusts the headways to 15/30 minutes for peak/off-peak service, increases travel speeds, and adds additional stops in Vineyard, Springville, Spanish Fork, and Payson. Figure 5.1 shows the FrontRunner network with the modeled changes. No other modifications were made to the baseline scenario; for example, a revised bus service network serving the Springville station is not included.

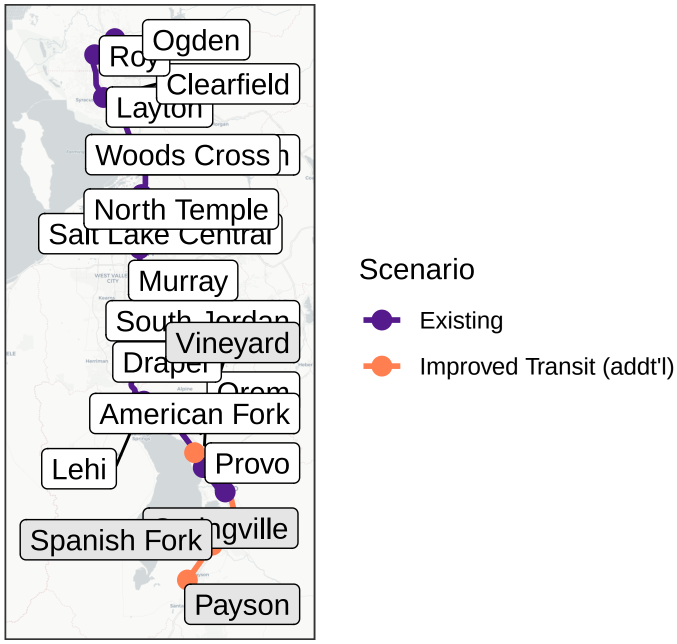


Figure 5.1: frontrunner map

5.1 Scenario Creation

In the WFRC model, this change is relatively easy to implement. The headways are stored directly in the input data and are easily modified, and a year-2050 network with increased speeds and additional stations is already built into the model for future-year analysis. The only additional change needed was to turn on the "park and ride" flag in the highway network at each new station. Wasatch Front Regional Council (WFRC)

To implement this scenario in ActivitySim, only updated travel skims are needed. As in the baseline scenario, the transit skims output from the WFRC model's network assignment in this model scenario are taken directly as inputs to ActivitySim. Because the mode share of transit is relatively low, it is not expected that the highway travel times will be affected very much by this change, and so the highway skims from the baseline scenario are used directly and not updated for this scenario. No other changes to ActivitySim are necessary to model this scenario.

purpose	mode	cube_tr	cube_by	cube_diff_pct	asim_tr	asim_by	asim_diff_pct
hbo	auto	4095127	4096688	0.000	3253047	3253220	0.000
hbo	nonmotor	510103	510143	0.000	532301	532274	0.000
hbo	transit	38912	37346	0.042	67540	67396	0.002
hbw	auto	1582865	1586414	-0.002	1523723	1524169	0.000
hbw	nonmotor	76396	76506	-0.001	83107	83119	0.000
hbw	transit	52380	48752	0.074	63262	62814	0.007
nhb	auto	2224420	2224878	0.000	1838808	1839065	0.000
nhb	nonmotor	146409	146404	0.000	162991	162979	0.000
nhb	transit	13870	13453	0.031	30688	30513	0.006

5.2 Scenario Analysis

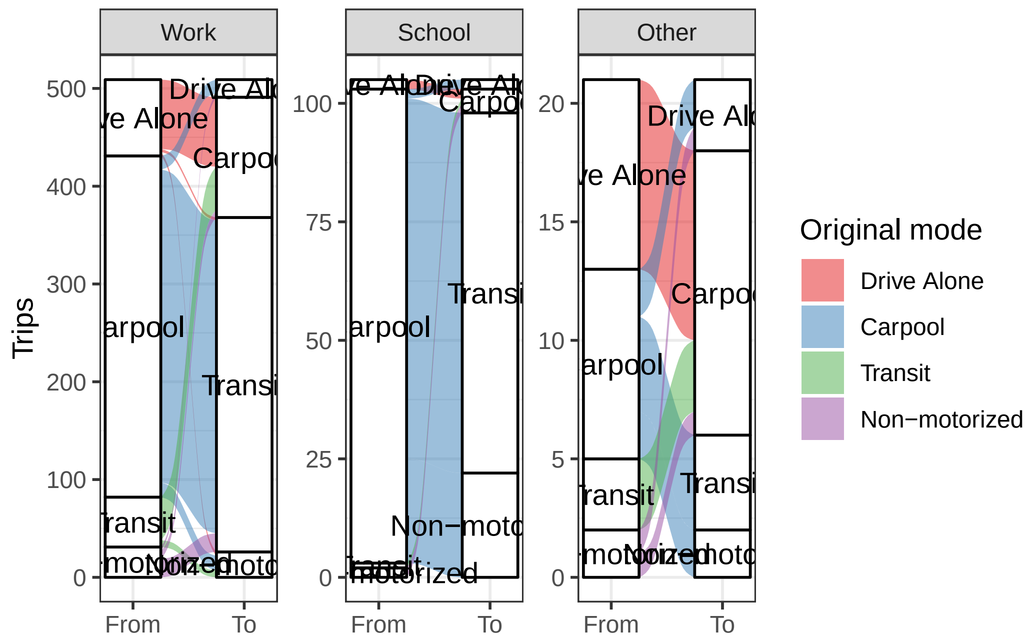


Figure 5.2: a

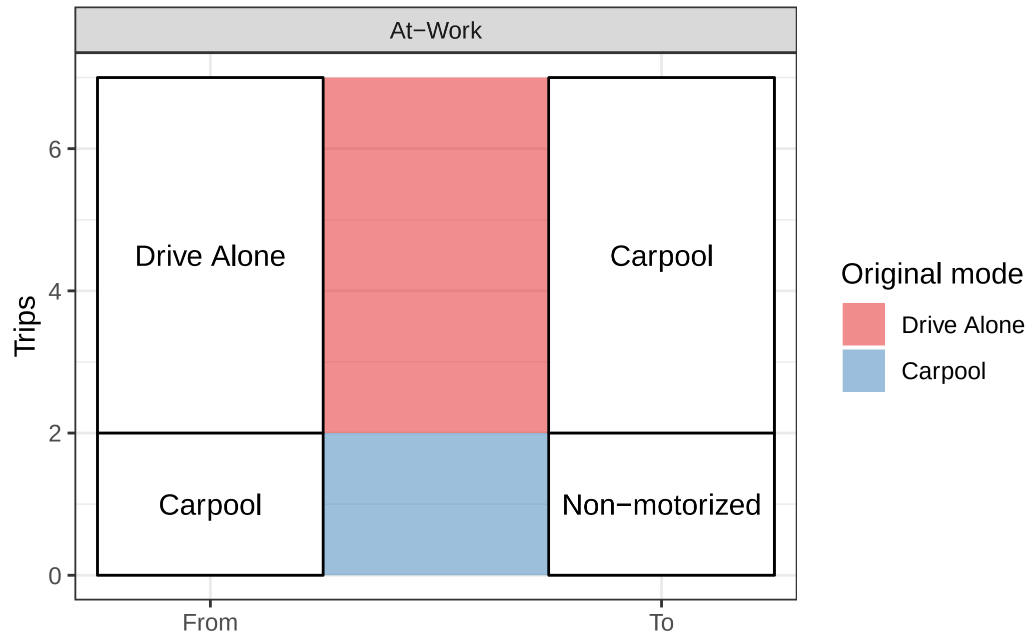


Figure 5.3: At-work trip modes of individuals who switched their work mode away from Drive Alone

With greater access the commuter rail by decreasing the headways, we wanted to see how the ridership changed in this scenario. We also wanted to see where the commuter rail riders were coming from.

Analyzing this with the trip-based model was straightforward since one of the outputs is a file listing the amount of trips made by each form of transit. There are also more detailed matrices that shows commuter rail transit (CRT) trip productions and attractions. There is a matrix for driving to the CRT and a matrix for walking to the CRT. With these matrices and the taz shape file, we were able to to visualize the catchment area in a plot like *(another figure that we can show)*

Implications: We saw that there was more than a 30% increase in commuter rail transit trips in this scenario but not much change in the other transit trips. We could see the areas where peoples' CRT trips began on a zonal and a district level and noticed a big increase in the people coming from zones that were closer to the new stations that were part of the extended rail line. (I think more can be added here as well)

Limitations: Apart from the increase in CRT trips and the catchment areas, there wasn't much more we could see with the trip-based model. By connecting the catchment areas with what we know of the zonal SE data, we could make some assumptions about the income of the new people taking the commuter rail, but we couldn't find anything more about the demographics of the riders.

Table 5.1: cube

purpose	transit_trips	TOTHH	ALLEMP	med_income
hbo	38912	456	426	51230
hbw	52380	468	357	60187
nhb	13870	103	1365	50921

Table 5.2: asim

purpose	transit_trips	income	age
hbw	63262	62712	37
hbo	67540	64384	15
nhb	30688	62159	32

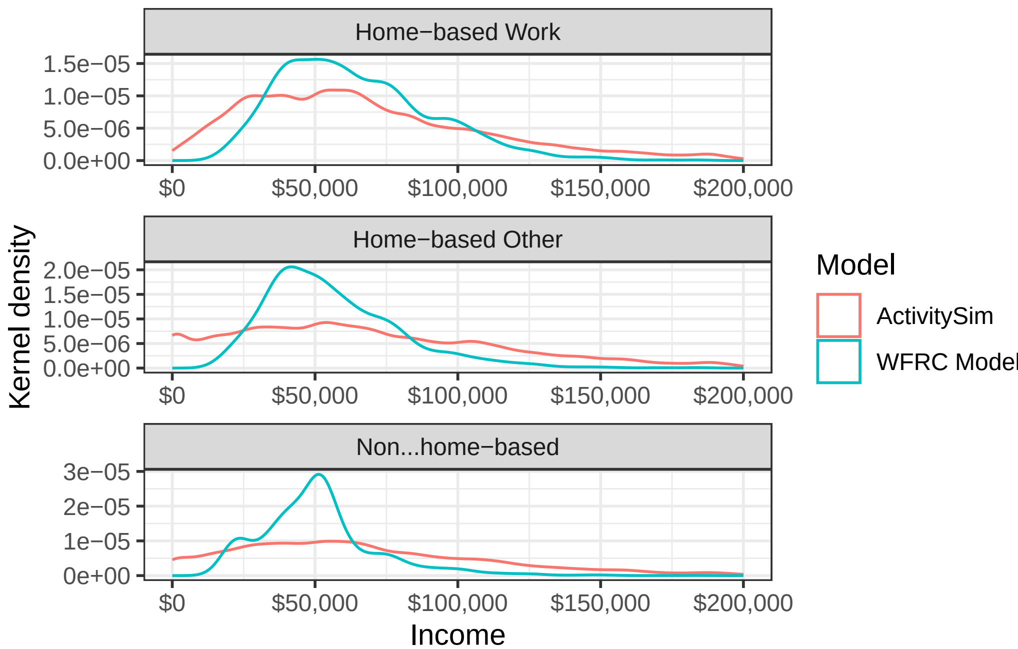


Figure 8 shows the increased productions and attractions of the “drive to CRT” mode by district. These could as an example be further analyzed by TAZ/district median income or similar variables. However, there is no indication of which types of individuals are switching their mode. In an ABM, this can be analyzed. Figure 9 shows the trips that switched modes from the base scenario, as well as which mode they switched to. Though some of this switching is due to the internal randomness in ActivitySim, the majority of the mode-switching was from auto to transit, and this shows a clear increase in transit usage over the base scenario.

ActivitySim also has an "at-work" tour purpose, indicating a subtour from the workplace. The team analyzed the trip modes of these subtours for the individuals who switched to transit for their work tour. Figure 10 shows that most people did not switch subtour modes from the base scenario. The similar number of switches between auto and non-motorized modes indicates that the switching here may be mostly due to ActivitySim's randomness and not any changes in the network.

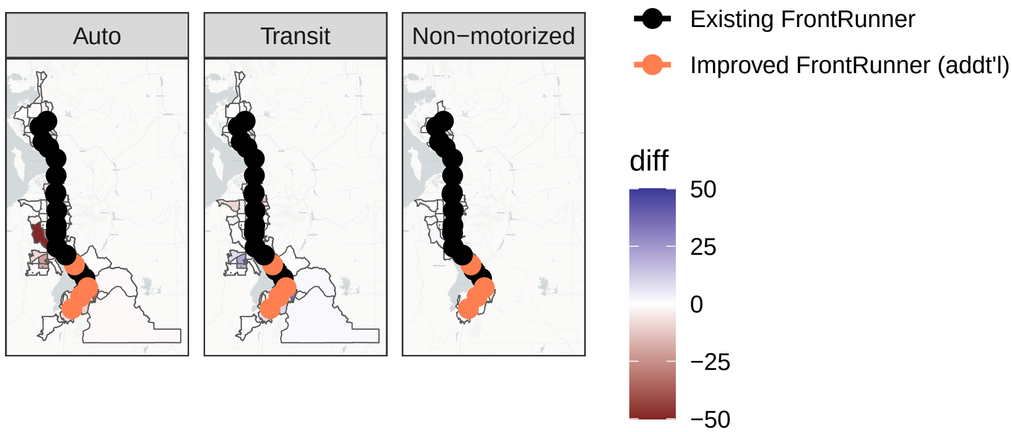


Figure 5.4: cube

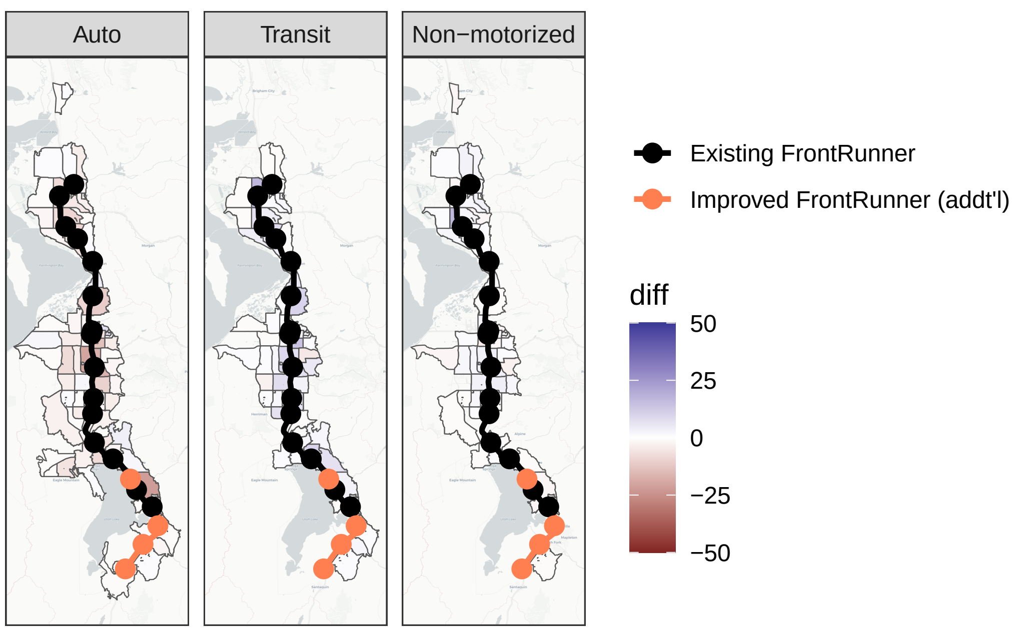


Figure 5.5: asim

6 Scenario 3: Increase in Remote Work

With the onset of the COVID 19 pandemic, there were unprecedented numbers of people working remotely (Bick, Blandin, and Mertens 2021). Though remote work is currently not as common as during the pandemic, remote work rates are increasing each year and are predicted to continue to rise (**cite?**). The WFRC model predicts a year-over-year increase in remote work rates of about XXX%, as illustrated in Figure 6.1.

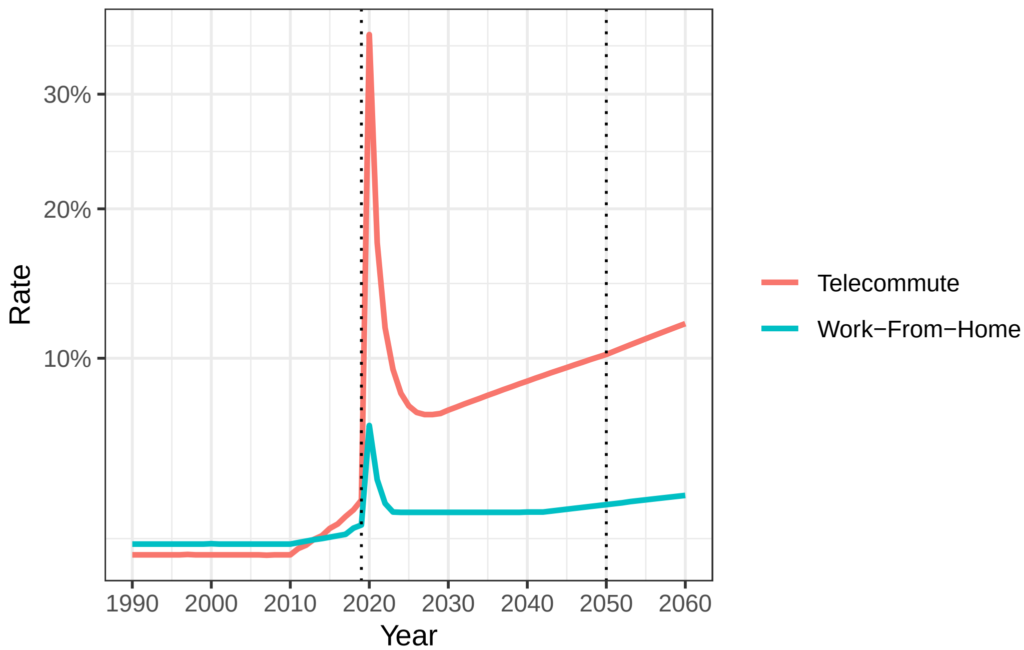


Figure 6.1: wfrc remote work plot

This scenario is a “what-if” analysis that models a significant increase in remote work rates. We use the WFRC model predicted remote work rates in the year 2050, but make no other changes from the baseline scenario. In other words, this scenario models the 2050 predicted remote work rates with the 2019 land use and infrastructure.

6.1 Considerations for Modelling Remote Work *This section maybe needs to go somewhere else* (probably lit review)

There has been much research, especially in recent years, on the implications of remote work. While many MPOs have adjusted their models to account for remote work, and most models follow similar principles, it is not obvious what the best method is. Bramberga (2023) even suggested that considerations for remote work should be made on a case by case basis because there is no single best approach.

Increasing remote work rates may affect several aspects of travel behavior. The most obvious effect is that people will on average make fewer work trips, and this effect will vary by job type (Yasenov 2020). Most travel demand models include a decrease in work trips based on remote work rates and job type (Bramberga 2023; Moeckel 2017; Sener and Bhat 2011).

While work trips decrease with an increase in remote work, Kim (2017) discusses a "rebound effect", where individuals make more discretionary trips on days they do not commute to work. Moreno and Moeckel (2017) similarly proposes the existence of a "travel time budget", where an increase in trips of one purpose will decrease the time people allocate for trips of another purpose.

This rebound effect is not straightforward, however. Elldér (2020), for example, finds that distinguishing between people that work from home all day and part of the day might make a difference. Compared to those who commute to work, the Sweden study shows that those who worked from home the whole day had less trips and miles traveled, but those who worked from home only part of the day had more trips and miles traveled.

Additionally, the types of trips people make can differ depending on remote work status. While the rebound effect proposes that the *number* of trips may increase on remote work days, (**mokhtarian_the_1998?**) finds a decrease in vehicle *miles* traveled for both work and discretionary trips on remote work days. This implies that longer trips are being replaced by shorter trips on days people do not travel to work. Moeckel (2017) additionally finds that those who travel to their job site less frequently are more likely to live further away from their job site, and so their longer but infrequent commute is dropped on remote work days, perhaps in favor of shorter, discretionary trips.

6.2 Scenario Creation

As noted in Section 3.3.2, both models make a distinction between "working from home" (no work location other than home) and "telecommuting" (working remotely some but not all days). The WFRC model contains a lookup table of both work-from-home (called "home-based jobs" in the WFRC model) and telecommute percentages by job type and year. Two changes are needed in the WFRC model for this scenario. The first is to replace the 2019 estimates for work-from-home and telecommuting with the 2050 estimates. Table 6.1 shows both the original and updated estimates. The second change is to the TAZ-level socioeconomic data. The WFRC model estimates a number of home-based jobs in each TAZ, and the original home-based job estimates are similarly replaced with the 2050 estimates.

The WFRC model additionally includes a global scaling factor for all remote work percentages. However, this was left unchanged (set at 1) as we considered that the 2050 predicted remote work percentages would better model a more realistic increase in remote work than simply adjusting the 2019 rates globally.

Table 6.1: wfrc remote work data

name	2019_tc	2050_tc	2019_wfh	2050_wfh
Retail	0.027	0.072	0.021	0.025
Food	0.019	0.050	0.015	0.017
Manufacturing	0.020	0.054	0.016	0.019
Office	0.067	0.180	0.052	0.062
Gov't/Education	0.017	0.046	0.013	0.016
Health	0.029	0.072	0.021	0.025
Agriculture	0.069	0.168	0.054	0.058
Mining	0.005	0.014	0.004	0.005
Construction	0.033	0.088	0.026	0.030
Other	0.054	0.146	0.042	0.050

We adjusted the remote work models in ActivitySim using the same process as in Section 3.3.2, but with the 2050 targets from the WFRC model. The "target work-from-home percent" value in ActivitySim's work-from-home submodel was changed to 3.5% based on a weighted average from the 2050 WFRC data, and the job type coefficients in the telecommute frequency submodel were calibrated to match the WFRC target telecommute shares by job type. Table 6.2 shows the WFRC 2050 telecommute percentages with the ActivitySim telecommute utility coefficients. As in the baseline scenario, this calibration allowed ActivitySim to match the WFRC telecommute percentages exactly.

Table 6.2: wfh telecommute

Job Type	WFRC Telecommute %	ActivitySim Telecommute Utility Coefficients		
		1 day	2–3 days	4 days
Retail	7.25%	2.021	0.809	0.505
Food	5.03%	1.376	0.551	0.344
Manufacturing	5.45%	1.636	0.655	0.408
Office	18.01%	4.792	1.916	1.197
Gov't/Education	4.56%	1.199	0.480	0.301
Health	7.21%	1.929	0.771	0.482
Agriculture	16.83%	4.764	1.906	1.191
Mining	1.43%	-0.694	-0.277	-0.174
Construction	8.82%	2.544	1.018	0.637
Other	14.58%	3.804	1.521	0.951

6.3 Scenario Analysis

Both models decrease the number of work trips made as remote work rates increase. However, the WFRC model does not account for a potential "rebound effect" where more discretionary trips are made by those who do not travel to their workplace on a given day. This is seen in Table 6.3, where the WFRC model shows a decrease in home-based work and non–home-based trips (many of which begin or end at work), but virtually no change in home-based other trips. ActivitySim on the other hand does account for this, in that individuals working remotely on any given day may be more likely to make discretionary tours. Table 6.3 shows this as well, where ActivitySim predicts a noticeable increase in home-based other trips as well as a decrease in work trips.

Table 6.3: wfh mode split comp

purpose	mode	cube_wfh	cube_by	cube_diff_pct	asim_wfh	asim_by	asim_diff_pct
hbo	auto	4097821	4096688	0.000	3278836	3253220	0.008
hbo	nonmotor	508869	510143	-0.002	534807	532274	0.005
hbo	transit	37359	37346	0.000	67593	67396	0.003
hbw	auto	1483120	1586414	-0.065	1430577	1524169	-0.061
hbw	nonmotor	71063	76506	-0.071	78703	83119	-0.053
hbw	transit	44977	48752	-0.077	59124	62814	-0.059
nhb	auto	2193201	2224878	-0.014	1790340	1839065	-0.026
nhb	nonmotor	144126	146404	-0.016	157632	162979	-0.033
nhb	transit	13199	13453	-0.019	29650	30513	-0.028

In addition to the number of trips, increasing remote work rates can also have an effect on the length of trips that are made. The "travel time budget" proposed by Moreno and Moeckel (2017) suggests that longer trips would be made less frequently, and Moeckel (2017) additionally found that those who travel to their job site less frequently are more likely to live further away from their job site, and so their longer but infrequent commute is dropped on remote work days, perhaps in favor of shorter, discretionary trips.

The WFRC model does not consider trip length when adjusting trip rates due to remote work. There is perhaps an implicit consideration in that remote work rates differ by job type and some job types are concentrated in certain areas, but there is no reference to trip length explicitly. Table 6.4 illustrates this, where for example home-based work driving trips decreased by 6.5% relative to the baseline scenario, but person-miles traveled decreased only by 5.8%. This shows that in fact the *shorter* work trips are being made less frequently with increased remote work rates, though notably this is only a side-effect of the WFRC model and the two specific model scenarios.

Table 6.4: cube

purpose	mode	wfh_trips	by_trips	trips_pct	wfh_pmt	by_pmt	pmt_pct
hbo	auto	4097821	4096688	0.000	19571300	19509401	0.003
hbo	nonmotor	508869	510143	-0.002	590349	591297	-0.002
hbo	transit	37359	37346	0.000	264432	264203	0.001
hbw	auto	1483120	1586414	-0.065	15015364	15941522	-0.058
hbw	nonmotor	71063	76506	-0.071	122930	132216	-0.070
hbw	transit	44977	48752	-0.077	500953	547804	-0.086
nhb	auto	2193201	2224878	-0.014	12275574	12427922	-0.012
nhb	nonmotor	144126	146404	-0.016	134784	136914	-0.016
nhb	transit	13199	13453	-0.019	72018	73563	-0.021

ActivitySim does model distance to work directly when predicting remote work status (see Section 3.3.2 and Table 3.5), so those who live further away from their job site are more likely to work remotely. ActivitySim therefore predicts a greater decrease in miles traveled than in trips for home-based work, as seen in Table 6.5.

Figures 6.2 and 6.3 show the trip length frequency distribution of "unmade" trips in the increased remote work scenario (i.e. the trip length frequency distribution of the *difference* in trips) compared to that of the baseline scenario. Similar to Tables 6.4 and 6.5, this shows that ActivitySim "removes" longer trips more frequently than shorter trips, and the WFRC model makes no distinction.

Table 6.5: asim

purpose	mode	wfh_trips	by_trips	trips_pct	wfh_pmt	by_pmt	pmt_pct
hbw	auto	1430577	1524169	-0.061	13438309	14351364	-0.064
hbw	transit	59124	62814	-0.059	549977	586362	-0.062
hbw	nonmotor	78703	83119	-0.053	147537	155798	-0.053
hbo	auto	3278836	3253220	0.008	18195390	18066305	0.007
hbo	transit	67593	67396	0.003	418217	418921	-0.002
hbo	nonmotor	534807	532274	0.005	906676	901975	0.005
nhb	auto	1790340	1839065	-0.026	8834052	9117282	-0.031
nhb	transit	29650	30513	-0.028	160403	166288	-0.035
nhb	nonmotor	157632	162979	-0.033	177834	183398	-0.030

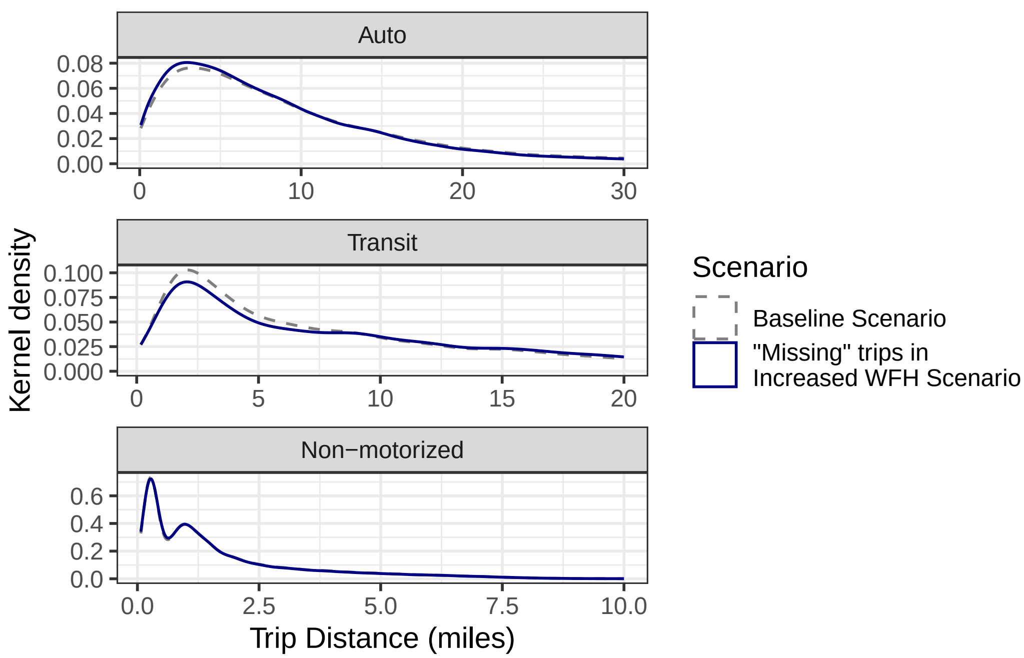


Figure 6.2: cube

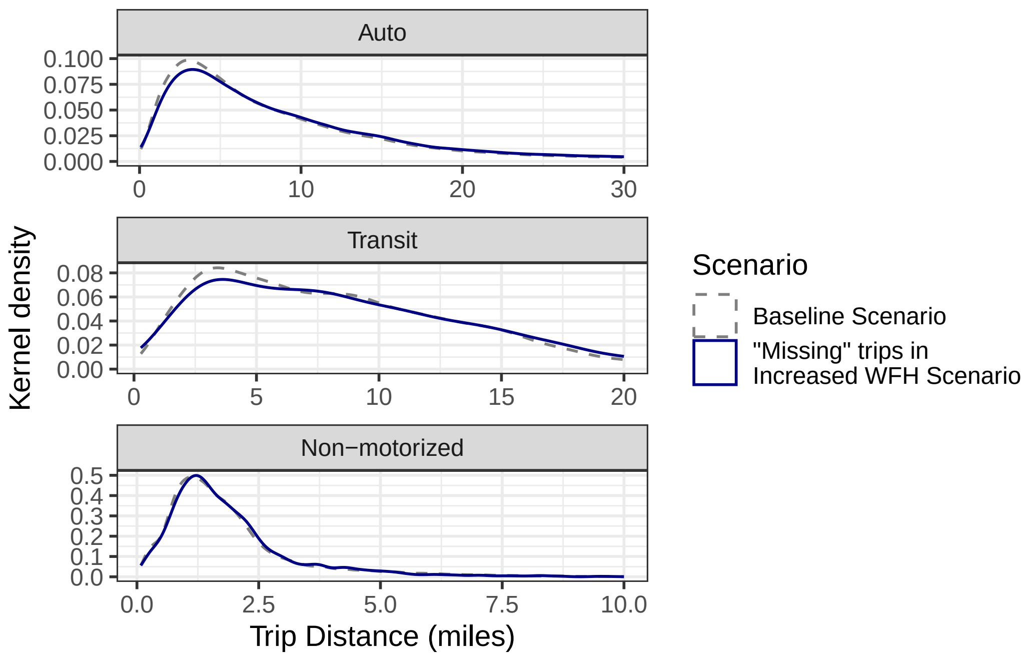


Figure 6.3: asim

7 Conclusions and Recommendations

Intro.

Many of the conclusions presented here are specific to the WFRC model and our ActivitySim implementation. However, *some conclusions can apply more broadly....*

7.1 Computational resources

As part of our recommendations, we include a discussion of the computational resources used for each model.

All runs of the WFRC model were done on a Windows 10 computer with 2 Intel Xeon Silver 4114 CPUs. The CPUs have a base frequency of 2.2 GHz with a maximum turbo frequency of 3.0 GHz, and 10 cores/20 threads each. The WFRC model is configured for multiprocessing in its destination and mode choice steps, **waiting to head back from Chad on how many processes it actually uses though**. This machine also has 128 GB of RAM installed, **and we need to check how much it actually uses**. There were not significant differences in runtimes between each model scenario, and each scenario had a runtime of 16–17 hours.

Most runs of ActivitySim were done on nodes of the BYU supercomputer. Each node runs Red Hat Enterprise Linux 7.9, and uses a 14-core Intel Broadwell CPU at 2.4 GHz. Each ActivitySim run requested 12 CPU cores and 360 GB of RAM. Running in single-threaded mode (i.e. only one CPU core was utilized), each run took roughly 5 hours to complete, and used nearly all of the 360 GB of RAM available. With multi-threading enabled, however, the runtimes decreased to around an hour per scenario, using 72% of the available CPU time across all 12 cores and 88% of the available RAM.

This is a huge difference in runtime between the two models, though crucially ActivitySim had 3 times as much RAM available for use. ActivitySim offers "chunking" options (**asim-chunking?**), where large tables are loaded into RAM in chunks rather than all at once. This can dramatically reduce the amount of RAM required to run an ActivitySim scenario, at the expense of increased runtimes. For comparison, we ran the baseline scenario in ActivitySim on the same computer used for the WFRC model scenarios, with chunking enabled to account for the amount of RAM available. With multi-threading set to use **36 of the 40 available (should probably match what the WFRC model actually uses if not the max amount** threads, the baseline ActivitySim scenario ran in XXX hours **(still need to do this)**.

7.2 Time Spent

In order to change from a trip-based to an activity-based model, agencies will need to spend time learning….

Table 7.1 shows the amount of time spent on creating and analyzing each scenario in both models. These are rough approximations, as detailed time logs are not available, but should serve to give a general idea of the time required to **learn activitysim**. Note as well that these tables show time spent by one graduate and one undergraduate research assistant. More experienced modelers would likely require significantly less time to create and analyze similar scenarios.

Table 7.1: time spent

task	hours
Synthetic population creation	50
Baseline mode choice calibration	20
Add remote work models to ActivitySim	20
Baseline remote work calibration	10
Scenario creation: Land Use	15
Scenario creation: Transit	2
Scenario creation: Remote Work	5

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.62	16.5	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.88	17.0	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.32	18.6	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.21	19.4	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.44	17.0	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.46	20.2	1	0	3	1

7.3 Notes

Each model works differently. - There will be a learning curve when changing from TBM to ABM - Planning agencies should take this into account when switching

ABM is more malleable. It was easy to throw on the WFH model without having to completely change the rest of the model, and it seemed more realistic than the TBM. - For planning agencies wanting a model that more easily adapts to unforeseen travel behavior change, an ABM would be preferable

More analyses can be done with ABMs - We were able to replicate each TBM analysis with the ABM and more - We could make more demographic-type analyses with ABM - We were able to compare changes in individual behavior with ABM - Simpler to go about the analysis when thinking on the individual level

ActivitySim doesn't have the built in analysis tools like CUBE does (I think this is true, but not sure) - We had to use different programs to analyze ActivitySim output (like R)

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