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ACTIVITY-BASED MODEL IMPLEMENTATION AND ANALYSIS CONSIDERATIONS

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16. Abstract
Tour-based and activity-based travel demand models are generally considered more theoretically robust compared to their trip-based counterparts, as activity-based models (ABMs) explicitly model individuals making travel choices 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.

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UNIT CONVERSION FACTORS

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

LIST OF ACRONYMS

ABM	Activity-based model
ASC	Alternative-specific constant
DAP	Daily activity pattern
TAZ	Transportation analysis zone
WFRC	Wasatch Front Regional Council

EXECUTIVE SUMMARY

Tour-based and activity-based travel demand models are generally considered more theoretically robust compared to their trip-based counterparts, as activity-based models (ABMs) explicitly model individuals making travel choices 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.

1.0 INTRODUCTION

In travel demand modeling, activity-based models (ABMs)[1] 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. 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 practical comparison of ABMs to trip-based models, with a particular focus on the practical considerations an agency would need to make in

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[1] The term "activity-based" model as used in practice usually refers to a "tour-based" model described in the academic literature (Miller, 2023). Both model types use disaggregate approaches to model travel demand, but in a tour-based model the focus is on re-creating travel journeys, while an activity-based model tries to model the need for and participation in activities, with trips as an outcome of activity participation. In this report, we use the practical language and refer to presently implemented disaggregate travel models as "activity-based" models.

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 discussed in the literature and experienced in this research.

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 development, 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 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 as follows: 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. Chapter 8 (Appendix) presents a related analysis of professional attitudes and perspectives on travel-model framework implementation from across the United States.

2.0 LITERATURE REVIEW

Travel demand modeling in the modern sense has its origins in the 1950s, 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 theoretically superior in certain aspects, they may also have practical 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 the tradeoff between increased labor for increased sensitivity make sense for every planning 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). For example, if a person took transit to work, they cannot “drive alone” from work to lunch. ABMs output a list of tours and trips by person, time, location, and type, and can assign these trips 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 of disaggregate person data, 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.[2] 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. For example, the model may represent a 2-worker, 1-vehicle household making 3.8 work trips on an average weekday, while it may represent a 1-worker, 1-vehicle household making fewer work

[2] The 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.

trips. 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 initial segmentation of the aggregate population data limits the types of analyses possible. 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 the model needs to carry these segmentations through each model step, modelers need to estimate trip rates, mode choice equations, etc. for every classification, and while relevant real-world data may exist, sample sizes approach zero quickly, and so the estimates have little statistical value (Moeckel et al., 2020; National Academies, 2012). Further, combining these segmentations at any point 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, 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 an analyst cannot use these variables 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. An ABM ties decisions in each model step 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.

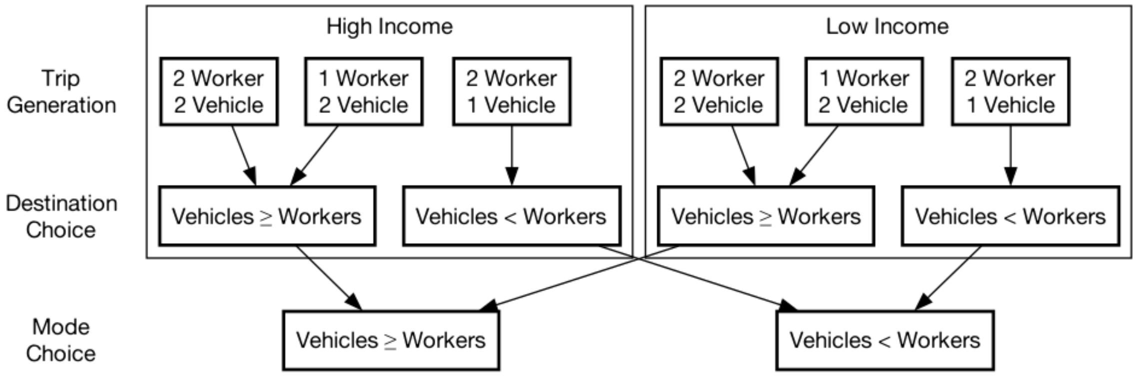
Bills and Walker (2017) used the 2000 Bay Area Travel Survey to create a synthetic population and compare the effects that certain scenarios had on high-income and low-income populations. With a 20% reduction in travel cost, they found that high-income workers benefited more than low-income workers. 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 or hybrid models—do exist (Walker, 2005), but these are relatively rare in practice.

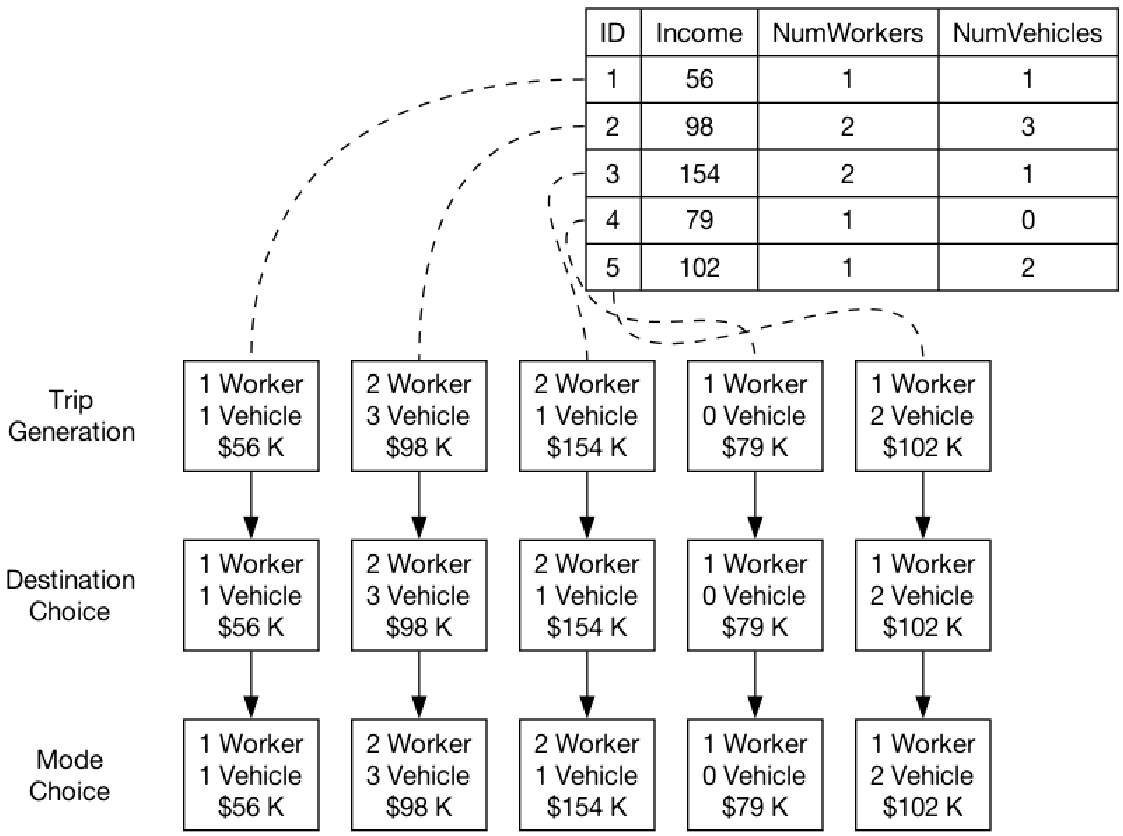
Figure 2.1 gives a visualization of an example "information pipeline" for a model using aggregate data and a model using a synthetic population. In the aggregate data model, it is impossible to know the trips made by, for example, 2-worker, 1-vehicle, low-income households after the mode choice step; it only describes trips made by households with fewer vehicles than workers. However, an activity-based model with a synthetic population models *individuals*, and so an analyst can trace each trip to a specific person. All information is known at each point in the model regardless of the data used in previous steps.

2.2.2 Travel Behavior

The other primary difference between trip-based models and ABMs—and the main difference from trip-based microsimulation models—is that ABMs organize travel into "tours," a sequence of trips that begin and end at the home, rather than just trips. We should note that Miller (2023) argues that many current "activity-based" models ought to be labeled "tour-based" due to this focus on building tours. In contrast, "activity scheduling" models explicitly model activity participation, 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.



(a) Aggregate data



(b) Synthetic population

Figure 2.1 Flow of data in an aggregate model (a) and a disaggregate model (b).

A typical trip-based model forecasts trips 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). The model then assigns an origin and destination, mode, and often a time of day (peak/off-peak, etc.) to these trips, 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 then chooses destinations and modes for each tour. After making the tour-level decisions, the model does the trip-level mode/destination choice 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 model represents the total number of trips between zones. These results show that 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 2.1 (a)). 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 using a synthetic population. Figure 2.3 (a) depicts the trip distribution that a trip-based microsimulation model could give for an individual. 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 2.3 (b), attempts to add consistency by modeling tours, and only generating trips consistent with each tour.

In addition to intra-person dependencies, Rasouli and Timmermans (2014) note that ABMs can model dependencies between members of a household as well. A vehicle cannot 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). A trip-based model cannot forecast these effects.

Another advantage of organizing travel into tours relates to accessibility analyses (e.g., How many people can a particular commercial building reach?). Dong et al. (2006) note that when an analyst uses trip-based models to analyze accessibility, they must analyze each zone based on proximity independently of travel behavior. They argue that this is a limited view of

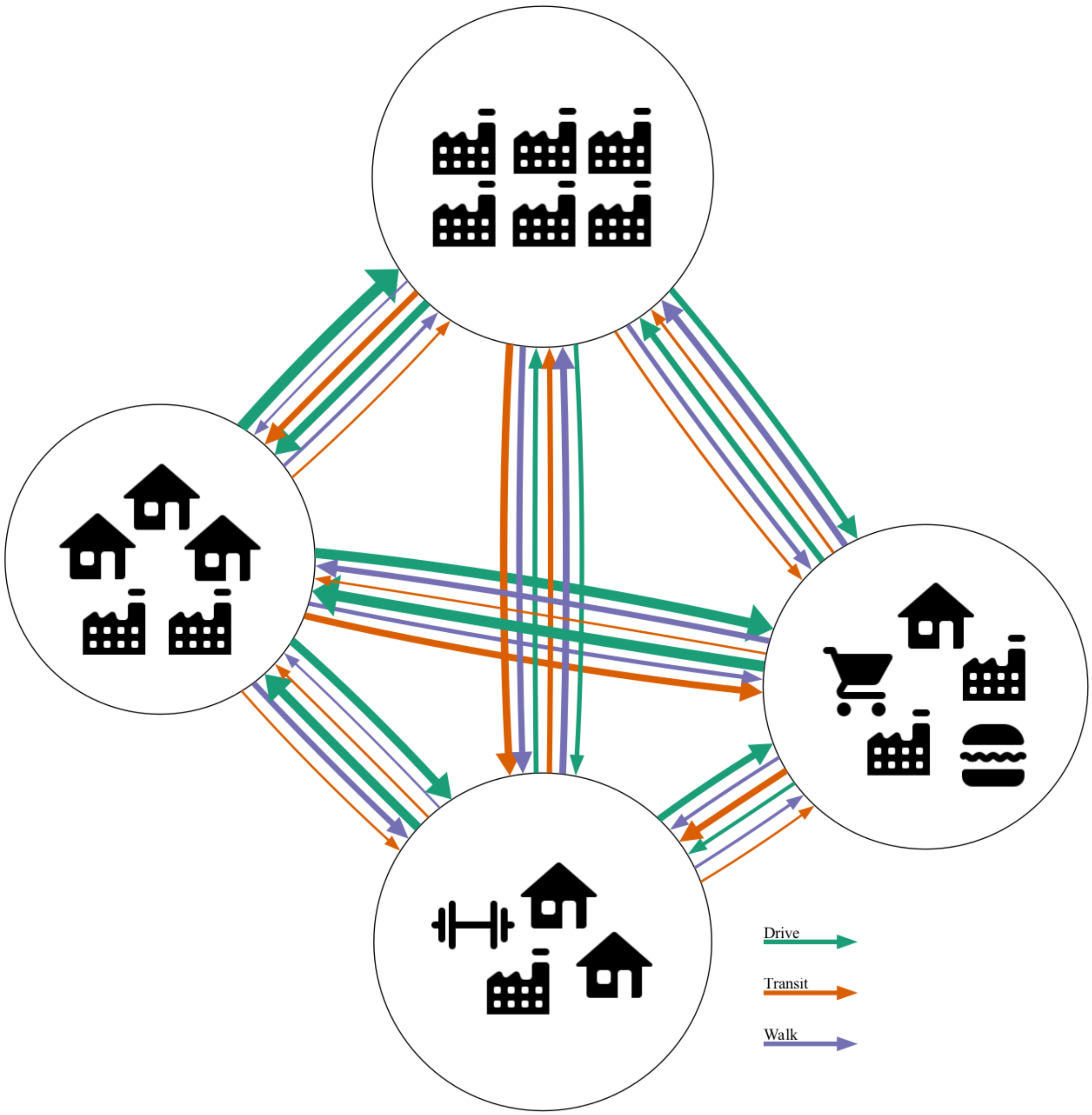
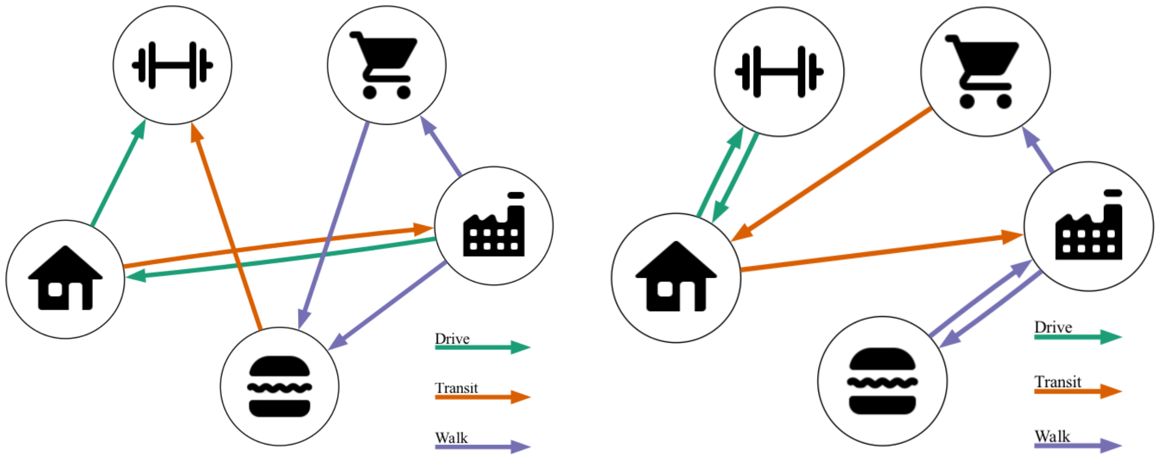


Figure 2.2 Example trip distribution using aggregate data. There is little information on who is making which trips, and it is not known how trips are related to each other.



(a) Trip-based microsimulation (b) Activity (tour)-based

Figure 2.3 Example trip distribution using trip-based microsimulation (a) and activity or tour-based models (b).

accessibility, and discuss the "activity-based accessibility measure," which considers 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 the accessibility should rate 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 professionals implement ABMs 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 ABM disadvantages:

Computational inefficiency and complicated program design: ABMs take more time, more computing power, and more money to run because the synthetic population needed for an ABM uses much more data. Areas with thousands of TAZs and millions of people have historically needed a supercomputer, and it has 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 the best approach and decide which one to implement. In relation to this, Miller also states that the pressures of publishing unique and ground-breaking research in academia can deter researchers from converging toward best theories and methods.

Lack of resources: Most ABMs 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 these organizations can be hesitant to promote software development and invest in new systems.

For these reasons, as well as the inertia of current practices, many agencies and organizations in the U.S. continue 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 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, focused on the *accuracy* of the two frameworks, but do not address the methodological differences between model types. What types of data collection/synthesis does each model type need? Can certain analyses only be done through (or made easier by) one of the model types? What would an agency need 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. The researchers ran several "proposed development" scenarios in each model and compared the strengths and weaknesses of each approach. We should note that this research does not focus 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 each model type can do.

3.0 METHODOLOGY

This research 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. Rather than comparing each of the various implementations of both model types, which is unreasonable, we use a representative model for both types and note when results apply to general trip- or activity-based models, and when results apply to the specific models used.

The representative trip-based model is the 2019 Wasatch Front (WF) travel demand model, and is the current production model used by the Wasatch Front Regional Council (WFRC) and the Mountainland Association of Governments (MAG). This model covers much of the Salt Lake City-Provo-Ogden, Utah Combined Statistical Area. We also used an ActivitySim implementation in the same study area as a representative ABM. The following sections discuss both models in detail.

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 WF Model

WFRC and MAG implemented the WF model in the CUBE software by Bentley (Bentley Systems 2023), and currently uses it for modeling travel in the Wasatch Front, 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 WF 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. WFRC provided this directly as an output of their land-use forecasting model(s).
- Travel skims detailing travel time, cost, etc. between each origin-destination TAZ pair. The WF model uses an iterative process of assigning volumes to the transportation network and recalculating the skims, which the model uses in the destination and mode choice model steps.
- Transportation networks, including highway, transit, etc. networks connecting the TAZs to each other. These networks contain information such as link speed and capacity. Though the WF model assigns travel volumes to the network, this paper does not analyze the model's network assignment results. However, we still used the network volumes to calculate the loaded network skims.
- Lookup tables, used in many model steps for information such as trip rates by household type. We took these directly from the WF model without modification.
- Model constants and coefficients, which some model steps such as mode choice require for calibration. We also took these directly from the WF model.

Figure 3.1 gives an overview of the WF model, showing broad model steps in a flowchart. Like many trip-based models, the WF model follows the "four-step" approach and has the main steps of trip generation, trip distribution, mode choice, and network assignment. The model also includes a household disaggregation step at the beginning to estimate the number of

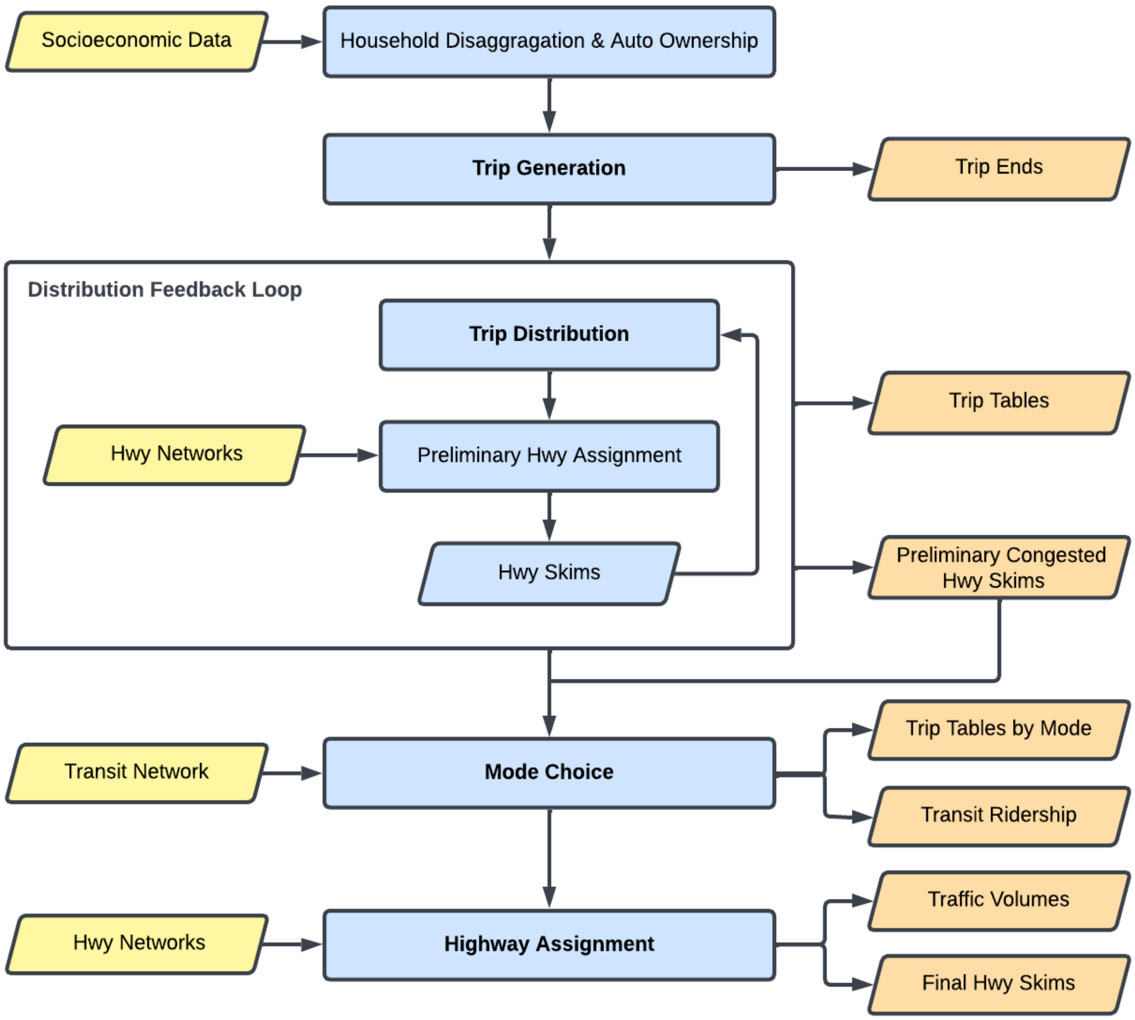


Figure 3.1 WF model flowchart. The distribution step includes a feedback loop where preliminary loaded network skims are used to perform subsequent iterations of trip distribution until the distribution converges.

households by size, income group, number of workers, and auto ownership using the TAZ-level data and lookup tables. This does not create a fully synthetic or disaggregated population, but is more segmented than the initial TAZ-level data.

The household disaggregation 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 model "caps" the household size, number of workers, and vehicle ownership categories at 6, 3, and 3, respectively (e.g., every household with 3 or more workers is grouped into a "3+ workers" category). Table 3.1 gives the WF model income groups.

Table 3.1 Income Groups in the WF Model

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

The WF model estimates an additional distribution termed "life cycle." This distribution places households into one of three categories, intended to represent the presence of children and/or working adults in the household. Table 3.2 shows the "life cycle" categories in the model based on the estimated age distribution in each TAZ.

Table 3.2 Life Cycle Categories in the WF Model

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

The trip generation step uses the disaggregated household data to estimate the number of trips produced from each TAZ by applying average rates differing by household type. The trip rates vary by trip purpose and household classification. The trip generation step multiplies the trip rates by the number of households in each category, giving the total number of trips by purpose each TAZ produces.

The WF model contains the following trip purposes:

- Home-Based Work
- Home-Based Shopping
- Home-Based School
- Home-Based Other
- Non–Home-Based Work
- Non–Home-Based Non-Work

The Home-Based Work and Non–Home-Based Work purposes use only the number of workers per household to determine the trip productions, and all other trip purposes use the cross-classification of household size and life cycle.

The trip generation step estimates the trip attractions for each purpose based mostly on the number of jobs by industry in each TAZ. The model also uses the number of households in a TAZ to estimate the home-based other and non–home-based trip attractions, and the school enrollment by TAZ for the school attractions. Each purpose has a different coefficient for each variable, and we left these coefficient values unchanged.

Trip distribution uses a gravity model of the form

$$T_{ij} = P_i \times \frac{A_j F_{ij}}{\sum_{j' \in J} A_{j'} F_{ij'}},$$

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 WF model includes a “distribution feedback loop,” where the model performs a preliminary highway assignment to obtain congested network skims iterates until the trip distribution converges.

The mode choice step uses a choice model to assign a percentage of trips by purpose to each mode, and the network assignment step assigns the vehicle trips through an iterative process to equalize travel time between potential routes. The WF model outputs include trip tables by purpose, mode, and time of day, as well as loaded highway networks.

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 implementation Macfarlane and Lant (2021) used, 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 to use in subsequent steps, and it can turn on and off many steps depending on the needs for the model implementation.

We can categorize the steps broadly into five groups, as shown in Figure 3.2:

- Aggregate: mainly involves determining impedance measures between each pair of zones (travel time, distance, cost, etc.). For this research, the WF model supplied these impedances directly from the network skims output.
- 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 we do not model transit pass ownership and assume that everyone pays the transit fare.
- Person 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. Tour-level choices operationalize the DAP. 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). The model schedules and assigns a primary mode to each tour, as well as a primary destination for non-mandatory and joint tours. ActivitySim then populates the tours with trips and assigns each trip a purpose, destination, time of day, and mode compatible with the tour-level assignment.

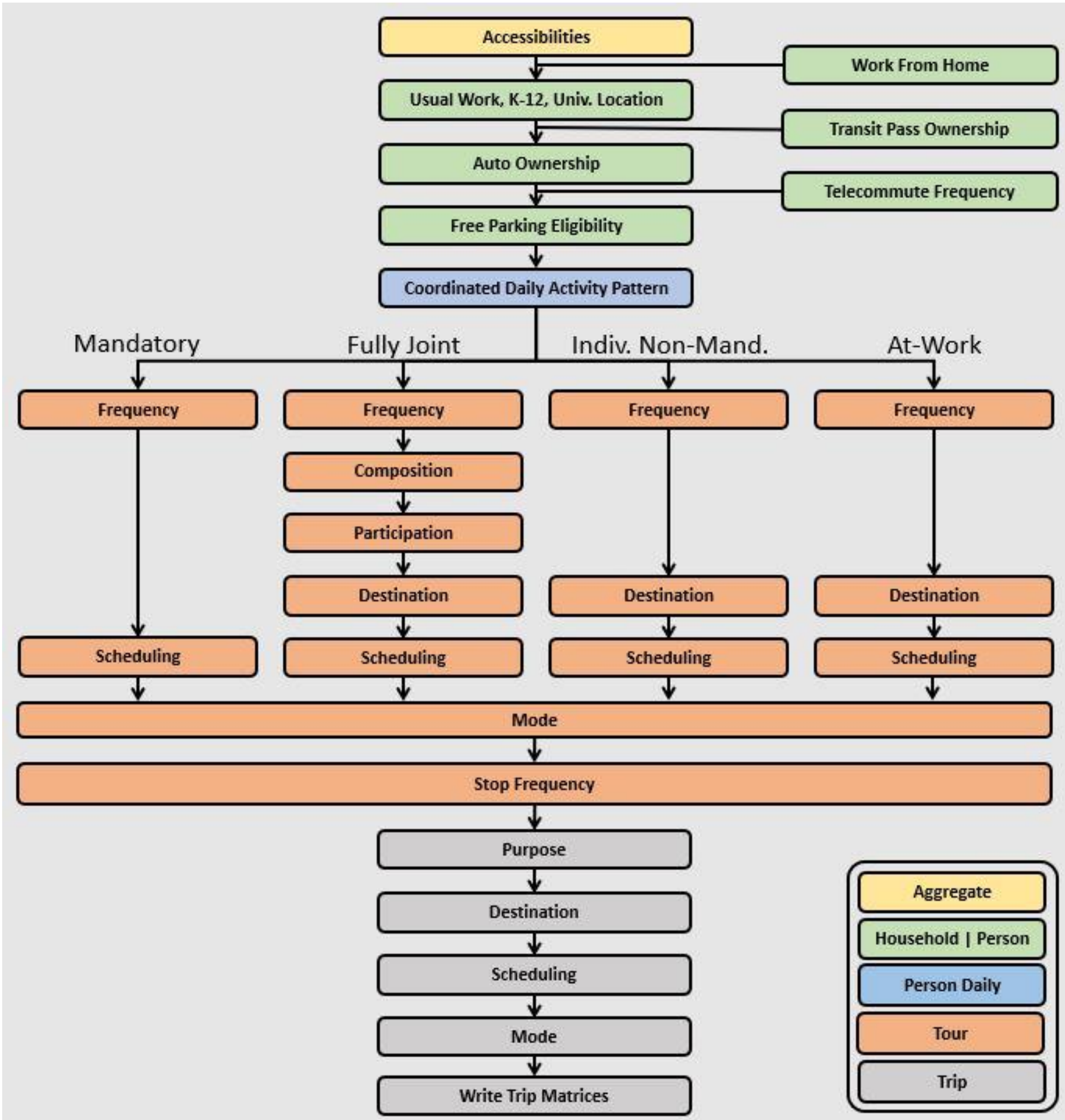


Figure 3.2 Activity Sim model flowchart.

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:

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

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 coefficients on variables such as income, age, and work status, determine the utility values, in addition to calibration constants for each alternative.

ActivitySim requires similar inputs to the WF model, though it does not include its own network assignment process. Instead, ActivitySim uses network skims supplied from any other process for information on travel time, cost, etc. 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 WF model directly. In practice, ActivitySim mates to CUBE or another network assignment algorithm for network skimming and travel time feedback. To clarify, ActivitySim replaces the first "three" steps of a traditional four-step trip-based model.

ActivitySim requires population data at an individual level, including information such as age, household income, and home location. Due to privacy concerns, analysts rarely use real data for this purpose and use instead a synthetic population representative of the study area. 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 represent the study area while maintaining privacy. Additionally, analysts can adjust a synthetic population in line with projected socioeconomic forecasts to perform future-year analyses. PopulationSim takes a "seed" of individuals and households as input, and populates the area with copies of these to match given controls such as the number of households by zone, the number of individuals by age group, and so on.

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 WF 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 also provides this information. 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 model cannot satisfy the two controls.

Table 3.3 PopulationSim Control Totals by Geography and Source

Control	Geography	Source	Weight
Population	Entire Region	Census	5,000
Number of Households	TAZ	WF 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 WF 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. We do not control for these variables, and they depend on the seed persons or households we copy to control 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 ActivitySim and WF model outputs, it is important to ensure similar performance between the two models for meaningful analyses. As such, we used a “baseline” scenario in both models to calibrate the ActivitySim implementation to the WF model. This baseline scenario uses the 2019 WF model as is. For ActivitySim, the baseline scenario uses 2019 Census and WF data to create the synthetic population, and it uses land use data and network skims from the baseline WF scenario for accessibility and socioeconomic measures (where jobs and households are located) before running through its series of models of individual trips and tours.

3.3.1 Validation of the Synthetic Population

We compared the PopulationSim output with the WF model outputs to validate the synthetic population. The controls for PopulationSim mostly come from the Census, shown in Table 3.3, and the WF model uses TAZ-level population and median income data and also has a household disaggregation step that estimates the number of households by size and income group. This section compares the PopulationSim output to the WF model output for each of the previously mentioned variables: population, median income, and number of households by income group.

Although the WF model provides data at the TAZ level, most PopulationSim controls are at the Census tract level, and these tracts are not a one-to-one match with the region's TAZs. Because of this, PopulationSim places households in a TAZ with some degree of randomness. As such, for small geographic areas such as TAZs the error distribution between the two models is noisy. Therefore, we compare the PopulationSim and WF data by aggregating each TAZ at the district level (as defined by WFRC and MAG). These districts include several contiguous TAZs.

Figure 3.3 shows the difference in district population between PopulationSim and the WF data. It is worth noting that since we controlled the number of households to the WF TAZ level data with an extremely high weight, the number of households per TAZ in the synthetic population match to the WF data exactly. The average household size will therefore follow a similar error distribution to the one shown in Figure 3.3.

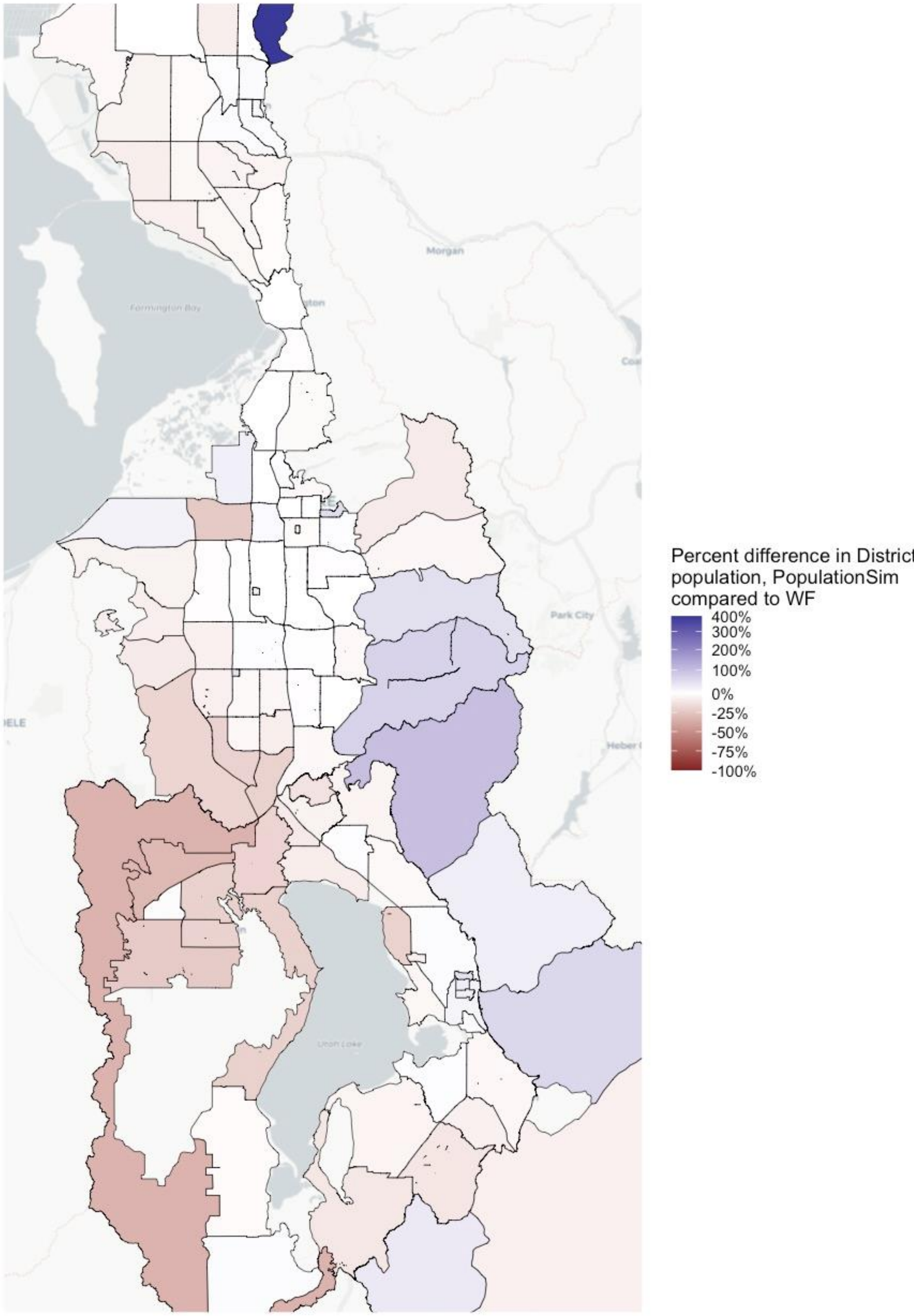


Figure 3.3 Population by district, PopulationSim compared to the WF TAZ-level socioeconomic data.

The population from PopulationSim per district is similar to the WF data in most places, though there are some discrepancies especially near Herriman and Lehi, and in the far north of Weber county. 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 WF 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 WF data. The synthetic population does have a lower median income compared to the WF data in many districts, but the error is, in most cases, fairly small, especially in more populated areas. However, both ActivitySim and the WF model use household income *groups* rather than individual household income to inform travel decisions. We used the income groups from the WF model (see Table 3.1), and we adjusted the groups in PopulationSim and ActivitySim to match. Figure 3.5 shows the difference in number of households by income group between PopulationSim and the WF model. This figure shows PopulationSim predicting slightly more high-income households and low-income households in many zones, and fewer middle-income households, though the error is smaller in regions with higher population.

It should be stressed that these graphics are not comparing PopulationSim's outputs to ground-truth socioeconomic data, but rather to the outputs of a different model, namely the household classification process in the WF model. Both models may have errors in different directions, thus amplifying the perceived discrepancy in these results.

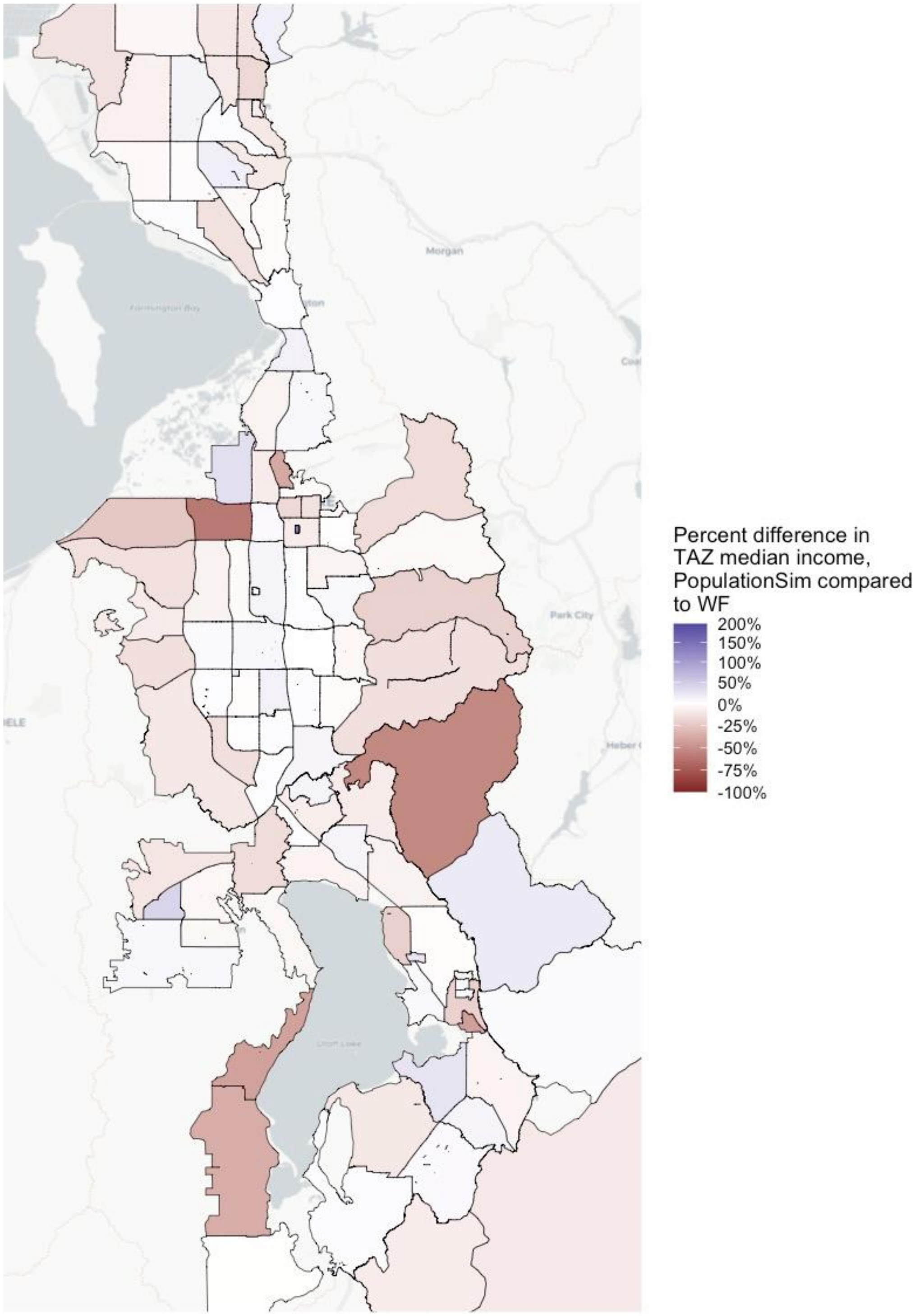


Figure 3.4 District-level median income, PopulationSim compared to the WF TAZ-level socioeconomic data.

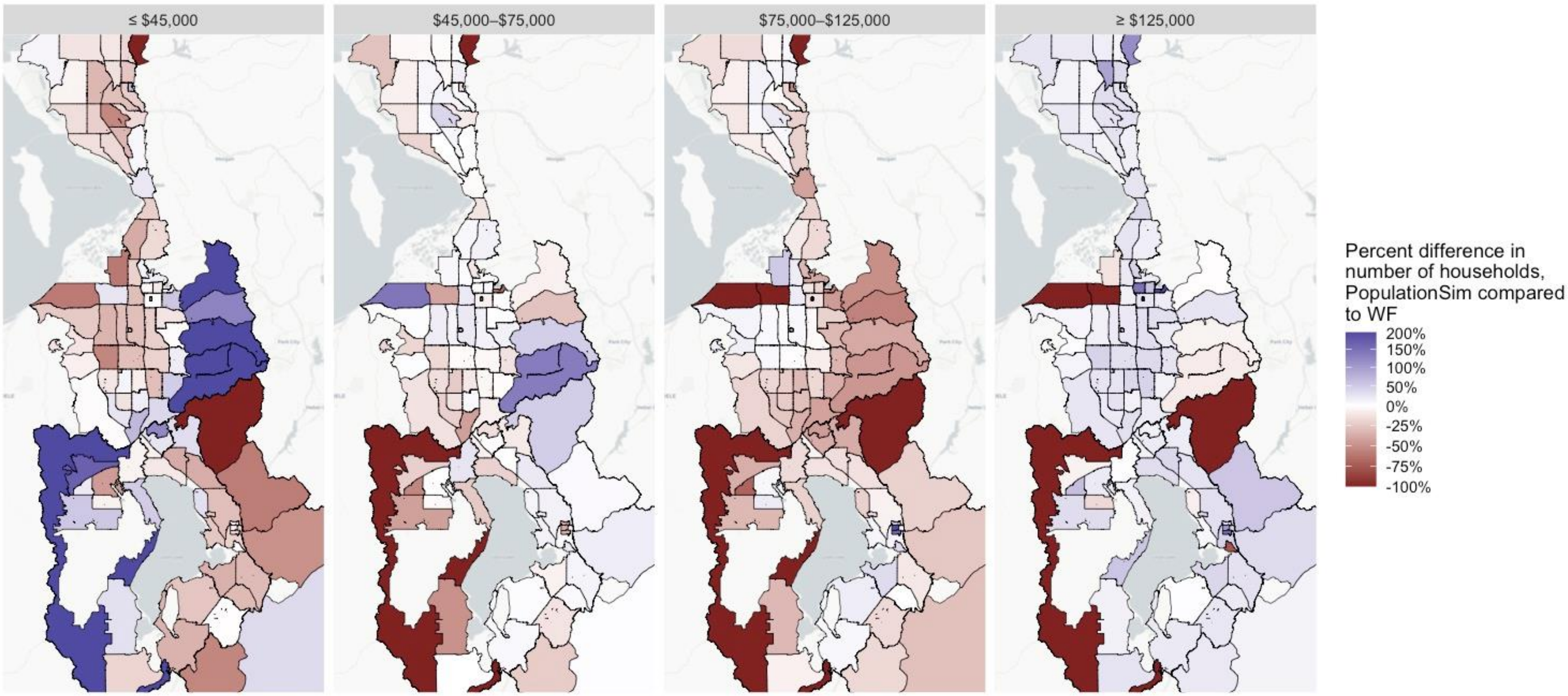


Figure 3.5 Households in each income group, PopulationSim compared to the WF TAZ-level socioeconomic data.

Note that in the synthetic population, each household has a specific income and so can be grouped directly, while the WF model requires a household disaggregation 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 WF 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 previously mentioned, this research focuses on the model process rather than model accuracy. Because of this focus, ActivitySim does not need to be perfectly calibrated to the WF 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. We make three comparisons between the two models' outputs: mode split, trip-length frequency distribution, and remote work.

The initial baseline ActivitySim scenario predicted a mode split significantly different from the WF model, so we needed to calibrate the model. 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 this research only needed a rough calibration. We therefore used the outputs of the baseline WF model scenario as the 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.

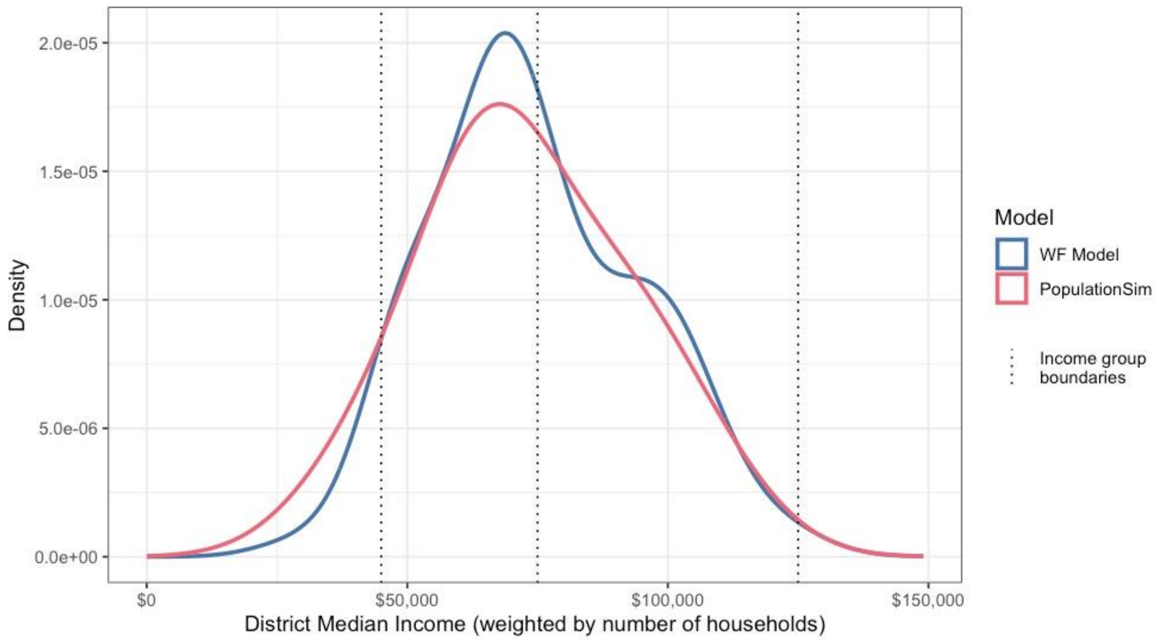


Figure 3.6 Distribution of TAZ median income, PopulationSim compared to the WF TAZ-level socioeconomic data.

Before beginning calibration, we matched the available modes in ActivitySim to those in the WF 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 one-to-one match between the models. However, not all modes have an exact match between models. Table 3.4 shows the modes in each model grouped to allow consistency during calibration.

ActivitySim additionally has ridehail modes, but the WF model does not, and therefore we do not have obvious calibration targets for ridehail. Based largely on the model results of Day (2022), we asserted the following mode shares for ridehail:

- 0.015% for Home-Based Work trips
- 0.38% for Home-Based Other trips
- 0.4% for Non–Home-Based trips.

Table 3.4 Crosswalk of Modes in WF Model and ActivitySim

Calibration Mode	WF 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

Additionally, since the WF 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 from 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 from ActivitySim into purposes that roughly match the WF 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 calibrated the model by iteratively adjusting the alternative-specific constants (ASCs) in ActivitySim's mode choice submodels. For each iteration, we compared the output mode split of ActivitySim to the target WF model mode split, and we adjusted ActivitySim's ASCs with 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.

We added this adjustment value to the current ASCs in ActivitySim iteratively until calibration was satisfactory.

There are two aspects of this calibration process worth noting. First, 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, we adjusted both the tour-level and trip-level ASCs with the calculated adjustment value for each mode. Second, 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 we calculated the adjustment values, we adjusted the ASCs as follows: All ActivitySim "at work" 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 calibration iteration. After a few iterations, the mode split more closely matches

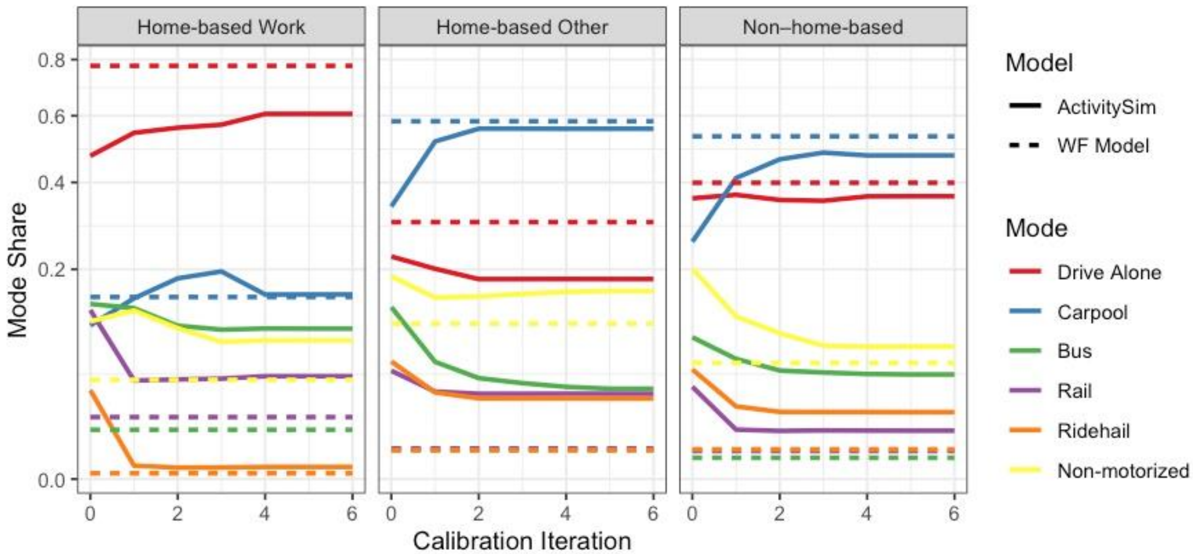


Figure 3.7 Mode choice calibration, target (WF) vs. ActivitySim shares over several iterations.

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. We left the difference across these categories unchanged and adjusted all ASCs for a given mode and purpose 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 partly cause 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 (for

Table 3.5 Comparison of Mode Split Between Models After Calibration

Purpose	Mode	ActivitySim		WF 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]We asserted ridehail mode shares for mode choice calibration, but we did not include them here

example, ActivitySim is predicting significantly more transit trips compared to the WF model). While the calibration is not perfect, for the purposes of this research, this calibration is determined to be reasonable enough.

Figure 3.8 compares the trip-length frequency distribution of the two models by mode and purpose. Both ActivitySim and the WF 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 ActivitySim configuration being originally developed for San Francisco, making transit more attractive. Note that further calibration may be required to create a production-ready ActivitySim implementation, but again our focus is more on process than accuracy. We determined that ensuring the mode split and trip length distribution model outputs between models are fairly similar is sufficient for this research.

The WF model has basic support for predicting remote work. This includes a lookup table of remote work percentages based on job type, year, and county. ActivitySim also has this functionality, and can additionally use individual- and household-level variables in its predictions. It is worth noting that both the WF model and ActivitySim make a distinction between "telecommuting" and "work from home," where telecommute refers to an individual that commutes to work some days but not all and "work from home" (called "home-based jobs" in the WF model) means 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. We made minor modifications to the remote work submodels to make the model compatible, but these modifications 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 WF 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

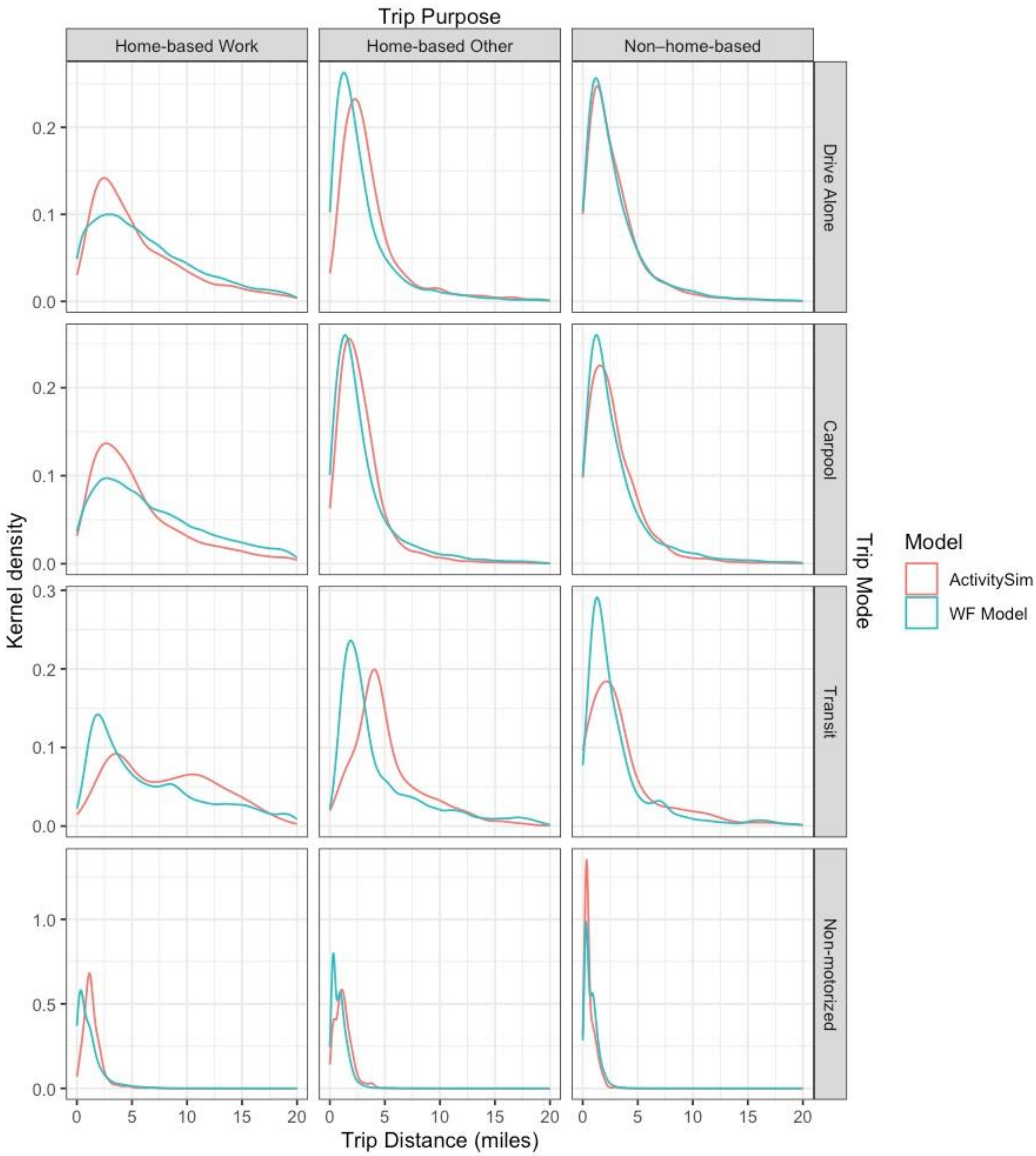


Figure 3.8 Comparison between models of trip-length frequency distribution

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	-0.14
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
Age Group - 45 yrs to 55 yrs	0.214
Age Group - 55 yrs to 65 yrs	0.452
Age Group - Older than 65 yrs	0.584

(we left these variable coefficients 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 WF model data. We made no other adjustments to the ActivitySim work-from-home submodel.

However, the two models differ in their approach to telecommuting. The WF 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

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	0	-0.864
Has children 6 to 12 years old	0	0.517	-0.81
One adult in household	0.177	0	-0.043
Part-time worker	0	0.425	1.112
College student	0	0.6	0
Pays to park	0.457	0	0
Income $60-100K	0.56	0.389	0
Income $100-150K	0.644	0.193	0
Income $150K+	0.92	0.765	0
0 autos	0	0.407	0
3+ autos	0	-0.73	0
Distance to work	0.016	0	0

individual's distance to work. We did not make any other changes to the existing variables in this submodel, and Table 3.7 shows the submodel coefficients.

To calibrate ActivitySim's telecommute frequency submodel to the WF data, shown in Table 3.8, we added additional job type variables to ActivitySim. Because these are choice coefficients rather than target percentages, we calibrated these values to match the WF targets. The calibration allowed ActivitySim to match these targets exactly, as shown in Table 3.8.

Because both remote-work submodels in ActivitySim run before choosing an individual's DAP, 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 WF model does not include this effect, we left the ActivitySim DAP model 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	0.01
Office	6.66%	1.782	0.712	0.445
Gov't/Education	1.67%	-0.56	-0.224	-0.14
Health	2.86%	0.158	0.063	0.039
Agriculture	6.93%	2.262	0.904	0.566
Mining	0.53%	-2.03	-0.81	-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	0
Part-time worker, works from home	-999	0	0

3.4 Example Scenarios

With these two calibrated models, we created three model scenarios to implement and compare processes. This is not a comprehensive list covering all potential scenario possibilities, but the scenarios identified intend to represent the main goals of travel demand modeling in representing changes in travel behavior. Change in travel behavior could arise in response to changes in land use, transportation infrastructure, and social/economic factors, so we created three hypothetical model scenarios to 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 a 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 WF.

Each of these scenarios is based on the 2019 baseline 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 in Chapter 6 uses remote work projections for 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 implementing and analyzing each scenario, as well as the analyses themselves.

<u>4.0 SCENARIO 1: CHANGE IN LAND USE</u>

Changes in land use is one of the primary ways to affect travel behavior. 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), this scenario only represents the additional households and jobs created from this development. The data for the land use changes comes from the WF land use forecast, which is 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 site for this scenario consists of five TAZs. 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 five TAZs were made relative to the baseline scenario.

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

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

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

TAZ	Households	Population	Employment			
			Retail	Industrial	Other	Total
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

This scenario is simple to implement in the WF model. This model uses the land use/socioeconomic data directly, so we only needed to replace 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 to update to the TAZ-level land use and socioeconomic data, which is identical to the process for the WF model. The second is to update the synthetic population. To keep consistency between model scenarios, we created a new population for only the five affected TAZs and joined it to the existing synthetic population. The affected zones did not have individuals or households in the existing synthetic population, so we did not need to remove individuals or households before joining the two populations.

Creating the new synthetic population followed a similar process as in the baseline scenario in Section 3.2, but used the new land use data as the 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, we used a Census tract covering part of downtown Salt Lake City to represent the new development patterns at The Point. Therefore, the income distribution, etc. of The Point site will match the downtown Salt Lake City income distribution, etc., though the TAZ-level controls and land use/socioeconomic data in the area will match the WF projections for 2050.

In a more realistic case, a transportation agency would forecast land use and socioeconomic data to use 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 WF model for the purposes of this project, and the method used here results in reasonable accuracy between the models. Additionally, we designed our ActivitySim implementation to be independent from the WF 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 land use change. 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 made.

Both model types allow for very easy analysis of trip numbers and lengths, as the WF 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. Figure 4.1 and Figure 4.2, for example, show the new trip-miles produced in the updated zones for the WF model and ActivitySim, respectively. It is important to note that there is a crucial difference between the model types: how the trips that do not begin or end at the home are treated.

In the WF model (and in many trip-based models), zones with households 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. Therefore, it is difficult to know how best to redistribute non–home-based trips in trip-based models, 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-

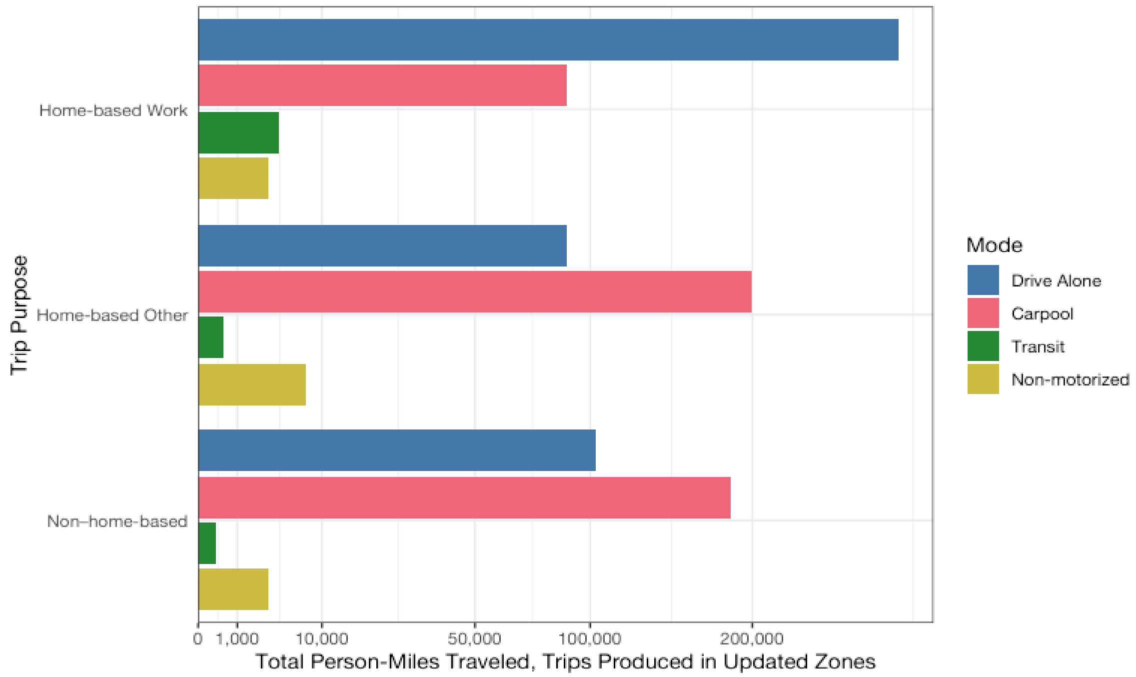


Figure 4.1 Trip-miles produced in updated zones in the Land Use scenario (WF model).

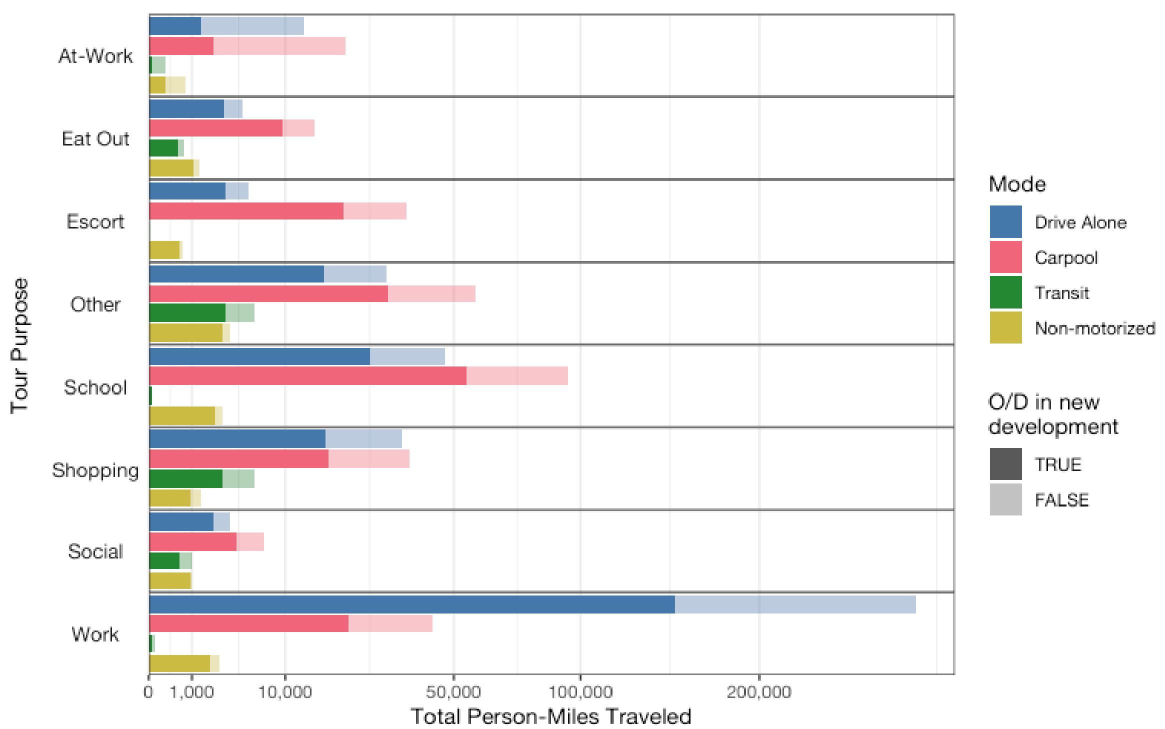


Figure 4.2 Trip-miles of individuals living in the updated zones (ActivitySim). Many of these trips do not have an origin or destination in the home zone of the individual.

decay function. The model can then represent the destinations of these non–home-based trips 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 WF model takes a different approach: Non–home-based trip ends have 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. Then the model globally scales this distribution 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 model or 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.

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 WF model. This figure is in line with our expectation: 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. The model includes both effects (the global increase in and the changed distribution of non–home-based trips), but the two effects are impossible to separate.

As previously mentioned, an ABM allows tracking individuals explicitly, and so analyzing non–home-based trips is much more straightforward. Figure 4.5 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 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, an analyst can analyze each development's full contribution to network congestion individually.

Figure 4.3 Desire lines of home-based trips produced in the new development in the WF model, by mode.

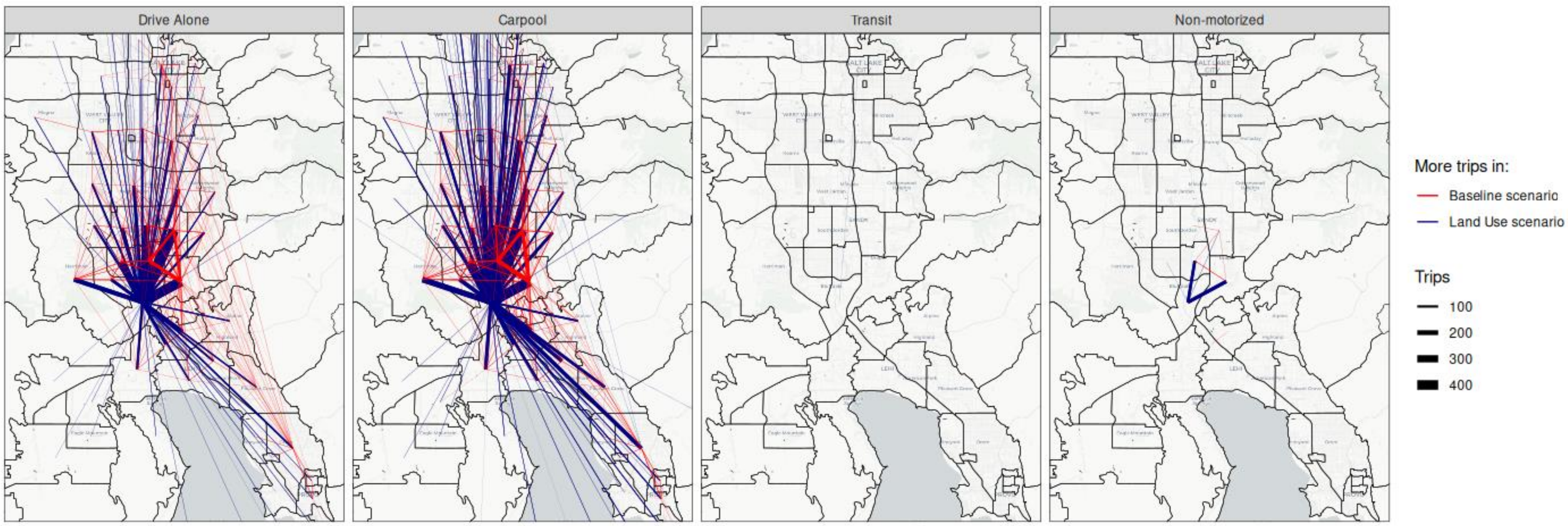


Figure 4.4 Desire lines of non–home-based trips made in the WF model, by mode.

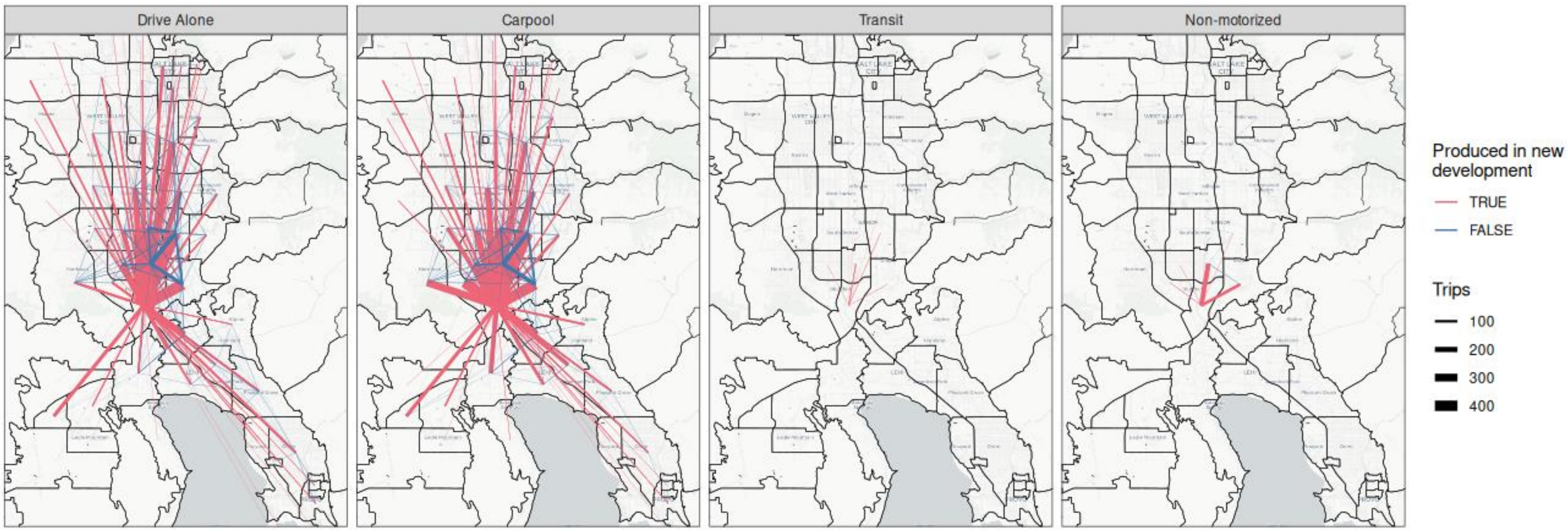


Figure 4.5 Desire lines of trips made in ActivitySim by mode.

5.0 SCENARIO 2: IMPROVED TRANSIT SERVICE

Our second scenario models travel behavior changes because of changes to transportation infrastructure.[3] This model scenario, termed the "Transit" scenario, is based on a planned improvement to the FrontRunner commuter rail line. 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 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 FrontRunner, allowing for faster travel speeds, and extending the track farther south with additional stops.

The Transit scenario models these improvements to FrontRunner. The scenario adjusts the headways to 15/30 minutes for peak/off-peak service, increases travel speeds, and adds additional stops in Vineyard[4], Springville, Spanish Fork, and Payson. Figure 5.1 shows the FrontRunner network along with the modeled changes. There would be additional transit improvements, such as a revised bus service network serving the Springville station, but for the

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[3] Though this scenario models transit, the findings will apply to a change in level of service for any transport mode.

[4] In 2019, the model year for the baseline scenario, the Vineyard station was not yet open, though the station has been operational since late 2022.

Figure 5.1 Map of the FrontRunner commuter rail line.

sake of simplicity, we did not include these additional improvements in this model scenario; we only model the changes to the FrontRunner service.

5.1 Scenario Creation

In the WF model, this scenario is relatively easy to implement. The input data stores the headways and we can easily modify them, and the model already includes a 2050 network with increased speeds and additional stations 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, we only needed updated travel skims. As in the baseline scenario, ActivitySim directly uses the WF model’s network assignment transit skims output in this model scenario. Because the mode share of transit is relatively low, we do not expect the change to affect the highway travel times very much. Therefore, we took the WF model baseline-scenario highway skims to use in ActivitySim, and we did not update them 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.

Table 5.1 Change in Mode Split with Improved Transit

Purpose	Mode	WF Model			ActivitySim		
		Baseline Trips	Transit[1] Trips	Change	Baseline Trips	Transit[1] Trips	Change
Home-Based Work	Drive Alone	1,328,609	1,326,191	-0.2%	1,012,180	1,010,565	-0.2%
	Carpool	257,783	256,654	-0.4%	258,459	256,550	-0.7%
	Local Transit	37,935	36,494	-3.8%	232,222	233,426	0.5%
	Commuter Rail	10,821	15,891	46.9%	19,846	22,265	12.2%
	Ridehail	—	—	—	1,108	1,099	-0.8%
	Non-Motorized	76,506	76,396	-0.1%	145,957	145,845	-0.1%
Home-Based Other	Drive Alone	1,394,415	1,394,095	0.0%	700,133	698,809	-0.2%
	Carpool	2,702,277	2,701,039	0.0%	2,148,429	2,145,135	-0.2%
	Local Transit	33,168	32,583	-1.8%	195,062	194,649	-0.2%
	Commuter Rail	4,180	6,332	51.5%	81,094	87,337	7.7%
	Ridehail	—	—	—	113,624	113,538	-0.1%
	Non-Motorized	510,143	510,103	0.0%	613,134	611,996	-0.2%
Non–Home-Based	Drive Alone	951,561	951,407	0.0%	716,143	714,854	-0.2%
	Carpool	1,273,279	1,272,977	0.0%	938,056	936,408	-0.2%
	Local Transit	12,213	12,068	-1.2%	107,526	108,395	0.8%
	Commuter Rail	1,243	1,806	45.3%	12,317	13,344	8.3%
	Ridehail	—	—	—	40,092	40,061	-0.1%
	Non-Motorized	14,6404	146,409	0.0%	156,819	156,587	-0.1%

[1]"Transit" refers to the Transit scenario, not the mode of travel

For Home-Based Other and Non–Home-Based trips, the WF model shows virtually no change in the number of auto and non-motorized trips, while there is a more 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, 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.[5] 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 WF 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. 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.

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

[5] The 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.

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[6], 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.

However, the improved transit service did not only affect the mode choice in ActivitySim. 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.

[6] ActivitySim 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.

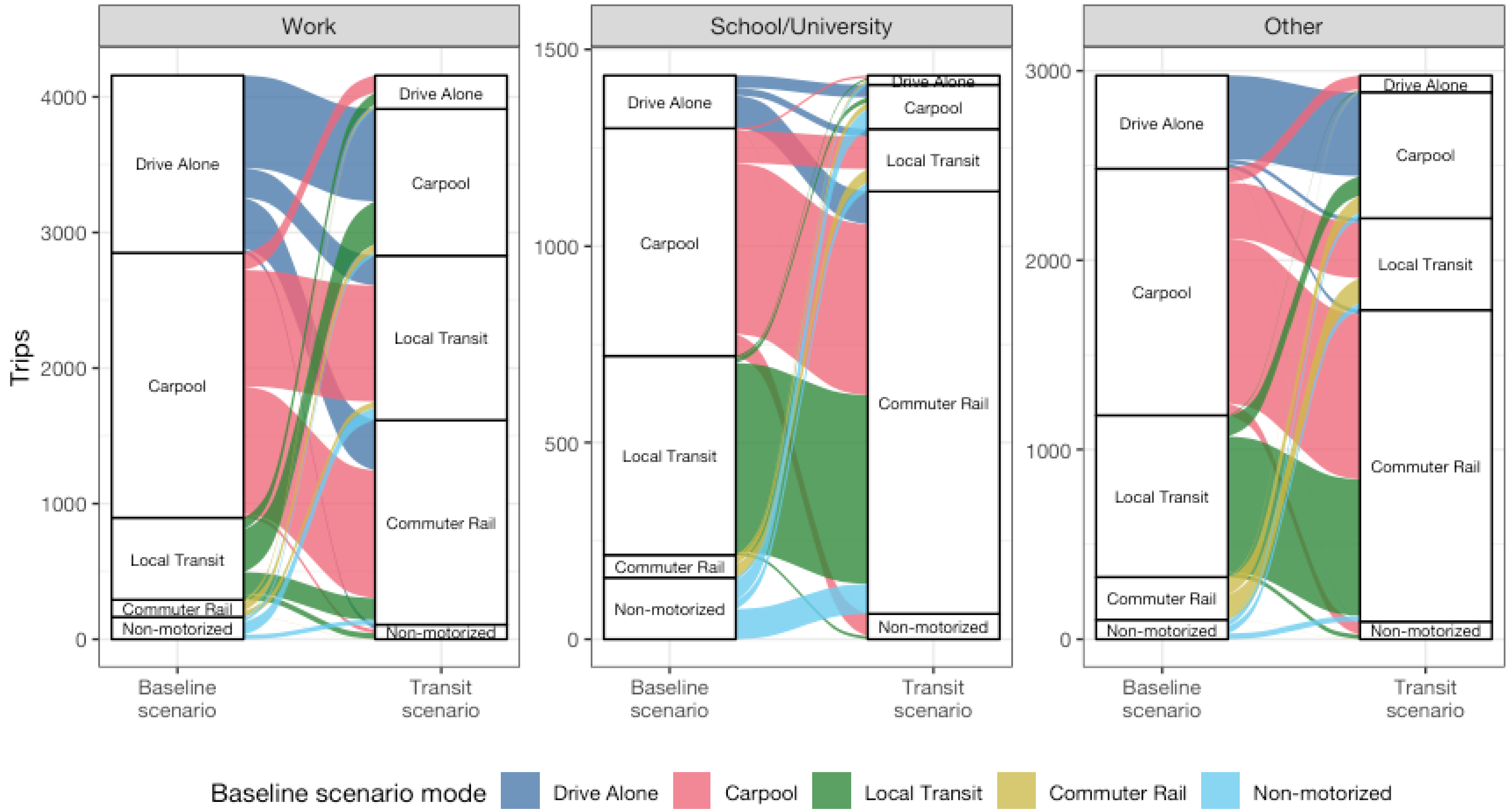

Figure 5.2 Trip modes of individuals who switched modes with improved commuter rail service.

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 as expected. All trips 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.

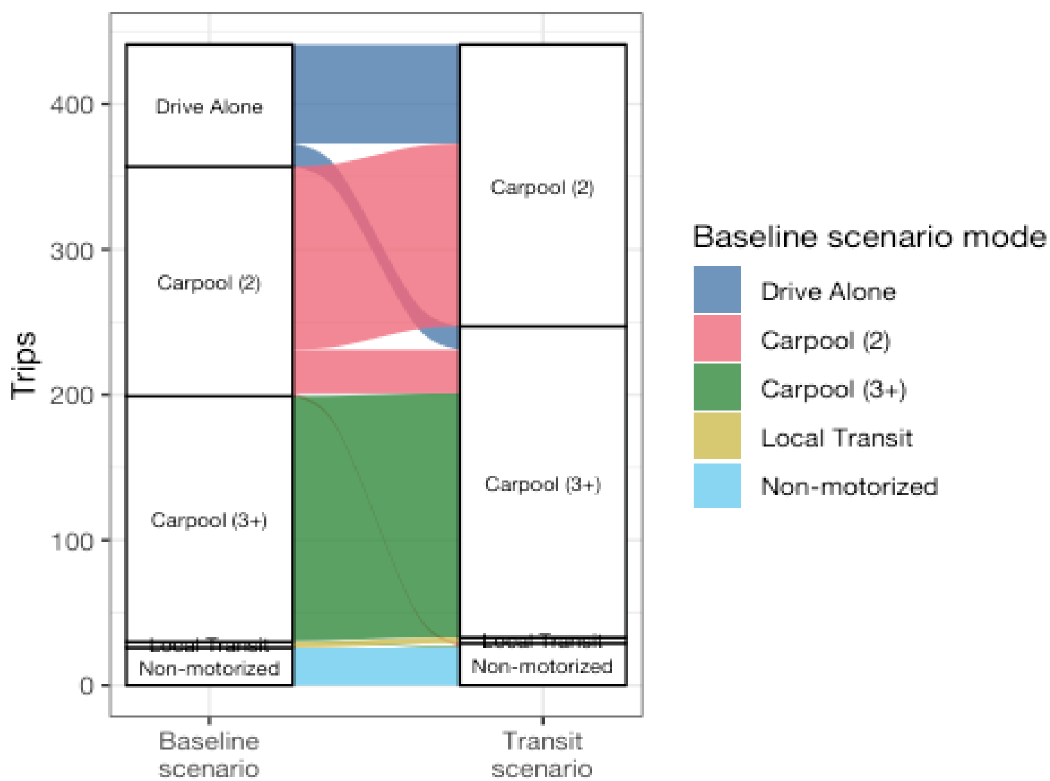

Figure 5.3 At-work subtour trip modes of individuals who switched their work mode away from "Drive-Alone" in ActivitySim.

Table 5.2 Example Socioeconomic Analysis of Transit Trips (WF Model)

Purpose	Mode	Trips	TAZ-Level Median (weighted by trips)			
			Households	Population	Jobs	Income
Home-Based Work	Local Transit	36,494	478	1,211	400	$54,208
	Commuter Rail	15,891	435	1,368	279	$76,529
Home-Based Other	Local Transit	32,583	460	1,147	454	$49,682
	Commuter Rail	6,332	423	1,306	317	$68,369
Non–Home-Based	Local Transit	12,068	97	182	1362	$50,921
	Commuter Rail	1,806	138	453	1487	$58,576

Both model types additionally allow for analyzing the types of people who use transit. The WF 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 WF 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, we can access information about each individual 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 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 WF model. Our synthetic population does overpredict high-income households along the length of 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 WF model and ActivitySim. Again, the WF model is not modeling individuals, so for the WF model Figure 5.4 shows the distribution of median TAZ income weighted by number of trip productions. For ActivitySim, however, the figure shows the true income distribution of individual transit riders.

ActivitySim shows a rather wide income distribution of transit riders, while the distribution of the WF model is much denser around $50,000–$75,000. This makes sense given that the WF 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. However, the income distribution of individuals taking transit in the WF model is unknown.

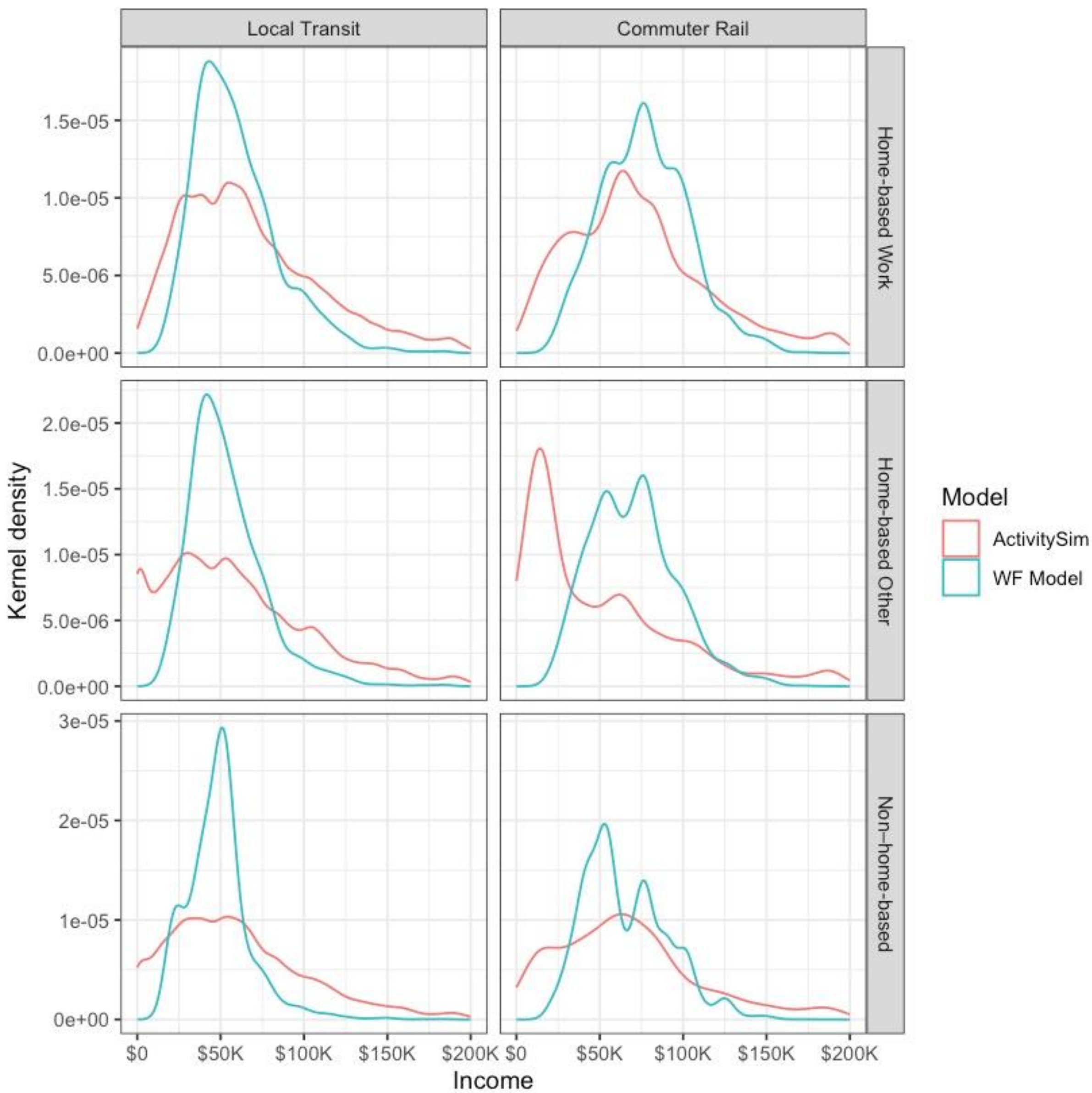

Figure 5.4 Income distribution of transit riders in both models. We used the distribution of production TAZ median income weighted by transit trips for the WF model, while we used the actual income distribution of transit riders for ActivitySim.

6.0 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 WF model contains a lookup table of both work-from-home (called "home-based jobs" in the WF 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 WF model by year.

This scenario is a "what-if" analysis that models a significant increase in remote work rates. We use the 2050 remote work rates from the WF 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.

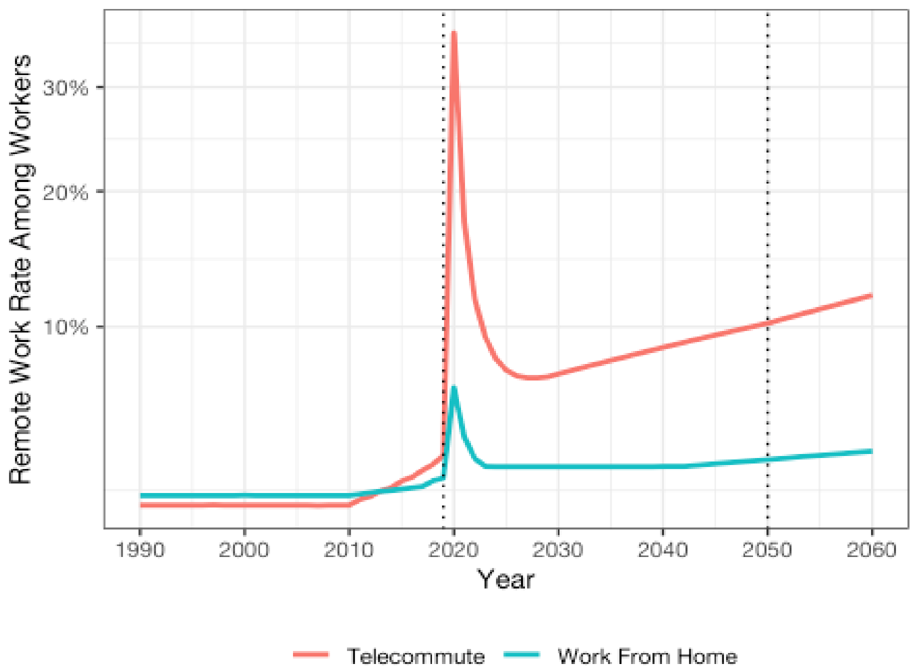

Figure 6.1 WF model remote work rates.

6.1 Considerations for Modeling 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 WF model, as discussed in Section 3.3.2.

6.2 Scenario Creation

We need to make two changes in the WF 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 WF model estimates a number of home-based jobs in each TAZ, so we replaced the original 2019 home-based job estimates with the 2050 estimates. The WF model additionally includes a global scaling factor for all remote work percentages. However, we left this scaling factor 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.

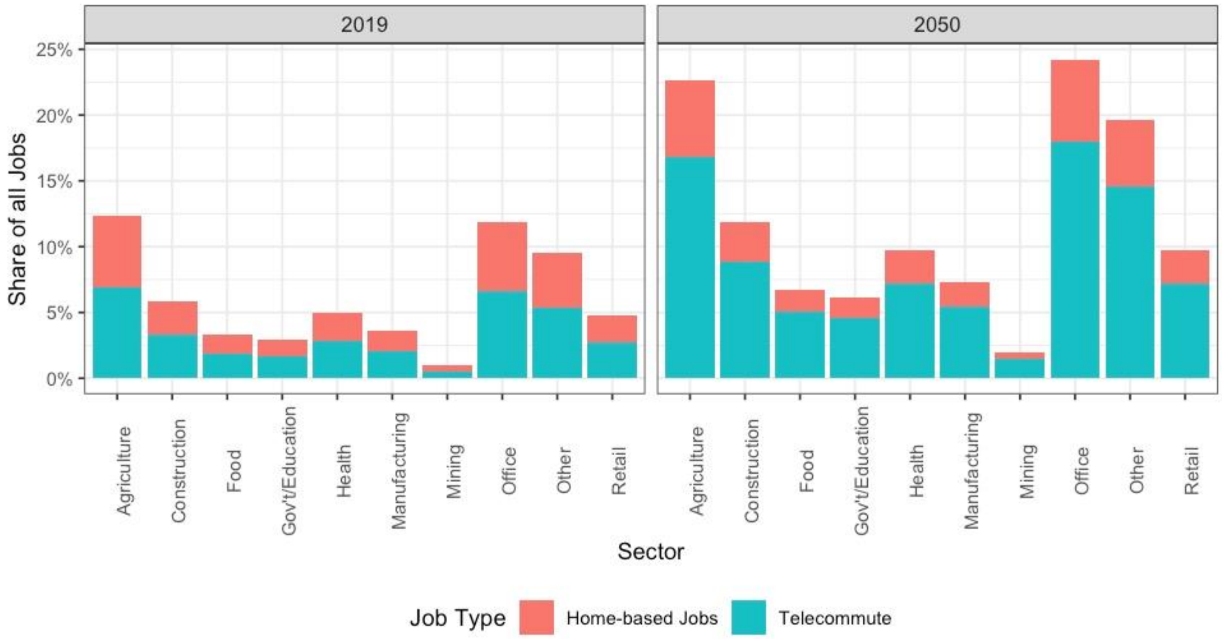

Figure 6.2 Comparison of remote work rates in the WF model by year and industry.

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 WF model. We changed the "target work-from-home percent" value in ActivitySim's work-from-home submodel to 3.5% based on a weighted average from the 2050 WF data, and we calibrated the job type coefficients in the telecommute frequency submodel to match the WF target telecommute shares by job type. Figure 6.2 shows the WF 2050 telecommute percentages with the ActivitySim telecommute utility coefficients. As in the baseline scenario, this calibration allowed ActivitySim to match the WF telecommute percentages exactly. 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, as discussed in Section 6.1 above. 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.

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Table 6.1 Change in Mode Split After Increased Remote Work Rates

Purpose	Mode	WF Model Trips			ActivitySim Trips		
		Baseline	Remote Work Scenario	Change	Baseline	Remote Work Scenario	Change
Home-Based Work	Drive Alone	1,328,609	1,244,451	-6.3%	1,012,180	950,306	-6.1%
	Carpool	257,805	238,669	-7.4%	258,459	242,497	-6.2%
	Transit	48,752	44,977	-7.7%	253,176	237,881	-6.0%
	Non-Motorized	76,506	71,063	-7.1%	145,957	137,684	-5.7%
Home-Based Other	Drive Alone	1,394,415	1,395,196	0.1%	700,133	709,957	1.4%
	Carpool	2,702,272	2,702,625	0.0%	2,148,429	2,171,566	1.1%
	Transit	37,346	37,359	0.0%	389,780	396,815	1.8%
	Non-Motorized	510,143	508,869	-0.2%	613,134	617,480	0.7%
Non–Home-Based	Drive Alone	95,1561	938,653	-1.4%	716,143	687,935	-3.9%
	Carpool	1,273,317	1,254,548	-1.5%	938,056	922,662	-1.6%
	Transit	13,453	13,199	-1.9%	159,935	158,366	-1.0%
	Non-Motorized	146,404	144,126	-1.6%	156,819	152,688	-2.6%

Table 6.2 Telecommute Rates and Coefficients by Job Industry

Industry	2050 WF 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	0.48	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

In addition to the number of trips, increasing remote work rates can also influence the length of trips made. The WF 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 WF model design.

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 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 (2017) and Moeckel (2017), where longer work trips are being exchanged for shorter discretionary trips.

Table 6.3 Comparison of Trips Taken and Miles Traveled (WF Model)

Purpose	Mode	Trips			Person-Miles		
		Baseline	Remote Work Scenario	Change	Baseline	Remote Work Scenario	Change
Home-Based Work	Drive Alone	1,328,609	1,244,451	-6.3%	12,736,970	12,070,213	-5.2%
	Carpool	257,805	238,669	-7.4%	3,204,552	2,945,150	-8.1%
	Transit	48,752	44,977	-7.7%	547,804	500,953	-8.6%
	Non-Motorized	76,506	71,063	-7.1%	132,216	122,930	-7.0%
Home-Based Other	Drive Alone	1,394,415	1,395,196	0.1%	6,088,804	6,122,517	0.6%
	Carpool	2,702,272	2,702,625	0.0%	13,420,596	13,448,784	0.2%
	Transit	37,346	37,359	0.0%	264,203	264,432	0.1%
	Non-Motorized	510,143	508,869	-0.2%	591,297	590,349	-0.2%
Non–Home-Based	Drive Alone	951,561	938,653	-1.4%	4,777,297	4,736,979	-0.8%
	Carpool	1,273,317	1,254,548	-1.5%	7,650,625	7,538,596	-1.5%
	Transit	13,453	13,199	-1.9%	73,563	72,018	-2.1%
	Non-Motorized	146,404	144,126	-1.6%	136,914	134,784	-1.6%

Table 6.4 Comparison of Trips Taken and Miles Traveled (ActivitySim)

Purpose	Mode	Trips			Person-Miles		
		Baseline	Remote Work Scenario	Change	Baseline	Remote Work Scenario	Change
Home-Based Work	Drive Alone	1,012,180	950,306	-6.1%	9,632,251	9,021,681	-6.3%
	Carpool	258,459	242,497	-6.2%	2,631,886	2,463,552	-6.4%
	Transit	253,176	237,881	-6.0%	2,911,616	2,728,897	-6.3%
	Non-Motorized	145,957	137,684	-5.7%	353,246	332,978	-5.7%
Home-Based Other	Drive Alone	700,133	709,957	1.4%	4,280,006	4,332,319	1.2%
	Carpool	2,148,429	2,171,566	1.1%	11,498,994	1,1624,928	1.1%
	Transit	389,780	396,815	1.8%	3,547,052	3,583,630	1.0%
	Non-Motorized	613,134	617,480	0.7%	1,090,176	1,098,043	0.7%
Non–Home-Based	Drive Alone	716,143	687,935	-3.9%	3,984,191	3,804,674	-4.5%
	Carpool	938,056	922,662	-1.6%	3,962,840	3,898,220	-1.6%
	Transit	159,935	158,366	-1.0%	867,867	852,243	-1.8%
	Non-Motorized	156,819	152,688	-2.6%	194,493	189,483	-2.6%

7.0 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 theoretical 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. These findings are largely echoed in the users’ survey presented in Chapter 8. Some of these reasons include heavy computational requirements, 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 discuss our experience as it relates to them. Note that many of the conclusions presented here are specific to the WF 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.

We performed all runs of the WF model on a Windows 10 computer with 2 Intel Xeon Silver 4114 CPUs. The CPUs have a base frequency of 2.2 GHz, and 10 cores/20 threads each. The WF model is configured for multiprocessing in its destination and mode choice steps, and we configured it to use 16 threads for our scenario runs. This machine also has 128 GB of RAM installed. 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 WF model. While ActivitySim does have a destination choice model analogous to the WF 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 WF 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 WF model runtime to compare with ActivitySim is 10–11 hours.

We did most runs of ActivitySim on compute 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 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 WF model scenarios, with chunking enabled to account for the reduced RAM available (128 instead of 360 GB). 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 WF model on the same hardware. This is counter to the idea that ABMs always 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 with a complex trip-based model 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, from Amazon Web Services or other cloud computing providers. 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.

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. The model can then use these assigned values 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"[1] by increasing the utility of a non-mandatory DAP for individuals who work remotely.

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[1] See Section 6.1

Since trip-based models exclusively deal with aggregate data, the interpretation of each model step is vaguer. 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 the model uses a separate "remote work" trip purpose, 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. An analyst can adjust and calibrate this step (and most model steps) 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 construct non–home-based trips in a somewhat arbitrary manner, especially if (like the WF 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 an ABM organizes trips 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.

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. We made some minor changes 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 WF model, but it was simple to add these.[1]

The WF model does already include different remote work rates by job industry, but it would be difficult to add 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 WF model is written, and may not apply equally to all trip-based models.

7.4 Training requirements

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.

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

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 undergraduate 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	
		WF 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
WFH	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 WF model, though there are a few important notes about this comparison: First, the scenarios in ActivitySim were somewhat dependent on the outputs of the WF model. ActivitySim depends on the WF 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 WF model's Transit scenario, and so in some sense the time spent for ActivitySim should possibly include the time spent for the WF 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 between these tables is not only the model type, but also the individual working on the task. Any comparisons between these tables should therefore take this into consideration.

One additional point to note is how we performed the analyses in each model. The outputs of the WF 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 WF 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

WF 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, aggregated these trips, and created the desire line plot. Both 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 WF model.

7.5 Recommendations

Our experience in this research runs counter to many of the cited "pain points" of ABM adoption. Our ActivitySim implementation was no more computationally intensive than the WF model, we found the interoperability between the example San Francisco and Michigan ActivitySim implementations relatively easy, 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 complex "under the hood" than the WF model, the interpretation of ActivitySim is in many 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).

The central finding of this statement is that commonly cited pain points in the activity-based model implementation and use may be decreasing with improvements in technology.

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 may 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 WF model (see Chapters 4–6).

It is important for agencies to realize – as stated previously – that ActivitySim and other activity-based models are only demand models, and rely on network skims obtained from other software. 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 to use ActivitySim. The extensibility of ActivitySim 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. It would also be possible to set up CUBE or other software to run ActivitySim.

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 in our findings is that for roughly the same amount of effort, we were able to perform more in-depth analyses with ActivitySim compared to the WF 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 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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8.0 PRACTITIONER INTERVIEW FINDINGS

8.1 Research Overview

As the first phase of the 2022 UTRAC problem statement on activity-based modeling, Fehr & Peers identified and held informational interviews with staff at agencies that have transitioned from a trip-based to an activity-based model framework and interviewed them to identify motivations for the transition as well as pain points faced during and after the transition process. The team also interviewed consultants who have developed and applied activity-based models in transitioning regions to understand their experience and commonalities seen across different agencies that have adopted activity-based modeling frameworks.

Practitioners with varying backgrounds were identified to interview about their experiences in adopting an activity-based model. The final interview list consisted of:

- 1 software vendor
- 2 model development consultants
- 7 MPO/regional agencies
- 2 statewide DOTs
- 1 research center / regional model owner

The individuals interviewed are presented in Table A.1.

8.2 Interview Findings

8.2.1 Interview Outline

Practitioners were interviewed using a semi-structured interview approach, with a set of prepared prompts/questions used as a jumping-off point to understand each

Table 8.1 Interviewees

Individual	Organization	Organization Type
Peter Vovsha	Bentley	Software Vendor
Bruce Griesenbeck	Fehr & Peers	Consultant
Mark Moran	MWCOG	MPO / regional agency
Wu Sun	SANDAG	MPO / regional agency
Hsi-Hwa Hu	SCAG	MPO / regional agency
Rosella Picado	WSP	Consultant
Joel Freedman	RSG	Consultant
Kristen Villanueva	Alameda CTC	MPO / regional agency
Stefan Coe	PSRC	MPO / regional agency
Jonathan Ehrlich	Met Council (MN)	MPO / regional agency
Rebekah Straub	Ohio DOT	DOT
Alex Bettinardi	Oregon DOT	DOT
Leta Huntsinger	NC ITRE	Research Center / Model Owner

interviewee's experiences and perspectives and practices around modeling within their organization. The outline of questions was as follows:

- When and why did your agency decide to transition from a trip-based to an activity-based model?
- What did development and adoption of the new model look like?
- What benefits have you seen?
- What downsides have you seen?

- Knowing what you do now, would you have made the same decision sooner/same time/later/never? (And other advice)

Different interviews spent greater or lesser amounts of time on each of these questions, and questions were modified in the case of non-agency practitioners to focus on the range of conditions they had observed across various client/partner agencies.

8.2.2 When and Why

Practitioners represented development timelines ranging from the early 2000s to 2020, with the first adopter in 2005 and the latest expected to be completed in 2023 or 2024. Those that adopted early typically did so as a result of ambitious staff or agency leadership who desired to be at the forefront of modeling practice. Those later in the adoption process were more likely to report being motivated by a perceived need to be consistent with the state of the practice of other major MPOs, coupled with challenges around answering questions from policymakers that traditional four-step models were poorly equipped to answer. At times, these decisions were spurred by specific legislative or agency mandates, such as climate change legislation passed by the Oregon legislature in 2010.

Specific policy questions that motivated this transition included the desire to better understand and predict the impacts of changing demographics, pricing and tolling, equity impacts of various policies and investments, and telecommuting/work-from-home behaviors. For example, the former modeling director of SACOG described having previously struggled with a four-step model that did not provide good answers to questions from leadership and elected officials regarding how an aging population would impact transportation needs.

Policy questions around connected and autonomous vehicles, improved understanding of time-of-day segmentation and peak spreading phenomena, and readiness to inform dynamic traffic assignment models were also mentioned as considerations in adopting activity-based models, but were not mentioned by practitioners as primary motivating factors.

8.2.3 Development Processes

Development timelines were typically 3-4 years for core model development and basic validation and calibration. However, practitioners reported needing additional time for internal modeling teams to build out needed infrastructure, skills, and familiarity with new models. In some cases, the overall timeline from initiating new model development to successful application to major planning efforts stretched up to 8 years. At one extreme, SACOG was able to conduct its model development process in approximately 2 years and successfully applied it to a regional transportation plan adopted just 2 years later. At the other end of the spectrum, SCAG began development efforts in 2012 but did not apply their ABM to an adopted RTP until 2020.

Model development costs ranged greatly. Based on estimates from consultants who had worked with a range of agencies, some small agencies at the low end reportedly had stood up relatively simple activity-based models (e.g., based on previously estimated ActivitySim donor models, without special generators, and with high-level calibration only) for budgets of $200,000 or less, although it was noted that these costs did not include data development conducted in-house or under separate contracts (which would be a significant portion of the overall effort). At the high end, larger agencies reported spending $1-2 million for a well-calibrated model with special generators addressed that was considered fully production-ready. These costs did not include expenses associated with developing input and validation data, model evaluation, and internal staff time to develop competence with the new model.

Several staff recommended that contracting for model development should be structured as a phased approach, with well-defined milestones for delivering different phases of the model and specified static and dynamic validation thresholds that a draft model must meet or exceed before considering a phase complete. For example, as Oregon DOT worked with a consultant team to set up the RVMPO's model, three phases of validation were built in with pre-specified static validation thresholds, as well as a set of five example projects to be implemented as a dynamic validation test. This approach was reported to have been useful in exposing problems and allowing correction prior to adopting the model.

Where practitioners encountered significant delays in meeting intended model development and adoption schedules, repeatedly cited causes of delay included challenges in obtaining needed input data, as well as difficulties encountered by staff in getting up to speed on new model workflows and addressing errors and software bugs.

8.2.4 Resource Needs

In-house modeling teams ranged from small teams of 3 FTEs to over 15 FTES, and included modeling, GIS, and land-use forecasting teams. Most MPOs used limited ongoing consultant support, but did pay vendor fees or ActivitySim consortium dues as well as software licenses. One exception, the Alameda County Transportation Commission, is heavily reliant on consultant support to both develop and apply models.

MPOs utilize a mix of cloud-based and physical computing resources, and several larger agencies maintain multiple models to varying degrees for different purposes and stakeholders. Agencies using Amazon Web Services (AWS) reported that they were able to achieve reduced runtimes compared to previous configurations, as well as reducing burdens that would otherwise be placed on their organization IT teams. However, one agency reported that they had seen additional errors or inconsistencies in model results occur when using cloud computing, indicating a need for testing on the intended configuration during the model development process. While specific configurations and resources varied across agencies, most practitioners emphasized that computing needs were secondary to model development, data collection, and staffing needs in terms of overall budget impact.

8.2.5 ABM Benefits

Interviewees highlighted several types of analyses that a shift to an ABM allowed, such as assessing equity impacts of policy choices, understanding road pricing impacts on various market segments, evaluating emerging modes and reflecting their anticipated operating characteristics, better quantifying greenhouse-gas-emissions scenarios, and understanding impacts of changing demographics. Some interviewees also commented on additional benefits such as additional time of day analyses and finer-grained zones that would better model active transportation, though those benefits were more a result of a more highly specified model than intrinsically tied to an ABM. In the post-COVID-19 era, the ability to better reflect work from home and telecommute modes was also raised as a significant value-add for scenario planning.

Multiple practitioners noted that enhanced visualization tools, such as automating accessibility mapping and side-by-side scenario-comparison dashboards, were highly valued outcomes of model enhancement efforts. While not a core model function, these auxiliary tools helped model users and planners easily communicate insights enabled by expanded functionality of an ABM.

8.2.6 ABM Downsides/Issues

Practitioners commented that with the greater power of an ABM there was also a need for additional staff with higher skill requirements. Many practitioners mentioned the relative difficulty of understanding the “under the hood” functioning of ABMs compared to trip-based models. Practitioners highlighted the need to develop post-processing scripts to fully leverage the potential of detailed activity pattern data and evaluate key policy questions. In smaller, less-well-staffed organizations, the trade-off between building up these tools and supporting infrastructure and meeting more immediate plan/project-level modeling needs was a challenge.

Several practitioners mentioned that being able to distinguish between signal and noise in model outputs was a challenge, especially when trying to evaluate relatively small changes to infrastructure, land use/socioeconomics, or policy in the context of a large regional model. Twin Cities Metropolitan Council staff mentioned this challenge as both a technical challenge and a potential political issue, as staff must evaluate whether they can trust model results to withstand scrutiny in the context of high-profile projects.

A related challenge observed by one consultant was that where advanced models provide the opportunity to conduct scenario testing of emerging trends or technologies, agency staff may not always be comfortable presenting decision makers with ranges of results that reflect the uncertainty behind these assumptions. These communication challenges can lead to staff not taking advantage of new model capabilities. If investments are made in these functions, planning and forecasting staff should consider ahead of time how much effort to invest in complex depictions of technologies that are not well understood (e.g., operational details of autonomous vehicles or drone delivery), as well as whether and how they can communicate their modeling assumptions and results in a way that can usefully inform decision-making.

Potential lock-in with a given vendor was also highlighted as a potential issue, and one reason why ActivitySim has been a more favored approach by agencies adopting ABMs in recent years.

8.2.7 Mixed Impacts

Interviewees also highlighted a number of items where the impact of an ABM was mixed between positives and negatives.

Practitioners reported little or no real benefit for “bread-and-butter” projects in terms of traffic assignment; several side-by-side comparisons of link-level validation results between old and new model versions mentioned by interviewees showed comparable results. Some agencies reported that their ABMs provided improvements to model results for transit and active modes, but this was not a consistent finding. For example, Met Council staff mentioned that their ABM’s mode choice module performed worse than the previous model, causing them to use a regional STOPS model for transit analysis purposes instead of the regional travel model.

The input and calibration data needs of different models were reported to be highly variable, with some agencies having increased their investment in disaggregate land use data, travel surveys and transit on-board surveys, and passive mobile data. Others reported limited differences in their input data needs relative to previous trip-based models, indicating that these differences are more a question of model design choices and level of detail desired than an inherent function of ABMs.

Some models used parcel-level or microzone-level land use data, while others continued to use pre-existing TAZ geographies as their unit of analysis. Entities that use parcel-level as the basis for their models noted that developing and maintaining this data is a major effort, and in one case transitioned from parcel-based to microzone-based geographies in a 2nd generation model to reduce complexity.

Post-processing of synthetic population travel diaries and generally building an understanding of how to mine output datasets was brought up by many practitioners as a substantial opportunity, but also a significant technical challenge that required more technically capable staff and significant training and investment in building up necessary tools and scripts to make analyzing these trip patterns possible and an integrated part of the forecasting workflow.

Practitioners were asked whether the transition to ABMs resulted in changes to the available pool of consultants able to contribute to modeling work. Responses to this question were mixed, with some interviewees recalling that travel-demand modeling practitioners quickly learned how to work with ABMs and did not see any significant obstacles. Others reported that usability challenges resulted in concerns and objections to transitioning to the ABM as a production model from consultant practitioners (or in one instance, other regional agencies). One interviewee noted that while some consultants withdrew from modeling work after adopting an ABM, other consultants from national firms became more interested in working in the market, with the net result that the overall quality of modeling expertise in the region improved over time.

8.2.8 Overall Evaluation

When asked if, knowing what they do now, they would choose to adopt an activity-based model again for their agency under the same set of needs and circumstances, nearly all interviewees responded affirmatively. The few exceptions that practitioners could point to of agencies that regretted this decision were small MPOs with limited staff capacity and early adopters who got ahead of well-developed practice and would have benefitted from waiting for modeling infrastructure to become better developed.

Several agencies expressed enthusiasm for in-progress or planned efforts to transition their models from proprietary platforms to ActivitySim. Practitioners expressed optimism that ActivitySim may fix key problems with existing models, improve model runtimes, and reduce lock-in/dependence on vendors and consultants to respond to issues. For example, Twin Cities Metropolitan Council staff mentioned that phase 1 work to adopt PopulationSim, ActivitySim's population synthesizer, has been very successful. Future follow-up with agencies currently transitioning to ActivitySim-based models may be useful in confirming whether these hopes have been realized.

Issues that interviewees raised as regrets or pain points included:

- Using parcel-based land use data: One practitioner reflected on as being too laborious to develop and maintain for negligible benefits to model results, while another agency noted that while they maintain parcel-based land use data, they have simplified their ABM to use aggregated microzone-level inputs instead.
- Adding too many complex features to the model, or investing in a high level of complexity in modeling speculative modes where operational characteristics are currently unclear.
- Inefficient code and long model runtimes.
- Poor tools for dealing with population/land use changes, which was noted as a significant pain point in several older models.

A comparison of several key characteristics of the agencies interviewed and their models is presented in the matrix below.

Table 8.2 Agency Comparison Matrix

Organization	Reason for adoption	Timeline					Cost
		Began Development	Draft Model	Production Model	Retired Old Model	2nd Generation	
SACOG	Land use responsiveness, capturing aging population impacts	2005	2006	2008	2008	2012	
MWCOG	Achieving state of practice model, match peer agencies	2015	2023	2023*	Still active		$900k
SANDAG	State guidelines, equity, VMT performance monitoring	2009	2013	2015	2015	2016	$1M
SCAG	State guidelines	2012	2016-17	2020	Plan to retire		$2M
Alameda CTC	Conformity with larger regional model	2021	2023*	2024*	Still active		$1.2M
PSRC	GHG reductions, road user charging, transit	2006	2012	2018	Still active	2025	$1M+
Met Council	Equity, road user charging	2012	2014	2015	2016-17	Ongoing	$1M (1st gen),
Ohio DOT	Road user charging	Early 2000s		2005	2005	2013	Various
NC ITRE	Answer policy questions	2019	2020-21	2021	Still active		$350k
Oregon DOT	GHG legislation, equity	2014 (RVMPO)	2017	2017	Still active	2030*	

* Anticipated dates

(continued from previous table)

Organization	Model Platform			Staff	Consultant Support	Data Requirements
	1st Generation	2nd Generation	Notes			
SACOG	DAYSIM, Cube			5 TDM	Yes, maintenance	Parcel-level land use/SE data
MWCOG	ActivitySim			15 in TDM	TBD	Need land use model, TAZs are ok
SANDAG	CTRamp, TransCAD	ActivitySim, EMME		5 LU, 13 TDM	Yes, limited on demand assistance	Microzone land use/SE data
SCAG	CTRamp, TransCAD	ActivitySim, TransCAD	Used alongside 4-step model	2 SE, 10 TDM	No or limited support	Higher level of effort, more challenging SE data development
Alameda CTC	CTRamp		Tied into MTC model with more zonal detail	1 program manager	Fully reliant on consultant support	Similar to trip based
PSRC	DAYSIM, EMME	ActivitySim		LU 4, TDM 5, 4 HHTS	Yes, significant support	Same but more finely detailed
Met Council (MN)	TourCast	ActivitySim		3 application, 2 LU	Prior CS on-call, currently none	Similar, frequent travel survey
Ohio DOT	CTRamp, Cube		Disaggregate tour-based model. Pop synth, trip list moving to simple ABM	3 DOT plus MPO staff	Yes, limited on-demand assistance	
NC ITRE	TransCAD		Disaggregate trip-based model	2 TDM plus external SE	Yes, recurring survey work	Additional household surveys
Oregon DOT	CTRamp, TransCAD	ActivitySim	Statewide is currently tour-based. Once all MPO models are ABM, intended to adopt statewide ABM.	7 development, 4 applications	No or limited support	More data, represent variables more explicitly

Based on a synthesis of the various practitioner interviews and agency/model characteristics, several key themes emerged as important considerations for Utah's MPOs and statewide agencies in considering their strategies for model development and enhancement.

8.2.9 Clarity on Goals of Advanced Models

Multiple practitioners emphasized that Utah's public agencies should begin their decision process on the directions for their model roadmap not from the question of "What is the best type of model?" but rather "What questions do we need our model to answer?" Practitioners repeatedly noted that activity-based models do not provide an inherent advantage in accurately depicting and forecasting network volumes, and stressed that the primary value of a more complex and costly model is the ability to answer new policy questions in a valid way, including topics discussed under "When and Why" above.

Accordingly, several interviewees noted that a clear understanding of the goals of an enhanced model can and should guide what model elements are built to a high degree of detail, and which should be excluded or adopted (at least initially) in a more simplified form. As one Twin Cities Metropolitan Council modeler said, "models need to earn complexity," and during the scoping and design phase it's valuable to consider whether more sophisticated components will result in meaningfully improved results for likely use cases. Another practitioner, Wu Sun, reported that SANDAG had concluded that its current model version had elements that added more complexity than they were worth, and has added projects to simplify these modules to their development roadmap.

***Takeaways*:** Prior to UDOT or partner agencies pursuing development of activity-based models, modeling staff, planners, and agency leadership should collaborate on identifying key policy needs that may require travel model analyses and which current modeling paradigms are inadequate to address. These policy questions and priorities should drive decision-making about whether activity-based models are a good solution, and if so what design features should be prioritized.

8.2.10 Differences Between Early and Late Adopters

Interviews with practitioners confirmed a trend that earlier models (those developed in the 2000s or early 2010s) tended to be more bespoke, required a much higher level of investment in programming key model components and estimating the model, and led to staff facing greater challenges around model usability.

For example, the SACOG model, the first version of which was completed in 2007, was described as having received “withering criticism” from forecasting consultants in the local market as being very challenging to use in applications where land use changes needed to be modeled. While best practices have been found, these efforts remain challenging and require multiple times as much budget or staff time to conduct compared to their prior model.

To mitigate these issues, some agencies have invested in major overhauls or redevelopment of subsequent versions of their models, including transitioning from proprietary platforms such as CTRamp to ActivitySim.

Later adopters were less likely to cite the same level of difficulty with their models, driven both by model development consultants having gained more experience through ‘learning by doing’ and greater availability of ‘donor models’ from other regions that can be adapted for a new region. Due to the availability of pre-existing model frameworks, multiple interviewees recommended that Utah agencies should ensure that they take advantage of existing resources and ensure they do not pay development costs for software that is available from vendors or other agencies.

Takeaways**:** Major usability issues that have been encountered by practitioners in older activity-based models are not representative of what Utah agencies can expect from a state-of-the practice model using more modern technology.

8.2.11 Staff/Agency Capacity

The size of an interviewee's agency tended to correlate with more positive descriptions of their modeling practice and experiences with activity-based models. At one extreme, groups with 12-15 modeling staff were more able to avoid overreliance on consultants, have separate model development and model application teams, and build technical infrastructure that improves model usability. They also appeared to have more capacity to develop detailed model input data that take full advantage of ABMs' potential. As one practitioner noted, "the power of a disaggregate model comes from disaggregate socioeconomic inputs," and those with larger staffs and dedicated land use / socioeconomic forecasting teams were better equipped to develop those inputs with a high level of detail, as well as leveraging detailed survey data. Opinions differed between practitioners on whether having separate model development and model application teams is advantageous.

At the opposite end, Ohio DOT reported that small MPOs with one or less than one FTE devoted to modeling often lack the capacity to run an activity-based model (and in some cases struggle to run or maintain a four-step model), while one consultant mentioned examples of a DOT and MPO that developed and then abandoned ABMs. In other cases, practitioners brought up examples of ABMs that have been developed and remain in use as a 'model of record' for regional planning and air-quality conformity processes, but are not used on a day-to-day basis by agencies for project-level or sub-regional planning processes due to their complexity (Baltimore and Chicago's MPO models were brought up as examples).

MPOs that have successfully deployed ABMs with small staff more frequently reported difficulties or persistent downsides to their models, including challenges with incorporating land use changes, achieving good performance from certain model modules (e.g., mode choice), adequately distinguishing signal vs. noise in model outputs when considering relatively small projects or policy changes, and usability problems (e.g., excessive runtimes).

***Takeaways*:** If Utah's agencies decide to pursue development of activity-based models, recruitment, training, and retention of skilled technical staff should be a key priority. Additional FTEs may be required in order to successfully apply and maintain ABMs. Caution should be used in developing ABMs for smaller agencies, which may not have adequate staffing and resources to make good use of a more complex and labor-intensive modeling paradigm.

8.3 Development Timeline and Model Transition Process

For many agencies, model development timelines are closely tied to their regional transportation planning and air-quality conformity timelines. A key difference in approaches to ABM adoption is whether agencies attempt to develop and complete an ABM to the point that it is ready for planning use within one four-year cycle, or whether this process is extended across multiple cycles. While some practitioners were able to achieve this compressed development timeline, the general consensus was that extending model development over two plan cycles is preferrable in terms of providing the agency adequate time to ensure the model is adequately validated and calibrated, and staff are sufficiently trained to deploy the model correctly and take advantage of new capabilities. This approach necessarily entails continuing to invest in maintaining the previous model through a longer duration than would be necessary under a more accelerated timeline.

As mentioned in the 'Development Processes' section above, several practitioners emphasized that clear benchmarks for both static and dynamic validation that a new model should be built into model development contracts at multiple milestones in the overall development process. In the event that a draft model does not meet these benchmarks, the owner agency should not accept the model as complete until validation benchmarks are met.

Takeaways: Utah agencies should be aware that development of an application-ready ABM in time for the next RTP cycle (beginning in 2027) would be a challenging development timeline and result in significant risk to those planning processes. Procurement documents and contracts should clearly lay out static and dynamic validation targets that must be met in order for owner agencies to accept new models as complete. Finally, agency staff beginning a model development process should plan for how long existing models will be maintained before they are retired and what resources will be required to do so; periodically revisit those plans as the model development and application process continues; and communicate those plans to model users and stakeholders.

8.3.1 Model Infrastructure

As previously mentioned, activity-based models varied substantially in terms of both model complexity and the level of investment in supporting scripts and tools to help modelers/analysts use the ABM for various tasks. Some of the supporting infrastructure that practitioners noted had been significant value-adds for their agencies included:

- **High-quality population synthesizers**: Population synthesis typically occurs outside of the main model flow, and ensuring that usable tools exist for manipulating disaggregate populations was mentioned as an important priority by one consultant.

Agencies that have not invested in this infrastructure, such as DRCOG and SACOG, were highlighted as causing significant ongoing challenges for users.

- **Model documentation**: Practitioners who had received models with limited documentation reported substantial difficulties in getting staff trained and fully competent to use the model and navigate operational issues, requiring substantial internal effort to produce adequate documentation. One practitioner emphasized that documentation should occur throughout the model development process, rather than being a final deliverable created separately from the main work effort.
- **Input checking**: Building in automated tools to check inputs for validity prior to launching the main model stream was recommended by PSRC staff as a valuable method of avoiding lost working time when running large models with long runtimes. This approach ensures that many input errors can be caught immediately, rather than putting multiple hours into an overnight model run.
- **Output visualization and mapping tools**: While these tools are not inherent to activity-based models, multiple practitioners mentioned that visualization tools developed as part of their model adoption process provided a high level of immediate value in being able to easily communicate model results to decision makers. Additionally, Oregon DOT reported that a side-by-side visualization tool was valuable for comparing new vs. old models as well as model vs. survey data for validation/calibration purposes.
- **Variable sampling rates**: The foundation of activity-based models is generation of a synthetic population sample. By default, this sample is equal to 100% of the estimated or projected actual population of the model region. However, multiple practitioners mentioned that building in the flexibility to adjust the sampling rates of

the activity-based model (in terms of the percentage of the synthetic population sampled) for different use cases was valuable. With this functionality, less or more than 100% of the true population is generated as a synthetic population, and then trips are scaled accordingly for assignment purposes (for example, a 50% sample rate would be expanded by a factor of 2). Less than 100% sample rates allow for faster model runtimes for early screening (e.g,. of major policy moves or early-stage evaluation of large numbers of projects or scenarios), while greater than 100% sample rates can reduce simulation variance between runs and provide greater confidence that differences between model runs are not driven by model noise.

Takeaways: While completing all of the above infrastructure may not be feasible during an initial model development contract, population synthesis and documentation should be prioritized from the beginning. Other assets that may not be completed during the initial development process should be prioritized for future updates within a model development roadmap.

8.3.2 Collaboration Frameworks

Many practitioners referred to the importance of developing venues for collaboration between the model owner agency and other key stakeholders, including municipalities, partner agencies, and consultants. A common theme was that ongoing working groups were highly useful for disseminating key information to the range of model users across a region, especially in the transition process as practitioners must adjust from a previous modeling paradigm to a new (and more complex) activity-based framework. Entities frequently reported meeting on an annual to quarterly basis to deliver training sessions, introduce new model updates/functionalities, and share project examples or potential directions for future practice.

An additional opportunity for collaboration in the model development and adoption process that was recommended by multiple interviewees was building in a peer or expert review panel into the model adoption process. Rebekah Straub of Ohio DOT mentioned that having a separate contract for an expert reviewer was valuable not only to ensure a new model was correctly implemented and yielded reasonable results, but also as way to guarantee that multiple consultants were familiar with and able to run the model prior to adoption. SCAG reported using this approach during a model enhancement process subsequent to adopting their ABM.

For DOTs that are responsible for maintaining or interfacing with multiple models, a key factor raised by one informant was the importance of standardization between various models in terms of software versions and compatibility with post-processors and other model infrastructure. Emphasizing this interoperability through ongoing collaboration can avoid duplicative effort or ongoing compatibility challenges.

Takeaways: The Utah Model Users Group (MUG) would likely be an appropriate venue for ongoing collaboration, knowledge sharing, and training on any new models developed in the state. Any agencies developing new models should strongly consider contracting for expert review at key milestones in the development process. If multiple models across the state transition from trip-based to activity-based, consistency between these models and sharing of technical resources should be prioritized.

8.3.3 Hybrid Models

Hybrid travel demand models represent an alternative to both traditional 4-step models and activity-based models. These models integrate more disaggregate data into the estimation of the model behavior process but contain other model processes that are more simplified which reduce the computational needs and processing time compared to activity-based models. Some hybrid models require the same input needs as traditional 4-step models, requiring housing and employment land use inputs by TAZ that are then converted into a synthetic population during the model process. Hybrid models may also incorporate machine learning and big data to better represent travel behavior while not requiring a full travel diary for each synthetic resident of the model area.

Hybrid models are now in use in places such as Charleston, SC; Hampton Roads, VA; Knoxville, TN; Indianapolis, IN; and for statewide models in North Carolina, Tennessee, Michigan, Iowa, Nebraska, and New Mexico.[9] While these models vary in complexity, they all have a common theme in that the models typically begin with a population synthesis, followed by disaggregate model steps, then aggregate trip distribution and assignment processes.

A contemporary version of a hybrid travel demand model has just been completed for the Triangle Regional Model (TRM) in the Raleigh-Durham Metropolitan region of North Carolina. This model utilizes machine learning processes for person-level trip production modeling to specify a large number of discrete variables, nested logit destination choice models, and linked non-home based and home-based trips by location and mode. Figure A.1 (below) shows a summary of the model process.

During the practitioner surveys, developers of the new Triangle Regional Model were interviewed to understand the impetus for transitioning to a hybrid model rather a full ABM. Rationale for selecting a hybrid model included:

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9 An Advanced State-of-the-Practice Hybrid Travel Demand Model for the North Carolina Research Triangle Region; Bernardin, Ward, Huntsinger, Balakrishna, and Sundaram; 2023; https://www.caliper.com/pdfs/trbam-23_trm.pdf

- Did not require substantial changes to how TAZ-level data was prepared and updated.
- Represents a step towards activity-based without having to introduce all of the complexity and drawbacks of a full ABM (including cost, run time, data needs, and overall complexity).
- Emphasis was placed on accessibility and disaggregate population which still allows for equity analysis and improved non-motorized modeling.
- Model development and implementation costs were less than $500K (excluding survey data or staff support hours) and the process was completed in approximately 18 months.

Development of a hybrid travel demand model can provide an intermediate step from trip-based to activity-based models, allowing agency staff and other users time to gain familiarity with some elements of an activity-based framework with a smaller increase in complexity. Development and adoption of a hybrid model may also allow for an accelerated timeline, such that a new model can be developed and staff can acquire proficiency with it within one regional planning cycle.

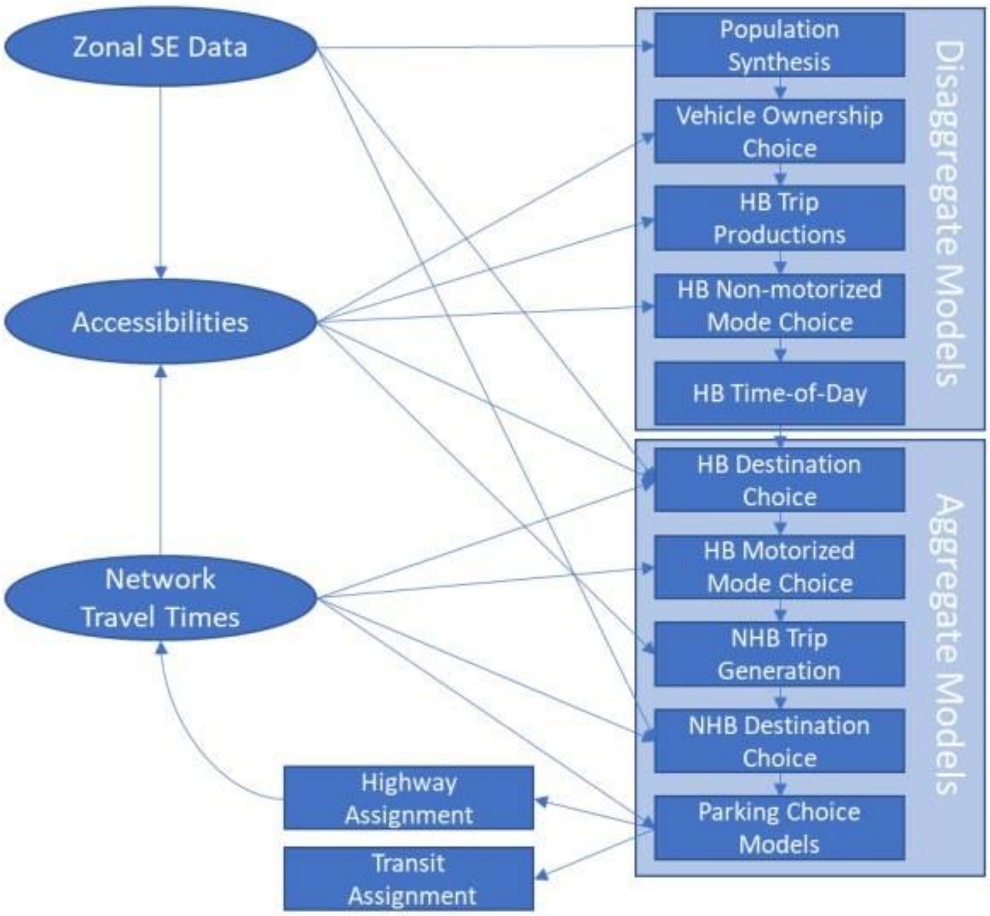

Figure 8.1 Triangle Regional Model Hybrid Structure

Takeaways: If Utah agencies determine that current trip-based models do not adequately meet their modeling needs, they should consider whether hybrid model designs may adequately meet near-to-mid-term policy priorities compared to a full activity-based model, and if so weigh the pros and cons between:

- Developing and adopting a hybrid model as a long-term solution
- Developing and adopting a hybrid model as a first step towards a planned transition
- Transitioning directly to a full activity-based model.