

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

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Abstract

Activity-based travel demand models are generally considered superior to their trip-based counterparts, as activity-based models (ABMs) explicitly model individuals in contrast to the aggregate nature of trip-based models. There have been a number of comparisons between trip- and activity-based models, but these comparisons focus almost exclusively on the technical ability of the two model types, while not considering the practical benefits an ABM may or may not have to a transportation agency. This research performs a more holistic comparison between trip- and activity-based models, focused specifically on the practical differences between model types, both in terms of usability and capability for complex analysis. We use the existing Wasatch Front model as a representative trip-based model, and an ActivitySim implementation in the same area as a representative ABM. We create three hypothetical scenarios in both models: a change in land use, an improvement to commuter rail service, and an increase in remote work. We discuss the process of creating each scenario in both models, and perform several example analyses with each scenario and model. We find that many commonly-cited reasons for the lack of ABM adoption may not be as applicable as previously thought. ABMs are often considered more complicated than trip-based models, requiring more data and computational resources. While ABMs do require more input data, we found that in our case the complexity of the model and the computational resources required were similar between model types. Additionally, the ABM allows for much more intuitive and straightforward interpretation of results.

Keywords: travel demand model; activity-based model; ActivitySim

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List of Acronyms

ABM activity-based model

ASC alternative-specific constant

DAP daily activity pattern

TAZ transportation analysis zone

WFRC Wasatch Front Regional Council

1

Introduction

In travel demand modeling, 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 (Rasouli and Timmermans 2014). ABMs explicitly model individuals, in contrast to the aggregate nature of trip-based models, and so in theory are able to represent travel behavior more accurately. Additionally, the focus on individuals in an ABM can allow for more detailed post-hoc analysis of model outputs compared to a trip-based model.

There have been a number of comparisons and case studies between trip- and activity-based models (Ferdous et al. 2012; Mouw 2022; Zhong et al. 2015), but these comparisons focus almost exclusively on the technical ability of the two model types. Though there are potential *theoretical* benefits to ABMs over trip-based models, there is little discussion in the literature of the *practical* benefits an ABM has, if any. In fact, while trip-based models are almost ubiquitous among transportation agencies, many agencies have delayed or declined to transition to an ABM citing additional data requirements, staff training, computational resources, and related concerns (Miller 2023).

In this research, we perform a more holistic comparison of ABMs to trip-based models, with a particular focus on the practical considerations an agency would need to make in transitioning to an ABM. We additionally discuss the potential practical advantages regarding the quality and characteristics of travel analyses that an ABM allows. Though this research occasionally makes quantitative comparisons between model types, we do not focus heavily on model *accuracy* (either to each other or to observed data), as this can be adjusted in any model type through model calibration. Instead, this research seeks to illustrate the differences between trip- and activity-based models in a way that would be practically useful to an agency considering transitioning to an ABM, noting potential pain points both in the literature and in our experience in this research itself.

To compare the model types, we first identify three main goals of travel demand modeling, which are to model travel behavior in response to changes in land use, transportation infrastructure, and social/economic factors. We then create three hypothetical model scenarios, one for each goal identified. These scenarios are the addition of a new devel-

opment, an increase in commuter rail service, and an increase in remote work, respectively. Each of these scenarios is created in both a trip-based and activity-based model representing the Wasatch Front (Salt Lake City) region of Utah, USA. We discuss the process of implementing each scenario, as well as perform a variety of post-hoc analyses, for both model types.

The document proceeds in a typical fashion: Chapter 2 provides an overview of the literature discussing the differences between trip-based models and ABMs, including the theoretical and analytical benefits of each framework. Chapter 3 first describes the models used in this research, namely the existing regional trip-based model and an activity-based model constructed to support research activities in the region; this section also describes the 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 related limitations and implications. Chapter 7 provides a summary of our findings and a discussion of our conclusions, along with a set of recommendations.

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, these models are strongly aggregate 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 travel behavior at an individual rather than aggregate level. An 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, for example, if an individual takes transit to work, they will

not be able to drive home. ABMs therefore attempt to 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 may be superior in certain aspects, they may 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 the increased costs 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 p. 28). Models can be more complicated than these four steps, 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 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 p. 14). Many trip-based models include a disaggregation step, where this aggregate data is 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.

ABMs 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 et al. 2005). These models use an activity or tour scheduler to assign a daily activity pattern (DAP) of zero or more tours to each individual, where 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. In effect, an ABM replaces the first “three” steps of the traditional “four-step” approach.

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 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 p. 14). This includes data such as number of households, average household income, population, number of workers, etc. Rather than predict travel behavior using only this zone-level aggregate data, many models include a “disaggregation” step, which classifies the households in a zone along variables such as household size, vehicle ownership, and number of workers. For example, a 1000-household zone with an average household size of 3 may be classified into 500 2-person and 500 4-person households.^a This disaggregation is useful, as travel behavior (such as the number of trips made) can vary significantly based on a household’s classification.

Subsequent model steps then use this disaggregated data in their estimations. A 2-worker, 1-vehicle household, for example, may be modeled to make 3.8 work trips on an average weekday, while a 1-worker, 1-vehicle household may make fewer. The trips are then added to obtain the total number of trips produced by each zone (National Academies 2012 p. 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. 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). Further, combining these segmentations at any point

^aThe specific method for classifying households may differ between models, so different models will have a different distribution of households along each variable used for classification.

precludes that segmentation from use in subsequent model steps as well as in any post-hoc analysis.

This approach 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; Yum 2020; Zmud and Arce 2001), including such variables in travel demand models can be 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 future planning years? Regardless of the reasons for their exclusion, in a trip-based model 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, and the approach that ABMs use, 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 attributes as the study area (National Academies 2012 p. 93). The goal is to have a population that is functionally similar to the actual population, but without the privacy concerns of using real 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 aggregated at the zone level. In an ABM, decisions in each model step are tied to a specific individual, and so the individual-level socioeconomic data remains available throughout the modeling process regardless of the specific variables used in each model step. This allows, for example, an equity analysis to identify 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 difficult with aggregate population data, can be very valuable in transportation planning and policy making, particularly when equity is a priority.

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 (Moeckel et al. 2020; Walker 2005), but these are relatively rare.

Figure 2.1 gives a visualization of an example “information pipeline” for a model using aggregate data and a model using a synthetic population. In the aggregate data model, it is impossible to know which trips are made by, for example, 2-worker, 1-vehicle, low-income households after the mode choice step; 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 the data used in previous steps.

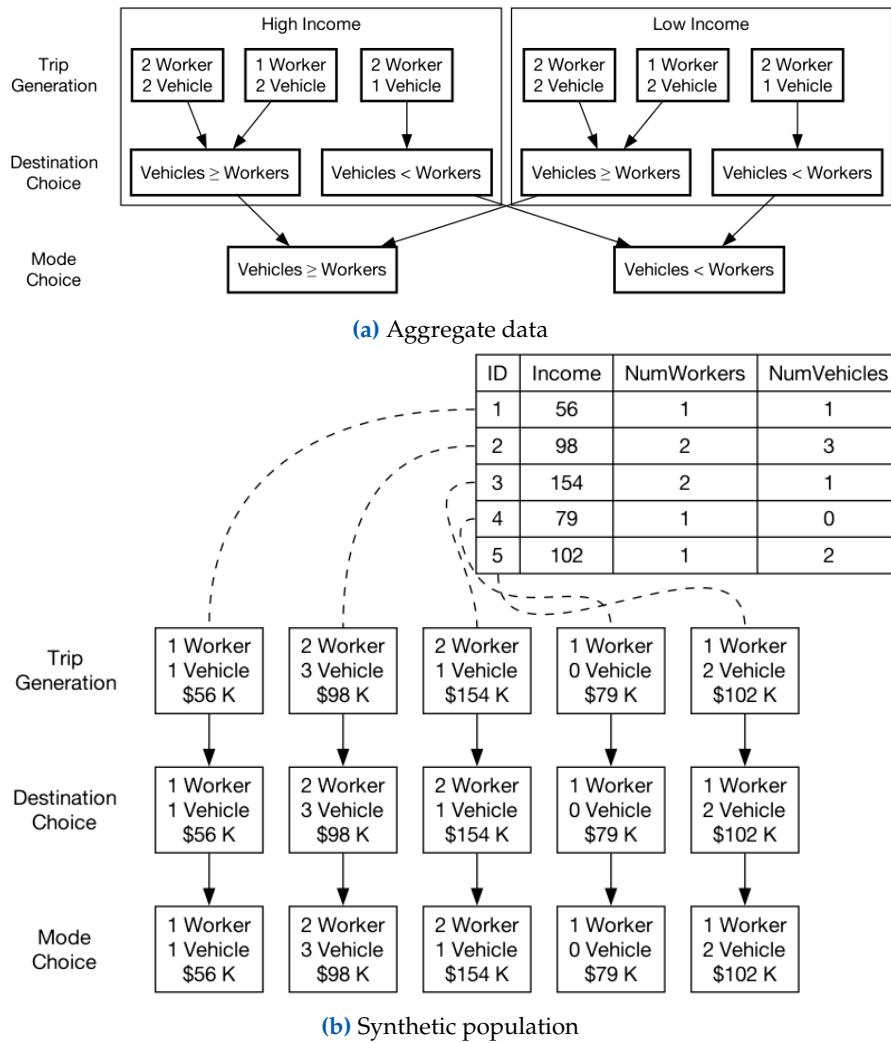


Figure 2.1: Example “information pipeline” for aggregate data vs. a synthetic population.

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 activity to the next. However, in practice there are few true “activity scheduling” models, and the term “activity-based” is commonly 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 choice 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 entire population the inconsistencies would cancel out, leaving an overall accurate forecast.

ABMs, on the other hand, explicitly model this trip-chaining in the form of “tours”, sequences of trips that begin and end at the home. This approach attempts to create consistency in trip origins/destinations, mode choice, and time of day: since each trip is a part of a 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 et al. (2005), fig. 18.1).

Figures 2.2 and 2.3 show examples of the trips distributed across several TAZs in the various model types. Figure 2.2 depicts the distribution in a typical trip-based model where the total number of trips between each zone is modeled. With these results, the mode and purpose of each trip is known, but because trip-based models can only model trips at the zone level, there is no way of telling who made which trips other than the segmentation used through each model step (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 distribution 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, a trip-based microsimulation model could predict that the individual takes transit to work but then drives home, or that the individual makes two trips to recreation without ever making a return trip. The

activity-based approach, depicted in Figure 2.3b, attempts to add consistency by modeling tours, and only generating trips consistent with each tour.

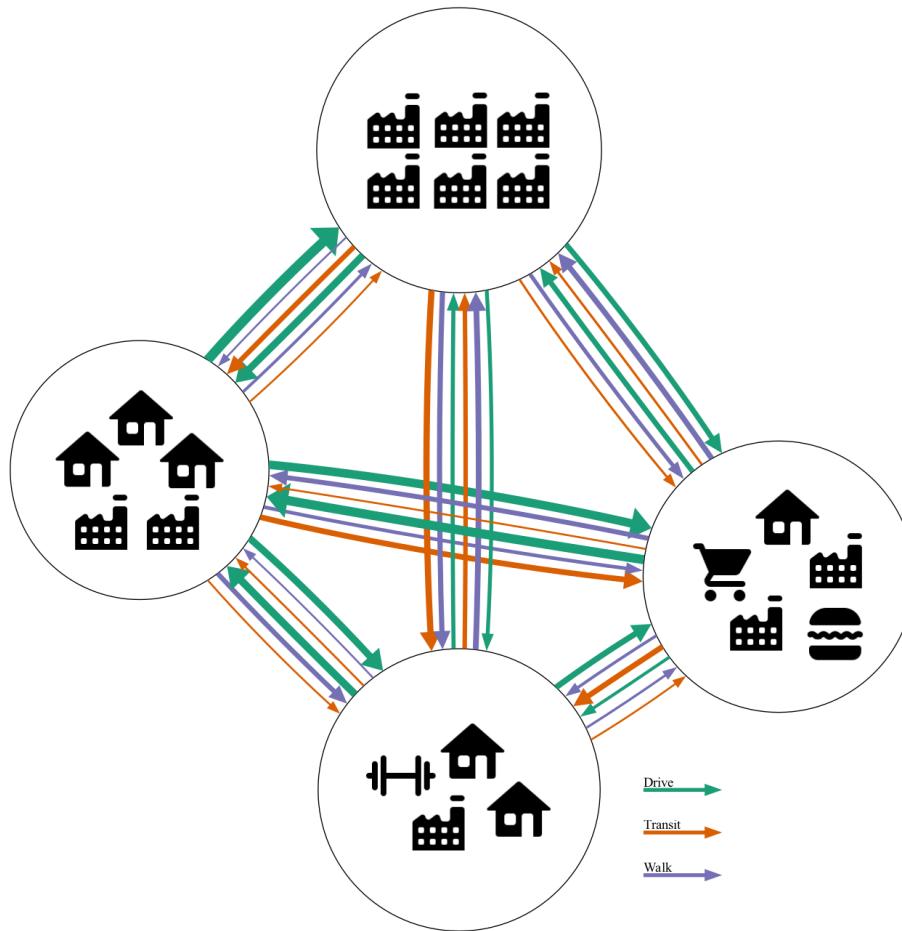


Figure 2.2: Example trip distribution using aggregate data. There is little information on who is making which trips, and it is not known how trips are related to each other.

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 in the household no matter how directly the policy connects to them (Macfarlane and Lant 2023; Vovsha et al. 2005). These effects are not 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

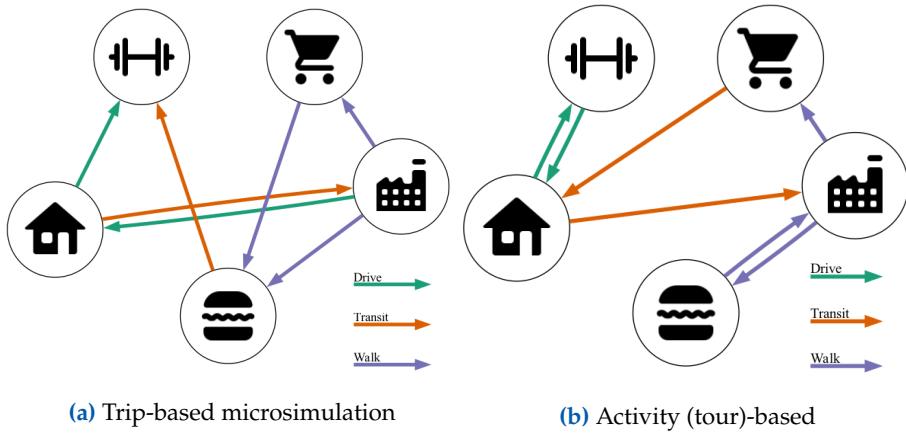


Figure 2.3: Example trip distribution using a synthetic population allows an individual's travel to be tracked.

discuss the “activity-based accessibility measure,” which is evaluated based on all trips in a day rather than particular trips. As an example, if an individual does not live within a 20-minute drive of a grocery store, traditional measures might rate this as poor accessibility. However, if a grocery store lies on their path between work and home, then in reality the accessibility should be rated much higher. Overall, they found that the “activity-based accessibility measure” predicts more reasonable accessibility outcomes compared to traditional measures.

2.3 Lack of ABM Adoption

Though ABMs have many clear theoretical 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 supercomputer is needed, and it will cost much more than what is spent to run trip-based models. If a region 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 groundbreaking 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, many 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 a 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 was slightly more accurate to observed data at the region level, but about the same at the project level. Zhong et al. (2015) found significant differences in the predictions from an ABM compared to a trip-based model in Tampa, Florida, but Mouw (2022) found that both model types had similar prediction quality when compared with observed data.

These comparisons have somewhat contradictory findings, and certainly do not present an overwhelming victory for ABMs. Each of these comparisons, however, is focused on the *accuracy* of the two frameworks, but do not address the methodological differences between model types. 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 in the literature (Lemp et al. 2007), a holistic methodological comparison is lacking. The answers in the current literature are mainly theoretical, with little use to an agency considering the transition. Additionally, much of the existing literature comparing the two model types is outdated, and the technology of both model types may have significantly changed in recent years.

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 research 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. Both model types have a wide variety of implementations, as individual agencies will adjust the basic model framework to match their specific needs. It would be unreasonable to compare each of the various implementations of both model types. Instead, we use a representative model for both types, and care is taken to note when results apply to trip- or activity-based models generally, and when results are specific to the models used.

The representative trip-based model is the 2019 Wasatch Front travel demand model, and is the current production model used by the Wasatch Front Regional Council (WFRC). This model covers much of the Salt Lake City-Provo-Ogden, Utah Combined Statistical Area. An ActivitySim implementation in the same study area is used as a representative ABM. Both models are discussed in detail in the following sections.

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.

3.1 WFRC Model

The WFRC model is implemented in the CUBE software by Bentley (Bentley Systems 2023), 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 to implement the scenarios studied in this research.

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 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 destination and mode 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 analyze 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.

Figure 3.1 gives an overview of the WFRC model, showing broad model steps in a flowchart. 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 household classification 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. This does not create a fully synthetic or disaggregated population, but is more segmented than the initial TAZ-level data.

The classification step takes TAZ-level socioeconomic data (such as population, number of households, and average income) and estimates the number of households belonging to each category of household size, number of workers, income group, and vehicle ownership. The categories of household size, number of workers, and vehicle ownership are “capped” at 6, 3, and 3, respectively (e.g., every household with 3 or more workers is grouped into a “3+ workers” category). The specific income groups used in the WFRC model are given in Table 3.1.

Table 3.1: Income Groups in the WFRC Model

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

There is an additional distribution estimated, which is termed “life cycle” in the WFRC model. This distribution places households into one of three categories, intended to represent the presence of children

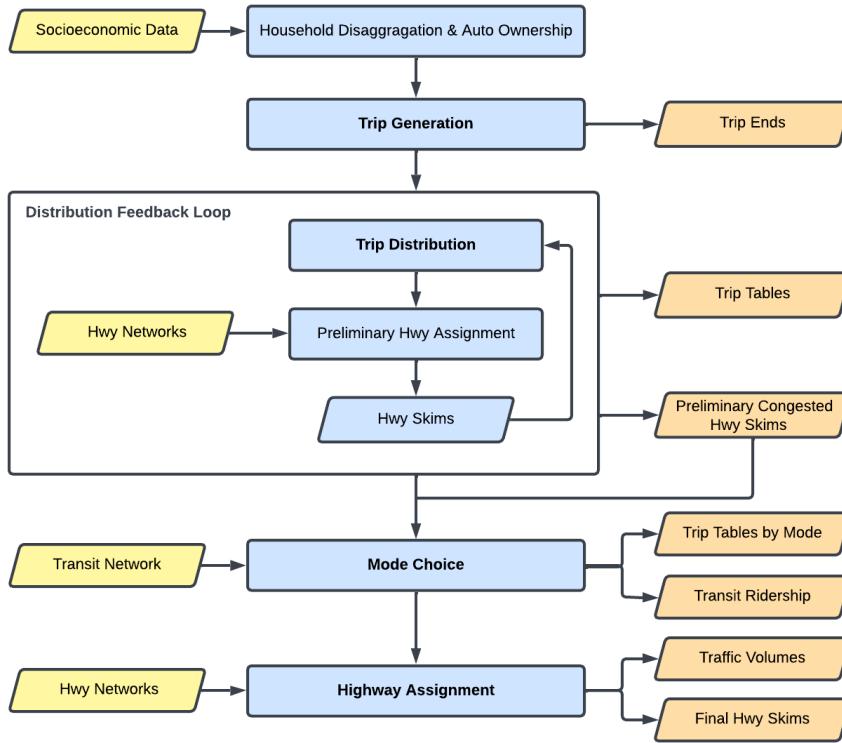


Figure 3.1: WFRC model flowchart. The distribution step includes a feedback loop where preliminary loaded network skims are used to perform subsequent iterations of trip distribution until the distribution converges.

and/or working adults in the household. This is done by estimating the age distribution in each TAZ and categorizing each household based on Table 3.2.

Table 3.2: Life Cycle Categories in the WFRC Model

Life Cycle	Presence of persons in household aged:		
	0–18	18–64	65+
1	—	✓	—
2	✓	✓	—
3	✓	—	✓

The segmented household data is then used in the trip generation step to estimate the number of trips produced from each TAZ. The trips are estimated using lookup tables which assert an average number of trips for each household type. There are separate lookup tables for each trip purpose, and depending on the trip purpose the lookup table uses a different household classification. The trip rates in the lookup tables are multiplied by the number of households in each category, and this gives a total number of trips by purpose produced in each TAZ.

The WFRC model contains the following trip purposes: Home-based Work, Home-based Shopping, Home-based School, Home-based Other, Non-home-based Work, and Non-home-based Non-work. The Home-based Work and Non-home-based Work purposes use only the number of workers per household in determining trip productions, and all other trip purposes use the cross-classification of household size with life cycle.

Trip attractions are estimated for each purpose based mostly on the number of jobs by industry in each TAZ. Home-based other and non-home-based trip attractions also are affected by the number of households in a TAZ, and school attractions are based on the school enrollment by TAZ. Each purpose has a different coefficient for each variable, and these are left unchanged from the existing values.

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. The WFRC model includes a “distribution feedback loop,” where preliminary highway assignment is performed to obtain congested network skims, and then the distribution process is repeated iteratively until the trip distribution converges.

The mode choice step uses a choice model to assign a percentage of trips of each purpose to each mode, and 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 whose development is 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 the one used in Macfarlane and 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 (BYU Transportation Lab 2024).

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 3.2). 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.

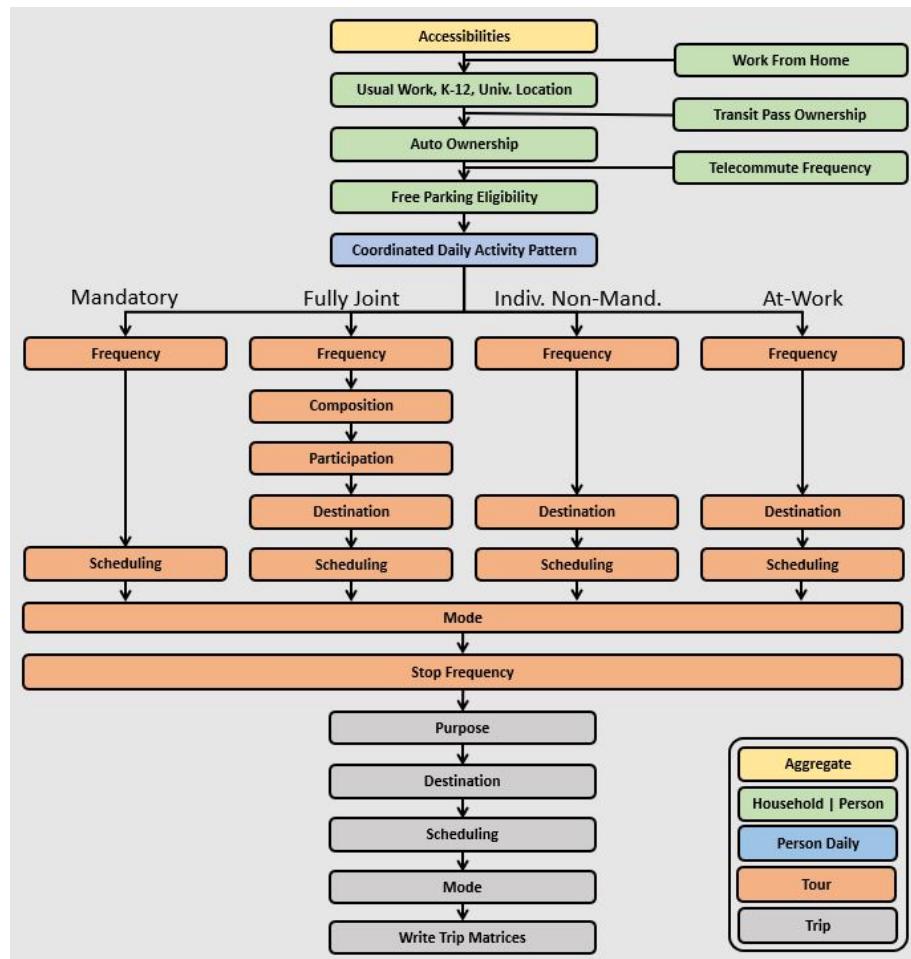


Figure 3.2: ActivitySim sub-model flowchart (Association of Metropolitan Planning Organizations 2022).

The steps can broadly be categorized into five groups, as shown in Figure 3.2: aggregate, household/personal, person 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 the 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. Our ActivitySim implementation models remote work status, work/school location, auto ownership, and free parking availability, but transit pass ownership is not modeled and it is assumed that everyone pays the transit fare.

The daily decisions primarily concern an individual's DAP. ActivitySim contains a step to assign mandatory, non-mandatory, and home DAPs based on personal and household information (a home DAP involves no travel). For example, full-time workers are more likely to have a mandatory DAP 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.

Most of ActivitySim's individual models are based on a multinomial logit model of the form:

$$P(k) = \frac{e^{V_k}}{\sum_{k \in K} e^{V_k}},$$

where $P(k)$ is the probability of choosing alternative k , V_k is the utility of alternative k , and K is the set of all alternatives (as discussed in McFadden 1974). The utility values are determined by coefficients on variables such as income, age, and work status, in addition to calibration constants for each alternative.

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, and this ActivitySim implementation uses the travel skims output from the WFRC model directly. In practice, ActivitySim is mated to CUBE or another network assignment algorithm for network skimming and travel time feedback.

ActivitySim 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. Using a synthetic population instead of real data also allows for modeling hypothetical scenarios, including future-year forecasts.

This research 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. Additionally, a synthetic population can

be adjusted in line with projected socioeconomic forecasts to perform future-year analyses. 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 geography (these geographies 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 3.3 shows these controls as well as their geographic level and source. The geography of a control dictates PopulationSim’s “level of precision” in matching the control totals. For example, with our configuration, PopulationSim will attempt to match the average number of workers per household to the Census average for each Census tract, while the total population is only controlled for across the entire region. PopulationSim also allows setting different weights to each control, and Table 3.3 gives this information as well. Because the Public Use Microdata Sample does not contain every possible combination of variable values, it is not possible to create a synthetic population that perfectly matches every control total. The weights allow certain controls to “take priority” over others; for example with this configuration PopulationSim will prioritize the average household size over the average number of workers per household if the two controls cannot both be satisfied.

Table 3.3: 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 gender, 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.

3.3 Initial Model Comparison/Calibration

While this research generally 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, we used a “baseline” scenario in both models 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 uses land use data and network skims from the baseline WFRC scenario for accessibility and socioeconomic measures.

3.3.1 Validation of the Synthetic Population

The controls for PopulationSim mostly come from the Census, as can be seen in Table 3.3. However, the WFRC model contains TAZ-level data including population and median income. The WFRC model also has a household classification 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. Though these outputs are given at the TAZ level, most controls to PopulationSim were given at the Census tract level, and these tracts are not a one-to-one match with the region’s TAZs. Because of this, PopulationSim has some amount of randomness in which TAZ it places each household in. As such, for small geographic areas such as TAZs the error distribution between the two models is noisy. The comparisons in this section are therefore made by aggregating each TAZ at the district level, where each district is defined by WFRC and includes several contiguous TAZs.

Figure 3.3 shows the difference in district 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 3.3.

The population per district 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 3.4 shows a district-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 districts, 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

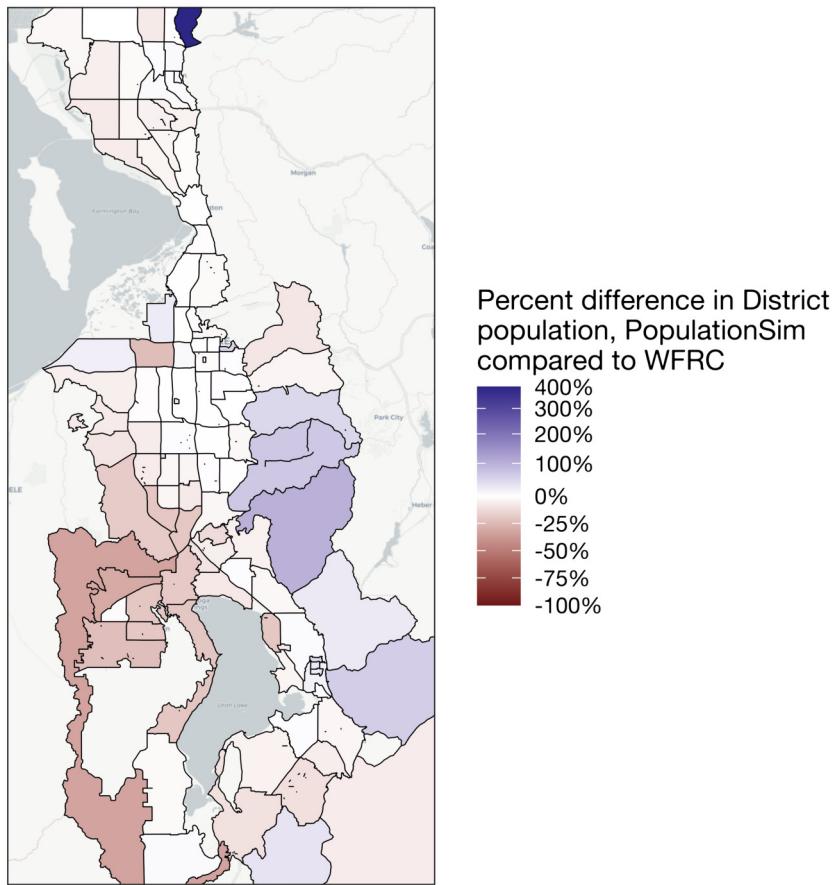


Figure 3.3: Population by district, PopulationSim compared to the TAZ-level socioeconomic data in the WFRC Model.

decisions. These groups are taken from the WFRC model (see Table 3.1), and the groups in PopulationSim and ActivitySim were adjusted to match. Figure 3.5 shows the difference in number of households by income group. This figure shows PopulationSim predicting slightly more high-income households, though the error for the lower three groups is more evenly distributed, especially in more populated areas.

Note that in the synthetic population, each household has a specific income and so can be grouped directly, while the WFRC model requires a household classification step to estimate the number of households in each income group. Figure 3.5 therefore is comparing two models for determining income groups, one a part of PopulationSim and the other in the WFRC model, rather than comparing the synthetic population to actual socioeconomic data. Additionally, the overall distribution of income is similar between the models, as Figure 3.6 shows. A production-ready synthetic population would match its income distribution more closely to the existing socioeconomic data, but as mentioned, in this research the focus is on the process, rather than accuracy, for each model. Because of this focus, ActivitySim does not need to be perfectly calibrated

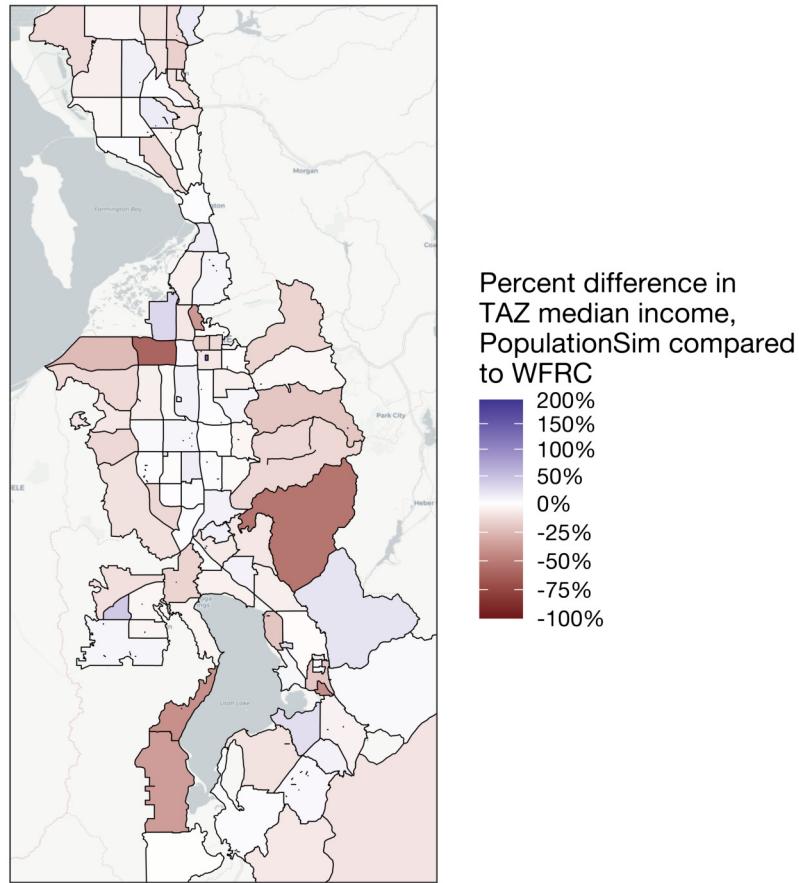


Figure 3.4: District-level median income, PopulationSim compared to the TAZ-level socioeconomic data in the WFRC Model.

to the WFRC model, and so for the purposes of this research the income distribution of the synthetic population is acceptable.

3.3.2 Validation and Calibration of ActivitySim

This section compares the outputs of both models to verify that trip patterns roughly agree. There are three comparisons of interest that we make 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. The ideal approach would be to calibrate the mode choice model to recent travel survey data, such as from the Utah Household Travel Survey. However, recent travel survey data was not available for this project, and only a rough calibration is needed for the purposes of this research. We therefore used the outputs of the baseline WFRC model scenario as mode split targets. A production model would certainly use travel survey data and perform a thorough calibration, but that is outside the scope of this project.

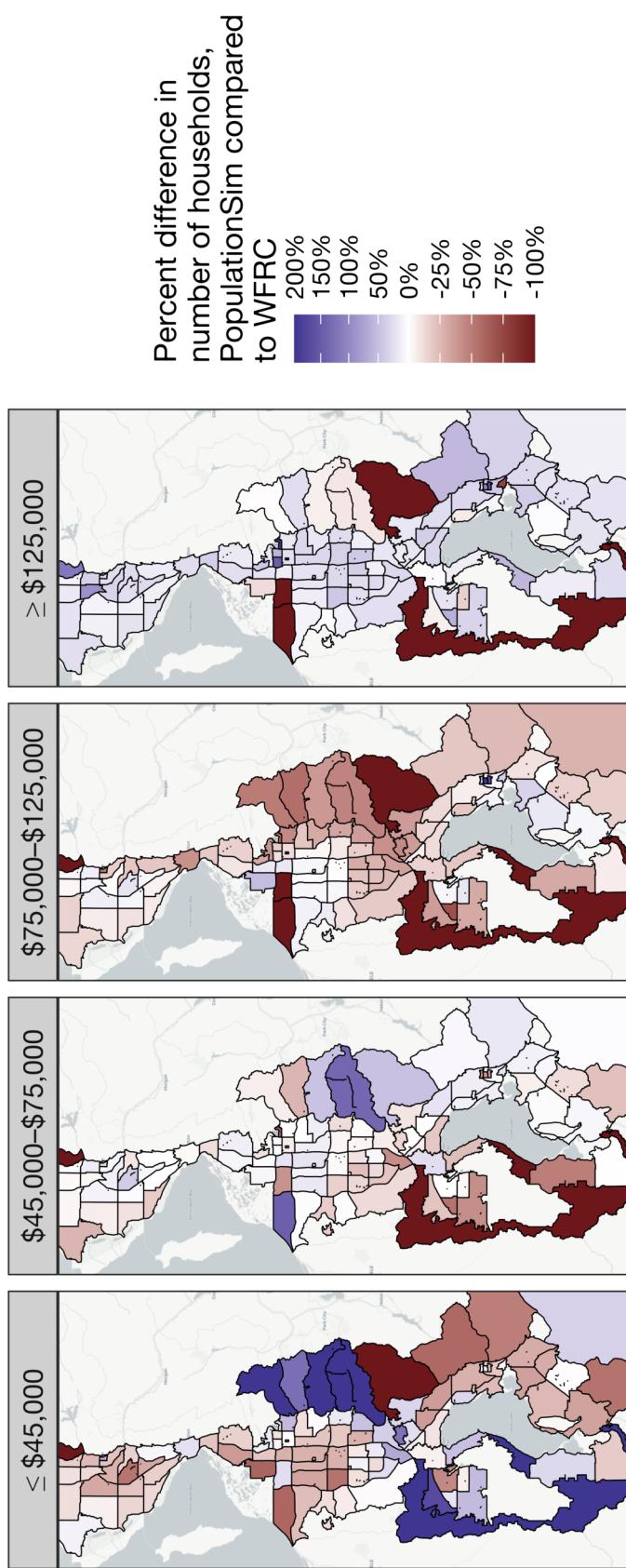


Figure 3.5: Households in each income group, PopulationSim compared to the TAZ-level socioeconomic data in the WFRCC Model.

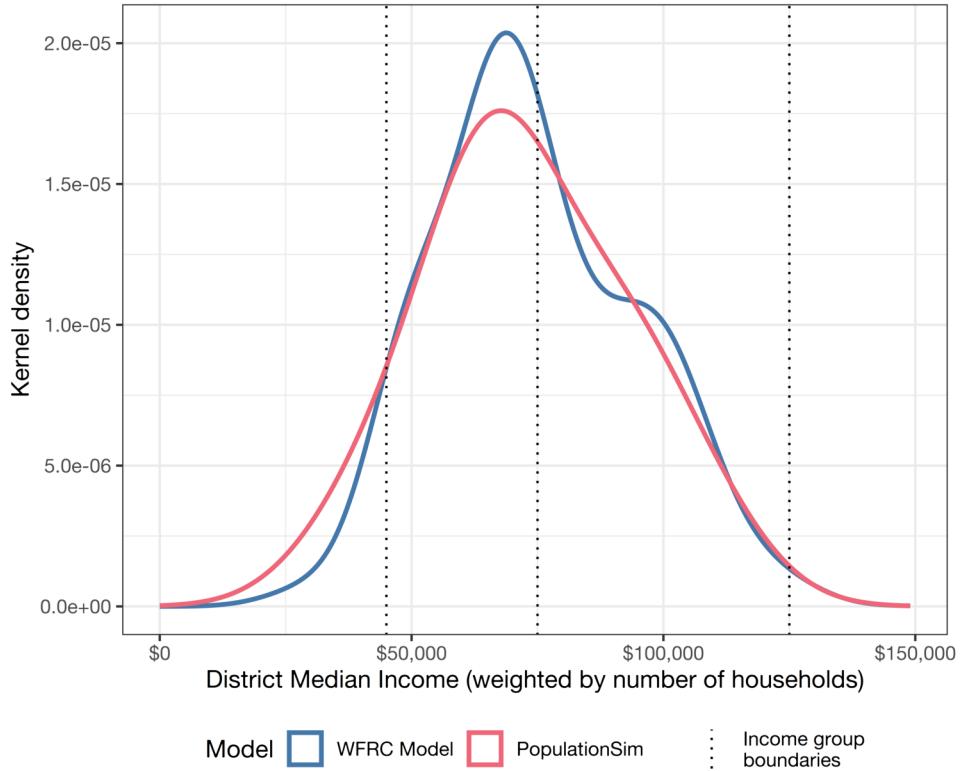


Figure 3.6: Distribution of TAZ median income, PopulationSim compared to the TAZ-level socioeconomic data in the WFRC Model.

Before beginning calibration, we matched the available modes in ActivitySim to those in the WFRC model, creating a “crosswalk” between the modes in each model. The available modes between ActivitySim and the WFRC model are not incredibly different, and in fact many modes have a 1-to-1 match between the models. However, not all modes have an exact match between models. Table 3.4 shows the modes in each model grouped in a way that allows for consistency during calibration.

ActivitySim additionally has ridehail modes, but the WFRC model does not, and so there are no obvious calibration targets for ridehail. Based largely on the model results of Day (2022), and partly on the existing (uncalibrated) mode split in ActivitySim, we asserted the following mode shares for ridehail: 0.015% for Home-based Work trips, 0.38% for Home-based Other trips, and 0.4% for Non-home-based trips.

Additionally, since the WFRC model has a significantly different mode split depending on the trip purpose, we calibrated each trip purpose individually. However, a crosswalk of trip purposes between the models is more complicated than the crosswalk for modes. Because ABMs create tours first, which are then populated with trips, an ABM’s idea of “trip purpose” is entirely different to that of a trip-based model. Specifically, an ABM does not have a concept of, for example, “home-based work” trips, there are simply trips on a “work” tour, some of which have an origin or destination at home. For simplicity, though, we converted the trips

Table 3.4: Crosswalk Between Modes in Both Models

Calibration Mode	WFRC Mode(s)	ActivitySim Mode(s)
Drive Alone	DA	DRIVEALONEFREE
Carpool (2)	SR2	SHARED2FREE
Carpool (3+)	SR3p	SHARED3FREE
Walk	walk	WALK
Bike	bike	BIKE
Local Bus	dBRT, dCOR, dLCL, wBRT, wCOR, wLCL	WALK_LOC, DRIVE_LOC
Commuter Rail	dCRT, wCRT	WALK_HVY, WALK_COM, DRIVE_HVY, DRIVE_COM
Express Bus	dEXP, wEXP	WALK_EXP, DRIVE_EXP
Light Rail	dLRT, wLRT	WALK_LRF, DRIVE_LRF

from ActivitySim into purposes that roughly match the WFRC model’s purposes. Any trip that doesn’t start or end at home is considered a Non-home-based trip, and if a trip starting or ending at home has its other end at work, it is considered a Home-based Work trip. All other trips are considered Home-based Other trips.

We performed the calibration by iteratively adjusting the alternative-specific constants (ASCs) in ActivitySim’s mode choice submodels. Each iteration, the output mode split of ActivitySim was compared to the target mode split output from the WFRC model, and we adjusted ActivitySim’s ASCs by the formula $A_k = \ln(T_k/M_k)$, where A_k is the adjustment value for mode k , T_k is the target mode share of mode k , and M_k is the ActivitySim-predicted mode share of mode k . This adjustment value was added to the current ASCs in ActivitySim, and this process was repeated until calibration was satisfactory.

There are two aspects of this calibration process worth noting. The first is that ActivitySim contains ASCs for both tour mode choice and trip mode choice, where the tour mode is the principal mode used on the tour, and the trip mode is the mode of the individual trip (for example, there could be a “walk” trip on a “transit” tour). Because tour-level mode choice influences trip mode choice, both the tour-level and trip-level ASCs were adjusted by the calculated adjustment value for each mode. The second is that while it is possible to categorize ActivitySim trips into purposes similar to a trip-based model, ActivitySim does not do this conversion internally. ActivitySim *does* have separate ASCs by purpose, but these purposes are ActivitySim’s tour purposes, rather than purposes resembling those in a trip-based model. Though it is not a perfect correspondence to how the adjustment values were calculated, we adjusted the ASCs as follows: All ActivitySim “atwork” ASCs are calibrated with the Non-home-based adjustment, all “work” ASCs are calibrated with the Home-based Work adjustment, and all other ASCs are calibrated with the Home-based Other adjustment.

Figure 3.7 shows the mode split from ActivitySim compared against the target mode split for each iteration of calibration. After a few iterations,

tions, the mode split more closely matches between the models; however, there are still some discrepancies. ActivitySim has mode choice ASCs separated not only by mode and purpose, but also by many personal variables, such as income, age, and vehicle ownership. The difference across these categories was left unchanged, and all ASCs for a given mode and purpose were adjusted equally. Our 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. Additionally, we did not calibrate the vehicle ownership model, and this may be partly the cause of the discrepancies.

In any case, we chose the calibration at Iteration 4 for the final ASC values, as subsequent iterations adjusted the ASCs without changing the mode split very much. At subsequent iterations ActivitySim was also less sensitive to changes in infrastructure due to over-calibration, which would not allow for effective policy analysis. Table 3.5 compares the mode split of both models after iteration 4 of calibration. Overall, the calibration resulted in a reasonably similar mode split between the two models, though there are still discrepancies (ActivitySim is for example predicting significantly more transit trips compared to the WFRC model). While the calibration is not perfect, for the purposes of this research this calibration is determined to be reasonable enough.

Table 3.5: Comparison of Mode Split Between Models After Calibration

Purpose	Mode	ActivitySim		WFRC Model	
		Trips	Share	Trips	Share
Home-based Work	Drive Alone	1012180	60.6%	1328609	77.6%
	Carpool	258459	15.5%	257783	15.1%
	Bus	171875	10.3%	18870	1.1%
	Rail	80193	4.8%	29847	1.7%
	Ridehail	1108	0.1%	—	— ¹
	Non-motorized	145957	8.7%	76505	4.5%
Home-based Other	Drive Alone	702594	18.2%	1394415	30.0%
	Carpool	2154115	55.8%	2702277	58.2%
	Bus	149217	3.9%	17717	0.4%
	Rail	127969	3.3%	19591	0.4%
	Ridehail	114278	3.0%	—	— ¹
	Non-motorized	614901	15.9%	510144	11.0%
Non-home-based	Drive Alone	716885	36.3%	951561	39.9%
	Carpool	939668	47.6%	1273279	53.4%
	Bus	99000	5.0%	4888	0.2%
	Rail	21010	1.1%	8538	0.4%
	Ridehail	40283	2.0%	—	— ¹
	Non-motorized	157006	8.0%	146404	6.1%

¹ Ridehail mode shares were asserted for mode choice calibration, but are not counted here

Figure 3.8 compares the trip length frequency distribution of the two models by mode and purpose. Both ActivitySim and the WFRC

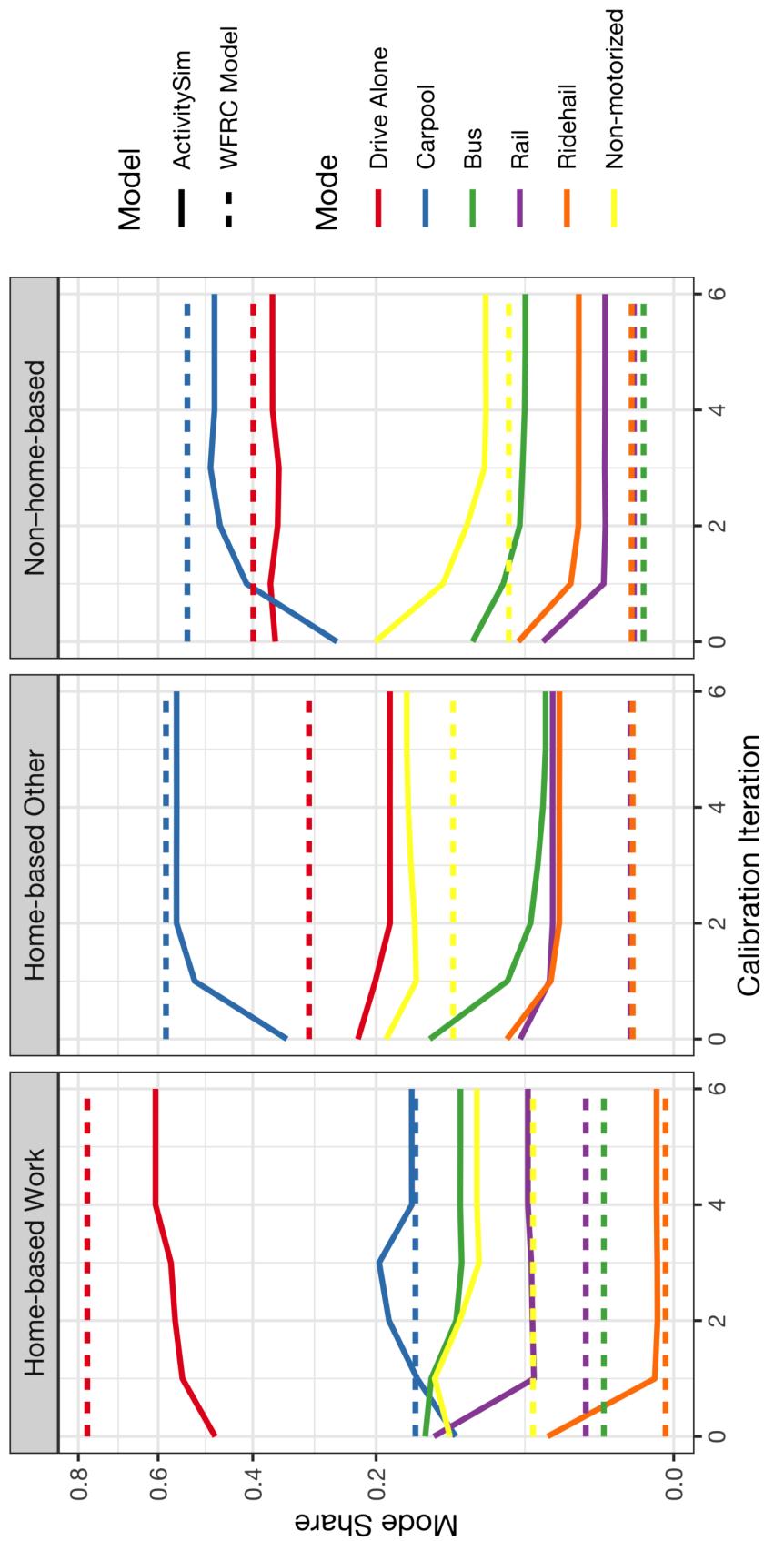


Figure 3.7: Mode choice calibration, target vs. actual shares over several iterations.

model contain trip distribution steps which can be adjusted to affect the distribution of trip length. However, as the figure shows, the two models have similar trip length frequency distributions, so no adjustment was necessary. The most significant discrepancies are with transit trips, again likely due to this configuration of ActivitySim being developed for San Francisco, making transit more attractive. Note that further calibration may be required to create a production-ready ActivitySim implementation, but again we are focused more on process than accuracy. It is sufficient to ensure the models very roughly agree on outputs such as mode split and trip length distribution, and we determined that this is the case.

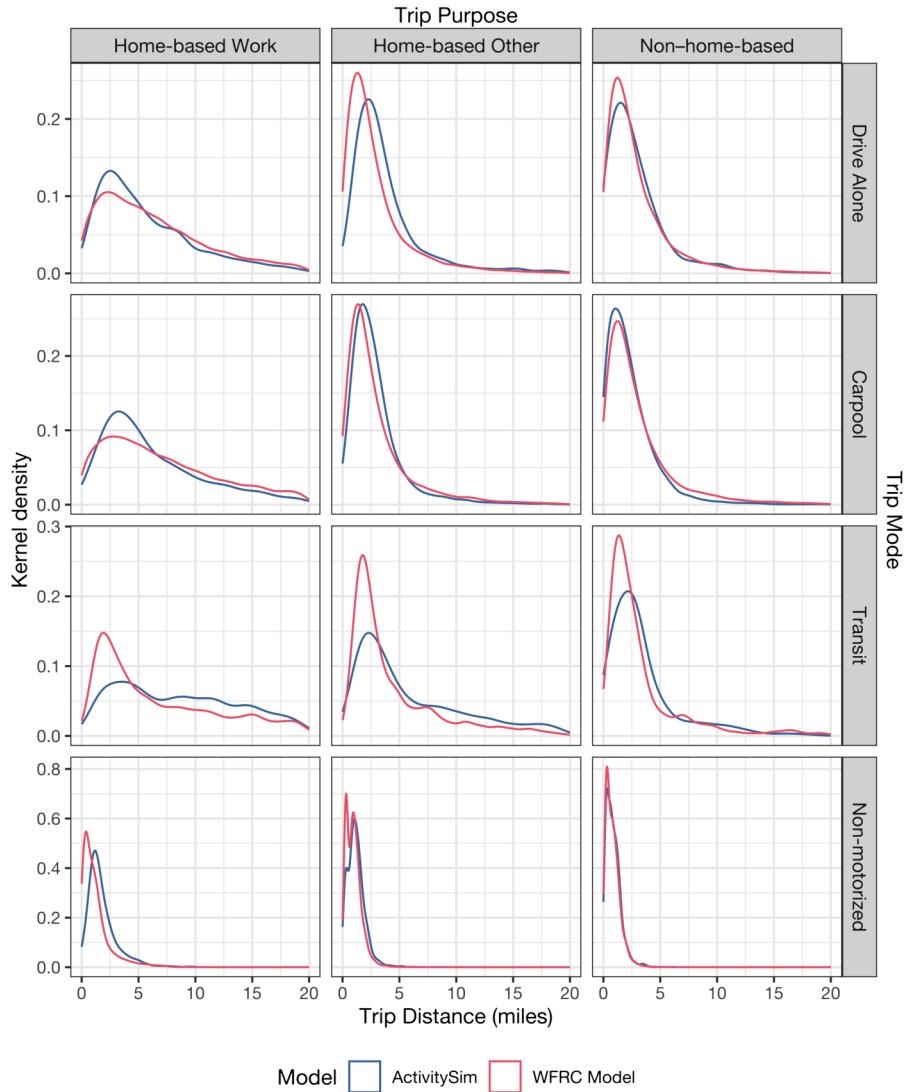


Figure 3.8: Comparison between models of trip length frequency distribution.

The WFRC model has basic support for predicting remote work. This includes a lookup table of remote work 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” (called “home-based jobs” in the WFRC model), where an individual’s workplace is always at their home.

The ActivitySim implementation discussed in Macfarlane and Lant (2021) does not include any submodels related to remote work. However, a separate ActivitySim example implementation, developed for the Southeast Michigan Council of Governments metropolitan planning organization in Michigan, *does* include these submodels, and our ActivitySim implementation takes these submodels directly from the Michigan example. Some modifications to the remote work submodels were needed for compatibility, but these modifications were minor and mostly involved ensuring the variable names from the remote work submodels were consistent with the existing ActivitySim implementation.

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, gender, and education (coefficients on these variables were left unchanged from the existing configuration, see Table 3.6). 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.

Table 3.6: Work-From-Home Submodel Choice Coefficients in ActivitySim

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

The two models differ in their approach to telecommuting, however. The WFRC model has a lookup table of telecommuting shares based on job type, 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 selecting a mandatory DAP. 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 3.7 shows the submodel coefficients.

Table 3.7: Telecommute Frequency Submodel Choice Coefficients in ActivitySim

Description	Telecommute Frequency Coefficients		
	1 day	2–3 days	4 days
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
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
3+ autos	0.000	-0.730	0.000
Distance to work	0.016	0.000	0.000

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 3.8. 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 3.8.

Because both remote work submodels in ActivitySim are run before an individual’s DAP is chosen, ActivitySim can model 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 3.9 shows the coefficients of the DAP model for individuals who work remotely.

Table 3.8: Telecommute Rates and Coefficients by Job Industry

Industry	2019 WFRC Telecommute %	Telecommute Frequency 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 3.9: Daily Activity Pattern Submodel Coefficients in ActivitySim

Status	Mandatory DAP	Non-mandatory DAP	Home DAP
Telecommutes 1 day per week	0	0.526	0.496
Telecommutes 2–3 days per week	0	1.387	1.584
Telecommutes 4 days per week	0	1.848	1.711
Full time worker, works from home	-999	0.000	0.000
Part time worker, works from home	-999	0.000	0.000

3.4 Example Scenarios

With these two calibrated models, we created three model scenarios to implement and run in each model for comparison. This is not a comprehensive list covering all potential scenario possibilities, but the scenarios identified here are intended to represent the main goals of travel demand modeling in modeling changes in travel behavior. Change in travel behavior could arise in response to changes in land use, transportation infrastructure, and social/economic factors, and so we created three hypothetical model scenarios that each implement one of these aspects.

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 a change in transportation infrastructure, namely an augmentation of commuter rail service along the Wasatch Front. The FrontRunner, a commuter rail 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 “Remote Work” scenario Chapter 6 uses remote work 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

One of the primary ways that travel behavior is affected is through changes in land use. Such changes involve the addition or removal of households and/or jobs in an area, and our first model scenario, termed the “Land Use” scenario, addresses this aspect of travel demand modeling by simulating a new development in a single area. The basis for the Land Use scenario is the redevelopment of a defunct prison site near Draper, Utah. This redevelopment is part of the actual plan for the area, and the new development is known as The Point (Point of the Mountain State Land Authority and Skidmore, Owings & Merrill 2021).

This scenario models the change in transportation behavior that a development such as The Point would create. Though the actual development plans for The Point include an expansion of transit services (Point of the Mountain State Land Authority and Skidmore, Owings & Merrill 2021), only the additional households and jobs created from this development are represented 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 (Point of the Mountain State Land Authority and Skidmore, Owings & Merrill 2021). The Point development is expected to be fully completed by 2050, and its projected land use and socioeconomic data is included in the 2050 WFRC forecast, so the 2050 WFRC land use and socioeconomic data projections are used for this site.

The site consists of five TAZs, as shown in Figure 4.1. Table 4.1 shows the households, population, and employment by type of these TAZs in the baseline scenario, and Table 4.2 shows this information 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 were made relative to the baseline scenario.

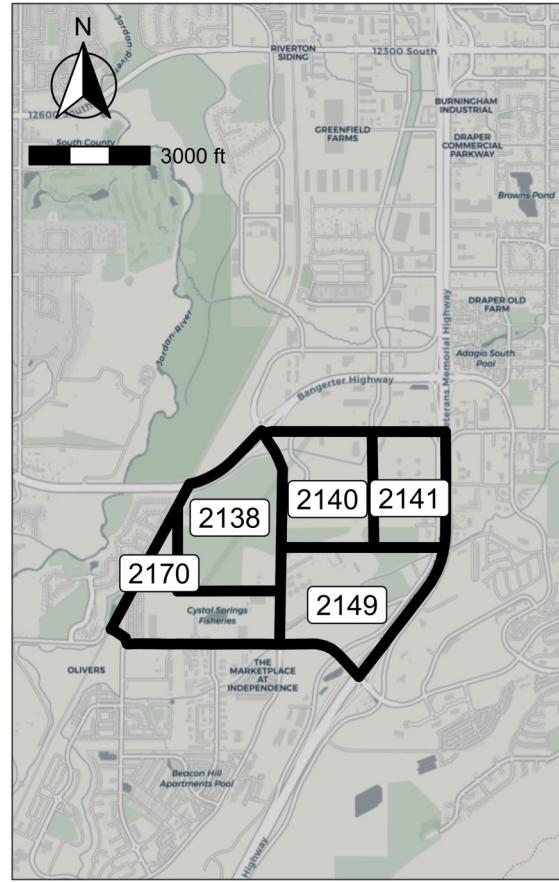


Figure 4.1: Map of each TAZ in The Point development.

Table 4.1: TAZ-level Socioeconomic Data for The Point (Baseline Scenario)

TAZ	Households	Population	Employment				Total
			Retail	Industrial	Other		
2138	0	0	0	0	0	0	0
2140	0	0	0	0	0	0	0
2141	0	0	0	0	277	277	277
2149	0	0	0	0	796	796	796
2170	0	0	3	359	71	433	

Table 4.2: TAZ-level Socioeconomic Data for The Point (Land Use Scenario)

TAZ	Households	Population	Employment				Total
			Retail	Industrial	Other		
2138	7431	17811	4	0	76	80	
2140	0	0	610	4	7390	8004	
2141	0	0	1449	0	5363	6812	
2149	0	0	962	2	7372	8336	
2170	0	0	7	357	106	471	

4.1 Scenario Creation

In the WFRC model, this scenario is simple 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 forecasted data. 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, but used the new land use data as new TAZ-level controls. Many of the controls for PopulationSim use tract-level data from the Census, but existing Census data for The Point site is unrepresentative of the new development, as currently the site lacks residential and economic activity. Because of this, a Census tract covering part of downtown Salt Lake City is used to represent the new development patterns at The Point. The income distribution, etc. of The Point site will therefore match that of downtown Salt Lake City, though the TAZ-level controls and land use/socioeconomic data in the area will match the WFRC projections for 2050.

In a more realistic case, a transportation agency would forecast land use and socioeconomic data that could be used as controls to PopulationSim, rather than using a separate Census tract to represent new development. However, our ActivitySim implementation only needs to be within a rough approximation of the WFRC model for the purposes of this project, and the method used here results in reasonable accuracy between the models. Additionally, our ActivitySim implementation is designed to be independent from the WFRC model where feasible.

4.2 Scenario Analysis

There are several kinds of analyses an agency likely would want to do in assessing the effects of a change in land use. Chief among them would be an analysis of the new trips resulting from the development. These analyses could include the number of trips, the distance traveled, and where the trips are being made.

Both model types allow for very easy analysis of trip numbers and lengths, as the WFRC model outputs origin-destination trip tables directly by mode and purpose, and ActivitySim outputs a list of trips containing information on origin, destination, and mode. Figures 4.2 and 4.3, for example, show the new trip-miles produced in the updated zones for the WFRC model and ActivitySim, respectively. However, there is a

crucial difference between the model types, and that is the treatment of trips that do not begin or end at the home.

In the WFRC model (and in many trip-based models), homes produce trips with different trip purposes, including Home-based Work, Home-based Other, and Non-home-based trips. “Home-based” trips have an origin or destination at the home, and are fairly straightforward to model, as the destination choice step can take for granted that these trips have one trip end in the zone that produced them. In addition to home-based trips, though, individuals make many “non-home-based” trips, which do not have an origin or destination at the home (e.g., traveling from work to a grocery store). Non-home-based trips can be a significant portion of total travel, as Figure 4.2 shows, but are not as straightforward to model as home-based trips.

Because Non-home-based trips by definition have neither an origin or destination at the home (where trips are produced in the trip generation step), these trips happen exclusively between zones that did not produce them. It is difficult therefore to know how best to redistribute Non-home-based trips, as they could in reality have any number of origins and/or destinations. Though modeling the destinations for Non-home-based trips could be done via a similar process to that of home-based trips, the origins of these trips need to be modeled as well. There are several methods to redistribute Non-home-based trips in trip-based models. One approach is to assign Non-home-based trip origins in a similar manner to trip destinations as part of the trip distribution step, either with a gravity model or some distance-decay function. The destinations of these Non-home-based trips can then be modeled as if they were any other trip. This results in Non-home-based trips that are more likely to have both an origin and destination relatively near to the home. The WFRC model takes a different approach. Here there are two sources of information for Non-home-based trip ends: a production model and an attraction model. In the trip generation step, households produce Non-home-based trips similarly to any other trip purpose. However, the trips produced in this step determine only the *quantity* of Non-home-based trips, not the trip ends. The *distribution* of Non-home-based trips is determined by a trip attraction model, largely based on TAZ employment. This distribution is then globally scaled to match the total quantity of Non-home-based trips produced in the trip generation step.

By contrast, an ABM models individuals and their travel explicitly, and this makes the treatment of Non-home-based trips much more straightforward. Each trip is tied to a specific individual with a defined home location, and so no extra “redistribution” step is needed to analyze Non-home-based trips: these are “built-in” to each individual’s tour pattern. In fact, as Figure 4.3 shows, Non-home-based trips can occur as part of any tour type/purpose; there is no separate “Non-home-based” purpose in ActivitySim. Note that Figure 4.3 counts person-miles by *tour* purpose, using the purposes as defined in ActivitySim, rather than converting the ActivitySim trips to the “common” trip purposes as discussed in Section 3.3.2.

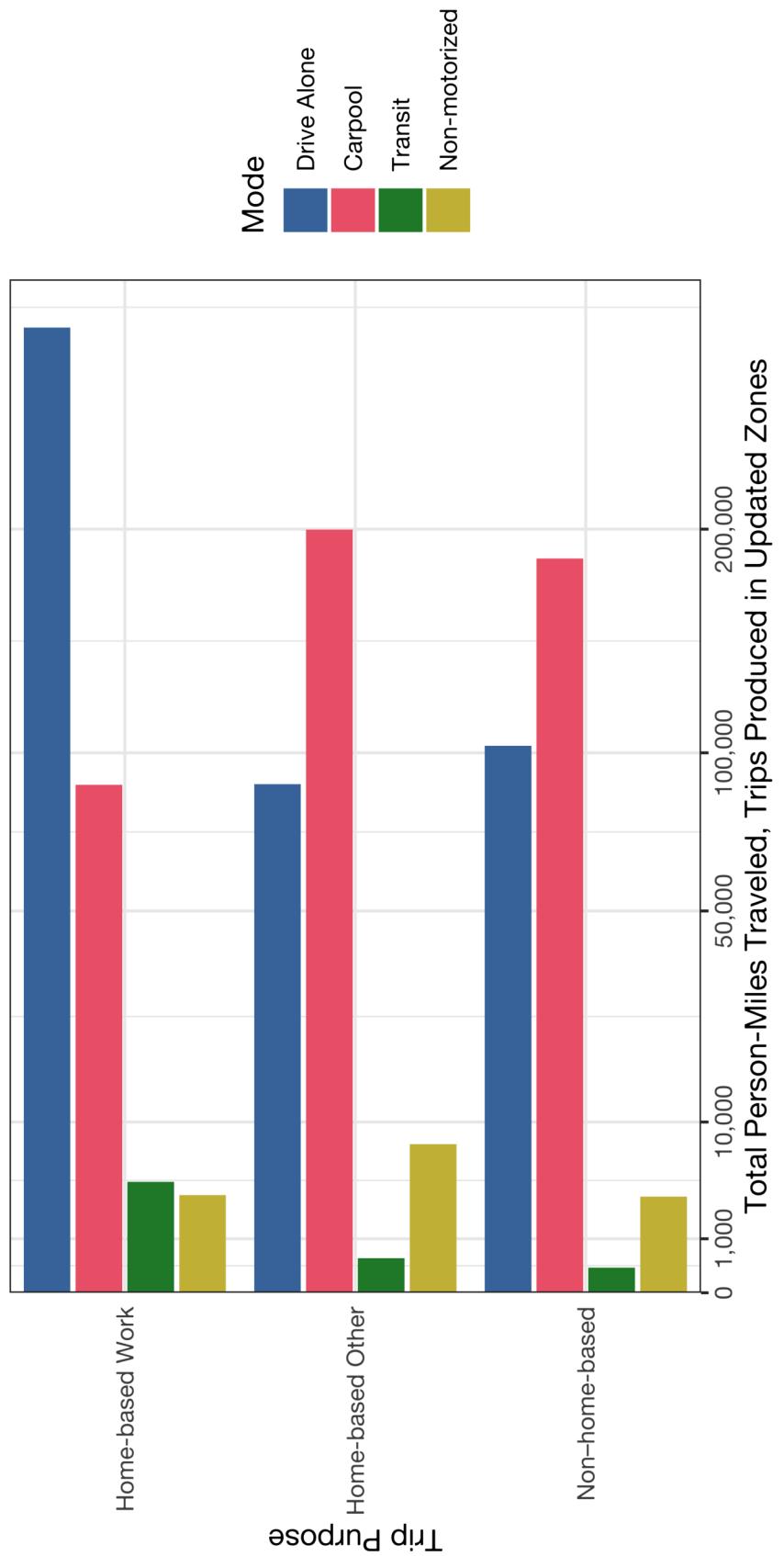


Figure 4.2: Trip-miles produced in the updated zones in the Land Use scenario (WFRC model).

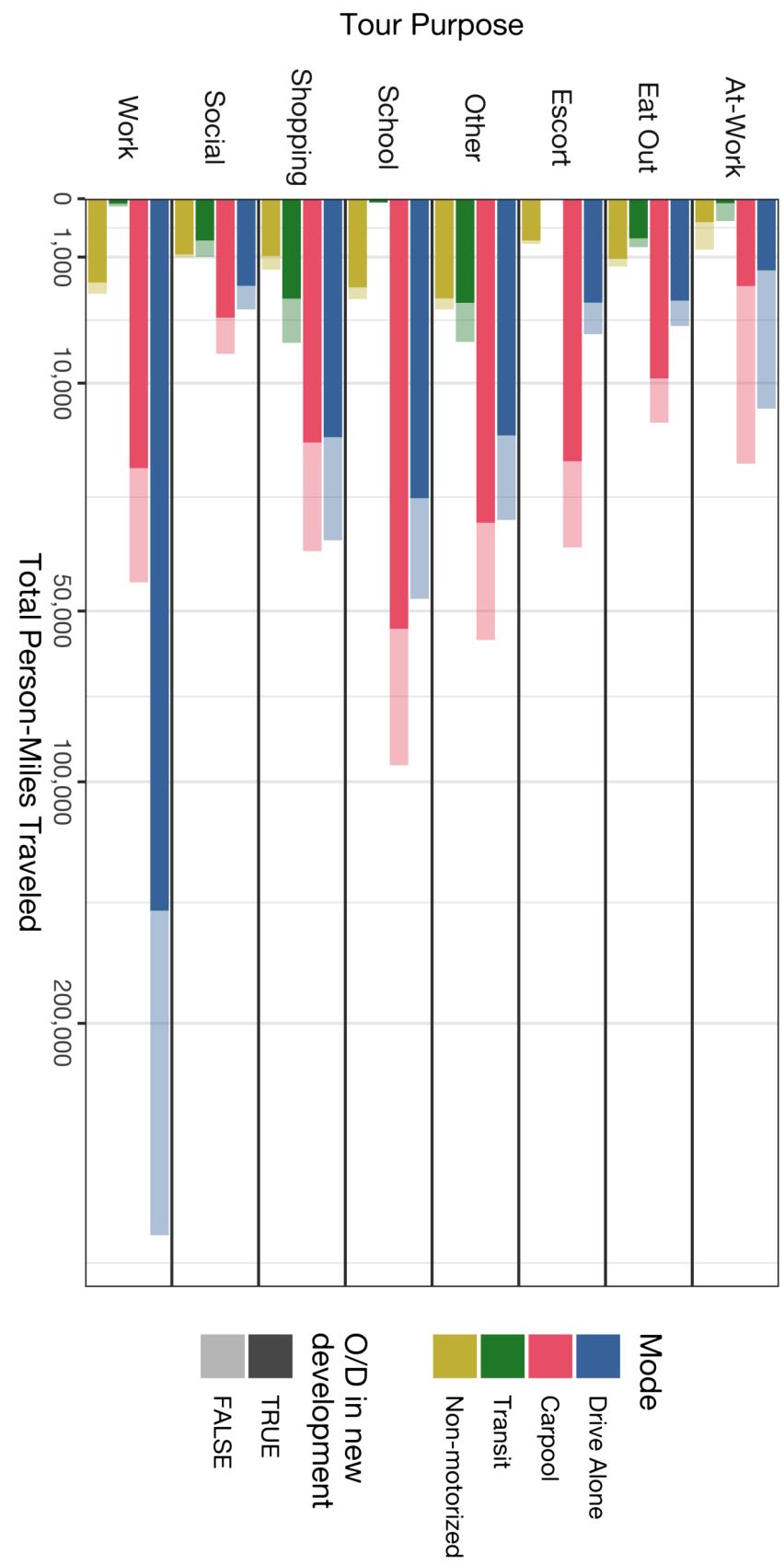


Figure 4.3: Trip-miles of individuals living in the updated zones (ActivitySim). Many of these trips do not have an origin or destination in the home zone of the individual.

In addition to looking at total person-miles traveled, it is also useful to analyze the origins and destinations of the new trips. One common way to visualize trip origins and destinations is with desire lines, which show lines for each trip origin/destination pair. The thickness of the line represents the number of trips between the pair of zones.

Figure 4.4 shows a desire line plot by mode of all home-based trips produced in the new development zones in the WFRC model. This figure is in line with what is expected: non-motorized trips are quite short, transit trips are exclusively to downtown areas, and many drive alone and carpool trips are made with varying lengths. Figure 4.4 also shows a similar mode split to Figure 4.2. Although the former depicts the *number* of trips and the latter depicts trip *distance*, there is a rough correlation between trip count and miles traveled, so it is not surprising that the mode split is similar between the figures.

There is difficulty in analyzing the Non-home-based trips, however. Typically in a trip-based model, once Non-home-based trips are assigned trip ends, they have no connection to the homes/zones that produced them, and are treated as “belonging” to either the origin or destination zone. Because of this, it is not possible to simply filter trips by origin or destination as can be done with the home-based trips. Instead, we took the difference between the entire Non-home-based trip matrices in both this scenario and the baseline scenario.

Figure 4.5 shows the desire line plot for the difference in Non-home-based trips between this scenario and the baseline scenario. Two things are immediately noticeable from this plot. The first observation is that many pairs of zones saw a decrease in Non-home-based trips between them compared to the baseline scenario (i.e., there were more Non-home-based trips in the baseline scenario between these zones). Certainly it makes little sense to predict *fewer* trips as the result of added population and employment. However, this is in fact not an *overall* decrease in Non-home-based trips; these trips are simply being assigned trip ends in different locations due to the nearby change in land use. The second observation is that the largest increases in Non-home-based trips include an origin or destination in the new development (the home zones of the new population). Because the change in employment was much more significant than the change in population (see Tables 4.1 and 4.2), many more Non-home-based trip ends were attracted to the development zones compared to the relatively little global increase in Non-home-based trips due to the increase in population. Both effects (the global increase in and the changed distribution of Non-home-based trips) are present in the model, but the two effects are impossible to separate.

As mentioned, an ABM allows for tracking of individuals explicitly, and so analyzing Non-home-based trips is much more straightforward. Figure 4.6 shows desire lines of all trips made by individuals living in the new development zones for ActivitySim. Non-home-based trips are colored differently from home-based trips.

In an ABM, Non-home-based trips are directly connected to their place of production, as each trip is linked to a specific individual who has

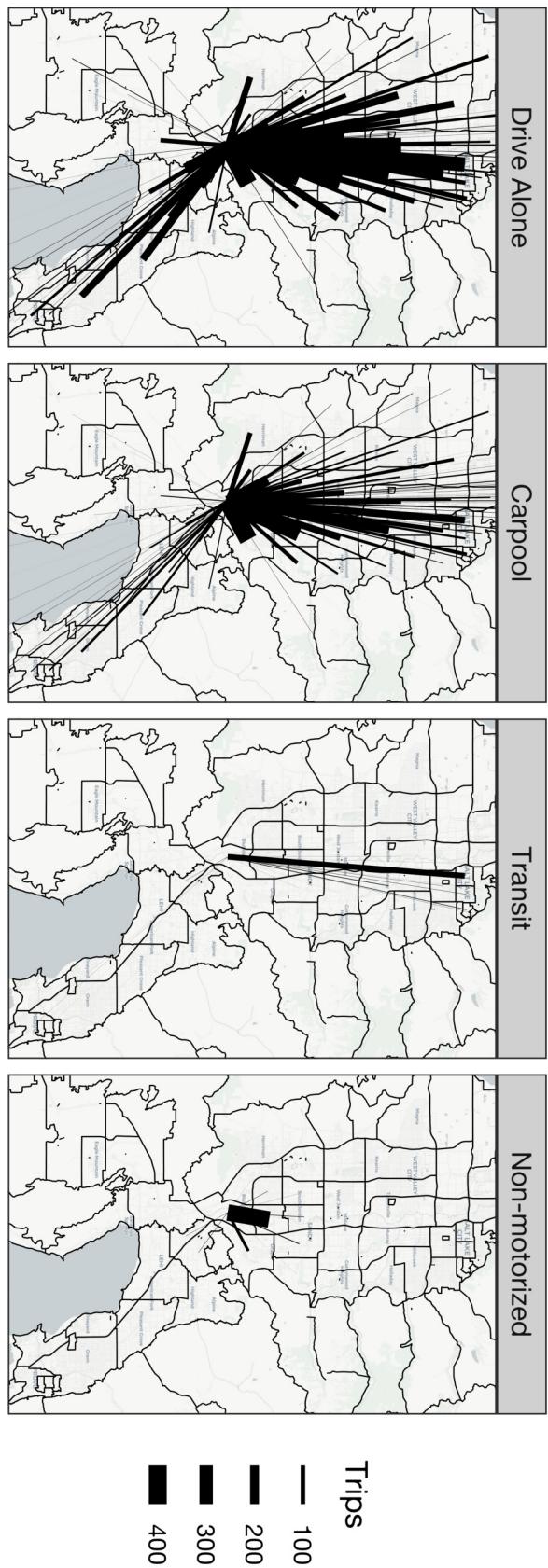


Figure 4.4: Desire lines of home-based trips produced in the new development in the WFRC model, by mode.

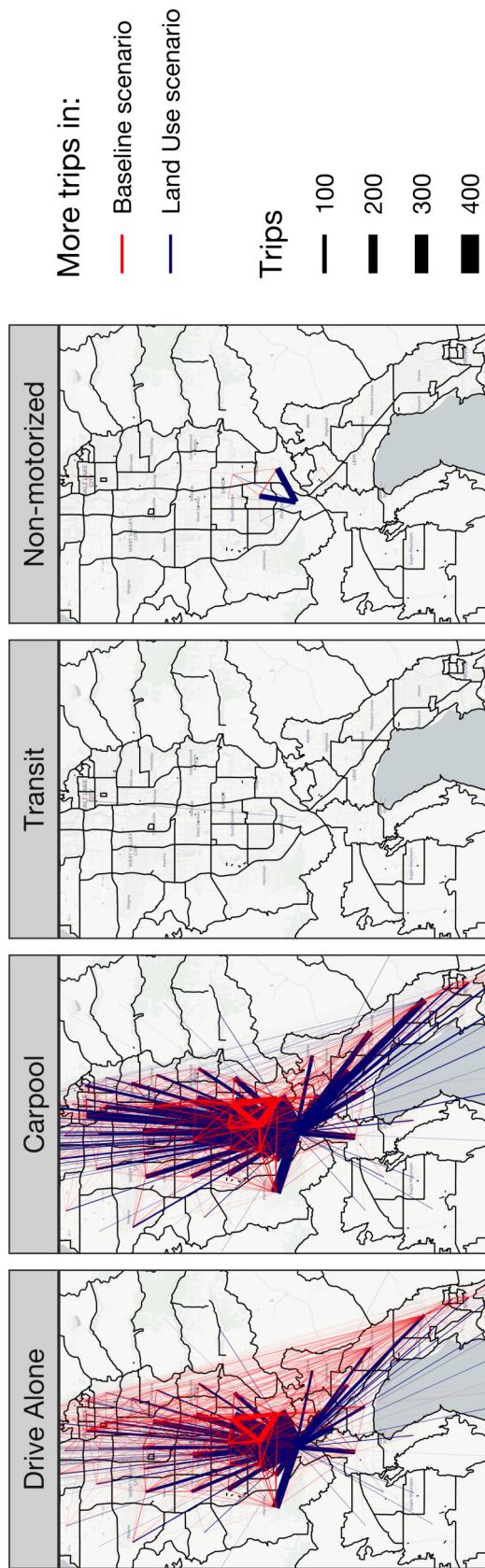


Figure 4.5: Desire lines of Non-home-based trips made in the WFRC model, by mode. The trip counts are obtained by differencing the Non-home-based trip matrix with the base year.

a defined home location. 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.

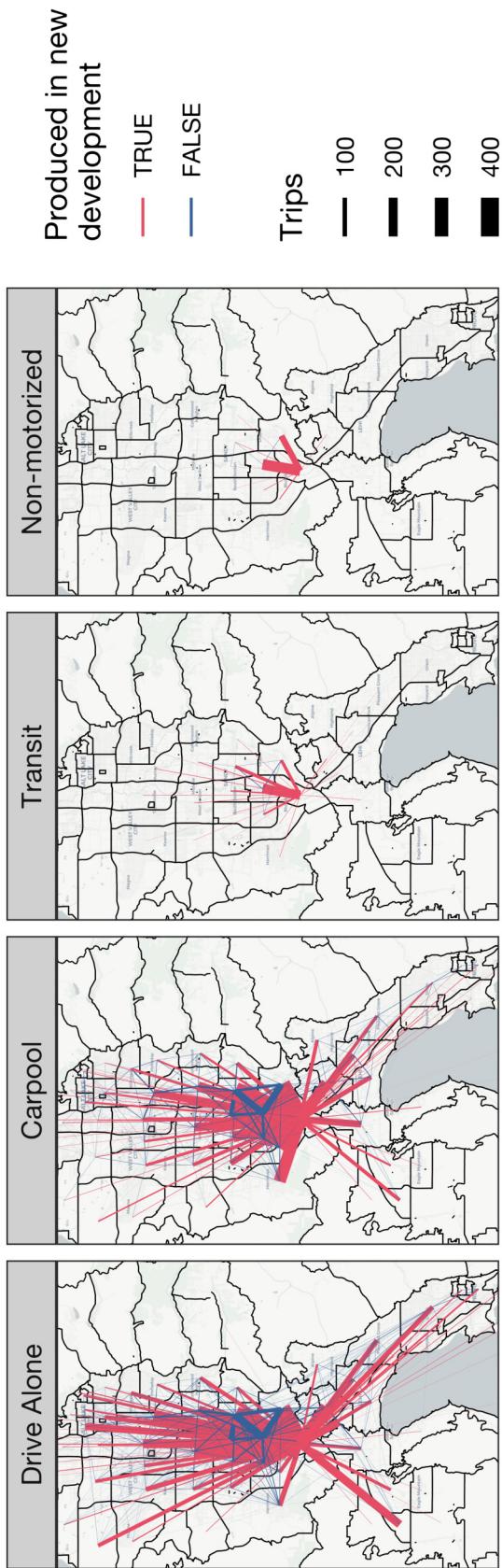


Figure 4.6: Desire lines of trips made in ActivitySim by mode.

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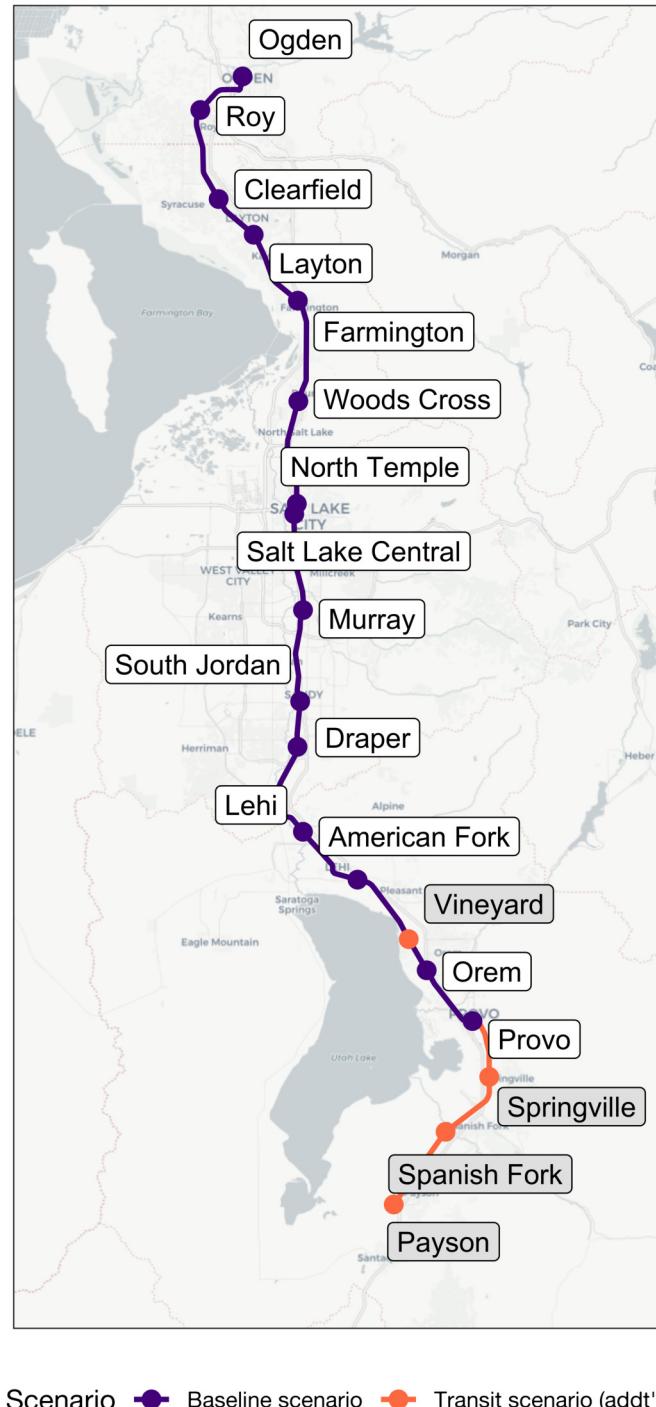
Scenario 2: Improved Transit Service

Our second scenario models changes in travel behavior as a result of changes to transportation infrastructure. This model scenario, termed the “Transit” scenario, is based on a planned improvement to the FrontRunner commuter rail line. The FrontRunner runs along the Wasatch Front between Provo and Ogden, Utah, with several stops in between. Currently, there is only one set of tracks for much of the line, and it is only possible for trains to pass each other near stations. Because of this, headways are quite large, with trains running every 30 minutes in peak periods and every 60 minutes in off-peak periods.

A potential improvement to the FrontRunner would “double track” the entire route, allowing trains to pass each other at any point. The main benefit of this improvement is a substantial decrease in headways, bringing them to 15 and 30 minutes for peak and off-peak service, respectively. Two additional improvements are partial electrification of the FrontRunner, allowing for faster travel speeds, and extending the track farther south with additional stops.

The Transit scenario models these 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^a, Springville, Spanish Fork, and Payson. Figure 5.1 shows the FrontRunner network along with the modeled changes. In reality there would be additional transit improvements, such as a revised bus service network serving the Springville station, but for the sake of simplicity these additional improvements are not included in this model scenario. Only the changes to the FrontRunner service are modeled here.

^aIn 2019, the model year for the baseline scenario, the Vineyard station was not yet open, though the station has been operational since late 2022.



Scenario ● Baseline scenario ○ Transit scenario (add'l)

Figure 5.1: Map of the FrontRunner commuter rail line.

5.1 Scenario Creation

In the WFRC model, this scenario 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 the node of each new station, which allows transfers between auto and transit modes at these nodes.

To implement this scenario in ActivitySim, only updated travel skims are needed. As in the baseline scenario, ActivitySim directly uses the transit skims that are output from the WFRC model’s network assignment in this model scenario. 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. The highway skims used for ActivitySim are therefore taken from the WFRC model baseline scenario and not updated for this scenario. No other changes to ActivitySim are necessary to model this scenario.

5.2 Scenario Analysis

One of the most straightforward analyses to perform is a comparison of the mode split between this and the baseline scenario. Table 5.1 shows the number of trips by purpose and mode for each model, and compares these results between this scenario and the baseline scenario. Unsurprisingly, both models predict a significant increase in commuter rail trips. The models differ, however, in which modes the new commuter rail trips come from.

For Home-based Other and Non-home-based trips, the WFRC model shows virtually no change in the number of auto and non-motorized trips, while there is a significant decrease in the number of local transit trips. Home-based Work trips do see a decrease in auto trips with the improved transit, but there are still significantly fewer local transit trips compared to the baseline scenario. This indicates that the new commuter rail trips are mostly coming from those who would have taken local transit in the baseline scenario.

ActivitySim, on the other hand, actually shows an *increase* in local transit trips for Home-based Work and Non-home-based trips. For Home-based Other trips, there is a decrease in local transit, but by percentage it is not nearly as significant as the decrease in the WFRC model.^b This shows that most new commuter rail trips in ActivitySim are coming from auto (drive alone and carpool) modes, rather than other transit modes.

The discrepancy may be partially explained by the difference in the way trips are modeled. In the WFRC model, trips are modeled in aggregate, with no interaction between separate trips. Regardless of trip purpose, trips are treated essentially the same, though potentially with different coefficients in mode choice equations. Even Non-home-based trips are treated like any other trip during mode choice. Additionally,

^bThe absolute difference in *number* of Home-based Other local transit trips between the scenarios is comparable between the two models, but since ActivitySim is predicting significantly more transit trips in the baseline scenario compared to the WFRC model, the percent change is much smaller in ActivitySim.

Table 5.1: Change in Mode Split with Improved Transit

Purpose	Mode	WFRC Model			ActivitySim		
		Baseline Trips	Transit ¹ Trips	Change	Baseline Trips	Transit ¹ Trips	Change
Home-based Work	Drive Alone	1328609	1326191	-0.2%	1012180	1010565	-0.2%
	Carpool	257783	256654	-0.4%	258459	256550	-0.7%
	Local Transit ²	37935	36494	-3.8%	232222	233426	0.5%
	Commuter Rail	10821	15891	46.9%	19846	22265	12.2%
Home-based Other	Ridehail	—	—	—	1108	1099	-0.8%
	Non-motorized	76506	76396	-0.1%	145957	145845	-0.1%
	Drive Alone	1394415	1394095	0.0%	700133	698809	-0.2%
	Carpool	2702277	2701039	0.0%	2148429	2145135	-0.2%
Non-home-based	Local Transit ²	33168	32583	-1.8%	195062	194649	-0.2%
	Commuter Rail	4180	6332	51.5%	81094	87337	7.7%
	Ridehail	—	—	—	113624	113538	-0.1%
	Non-motorized	510143	510103	0.0%	613134	611996	-0.2%
	Drive Alone	951561	951407	0.0%	716143	714854	-0.2%
	Carpool	1273279	1272977	0.0%	938056	936408	-0.2%
	Local Transit ²	12213	12068	-1.2%	107526	108395	0.8%
	Commuter Rail	1243	1806	45.3%	12317	13344	8.3%
	Ridehail	—	—	—	40092	40061	-0.1%
	Non-motorized	146404	146409	0.0%	156819	156587	-0.1%

¹"Transit" here refers to the Transit scenario, not the mode of travel²"Local Transit" includes both light rail and bus travel

there is a nesting structure to the mode choice step in the WFRC model. The transit “nest” contains all transit modes, and so when the commuter rail service is improved the utility of commuter rail compared to other transit modes increases more than the utility of commuter rail compared to non-transit modes. Many of the new commuter rail trips therefore come from those who would have taken transit otherwise.

ActivitySim, however, *does* model interactions between trips. An individual who makes a commuter rail trip will (usually) not be able to drive for subsequent trips until they have returned home. Because of this, individuals taking commuter rail are more likely to then take other forms of transit on the same tour. There is a similar nesting structure in the mode choice model of ActivitySim as in the WFRC model, but this effect is less pronounced in part due to this structuring of trips into tours.

One particularly interesting analysis that can be done with an ABM is to see who changed modes with the improved transit. Because trips are modeled individually rather than in aggregate, it is possible to identify trips that switch modes between the scenarios. Figure 5.2 shows the distribution of these “switched” trips. These are trips that are “the same” between scenarios and differ only by mode. For the purposes of this analysis, trips are considered “the same” between scenarios if they are made by the same person and have the same origin and destination zones, time of day^c, and tour and trip purpose. Most of these trips also share the same mode, which is to be expected, but many do not. Figure 5.2 is filtered to show only trips that do not share the same mode between scenarios.

There is some amount of randomness in the way ActivitySim determines trip modes, though. This randomness is seen partly in trips that switch away from commuter rail despite the improved commuter rail service, as well as some trips that switch to modes other than commuter rail, especially to drive alone. Although, part of the switch from carpool to drive alone can be explained as previously-carpool trips where all but one vehicle occupant switched to another mode, leaving one person in the vehicle for the trip. Overall, though, the randomness is not a significant portion of the overall mode switching seen in Figure 5.2.

Mode choice is not the only step of ActivitySim affected by the improved transit service, however. In fact, there are many trips that do not have a match between scenarios, where origin, destination, time of day and/or purpose differ. The number of trips an individual makes may also differ between scenarios, as each person’s DAP is partially dependent on accessibility measures (see Figure 3.2). Notably, Figure 5.2 also does not include any of these trips; the figure only shows trips which do have a match between scenarios.

ABMs also allow for even more granular analysis than shown in Figure 5.2. For example, Figure 5.3 shows the trip modes of at-work subtours made by individuals who switched their work tour mode away from drive alone. The figure shows the at-work subtour trip modes for *all* these individuals, not just those who also switched their at-work subtour trip modes. These results are essentially as expected. All trips

^cActivitySim models time of day as the “departure hour” for each trip. If two trips share the same departure hour, they are considered here to have happened at the same time.

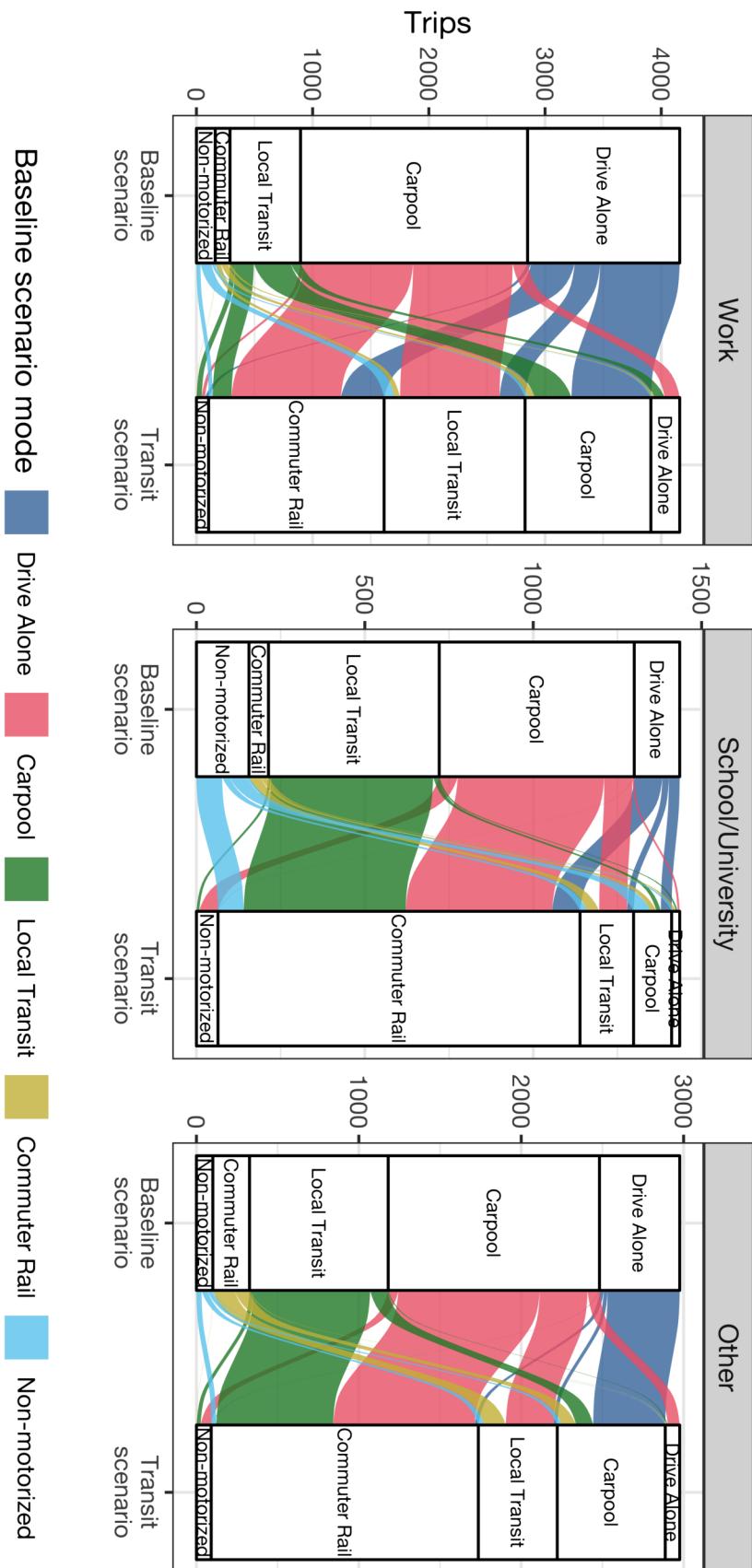


Figure 5.2: Trip modes of individuals who switched modes with improved commuter rail service in ActivitySim, by tour purpose.

that were drive alone in the baseline scenario switched to carpool, and there was virtually no mode switching otherwise, except a few trips that switched from carpool to non-motorized. This switching from carpool to non-motorized can again be largely explained by the randomness in ActivitySim's mode choice models, and again is relatively insignificant.

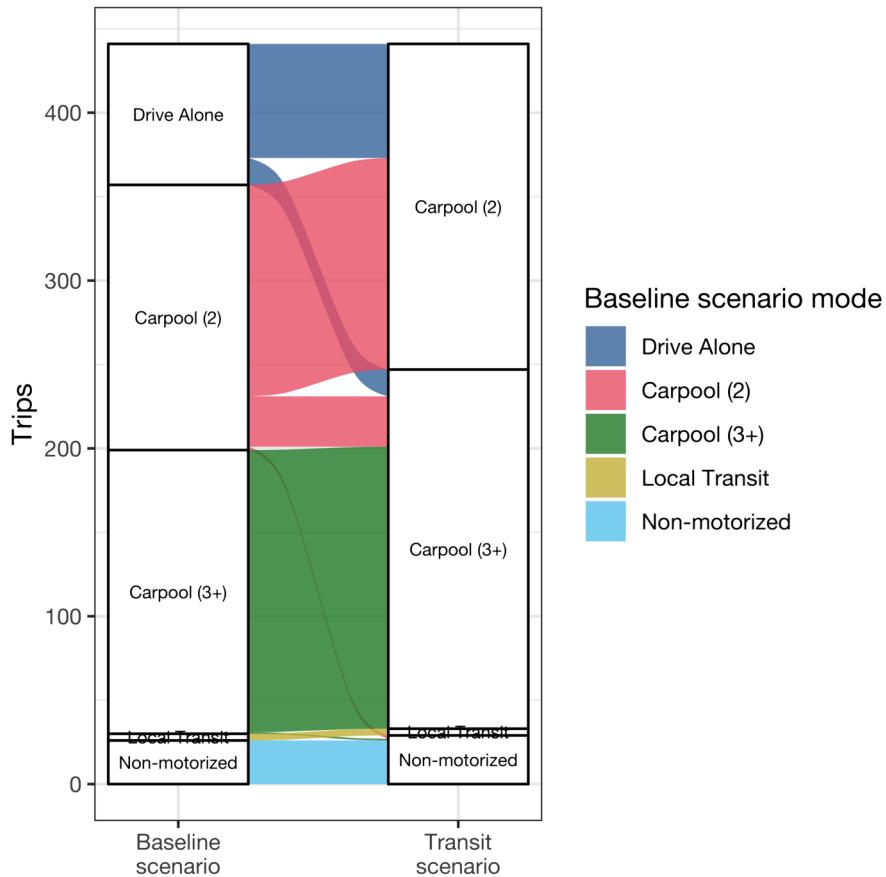


Figure 5.3: At-work subtour trip modes of individuals who switched their work mode away from “Drive Alone” in ActivitySim.

Both model types additionally allow for analyzing the types of people who use transit. The WFRC model, however, is limited to analyses using aggregate, TAZ-level data. Table 5.2 shows, for example, the median number of households, people, and jobs per TAZ weighted by the number of transit trip productions in each TAZ for the WFRC model. Additionally, Table 5.2 shows a median income associated with transit trips, but note that this is not a median income of transit *riders*, but a median of *TAZ median income*, weighted by trip productions. It is difficult to know the actual income distribution of transit riders since individuals are not modeled explicitly.

Because an ABM *does* model individuals explicitly, information about each individual is accessible at every stage of the model, including in post-hoc analysis. We can therefore determine the individual-level distribution of age and income for transit riders, for example. Table 5.3

Table 5.2: Example Socioeconomic Analysis of Transit Trips (WFRC Model)

Purpose	Mode	Trips	TAZ-level Median (weighted by trips)			
			Households	Population	Employment	Income
Home-based Work	Local Transit	36494	478	1211	400	\$54,208
	Commuter Rail	15891	435	1368	279	\$76,529
Home-based Other	Local Transit	32583	460	1147	454	\$49,682
	Commuter Rail	6332	423	1306	317	\$68,369
Non-home-based	Local Transit	12068	97	182	1362	\$50,921
	Commuter Rail	1806	138	453	1487	\$58,576

shows a similar summary as Table 5.2, but for ActivitySim. Table 5.3 presents median values for the individuals who made transit trips, not simply TAZ averages. Notably, Tables 5.2 and 5.3 show that ActivitySim is predicting a higher median income of transit riders than the WFRC model. Our synthetic population does over-predict high-income households along the length of the FrontRunner (see Figure 3.5), and this may partially be the cause of the discrepancy.

Table 5.3: Example Socioeconomic Analysis of Transit Trips (ActivitySim)

Purpose	Mode	Trips	Individual-level Median		
			Income	Age	Distance to work (mi)
Home-based Work	Local Transit	233426	\$78,735	37	7.4
	Commuter Rail	22265	\$85,314	33	24.3
Home-based Other	Local Transit	194649	\$58,408	28	4.9
	Commuter Rail	87337	\$68,603	23	3.8
Non-home-based	Local Transit	108395	\$63,718	33	6.2
	Commuter Rail	13344	\$58,408	25	3.9

Additionally, Figure 5.4 shows the income distribution of transit riders for the WFRC model and ActivitySim. Again, the WFRC model is not modeling individuals, so for the WFRC model Figure 5.4 shows the distribution of median TAZ income weighted by number of trip productions. For ActivitySim, however, the true income distribution of individual transit riders is shown.

ActivitySim shows a rather wide income distribution of transit riders, while the distribution of the WFRC model is much denser around \$50,000–\$75,000. This makes sense given that the WFRC model shows a distribution of *median* incomes, while ActivitySim shows the distribution of *individual* incomes. It is clear that ActivitySim considers transit to be more attractive for a wider range of incomes than the overall income distribution, though notably low- to medium-income individuals are somewhat more likely to take transit. In the WFRC model, however, the income distribution of individuals taking transit is unknown.

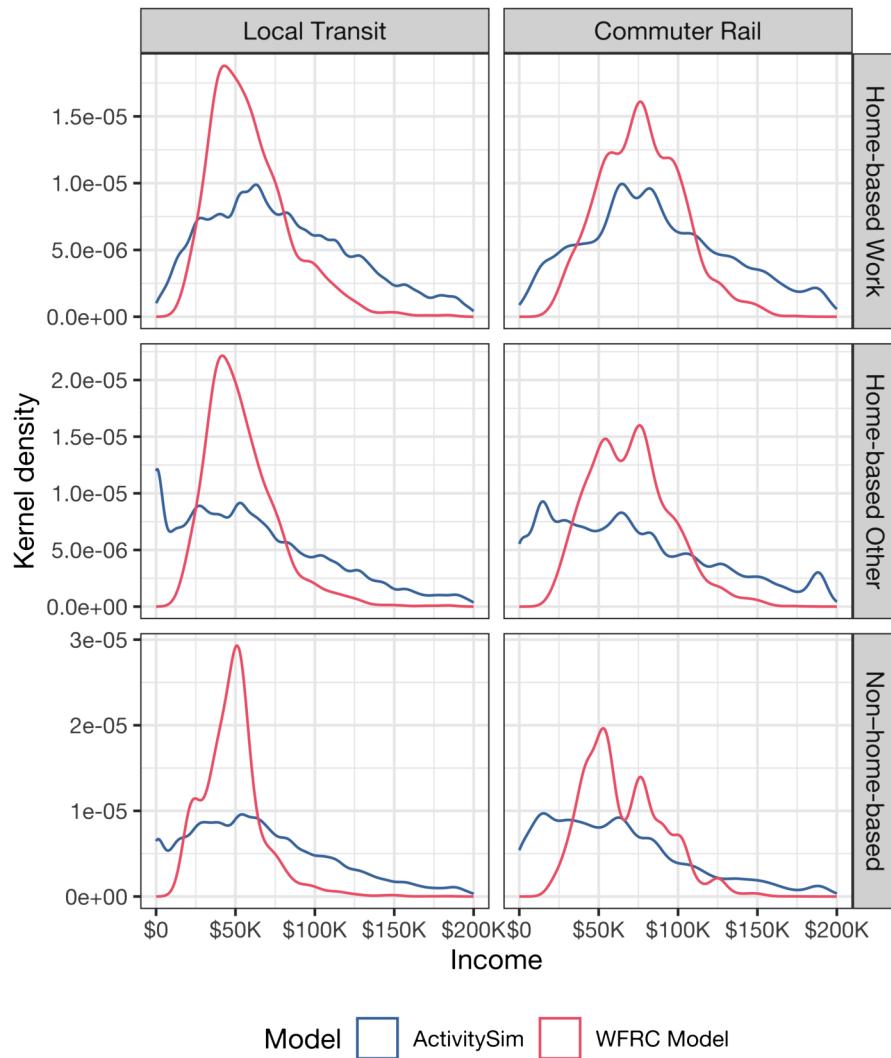


Figure 5.4: Income distribution of transit riders in both models. The distribution of TAZ median income weighted by transit trips is used for the WFRC model, while for ActivitySim the actual income distribution of transit riders is used.

6

Scenario 3: Increase in Remote Work

Our final model scenario, termed the “Remote Work” scenario, addresses changes in travel behavior as a result of social and/or economic factors. Specifically, we represent an increase in remote work rates since the COVID-19 pandemic. With the onset of the COVID-19 pandemic, there were unprecedented numbers of people working remotely (Bick et al. 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 (Ozimek 2020).

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, and predicts an increase in both remote work rates over time. Figure 6.1 shows the remote work rates predicted in the WFRC model by year.

This scenario is a “what-if” analysis that models a significant increase in remote work rates. We use the remote work rates from 2050 as predicted by the WFRC model, 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.

There has been much research, especially in recent years, on the implications of remote work. While many agencies 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 suggests that considerations for remote work should be made on a case-by-case basis because there is no single best approach. The following section discusses some of these considerations.

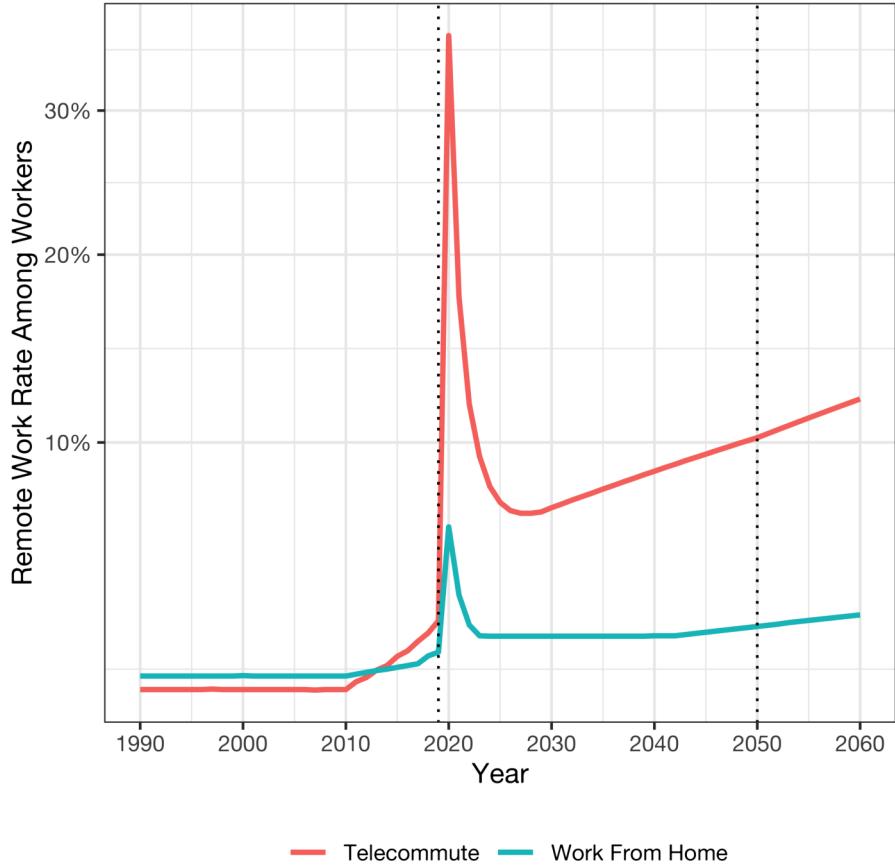


Figure 6.1: Remote work rates as given in the WFRC model.

6.1 Considerations for Modelling Remote Work

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 (2016) similarly discuss the idea of a “travel time budget”, where a decrease in trips of one purpose will increase the time people allocate for trips of another purpose and vice versa.

This rebound effect is not straightforward, however. Elldér (2020), for example, finds that distinguishing between people that work from home all day and those who work from home only part of the day might make a difference. Compared to those who commute to work, those who worked from home the entire day had fewer 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 (He and Hu 2015), Mokhtarian and Varma (1998) find 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.

In our case, we are using the existing frameworks for modeling remote work in both ActivitySim and the WFRC model, as discussed in Section 3.3.2.

6.2 Scenario Creation

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 2019 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 scaling factor was left unchanged, as we considered that the 2050 predicted remote work percentages would better model a more realistic increase in remote work than simply scaling the 2019 rates globally.

Table 6.1: Comparison of Remote Work Rates in the WFRC Model by Year

Industry	Telecommute %		Home-based Jobs %	
	2019	2050	2019	2050
Retail	2.70%	7.25%	2.12%	2.50%
Food	1.87%	5.03%	1.46%	1.73%
Manufacturing	2.02%	5.45%	1.59%	1.88%
Office	6.66%	18.01%	5.22%	6.23%
Gov't/Education	1.67%	4.56%	1.31%	1.57%
Health	2.86%	7.21%	2.11%	2.49%
Agriculture	6.93%	16.83%	5.44%	5.82%
Mining	0.53%	1.43%	0.42%	0.50%
Construction	3.28%	8.82%	2.57%	3.04%
Other	5.37%	14.58%	4.21%	5.04%

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: Telecommute Rates and Coefficients by Job Industry

Industry	2050 WFRC Telecommute %	Telecommute Frequency 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.

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 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 drive alone trips decreased by 6.3% relative to the baseline scenario, but person-miles traveled decreased only by 5.3%. 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.

ActivitySim does model distance to work directly when predicting remote work status (see Section 3.3.2 and Table 3.7), so those who live

Table 6.3: Change in Mode Split After Increased Remote Work Rates

Purpose	Mode	WFRC Model Trips			ActivitySim Trips		
		Baseline	Remote Work Scenario	Change	Baseline	Remote Work Scenario	Change
Home-based Work	Drive Alone	1328609	1244451	-6.3%	1012180	950306	-6.1%
	Carpool	257805	238669	-7.4%	258459	242497	-6.2%
	Transit	48752	44977	-7.7%	253176	237881	-6.0%
	Non-motorized	76506	71063	-7.1%	145957	137684	-5.7%
Home-based Other	Drive Alone	1394415	1395196	0.1%	700133	709957	1.4%
	Carpool	2702272	2702625	0.0%	2148429	2171566	1.1%
	Transit	37346	37359	0.0%	389780	396815	1.8%
	Non-motorized	510143	508869	-0.2%	613134	617480	0.7%
Non-home-based	Drive Alone	951561	938653	-1.4%	716143	687935	-3.9%
	Carpool	1273317	1254548	-1.5%	938056	922662	-1.6%
	Transit	13453	13199	-1.9%	159935	158366	-1.0%
	Non-motorized	146404	144126	-1.6%	156819	152688	-2.6%

Table 6.4: Comparison of Trips Taken and Miles Traveled (WFRC Model)

Purpose	Mode	Trips			Person-miles		
		Baseline Scenario	Remote Work Scenario	Change	Baseline Scenario	Remote Work Scenario	Change
Home-based Work	Drive Alone	1328609	1244451	-6.3%	12736970	12070213	-5.2%
	Carpool	257805	238669	-7.4%	3204552	2945150	-8.1%
	Transit	48752	44977	-7.7%	547804	500953	-8.6%
	Non-motorized	76506	71063	-7.1%	132216	122930	-7.0%
Home-based Other	Drive Alone	1394415	1395196	0.1%	6088804	6122517	0.6%
	Carpool	2702272	2702625	0.0%	13420596	13448784	0.2%
	Transit	37346	37359	0.0%	264203	264432	0.1%
	Non-motorized	510143	508869	-0.2%	591297	590349	-0.2%
Non-home-based	Drive Alone	951561	938653	-1.4%	4777297	4736979	-0.8%
	Carpool	1273317	1254548	-1.5%	7650625	7538596	-1.5%
	Transit	13453	13199	-1.9%	73563	72018	-2.1%
	Non-motorized	146404	144126	-1.6%	136914	134784	-1.6%

farther away from their job site are more likely to work remotely. ActivitySim, therefore, predicts a greater decrease in person-miles than in number of trips for Home-based Work trips, as seen in Table 6.5. This discrepancy is not especially large, showing that ActivitySim is not considering the trip distance too heavily (see Table 3.9), but the discrepancy is consistent across all modes. Additionally, for Home-based Other trips, ActivitySim predicts a greater increase in the number of trips than in person-miles, which shows that ActivitySim is modeling the effects found by Moreno and Moeckel (2016) and Moeckel (2017), where longer work trips are being exchanged for shorter discretionary trips.

Table 6.5: Comparison of Trips Taken and Miles Traveled (ActivitySim)

Purpose	Mode	Trips			Person-miles		
		Baseline Scenario	Remote Work Scenario	Change	Baseline Scenario	Remote Work Scenario	Change
Home-based Work	Drive Alone	1012180	950306	-6.1%	9632251	9021681	-6.3%
	Carpool	258459	242497	-6.2%	2631886	2463552	-6.4%
	Transit	253176	237881	-6.0%	2911616	2728897	-6.3%
	Non-motorized	145957	137684	-5.7%	353246	332978	-5.7%
Home-based Other	Drive Alone	700133	709957	1.4%	4280006	4332319	1.2%
	Carpool	2148429	2171566	1.1%	11498994	11624928	1.1%
	Transit	389780	396815	1.8%	3547052	3583630	1.0%
	Non-motorized	613134	617480	0.7%	1090176	1098043	0.7%
Non-home-based	Drive Alone	716143	687935	-3.9%	3984191	3804674	-4.5%
	Carpool	938056	922662	-1.6%	3962840	3898220	-1.6%
	Transit	159935	158366	-1.0%	867867	852243	-1.8%
	Non-motorized	156819	152688	-2.6%	194493	189483	-2.6%

7

Conclusions and Recommendations

As discussed in Chapter 2, there is a large base of literature discussing activity- and trip-based models and their differences, but much of that literature focuses primarily on the technical aspects of the respective models. There is little research into the practicality of either model type that would be useful to an agency in deciding which type to use. Therefore, while some of the conclusions presented here address quantitative differences between the two models, the more relevant discussion in this chapter relates to the subjective experience of configuring and using each model.

Specifically, this section focuses on potential “pain points” an agency may encounter when transitioning from a trip-based model to an ABM, both as discussed in the literature and from our experience in this research. Miller (2023) notes several reasons agencies may not be adopting ABMs, as discussed in Section 2.3. Some of these reasons include computational inefficiency, complicated design, and lack of interoperability between areas. Additionally, switching to an ABM would require an agency to expend resources on staff training, though notably this is true for switching to any new modeling system, regardless of model type. The following sections address each of these difficulties in detail, and discusses our experience as it relates to them. Note that many of the conclusions presented here are specific to the WFRC model and our ActivitySim implementation, though many conclusions can apply to trip- and/or activity-based models more broadly.

7.1 Computational Resources

The first potential difficulty for an agency transitioning to an ABM is the computational resources required to run the model. This section discusses the hardware used to run both models in our research, as well as the model runtimes.

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, and was configured to use 16 threads for our scenario runs. Notably, this is a specialized computer, but would not be prohibitively expensive to most agencies.

There were not significant differences in runtimes between each model scenario, and each scenario had a runtime of 16–17 hours. However, this runtime includes the distribution feedback loop (including both trip distribution and a preliminary network assignment each iteration) and the network assignment step of the WFRC model. While ActivitySim does have a destination choice model analogous to the WFRC model’s trip distribution step, ActivitySim has no distribution feedback loop, as there is no preliminary network assignment. ActivitySim also does not include a final assignment step. A better runtime to report for the WFRC model ignores the time spent in the distribution feedback loop (except for one iteration of trip distribution) and the network assignment step. The entire distribution feedback loop took around 4 hours to complete, and the trip distribution step took 1–2 minutes each iteration. Additionally, the final network assignment step took around 2 hours, and so the runtime of the WFRC model to compare with ActivitySim is 10–11 hours.

Most runs of ActivitySim were done on parallel computing nodes hosted by Brigham Young University. Each node runs Red Hat Enterprise Linux 7.9, and uses an AMD EPYC 7763 CPU at 2.45 GHz. Each ActivitySim run requested 12 CPU cores and 360 GB of RAM. A dedicated workstation with similar resources would again be a specialized computer, but again not prohibitively expensive. 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 can significantly reduce the RAM required, at the expense of increased runtimes, through “chunking” options (Association of Metropolitan Planning Organizations 2023c), where large tables are loaded into RAM in chunks rather than all at once. 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 16 threads, and the chunk size set to 112 GB, the baseline ActivitySim scenario ran in about 13 hours.

ActivitySim completed its scenario runs in a similar time to the WFRC model on the same hardware. This is counter to the idea that ABMs require significantly increased resource and runtimes compared to trip-based models. Notably, our experience is certainly not universal, and the runtime of any model will greatly depend on several factors, including the specific modeling software and the hardware configuration. But at least in our case, ActivitySim performed similarly to the WFRC model with the same hardware, and was an order of magnitude faster when provided with enough RAM to avoid chunking.

Based on these results, an agency looking to switch to an ABM would likely not need additional computational resources beyond those used for

trip-based models. However, considering the potential gains in runtime (in the case of ActivitySim, given enough RAM to avoid chunking), it may be worth considering buying or renting additional computational resources. Computer hardware prices certainly change over time, but as of early 2024, a 12-core, 360 GB RAM computer (using very rough price estimates) would likely cost a few thousand dollars. Depending on the budget of a given agency, this expense may be worthwhile.

7.2 Complication of Model Design

The second potential difficulty is the complication of an ABM's design. ABMs may in theory be more complicated than trip-based models, as ABMs model individuals rather than simply using aggregate values. ABMs therefore have more "moving parts" than trip-based models. However, these "parts" are often much more straightforward to interpret in an ABM, as each model step simply assigns a household or individual a specific value, such as vehicle ownership or the individual's DAP. These assigned values can then be used in subsequent model steps. In our ActivitySim implementation, for example, an individual's distance to work has a direct effect on their remote work status, which in turn affects the DAP assigned to that individual. It is easy to then model a remote work "rebound effect"^a by increasing the utility of a non-mandatory DAP for individuals who work remotely.

^aSee Section 6.1

Since trip-based models exclusively deal with aggregate data, the interpretation of each model step is more vague. For example, while it may be possible in a trip-based model to model distance to work as it relates to remote work, it is not clear how best to do this, and may require a separate trip purpose and/or trip distribution model specifically for remote work. If a separate "remote work" trip purpose is used, then the trip generation step must generate a number of remote work "trips," which is somewhat paradoxical. In ActivitySim, on the other hand, distance to work is simply another model step that "slots in" to the model pipeline. This step (and most model steps) can be adjusted and calibrated independently of the rest of the model, and it is much easier to understand and interpret what each model step is doing.

Another example that highlights the difference in interpretation between models regards non-home-based trips. Trip-based models model non-home-based trips quite abstractly, especially if (like the WFRC model) the model does not include a non-home-based trip redistribution step. While the idea of a trip that does not begin or end at home is conceptually simple, it is difficult to model concretely in a trip-based model. Homes may "produce" non-home-based trips, but it is not clear where the origins or destinations of those trips should be. By contrast, the interpretation of non-home-based trips in an ABM is trivial. Because trips in an ABM are organized into tours, it is easy to "follow" an individual throughout the day; each trip has an origin and destination consistent with the other trips in the tour. "Non-home-based" trips are not really a

concept in ABMs, as individuals simply make trips, some of which begin or end at home.

A point worth noting, though, is that ABMs do require additional input data compared to a trip-based model. However, essentially the only additional input data needed for ActivitySim over the WFRC model is the synthetic population (see Section 3.2). While the synthetic population did require a significant amount of initial configuration, modifying the synthetic population (e.g., for the Land Use scenario) did not require much additional effort.

7.3 Model Interoperability

A third potential difficulty is the interoperability/transferability of an ABM from one area to another. Collaboration between agencies could be difficult if each ABM implementation is bespoke and tailored to a specific area. We found, however, that at least with ActivitySim this is not the case. In fact, ActivitySim is relatively easy to customize and extend. Our ActivitySim implementation originally did not include remote work submodels, but it was simple to copy the remote work models from the Michigan example configuration into our implementation. Some minor changes were made to ensure consistent variable names, but this process was not very involved (see Table 7.1). Additionally, the example remote work models did not include provisions for different remote work rates based on job industry as in the WFRC model, but it was simple to add these.^b

^bThe synthetic population we created has information on job industry for each worker, and so this was referenced in the remote work submodel in ActivitySim.

The WFRC model does already include different remote work rates by job industry, but it would be difficult to add in different rates based on, for example, vehicle ownership or TAZ average income. It is worth noting though that this difficulty may be a result of the specific way that the WFRC model is written, and may not apply equally to all trip-based models.

7.4 Training Requirements

In order to change from a trip-based to an ABM, an agency will need to spend time to understand the model and train its staff. We analyzed the time spent on each part of the modeling process for this project, and this section provides discussion on this. Obviously the actual time an agency would require to transition to and use an ABM depends on many factors such as specific staff experience, but this section is intended to give a very rough approximation of the time and effort needed.

Table 7.1 shows the amount of time spent on creating and analyzing each scenario in both models. These are approximations, as detailed time logs are not available. Additionally, many of the tasks are interrelated or use the same code between models and scenarios, so it is sometimes hard to separate the time spent into individual tasks. However, Table 7.1 should serve to give a very rough idea of the time spent on each task. Note as well that this table shows time spent by one graduate and one un-

dergraduate research assistant; more experienced modelers would likely require significantly less time to create and analyze similar scenarios.

Table 7.1: Estimated Time Spent on Modeling Tasks

Scenario	Task	Hours Spent on Task	
		WFRC Model	ActivitySim
—	Synthetic population creation (baseline)	—	50
	Add remote work models to ActivitySim	—	20
	Convert data to "common" structure ¹	60	50
Land Use	Scenario creation	15	20
	Trip-miles plot	5	5
	Desire lines	15	10
Transit	Scenario creation	10	2
	Mode split ²	5	5
	Mode switching	—	25
	SE summary for transit riders	10	12
Remote Work	Scenario creation	20	5
	Mode split ²	5	5
	Trips and miles traveled ²	5	5

¹ This task was iterative and the "common" structure changed over time to reflect new analyses as they came up

² These analyses use the "common" structure directly and so took identical time and effort between the two models

The overall time spent for ActivitySim is on par with that for the WFRC model, though there are a few important notes about this comparison:

First, the scenarios in ActivitySim were somewhat dependent on the outputs of the WFRC model. ActivitySim depends on the WFRC model's travel skims, as ActivitySim does not perform network assignment and so is unable to determine congested travel times on its own. In the Transit scenario, for example, the only change needed for ActivitySim was to use updated transit skims, which was extremely quick to implement. However, these updated skims came from the results of the WFRC model's Transit scenario, and so in some sense the time spent for ActivitySim on this task should possibly include the time spent for the WFRC model.

Second, the tasks were divided between two research assistants largely in line with the model type. This means that Table 7.1 is showing the time spent with each model type by a specific individual. In other words, the difference within this table is not only the model type, but also the individual working on the task. Any comparisons between the time spent on the two models should therefore take this into consideration.

One additional point to note is how the analyses were performed in each model. The outputs of the WFRC model relevant to our analyses consist mainly of matrices listing the number of trips between zones. There is a separate matrix for each mode and purpose, and so analyzing the data from the WFRC model requires making comparisons between several matrices for each scenario, and potentially aggregating values across different matrices. The only output of ActivitySim relevant to our analyses is a table listing every trip made in the scenario, which includes

information on person id, mode, time of day, purpose, etc. There is therefore only one table per scenario that we used in our analyses, as this table contained all the necessary information for each analysis. For example, to create the Non-home-based desire line plot for the WFRC model (Figure 4.5), we took the Non-home-based trip matrices and took the difference between the Land Use and baseline scenario for each mode. For the desire line plot in ActivitySim (Figure 4.6), we took the table of trips and filtered the list to only persons whose home zone was in the new development. We then had a list of trips made by residents of the new development and were able to aggregate these trips and create the desire line plot. Both of these figures took roughly the same amount of effort to create, and the analysis in ActivitySim gives more detailed information than the equivalent analysis in the WFRC model.

7.5 Recommendations

Our experience in this research runs counter to many of the commonly discussed “pain points” of ABM adoption. Our ActivitySim implementation was no more computationally intensive than the WFRC model, we found relatively easy interoperability between the example San Francisco and Michigan ActivitySim implementations, and the amount of time and effort required to understand and configure ActivitySim was on the whole rather small. Additionally, while ActivitySim may be more complicated “under the hood” than the WFRC model, the interpretation of ActivitySim is in some ways significantly simpler. It is possible that these “pain points” are outdated, as there have not been many comparisons between model types in recent years (as discussed in Section 2.4).

Our central recommendation, then, is for an agency considering transitioning to an ABM to recognize that some of the commonly-cited difficulties of ABMs may not actually be as relevant as initially thought.

There are, however, certainly still valid reasons for an agency to continue to use a trip-based model over an ABM. Though in our experience the effort required to configure ActivitySim was not unreasonable, the effort was non-trivial. An agency would need to spend time and effort to re-train its staff and modify its existing workflow pipeline. Additionally, an agency switching to an ABM would lose conformity with previous analyses. Comparing model results from before and after the transition could therefore be difficult, though this would depend on the specific comparisons desired. In this research, we were for example able to make several direct comparisons between ActivitySim and the WFRC model (see Chapters 4–6).

One crucial consideration to make is that ActivitySim does not perform network assignment. Many agencies that currently use ActivitySim in fact use CUBE or other similar software to perform assignment, though there are also several open-source network assignment programs such as MATSim (Horni et al. 2016) and AequilibraE (Camargo et al. 2024) that are also in use. Regardless of the software used for network assignment, an agency will need to determine how best to integrate assignment into

their modeling workflow in order to use ActivitySim. This issue is specific to ActivitySim, and other ABMs may incorporate network assignment directly. However, even ActivitySim itself is designed to be extensible, and as discussed above it is relatively easy to modify ActivitySim's model pipeline to allow for adding model steps. This extensibility also includes the ability to add custom pipeline steps, so it would be possible to add a feedback loop between network skims/accessibility calculations and network assignment.

An additional point worth noting is that the scenarios chosen and the analyses demonstrated in Chapters 4–6 are only examples. The number of scenarios and analyses that we could theoretically create is limitless, and we chose scenarios and analyses that we thought would illustrate well the differences between model types. A common trend, though, is that for roughly the same amount of effort, we were able to perform more in-depth analyses with ActivitySim compared to the WFRC model. This further shows that ABMs are not necessarily more difficult to work with than trip-based models.

The goal of this research is not to determine unilaterally which model type an agency should use, nor is the goal even to specify exact criteria under which an ABM should be used over a trip-based model. Rather, the research presents our experience with both model types as an illustration for agencies to reference in determining which model type to use. We therefore encourage each agency to review our findings in the context of their individual circumstances, and then determine which model type will best fulfill their specific modeling needs.

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