Repurposing City Streets: Assessing City-Scale Congestion and VMT Impacts with a System Dynamics Scenario Analysis

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ABSTRACT

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Alternate street uses (ASUs) have been explored worldwide to capitalize upon public space to meet other societal needs. One widely adopted strategy catalyzed by the COVID-19 pandemic is the repurposing of roadway space from vehicular travel to other purposes, such as nonmotorized mobility, commercial use, or as social/recreational space. This thesis presents a scenario analysis of ASU policies using a system dynamics (SD) framework to investigate downstream and interacting effects of ASU policies and allocation in Seattle, WA and Phoenix, AZ. Model calibration was done with the Puget Sound Regional Council 2019 Household Travel Survey and Federal Highway Administration 2017 National Household Travel Survey datasets. It was found that increasing the existing amount of street space repurposed for commercial and social/recreational use led to decreased congestion in both Seattle and Phoenix models, while also increasing the non-motorized transportation (NMT) mode share. In higher-density cities with lower drive mode share like Seattle, increasing lane reallocation for uses that increase the

capacity, safety, and reliability of NMT and transit modes can reduce both congestion and VMT. In lower-density cities with higher drive mode share like Phoenix, repurposing more street space for NMT would lower VMT; repurposing street space for transit use, however, yields little meaningful benefit. These findings support policies promoting widespread ASU placement and concerns about generating increased congestion by removing travel lanes are refuted. The thesis concludes that at least in higher-density cities, the reallocation of street space is not a zero-sum game, as those who still choose to drive experience reduced congestion, and the non-drivers receive safety and capacity enhancements. Furthermore, reduced total VMT supports broader traffic safety and emissions reduction goals.

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BROADER RESEARCH CONTEXT

Cities are dynamic social-technological systems: within a city, people and the built environment around them are engaged in near-constant co-evolutionary processes as people design and capitalize upon their built environment to meet their needs, and the built environment presents opportunities and constraints to individual and societal behavior. An example of this endogenous co-interaction in a city's transportation context would be that an intrinsic demand for bicycling would give rise to bicycle paths and lanes to be constructed, which reduces barriers to entry for bicycling, thereby influencing the level of demand for bicycling.

Natural climactic cycles between the seasons also give rise to this human-built environment interaction; some outdoor farmers' markets that utilize public spaces such as streets, or private spaces such as parking lots, may only be in operation during the summer season. People's commercial activity choices may be influenced by whether urban spaces are used for farmers' markets during summer months – without an adaptation of the urban space for commercial use, citizens who may have visited a farmers' market would make alternate travel and activity choices to meet their food access needs.

Systems may also be perturbed by external forces. New technologies in construction and utilities delivery led to the ability for denser, higher-rise housing to become part of the city ecosystem. More recently, the COVID-19 pandemic precipitated many adjustments to urban life, as people sought to socialize and shop outdoors for health reasons. Flexible uses of urban spaces were designed to prioritize public health, while transportation operations adapted to reduced commuting demand due to widespread telework.

Within the context of cities as dynamic systems with endogenous and exogenous effects, the study presented in this thesis was conducted as part of a wider project that investigated the adaptability of various components of urban systems under external perturbations. The project conceives of four major components of cities that may flexibly adapt to disruptions; each component was investigated under distinct research “thrusts”: 1) adaptable urban spaces; 2) adaptable business operations; 3) adaptable transit systems, and; 4) adaptable human behaviors. This thesis presents the integration of these four thrusts into a single city-wide model and the overall effects of the interconnections between the city components represented in the four thrusts.

Thrust 1 is concerned with how urban spaces, in particular, streets in the public right-of-way, could be adapted and used flexibly to meet cities’ and citizens’ needs under external disruption events. Examples of such flexible uses of urban space considered in Thrust 1 include temporary dining structures constructed during the COVID-19 pandemic, farmers’ markets constructed on public streets, and sports and recreational equipment being placed on streets closed off to vehicular traffic. These flexible uses of street space enable many other societal needs to be met and have implications on human mobility and activity choice. Narrowing or closure of streets would impede immediate vehicular access. Temporary outdoor dining or recreational spaces may tap into latent demand for restaurant visits or social/recreational/physical activities. The downstream effects of how street spaces are used on travel and activity choices could thus have broader implications on other thrusts in the wider project.

This thesis generalizes and expands upon the scope covered in Thrust 1. While Thrust 1 is concerned with effects of urban form and urban design on a site- or neighborhood-level, this study envisions that cities may employ a wide variety of street use adaptations to accommodate for a broad range of changing activity demands and behaviors that have city-wide network effects. To accomplish this, a broad categorization of alternate street uses (ASUs) was created to accommodate for the differences in transportation behavioral responses to different types of ASUs, while still having each category have enough generality to allow for diversity of uses within each category. Building upon the work of Thrusts 1 and 3, the four ASU categories in this thesis are defined to be commercial, social/recreational, transit, and non-motorized transportation (NMT). These types are expanded upon with greater detail in the Study Introduction section.

Thrust 2 explores how businesses can operationalize space to enhance both the customer experience and business revenue. Although Thrust 2 approaches their investigation of adaptable business operations from the individual business perspective and this thesis focuses on a top-down, city-wide perspective, there are crossover implications on how individual businesses could take advantage of ASUs as permitted at the city-level. Businesses could capitalize upon additional spaces for commercial use by using ASUs: one method would be through additional seating capacity for restaurants with outdoor dining structures built in the parking lane; another method would be through increasing customer interaction points by taking advantage of street markets. Furthermore, increased pedestrianization of public spaces and provision of public recreational spaces may increase foot traffic for co-located or adjacent commercial areas, which may have a secondary benefit for businesses in those areas.

The goal of Thrust 3 is to balance the efficiency and resilience of transit systems, which is a salient balancing act when a transit system is affected by external disruptions. Whereas efficiency describes the ability of a system to maintain its demonstrated level of service, resilience represents the ability of the system to restore itself to that level of service within a specific timeframe. Thrust 3 identifies acceptable service levels (service frequency) and physical constraints on bus routing and frequency as problem constraints. Transit operational efficiency could be enhanced by using street space for dedicated bus lanes, as these transit-only lanes would improve in-service vehicle speed and reliability. This would allow for either increased route capacity with the same number of transit vehicles, or reduced route cost at the same prior capacity by using less transit vehicles. These route-level operational adaptations made possible by adapting street space could also apply at the system-level. Transit system resilience could be enhanced since transit lanes enable mode separation, giving priority access to transit vehicles, thereby mitigating the impact of traffic congestion caused by external disruptions. By increasing the amount of street space dedicated to transit-priority use, the transit system optimization problem space is enlarged by increasing vehicle speeds.

The new destinations created by adapting street space for alternate uses alongside the changing transportation environment due to altered congestion conditions and transit operations would then lead to changes in how citizens may use the spaces and transportation options available to them. In this way, Thrust 4's investigation of activity-travel patterns of agents in their agent-based activity-travel model would shift under shifting land and street use patterns. While Thrust 4's modelling efforts represent a bottom-up approach to understanding travel behavior and demand, the methodology and results presented in this thesis (which is top-down) would provide a complementary comparison and potential validation case for Thrust 4's work, and vice-versa.

STUDY INTRODUCTION

Alternate street use experiments have been performed globally over the previous decade to utilize the right-of-way (ROW) for non-vehicular purposes (*1*). Widespread adoption of ASUs, particularly temporary uses that have pre-determined lifespans, was catalyzed by the COVID-19 pandemic, during which outdoor social and commercial activity was prioritized to promote public health. The adaptable use of public space through temporary ASUs to meet short-term societal needs also facilitated health and social benefits through providing recreational space and a means for social interaction (*2*). Concurrently, policies that reduced the need for travel to workplaces and schools lowered the need for streets as tools for mobility. A 2022 roadway survey in Barcelona, Spain indicated that interventions replacing general-purpose traffic lanes with alternate mobility uses (such as bike lanes, bus-only lanes, and/or widened sidewalks) resulted in "traffic evaporation" - a net traffic reduction that was not replaced by increased traffic on adjacent roadways (*3*). In Christchurch, New Zealand, a neighborhood street closed to cars but not bicycles or pedestrians for utilities improvements led to improved public perceptions of walking safety and strong support for further temporary or permanent closure (*4*). As such, adopting ASUs that replace portions of ROW for automobility and parking in favor of other activity purposes show promise as a tool for cities to reduce vehicle-miles travelled (VMT) and congestion, while simultaneously enabling uses to meet other societal needs.

Cities are such dynamic and interconnected systems, such that when the function of streets change, there is no single way that a city responds. The repurposing of roadway for a new BRT line would affect transit mode shares, but also affect traffic flows and congestion by simultaneously replacing some car trips with transit trips while also reducing roadway capacity and increasing traffic density (*5*, *6*). Pedestrianization of commercial areas may improve the safety and directness of walking routes, which may increase walking mode share, but this may also induce a greater number of shopping trips, some of which may be made on foot (*7*, *8*). Extending beyond these two examples, we may conceive of cities displaying dynamic interactions among four components when a street is repurposed for use as a destination or to enhance non-drive mobility. The four components are: 1) the ASU component: how much street space is used for alternate purposes and the public desire for ASUs; 2) the roadway traffic component: how roadway traffic responds to varying levels of street space usage and the changed travel choices that ASUs affect; 3) the transit operations component, which are affected by traffic conditions, mode choice, and ASUs that improve transit, and finally; 4) the travel behavior component, which consists of the mode and activity purpose choices made by travellers.

There are several types of interactions across these four city components, with static effects, temporal dynamics, and system-level dynamics at play, sometimes across differing fast and slow timescales. Static effects describe effects that are time-insensitive, such as reducing roadway lane-miles increasing vehicle density for fixed traffic flow. Temporal dynamics describe time-dependent effects, such as the future lane-miles of bus lanes being affected by the current lane-miles of bus lanes, or the effects of time delays such as when increasing roadway capacity leads to future induced driving demand (*9*). Some effects consider the aggregate of several interactions across the entire system and may result in feedback behavior, such as bus lanes reducing roadway lane-miles, which increases congestion, incentivizing some travellers to use transit, therefore increasing potential demand for more bus lanes. This feedback loop also identifies the existence of fast and slow dynamics in how cities evolve: congestion effects change at fast timescales, with congestion conditions changing on the order of minutes. This is contrasted to the slow timescale of infrastructure planning and construction, with changes observed on the order of months and years. Taken together, the multitude of temporal and cross-scale dynamic effects caused by, and causing changes in allocation of ASUs, are hypothesized to exhibit dynamic effects on transportation outcomes in cities. Where systems featuring dynamics across temporal timescales exist, various states of system stability often follow, with threshold levels between switching between these states (*10*, *11*).

To date, the city (system)-level consequences of repurposing street space on traffic, transit, and travel behavior have yet to be studied from a dynamical perspective. Also, the net effects that result from the multitude of competing feedback loops and interactions across temporal scales and system scales between city components remain unclear. This thesis seeks to fill these gaps by presenting an analysis of how cities' transportation outcomes respond dynamically to changes in allocation of street space for non-drive purposes.

These dynamic effects across the previously-identified four components of a city's transportation behavior due to ASU allocation would be analyzed in two contrasting contexts: Seattle and Phoenix. Cities of different typologies are hypothesized to respond differently to repurposing street space. These two cities were chosen as representative of differing land use and transportation patterns, spatial scales, climates, and city-wide responses to ASU adoption both during and in the years after emergency orders due to the COVID-19 pandemic. A comparison of city dynamics when responding to repurposing city streets in the two study settings may offer insights to planners and policymakers on transportation effects when deciding what types of ASUs to deploy and at what scale.

As cities grapple with a broader scope of options for using the space on city streets, there arises a need to analyze their impacts on the city's transportation system and travel behaviors (*2*, *12*, *13*). This thesis explores the questions: to what extent do various alternate uses of city streets impact congestion, VMT, and mode split, and are there feedback, interacting, or threshold effects that must be considered when repurposing city streets? What are the overall effects on transportation, when repurposing city streets affect several city components (each with competing static and dynamic effects within their own and among other city components)? How do these transportation effects vary between cities with differing aggregate transportation and land use characteristics? To that end, a system dynamics approach is proposed to model the city-level systemwide interactions to understand and quantify the dynamic effects of ASUs. System dynamics (SD) is a method developed for the analysis of urban systems with many interacting elements (*14*). SD has been identified as advantageous in identifying feedback behavior, interdependent relationships, and sensitive variables in systems, and providing a testbed for hypothetical scenarios, thus supporting its suitability in transportation policy analysis (*15*). Examples of SD modelling employed in transportation policy analysis include a case study of autonomous vehicle policy and its downstream effects on traffic composition, law enforcement, and infrastructure investment in Washington, D.C., the Metropolitan Activity Relocation Simulator (MARS) Land-Use and Transport Interaction (LUTI) model used to study transportation-land use-emissions interactions in Hanoi, Vietnam and employed for policy analysis in other SE Asian and European cities, a model investigating the interactions between housing, employment, car trips, and transit trips in Bogotá, Colombia, and a classification of policy environments as car-dependent, transit-oriented, or active-mode-based through a dominant feedback loop analysis (*16*–*19*). SD models are inherently aspatial; insights into ASU usage and travel behavior that inform the model are aggregated city-wide or informal, thus SD is preferred for macro-scale analyses.

The next section outlines the choice of study settings of Seattle and Phoenix. An overview of the general SD model structure then follows. Next, the model specification section describes the mathematical underpinnings of the SD model. Then, the SD model is calibrated for case studies of Seattle and Phoenix, followed by a presentation of key results from a scenario analysis under varying levels of ASU allocation. A discussion of the implications of our key results on ASU adoption, traffic and transit system performance, and travel behaviors is then presented. Finally, the implications of this study on the broader project context is provided.

STUDY SETTINGS

During and after the pandemic, cities that demonstrated a higher acceptance of streetscape changes alongside a willingness to adopt alternate uses into the city's planning agenda displayed a stronger persistence of both permanent and temporary ASUs beyond the pandemic (*20*). One city that exhibited such characteristics is Seattle, WA. In 2015, Seattle had dedicated 27% of its land area to the public right-of-way (*21*). This proportion is comparable to other major US cities: Chicago (23%), Phoenix (26%), and Washington, D.C. (25.5%) (*22–24*). Within the policy landscape of reducing transportation emissions, commute trips, and improving safety and accessibility, it was recognized that leveraging public space could help achieve these goals. ASU adoption during the pandemic occurred predominantly in the commercial realm (e.g. outdoor dining) and social/recreational uses (e.g. Seattle's Healthy Streets program, that closes streets to through-traffic to encourage nonmotorized travel and play) (*25*). Such alternate uses of the city's streets joined two pre-existing reallocations of the ROW in Seattle: transit-only lanes and protected bike lanes. Recently, other ASUs have appeared, such as popup pickleball courts on 6th Avenue in Seattle's Denny Triangle (*13*).

Seattle's adoption and embrace of ASUs is contrasted with the adoption and disappearance of ASUs in the Phoenix area (*26–28*). Ad-hoc observations of cities in the Phoenix metropolitan area seem to suggest that a climate with frequent extreme heat, large blocks in the street grid, lower population density, and heavier car-dependency for personal travel in Phoenix may have been factors for ASUs to fade away as the public health needs of the COVID-19 pandemic also diminished over time. Particularly for commercial uses, Phoenix-area restaurants tended to utilize outdoor dining patios on-property or on sidewalks, rather than repurposing street space (*26*). As such, ASUs were found to be far less "sticky" in a city with transportation and land use patterns typical of other Sun Belt cities, compared to a city with land use and modal characteristics akin to those of the Pacific Northwest and the Northeastern United States. A comparison of relevant city-level aggregate parameters is presented in **Table 1**.

Table 1 Comparison of city-level aggregate parameters for Seattle and Phoenix

Parameter	Seattle (2019)	Phoenix (2017)
Population	724,305	1,574,421
Land area (sq. mi)	84	518
Population density (residents per sq. mi)	8637	3041
Mean household size	2.325	2.444
Mean number of days per year with daily maximum temperature above 100 °F (2005 – 2024)	5.65	177.4
Mean number of days per year with daily minimum temperature below 32 °F (2005 – 2024)	20.0	0.55
Roadway Lane-Miles (mi)	3,952	12,557
Annual transit vehicle revenue-miles (million mi)	42.7	18.5
Annual trips made (millions)	963	1417
Drive mode share	53.2%	85.15%
Non-motorized transportation mode share	33.5%	11.45%
Transit mode share	11.9%	3.25%

Data sources: (*29–41*)

GENERAL MODEL STRUCTURE

An ASU policy analysis tool was developed using an SD approach that modelled four interacting components. An overview of the general model structure with its primary and secondary feedback loops is provided in **Figure 1**. Greater detail, including key equations, is provided in the Model Specification section of this thesis.

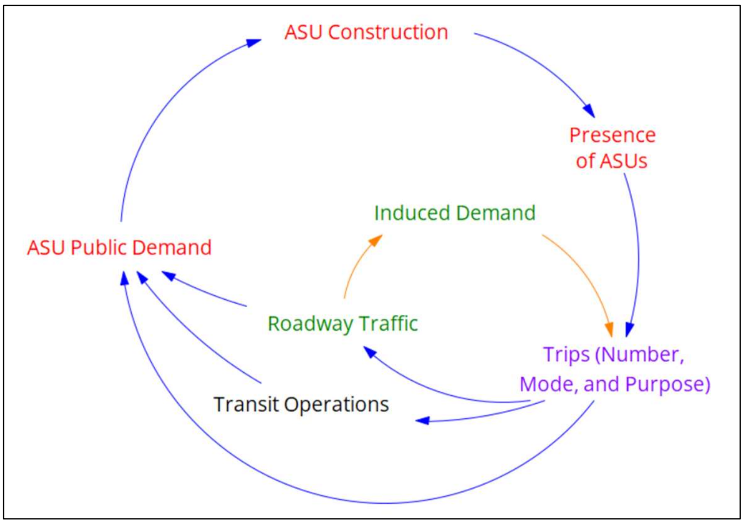


Figure 1 General model feedback structure: model components denoted by color (red: ASUs; purple: trip behavior; black: transit operations; green: roadway traffic), arrows indicate directionality of influence, blue arrows indicate primary feedback loop, orange arrows indicate secondary feedback loop.

The first component (red) determines the public demand for ASUs and captures their construction in the ROW. This component is characterized by slow dynamics, as construction and delays from public demand flowing into realized ASU allocation takes time, often on the order of months.

The second component (green) calculates roadway traffic performance, which is affected by the amount of ROW replaced by ASUs and changes in mode split under changing street uses. Roadway traffic display fast dynamics, as sudden changes in usage have realized effects within seconds and minutes.

The third component (black) captures the city's transit operations, determining whether there is sufficient capacity under current mode splits, and capturing the perception of transit quality and reliability which has downstream influences on mode choice. Transit operations are governed by slow dynamics, as transit operations change over longer periods; for example, service frequencies and networks are often reviewed and altered on a quarterly basis.

The fourth component (purple) considers the influence of ASU allocation, traffic performance, and transit operations from the first three components to allocate combined mode-and-trip-purpose shares (MPS) of all trips in the study region. These MPSs are then used as inputs for defining public demand of ASUs and informing congestion and traffic operations, thus completing the primary feedback cycle across the four components of the SD model. There is also a secondary feedback cycle due to induced demand, whereby increases in congestion have a time-delayed effect in reducing the total trips taken in the study region, and vice versa.

The causal loop diagram (CLD) in **Figure 2** indicates the relationships analyzed in the SD model. Note that this figure depicts one MPS out of 15 combinations analyzed in the model[1]; combinations comprise of 1 travel mode out of 3 choices (drive, NMT, transit) and one travel purpose out of 5 choices (home, work/school, commercial, social/recreational, errand/escort). Each color represents one of the model components, as with Figure 1. The CLD shows how variables in the model are related using directed links with an assigned polarity. A cause variable

[1] The 15 MPS combinations are listed in Table 4.

points to an effect variable. Positive polarity indicates that an increase in the cause leads to an increase in the effect, while negative polarity indicates that an increase in the cause leads to a decrease in the effect. A link polarity is determined in isolation of any other links (all other variables remain constant). Finally, links denoted by cross-markings indicate a delay between changes in cause and effect. Feedback loops are formed by a sequence of links returning to its origin variable; balancing loops tend towards stability and have an odd number of negative links, while reinforcing loops tend towards exponential growth or decay and have an even number of negative links.

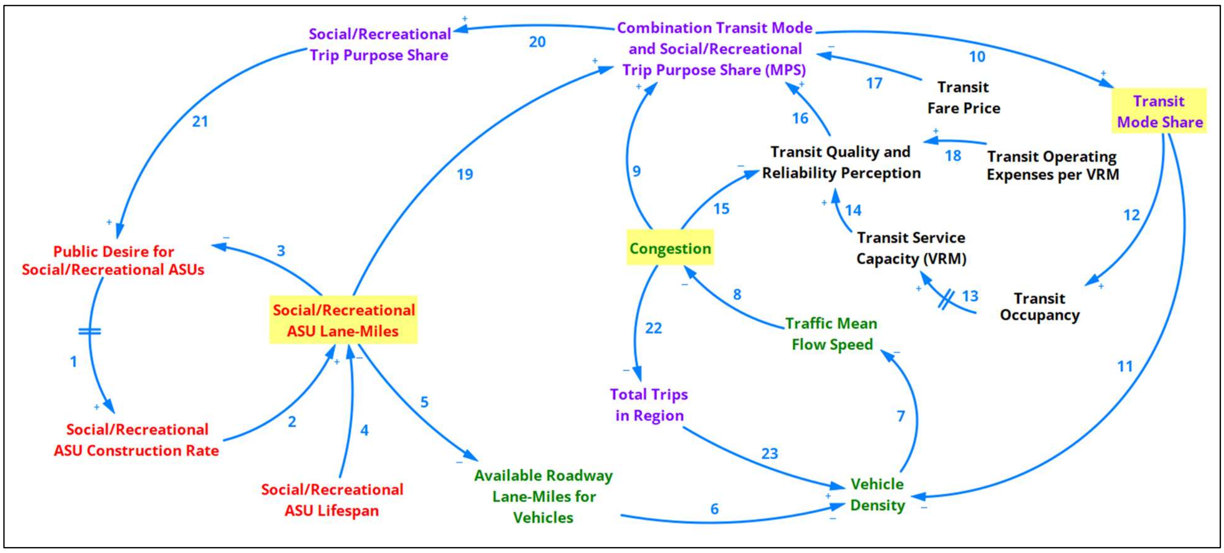


Figure 2 The CLD of the feedback structure in the SD model for the transit-social/recreational MPS (out of 15 MPS combinations) (Note: VRM is vehicle revenue-miles; links denoted by cross-markings indicate a delay between changes in cause and effect; key input and output variables highlighted in yellow)

Table 2 Feedback loops related to key input and output variables for the transit-social/recreational MPS (balancing loops labelled B, reinforcing loops labelled R)

		Key Variable Directly Involved in Loop			
Loop Number	**Loop Links**	**Social/Recreational ASU Lane-Miles**	**Congestion**	**Transit Mode Share**	**Loop Description**
B1	9-10-11-7-8	-	✓	✓	Congestion-driven transit uptake loop
B2	5-6-7-8-15-16-20-21-1-2	✓	✓	-	Whole-system loop
B3	3-1-2	✓	-	-	ASU demand satisfaction loop
B4	22-23-7-8	-	✓	-	Induced demand loop
R1	15-16-10-11-7-8	-	✓	✓	Congestion hurts transit reliability loop
R2	5-6-7-8-9-20-21-1-2	✓	✓	-	Whole-system loop
R3	19-20-21-1-2	✓	-	-	Increasing ASU attractiveness loop
R4	12-13-14-16-10	-	-	✓	Transit expansion increases ridership loop

An example of key loops investigated in this SD approach are displayed in **Figure 2** and listed in **Table 2**. The 8 feedback loops identified in this CLD show the extent of interacting effects between the four main components of the model. While direct, deterministic effects comprise much of each feedback loop's cause-effect behavior, the study presented here focuses on investigating the net effect on transportation outcomes due to the existence of, and interaction between, several competing balancing and reinforcing feedback loops. For conciseness, three loops that cover involvement of all 3 key input/output variables are chosen to explain the feedback behavior being modelled in this analysis: B1, B4, and R3.

Loop B1 begins at congestion; assuming an initial increase in congestion, this would subsequently increase the transit-social/recreational MPS since transit is preferable to driving under increased congestion (link 9). Increased transit-social/recreation MPS also increases overall transit mode share (link 10), which then reduces overall vehicle density since increased transit mode share reduces the number of vehicles using roadways (link 11). When the number of vehicles decreases, traffic mean flow speed responds by increasing (link 7), and increased traffic mean flow speed results in reduced congestion (link 8). Since an initial increase in congestion results in an eventual decrease in congestion, this loop is labelled a balancing loop. This loop represents people shifting towards transit when congestion worsens, which then takes cars off the road, thus ameliorating congestion.

Loop B4 begins at congestion; instead, we may assume initial decreasing congestion, the phenomenon of induced demand then increases the total number of trips taken in the region due to the lowered cost of travel (link 22). Since total trips taken increases, vehicle density on roads also rises (link 23). Increased vehicle density thus reduces traffic mean flow speed (link 7), which thus increases congestion (link 8). Again, an initial change in the origin variable results in a directionally opposite change after moving through the whole loop, thus this is a balancing loop.

Loop R3 begins at social/recreational ASU lane-miles; assuming an initial increase in social/recreational ASU lane-miles, the provision of additional destination capacity thus increases the mode-purpose share of transit-social/recreational trips (link 19). More MPS of transit-social/recreational trips thus increases the share of social/recreational trips (link 20). When social/recreational trip purpose share rises, so does the public desire for more spaces to engage in social/recreational activities (link 21). Therefore, the construction rate of social/recreational ASUs increases, with a delay representing construction time (link 1), eventually resulting in the construction of more social/recreational ASUs (link 2). Since the initial assumed increase in social/recreational ASUs led to eventual further increase in social/recreational ASUs, this loop represents a reinforcing loop.

This CLD is a graphical representation of the numerical model, which contains the governing equations and parameter values that simulate transportation behavior; the mathematical model specification is outlined in the next section. As stated earlier, there are 3 travel modes and 5 trip purposes, and each MPS combination can be described with a single CLD, thus there are 15 total CLDs. **Figure 2** also omits the effect of the transit and social/recreational MPS on commercial, NMT, and transit ASUs for simplicity of communication. The full model specification that includes all governing equations and parameters for all 15 combinations and the omitted effects from this CLD is included in the Supplementary Materials.

As an approach for investigating causal and interrelating system behaviors over time, SD requires the definition of a modelling time horizon and time step. A time horizon of 5 years was chosen to capture the effects of both long-term ASUs (e.g. transit lanes and bike lanes) and temporary/short-term ASUs (e.g. street markets and play streets). A time step of 1 week was chosen as to best represent events both on shorter timescales (e.g. congestion and temporary ASUs) and longer timescales (e.g. construction times and policy implementation delays). SD models are spatially aggregated; the model represents the city as a single unit. The analysis tool was created in the SD software package, Vensim PLE+ 10.2.1.

MODEL SPECIFICATION

Throughout the modelling process, several relationships regarding travel behavior, public perception, and facilities operations are modelled using logistic functions. Logistic functions were chosen due to their ability to represent growth/decay behavior between two limit values with diminishing returns near the limits, and simplicity of interpretation for users of the policy analysis tool. Such functions have been used in existing SD research in transportation and economics (*18*, *42*). Logistic functions used throughout the model have the general form shown in **Equation 1**:

$$y = \left(1 + \exp\left(\sum_i -Sensitivity_i \cdot \left(Input_i - Shift_i\right)\right)\right)^{-1} \qquad (1)$$

In this equation, the subscript *i* represents each input variable for the output variable *y*. $Sensitivity_i$ is thus the sensitivity parameter for i^{th} input variable. $Input_i$ represents i^{th} input variable. $Shift_i$ represents the value of the input variable corresponding to an output value of 0.5 (this is the horizontal translation of the logistic curve). Each logistic function used in the model has its own specification of inputs and associated sensitivities and shifts. Input variables include mode share, trip purpose share, congestion, transit quality and reliability perception, transit service capacity, and lane-miles of ASU types. Output variables include public demand for ASUs, mode-and-trip-purpose shares, and transit quality and reliability perception. Full specification of inputs for each output is listed in the following component descriptions and provided in the Supplementary Materials.

Component 1: ASUs. The ASU component concerns the funding, construction, lifespan, and public demand of ASUs for four purposes: commercial (e.g. outdoor dining, street markets), social/recreational (e.g. popup parks), nonmotorized transportation (NMT) (e.g. bike lanes, widened sidewalks), and transit (e.g. bus-only transit lanes). The commercial and social/recreational ASUs can be grouped together as destination ASUs, where travelers use the ASU as a location to conduct an activity. The NMT and transit ASUs can be grouped as mobility ASUs, where their use facilitates non-driving mobility. From initial time t_0 to time horizon T ($t_0 \leq t \leq T$), accumulation of lane-miles of each ASU type at time t, ASU_t, is determined through an integral of the form in **Equation 2**:

$$ASU_{t+1} = ASU_{t_0} + \int_{t_0}^{t} \left(pd_{ASU} \cdot \frac{funding_{ASU}}{cost_{ASU}} \cdot mileage_{ASU} - \frac{ASU_t}{lifespan_{ASU}} \right) dt \tag{2}$$

where pd_{ASU} is the public demand for an ASU type (where the maximum of 1 means all allocated funding for ASU construction is realized, and the minimum of 0 means no allocated funding is realized), $funding_{ASU}$ is the weekly funding allocated to construction of an ASU type, $cost_{ASU}$ is the construction cost per project of an ASU type (together, these two parameters are defined as a single funding-to-cost ratio (FtCR)), $mileage_{ASU}$ is the average number of lane-miles in each type of ASU project, and $lifespan_{ASU}$ represents the number of weeks it takes for the ASU type to deteriorate. Contrasting to public demand, which acts as a funding filter, FtCR represents the city's financial willingness to invest in ASUs (or business willingness for commercial ASUs). Zero FtCR represents no financial willingness, 1 represents willingness to financially support 1 ASU project construction and maintenance per week. No theoretical upper limit on

FtCR exists. In the SD model, ASU construction rate is delayed by a user-defined construction time.

The public demand of each ASU type is defined by a logistic function in the form of **Equation 1** with the input variables listed in **Table 3**, each with a (+) symbol to indicate positive correlation, or a (-) to indicate negative correlation. For each of the four ASU types, there is a public demand logistic function and an integral that informs the construction rate and accumulated allocation of ASUs.

Since the integrals defining the allocation of ASU lane-miles at time $t + 1$ depend on many variables from the previous time-step t (e.g. ASU lane-miles, congestion, mode shares of driving, NMT, or transit), the temporal dynamics of the system dynamics model are driven by these integrals. The aforementioned construction time delay also contributes to the model's temporal dynamics.

Component 2: Roadway Traffic. The roadway traffic model component calculates vehicle counts (both driving and road-based transit) and lane-miles of roadway available for vehicular mobility to determine congestion. Vehicle counts are based on driving and transit mode shares determined in Component 4, and a baseline assumption of total trips in the study region, starting at a fixed historical value and growing with population growth. Lane-miles of roadway for vehicular mobility is defined as a baseline number of lane-miles in the study region, with the number of lane-miles of ASUs that remove a travel lane subtracted from this baseline.

Congestion is calculated as a fractional reduction of free-flow speed for the mean flow speed of traffic in the city. The mean flow speed of traffic in the city is determined using the macroscopic fundamental diagram, first proposed by Newell, based on vehicle density (*43–46*). The functional form of the fundamental diagram used is given by **Equation 3**:

$$v_m = v_f\left(1-e^{-\frac{g}{v_f}\left(\frac{1}{k}-\frac{1}{d}\right)}\right) \qquad (3)$$

where v_m is the mean traffic flow speed [miles/hour], k is the vehicle density [vehicles/mile], v_f is the free-flow speed [miles/hour], g is the gradient of the flow-density curve at jam density [1/hour], and d is the vehicle spacing at jam density [miles/vehicle].

The lane-miles of roadway used in the vehicle density calculation is based on the total lane-miles of roadway in Seattle minus lane-miles of ASUs that remove a travel lane. The number of vehicles in the vehicle density calculation is calculated using mode shares and total number of trips in the study region. Drive-mode trips contribute 1 vehicle per 1.2 trips. The number of transit vehicles is calculated using the number of transit trips and the percentage of transit trips by bus (therefore, on a roadway) and average number of trips per bus (*37–39*). A logisitic function in the form of **Equation 1** with one input (transit ASU lane-miles) estimates the fraction of transit vehicles that use transit lanes, up to a user-defined maximum fraction. This proportion of vehicles using transit lanes are not counted towards congestion calculations.

Congestion is defined using **Equation 4**:

$$Congestion = 1-\frac{v_{m,w}}{v_f} \qquad (4)$$

where $v_{m,w}$ is a weighted mean flow speed using the speed, defined using **Equation 5**:

$$v_{m,w} = \frac{v_m}{r_{eff}}\left(f_{tc}\cdot r_{calm}+\left(r_{eff}-r_{calm}\right)\right) \qquad (5)$$

where r_{eff} is the roadway lane-miles useable for automobility, r_{calm} is the ASU lane-miles that have a traffic-calming effect (e.g. outdoor dining stalls), and f_{tc} is the traffic-calming factor (where a value of 0.8 represents a 20% slowing of traffic adjacent to a traffic-calming ASU). A traffic-calming ASU is one that does not remove a travel lane. The congestion variable calculated in this component is an input for several logistic functions throughout the SD model.

The congestion variable contributes towards feedback to the total number of trips in the study region to model the effect of induced demand. An induced demand factor multiplies the baseline number of total trips to define the total trips at the current model timestep. This induced demand factor is defined using **Equation 6**:

$$Induced\ Demand\ Factor = 1 - \gamma\left(\frac{c_{prev} - c_{current}}{c_{prev}}\right) \tag{6}$$

where γ is the elasticity of traffic volume with respect to travel time, c_{prev} is the congestion at a previous timestep, and $c_{current}$ is the congestion in the current timestep. The previous timestep acts as a reference level for current trip-making behaviour; this is defined as 2 weeks prior to the current timestep in the SD model. This delay between previous congestion and current amount of trip-making also contributes towards the SD model's temporal dynamics. The value of γ is set to -0.5, the average short-term elasticity of traffic volume with respect to travel time on urban roads as reported by Goodwin (*9*).

<u>Component 3: Transit Operations.</u> The transit operations component provides a mechanism for the study region's transit agency to modify the level of service provided (in terms of total vehicle revenue-miles) at periodic intervals based on transit system occupancy. The formulation of this component is operator-neutral; operations are assumed to be managed by a single generic agency. Parameters controlling service adjustment intervals and levels of increase/decrease are modeler-defined, reflecting the model's capacity to analyze differing transit policies.

Public perception of transit quality and reliability is also defined as a logistic function with the following inputs and their positive or negative associations with the output: congestion (-), transit service capacity (+), lane-miles of transit ASUs (+), operating expenses per VRM (+). Since the model focuses on the influence of factors related to traffic and level of service, the influence of other factors outside of roadway conditions such as personal safety, comfort, cleanliness, and information on transit quality and reliability are accounted for in the "operating expenses per VRM" (*47*).

<u>Component 4: Travel Behavior.</u> The travel behavior component considers the outputs of the previous three components as inputs to determine combined MPSs of all trips in the study region. For the aforementioned three modes and five purposes, 15 total MPS combinations are considered. Each MPS is determined using a logistic function in the form of **Equation 1**. The inputs for each MPS with their positive or negative associations are summarized in **Table 4**.

These MPSs are then converted into mode shares by summing each mode's MPSs across all purposes, then normalizing the mode shares for a unit total. Likewise, MPSs are converted into purpose shares by summing each purpose's MPSs across all modes, then normalizing the purpose shares for a unit total. During this process, mode and purpose shares are calibrated by applying adjustment factors to match historical mode and purpose shares. Mode and purpose shares calculated through this aggregation and normalization process across disaggregate MPS combinations are used to determine public demand for the four ASU types and roadway traffic performance measures, thus closing the loop in the SD feedback structure. Numbers of trips made by each mode are determined by multiplying the mode shares by the total trips made in the study region.

Total drive VMT is also output in the model by adding the VMT from bus transit to the VMT of all drive trips in the model. VMT from drive trips are calculated by multiplying the number of drive trips for each purpose by a reference drive trip distance for each trip purpose. These reference trip distances were defined as median drive trip mileage, as calculated using data from the Puget Sound Regional Council's (PSRC) 2019 Household Travel Survey (HTS) for Seattle, and the US Federal Highway Administration's (FHWA) 2017 National Household Travel Survey for Phoenix (*40*, *41*).

MODEL CALIBRATION AND VERIFICATION

The SD model was calibrated to match historical values of mode-purpose shares in both Seattle and Phoenix. Regional travel behavior data such as total trip counts and baseline mode and purpose splits were derived from the PSRC 2019 HTS for Seattle and FHWA 2017 NHTS for Phoenix (*40*, *41*). Roadway traffic performance parameters are derived from Newell's hypothesized parameters and the FHWA Highway Capacity Manual (HCM) Reference Guide (*43*, *48*). Transit operations data was obtained from the Federal Transit Administration's (FTA) National Transit Database (NTD) annual agency profiles for King County Metro (KCM) and Sound Transit (ST) for Seattle, and Valley Metro for Phoenix (*37–39*). Since transit in the SD model is operator-neutral and assumes a single agency, parameters for Seattle were derived from an average of KCM and ST, weighted by VRM, and a knockdown factor applied to service provision due to both KCM and ST operating beyond Seattle city limits. A similar knockdown factor was applied to Valley Metro service provision due to their operations outside of Phoenix city limits.

Aside from parameter values obtained from external data sources, several exogenous variables were set for a baseline reference based on estimates of ASU construction times and lifespans, and the number of lane-miles used by previous ASU projects for each type (commercial, social/recreational, NMT, transit) in Seattle and Phoenix.

Model calibration was performed by tuning parameters in the model associated with MPS logistic functions, with a baseline reference simulation for each city meeting several criteria:

1. Mode-purpose shares fell within 0.5% of mode splits reported in the PSRC 2019 HTS and FHWA 2017 NHTS.
2. The number of lane-miles of each ASU type reaches a long-term equilibrium within 5% of the initial number of lane-miles of that type (i.e., no change to the existing alternate uses of city streets).
3. No changes in output behavior when altering the baseline timestep of 1 week to 0.1 or 10 weeks.

The baseline funding-to-cost-ratios (FtCR) that generate model outputs meeting these 3 criteria are listed in **Table 5**. The full calibration procedure and verification metrics are provided in the Supplementary Materials.

The model was verified by comparing the effect of lane-miles of ASU allocation on mode share from the model to values in literature. Each additional lane-mile of transit ASU is associated with a 0.039 percentage-point increase in transit mode share in the Seattle model and a 0.0019 percentage-point increase in the Phoenix model. An 2018 analysis of the New York Metropolitan Transit Authority’s Select Bus Service (SBS) improvements found that 41.4 miles of SBS improvements over six routes were associated with a 1.9 percentage-point increase bus mode share, corresponding to a 0.046 percentage-point increase in bus mode share per mile of improvement (*6*). While the correlation between lane-miles of bus improvements and mode share are not expected to be exactly linear, our SD models generated similar associations to the New York study's finding.

A similar comparison can also be made regarding NMT: each additional lane-mile of NMT ASU is associated with a 0.061 percentage-point increase in NMT mode share in the Seattle model and a 0.014 percentage-point increase in the Phoenix model. A study of the bike lane network expansion in Minneapolis-Saint Paul found that each mile of bike lane was associated with a 0.0038 percentage-point increase in cycling mode share (*49*). Although our per-lane-mile increase in NMT mode share is greater than the reported figures in literature for cycling, the model is specified for both cycling and walking modes, not cycling alone. If the percentage-point increases in NMT mode share from the model is split according to the walking-to-cycling ratio reported in the PSRC 2019 HTS (15.2 : 1 ratio walking : cycling) and in the FHWA 2017 NHTS (20.1 : 1 ratio walking : cycling), each additional mile of NMT ASU becomes associated with 0.0040 percentage points of cycling mode share in Seattle and 0.0007 percentage-points in Phoenix. The Seattle value is closer to the value from the Minneapolis-Saint Paul study; these values are comparable as the scale of Seattle's and Minneapolis's bike infrastructure are also similar (approximately 100 miles of on-street bike lanes) (*50*, *51*). The discrepancy in the Phoenix value may be attributed to the scale of Phoenix's on-street bike infrastructure: currently, there are 1190.81 miles of on-street bike lanes, thus each additional lane-mile of NMT ASU infrastructure in Phoenix may have diminished returns compared to Seattle or Minneapolis-Saint Paul (*52*).

Table 3 Positive and negative associations of input variables for logistic functions indicating public demand for ASU types

	Input Variable Association								
ASU Type	Commercial Trip Purpose Share	Social-Recreational Trip Purpose Share	NMT Mode Share	Transit Mode Share	Commercial ASU Lane-Miles	Social-Recreational ASU Lane-Miles	NMT ASU Lane-Miles	Transit ASU Lane-Miles	Transit Quality and Reliability
Commercial	+				–				
Social/Recreational		+				–			
NMT			+	+			–		
Transit			+	+				–	+

Table 4 Positive and negative associations of input variables for logistic functions indicating mode-purpose shares

	Input Variable Association							
MPS	Congestion	Transit Quality and Reliability	Transit Service Capacity	Fare Price	Commercial ASU Lane-Miles	Social-Recreational ASU Lane-Miles	NMT ASU Lane-Miles	Transit ASU Lane-Miles
Drive-Home	–							
Drive-Work/School	–							
Drive-Commercial	–							
Drive-Social/Recreational	–							
Drive-Errand/Escort	–							
Transit-Home	+	+	+	–				+
Transit-Work/School	+	+	+	–				+
Transit-Commercial	+	+	+	–	+			+
Transit-Social/Recreational	+	+	+	–		+		+
Transit - Errand/Escort	+	+	+	–	+	+		+
NMT-Home	+						+	
NMT-Work/School	+						+	
NMT-Commercial	+				+		+	
NMT-Social/Recreational	+					+	+	
NMT-Errand/Escort	+				+	+	+	

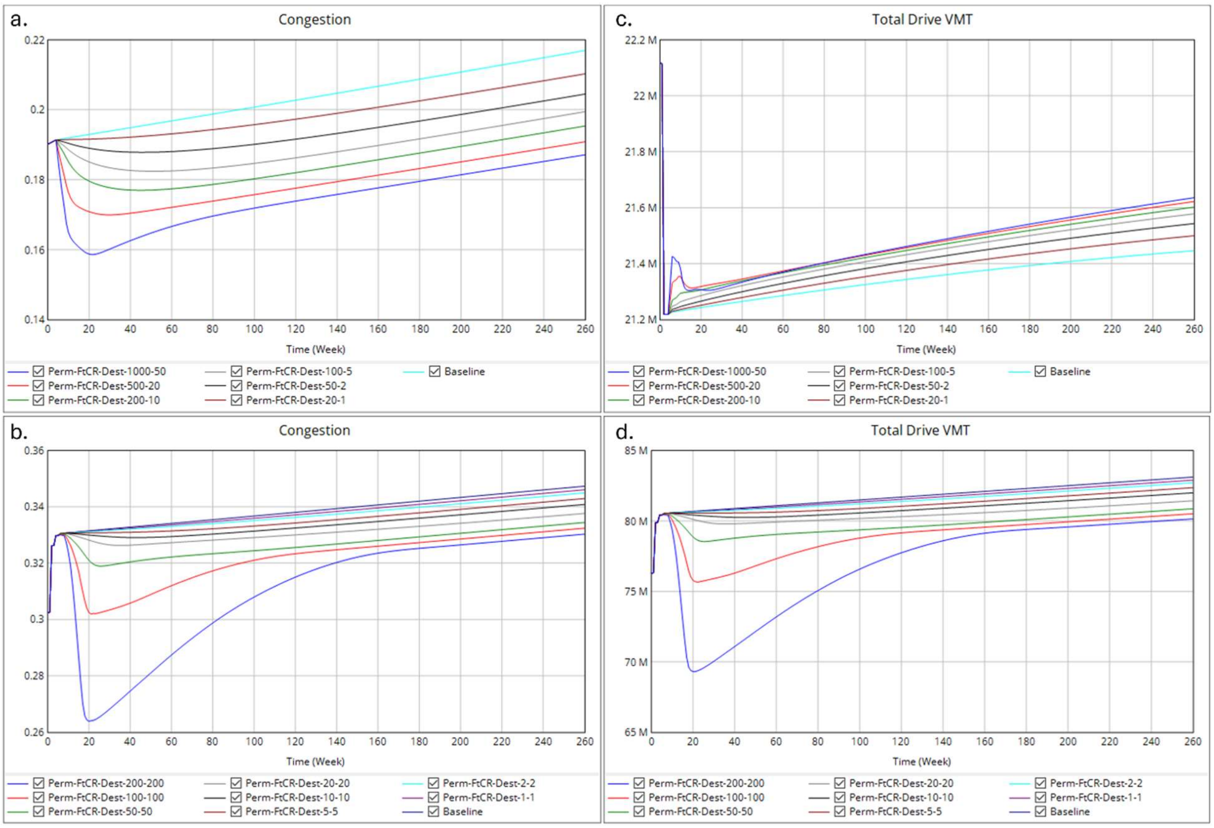
The total drive VMT output from the model was also verified against VMT estimates from historical data. The Seattle model baseline reference outputs a daily VMT of 3.22 million miles, which is within 2.5% of the daily VMT estimate for Seattle of 3.29 million miles, derived from Washington State Department of Transportation (WSDOT) data for Seattle (*53*). The Phoenix model baseline reference outputs a daily VMT of 11.1 million miles, which is also within 2.5% of the daily VMT estimate for Phoenix of 10.85 million miles, derived from Arizona Department of Transportation data for Phoenix (*54*).

The ability of the model to emulate both the associations between ASUs and mode share reported in New York City and Minneapolis-Saint Paul, and historical VMT estimates for both Seattle and Phoenix validates its use for investigating further associations between ASUs and travel behavior, transit operations, and traffic performance in the context of major US cities like Seattle and Phoenix.

RESULTS

Using the baseline reference simulations determined in the model calibration and validation process as a comparison, varying levels of ASU implementation were tested to investigate potential downstream and interacting effects, temporary or delay effects, and thresholds in system behavior. The effect of varying funding-to-cost-ratios (FtCR) for each type of ASU was investigated by increasing FtCRs from its baseline level according to the scheme specified in **Table 5**. This scheme represents a sensitivity analysis of changing roadway allocation. The FtCR levels within scenario were chosen to represent increases in funding levels, thus an increase in allocation of roadway lane-miles for each ASU focus. The initial value was chosen as one or two steps above the baseline FtCR value, then FtCRs are increased according to the pattern 1, 2, 5, 10 within each order of magnitude. Recall that an FtCR of 1 represents a city's financial capability of supporting the construction and ongoing maintenance costs of 1 ASU of that type for 1 week. Baseline values of FtCR vary in magnitude as they reflect the initial "ground truth" lane-miles of ASU of each type in each city model, as described in the previous Model Calibration section.

Six scenarios were tested: commercial, social/recreational, NMT, transit, destination (combined commercial and social/recreational), and mobility (combined NMT and transit). For each of the Seattle and Phoenix models, transportation outcomes across the FtCRs in each scenario were plotted against the baseline to observe the effects of each scenario. A note on the curves and legends presented in **Figure 3** to **Figure 6** and **Figure 9** to **Figure 15**: each scenario's output includes results from a set of simulation runs comprising of the baseline FtCR level, plus each FtCR level specified in **Table 5**. Each curve represents the response under a single FtCR level. The name of each curve is indicated in the legend following the naming convention "Perm-FtCR-[Scenario Name]-[FtCR level]". For example, the curve named "Perm-FtCR-Dest-1000-50" in Error! Reference source not found.



a represents the dynamic response of congestion over time under the Destination scenario when the commercial ASU FtCR is 1000 and the social/recreational ASU FtCR is 50.

Under monotonically increasing FtCRs of each ASU type, the model outputs monotonically increasing lane-miles of the respective ASU type. Aside from the number of transit ASU lane-miles (which are modelled with reduced deterioration rates to represent greater installation permanence), the other three ASU types exhibit long-term stability after a potential initial transition shock at high FtCRs, as depicted in **Figure 3**. For conciseness, all plots of ASU lane-miles under each of the six ASU scenarios for each city model are provided only in the Supplementary Materials, as the monotonic positive correlation between FtCR and ASU lane-miles has been established.

Table 5 FtCR scheme for investigating effect of ASU allocation on transportation outcomes

	Seattle	Phoenix
Alternate Street Use Scenario (ASU FtCR varied)	**FtCRs**	**FtCRs**
Baseline Values (Commercial – Social/Recreational – NMT – Transit)	6.65 – 0.279 – 0.047 – 0.0069 (no further levels)	0 – 0 – 0.94 – 0.001014 (no further levels)
Commercial (Commercial)	20, 50, 100, 200, 500, 1000	1, 2, 5, 10, 20, 50, 100, 200
Social/Recreational (Social/Recreational)	1, 2, 5, 10, 20, 50	1, 2, 5, 10, 20, 50, 100, 200
NMT (NMT)	0.2, 0.5, 1, 2, 5, 10, 20	2, 5, 10, 20, 50, 100
Transit (Transit)	0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1	0.002, 0.005, 0.01, 0.02, 0.05, 0.1, 0.2, 0.5
Destination (Commerical – Social/Recreational)	20 – 1, 50 – 2, 100 – 5, 200 – 10, 500 – 20, 1000 – 50	1 – 1, 2 – 2, 5 – 5, 10 – 10, 20 – 20, 50 – 50, 100 – 100, 200 – 200
Mobility (NMT-Transit)	0.2 – 0.01, 0.5 – 0.2, 1 – 0.05, 2 – 0.1, 5 – 0.15, 10 – 0.2, 20 - 0.25, 5 – 0.2, 10 – 0.5, 20 – 1	2 – 0.002, 5 – 0.005, 10 – 0.01, 20 – 0.02, 50 – 0.05, 100 – 0.1, 200 – 0.2

Notes: FtCR value indicates the number of ASU projects of that type that are financially supported per week; hyphens between FtCR values separate ASU types in the order specified in parentheses; commas between sets of FtCR values separate between simulation runs of that row’s scenario.

For each scenario, major transportation outcomes are mode share, congestion, and VMT. Comparing the response curves of these outcomes under changing FtCRs in each scenario, four key results emerge:

1. The increased allocation of destination ASUs above baseline levels leads to decreased congestion in both study regions.

2. Threshold levels in NMT ASU allocation must be exceeded before transportation benefits are observed in both study regions.
3. The influence of transit ASUs is only notable in the Seattle model.
4. In the Seattle model, transit ASUs complement NMT ASUs to reduce congestion and VMT up to a threshold level in transit ASU allocation.

Key Result 1: Destination ASUs reduce congestion. Increasing allocation of destination ASUs leads to lower congestion than the baseline for both Seattle and Phoenix models. As stated in our methodology, lower congestion is defined as higher mean traffic flow speed. The effect of increasing ASU lane-miles for commercial and social/recreational purposes on congestion and VMT is presented in Error! Reference source not found.. In both city models, a monotonic increase in destination ASU lane-miles above the baseline amount is associated with a monotonic decrease in congestion. Additionally, there is also a monotonic decrease in VMT in Phoenix. However, the total drive VMT in the Seattle model increased under increasing destination ASU lane-miles.

This difference in VMT response to increased destination ASU lane-miles is due to the difference in the two cities' mode share responses, presented in **Figure 5**. In both models, increased destination ASU is associated with increased NMT mode share, a response due to the increased spatial density of destinations. However, in Seattle, the high initial transit mode share and low initial drive mode share leads to the increase in NMT mode share being drawn disproportionately from transit rather than driving. There is also sufficient congestion decrease from the overall effect of decreased drive and transit mode share, such that driving remains an attractive enough travel mode, thus sustaining higher total drive VMT compared to the baseline under increasing destination ASU lane-miles. Phoenix enjoys both decreases in VMT and congestion due to its high initial drive mode share and low transit mode share; destination ASU lane-miles lead to increased NMT and transit mode shares, thus reducing VMT and congestion.

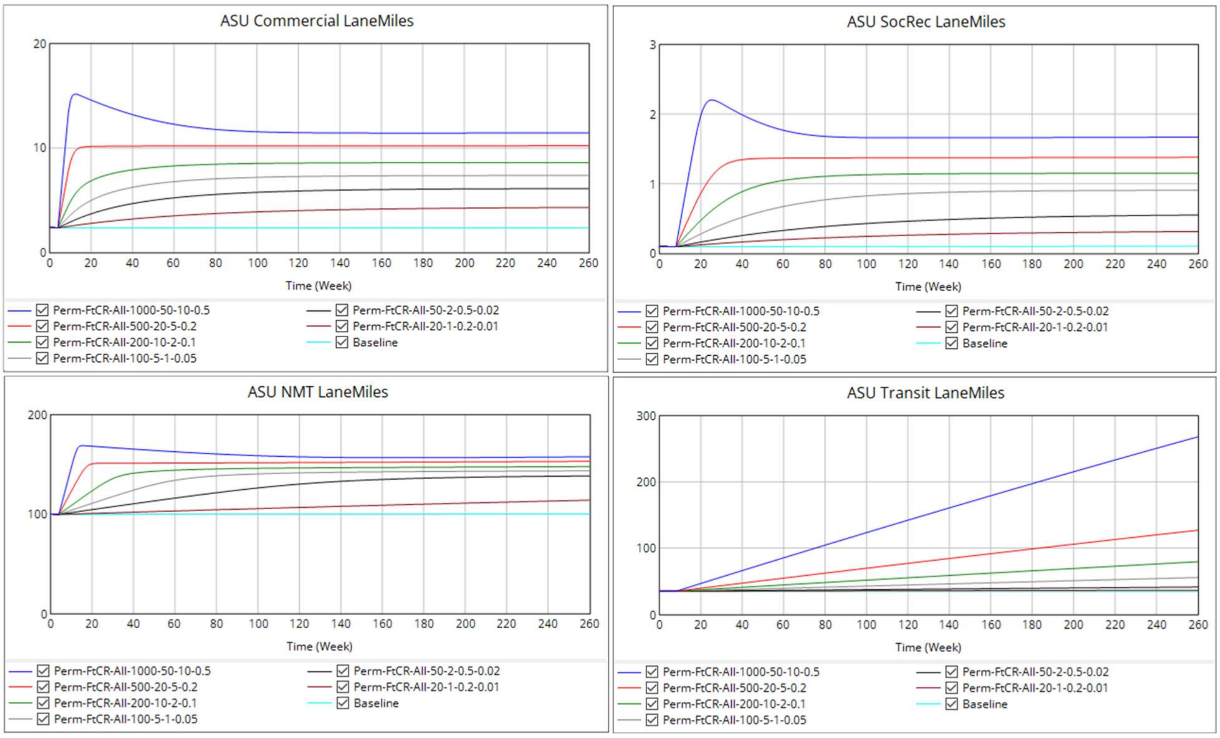


Figure 3 Lane-miles of all ASU types in the Seattle model when FtCR is increased for all ASU types; ASU levels in figure legends shown in the order: commercial – social/recreational – NMT – transit (baseline FtCR level in cyan, highest FtCR level in blue)

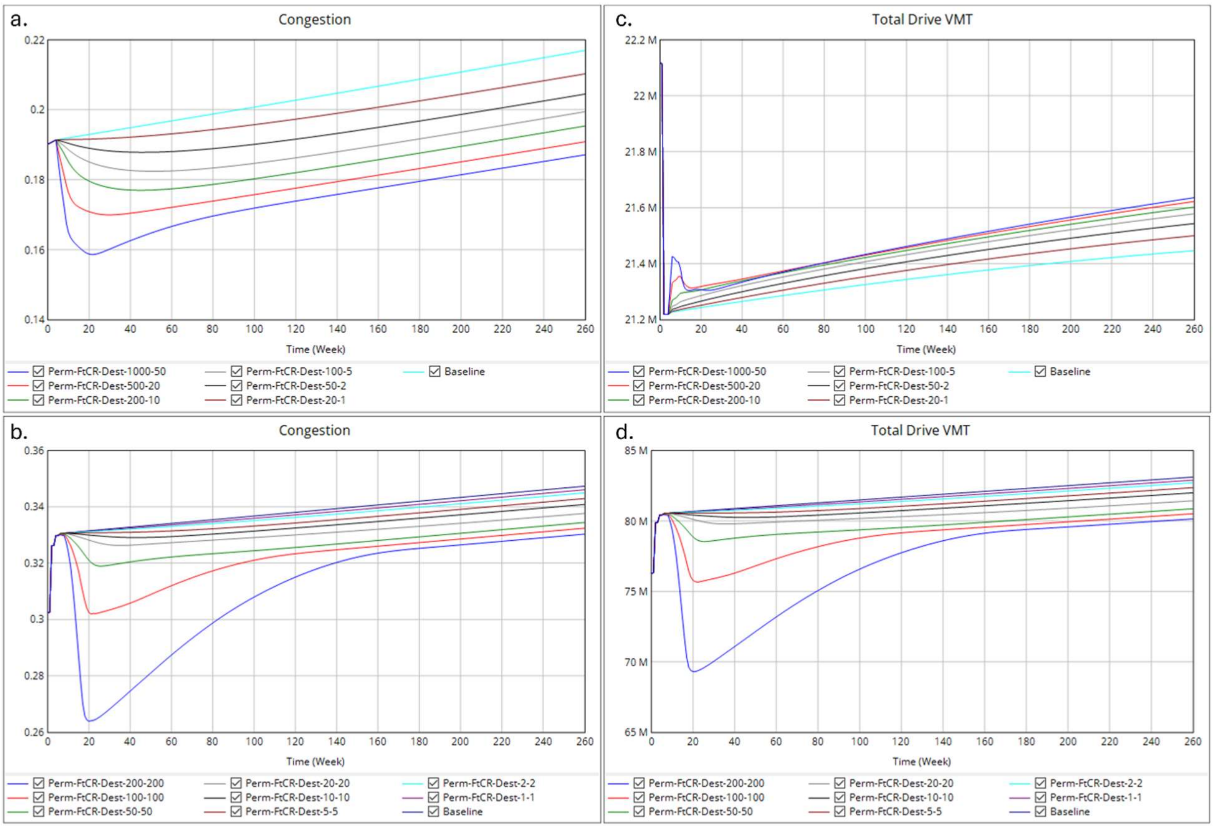


Figure 4 Under the destination ASU scenario, congestion in models for a. Seattle and b. Phoenix, and total drive VMT in models for c. Seattle and d. Phoenix (baseline FtCR level in dark blue, highest FtCR level in blue)

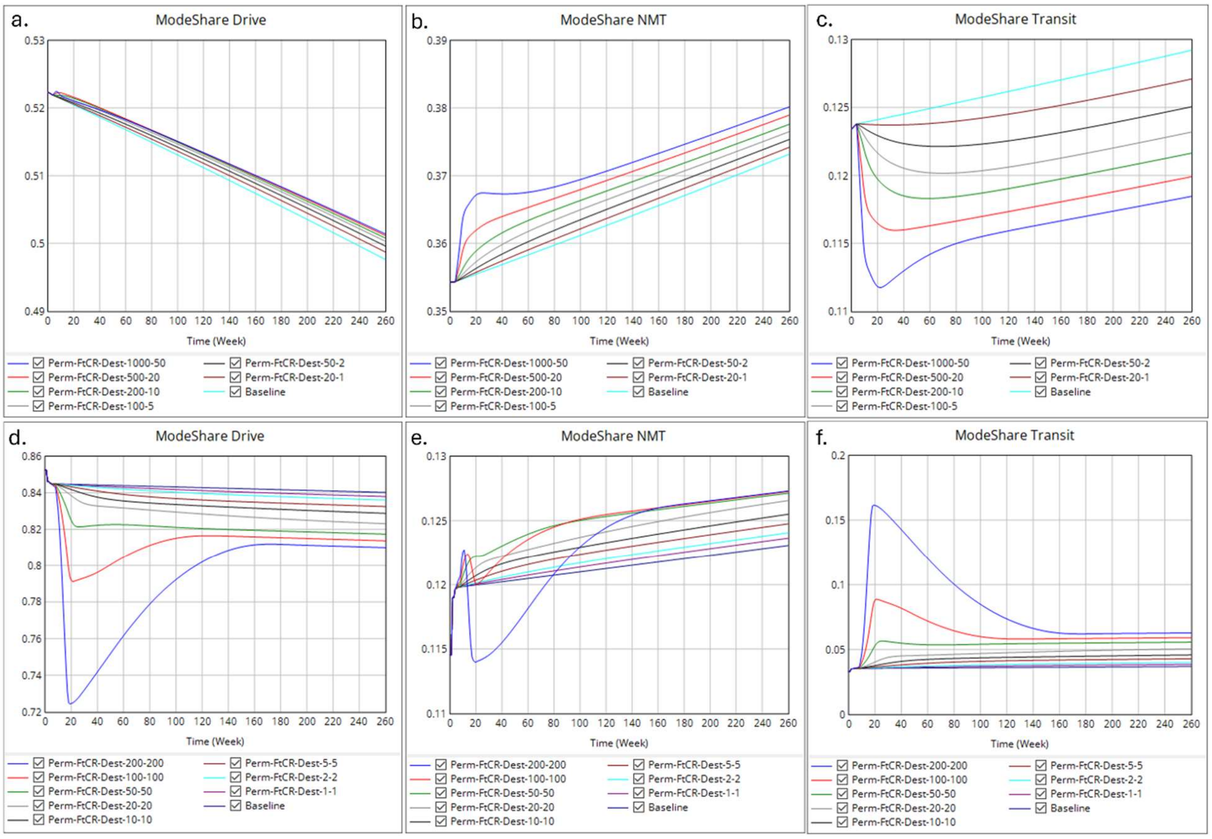


Figure 5 Under the destination ASU scenario, mode shares for Seattle (a., b., and c., baseline in cyan, highest FtCR level in blue) and Phoenix (d., e., and f., baseline in dark blue, highest FtCR in blue)

<u>Key Result 2: NMT ASU thresholds exist for transportation benefits.</u> Under the NMT-only scenarios, both the Seattle and Phoenix models exhibit the need for reaching a threshold level of NMT ASU allocation before a transportation benefit is achieved. The congestion and total drive VMT under the NMT scenario are presented in **Figure 6**. While the Seattle model shows that monotonically increasing NMT ASU allocation decreases congestion monotonically, there exists a threshold FtCR of approximately 0.5, at which the greatest total drive VMT is achieved in the medium-term of 1 to 3 years (52 to 156 weeks). When FtCR is greater than the threshold at 0.5, total drive VMT in the medium-term is less than the threshold VMT, however,

VMT never reduces to below the baseline amount of total drive VMT in the long-term (beyond 3 years, or 156 weeks). The VMT threshold is observed more clearly in **Figure 7**; the peak amount of VMT in the Seattle model at the time horizon of 260 weeks occurs at approximately 130 lane-miles of NMT ASUs – beyond this point, any additional NMT ASU allocation reduces both congestion and VMT.

The Phoenix model displays an inverse of this response in **Figure 6**; for monotonically increasing NMT ASU allocation, total drive VMT decreased monotonically, whereas congestion exhibits a threshold FtCR of approximately 50, at which the greatest congestion is experienced in the long-term. When FtCR is greater than the threshold at 50, congestion in the long-term is less than the threshold congestion, however, congestion never reduces to below the baseline level of congestion in the long-term. The congestion threshold is also observed clearly in **Figure 8**; the highest congestion in the Phoenix model at the time horizon of 260 weks occurs at approximately 2350 lane-miles of NMT ASUs. As with the Seattle model, higher allocation of NMT ASUs beyond this threshold value reduces both congestion and VMT.

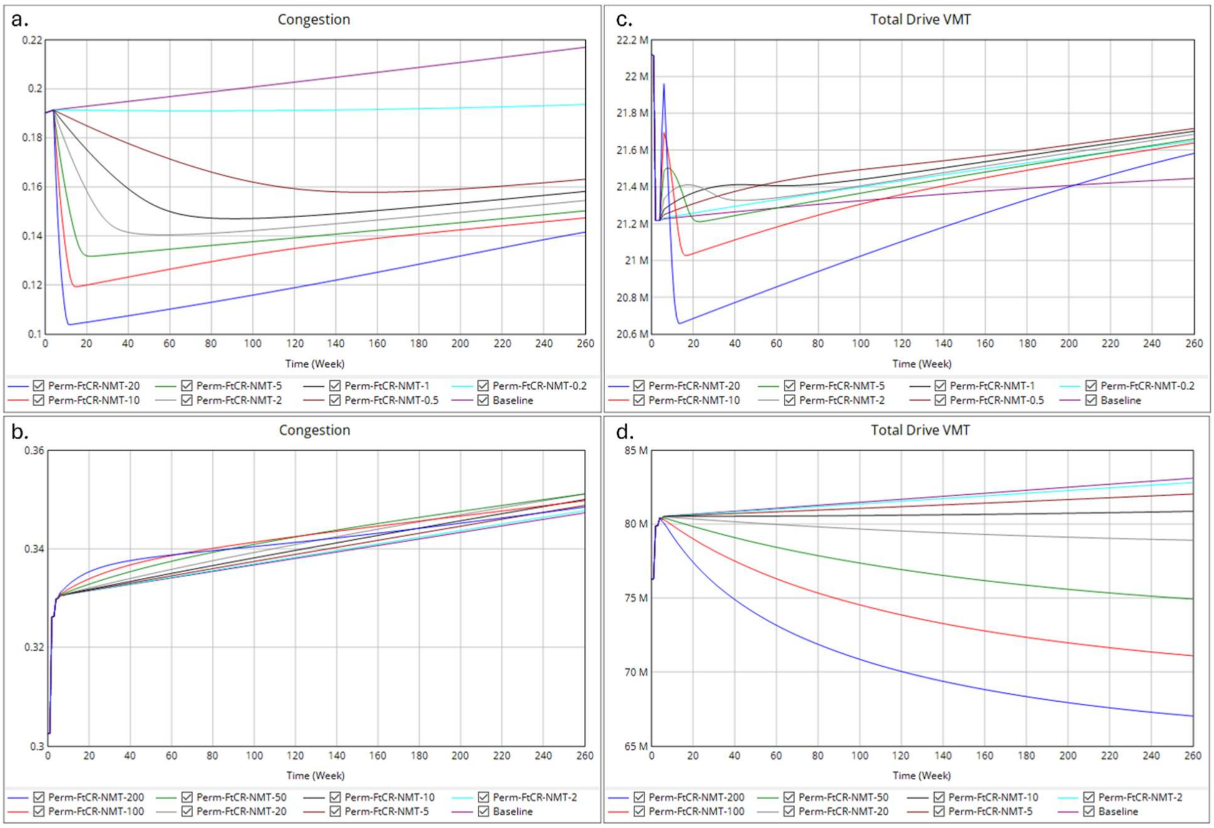


Figure 6 Under the NMT ASU scenario, congestion in models for a. Seattle and b. Phoenix, and total drive VMT in models for c. Seattle and d. Phoenix (baseline in purple, highest FtCR in blue)

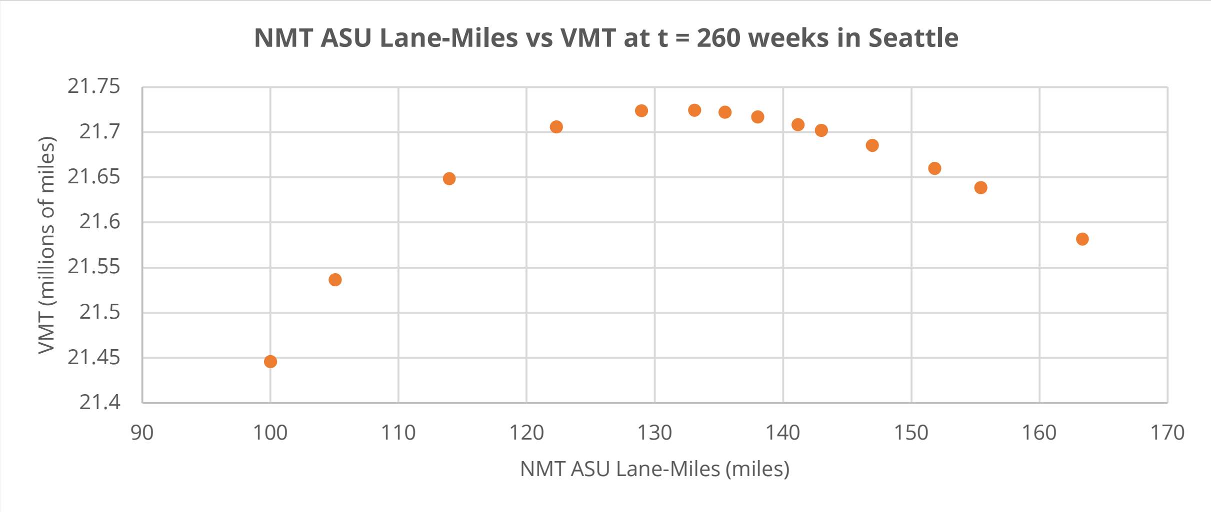


Figure 7 Under the NMT ASU scenario, NMT ASU lane-miles versus total drive VMT at the time horizon (t = 260 weeks) in the Seattle model

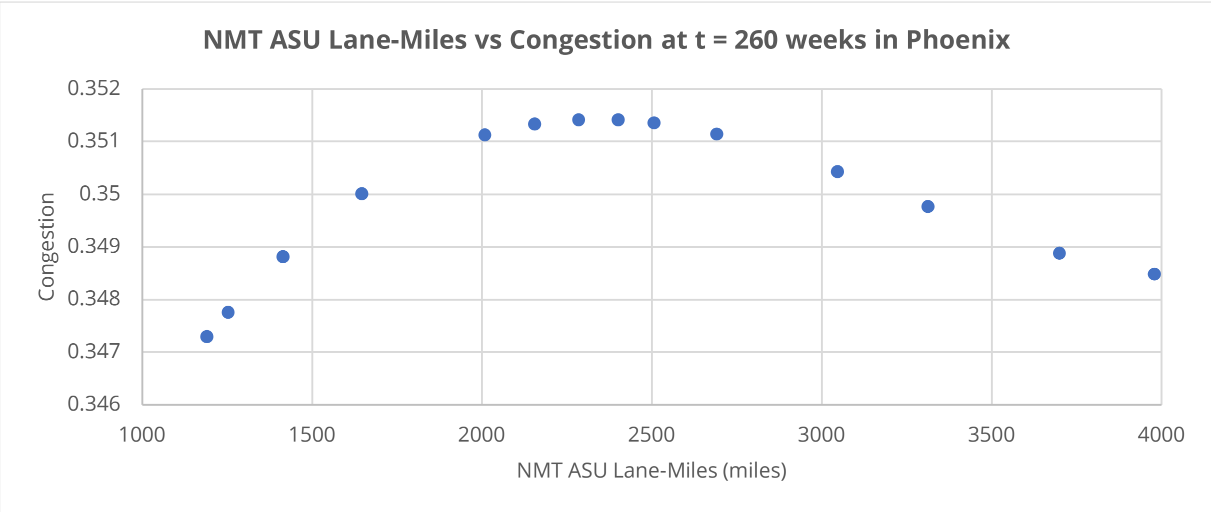


Figure 8 Under the NMT ASU scenario, NMT ASU lane-miles versus congestion at the time horizon (t = 260 weeks) in the Phoenix model

The Seattle threshold observed in **Figure 6** may be explained by also inspecting the mode share response in both city models under the NMT scenario shown in **Figure 9**. The VMT threshold is due to NMT ASUs attracting mode share towards NMT away from transit disproportionately over driving, even though the increased NMT mode share reduces congestion sufficiently to induce higher drive mode share above baseline levels until the threshold is reached. Beyond the threshold, the level of NMT ASU allocation becomes attractive enough to begin reducing drive mode share. The Phoenix model mode share response under the NMT scenario is provided to demonstrate that there are no interacting effects between modes under increased NMT ASU allocation. Rather, the Phoenix effect is due to the high proportion of total city roadway lane-miles that are repurposed for NMT use and no longer available for driving. **Figure 10** shows that at the threshold FtCR of 50, at the model time horizon of 260 weeks, there are 2687 lane-miles of NMT ASUs: this represents a 126% increase over the baseline amount of 1191 lane-miles of NMT ASUs and 21.4% of the total number of lane-miles in the City of Phoenix of 12,557 lane-miles (*35*, *36*). This high proportion of repurposed roadway has the effect of increasing traffic density, which in turn reduces traffic flow speed, thereby increasing congestion. The maximum level of congestion at the threshold is relieved by further increasing NMT ASU allocation to the extent that the effect of reducing drive mode share overcomes the effect of increasing traffic density.

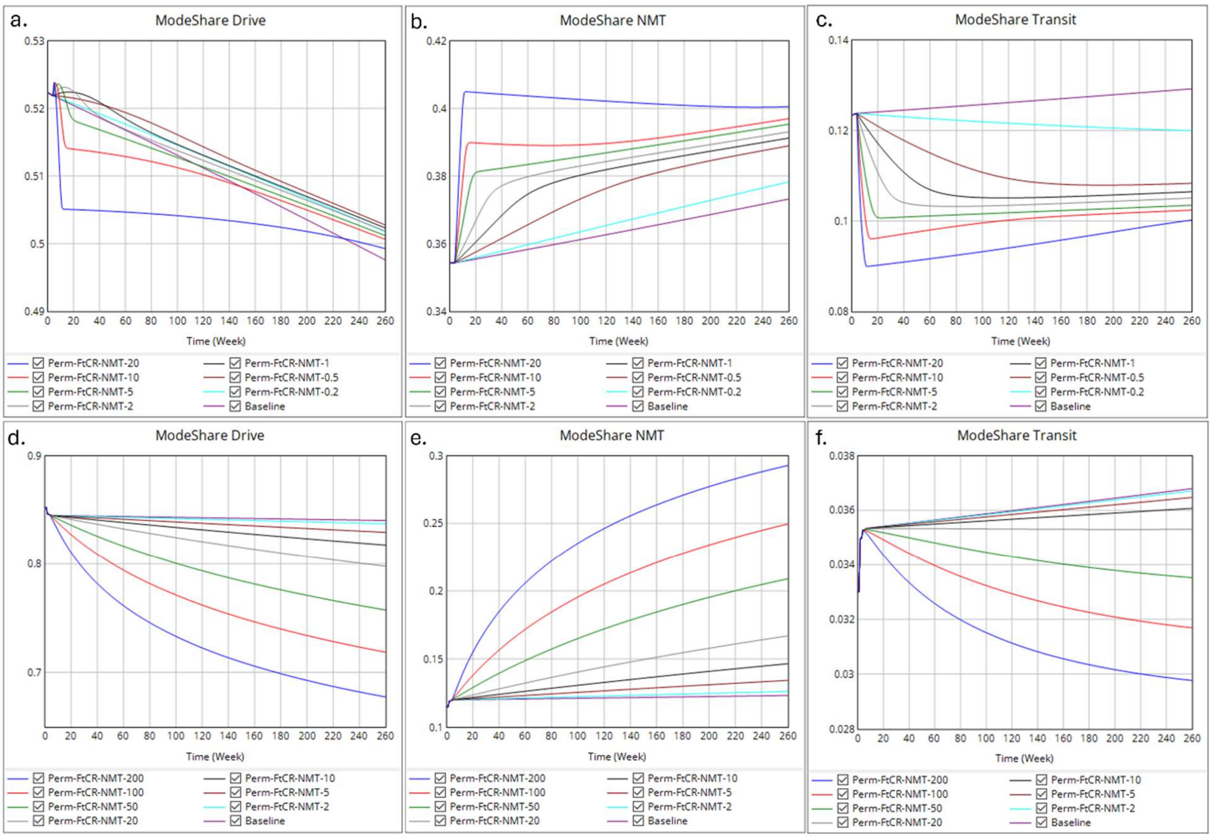


Figure 9 Under the NMT ASU scenario, mode shares for Seattle (a., b., and c) and Phoenix (d., e., and f.) (baseline in purple, highest FtCR in blue)

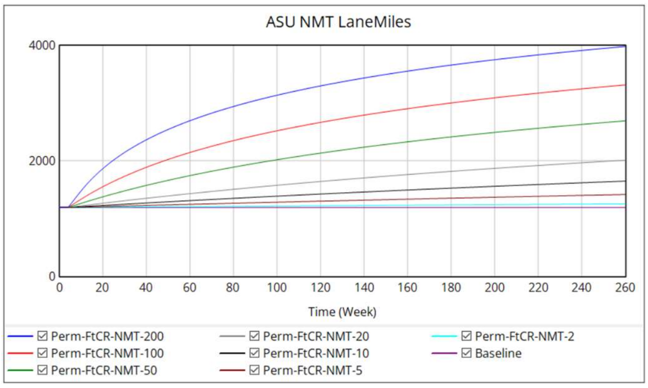


Figure 10 Lane-miles of NMT ASUs in the Phoenix model under the NMT ASU scenario

Key Result 3: Transit ASU influence is only notable in Seattle. Increasing the number of transit ASU lane-miles has a more significant influence on shifting the level of congestion and total drive VMT away from baseline levels in Seattle compared to in Phoenix. The comparison of the two cities' transportation outcomes under the transit ASU scenario is shown in **Figure 11**. The relevance of this result is also apparent when comparing the transportation outcomes between the NMT-only and mobility (combined NMT and transit) ASU scenarios. While including transit alongside NMT leads to differences in transportation outcomes compared to the NMT-only scenario in the Seattle model (explored further under Key Result 3), there is little discernible difference in congestion and VMT when comparing the two scenarios in the Phoenix model, as depicted in **Figure 12**. The Phoenix model only shows discernible differences in transit mode share under the NMT-only and mobility scenarios (**Figure 13**), however, the baseline transit ridership is so low that these differences do not result in meaningful shifts in other transportation outcomes.

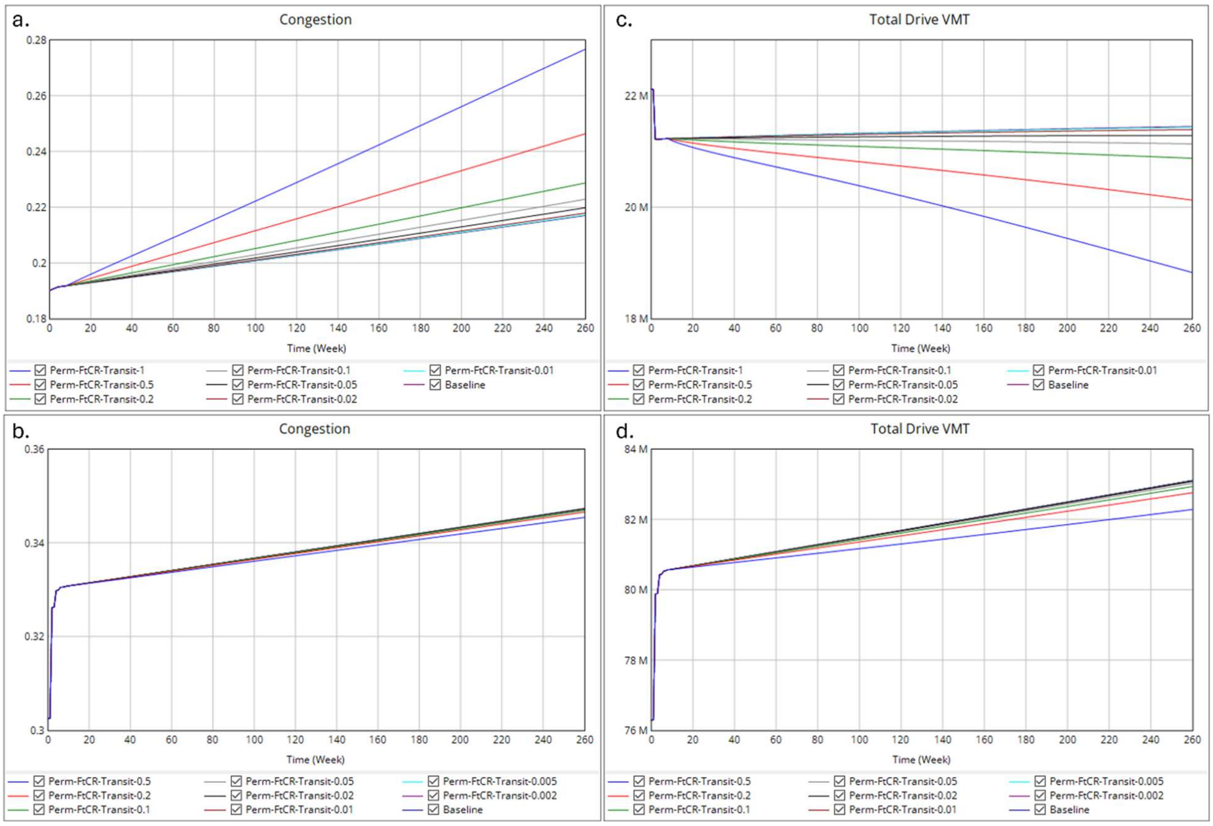


Figure 11 Under the transit ASU scenario, congestion in models for a. Seattle and b. Phoenix, and total drive VMT in models for c. Seattle and d. Phoenix (baseline for a. and c. in purple, baseline for b. and d. in dark blue, highest FtCR in blue for all sub-figures)

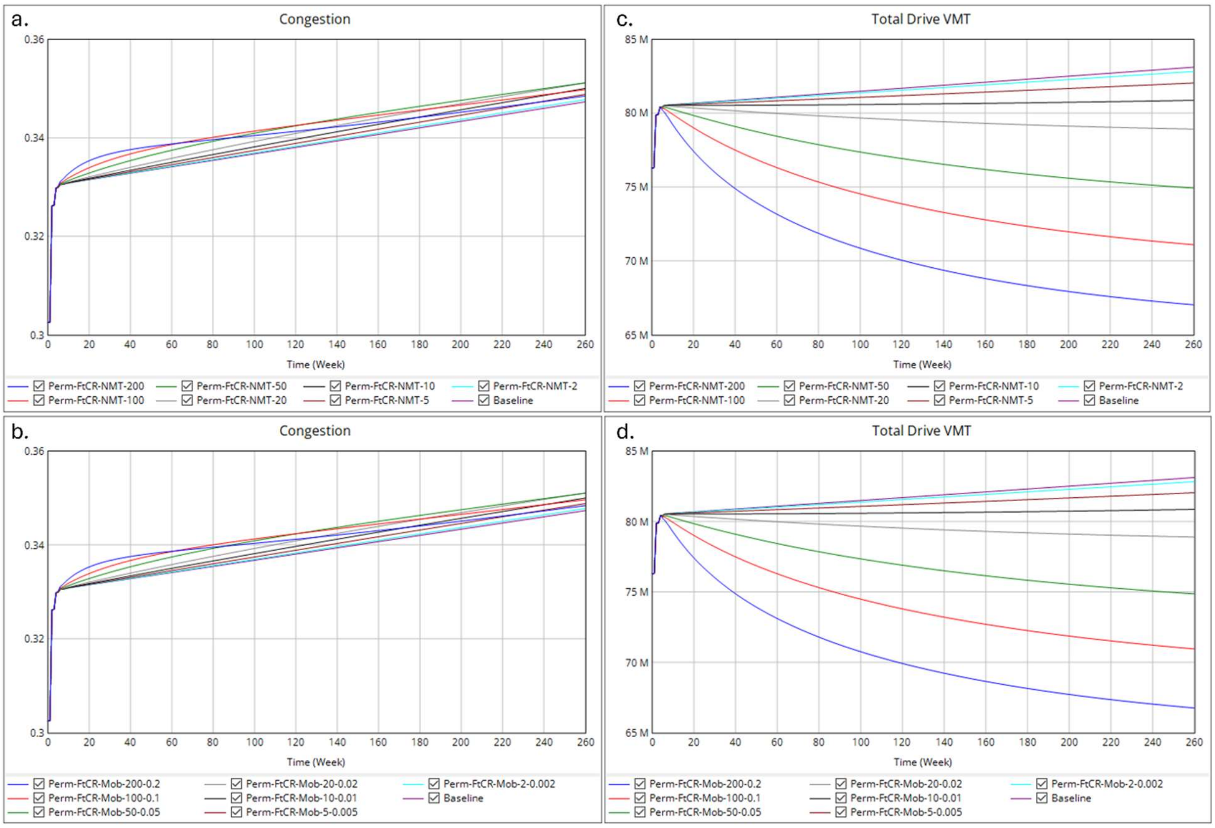


Figure 12 Comparison of congestion and VMT in the Phoenix model under the NMT-only scenario (a. and c.) and under the mobility scenario (b. and d.) (baseline in purple, highest FtCR in blue)

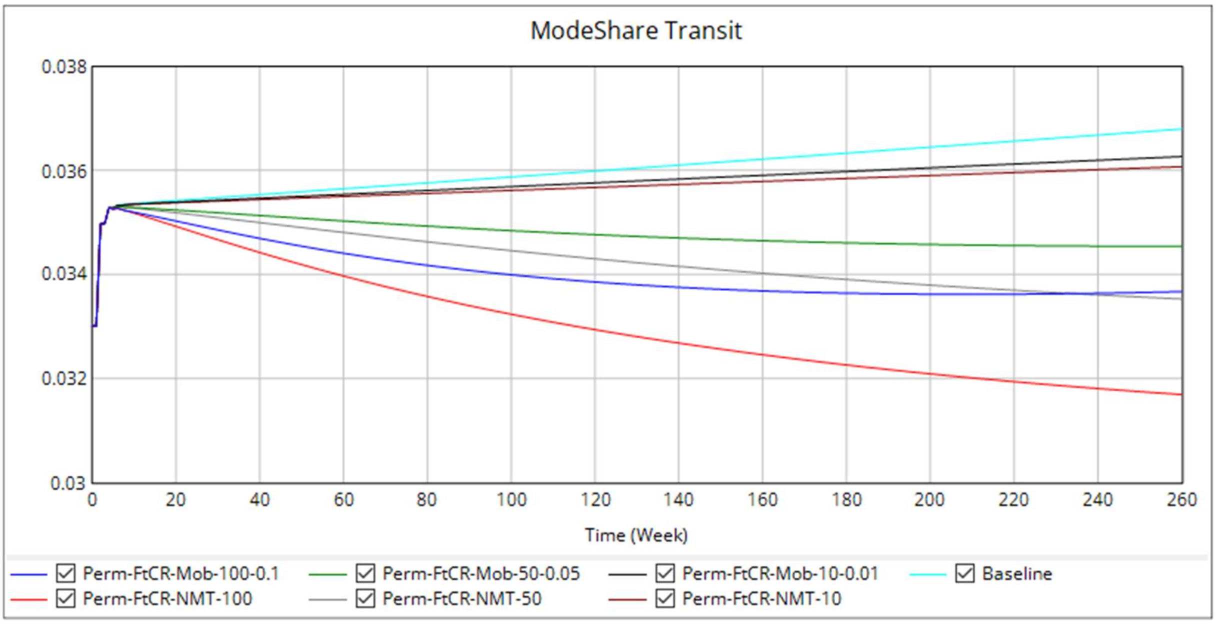


Figure 13 Transit mode share in the Phoenix model under the NMT-only scenario (brown, grey, red) and the mobility scenario (black, green, blue); note the paired NMT ASU FtCRs in the legend for NMT and mobility scenario simulations

<u>Key Result 4: Transit ASUs complement effects of NMT ASUs to reduce both congestion and VMT in the Seattle model, up to a threshold level; this was not observed in the Phoenix model.</u> As discussed in the previous result, the Seattle model demonstrates a threshold in NMT ASUs that must be exceeded to generate reduced total drive VMT in the long term (**Figure 6c.**). Under the mobility scenario, the combined effect of NMT and transit ASUs leads to a more sustained reduction in total drive VMT compared to the baseline, as shown in **Figure 14**. Although a VMT threshold remains apparent when the NMT FtCR is 0.5 and transit FtCR is 0.02, the higher combined FtCRs from 2 – 0.1 to 20 – 0.25 display lower VMT than the baseline, sustained over the long-term. The sustained VMT reduction in the long-term is evident beyond a threshold of 170 lane-miles of combined NMT and transit ASUs (**Figure 16a.**). Furthermore, this sustained reduction in VMT occurs alongside congestion reduction, although the level of

congestion under the mobility ASU scenario (**Figure 14a.**) is marginally higher than under the NMT-only scenario (**Figure 6a.**) when transit FtCR is greater than 0.05. Also, the congestion improvements at the time horizon significantly flatten beyond the threshold 200 lane-miles of combined NMT and transit ASUs (**Figure 16a.**). Nonetheless, congestion is lower in all funding and ASU allocation levels compared to the baseline.

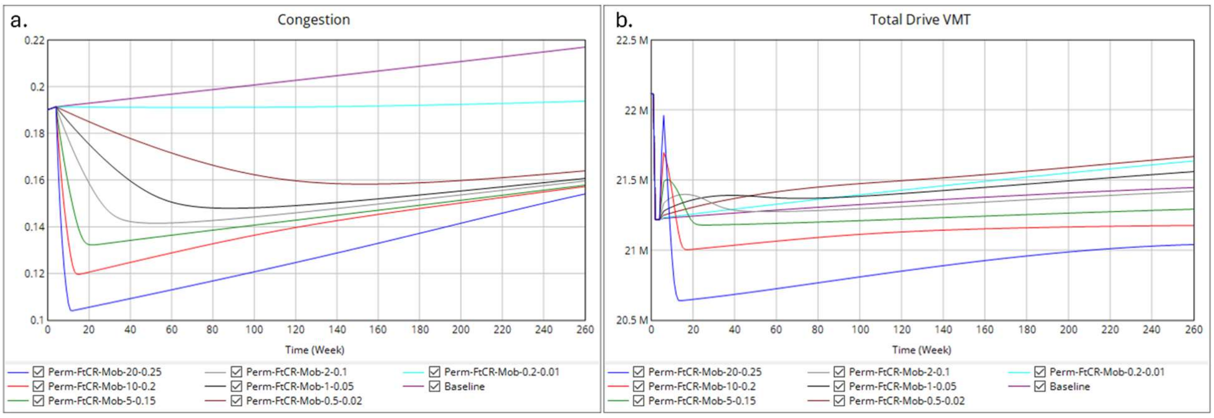


Figure 14 Under the mobility ASU scenario with low-to-moderate transit FtCRs, a. congestion and b. total drive VMT in the Seattle model (baseline in purple, highest FtCR in blue)

The ability for transit ASUs to complement NMT ASUs in reducing both congestion and total drive VMT in the long-term compared to the baseline is limited to moderate transit FtCRs. At higher levels of transit funding (i.e. transit ASU FtCR exceeds a threshold of 0.5), the medium-to-long-term congestion level in the Seattle model begins to exceed the congestion of the threshold level, shown in **Figure 15**. The red and blue curves indicate a level of investment in transit ASUs that lead to a significant-enough proportion of roadway lane-miles in Seattle being repurposed for transit use. At the model time horizon of 260 weeks, the congestion threshold transit FtCR of 0.5 leads to 268 lane-miles of roadway being repurposed for transit use, representing 6.8% of Seattle's total available roadway lane-miles (*34*). This repurposing of street space increases traffic density, which in turn reduces traffic flow speed, thus increasing congestion. The congestion response to increasing mobility ASUs at the time horizon shown in **Figure 16b**; this subfigure also shows that congestion initially decreases until a threshold combined NMT and transit ASU allocation of approximately 270 lane-miles, then congestion increases once again. Despite the inflection in congestion response, total drive VMT nonetheless decreases monotonically beyond the VMT threshold of approximately 170 lane-miles of combined NMT and transit ASUs, as higher levels of NMT and transit ASU allocation incentivize adoption of those modes away from driving.

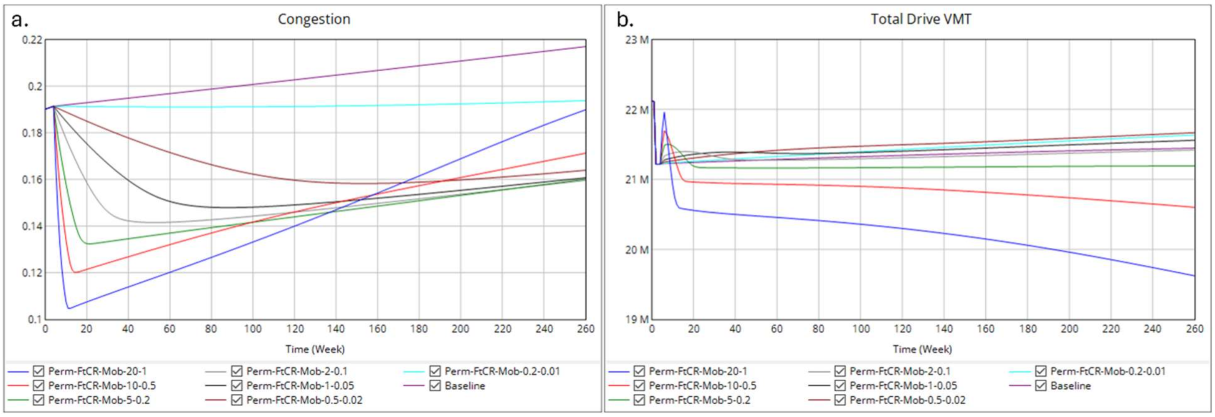


Figure 15 Under the mobility ASU scenario with a higher transit FtCR ceiling, a. congestion and b. total drive VMT in the Seattle model (baseline in purple, highest FtCR in blue)

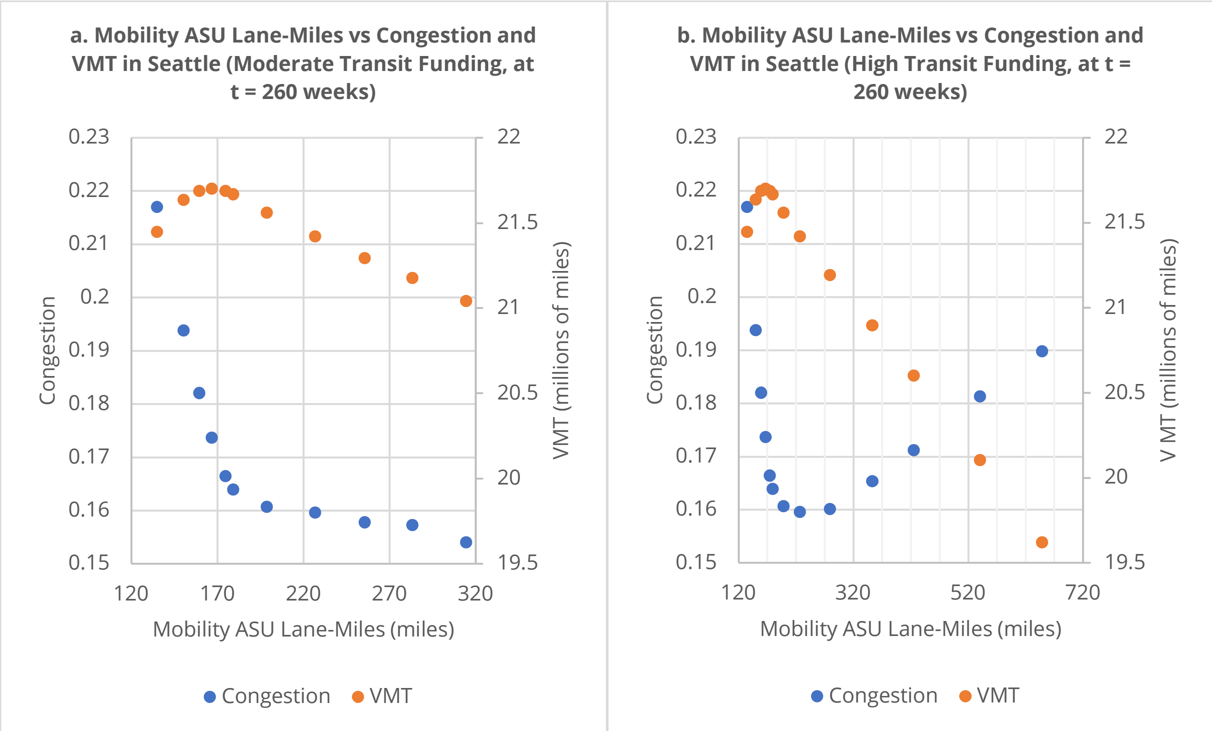


Figure 16 Under the mobility ASU scenario, congestion and VMT at the time horizon (t = 260 weeks) versus mobility ASU lane-miles with: a. moderate transit funding, and b. high transit funding

DISCUSSION

Major policy implications from the results of the SD policy analysis are in two areas: repurposing ROW as destinations, and repurposing ROW for non-automobility purposes. These two areas offer distinct implications for travel behavior and how cities can utilize the vast amount of street space. In both areas, there are transportation benefits for reductions in citywide congestion, total drive VMT, or both. Implications for higher-density land use and lower-drive mode share cities like Seattle however differ from those for lower-density land use and higher-drive mode share cities like Phoenix. In addition to demonstrating the value of SD in quantifying the complex downstream and feedback effects from repurposing street space, this work also provides translational benefits to planners for the communicating benefits of repurposing street space, which is often a controversial topic in most communities.

Our analysis demonstrates that ROW reallocation by building destination ASUs may modestly reduce congestion through encouraging walking and cycling trips. While the Seattle model suggests that the implementation of destination ASUs also mildly increases driving due to the attractiveness of driving under less-congested conditions, there is still an overall reduction in driving over the time horizon of the model. Since overall drive VMT is increased by the higher drive mode share under destination ASU allocation in high-density cities, these cities would need to consider other programs alongside destination ASU allocation should the goal be to reduce both congestion and VMT, such as making improvements to transit service, or land use changes or development incentives to reduce trip distances and disincentivize driving. In low-density cities, the Phoenix model demonstrates that even without additional policy changes, repurposing streets as destination ASUs may reduce both congestion and total drive VMT: given the abundance of wide roadways in low-density cities, there is great promise in this approach to increasing destination density without costly rezoning and redevelopment. In fact, the adaptable and flexible nature of ASUs could be leveraged for city planners to locate them in a more homogeneously-distributed manner throughout a city, thereby mitigating the need to construct ASUs in areas with pre-existing concentrations of commercial or social/recreational destinations due to prior zoning and development patterns.

From a communications and public engagement perspective, the finding that additional destination ASUs mitigate roadway congestion may assist business groups and policymakers in supporting economic growth and revitalization of business districts by ameliorating a major negative perception of businesses, as shared by staff at both local Seattle neighborhood business associations and the Seattle Department of Transportation. Also, destination ASUs increase the share of walking and cycling modes – these modes have a much lower barrier to chain trips between several destinations compared to driving (due to parking constraints) and transit (due to transit route network and frequency constraints). Thus, increased NMT mode share further enhances the ability for potential customers to access local businesses and significant locations in the community which may have previously been limited by parking availability and/or poor transit connectivity.

The Seattle and Phoenix response thresholds to NMT ASU allocation have implications on policy implementation: the intended improvements on congestion and/or VMT may come after an initial period of perceived failure. The existence of a threshold level of NMT allocation for improvements to be seen in VMT for Seattle and congestion for Phoenix suggests that when cities make incremental additions to their NMT networks, it is plausible for transportation metrics to worsen initially, and it is incumbent on cities to continue the trajectory of providing NMT facilities for those same metrics to begin improving. This is especially salient in the Phoenix case, where the combination of investment towards NMT and transit ASUs did not alter the threshold in congestion response since additional transit ASUs were ineffective in changing transportation outcomes. Should low-density cities invest in shifting mode share away from driving, the Phoenix case study indicates that while possible, congestion will get worse before it gets better; planners and the public must be in patient agreement for future benefits.

The Seattle model demonstrates a stronger sustained VMT benefit beyond the NMT ASU allocation threshold when a moderate amount of transit ASUs were allocated. Whereas NMT-only allocation resulted in eventual higher total drive VMT for all levels of NMT ASU allocation, moderate levels of transit ASU allocation (FtCRs from 0.1 to 0.25) alongside NMT ASU allocation also resulted in sustained levels of VMT below the baseline; this result supports coordination between NMT and transit planning efforts, as only when combined were there long-term reductions in VMT alongside congestion. A caveat to this implication is that should transit ASU allocation levels be raised beyond moderate levels, congestion was shown to return due to a significant-enough proportion of roadway lane-miles being repurposed for transit use. While this result (depicted in **Figure 15**) may give planners pause, one must consider the trade-offs between increased congestion at high transit ASU allocation and the significant decreases in drive VMT this may offer; cities that may be considered to have made this trade-off between increased congestion and reduced VMT through BRT investment like those in Rio de Janeiro and Jakarta.

Methodologically, our study demonstrates that SD can be a valuable methodology to quantify city- or regional-scale feedback loops and interacting effects for both high-density cities such as Seattle as well as low-density ones such as Phoenix. On results, two findings hold for both Seattle and Phoenix. One is that destination ASUs reduce congestion; the other is that in order to reap transportation benefits, NMT ASUs must exceed a certain threshold. Given the significant differences in the two cities in population, land use and travel patterns, the fact that these results hold for both two cities is promising as it suggests that the results may also hold for many other cities in between. This speculation of course needs to be tested with additional cities.

As noted earlier, the present study is conducted at the city level. As such, the models and their results are specified and calibrated upon parameters aggregated at the city-scale, such as total roadway lane-miles, population growth rate, average number of passengers in each drive trip, combination mode-purpose shares of all personal trips, and median drive trip distance for each trip purpose. Beyond city-level aggregate parameters, the models are agnostic to disaggregate spatial phenomena such as localized geography, spatial distributions of socio-demographics (income, household size, race, etc.), or the spatial arrangement of roadway and transit networks. In other words, the present study is not about answering questions regarding effects due to spatial heterogeneity within a city, nor does it consider network effects of traffic flow and trip route choices on roadway and transit networks when streets are repurposed for alternate uses.

While the SD approach used here has strengths in assessing interacting and threshold effects at macro-scale, questions considering the spatial effects of ASUs in addition to their temporal effects remain important. In the future, a potential approach to incorporate the spatial dimension while retaining the SD methodology is to cellularize the model; rather than applying a single model to represent an entire city in aggregate, the city may be divided into a small number of cells. This approach mirrors the conceptual foundation of MFD theory proposed by Daganzo (*55*). Whereas traffic flows are conventionally investigated on the corridor-level, Daganzo's exploration of "neighborhoods" that produce trips, accumulate trips, and in which trips are completed led to the development of MFD theories that spatially scales traffic flow theory to the neighborhood-, city-, and region-level (*56*). Furthermore, city roadway networks may be spatially partitioned into neighborhoods to model traffic densities and flows in regions where traffic networks are heterogeneously loaded and congestion is concentrated in multiple neighborhoods or sub-regions for the purpose of devising traffic control schema (*57*). The SD modelling completed here considers the city-level just as the MFD approach models traffic flow at the neighborhood- or city-level.

The integration between SD and cellular automata methodologies has already been applied to studying urban population growth in Shanghai, China (*58*). There have also been integrations of SD methods with GIS to investigate urban residential development in one study, and to estimate road icing locations in another (*59*, *60*). Incorporating these techniques to study the transportation effects of ASU allocation would involve partitioning the study region of interest into smaller sub-regions, then identifying parameter values characterizing each sub-region. One challenge that would be novel in such an approach would be the propagation of boundary effects from one sub-region to another, when the effects involve traffic and transportation networks, rather than physical or environmental phenomena that distribute according to clearly defined physical laws. Should such an integration between SD and geospatial methods be conducted, this may assist in identifying spatial distributions of ASUs that would provide greater benefit to a city's transportation network.

Finer spatial analysis of ASU allocation, such as on the street- or block-face level may require methods more suited to that level of spatial granularity. For example, a question of how varying spatial allocation of ASUs throughout a city's street network may give rise to aggregate, city-level effects of congestion and VMT may not be readily answered by SD. Instead, more complicated models such as those involving network assignment or agent-based models may be required.

BROADER PROJECT AND FUTURE RESEARCH IMPLICATIONS

The previous section has discussed the implications of the present study as they stand on their own. This study also sits within the context of a broader project and its four thrusts[2]. The implications on each of the four thrusts and future research directions are outlined in this section.

The results presented in this thesis have many implications on Thrust 1, which is concerned with adaptable uses of urban space from a site- and neighborhood-level. As previously mentioned, the SD model describes only the aggregate lane-miles of commercial or social/recreational ASUs. While this ignores the spatially-dependent effects of specific ASU placements that Thrust 1 is primarily concerned with, a benefit of the SD model aggregation is that there is no prescription for exact spatial fixity of the ASU lane-miles within the city as a whole. Thus, there is flexibility for the spatial distribution within the city of all ASUs that sum to the total lane-miles as suggested in the SD model. A further implication of using SD models and spatial homogeneity: destination ASUs have their strongest ability to induce mode shift towards NMT precisely when they are spatially distributed in a quasi-homoegeneous manner, rather than being concentrated in a select number of "hub" locations (such as in existing commercial corridors). Therefore, this quasi-homogeneous distribution of destination ASUs would support the "15-minute city" principle, where frequently-visited destinations that meet everyday

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[2] Recall the four thrusts: 1) adaptable urban spaces, 2) adaptable business operations, 3) adaptable transit systems, and 4) adaptable human behaviors.

community needs are located within close proximity to housing, thereby reducing barriers to walking and cycling access (*61*, *62*).

A limitation of the current modelling process is that it did not explicitly account for lane widths when assessing the impact of ASU allocation on lane-miles of roadway available for vehicular mobility. Each lane-mile of ASU generated in the model would subtract a lane-mile from the available roadway capacity. While this may be true for cities such as Seattle, where street cross-sections are generally sufficiently narrow such that ASU allocation would remove a travel lane, in cities such as Phoenix, where street cross-sections lend themselves to rather wide lanes (especially on non-arterial streets), the allocation of an ASU may not require the removal of a roadway lane-mile. In future, the model may be modified to include a factor that throttles the proportion of ASU lane-miles that remove roadway lane-miles. The current model implies a 100% roadway removal rate; a sensitivity analysis could be conducted to investigate the effect of changing this roadway removal rate.

One factor of salience to Thrust 1 is the impact of adapting urban space on parking supply. While the SD model in the present study implicitly models a reduction in driving mode share under ASU allocation, it does not explicitly track the parking supply or parking utilization of a city. While reallocation of street space does not automatically imply reduction of parking capacity along a street's curb face, when aggregated at the city-wide level, there invariably will be reductions to on-street parking capacity when either entire street segments or travel lanes are repurposed for alternate uses. Parking supply changes have been shown to influence driving mode share and location choice (*63*, *64*). While the model implicitly models this influence, the explicit modelling of parking supply changes could be encoded within the model as a variable, where each lane-mile of ASU that exists in the city would remove a set number of parking spaces. The total parking supply capacity of the city could then be modelled as a positively-associated factor in the drive MPS logistic functions.

A major implication for Thrust 2, which explores ways to optimize individual business operations for customer experience and business revenues, is that commercial ASUs provide another means for boosting business capacity. While the number of lane-miles of commercial ASUs in the SD models for both Seattle and Phoenix may be smaller integers (up to around 15 lane-miles at the highest funding scenarios for commercial-only and destination ASUs), these represent a significant increase in potential floor area when considering the linear lane-miles as a total added width of commercial frontage in a city.

The model also demonstrated that for higher-density cities, increasing NMT ASU allocation is associated with a modest increase in commercial trip purpose shares. This may reflect the greater trip-chaining ability when citizens walk to access destinations, as station cost and station capacity concerns (such as parking cost and parking supply when driving) are eliminated when walking, compared to when driving. Another implication for higher-density cities is that with the modest increase in commercial trip purpose shares under increasing NMT ASU allocation, the business environment of the city may improve; there is also synergy between widened sidewalks and pedestrianized plazas and commercial uses of these spaces – urban spaces that offer safer and more pleasant spaces to walk in would increase foot traffic for local businesses, and utilizing these spaces for expanding opportunities for commercial activity may further increase visitors accessing these destinations on foot. Therefore, commercial and NMT ASUs offer cities a unique opportunity to benefit the overall business environment of a city.

While parking and freight vehicle access remains a concern communicated to project team members by local businesses and business groups when discussing the potential of repurposing city street space, there is also potential for ASUs to provide increased local freight accessibility. Some cities such as New York City and Paris have begun reallocating curbspace for freight micro-hubs or mobile hubs; these innovations of street space usage alongside expanded bicycle lane networks may enhance local freight access, since individual businesses may no longer require large, dedicated large freight vehicle loading bays or loading areas, instead, freight for small businesses may be delivered from a local on-street hub via manual trolleys or cargo bikes (*65*, *66*). These changes to street use and local, last-mile freight delivery to a hub-and-spoke model where large freight vehicles need only access one hub rather than individual businesses may enhance delivery reliability. These benefits from freight uses of street space could also be reflected in optimization models being developed by Thrust 2.

The destination and NMT ASU scenarios tested in the Seattle and Phoenix models suggest that while NMT mode share increases, this is partially at the cost of reducing transit mode share. One implication that is relevant for Thrust 3 and their optimization of transit agency operations is that transit agencies could consider employing fleets of smaller vehicles. The benefits of operating fleets of smaller vehicles are that while transit mode share was shown to be reduced in several ASU scenarios, the same spatial (route) coverage at the same frequencies could be attained, with a reduced operating cost, since smaller vehicles have lower maintenance and fuel costs. A transition to fleets with smaller vehicles alongside conventionally-sized buses is especially salient nationwide, as transit agencies consider how to transition to zero-emission fleets, and vehicle type is a major consideration within these fleet composition decisions.

The scenarios explored in this study that reduced city-wide congestion would also improve road-based transit reliability. The destination ASU scenario in both city models, the NMT ASU scenario in the Seattle model, and the mobility ASU scenario in the Seattle model all produced reduced congestion under increasing ASU allocation. While the provision of destination ASUs would be beyond the purview of transit agencies to institute, there is broader scope for transit agencies in higher-density cities to collaborate with local jurisdictions and departments of transportation for the allocation of street space for either permanent or temporary NMT and transit ASUs. Especially during external disruptions to status quo operations, such as during the COVID-19 pandemic or when surges in tourism are experienced during major sporting events, temporary NMT and transit-priority uses of street space could enhance transit efficiency and resilience.

Since reduced congestion was not always achieved in the Phoenix model, this suggests that transit for lower-density cities could not be improved solely by repurposing the street ROW. Therefore, other adaptations may be more worthwhile to investigate, particularly those that are contextually-relevant (e.g. sheltered or climate-controlled bus stops in Phoenix). A corollary to this implication is that in higher-density cities, repurposing street space for NMT and transit use can provide speed and reliability benefits to transit vehicles, independent of any other operational changes; the presence of these street uses should be modelled in further transit system optimization studies.

An implication of the SD modelling on Thrust 4 of the broader project is that there was a demonstrated general preference for mode shares to shift towards walking and cycling when ASUs are allocated in increasing amounts. This result would be helpful to compare against Thrust 4’s agent-based modelling. This preference could also be investigated further with surveys run by Thrust 4, to identify potential attitudinal and perception correlations underlying the walking and cycling preference when there are more plentiful alternate uses of street space.

Thrust 4 had also completed a survey describing travel and activity behavior stated preferences under various disruption scenarios. A potential future research direction using the models presented in this thesis would be to utilize the attitudinal factors from that survey as factors for the public demand of ASUs, mode-purpose share, and perceptions of transit quality and reliability. Incorporating these factors into the determination of these endogenous variables, and accounting for how these factors may themselves change under changing traffic and transit conditions, may be insightful. The explicit inclusion of attitudes may reveal more nuanced responses in ASU allocation and transportation outcomes.

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APPENDICES

1. MODELLING DECISIONS AND ASSUMPTIONS

In a system dynamics (SD) model, key modelling decisions and assumptions must be made to simulate the dynamic response of a city's transportation and travel behavior. Primarily, the largest modelling decision is that the transportation phenomena and travel behavior can be studied at the city-level, rather than at other spatial/agent scales such as the neighborhood-level or individual traveller-level. The rationale behind this decision to use the city as the model spatial unit is due to the model's purpose for informing policy decisions that are based on city-level and city-wide phenomena. City street space is managed by city agencies: in Seattle, the Seattle Department of Transportation manages street operations and policy, and in Phoenix, the City of Phoenix Street Transportation Department performs these duties. While we acknowledge that localized corridor- or neighborhood-level phenomena remain valid and may exhibit heterogeneity across an entire city, we have chosen the city-level in this analysis for the sake of identifying impacts and opportunities for city transportation departments to effect policy on how to use streets as broadly applicable to the entire city that they hold jurisdiciton over. Furthermore, when considering the time horizons on the magnitude of several years (as was chose in the SD analysis presented in this thesis), city- or regional-level modelling has been regarded as valid and sufficient, as the evolution of localized effects at smaller spatial scales may exhibit variance across a city that may not be representative of macroscopic city trends (*14*, *15*, *17*, *18*, *67*).

From a whole-model perspective, key assumptions involve choices around spatial and temporal scales. Spatially, the choice of a city as the spatial unit represents a spatial scale small enough at which means and medians of travel behavior descriptors (such as MPS, median travel distances, etc.) could be representative, while the scale would also be large enough to provide meaningful insights into policy impacts at a broader spatial scale beyond the blockface- or neighborhood-only level. Furthermore, SD models assume that all behavior occurs within a closed boundary, therefore the spatial unit must be sufficiently large so that observed effects may be assumed to only be due to dynamics within the spatial unit; no external interactions are modelled. The choice of a city as the spatial unit meets these scale compromises; another benefit of using a city as the spatial unit is that policies regarding street use, transit, and land use are enacted at the city-level. Thus, the two SD models represent the City of Seattle and the City of Phoenix.

Temporally, a modelling time horizon and time step were selected on the basis of balancing between competing priorities. While a long time horizon would allow for a longer timeframe for dynamics of street use, transportation and land use policies, and travel behavior to unfold, a time horizon that is too far into the future would conflict with the assumption that the city being modelled is static outside of all variables invovled in the model. Therefore, a time horizon of 5 years offers a balance between a long-term view of a city while still representing static land use and transportation infrastructure conditions outside of those being studied by the model. A time step must also balance the ability to quantify phenomena with fast dynamics that change on a minute-by-minute basis (e.g. congestion) and those with slow dynamics that change on a longer time scales of weeks and months (e.g. policy changes, ASU construction time). The time step would also define the time period over which certain parameters are aggregated for use in the model (e.g. trip counts). Within these sets of priorities, a time step of 1 week was chosen, so that phenomena with both fast and slow dynamics could be represented, and model parameters could be imputed with a meaningful unit of time.

The initial time of the model is mostly informed by data availability for model calibration (see Section 4 of the Supplementary Materials). The initial time was chosen to be the most recent year for which complete household travel survey data could be obtained for each city being modelled. As such, 2019 was chosen as the initial model year for Seattle, and 2017 for Phoenix.

Below the whole-model aggregate level, the SD model has four interacting components, each constructed with several assumptions in mind. This section will outline modelling assumptions, but all assumed numerical parameter values will be stated in Section 2, parameter selection. The model's components are:

1. ASUs: ASU construction, deterioration, and public desire
2. Roadway traffic: roadway vehicle density, flow speed, congestion
3. Transit operations: transit capacity and reliability
4. Travel behavior: trip mode-purpose shares and trip generation

Component 1 (ASUs), which concerns the construction, deterioration, and public desire towards ASUs, is based on a set of four differential equations governing the number of lane-miles of each of the 4 ASU types. The ASU construction rate is assumed to be determined by public demand and the funding-to-cost ratio (FtCR). The initial FtCR level for each ASU type is determined by finding the value which results in the long-term equilibrium number of lane-miles of that ASU type equal to the historical value at the model initial time. FtCR values may be zero or any positive real number; the FtCR value indicates the number of ASU projects that the city can support the construction and maintenance of per week. Public demand is a variable between 0 and 1, and is assumed to follow the form of a logisitic function; all ASU types have public demand that diminishes as ASU allocation of that type increases. Commercial ASU public demand increases with greater commercial trip purpose share, as does social/recreational ASU public demand with social/recreational trip purpose share. Both NMT and transit ASU public demand increase with greater NMT and transit mode share.

The construction rate is thus the public demand multiplied by FtCR. This generates a number of projects that is converted into lane-miles of ASUs by multiplying by an assumed fixed number of lane-miles per ASU project. This assumed number of lane-miles is fixed for each ASU type in each model. Therefore, the number of projects constructed due to available funding and public demand is converted into lane-miles by multiplying this assumed fixed project lane-mileage. It is then assumed that ASUs take a fixed amount of time to construct, which is modelled as a fixed time delay in Vensim PLE+ 10.2.1. (hereby referred to simply as "Vensim"). This fixed construction time results in a construction rate that occurs at a delayed time in the future. Deterioration of ASUs is assumed to follow a population decay, where the deterioration rate is equal to the inverse of the assumed fixed lifespan of the ASU type. Furthermore, a knockdown to the deterioration rate is applied specifically to NMT and transit ASUs, as they require the most significant investment of public funds, public input, planning, and engineering: therefore their deterioration rate is reduced by a fixed factor.

Component 2 (Roadway Traffic) concerns roadway traffic conditions, which encompasses traffic density, traffic speeds, and congestion. Baseline roadway lane-miles available in the city are assumed to be a fixed value from historical data at the initial model time. The effective roadway lane-miles is then the baseline roadway lane-miles, less the lane-miles used by ASUs. Vehicle density (vehicles per linear lane-mile) is calculated by assuming a homogeneous distribution of all vehicles on the the effectie roadway lane-miles. Number of vehicles from personal drive trips is determined by dividing the number of drive trips in the study region by the average number of people travelling in the same vehicle per drive trip (as determined through household travel surveys) (*40*, *41*). Number of vehicles from transit trips are calculated similarly by dividing the number of transit by bus in the study region by the average number of people travelling in the same vehicle per bus trip (as determined through National Transit Database agency profiles) (*37*, *37*, *39*). Since transit ASUs encompass bus lanes, not all bus trips operate within general travel lanes. Therefore, an assumed fraction of all bus vehicles operate in bus lanes. This assumed fraction is also calculated using a logistic function, which is sensitive only to the number of lane-miles of transit ASUs. This assumed fraction of buses operating in a transit lane is also limited to a researcher-defined upper limit.

Vehicle density is then used as the variable input to calculate a nominal roadway flow speed, which assumes that traffic flow in the study region follows the macroscopic fundamental diagram proposed by Newell (*43*, *44*). There is also an assumed effect of trafic calming due to ASUs removing travel lanes, where the aggregate roadway flow speed is calculated as a weighted average of flow speed on non-calmed roadway lane-miles flowing at the nominal speed and of calmed roadway lane-miles flowing at a reduced speed (*45*, *46*). Congestion is defined as the fractional slowdown of the aggregate roadway flow speed from the free-flow reference speed.

The assumptions regarding VMT calculations are outlined with other assumptions in Component 4, as the calculation of mode-purpose splits is most relevant to VMT calculations in the SD model.

<u>Component 3 (Transit Operations)</u> describes transit operations in the study region. An assumption made for adjusting transit service capacity (measured by supplied vehicle revenue-miles, VRM) is that adjustments are made by multiplying by a fixed factor to either increase or decrease service; these adjustments occur every 13 or 26 weeks (quarterly or half-yearly), and

only if transit occupancy passes an upper or lower threshold to trigger an increase or decrease respectively. While there is only a theoretical minimum amount of service capacity that can be supplied per week (zero VRM) without any theoretical maximum, there is a practical maximum that is determined due to operator limits. In the cases of King County Metro, Sound Tranist, and Valley Metro, the theoretical maximum weekly VRM is set to 1.25 million VRM for Seattle, and 600,000 VRM for Phoenix (from personal communication with transit agency staff).

The supplied VRM is then converted into a service capacity measured in trips by multiplying by a fixed trips capacity per vehicle (equivalent to passenger capacity) and dividing by the average passenger-miles per trip (imputed from NTD agency profiles). In the event that the number of transit trips generated by the model exceeds the supplied service capacity, these transit overflow trips are split equally and added to the number of drive and NMT trips. In our study, the model never generated an excess demand over supplied transit service capacity.

The perceived transit quality and reliability (TQR) is measured using a single variable in the form of a logistic function. TQR is positively dependent on operating expenses per VRM, supplied transit service capacity, and transit ASU lane-miles. TQR is negatively dependent on congestion. Although the SD model also calculates transit agency operating resources as differential equation with operating revenue and expenses, this sub-component of Component 3 was not used in the analysis presented for this thesis. Also, there is no functional dependency on congestion, total drive VMT, and mode shares, thus the inclusion of this un-used subcomponent has no effect on the results of the present analysis.

<u>Component 4 (Travel Behavior)</u>, which concerns travel behavior and trip generation, is based upon the calculation of combined trip mode-purpose shares, which are then used to determine mode shares, trip purpose shares, trip counts, and VMT. This component also contains

the mechanism for modelling increased trip-making due to induced demand. A key assumption in the model is that all modeled trips are personal trips; no commerical trips (those made in the service of freight, logistics, commerce, etc.) are modelled, since travel behavior data sources for commercial trips are not widely available, unlike for household/personal travel.

The combined trip modes and purposes were selected to encompass the majority of the trips made in either study region. The travel modes of drive, NMT, and transit only exclude trips made by air and on water. The trip purposes of home, work/school, commercial, social/recreational, and errand/escort only exclude trips tagged in household travel surveys with a purpose of “other” and to change modes of transportation (which did not fit into any of the 5 purposes in the model). These excluded modes and purposes lead to the model only missing <1.6% of all trips in Seattle and <0.8% of all trips in Phoenix.

Individual combined mode-purpose shares (MPS) are calculated using logistic functions. These unweighted MPSs are then weighted according to the procedure described in Section 4 of this document, so that the model can be calibrated to match historical MPS values. The weighted MPSs are then summed over all purposes to generate an unweighted mode share, and summed over all modes to generate an unweighted purpose share. These mode and purpose shares are also weighted according to the calibration procedure described in Setion 4. The final reported MPS, mode shares, and purpose shares are calculated by normalizing these shares to a unit sum.

Another key assumption in the trip generation subcomponent of travel behavior concerns the total number of trips taken per week in the study region. The baseline number of trips is calculated from trips with OD pairs within the study region. Since household travel surveys report typical weekday travel behavior, weekday counts are converted into typical weekly counts (*68*). This baseline trip count is then inflated by a fixed population growth rate, compounded weekly. The final adjustments to trip count is the effect of induced demand: the key assumption when modelling induced demand is that the traffic volume-travel time short-term elasticity is applied to increase the total trip count. Induced demand due to changes in travel times is also assumed to cause an effect in travel volumes after a delay of 2 weeks; this is implemented by comparing the current congestion level (based on traffic flow speed) to the congestion level from 2 time steps prior. The uneven spatial and temporal distribution of traffic over the week is also accounted for with exogenous adjustment factors. This population growth-, induced demand-, and uneven spatiotemporal distribution-adjusted trip count is thus considered the total number of trips made in the study region for the week represented by the current time step.

Total drive VMT is calculated by summing the VMT from all drive trips across each of the trip purposes. VMT for each drive trip purpose is calculated by multiplying the MPS for each drive trip purpose by the total number of trips in the study region and the median drive trip distance for each trip purpose. The median drive trip distance for each trip purpose was calculated from household travel survey data, filtering only for drive trips with OD pairs within the study region (*40*, *41*). The median was used to represent drive trip distances for each trip purpose, as trip distance distributions are right-skewed, as seen in **Figure 17** and **Figure 18**.

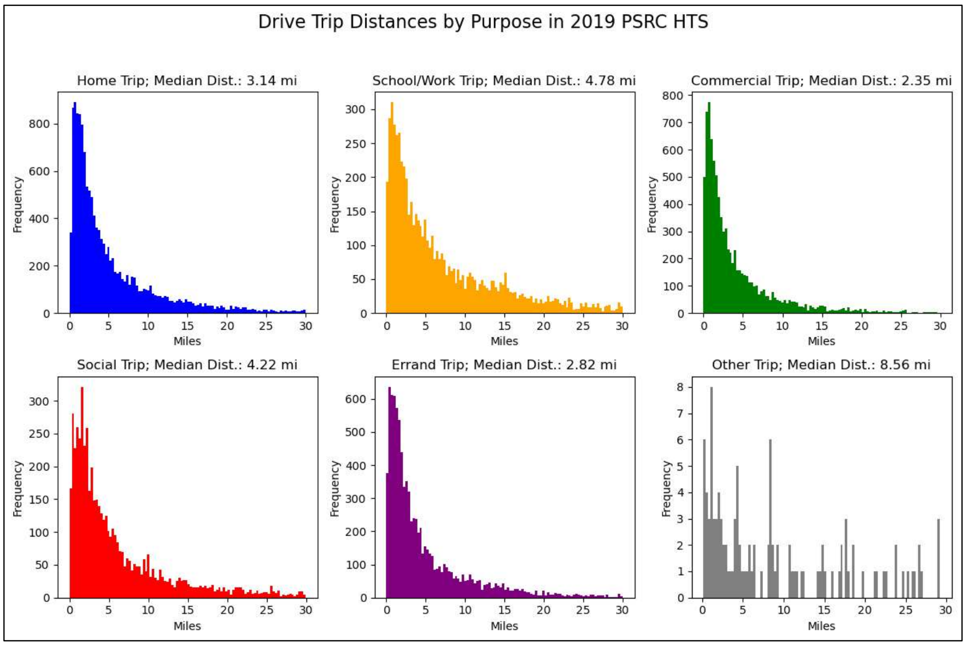

Figure 17 Seattle drive trip distance distributions by trip purpose in the PSRC 2019 HTS

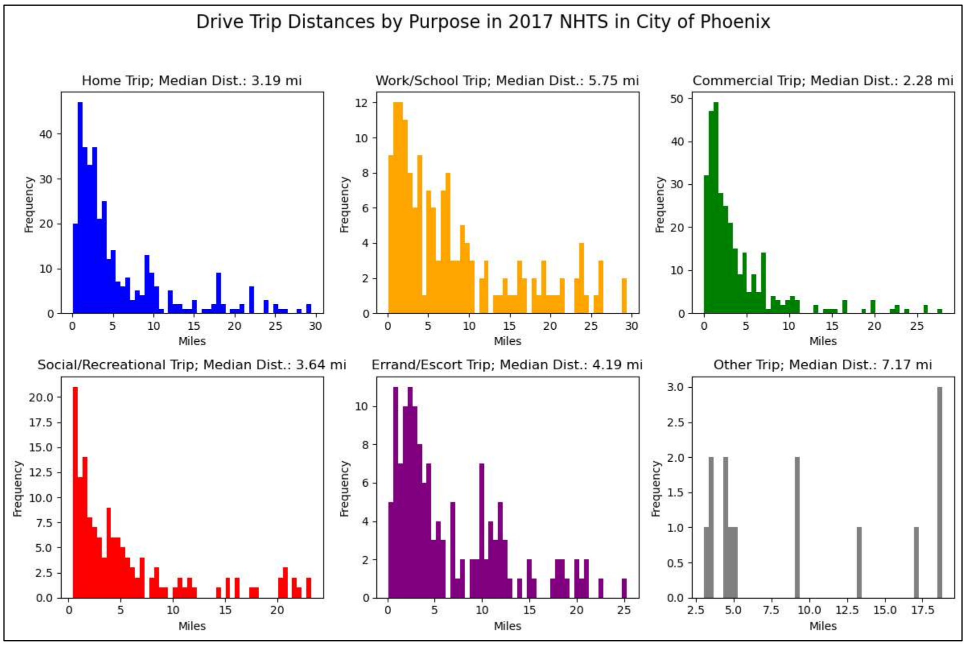

Figure 18 Phoenix drive trip distance distributions by trip purpose in the FHWA 2017 NHTS

2. PARAMETER SELECTION

Exogenous parameters in the SD model can be classified into two categories: the first category are the parameters which were directly input from a data source; the second category are parameters that required additional analysis before being used in the model. While most parameters could be determined from similar sources for both Seattle and Phoenix models, some analysis steps differed due to differing data sources. All Python scripts used in the data analysis for parameter calculations are also included as supplementary materials. The parameter values and their units used in the Seattle and Phoenix models are listed in **Table 6**. Note that for Component 3, the unused subcomponent handling transit agency operating resources mentioned in Section 1 is not described in **Table 6**.

Table 6 Parameter name, units, and baseline value in the Seattle and Phoenix models

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
Initial Time	Weeks	0	0
Final Time	Weeks	260	260
Time Step	Weeks	1	1
Component 1: ASUs and Public Demand			
ASU Commercial FtCR	Dimensionless	6.65	0
ASU Commercial Construction Time	Weeks	4	4
ASU Commercial Average Project Mileage	Lane-Miles	0.004	0.004
ASU Commercial Baseline Lane-Miles	Lane-Miles	2.4	0
ASU Commercial Lifespan	Weeks	156	156
ASU Social/Recreational FtCR	Dimensionless	0.279	0
ASU Social/Recreational Construction Time	Weeks	8	8
ASU Social/Recreational Average Project Mileage	Lane-Miles	0.004	0.004
ASU Social/Recreational Baseline Lane-Miles	Lane-Miles	0.1	0
ASU Social/Recreational Lifespan	Weeks	104	104

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
ASU NMT FtCR	Dimensionless	0.122	0.94
ASU NMT Construction Time	Weeks	4	4
ASU NMT Average Project Mileage	Lane-Miles	0.8	2
ASU NMT Baseline Lane-Miles	Lane-Miles	100	1190.81
ASU NMT Lifespan	Weeks	104	104
ASU Transit FtCR	Dimensionless	0.0069	0.001014
ASU Transit Construction Time	Weeks	8	8
ASU Transit Average Project Mileage	Lane-Miles	2	1
ASU Transit Baseline Lane-Miles	Lane-Miles	35	2
ASU Transit Lifespan	Weeks	520	520
ASU NMT Deterioration Multiplier	Dimensionless	0.1	0.1
ASU Transit Deterioration Multiplier	Dimensionless	0.2	0.2
Sensitivity of Public Demand of Commercial ASUs to Commercial ASU Lane-Miles	Dimensionless	-0.5	-0.5
Sensitivity of Public Demand of Commercial ASUs to Commerical Purpose Share	Dimensionless	20	20
Sensitivity of Public Demand of Social/Recreational ASUs to Social/Recreational ASU Lane-Miles	Dimensionless	-3	-3
Sensitivity of Public Demand of Social/Recreational ASUs to Social/Recreational Purpose Share	Dimensionless	30	30
Sensitivity of Public Demand of NMT ASUs to NMT ASU Lane-Miles	Dimensionless	-0.2	-0.004
Sensitivity of Public Demand of NMT ASUs to NMT Mode Share	Dimensionless	20	10

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
Sensitivity of Public Demand of NMT ASUs to Transit Mode Share	Dimensionless	10	5
Sensitivity of Public Demand of Transit ASUs to Transit ASU Lane-Miles	Dimensionless	-0.01	-0.05
Sensitivity of Public Demand of Transit ASUs to NMT Mode Share	Dimensionless	10	10
Sensitivity of Public Demand of Transit ASUs to Transit Mode Share	Dimensionless	20	7
Sensitivity of Public Demand of Transit ASUs to TQR	Dimensionless	3	3
Component 2: Roadway Traffic			
Baseline Roadway Lane-Miles	Lane-miles	3952	12557
Roadway Free-flow Reference Speed	Miles/hour	25	30
Roadway Critical Density	Vehicles/Mile	190	190
Lambda Jam (Slope of Flow-Density Curve at Jam Density)	1/Hour	2850	2850
Average Number of Trips per Drive Vehicle	Trips/Vehicle	1.6668	2.11
Average Number of Trips per Transit Vehicle	Trips/Vehicle	15	8
Fraction of Transit Trips by Bus	Dimensionless	0.85	0.75
Sensitivity of Fraction of Bus Trips in Bus Lane to Transit ASU Lane-miles	Dimensionless	0.02	0.02
Fraction of Buses in Bus Lane Maximum Limit	Dimensionless	0.5	0.2
Fraction of ASUs Removing a Travel Lane	Dimensionless	0.9	0.7
Traffic Calming Factor	Dimensionless	0.7	0.7
Component 3: Transit Operations			
Baseline Transit Service Capacity (VRM)	Vehicle Revenue-Miles	800,000	400,000
Transit Service Capacity Limit (VRM)	Vehicle Revenue-Miles	1,250,000	600,000

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
Average Trips (Pax) Capacity per Transit Vehicle	Trips/Vehicle	90	20
Average Pax-Miles per Trip	Miles/Trip	4	3.6
Transit Service Capacity Adjustment Interval	Weeks	26	13
Transit Service Capacity Multiplier (TSCM) Upper Threshold	Dimensionless	0.5	0.5
TSCM Lower Threshold	Dimensionless	0.1	0.1
TSCM Increase	Dimensionless	1.25	1.25
TSCM Decrease	Dimensionless	0.75	0.75
Uneven Transit Spatio-Temporal Distribution	Dimensionless	1	1
Operating Expenses (OE) per VRM	U.S. Dolalrs/VRM	20	8.12
Sensitivity of TQR to Congestion	Dimensionless	-3	-3
Sensitivity of TQR to OE per VRM	Dimensionless	0.3	0.3
Sensitivity of TQR to Transit Service Capacity (VRM)	Dimensionless	4.0E-6	4.0E-6
Sensitivity of TQR to Transit ASU Lane-Miles	Dimensionless	0.05	0.015
TQR Multiplier	Dimensionless	0.8	0.8
Component 4: Travel Behavior and Trip Generation			
Baseline Number of Trips	Trips/Week	18,518,137	27,249,709
Population Growth Rate	% p.a.	1.2	0.76
Fraction of Transit Overflow as Drive Trips	Dimensionless	0.5	0.5
Uneven Spatial Distribution	Dimensionless	1	0.25
Uneven Temporal Distribution	Dimensionless	1	0.25
Traffic Volume-Travel Time Elasticity	Dimensionless	-0.57	-0.57
Baseline Congestion	Dimensionless	0.245745	0.1
Sensitivity of Mode-Purpose Share (MPS) Drive-Home to Congestion	Dimensionless	-4	-2

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
Sensitivity of MPS Drive-Work/School to Congestion	Dimensionless	-6	-2
Sensitivity of MPS Drive-Commercial to Congestion	Dimensionless	-5	-3
Sensitivity of MPS Drive-Social/Recreational to Congestion	Dimensionless	-5	-2
Sensitivity of MPS Drive-Errand/Escort to Congestion	Dimensionless	-5	-2
Sensitivity of MPS Transit-Home to Congestion	Dimensionless	1	3
Sensitivity of MPS Transit-Home to TQR	Dimensionless	5	5
Sensitivity of MPS Transit-Home to Transit Service Capacity (VRM)	Dimensionless	1.0E-6	1.0E-6
Sensitivity of MPS Transit-Work/School to Congestion	Dimensionless	1	3
Sensitivity of MPS Transit-Work/School to TQR	Dimensionless	5	5
Sensitivity of MPS Transit-Work/School to Transit Service Capacity (VRM)	Dimensionless	1.0E-6	1.0E-6
Sensitivity of MPS Transit-Commercial to Congestion	Dimensionless	1	3
Sensitivity of MPS Transit-Commercial to TQR	Dimensionless	5	5
Sensitivity of MPS Transit-Commercial to Transit Service Capacity (VRM)	Dimensionless	1.0E-6	1.0E-6
Sensitivity of MPS Transit-Commercial to Commercial ASU Lane-Miles	Dimensionless	0.3	0.3
Sensitivity of MPS Transit-Social/Recreational to Congestion	Dimensionless	1	3

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
Sensitivity of MPS Transit-Social/Recreational to TQR	Dimensionless	5	5
Sensitivity of MPS Transit-Social/Recreational to Transit Service Capacity (VRM)	Dimensionless	1.0E-6	1.0E-6
Sensitivity of MPS Transit-Social/Recreational to Social/Recreational ASU Lane-Miles	Dimensionless	1	1
Sensitivity of MPS Transit-Errand/Escort to Congestion	Dimensionless	1	3
Sensitivity of MPS Transit-Errand/Escort to TQR	Dimensionless	5	5
Sensitivity of MPS Transit-Errand/Escort to Transit Service Capacity (VRM)	Dimensionless	1.0E-6	1.0E-6
Sensitivity of Mode Share (MS) Transit to Transit Fare	Dimensionless	-0.4	-0.15
Sensitivity of MS Transit to Transit ASU Lane-Miles	Dimensionless	0.03	0.01
MS Transit to Transit Fare Logistic Function Shift (LFS)	Lane-Miles	3	2
Sensitivity of MPS NMT-Home to Congestion	Dimensionless	0.5	2
Sensitivity of MPS NMT-Home to NMT ASU Lane-Miles	Dimensionless	0.01	0.001
Sensitivity of MPS NMT-Work/School to Congestion	Dimensionless	0.5	2
Sensitivity of MPS NMT-Work/School to NMT ASU Lane-Miles	Dimensionless	0.01	0.001
Sensitivity of MPS NMT-Commercial to Congestion	Dimensionless	0.5	2

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
Sensitivity of MPS NMT-Commercial to NMT ASU Lane-Miles	Dimensionless	0.02	0.001
Sensitivity of MPS NMT-Commercial to Commercial ASU Lane-Miles	Dimensionless	0.08	0.08
Sensitivity of MPS NMT-Social/Recreational to Congestion	Dimensionless	0.5	2
Sensitivity of MPS NMT-Social/Recreational to NMT ASU Lane-Miles	Dimensionless	0.02	0.0015
Sensitivity of MPS NMT-Social/Recreational to Social/Recreational ASU Lane-Miles	Dimensionless	0.2	0.2
Sensitivity of MPS NMT-Errand/Escort to Congestion	Dimensionless	0.5	2
Sensitivity of MPS NMT-Errand/Escort to NMT ASU Lane-Miles	Dimensionless	0.02	0.001
Sensitivity of MPS NMT-Errand/Escort to Commercial ASU Lane-Miles	Dimensionless	0.08	0.08
Sensitivity of MPS NMT-Errand/Escort to Social/Recreational ASU Lane-Miles	Dimensionless	0.2	0.2
Congestion LFS	Dimensionless	0	1.5
Transit Mode LFS	Dimensionless	0.04	0.05
NMT Mode LFS	Dimensionless	0.07	0.15
Commercial Purpose LFS	Dimensionless	0.15	0.15
Social/Recreational Purpose LFS	Dimensionless	0.08	0.08
TQR LFS	Dimensionless	0.5	0.5
Commercial ASU LFS	Lane-Miles	2.5	8
Social/Recreational ASU LFS	Lane-Miles	0.2	0
NMT ASU LFS	Lane-Miles	100	600
Transit ASU LFS	Lane-Miles	25	80

Parameter Name	Units	Seattle Baseline Value	Phoenix Baseline Value
OE per VRM LFS	U.S. Dollars/VRM	15	8
Transit Service Capacity (VRM) LFS Fraction of Baseline Transit Service Capacity (VRM)	Dimensionless	0.7	0.7
Baseline Regional Population	People	753291	1.65E+6
Median Drive-Home Trip Mileage	Miles	3.14	3.19
Median Drive-Work/School Trip Mileage	Miles	4.78	5.75
Median Drive-Commercial Trip Mileage	Miles	2.35	2.28
Median Drive-Social/Recreational Trip Mileage	Miles	4.21	3.64
Median Drive-Errand/Escort Trip Mileage	Miles	2.12	4.19

3. SCENARIO ANALYSIS SIMULATION METHOD

As outlined in the body of this thesis, each scenario analysis consists of a set of simulation runs, where the Vensim model was run at increasing funding-to-cost ratios (FtCR) for various ASU types. The scenarios and the ASU types in each scenario are summarized in **Table 7**.

Table 7 FtCR scheme for investigating effect of ASU allocation on transportation outcomes

	Seattle	Phoenix
Alternate Street Use Scenario (ASU FtCR varied)	**FtCRs**	**FtCRs**
Baseline Values (Commercial – Social/Recreational – NMT – Transit)	6.65 – 0.279 – 0.047 – 0.0069 (no further levels)	0 – 0 – 0.94 – 0.001014 (no further levels)
Commercial (Commercial)	20, 50, 100, 200, 500, 1000	1, 2, 5, 10, 20, 50, 100, 200
Social/Recreational (Social/Recreational)	1, 2, 5, 10, 20, 50	1, 2, 5, 10, 20, 50, 100, 200
NMT (NMT)	0.2, 0.5, 1, 2, 5, 10, 20	2, 5, 10, 20, 50, 100
Transit (Transit)	0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1	0.002, 0.005, 0.01, 0.02, 0.05, 0.1, 0.2, 0.5
Destination (Commerical – Social/Recreational)	20 – 1, 50 – 2, 100 – 5, 200 – 10, 500 – 20, 1000 – 50	1 – 1, 2 – 2, 5 – 5, 10 – 10, 20 – 20, 50 – 50, 100 – 100, 200 – 200
Mobility (NMT-Transit)	0.2 – 0.01, 0.5 – 0.2, 1 – 0.05, 2 – 0.1, 5 – 0.15, 10 – 0.2, 20 - 0.25, 5 – 0.2, 10 – 0.5, 20 – 1	2 – 0.002, 5 – 0.005, 10 – 0.01, 20 – 0.02, 50 – 0.05, 100 – 0.1, 200 – 0.2

Notes: Each row represents a particular scenario. FtCR value indicates the number of ASU projects of that type that are financially supported per week; hyphens between FtCR values separate ASU types in the order specified in parentheses; commas between sets of FtCR values separate between simulation runs of that row's scenario.

In Vensim, each scenario's output includes results from a set of simulation runs comprising of the baseline, plus each FtCR level specified in **Table 7**. Simulation run outputs are generated and compiled for each scenario by using Vensim's "Run simulation on each slider change" feature. The name for each simulation run is set as "Perm-FtCR-[Scenario Name]-[FtCR level]", then sliders for the FtCR level that is being altered under the specified scenario and FtCR level are adjusted to the specified level. Sets of outputs are then collated together to form scenario result plots by selecting the required datasets to plot in Vensim's "Control Panel" feature.

The only exception to the set of outputs comprising all named FtCR levels in **Table 7** is the Seattle model Mobility scenario, which has its outputs split into two sets of outputs: one for the moderate transit funding sub-scenario, and the other for the high transit funding sub-scenario. The FtCR levels for the two sub-scenarios are identical for the first four FtCR levels; only the last 3 differ on the transit FtCR level. The sets of FtCR simulation runs for each of these sub-scenarios is oultined in **Table 8**.

Table 8 FtCR schemes for the two Seattle Mobility ASU sub-scenarios

	Moderate Transit Funding	**High Transit Funding**
ASU Scenario	**FtCRs**	**FtCRs**
Mobility (NMT-Transit)	0.2 – 0.01, 0.5 – 0.2, 1 – 0.05, 2 – 0.1, 5 – 0.15, 10 – 0.2, 20 - 0.25	0.2 – 0.01, 0.5 – 0.2, 1 – 0.05, 2 – 0.1, 5 – 0.2, 10 – 0.5, 20 – 1

Notes: hyphens between FtCR values separate ASU types in the order specified in parentheses; commas between sets of FtCR values separate between simulation runs of that row's scenario.

4. MODEL CALIBRATION RESULTS

The SD model is calibrated to match historical values of combined mode-purpose shares (MPS) for each city being modelled. The MPS for Seattle were calculated from the Puget Sound Regional Council (PSRC) 2019 Household Travel Survey (HTS) and the MPS for Phoenix were calculated from the Federal Highway Administration (FHWA) 2017 National Household Travel Survey (NHTS) (*40*, *41*). Each of the 15 MPS logistic functions, 3 summed mode share across all purposes, and 5 summed purpose share across all modes had a weight applied. These 15 + 3 + 5 = 23 weights were adjusted such that the model's output MPS (after normalization) at the initial time step matched the historical MPS within 0.5 percentage points. The calibration target MPS and model output results are presented in **Table 9** for Seattle and **Table 10** for Phoenix.

Table 9 Model calibration targets and output results for Seattle model

	a. Target Mode-Purpose Shares (%)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	7.83	14.00	16.95	8.51	5.89
NMT	6.23	3.36	9.84	7.71	6.33
Transit	1.54	1.91	4.07	3.64	0.61
	b. Model Outputs (%)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	7.77	14.01	16.94	8.54	5.91
NMT	6.51	3.38	10.15	8.12	6.61
Transit	1.55	1.92	4.04	3.66	0.61
	c. Absolute Difference from Target (percentage points, %)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	-0.06	0.01	-0.01	0.03	0.02
NMT	0.28	0.02	0.31	0.41	0.28
Transit	0.01	0.01	-0.03	0.02	0.00
	d. Percentage Difference from Target (percentages of percentages)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	-0.77	0.07	-0.06	0.35	0.34
NMT	4.49	0.60	3.15	5.32	4.42
Transit	0.65	0.52	-0.74	0.55	0.00
Total absolute difference (sum of c.)				1.5%	
Total absolute percentage difference (sum of d.)				22.03%	

Table 10 Model calibration targets and output results for Phoenix model

	a. Target Mode-Purpose Shares (%)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	21.79	9.97	28.78	11.76	12.46
NMT	1.69	0.31	4.92	1.29	3.06
Transit	0.32	0.20	1.20	1.06	0.42
	b. Model Outputs (%)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	21.93	10.19	28.91	11.84	12.39
NMT	1.73	0.31	5.00	1.33	3.08
Transit	0.36	0.20	1.24	1.09	0.43
	c. Absolute Difference from Target (percentage points, %)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	0.14	0.22	0.13	0.08	-0.07
NMT	0.04	0.00	0.08	0.04	0.02
Transit	0.04	0.00	0.04	0.03	0.01
	d. Percentage Difference from Target (percentages of percentages)				
	Commercial	Errand	Home	WorkSchool	SocRec
Drive	0.64	2.21	0.45	0.68	-0.56
NMT	2.37	0.00	1.63	3.10	0.65
Transit	12.50	0.00	3.33	2.83	2.38
Total absolute difference (sum of c.)				0.94%	
Total absolute percentage difference (sum of d.)				33.33%	

The final weights used in the calibrated model are outlined in **Table 11**. Note that the weights associated with a mode and purpose were applied to logistic functions that calculated MPS, whereas mode-only and purpose-only weights were applied to the sums of MPS for that mode or purpose (before normalization, which sets the sum of mode shares to 1 and sum of purpose shares to 1).

Table 11 Final calibration weights used for the SD models

	Seattle Model Calibration Weights					
	Mode-only	Commercial	Errand	Home	WorkSchool	SocRec
Purpose-only	N/A	0.8	1.1	1.64	1	0.56
Drive	0.51	1.16	1.52	1.09	1.16	1.26
NMT	0.435	0.63	0.24	0.48	0.63	0.92
Transit	0.039	0.93	0.84	1.18	1.75	0.52
	Phoenix Model Calibration Weights					
	Mode-only	Commercial	Errand	Home	WorkSchool	SocRec
Purpose-only	N/A	1	1	1	1	1
Drive	0.96	0.75	0.37	1.05	0.43	0.45
NMT	1.2	0.56	0.1	1.22	0.38	0.66
Transit	0.96	0.66	0.42	1.25	1.1	0.25

Additional verification was conducted by comparing elasticities quoted in literature. Two elasticities were compared against: first, an analysis in 2018 of the New York Metropolitan Transit Authority's Select Bus Service (SBS) improvements found that 41.4 miles of SBS improvements over six routes were associated with a 1.9 percentage-point increase bus mode share, corresponding to a 0.046 percentage-point increase in bus mode share per mile of improvement (*6*). Secondly, a study of the bike lane network expansion in Minneapolis-Saint Paul found that each mile of bike lane was associated with a 0.0038 percentage-point increase in cycling mode share (*49*). These two elasticities were compared to imputed elasticities from the the SD model for both Seattle and Phoenix.

From the SD model, elasticities were imputed from the gradients from linear regions of the curves depicting mode shares under changing ASU lane-miles. The ASU lane-miles and mode shares used to impute SD model elasticities are presented in **Table 12** to **Table 15**. The imputed elasticity is the average of gradients of each successive pair of points in each of the tables. Average gradients for NMT mode share increases per unit increase of NMT ASU lane-miles are decomposed according the ratio of walk mode share to bike mode share to determine the bike mode share component of the NMT mode share. The ratios of walk to bike mode share used is reported in **Table 12** and **Table 14** for the Seattle and Phoenix model, respectively, which are determined from household travel surveys (*40*, *41*). There is no need to decompose the average gradient for transit mode share in **Table 13** or **Table 15**, since the average gradient already represents the increase in transit mode share per unit increase in transit ASU lane-miles.

Table 12 Seattle model outputs used to impute bike mode share – NMT ASU lane miles elasticity (NMT ASU FtCR = 1, all other FtCRs at baseline level)

Time (week)	NMT ASU Lane-Miles (mi)	NMT Mode Share (%)	Gradient (%/lane-mile)
5	4.60967	34.8277	-
15	11.8252	35.2453	0.057875166
25	18.3151	35.6441	0.061449329
35	24.0137	36.0098	0.064173657
Average Gradient	+0.0612% NMT mode share per +1 lane-mile of NMT ASU		
Bike Mode Share-NMT ASU Lane-Mile Elasticity	+0.0040% bike mode share per +1 lane-mile of NMT ASU		
NMT Walk:Bike Mode Share Ratio	31.3052 : 2.168		

Table 13 Seattle model outputs used to impute transit mode share – transit ASU lane miles elasticity (transit ASU FtCR = 0.05, all other FtCRs at baseline level)

Time (week)	Transit ASU Lane-Miles (mi)	Transit Mode Share (%)	Gradient (%/lane-mile)
10	35.0645	12.096	-
20	35.9225	12.1295	0.039044289
30	36.7773	12.1627	0.038839495
40	37.6289	12.1955	0.038515735
50	38.4772	12.2279	0.038194035
60	39.3223	12.2601	0.038102
70	40.1642	12.2951	0.041572633
Transit Mode Share-Transit ASU Lane-Mile Elasticity	+0.0390% transit mode share per +1 lane-mile of transit ASU		

Table 14 Phoenix model outputs used to impute bike mode share – NMT ASU lane miles elasticity (NMT ASU FtCR = 1.5, all other FtCRs at baseline level)

Time (week)	NMT ASU Lane-Miles (mi)	NMT Mode Share (%)	Gradient (%/lane-mile)
10	1190.71	11.9885	-
20	1192.08	12.0079	0.014160584
30	1193.45	12.027	0.013941606
40	1194.82	12.0461	0.013941606
Average Gradient	+0.0140% NMT mode share per +1 lane-mile of NMT ASU		
Bike Mode Share-NMT ASU Lane-Mile Elasticity	+0.0007% bike mode share per +1 lane-mile of NMT ASU		
NMT Walk:Bike Mode Share Ratio	20.122 : 1		

Table 15 Phoenix model outputs used to impute transit mode share – transit ASU lane miles elasticity (transit ASU FtCR = 0.1, all other FtCRs at baseline level)

Time (week)	Transit ASU Lane-Miles (mi)	Transit Mode Share (%)	Gradient (%/lane-mile)
10	2.14738	3.53803	-
20	2.9158	3.5524	0.018700711
30	3.67991	3.56666	0.018662234
40	4.43922	3.58091	0.018767038
50	5.19375	3.59516	0.018885929
60	5.94352	3.6094	0.018992491
70	6.68854	3.62364	0.019113581
Transit Mode Share-Transit ASU Lane-Mile Elasticity	+0.0189% transit mode share per +1 lane-mile of transit ASU		

5. OTHER SUPPLEMENTARY RESULTS

Due to space limits, not all sets of simulation results from all scenarios detailed in Table 5 were presented in the main body of this thesis. This section includes all graphical result outputs for each scenario from each city model. Three sets of figures are presented for each scenario: lane-miles of ASU for each ASU type, mode shares across the 3 modes in the model, and congestion and VMT responses over time. The Seattle model results are presented first in **Figure 19** to **Figure 39**, then Phoenix model results are presented in **Figure 40** to **Figure 57**.

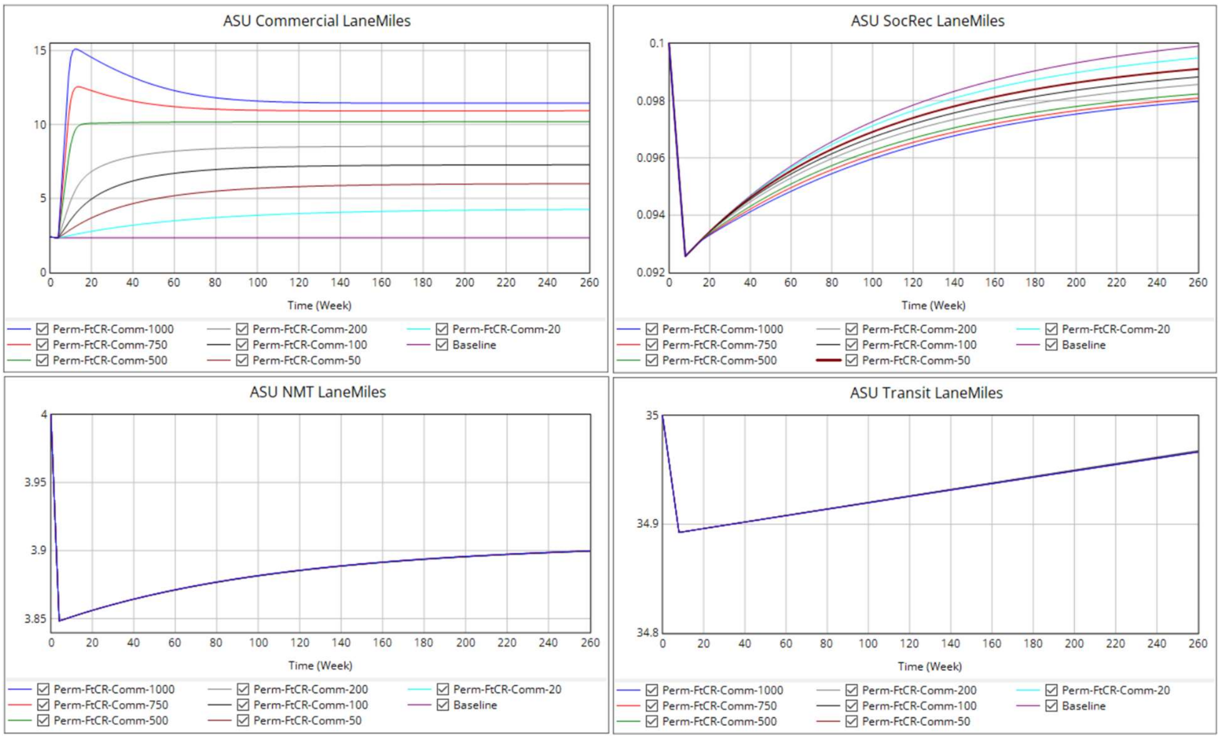

Figure 19 Seattle model commercial scenario ASU lane-miles

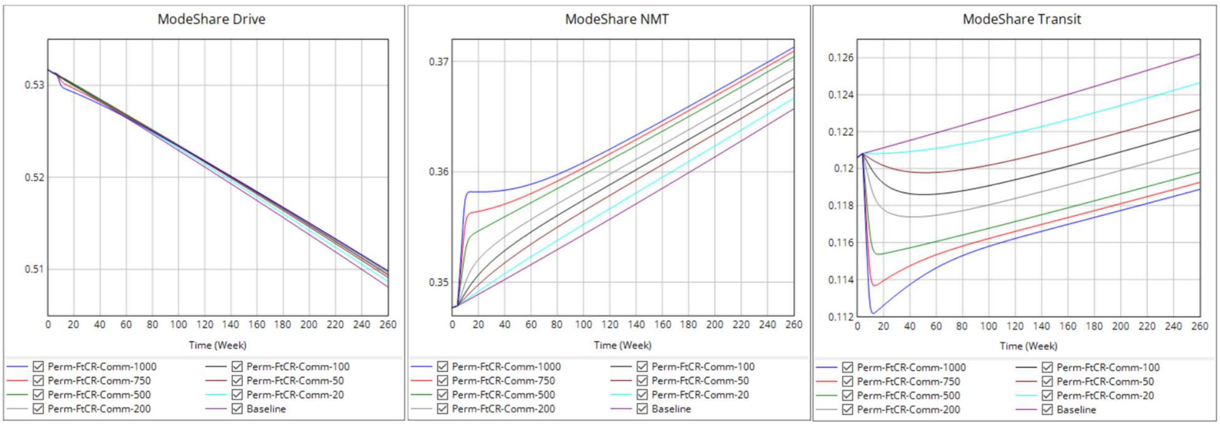

Figure 20 Seattle model commercial scenario mode shares

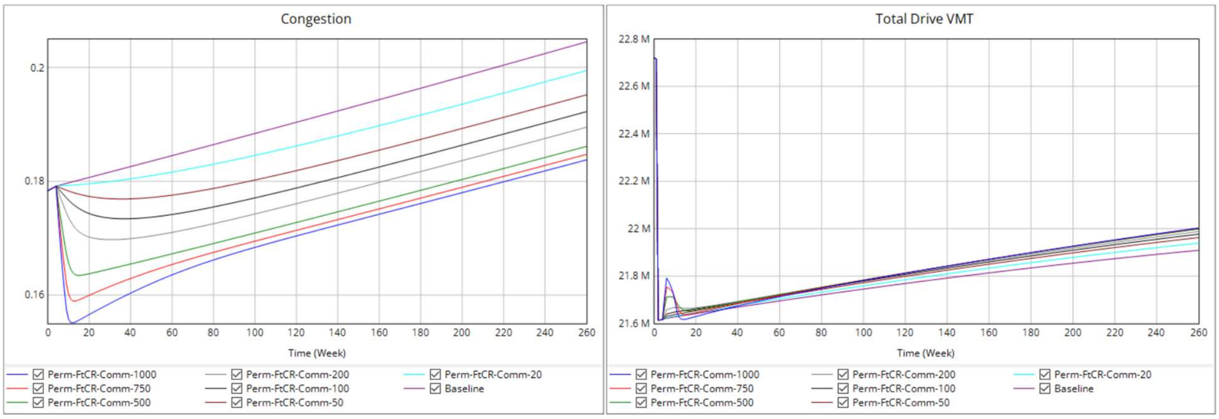

Figure 21 Seattle model commercial scenario congestion and total drive VMT

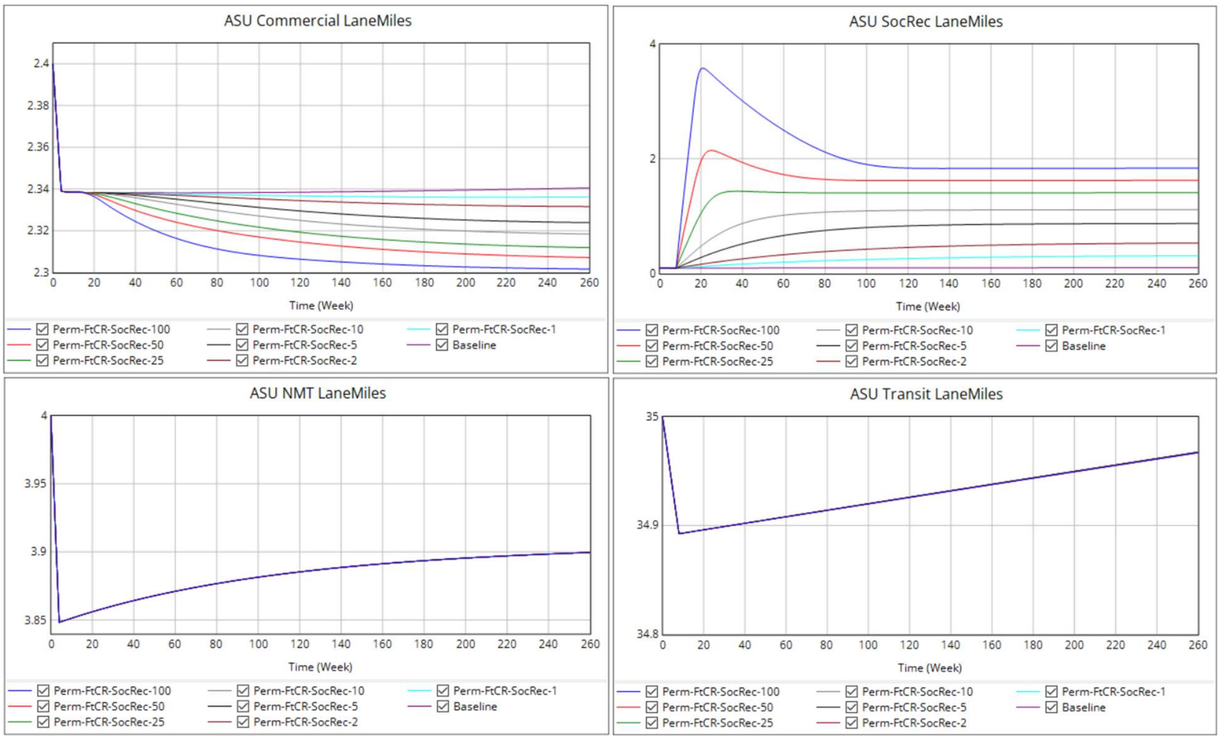

Figure 22 Seattle model social/recreational scenario ASU lane-miles

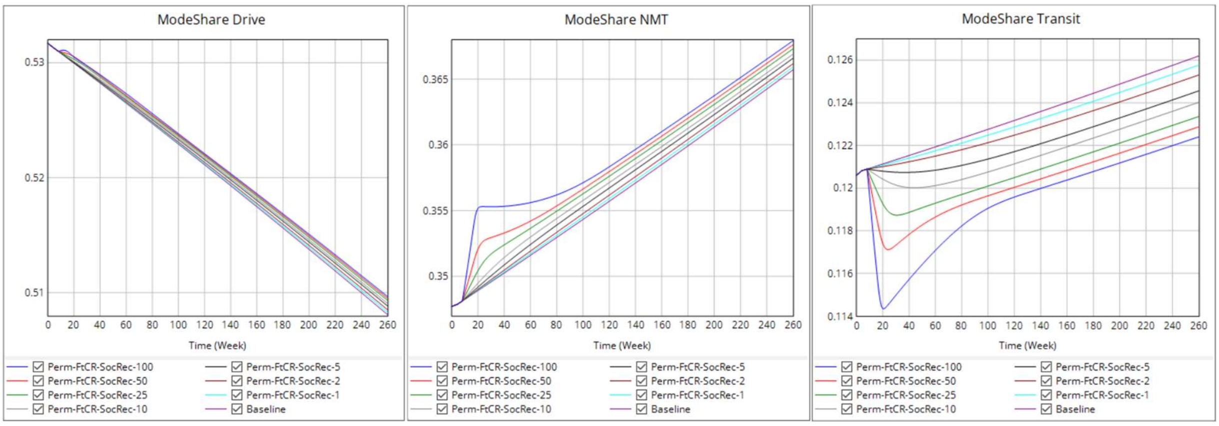

Figure 23 Seattle model social/recreational scenario mode shares

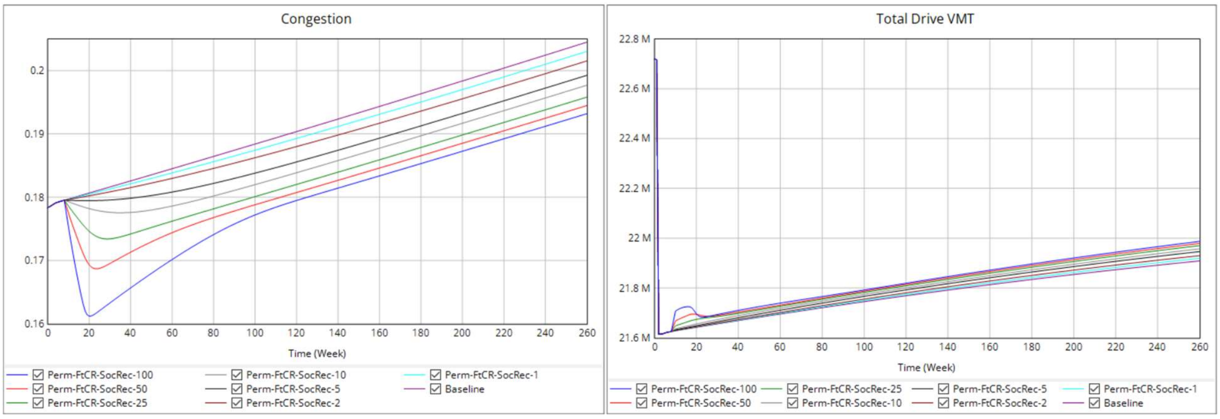

Figure 24 Seattle model social/recreational scenario congestion and total drive VMT

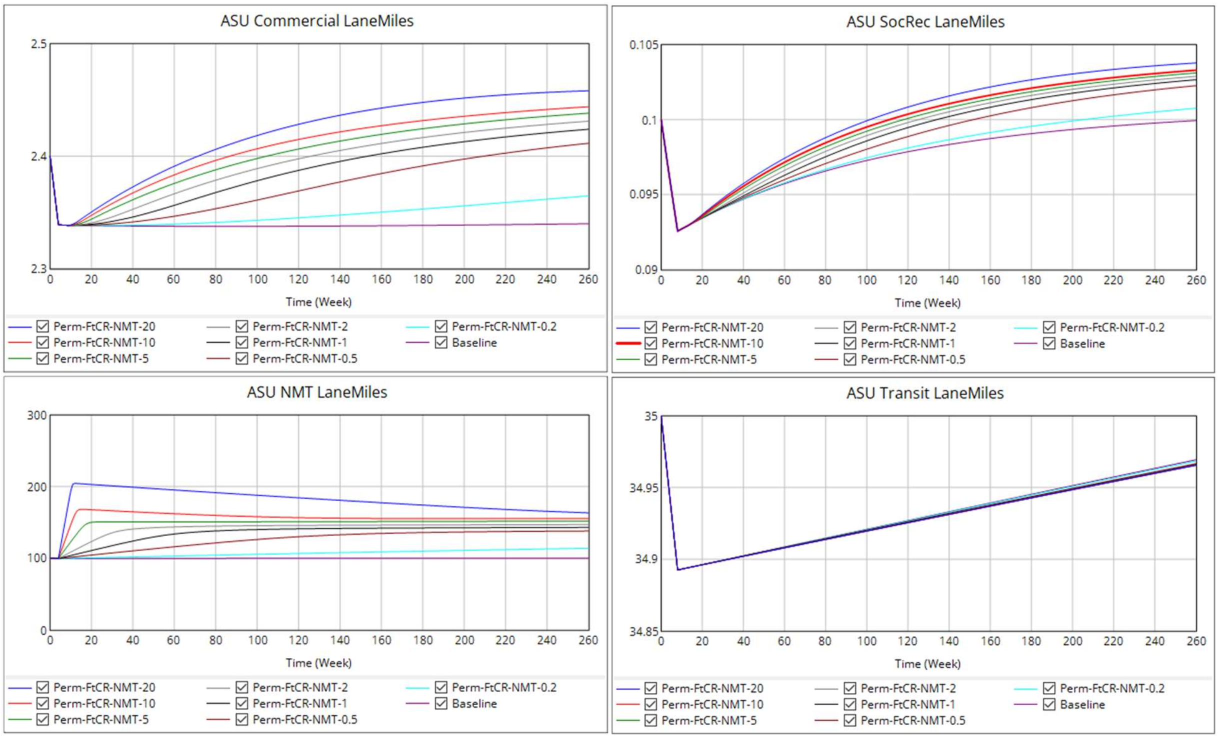

Figure 25 Seattle model NMT scenario ASU lane-miles

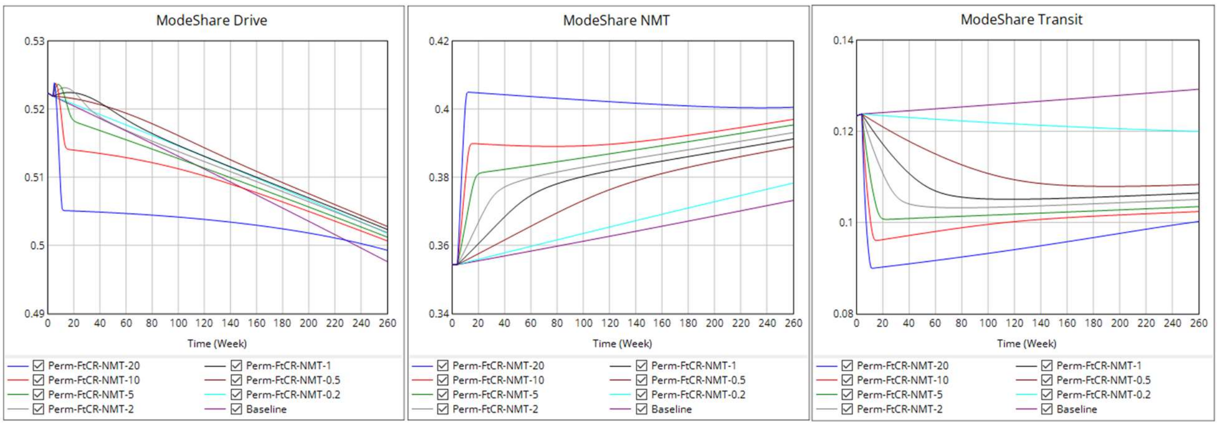

Figure 26 Seattle model NMT scenario mode shares

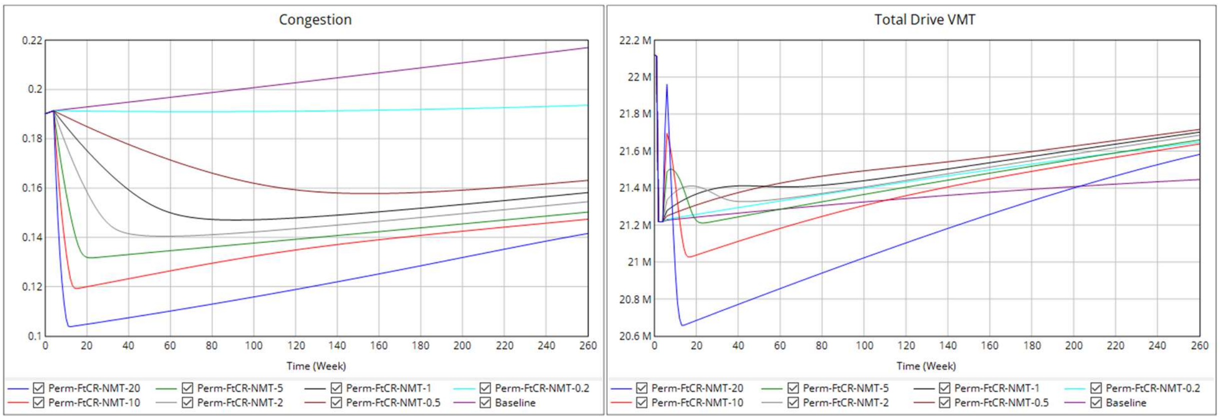

Figure 27 Seattle model NMT scenario congestion and total drive VMT

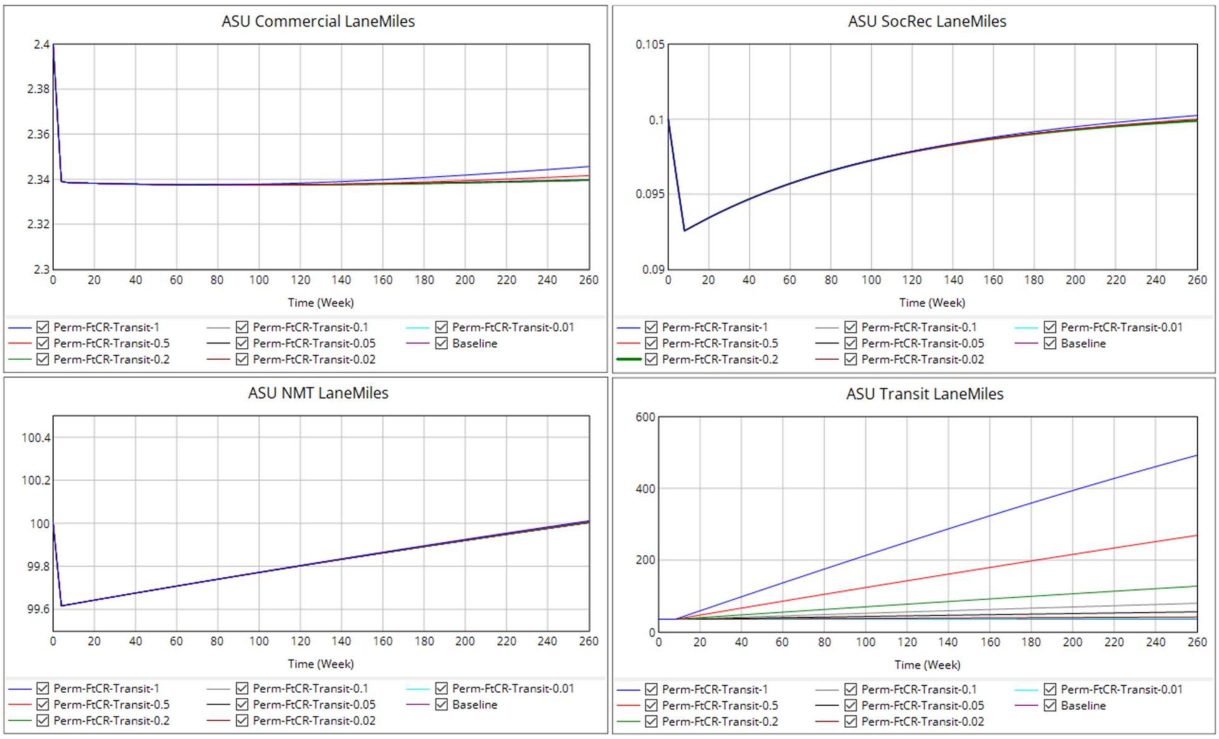

Figure 28 Seattle model transit scenario ASU lane-miles

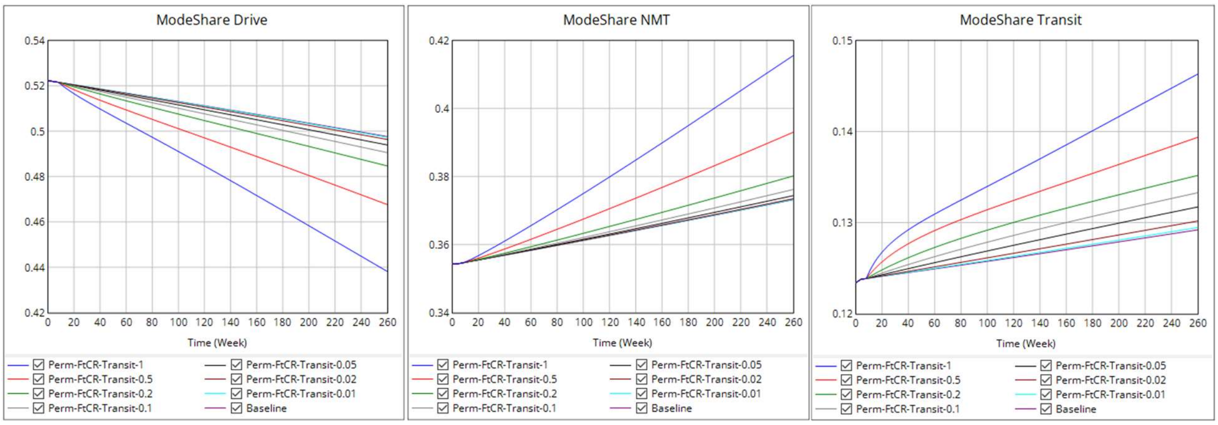

Figure 29 Seattle model transit scenario mode shares

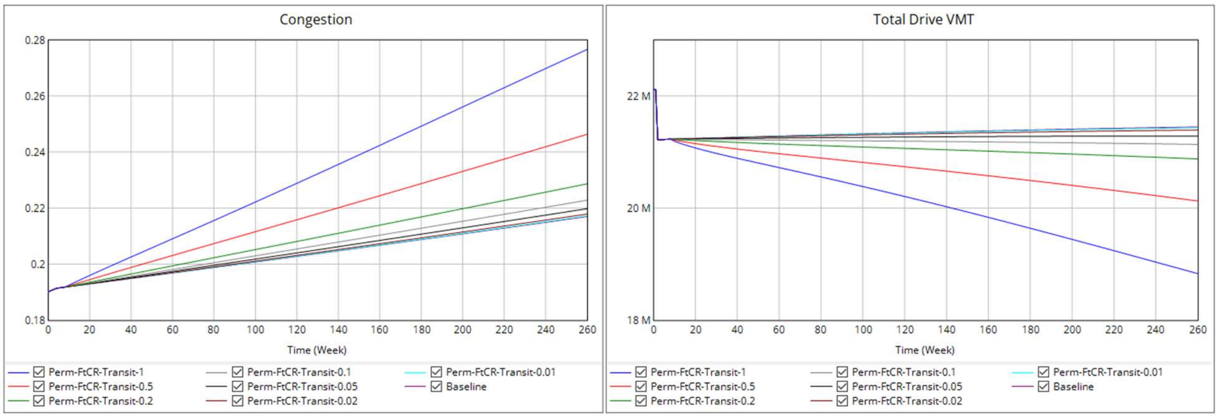

Figure 30 Seattle model transit scenario congestion and total drive VMT

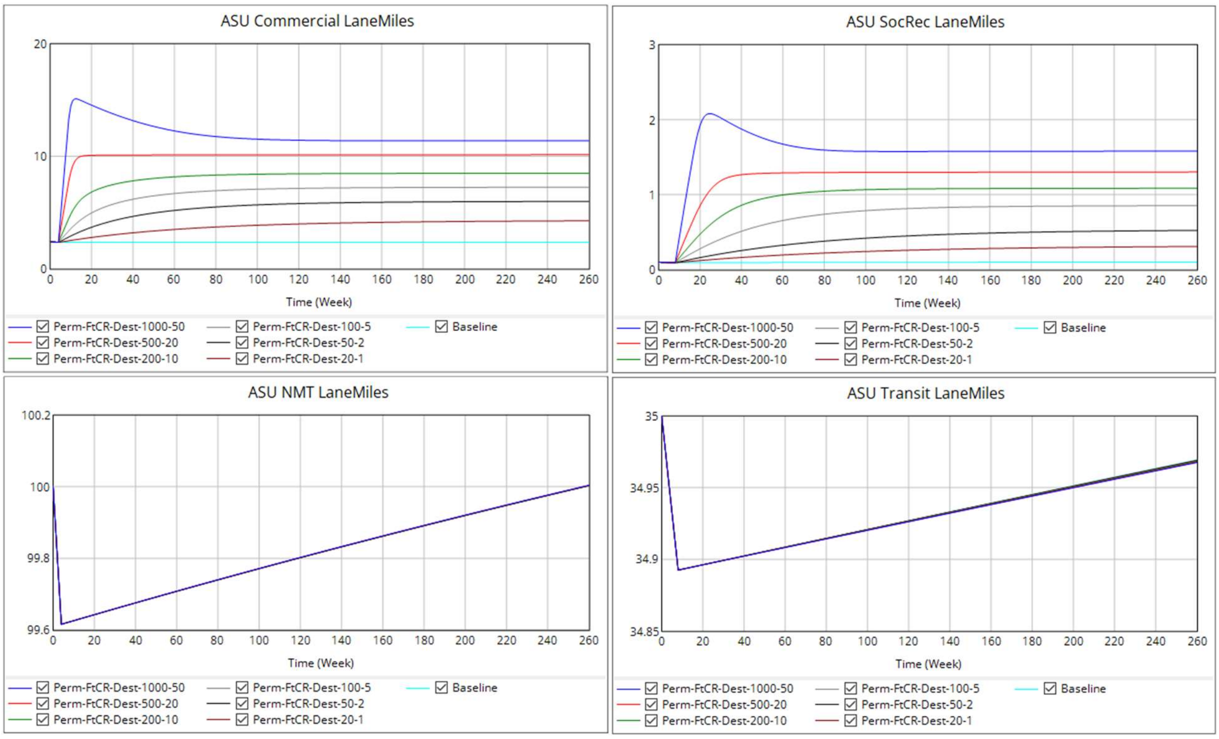

Figure 31 Seattle model destination scenario ASU lane-miles

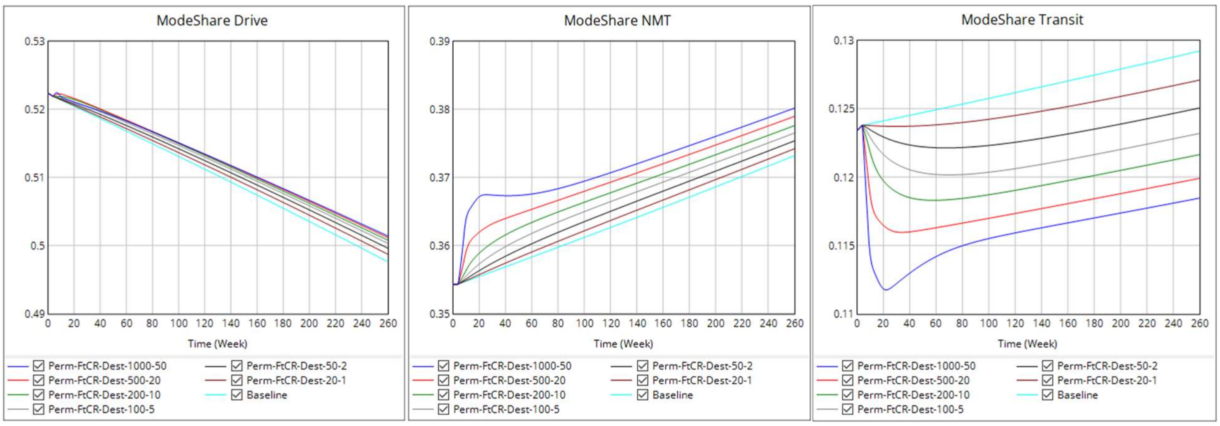

Figure 32 Seattle model destination scenario mode shares

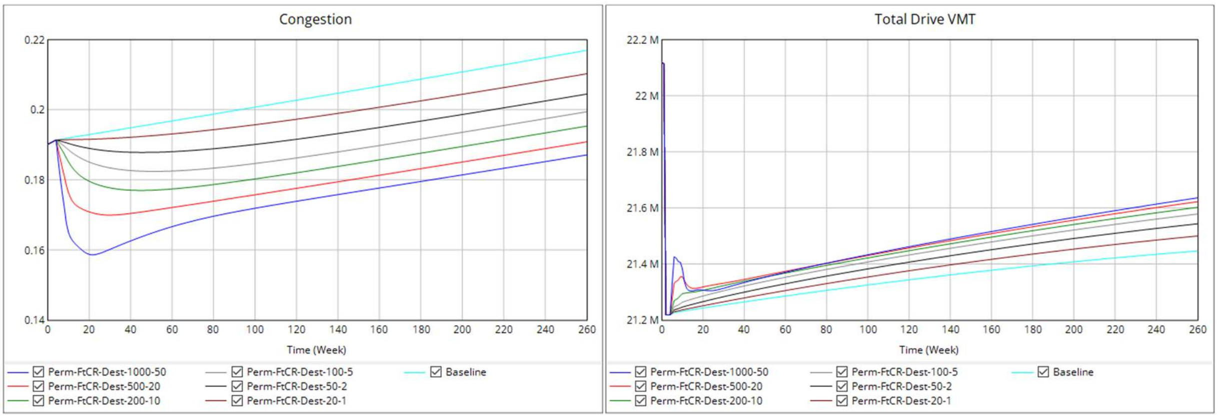

Figure 33 Seattle model destination scenario congestion and total drive VMT

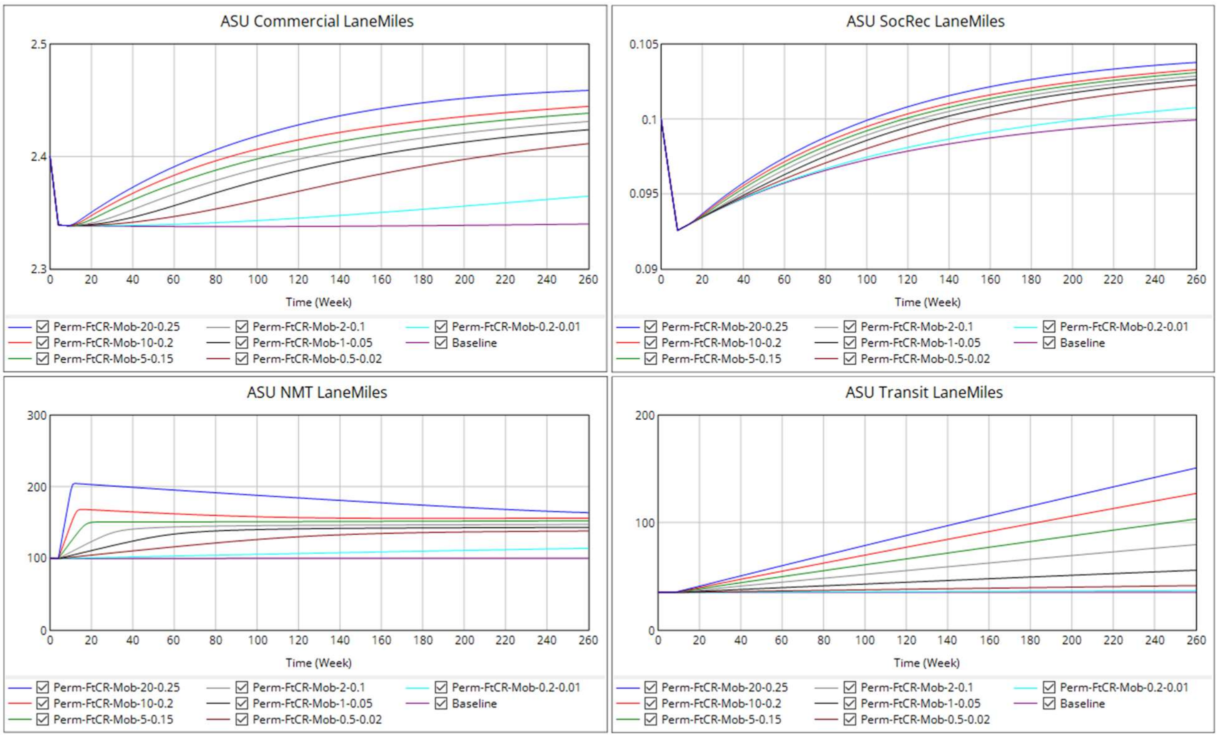

Figure 34 Seattle model mobility scenario (moderate transit funding sub-scenario) ASU lane-miles

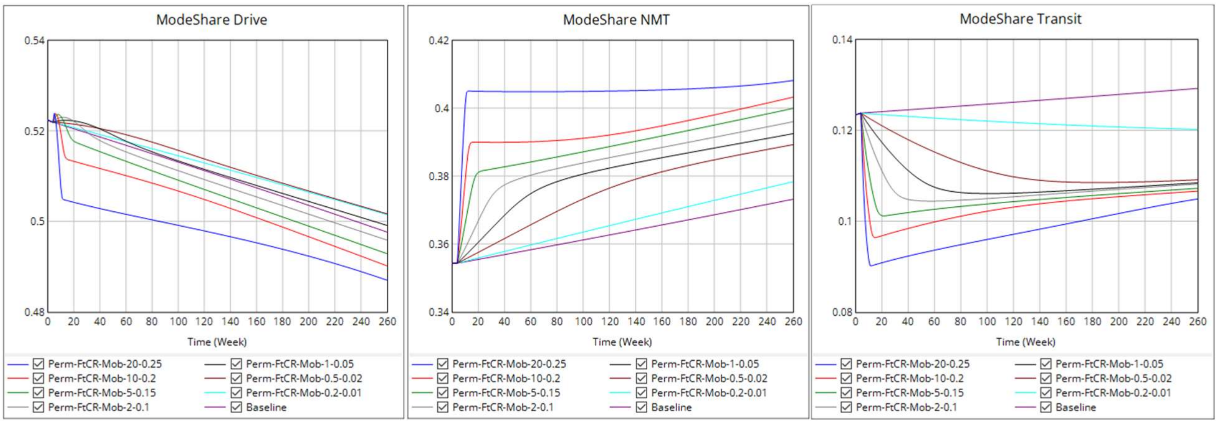

Figure 35 Seattle model mobility scenario (moderate transit funding sub-scenario) mode shares

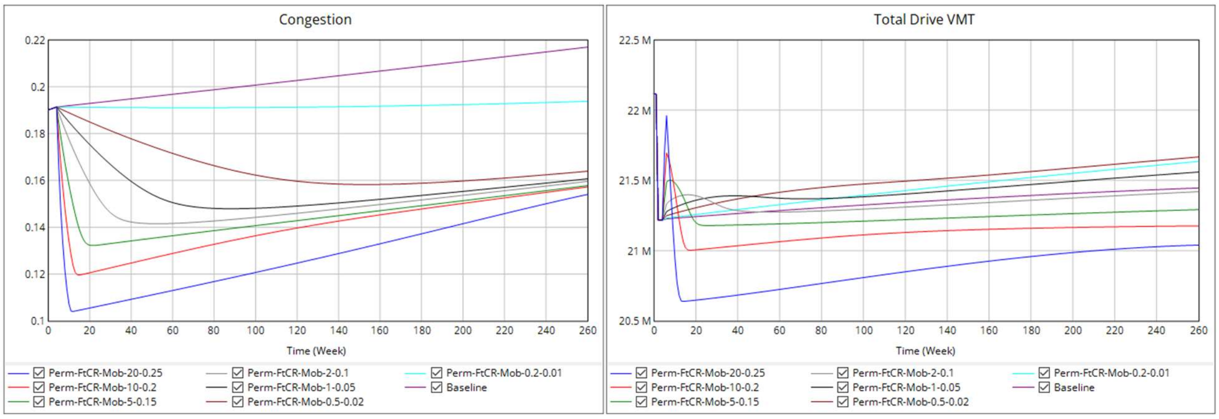

Figure 36 Seattle model mobility scenario (moderate transit funding sub-scenario) congestion and total drive VMT

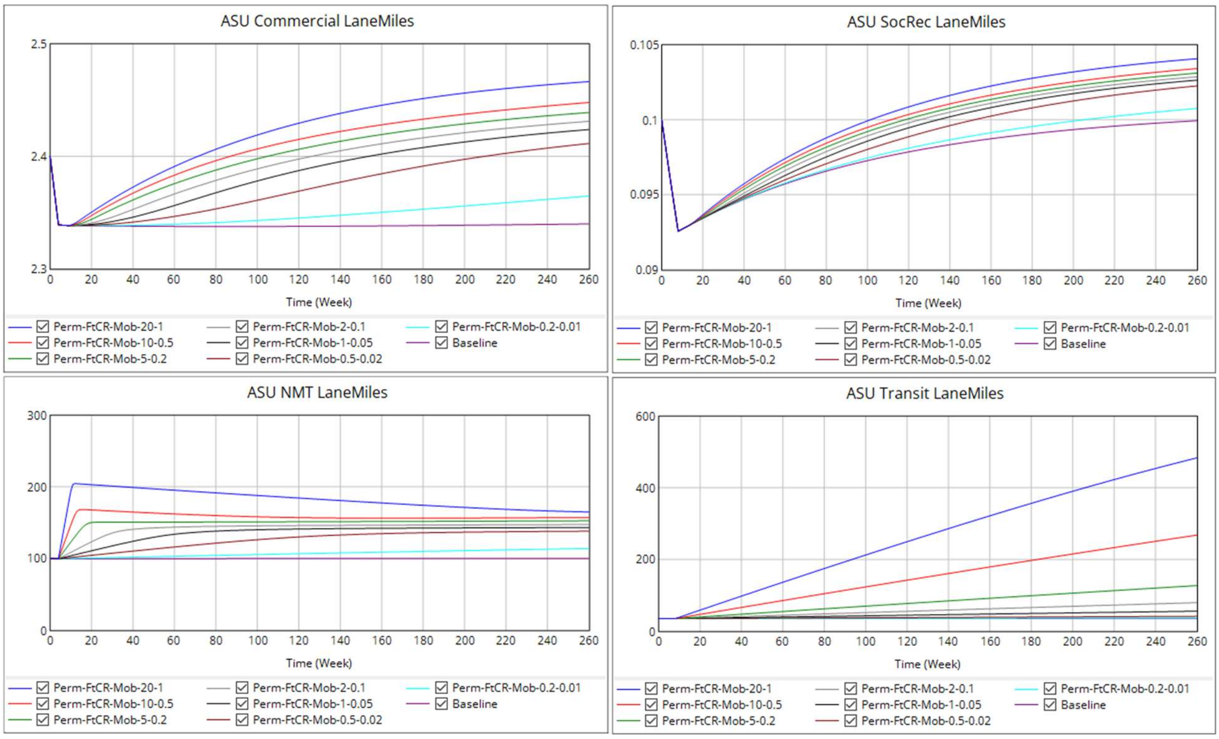

Figure 37 Seattle model mobility scenario (high transit funding sub-scenario) ASU lane-miles

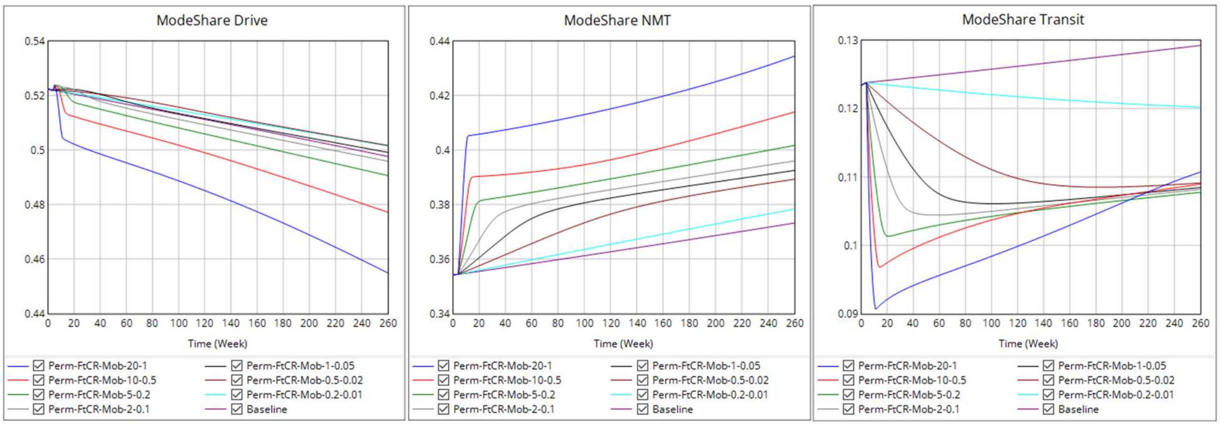

Figure 38 Seattle model mobility scenario (high transit funding sub-scenario) mode shares

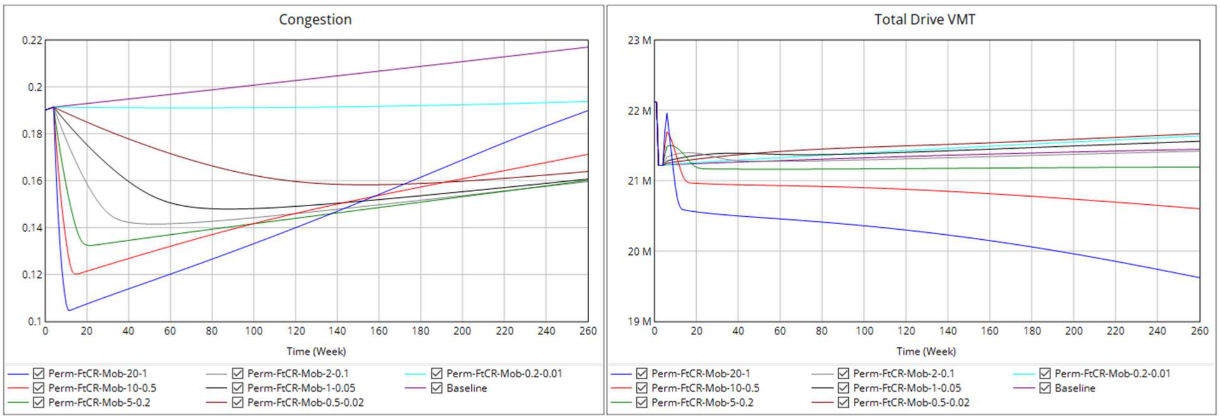

Figure 39 Seattle model mobility scenario (high transit funding sub-scenario) congestion and total drive VMT

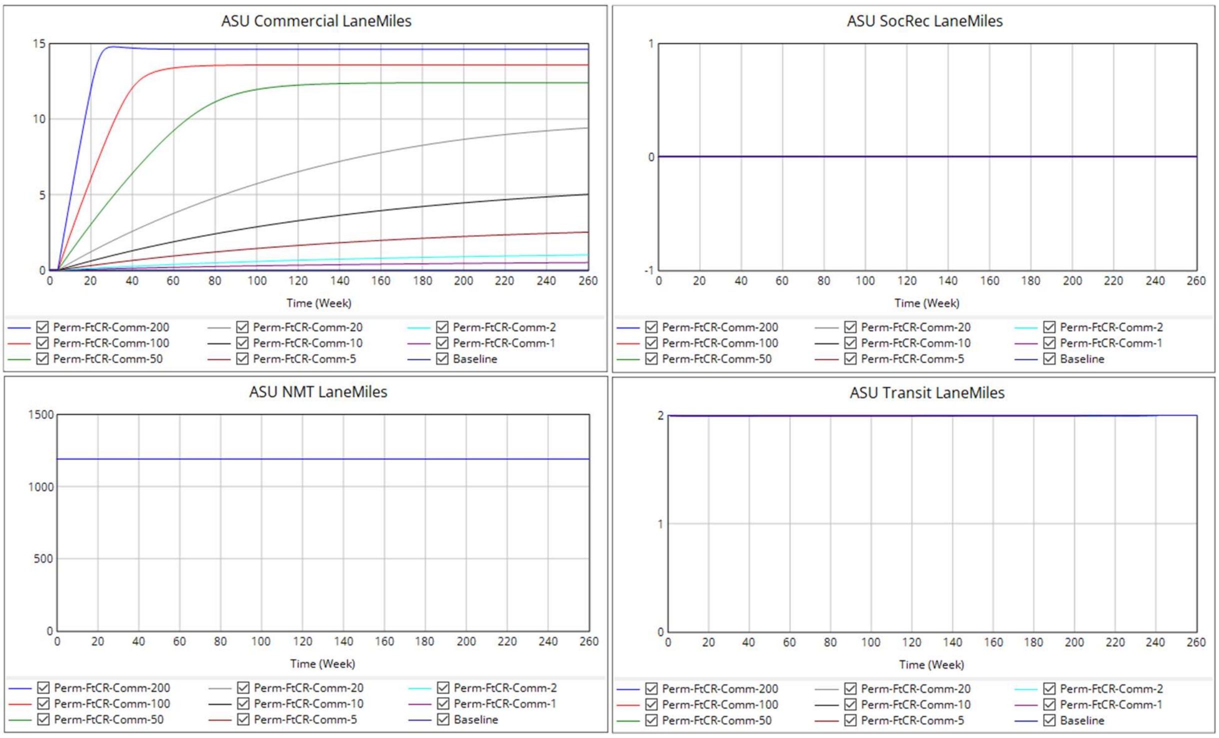

Figure 40 Phoenix model commercial scenario ASU lane-miles

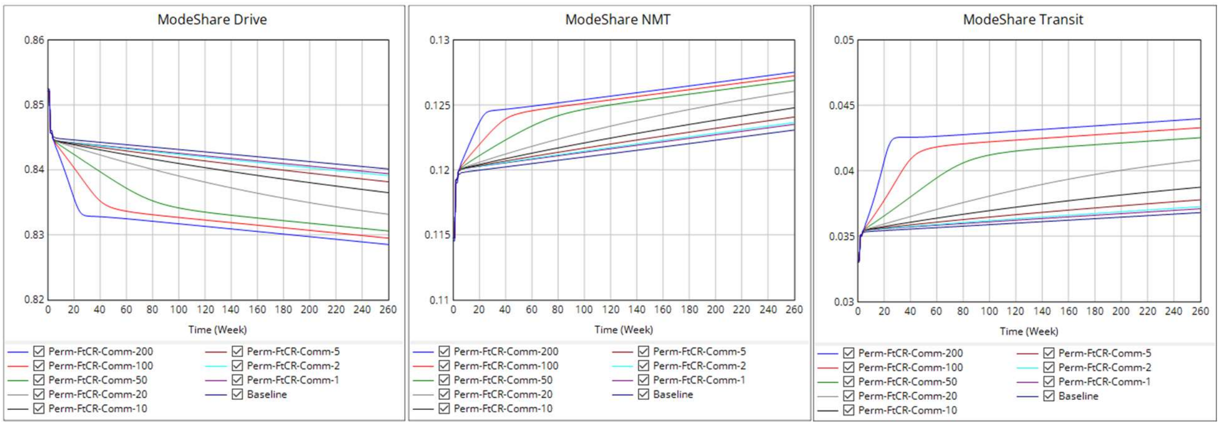

Figure 41 Phoenix model commercial scenario mode shares

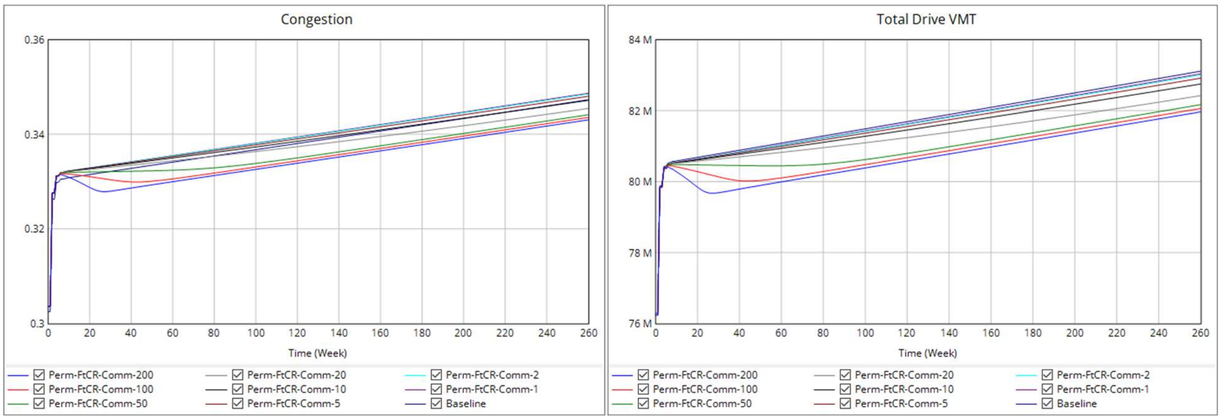

Figure 42 Phoenix model commercial scenario congestion and total drive VMT

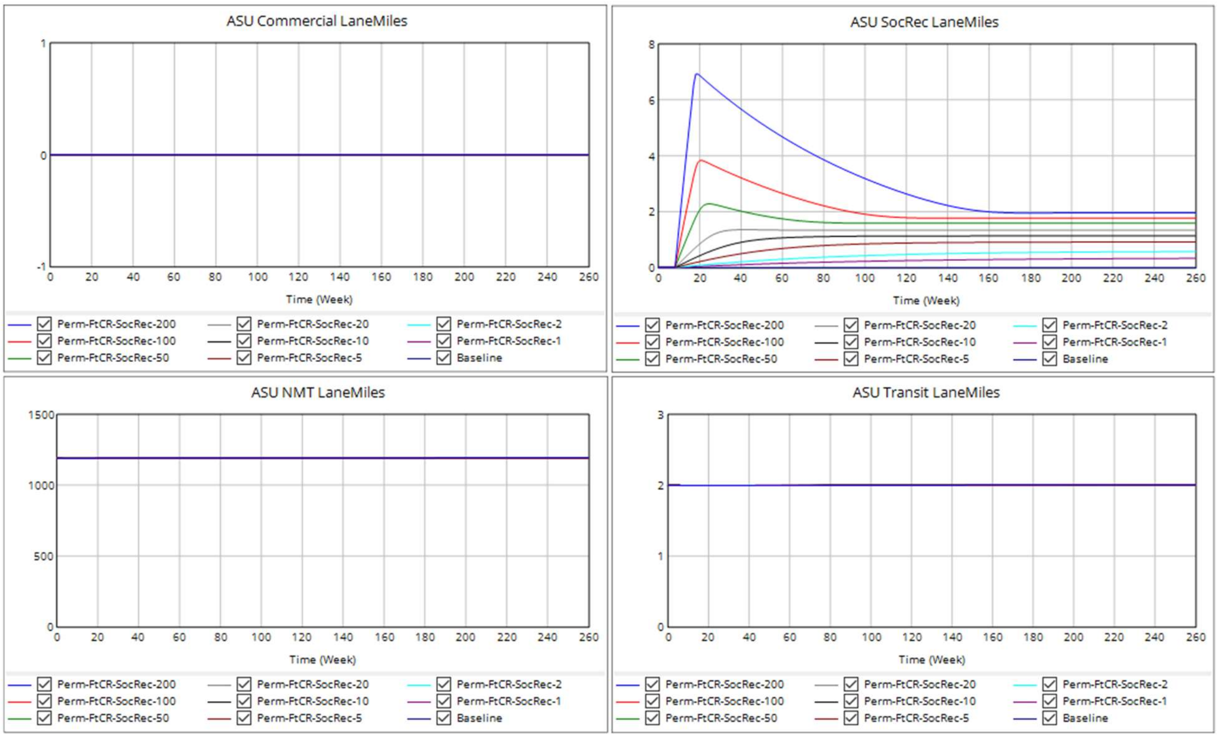

Figure 43 Phoenix model social/recreational scenario ASU lane-miles

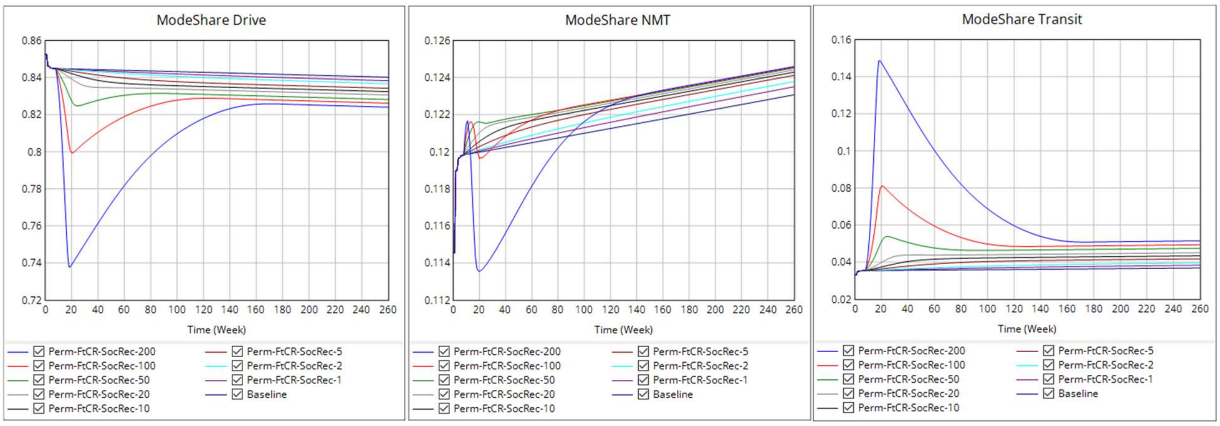

Figure 44 Phoenix model social/recreational scenario mode shares

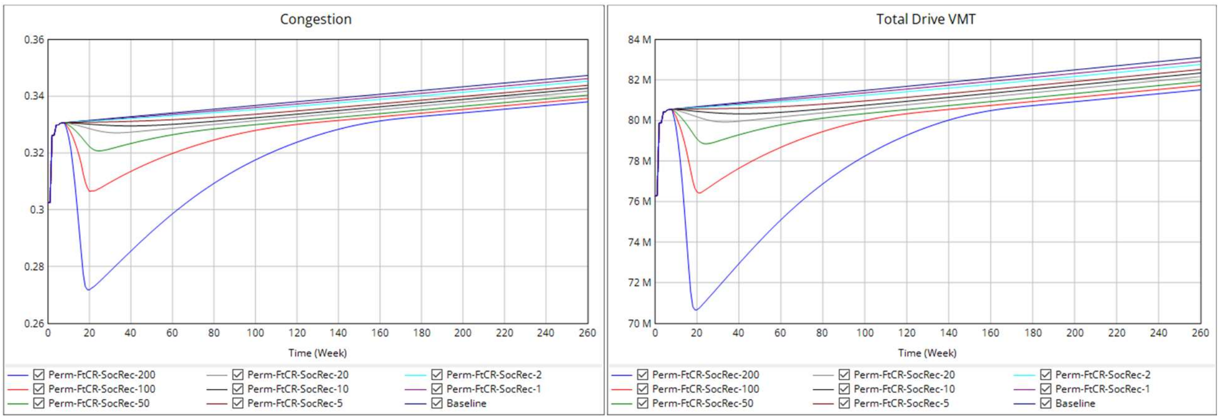

Figure 45 Phoenix model social/recreational scenario congestion and total drive VMT

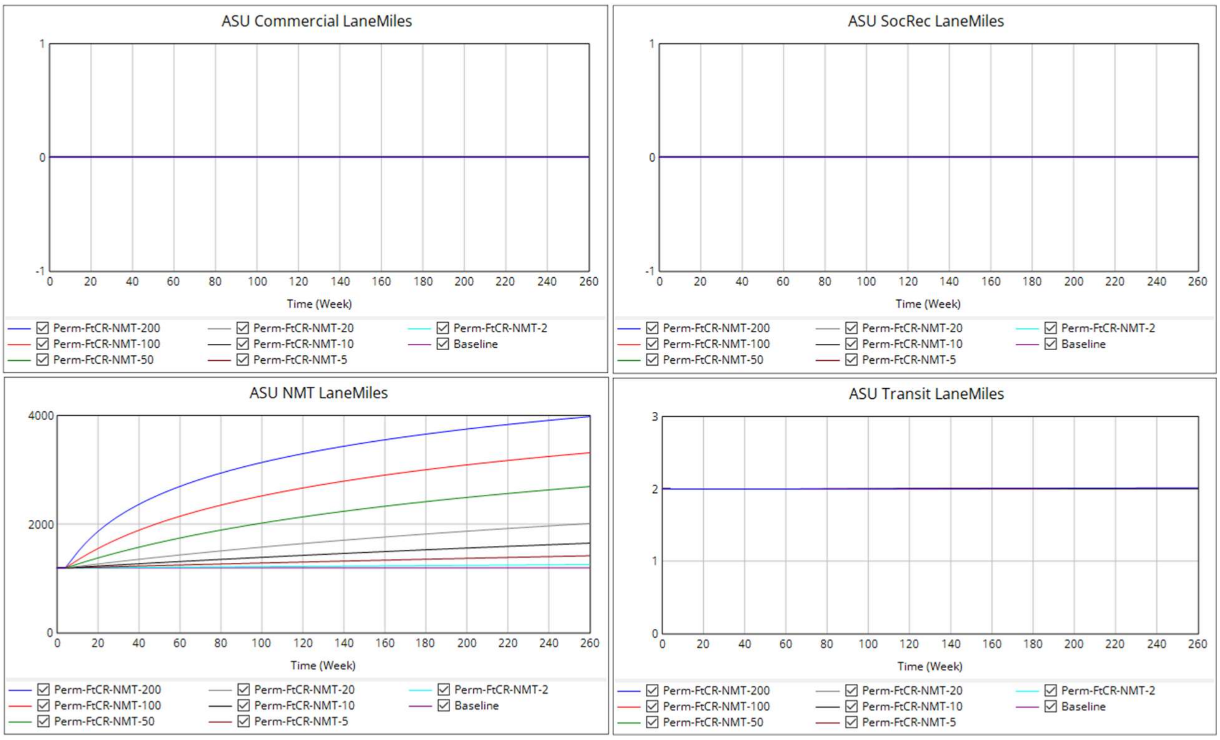

Figure 46 Phoenix model NMT scenario ASU lane-miles

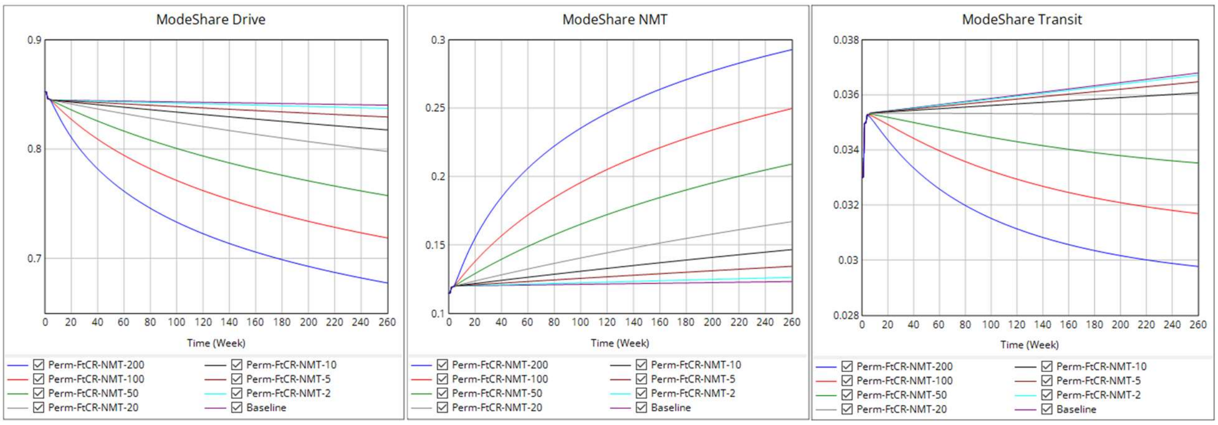

Figure 47 Phoenix model NMT scenario mode shares

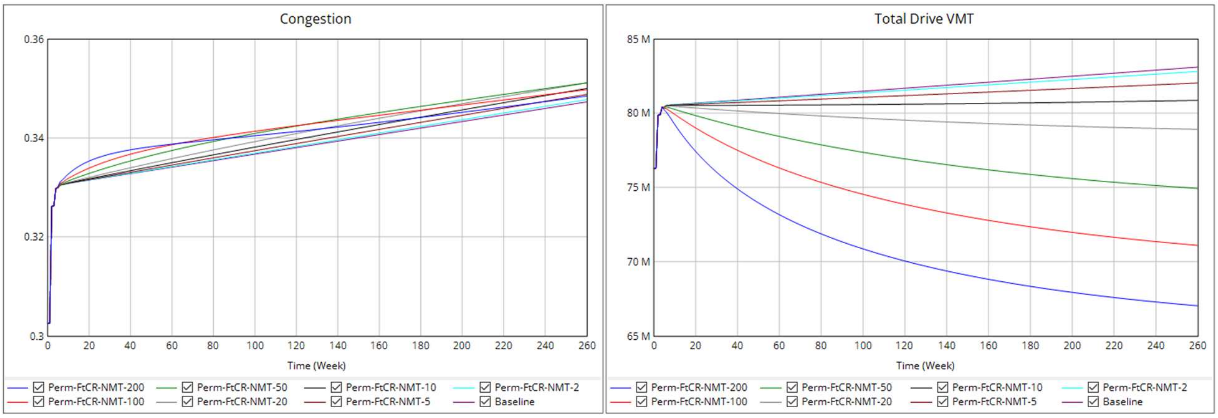

Figure 48 Phoenix model NMT scenario congestion and total drive VMT

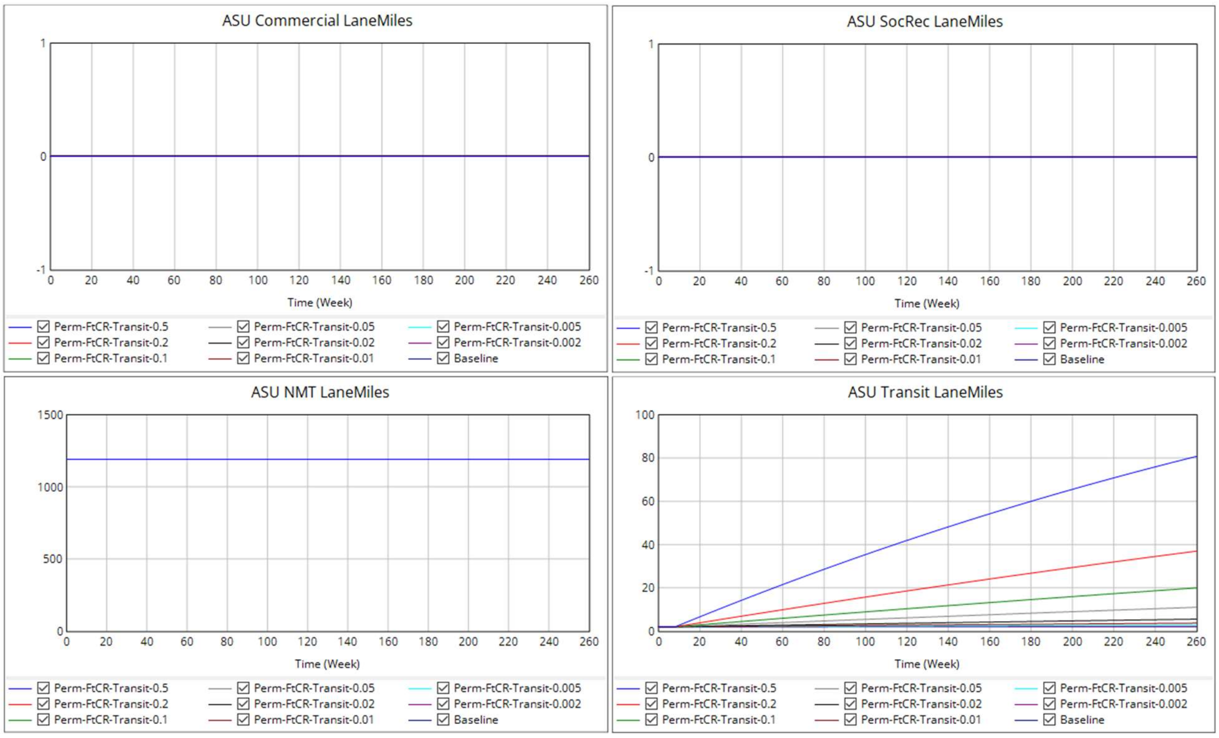

Figure 49 Phoenix model transit scenario ASU lane-miles

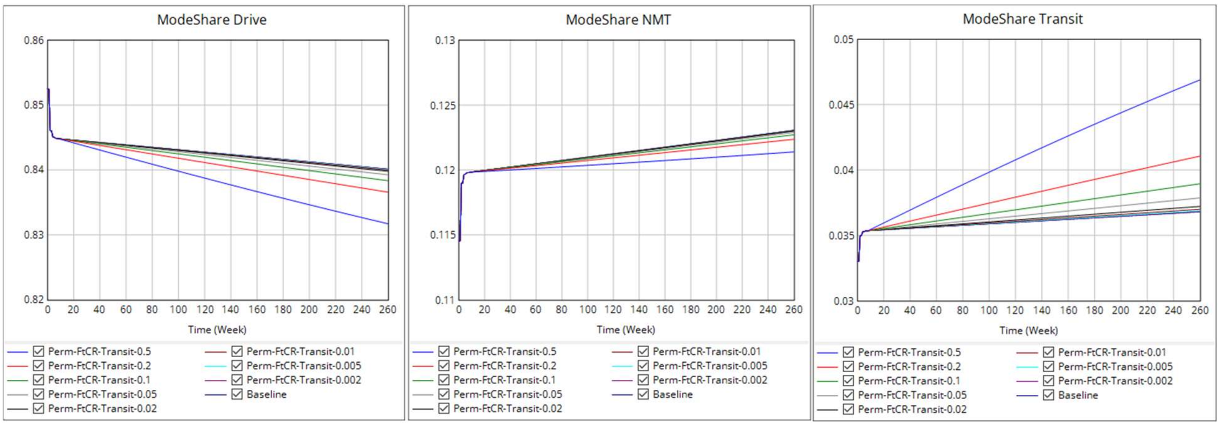

Figure 50 Phoenix model transit scenario mode shares

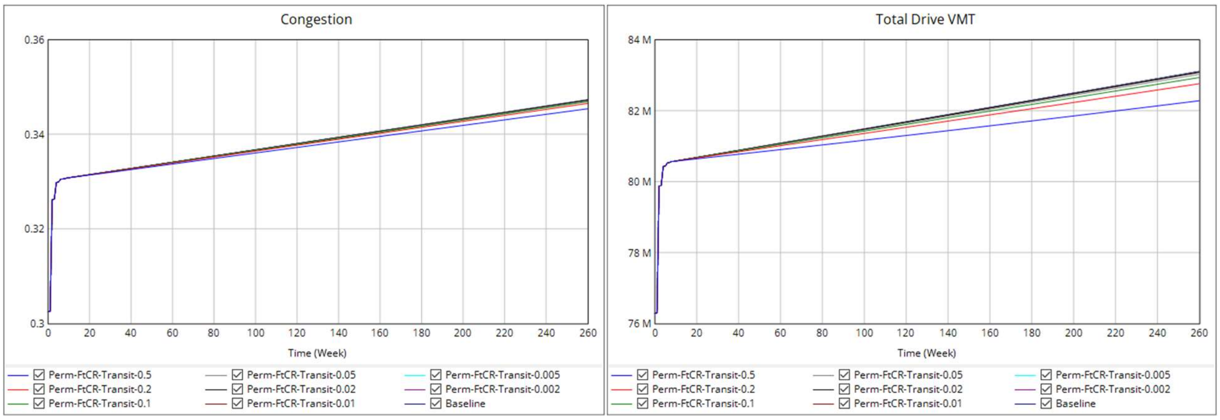

Figure 51 Phoenix model transit scenario congestion and total drive VMT

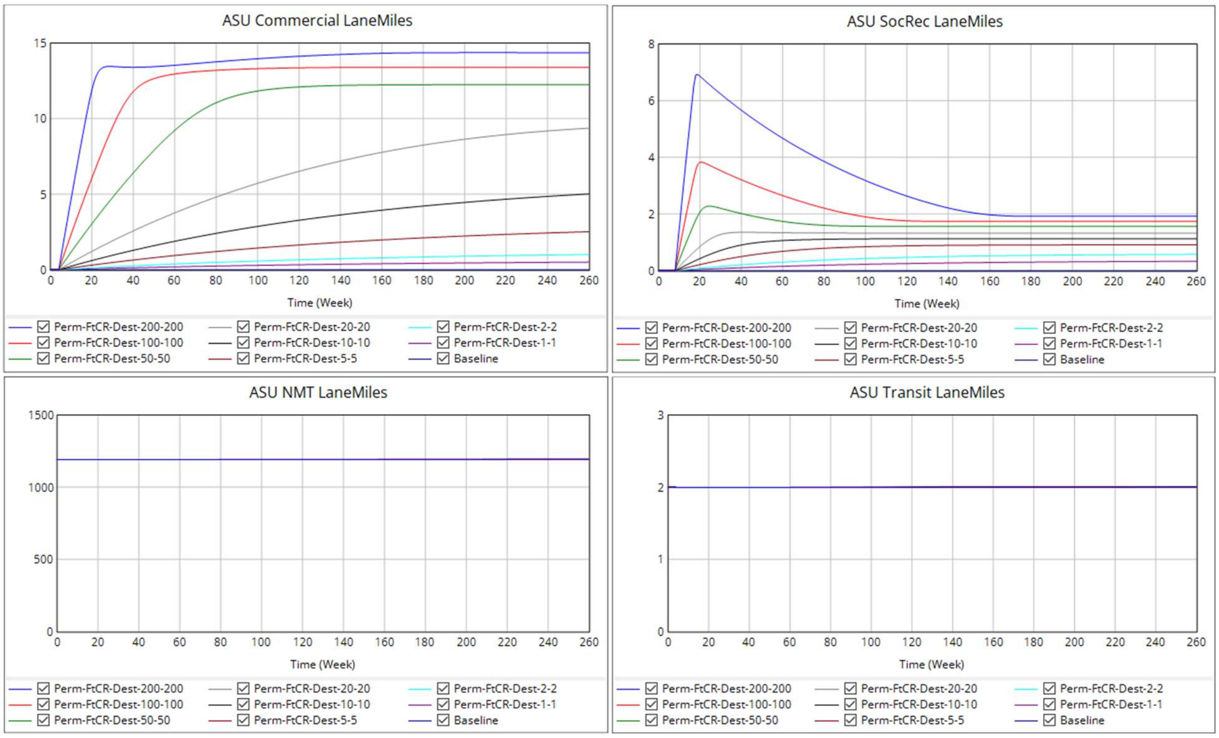

Figure 52 Phoenix model destination scenario ASU lane-miles

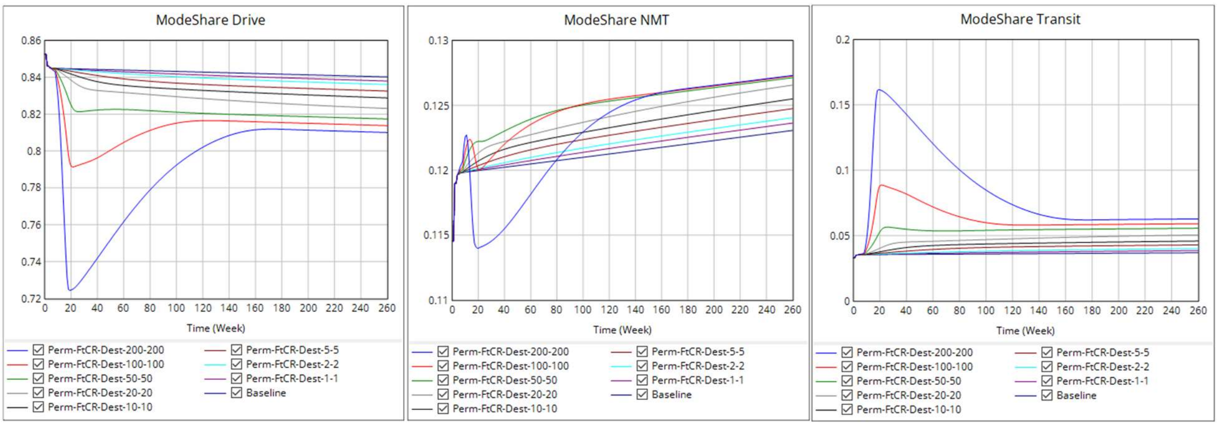

Figure 53 Phoenix model destination scenario mode shares

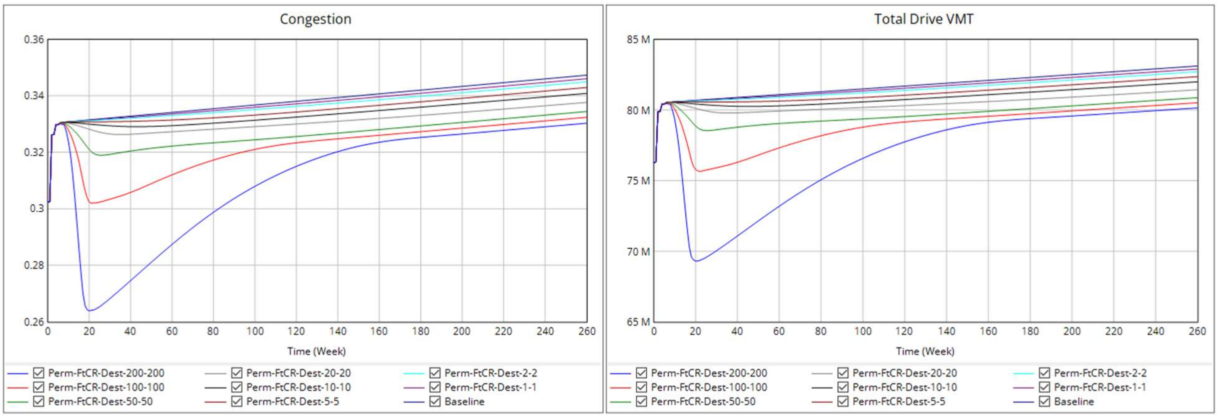

Figure 54 Phoenix model destination scenario congestion and total drive VMT

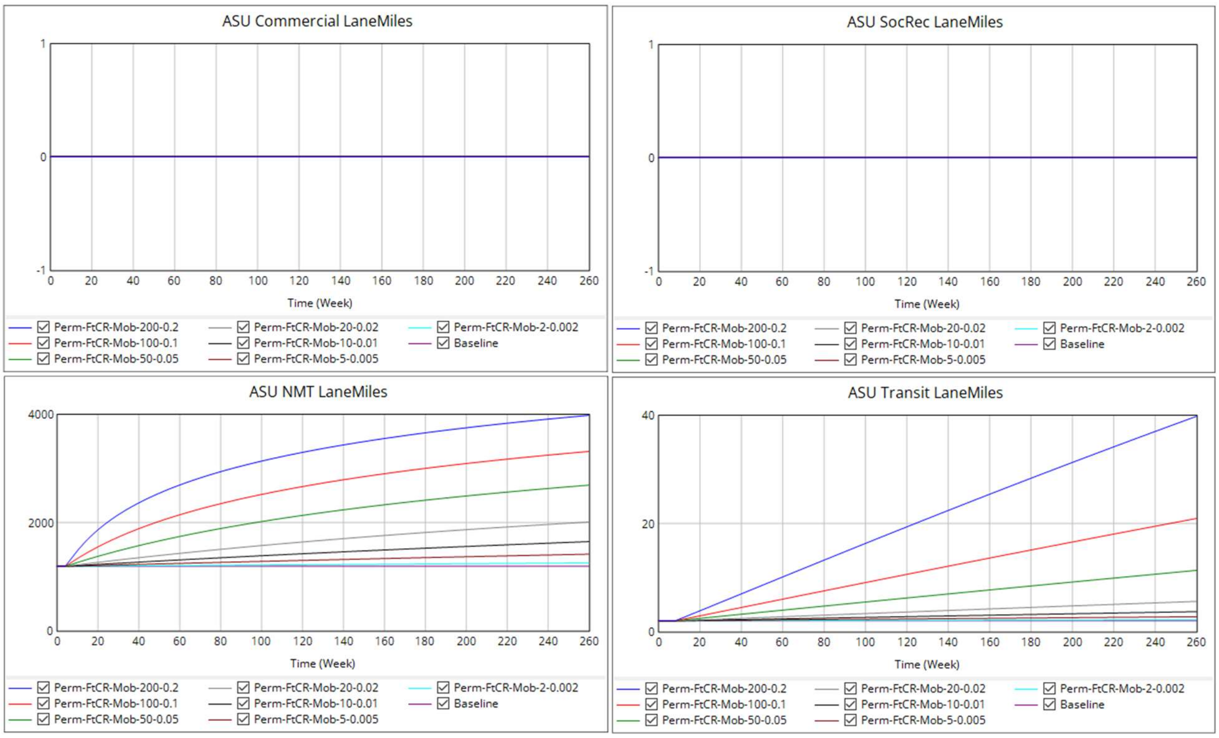

Figure 55 Phoenix model mobility scenarioASU lane-miles

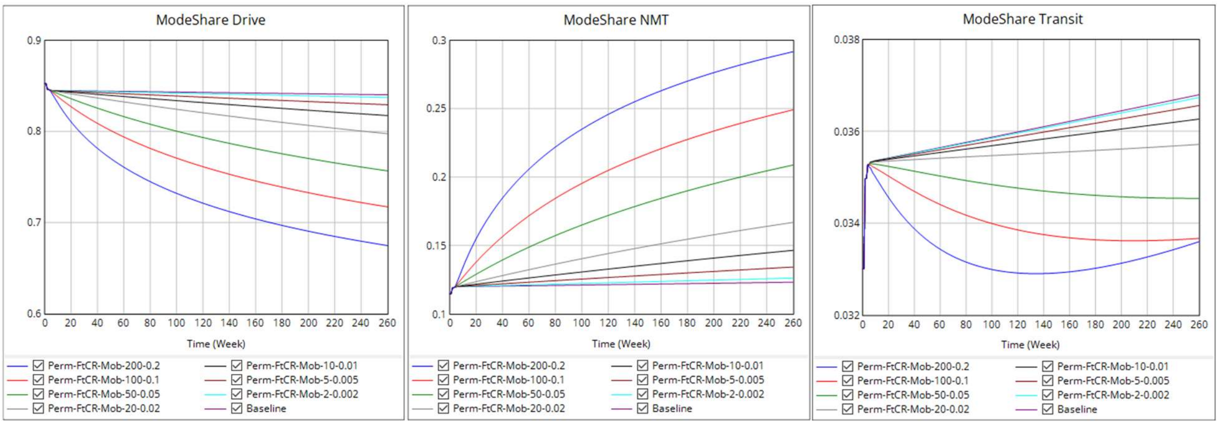

Figure 56 Phoenix model mobility scenario mode shares

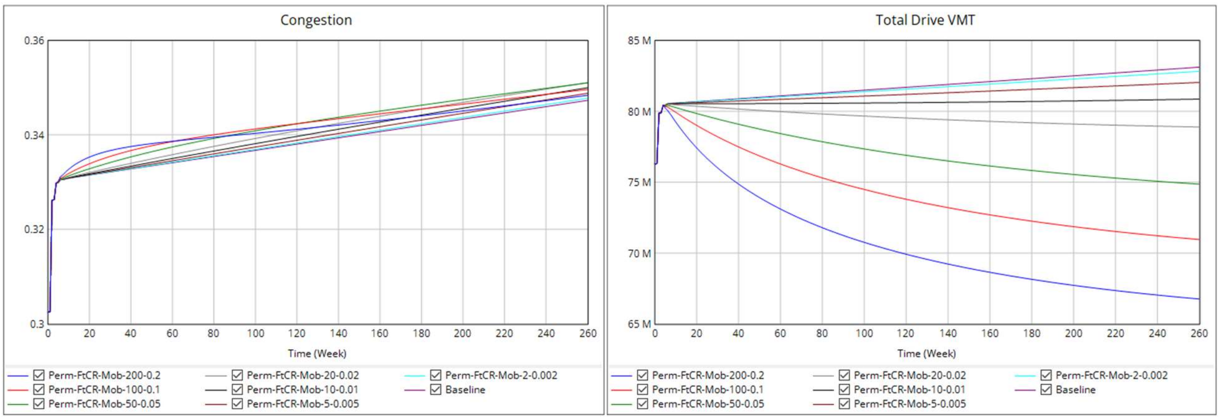

Figure 57 Phoenix model mobility scenario congestion and total drive VMT

6. GITHUB REPOSITORY AND VENSIM SOFTWARE

A GitHub repository has been created to host all supplementary files used in this analysis. The repository contains the following:

- Vensim model files (one for the Seattle model, one for the Phoenix model, and one for creating the example CLD figure)
- Data files (e.g. household travel survey data, transit agency data)
    - Note: one data file used in the analysis is not made publicly available (the FHWA 2017 NHTS Trips dataset at the census block group-level; please contact the FHWA NHTS program for access: https://nhts.ornl.gov/contact-us)
- Python code (used for data analysis for determining model parameters)
- Additional analysis files (such as for non-Python-based analysis and model calibration)
- Results figures (full sets of supplementary results figures, as replicated here in Section 5)

The repository may be accessed via the link: https://github.com/UW-THINKlab/street-repurposing-system-dynamics-analysis.

The SD models in this study were created using the software Vensim PLE+ 10.2.1. Vensim software may be accessed via their website: https://vensim.com/download/.

7. DISRUPTION-AFFECTED MODEL

The SD model developed in this thesis was adapted to investigate the effect of changing travel behavior decisions during a city-wide disruption. Disruption behavior changes were inferred from the LEAP-HI Survey conducted by Thrust 4. Of the disruption types that survey participants were asked about, extreme heat and extreme cold were chosen as the two disruptions that would be tested in the SD model. These two disruptions were chosen because they would affect a city with the greatest degree of spatial homogeneity, compared to other disruptions of earthquake, flooding, heavy snowfall, and power outage. Note that for modelling disruptions with greater spatial heterogeneity, it may be possible to employ a spatially-cellularized system dynamics model (as mentioned in the Discussion section in the main body of this thesis). Spatial variation in both disruption intensity and impacts may be accounted for, to the cellular scale of the cellularized model. However, for the initial exploration of the system dynamics model's applicability to investigating transportation and urban system responses to a disruption, the spatially homogeneous disruptions of extreme heat and cold were applied to the whole-city model.

The LEAP-HI Survey questions of greatest interest are outlined in **Table 16**. Survey items asked respondents to rate their likelihood to engage in a particular activity during a disruption, or whether they would engage with an activity less, more, or about the same during a disruption. Each survey item was associated with a variable in the SD model out of the following: total trip count (Trips), mode share of driving, NMT, or transit, and purpose share of work/school, commercial, social/recreational, or errand/escort trips. Whether the survey item's response was positively or negatively associated with the SD model variable is also indicated in **Table 16**.

Table 16 LEAP-HI Survey items and their associated travel variable of influence in the SD model

Variable Name	Short Description	Survey Scale	Related Variable in SD Model (+/- Assoc.)
ext_heat_lkly_stay_home	Try to stay home as much as possible	1: Very unlikely; 5: Very likely	Trips (-)
ext_heat_lkly_social_connection	Go to friend or family's house nearby for support/safety	1: Very unlikely; 5: Very likely	PS Social/Recreational (+)
ext_heat_lkly_leave_town	Leave town to avoid worst disruption impacts	1: Very unlikely; 5: Very likely	Trips (-)
ext_heat_lkly_supplies	Stock up on essential supplies and prepare an emergency kit	1: Very unlikely; 5: Very likely	PS Commercial (+)
ext_heat_lkly_comm_supports	Engage with community support networks or local response effots	1: Very unlikely; 5: Very likely	PS Errand/Escort (+)
ext_heat_indoor_restaurant	Eating indoors at a restaurant	1: Less; 2: Same; 3: More	PS Commercial (+)
ext_heat_takeout_pickup	Picking up takeout from a restaurant	1: Less; 2: Same; 3: More	PS Commercial (+)
ext_heat_public_indoors	Hanging out indoors in a public space	1: Less; 2: Same; 3: More	PS Social/Recreational (+)
ext_heat_wfh	Work from home	1: Less; 2: Same; 3: More	PS Work/School (-)
ext_heat_commute	Work from office	1: Less; 2: Same; 3: More	PS Work/School (+)
ext_heat_car_travel	Use a car for traveling	1: Less; 2: Same; 3: More	MS Drive (+)
ext_heat_public_transit	Take public transit	1: Less; 2: Same; 3: More	MS Transit (+)
ext_heat_stay_home	Staying at home	1: Less; 2: Same; 3: More	Trips (-)
ext_heat_check_family_friends	Checking in on friends and family	1: Less; 2: Same; 3: More	PS Social/Recreational (+)
ext_heat_volunteer_community	Volunteering to help my community	1: Less; 2: Same; 3: More	PS Errand/Escort (+)
ext_cold_lkly_stay_home	Try to stay home as much as possible	1: Very unlikely 5: Very likely	Trips (-)
ext_cold_lkly_social_connection	Go to friend or family's house nearby for support/safety	1: Very unlikely 5: Very likely	PS Social/Recreational (+)
ext_cold _lkly_leave_town	Leave town to avoid worst disruption impacts	1: Very unlikely 5: Very likely	Trips (-)

ext_cold _lkly_supplies	Stock up on essential supplies and prepare an emergency kit	1: Very unlikely 5: Very likely	PS Commercial (+)
ext_cold_lkly_comm_supports	Engage with community support networks or local response effots	1: Very unlikely 5: Very likely	PS Errand/Escort (+)
ext_cold_indoor_restaurant	Eating indoors at a restaurant	1: Less; 2: Same; 3: More	PS Commercial (+)
ext_cold_takeout_pickup	Picking up takeout from a restaurant	1: Less; 2: Same; 3: More	PS Commercial (+)
ext_cold_public_indoors	Hanging out indoors in a public space	1: Less; 2: Same; 3: More	PS Social/Recreational (+)
ext_cold_wfh	Work from home	1: Less; 2: Same; 3: More	PS Work/School (-)
ext_cold_commute	Work from office	1: Less; 2: Same; 3: More	PS Work/School (+)
ext_cold_car_travel	Use a car for traveling	1: Less; 2: Same; 3: More	MS Drive (+)
ext_cold_public_transit	Take public transit	1: Less; 2: Same; 3: More	MS Transit (+)
ext_cold_stay_home	Staying at home	1: Less; 2: Same; 3: More	Trips (-)
ext_cold_check_family_friends	Checking in on friends and family	1: Less; 2: Same; 3: More	PS Social/Recreational (+)
ext_cold_volunteer_community	Volunteering to help my community	1: Less; 2: Same; 3: More	PS Errand/Escort (+)

The Seattle- and Phoenix-area survey item mean responses were calculated, then normalized on a scale from -1 to 1, where a survey response at the lowest end of the scale corresponded to -1, a survey response at the middle of the scale corresponded to 0, and a survey response at the highest end of the scale corresponded to +1. The mean survey item response for items that corresponded to the same SD model variables were averaged together to produce a mean behavior shift for that SD model variable under an external disruption.

The mean behavior shift (which was a value from -1 to +1) was then used to multiply the baseline reference SD model variable to either scale the variable up or down. Since the survey item responses only provided directionality of behavioral change rather than any quantitative estimate of behavioral change, a sensitivity analysis was conducted. The mean behavior shifts were used as a guide to determine how much a SD model variable would move towards an upper limit multiple when behavior increased, or towards a lower limit multiple when behavior decreased. Sensitivity levels of very low (VL), low (L), medium (M), high (H), and very high (VH) were assigned for the sensitivity analysis. At the highest sensitivity level (VH), if a mean behavior shift suggested a normalized behavior shift of -1, the associated SD variable would be multiplied by 0.1 to represent that variable having a 10% value of the baseline amount under disruption. Likewise, at the VH sensitivity level, if a mean behavior shift suggested a normalized behavior shift of +0.5, then the associated SD variable would be multiplied by 1.9 (halfway to the upper limit of 2.8) to represent a 90% increase of that behavior under disruption. A graphical explanation of the multiplier limits is provided in **Figure 58**. The overall set of SD variable multipliers inferred from the LEAP-HI Survey responses at each sensitivity level is presented in **Table 17**.

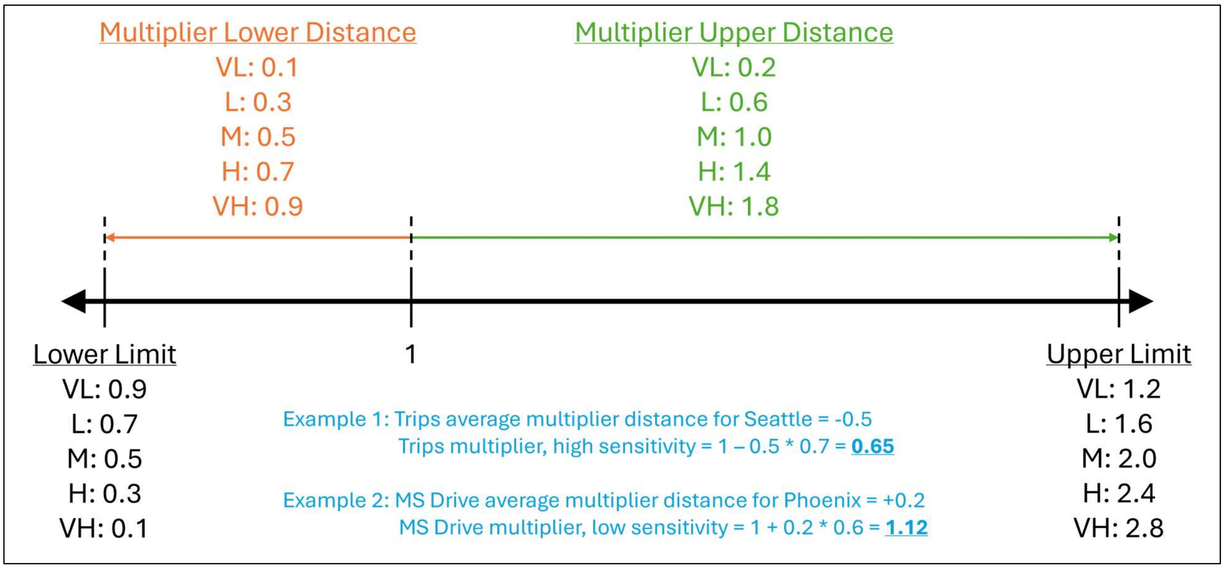

Figure 58 Graphical explanation of multipliers and limits for disruption-affected SD model sensitivity analysis

The multipliers on the SD variables affected under a disruption were applied to the models for Phoenix and Seattle. Disruption-affected transportation responses were assessed using three baseline reference cases, where ASUs of all types were allocated simultaneously:

1. The status quo baseline reference: this is the baseline reference used in the non-disrupted case, where ASU allocation remains at the status quo level.
2. The moderate ASU reference: the FtCR for each ASU type was set to approximately 5 times the baseline level.
3. The high ASU reference: the FtCR for each ASU type was set to approximately 5 times the moderate level.

Disruption multipliers were applied at the model timestep of t = 52 weeks, to allow the model time to reach equilibrium prior to the disruption occurring. Since there are 5 levels of multiplier sensitivity and 1 level of non-disruption, there are 6 total sensitivity levels. Each sensitivity level was applied to each reference case, leading to 6 x 3 = 18 disrupted scenarios.

Table 17 SD variable multipliers and limits for the disruption-affected SD model

Disruption Scenario	City	Affected Variable	Mean Behavior Shift	Multiplier VL	Multiplier L	Multiplier M	Multiplier H	Multiplier VH
Heat	Seattle	Trips	-0.202	0.980	0.939	0.899	0.858	0.818
		MS Drive	0.071	1.014	1.043	1.071	1.099	1.128
		MS Transit	-0.198	0.980	0.941	0.901	0.861	0.822
		PS Work/School	-0.013	0.999	0.996	0.994	0.991	0.989
		PS Commercial	0.088	1.018	1.053	1.088	1.123	1.159
		PS Soc/Rec	0.238	1.048	1.143	1.238	1.333	1.429
		PS Errand/Escort	0.143	1.029	1.086	1.143	1.201	1.258
	Phoenix	Trips	-0.225	0.978	0.933	0.888	0.843	0.798
		MS Drive	0.068	1.014	1.041	1.068	1.095	1.123
		MS Transit	-0.359	0.964	0.892	0.820	0.748	0.677
		PS Work/School	-0.244	0.976	0.927	0.878	0.829	0.781
		PS Commercial	-0.002	1.000	0.999	0.999	0.999	0.998
		PS Soc/Rec	0.031	1.006	1.018	1.031	1.043	1.055
		PS Errand/Escort	0.021	1.004	1.013	1.021	1.029	1.038
Cold	Seattle	Trips	-0.235	0.977	0.930	0.883	0.836	0.789
		MS Drive	0.146	1.029	1.088	1.146	1.205	1.263
		MS Transit	-0.304	0.970	0.909	0.848	0.788	0.727
		PS Work/School	-0.289	0.971	0.913	0.855	0.797	0.740
		PS Commercial	0.113	1.023	1.068	1.113	1.158	1.203
		PS Soc/Rec	0.162	1.032	1.097	1.162	1.227	1.291
		PS Errand/Escort	0.259	1.052	1.156	1.259	1.363	1.467
	Phoenix	Trips	-0.246	0.975	0.926	0.877	0.828	0.779
		MS Drive	0.117	1.023	1.070	1.117	1.163	1.210
		MS Transit	-0.404	0.960	0.879	0.798	0.717	0.636
		PS Work/School	-0.224	0.978	0.933	0.888	0.843	0.798
		PS Commercial	0.063	1.013	1.038	1.063	1.088	1.113
		PS Soc/Rec	0.113	1.023	1.068	1.113	1.159	1.204
		PS Errand/Escort	0.169	1.034	1.101	1.169	1.237	1.304

The 18 disruption-affected scenarios were run for the Seattle study region using 4 different disruption durations: 1, 4, 8, and 12 weeks. The range of disruption durations were chosen after first modelling a 1-week disruption. The 1-week disruption appeared to only create a “spike” at the time of disruption, then all system outputs returned to their previous trajectories. Therefore, disruptions of longer durations were investigated to observe whether system responses followed the same instant “snap-back” to the pre-disruption trajectory. The results for two cases are presented below: the mode shares under a 4-week long extreme heat disruption (**Figure 59**) and the mode shares under a 12-week long extreme heat disruption (**Figure 60**).

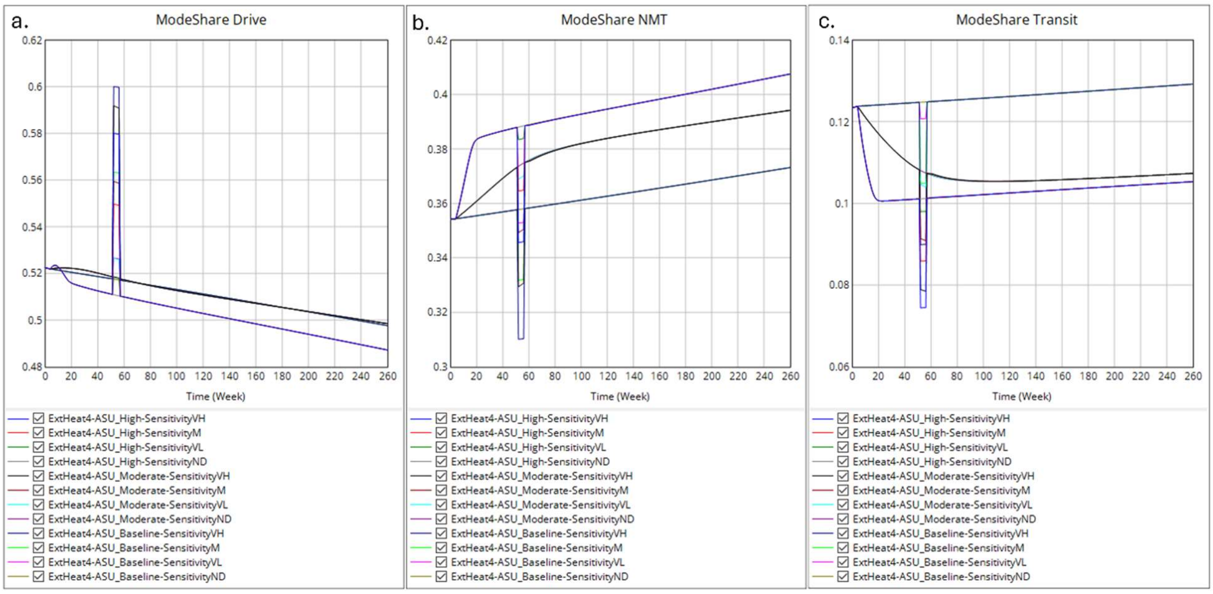

Figure 59 Seattle model affected by a 4-week long extreme heat disruption, mode shares for a. driving, b. NMT, and c. transit

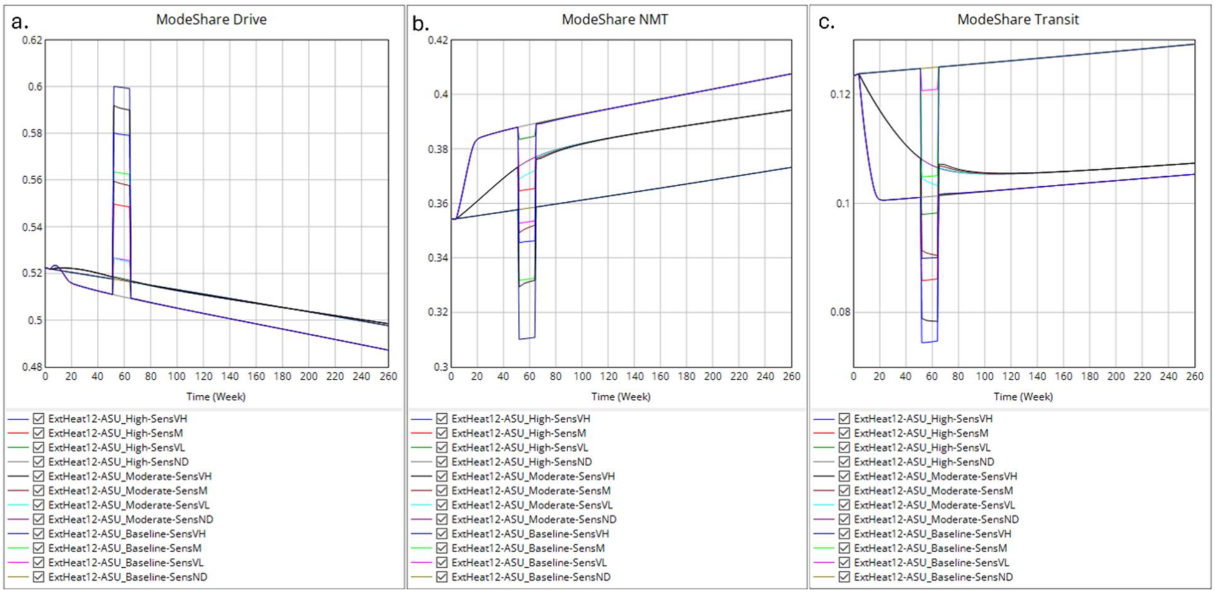

Figure 60 Seattle model affected by a 12-week long extreme heat disruption, mode shares for a. driving, b. NMT, and c. transit

From the above two figures, the disruption affects mode shares during the specified duration of disruption, but then mode shares either immediately snap back to the reference case, or the post-disruption impact is so minor, that effectively the impact amounts to a near-perfect, near-immediate recovery. The most pronounced post-disruption deviation from the reference case is in **Figure 60**, where the moderate ASU scenario leads to an extremely minor, yet observable increase in transit mode share from t = 65 weeks to t = 100 weeks. Similarly, the NMT mode share exhibits a minor yet observable decrease in NMT mode share in the same time period. These differences become more pronounced as the sensitivity level increases. However, even at the highest sensitivity level (VH), the transit mode share and NMT mode share curves do not deviate markedly from the moderate ASU reference curve, nor they do not cross over the reference curves for the baseline ASU or high ASU reference cases.

This immediate “snap back” to pre-disruption mode shares indicates that even a fairly significant, yet temporary, shift in travel behaviors induced by external disruptions may not have ongoing effects after the disruption passes. While other disruption types may impact infrastructure in ways that would delay recovery (e.g. flooding or earthquake necessitating roadway repairs and reconstruction), the city-wide homogeneous disruptions of extreme heat and cold may not induce any delayed effects. Rather, citizens may return to prior travel and activity behaviors rather quickly. However, there remain reservations as to whether this observed behavior from the model is representative of true travel and activity behavior patterns in the immediate aftermath of disruptions.

These model results were obtained from a model that was created for assessing mid-to-long term congestion and VMT changes under increasing allocations of ASUs. While the results presented in **Figure 59** and **Figure 60** may be representative of travel behavior under the stated preferences of survey participants in the LEAP-HI survey, there remain some open questions that lead to skepticism towards the model output. The observed “snap back” behavior may be true for disruptions of shorter durations (e.g. on the order of about 1 week), though there remain open questions as to whether there are either lingering or longer-term adaptations that happen to activity and travel behavior when disruptions happen over a longer period of time (e.g. on the order of months). While this hypothesis remains untested, there remains a reasonable expectation that if behaviors have changed during a 2- or 3-month long disruption, that there may be some behavioral “stickiness” to those adapted behaviors when the disruption abates. Therefore, the results here do not appear to align with the expectations of a longer “recovery” phase.

It is also possible that the model may have generated this “snap back” response due to the nature of how the disruption behavior changes were modelled, and the data available to inform the disruption behavior changes. The LEAP-HI survey data used to determine the disruption-affected travel behaviors only provided data on respondents' stated preferences and intentions during a disruption. There was no data from the survey that could inform modelling of the post-disruption recovery phase. In the absence of this data, all modelling parameters were assumed to return to non-disruption conditions outside of the specified disruption duration. The model may still be appropriate for modelling congestion, VMT, travel mode, and activity purpose share outcomes when provided with appropriate time-varying travel behavior adjustments that is responsive to how citizens' behavior changes through the various phases of pre-disruption, disruption, immediate aftermath, recovery, and return to long-term equilibrium, but the currently available data does not allow for this modelling of time-varying adaptations to disruption.

Finally, the system dynamics model built for this study was for the purpose of studying the effects of increasing ASU allocations on transportation outcomes during non-disrupted "bluesky" operations. While the impact of ASUs on congestion and VMT may be an important relationship during bluesky operations, there are also open questions regarding the relevance of studying the impact of ASU allocation on congestion and VMT during a disruption and its recovery. While the presence, design, and use of ASUs during disruptions have been demonstrated to have a positive impact on urban life and disaster recovery, such as in enabling outdoor socialization, recreation, and commerce during the COVID-19 pandemic , city-wide congestion and VMT are likely not the most salient metrics to quantify the impact of ASUs during disruption (*20*, *69–71*). Other functions, such as accessibility of essential goods and services, connectedness within social, neighborhood, and community groups, and capacity to safely shelter-in-place versus requiring to evacuate may be more relevant to measure when assessing the impacts of ASUs during disruptions and recovery – these functions are either not present in the system dynamics model presented here, or not able to be modelled using non-spatial and non-network-based methodologies.

Accessibility of essential goods and services could be supported using destination ASUs to set up either public or non-governmental, community-based hubs to distribute food, supplies, and act as temporary locations for communications or medical services. This type of usage is especially appropriate in situations where using enclosed or indoor locations may be unsafe, such as in the event of earthquakes, disease outbreaks, or extended power outages during extreme heat events. NMT and transit ASUs could also support the movement of goods by human-powered means, should disruptions lead to impracticality of operating motorized vehicles due to shortages in petroleum supplies or lack of electric charging capability. How ASUs influence the accessibility of goods and services could be investigated by incorporating ASUs in a geospatial or network model. Accessibility could be measured in terms of time required to walk or cycle to the nearest hub location, or the number of hub locations accessible within a prescribed time budget on foot or by bicycle.

These outdoor public or community hubs for distribution of goods and services could also function as a means of gathering community support and help catalyze local efforts during disruption recovery, as they represent local meeting places that may be readily deployed across cities. When optimizing for where to locate these outdoor hubs, the ability to use the public ROW for destination ASUs greatly increases the number of potential locations for hubs to be placed. Whereas previously, such hubs may have been restricted to locations such as schools, parks, community centers, and religious facilities, the ability to use street space to locate outdoor hubs could greatly enhance the spatial decision space for locating hubs in an optimal manner. A research question to extend this idea would be: how many more citizens could access an emergency hub within a 10-minute walkshed, if hubs could be located within the public ROW, rather than being restricted to existing publicly-managed property or community centers?

Both destination and mobility ASUs may also influence the decision-making for citizens to safely shelter-in-place or evacuate during disruptions. The aforementioned functions of outdoor hubs (destination ASUs) as gathering points for sharing supplies, information, and seeking aid, and the improvement in flow of goods and personal mobility through human-powered means (mobility ASUs) may cause shifts in how public officials and private citizens make their evacuation advice and decisions respectively. Should these ASUs enhance the ability of local governmental authorities to respond to the needs of citizens during certain types of disruptions, then emergency management officials may be able to alter their advice to the public during those disruptions such that evacuations may be required in less situations. Private citizens may also make different shelter-in-place/evacuation decisions, should the provision of essential goods and services and social connectedness be enhanced by ASUs. Stated explicitly, a potential research question could be: how would proposed outdoor hubs and improved NMT infrastructure support the ability for citizens to shelter-in-place during various disruption types and severities, in terms of where and what kinds of logistics that may be involved? These perceptions and stated intentions may be further explored through pilot studies and surveys.

Apart from considering the effect of ASUs during disruptions and their associated recovery period, the system dynamics method could also be applied to study the supply, distribution, and transport of goods and information within a city and its populace during a disruption event. Humanitarian supply chain logistics have been studied using SD methods, though typically in reference to generic “supply chain systems” or “affected populations” rather than at the city-level, where ASUs and transportation infrastructure may be important to consider when modelling the transport and distribution of goods. Potential next steps when using the SD method to investigate disaster response would be to incorporate the use of ASUs into existing models, while also extending models beyond considering solely the distribution of essential goods such as food and medicine, but also to consider provision of "non-essential" yet still critical amenities such as internet access and device charging.

Modelling the use of destination ASUs as community hubs for disaster response and recovery could also align with existing frameworks that have been prepared for regional disaster preparedness. One example is the Puget Sound Regional Catastrophic Preparedness Grant Program (RCPGP), which collaborated with city and county jurisdictions within the Puget Sound region (encompassing Washington state's King, Pierce, Snohomish, Kitsap, Island, Skagit, Thurston, and Mason Counties) to establish the siting of Community Points of Distribution (CPODs) for the delivery of critical commodities in response to major disasters (*72*, *73*). RCPGP identified both CPOD locations and population islands. CPOD siting was typically found in schools, community centers, park-and-ride facilities, and larger private facilities such as casinos and golf clubs. Population islands represented spatially discrete regions within the 8 collaborating counties, delineated by major roadway or geographic features, within which populations would be served by CPODs in the island boundary. The system dynamics modelling performed in this thesis may be adapted and cellularized to either perfectly match the population islands identified by RCPGP, or match clusters of population islands together as superislands for cellularized modelling. System dynamics modelling would be particularly apt for this purpose, as individual cells of population islands may be presumed to have a minimal level of interaction with other population islands in the event of major disaster events, as regional travel may be deprioritized behind meeting personal and community needs in an immediate and local manner.

RCPGP has identified population and the level of need within each population island; SD modelling may be employed to investigate the evolution of commodity demand and disaster severity within each island. Potential scenarios that may be explored include varying the number of type of CPODs within each island (especially in the case of street space being used for CPODs), and also varying the amount and ease of commodity flow between population islands in the cellularized SD model. While the transportation behavior of residents within each population island may not be relevant in the immediate aftermath of major disasters, the application of SD modelling demonstrated in this thesis may be applied to a scenario analysis of disaster recovery and commodity distribution within and between population islands.

The current study suggests that destination ASUs, which would be most relevant during disaster scenarios as locations for communities to gather, share information and resources, and seek aid, would provide the benefit of reduced city-wide traffic congestion during bluesky operations. This result provides a strong basis for cities to identify and plan for sections of the public ROW to be repurposed as on-street destinations during non-disrupted city operations. These spaces could then be flexibly used: both to accommodate for seasonal bluesky variations in activity choices and business operations, and to provide for disruption response hubs where communities may gather. NMT ASUs were also shown to reduce congestion in the Seattle model and VMT in the Phoenix model at all lane-mile allocations (whereas thresholds were observed for VMT reduction in the Seattle model and congestion reduction in the Phoenix model). Alternative modes of transportation, particularly human-powered modes, are currently used in contexts such as the Cascadia Bicycle Club in Seattle delivering food by bike from food banks to food-insecure residents. While programs like this one enhance access to essential goods enhance food accessibility during bluesky operations, NMT infrastructure would further improve the ability for residents, community groups, and businesses to deliver goods during bluesky operations. It could then be hypothesized that increasing the safety, capacity, and spatial reach of NMT infrastructure would also translate to reduced barriers in human-powered deliveries of goods and services during disruptions, since there would already have been a heightened level of existing human-powered goods and services delivery capacity due to increased NMT ASU allocation. Future research directions regarding use of destination and NMT ASUS could be informed through reviews of the status quo: both in existing literature regarding flexible uses of space in bluesky operations being adapted during disruptions, and also in surveying the history and operations of human-powered freight and service delivery in the developed world, and how those operations were impacted by expansions of NMT infrastructure.