An Austin Without Cars?
A Travel Demand Model

Chris Dsida & Reuven Herzog

Image source: Culture Map Austin

Austin-Round Rock, TX **SES 5394**

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Chapter 1: Introduction

Image source: Culture Map Austin

Project Definition

Our project is a hypothetical study of closing an entire district to cars. We are exploring the Austin, Texas, MSA, and our alternative scenario envisions making the entire downtown district - bounded by Interstate 35, Martin Luther King, Jr. Blvd; Lamar Blvd; and Cesar Chavez St - accesible only to public transit vehicles and active transportation (e.g. pedestrians and cyclists).

Our primary concern is the direct effects of the institution of this “moat.” Will drivers aggressively shift to alternative modes, or will they instead direct their trips elsewhere? How many trips currently use downtown as a cut-through, and where will these trips be re-routed?

A proposal as bold as this will surely have effects beyond the traffic realm. The most obvious one is a question of economics: how many businesses will flee the downtown car-free zone; will this kill the downtown core? While these questions are fascinating, they are beyond the scope of our study.

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Chapter 2: Zones

Image source: Culture Map Austin

Study Area

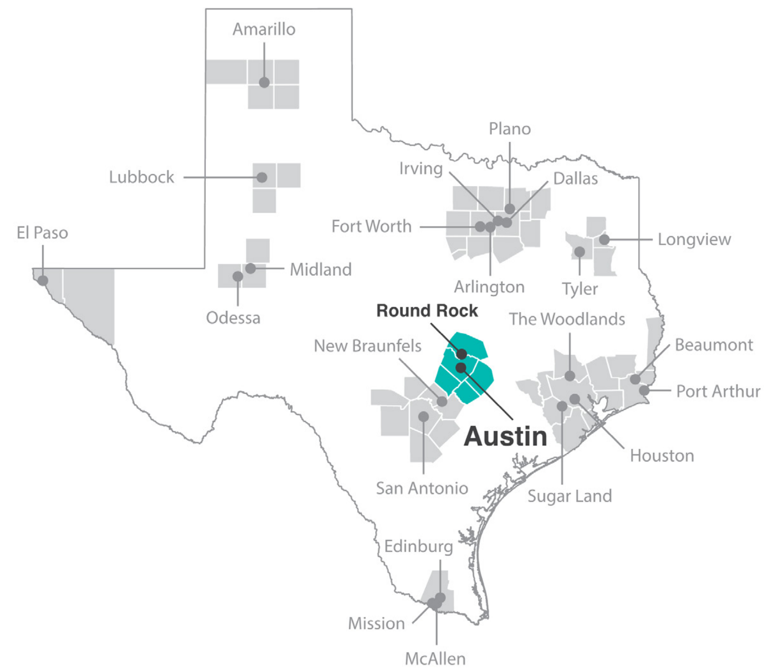


Image source: Dallas Federal Reserve

The Austin-Round Rock, Texas Metropolitan Statistical Area* (MSA) consists of five counties in central Texas: Bastrop, Caldwell, Hays, Travis, and Williamson Counties. The city of Austin in Travis County anchors the region in terms of population and employment. Nearly half of the MSA's 2.2 million inhabitants reside in Austin itself, while the census tracts with the highest concentration of jobs are located in its central business district.

For the purposes of this travel modeling exercise, the MSA will be broken into travel analysis zones (TAZs) consisting of census tracts. Relevant employment and population information about these census tracts is included in the following sections of this report. Because the alternative being studied does not involve any land use or population changes, the relevant data for our modeling scenarios will be the same as the existing conditions.

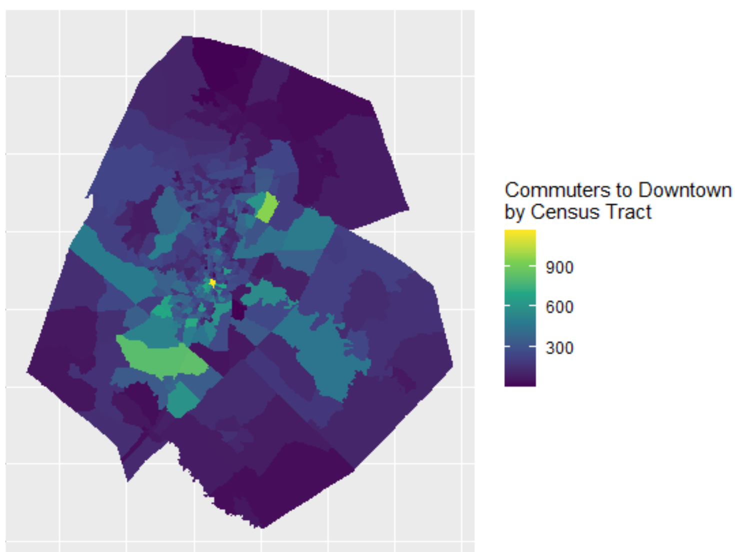
*Also known as Greater Austin, sometimes including Georgetown, TX in the official MSA name.

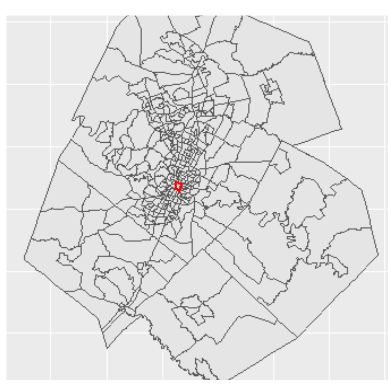
Alternative Description

Our study alternative arises from a hypothetical question: What if we completely closed downtown Austin to cars? We are imagining a scenario where downtown Austin is surrounded by a cordon that only public and active transit can pass through. This cordon is defined by Interstate 35; Martin Luther King, Jr. Blvd.; Lamar Blvd.; and Cesar Chavez St.
For the following zonal analysis, this closely corresponds to Travis County Census Tracts 7 and 11, and is encircled in red on the map below.

These two districts include roughly 107,000 jobs, around 10% of the entire Austin MSA's employment, and a negligible percentage of residents. Still, it is worth examining how this restriction of acess affects traffic, total VMT, and accessibility.

It's also notable that the pattern of who commutes into downtown is not strictly correlated with distance. While the largest share of commuters into downtown comes from downtown itself, other areas that send high numbers of commuters to downtown are middle-and outer-ring suburbs.

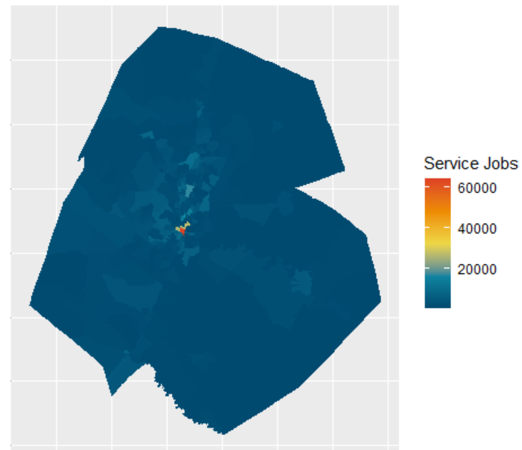


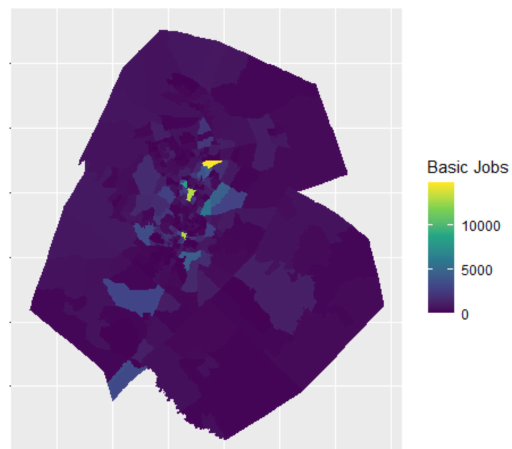


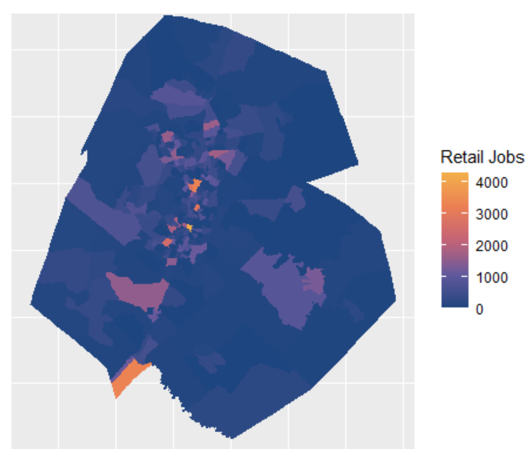
Employment Characteristics

The Austin MSA has 1.1 million jobs. Of these, the service sector dominates (67%), followed by basic (23%), and retail (10%).

The spatial distribution does vary across sectors, however. The service sector features a high concentration near downtown. The basic sector also highlights downtown, though other regions of high employment emerge in clusters in the northern part of the MSA, as well as higher pockets of employment across the region. Retail is the most balanced across the region, with tracts of high employment across the northern and southern suburbs.

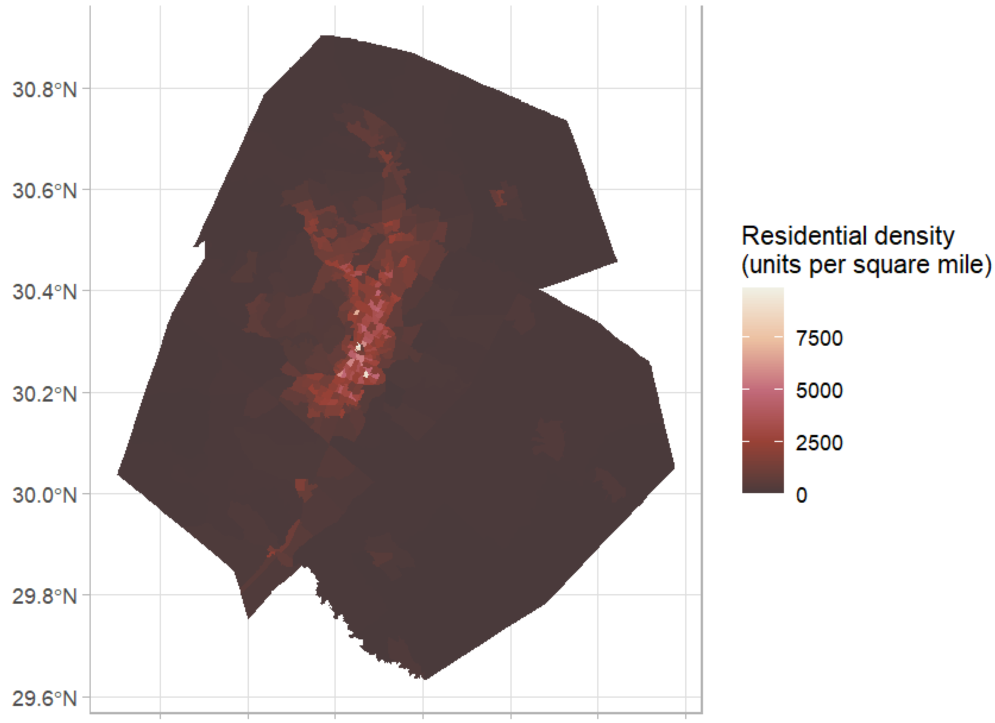






Population Characteristics

Residential Density

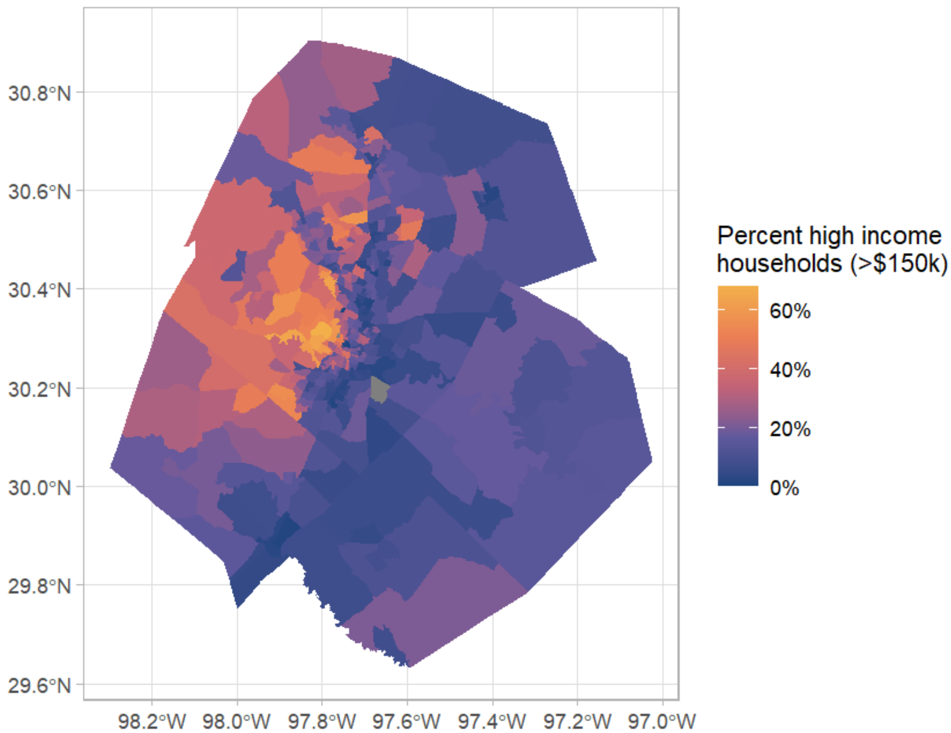


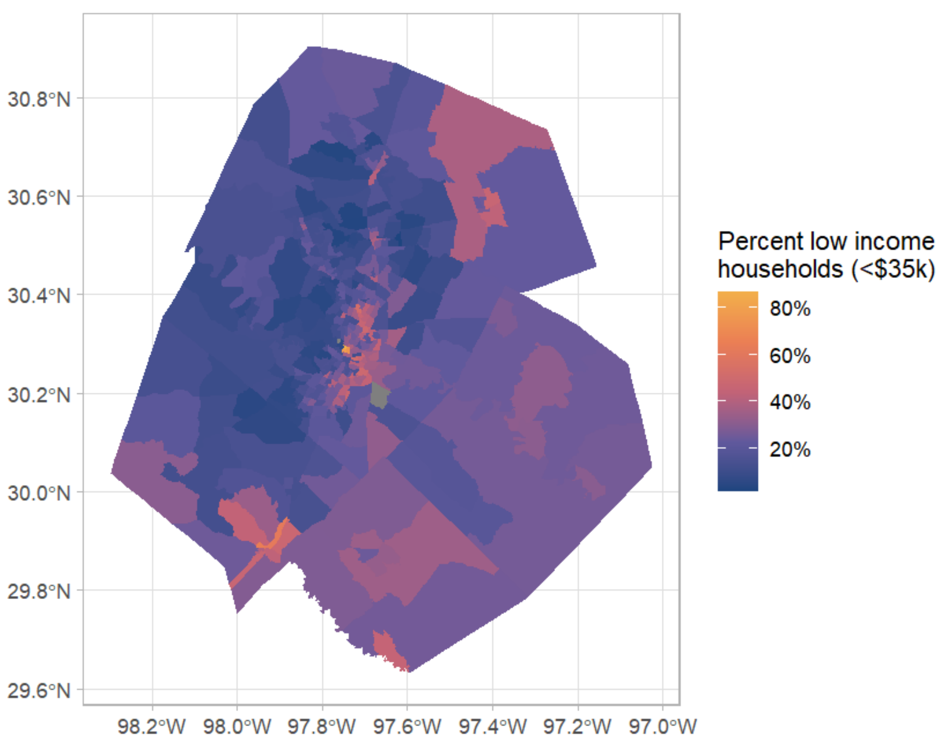
The region's residents live in areas concentrated along a generally north-south axis, with densities highest closer to Downtown. Housing unit density can be useful in determining an area's suitability for different travel modes. For instance, transit service works best in areas where a large number of people live or work in a relatively compact area.

On the following page, the percentage of households in a given census tract that fall into the highest and lowest income quintiles are mapped. Given the relationship between household income and travel patterns (both in terms of mode and volume of travel), this will likely be important in our model. Tracts that are on the west side of the region tend to have greater percentages of high-income households, while the east side and center tend to have greater percentages of low-income households.

Population Characteristics (cont.)

Spatial Distribution of Income

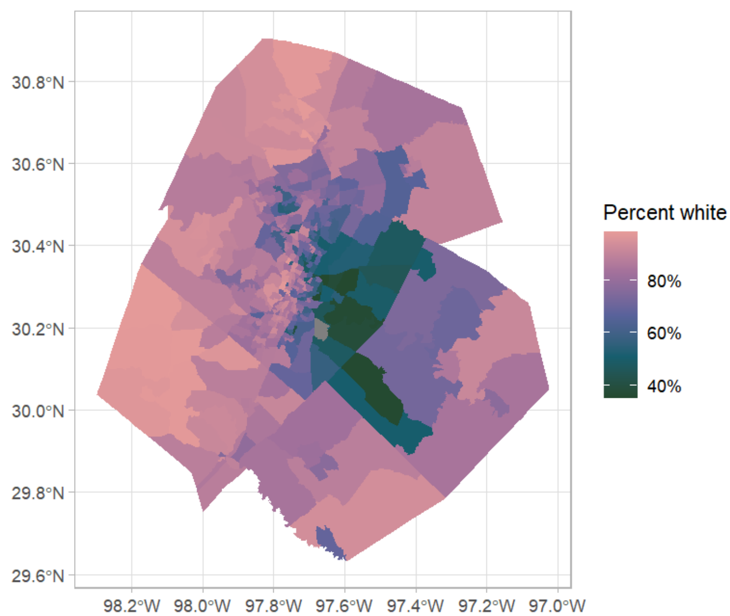




Population Characteristics (cont.)

Race and Segregation

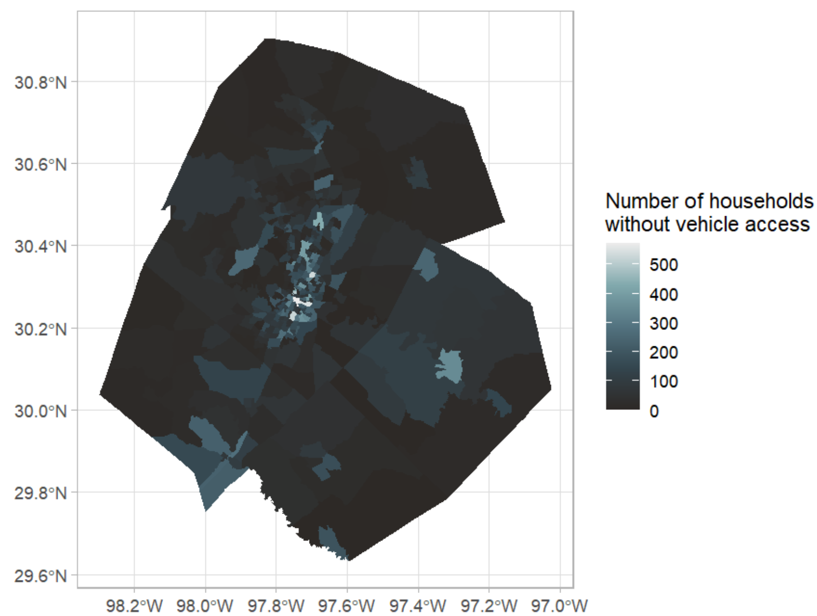
Much like with income, the Greater Austin region is divided geographically in terms of race. The western portion of the region is significantly whiter, on average, than the central and eastern portions. While race may not play a role in terms of how we model travel behavior in the MSA, this data will allow us to assess whether the alternative has any disproportionate impacts on different racial or ethnic groups.

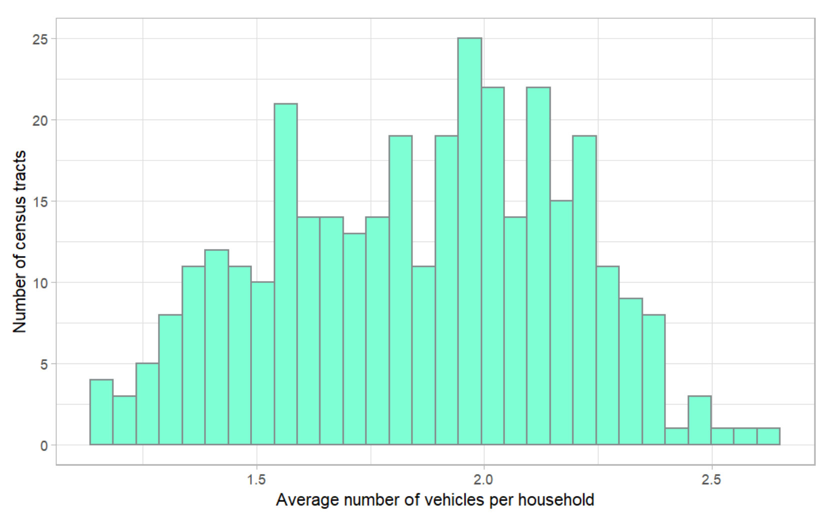


Population Characteristics (cont.)

Vehicle Access

Access to a car (obviously) plays a major role in one's ability to drive places as a form of travel. Therefore, we have calculated both the average number of available vehicles per household, as well as the number of households with no vehicle access for the MSA.

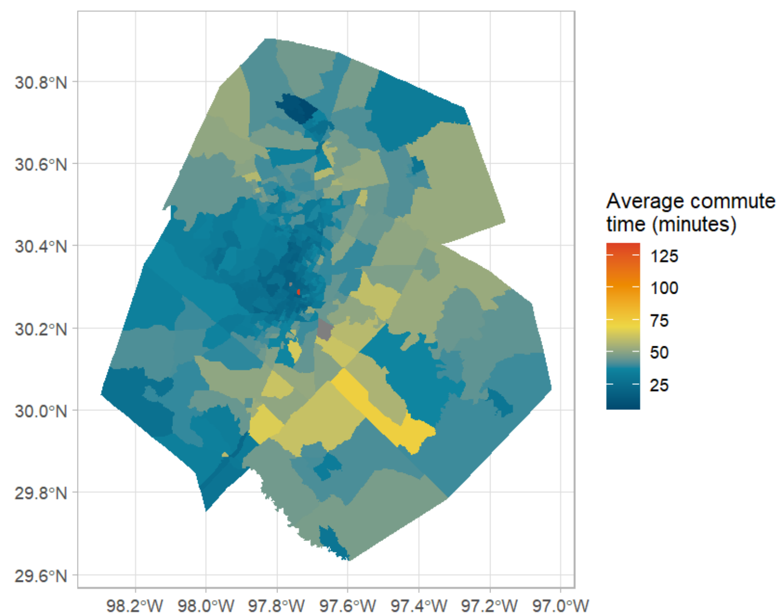


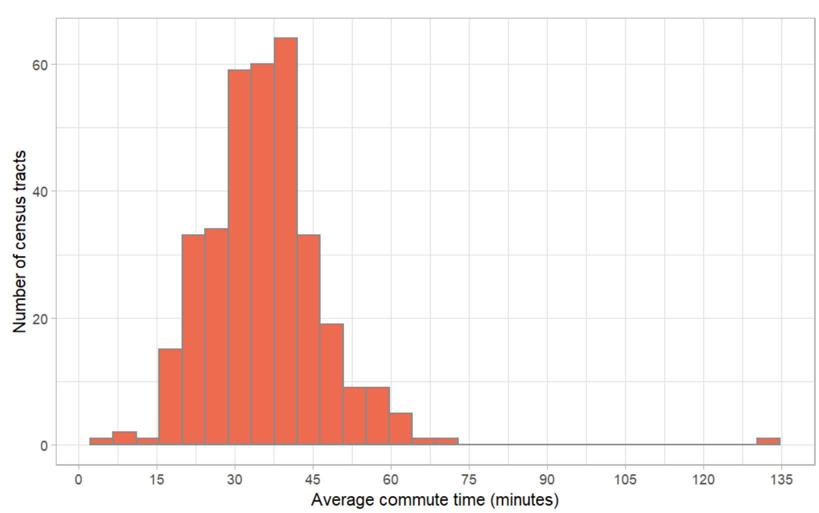


Population Characteristics (cont.)

Commute Times

Intuitively, people who live closer to the center of the MSA, which is where the jobs are concentrated most heavily, experience the shortest commute times. The bulk of workers' commutes are between 15 and 45 minutes, as shown below.





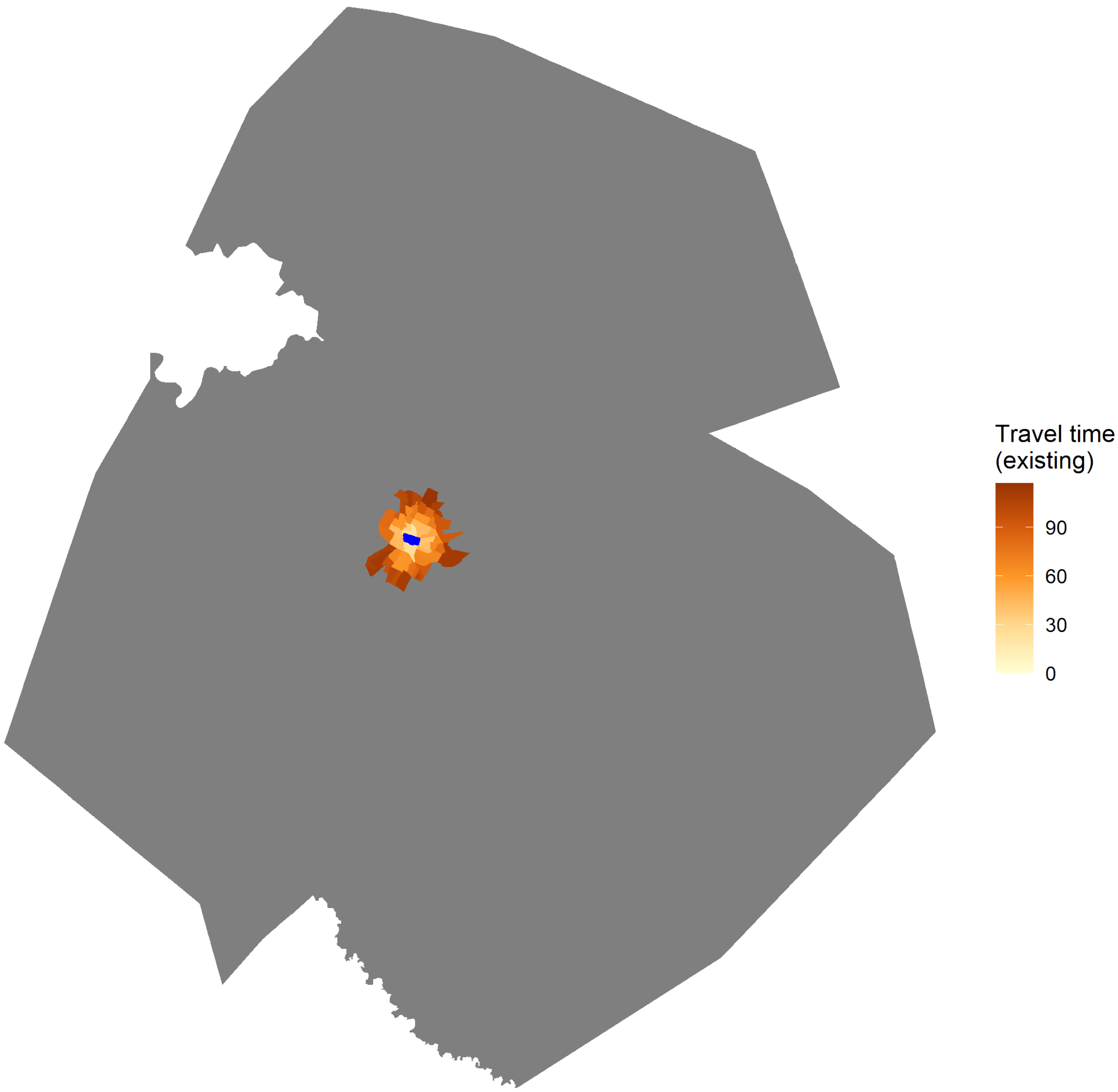
Chapter 3:
Network Analysis

Dismantling Downtown Austin's Street Network

After merely restricting car access to downtown, we attempted to see what happened if the grid were removed entirely. No changes, at least in terms of driving travel times to downtown, were measured.

Existing Conditions

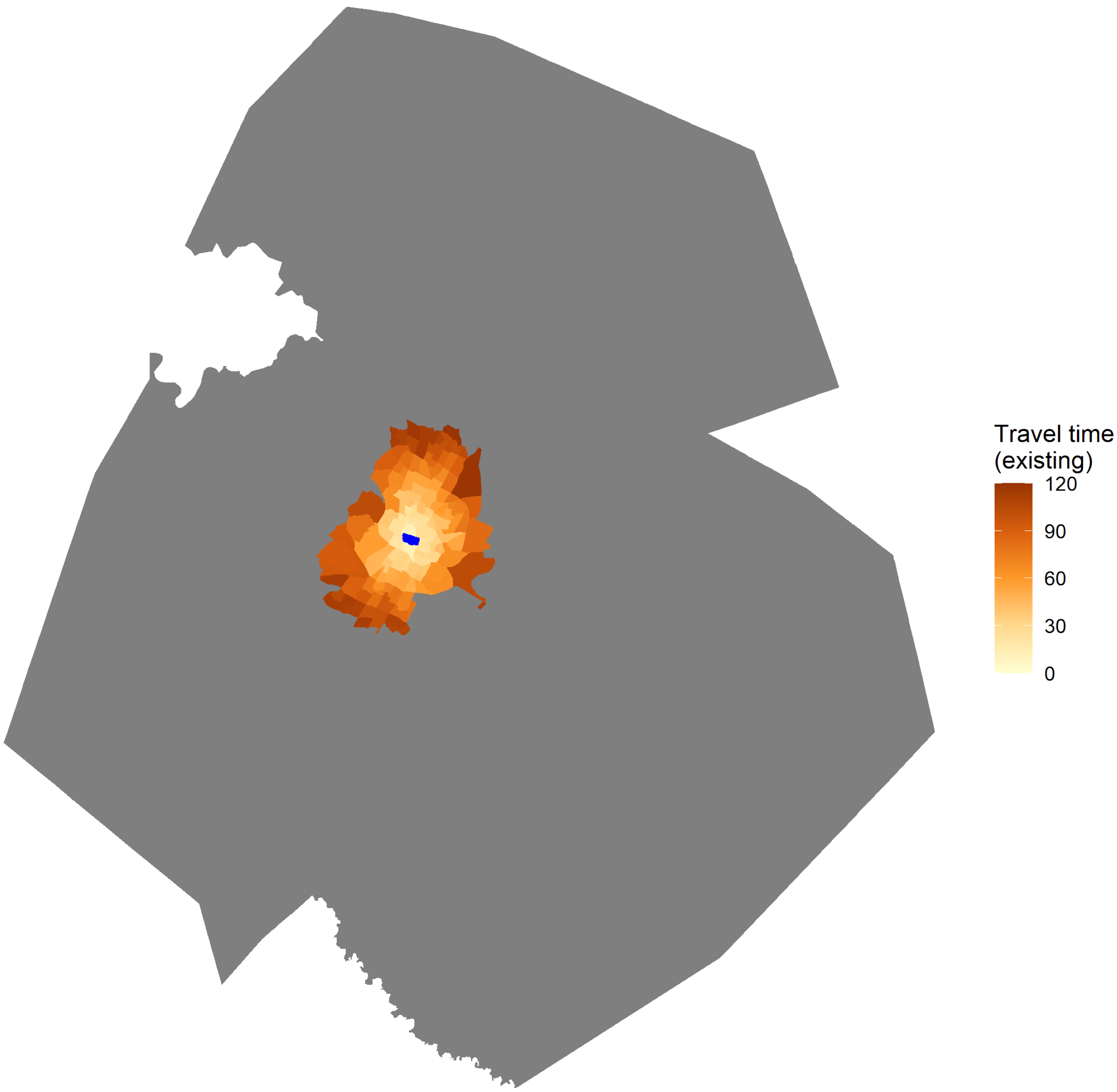
Walking



This chapter is devoted to analyzing the effect of restricting car access to Downtown Austin, focusing on changes to travel times across the region. Specifically, it will focus on travel time impacts where the destination is downtown itself, in one of the two tracts located there. The alternative and existing conditions do not differ for walking, biking, and public transit. The first three maps presented here are to illustrate the level of access provided by different modes on a regional scale. Walking, even with a generous maximum travel time of two hours, does not extend very far beyond the central city.

Existing Conditions

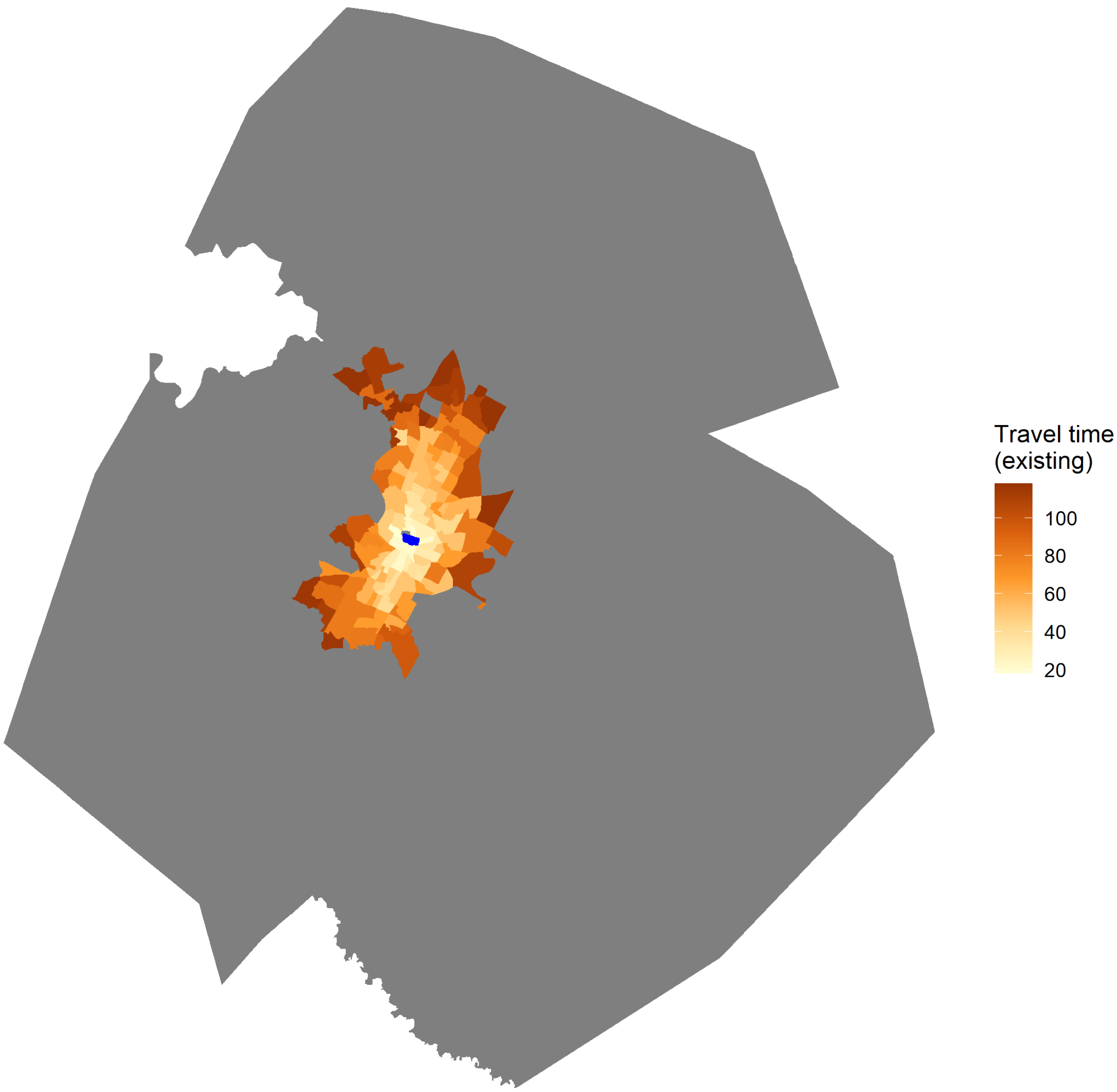
Biking



Biking, with a significantly faster travel speed when compared to walking, means that more of the MSA is within a two hour trip of the downtown tracts. In the package used for network analysis, walking speed is set to a default of 3.6 km/h, while travelers on bikes are assumed to cover 12 km every hour (on the more conservative end of cycling travel speeds). Because bicycles are not excluded from the streets closed in Downtown Austin, there are no measurable changes in travel times when comparing the existing conditions to the alternative.

Existing Conditions

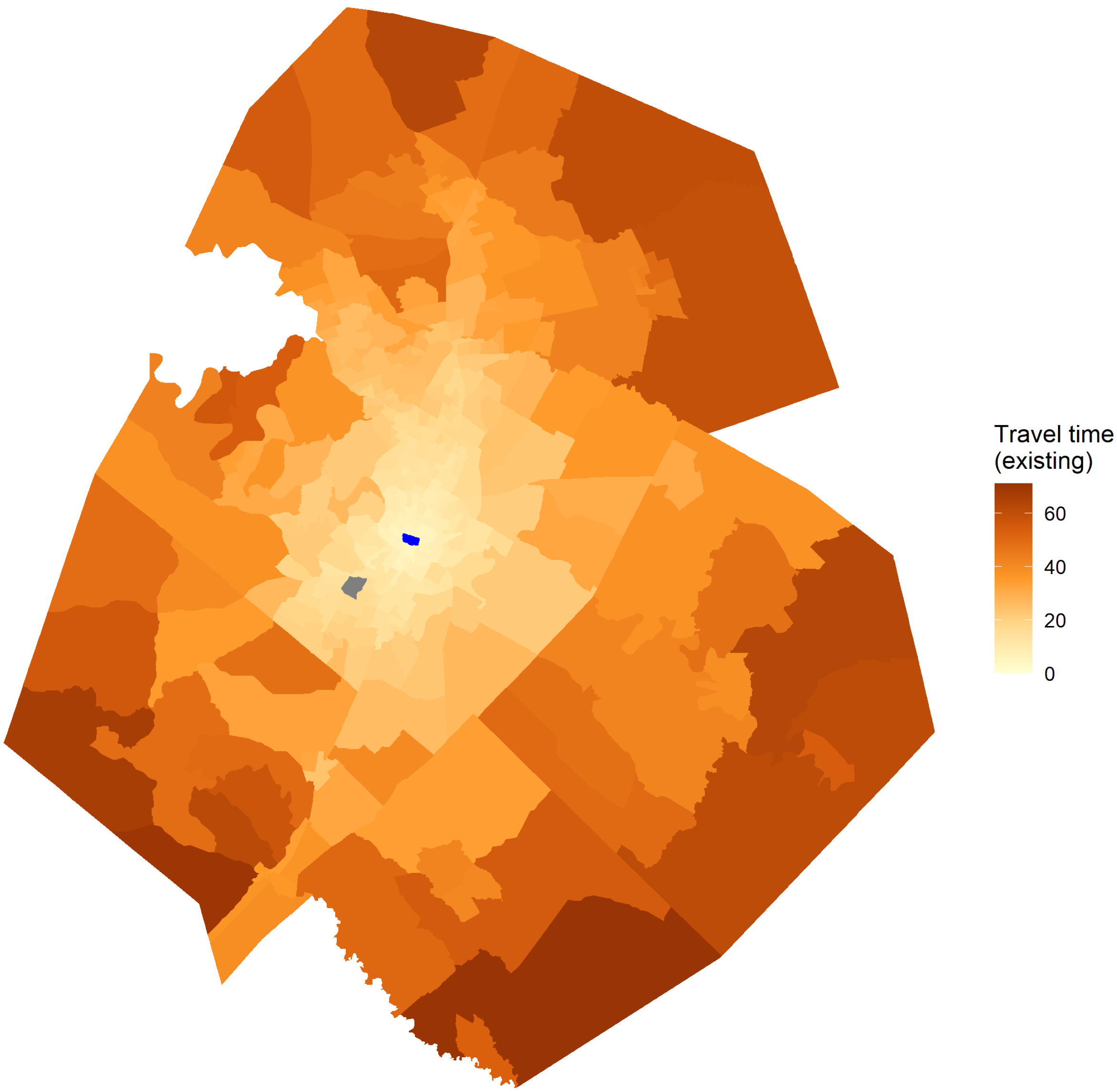
Public Transit



At 8:30am on Wednesday, April 6, 2022 (a typical morning commuting time), this is the amount of the MSA that is within two hours of Downtown Austin via public transit. Notably, transit does not increase the area accessible within this time greatly when compared to biking. Some public transit trips require long walks (as much as an unrealistic 68.2 minutes) and long waits (43 of 174 possible transit trips require waiting at least 15 minutes). However, these are just point-in-time measures, and not necessarily reflective of Capital Metro's service practices. They can be eliminated with more reasonable parameters about riders' willingness to walk or wait for transit.

Existing Conditions

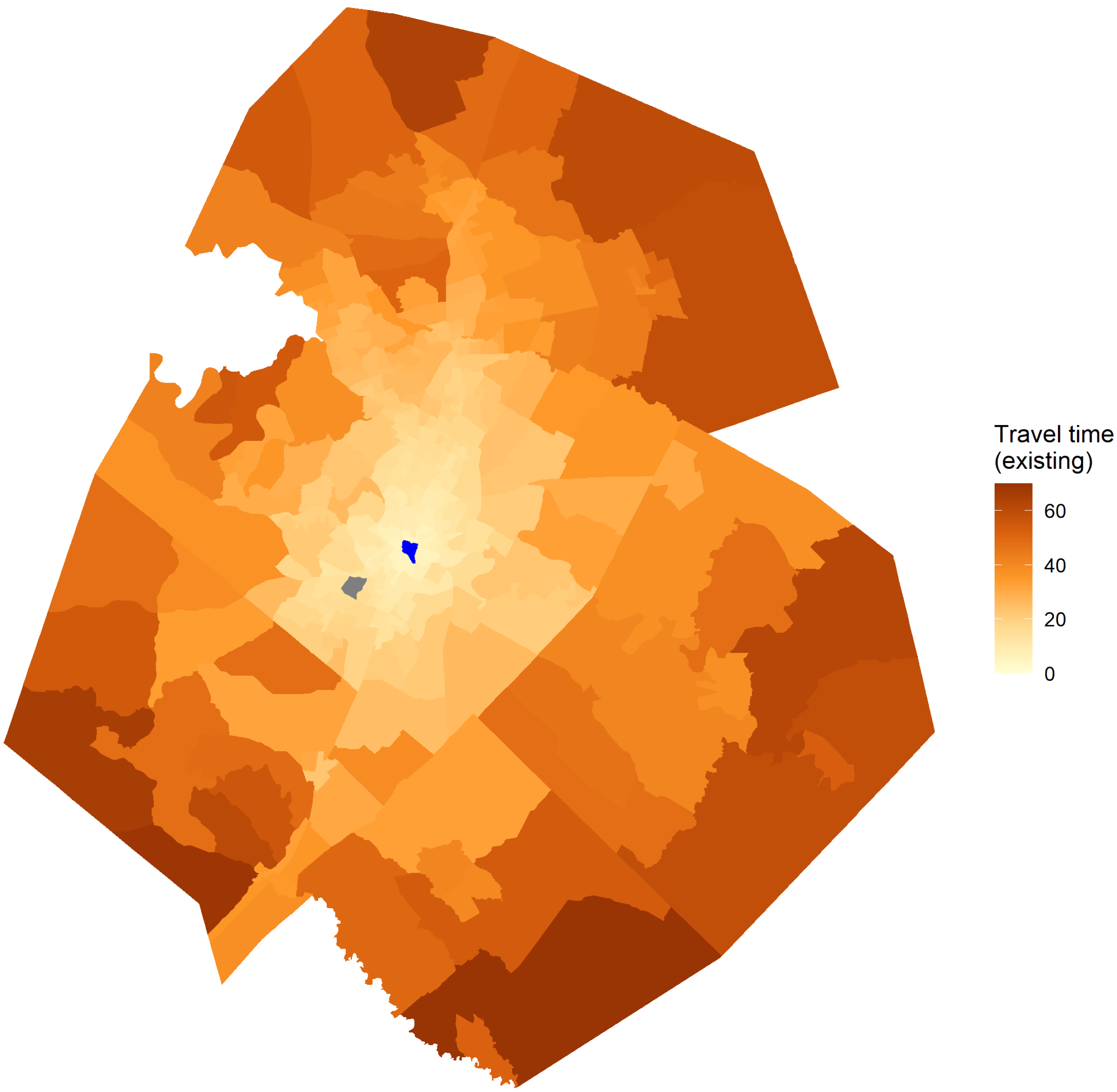
Driving



Remarkably, the entire MSA is within a 71-minute drive of Downtown Austin, with a median trip time of 21 minutes. The existing conditions feature a robust network of highways that provide speedy travel by car to the central business district. In contrast, areas where it would take multiple hours to access downtown by public transit or biking are often within a 30 minute (or shorter) drive. Shown above is the access to one of the downtown tracts (GEOID 48453000700). This tract makes up one of the two zones affected by the street access restrictions.

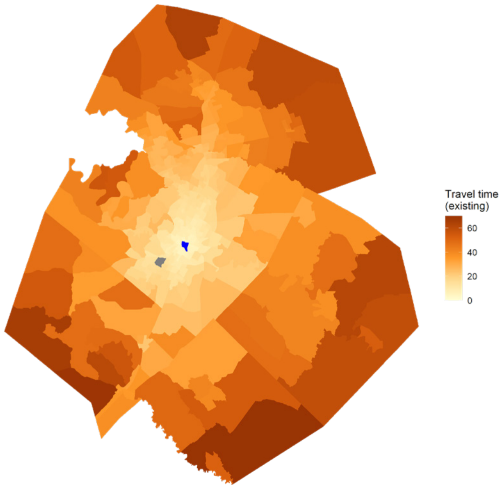
Existing Conditions

Driving (cont.)

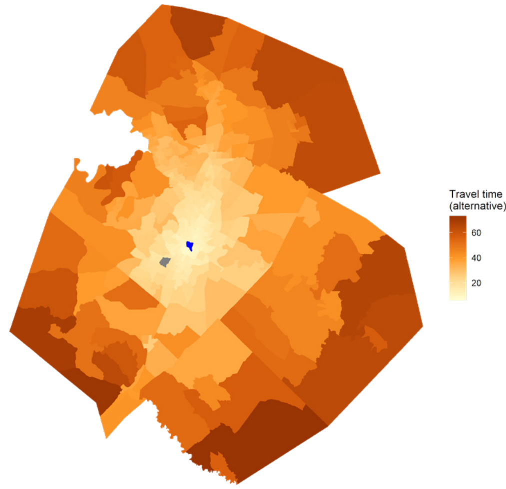


A similar pattern can be seen for the other tract located in Downtown Austin. The entire region is within a 70-minute drive of this zone (GEOID 48453001100). On the following page, we will consider whether closing a substantial section of downtown streets impacts travel times in a meaningful way. An initial comparison of travel time maps makes it difficult to discern any differences (existing on the left, alternative on the right), so the largest map highlights additional time spent driving in the alternative.

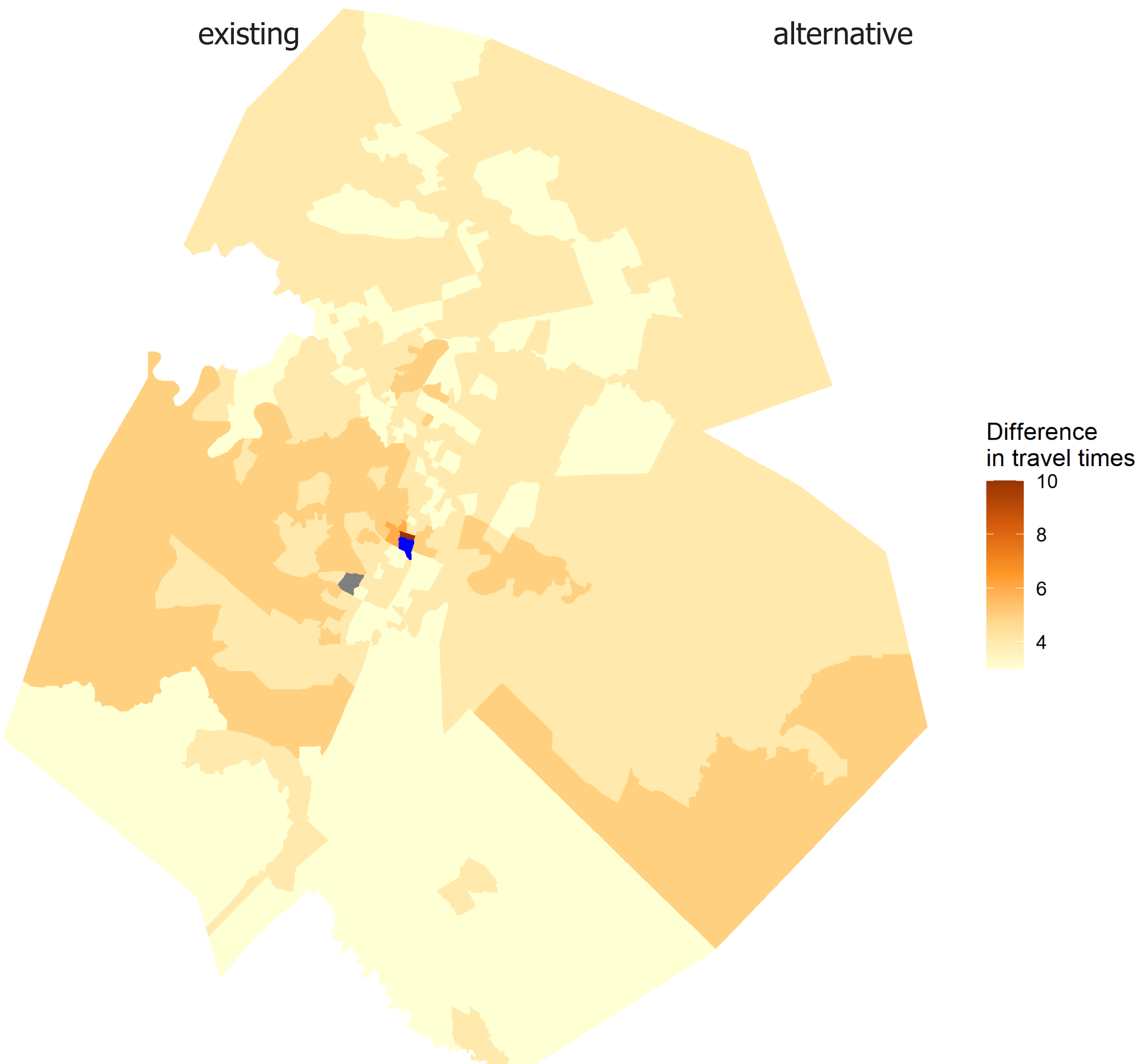
Comparison



existing

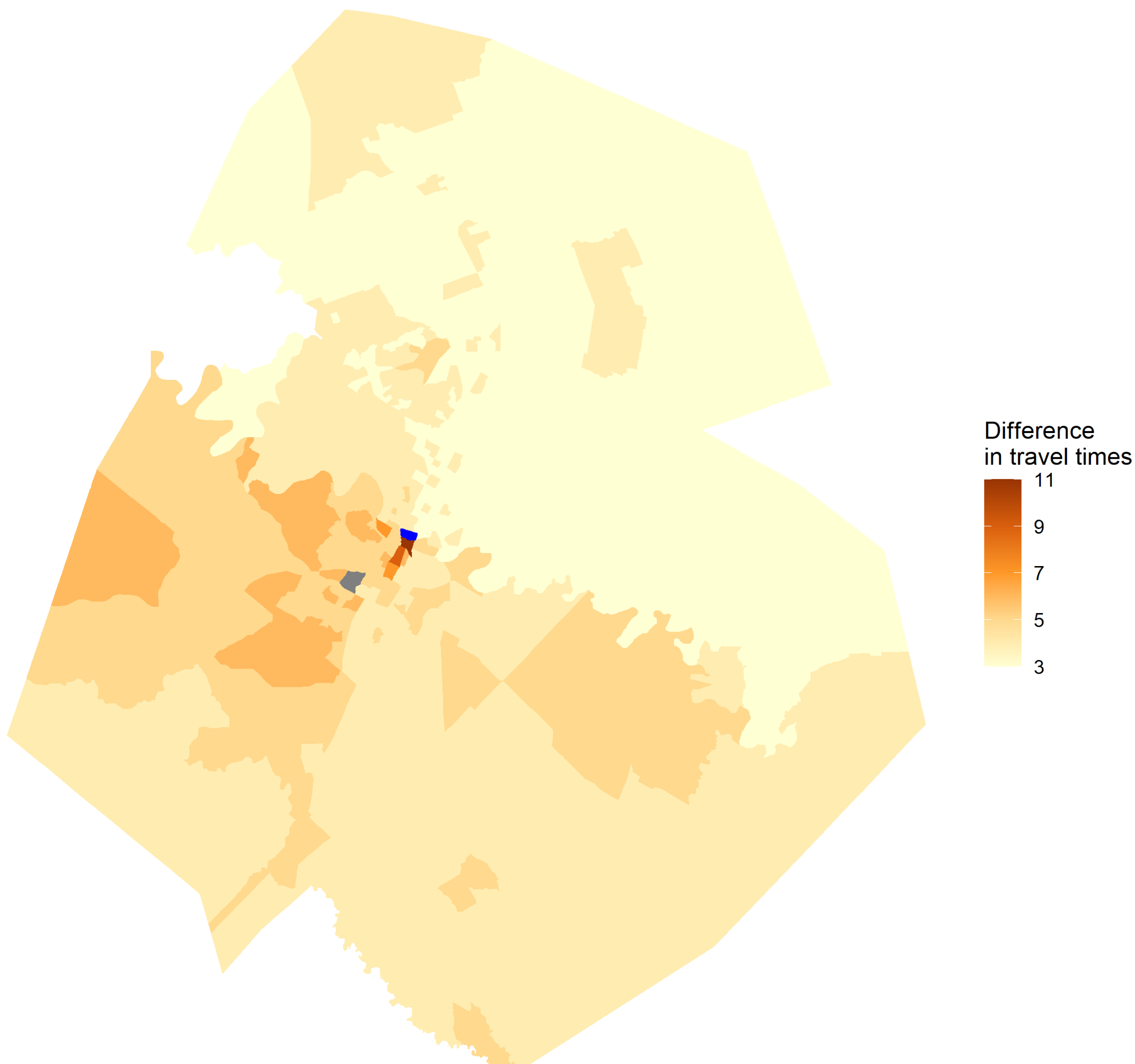


alternative



Comparison

Remarkably, closing over a square mile of Austin's streets barely makes a difference in travel times to the area. The same pattern emerges for the other tract. The only zone where a substantial increase in travel times occur is the other tract in Downtown! This is somewhat strange, since both of these tracts' centroids are located in the area entirely closed to cars. After further experimentation, including limiting maximum walking time (imagining very lazy drivers) or deleting Downtown's streets altogether, we were unable to prevent car access entirely. It seems as though drivers are parking on the edge of the cordon and finishing their journey on foot. Since tracts are not that large, this ultimately does not add much time to car trips at all.



Chapter 4: Accessibility Calculations

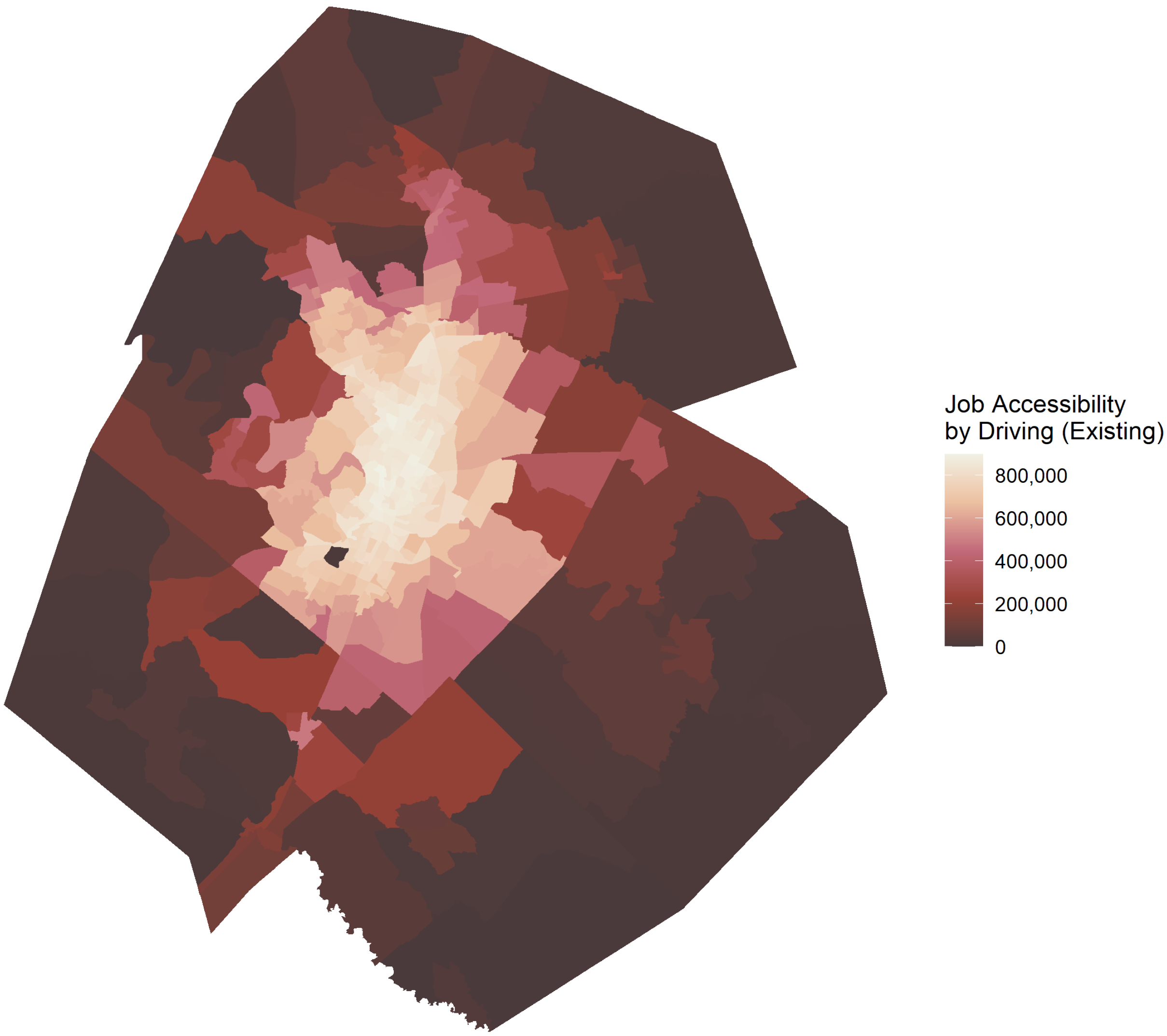


Figure 4-1

This chapter will compare accessibility within the Austin-Round Rock MSA across a few dimensions. First, we will compare accessibility by mode, mainly the difference between driving and public transit. Then, we will see how this differs between existing conditions and the proposed alternative, where cars are not allowed to drive in Downtown Austin. Job accessibility is used as a proxy for general accessibility. As can be seen in Figure 4-1, driving provides a great deal of job accessibility for most central tracts in the region. There is a sharp drop-off on the periphery, though this is more likely due to our decay function, which assumes accessibility weights drop off by half at 30 minutes.

Accessibility by Transit

Existing Conditions

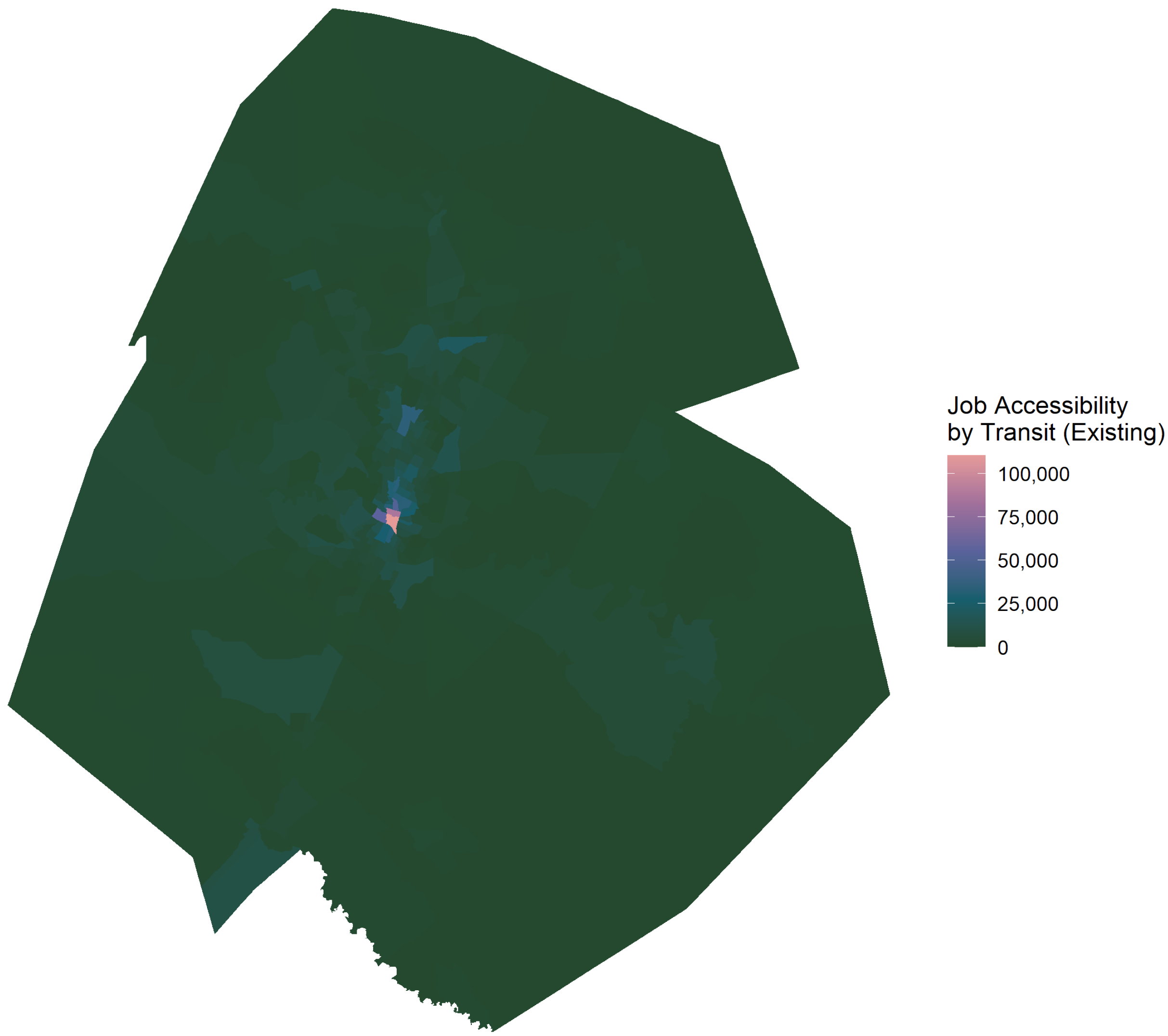


Figure 4-2

In contrast with driving, transit only provides a small fraction of the job accessibility that driving does. Even then, it is only a handful of tract TAZs that have any meaningful level of accessibility at all, as is evident from Figure 4-2. There are most likely a couple factors that can explain this pattern. On the one hand, transit travel times are longer than driving in this region, meaning that for a given accessibility decay curve, transit will already by providing less access than a car. Additionally, because of the radial nature of the transit network, there will only be a significant number of jobs accessible when starting in the center of the network.

Accessibility by Car

Alternative

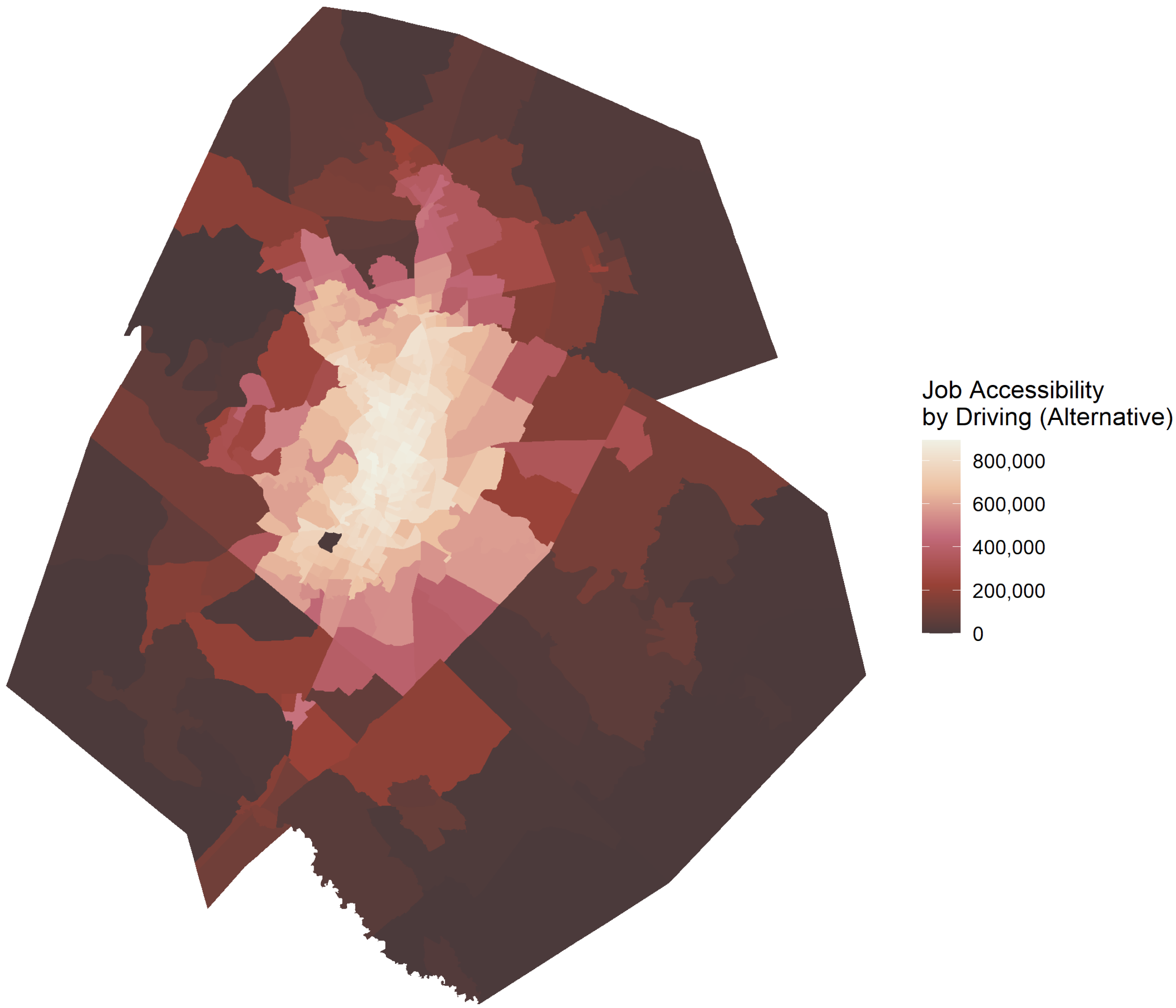


Figure 4-3

In Figure 4-3, we can (or more likely, cannot) see the effect of the proposed alternative on accessibility by car. The spatial distribution of accessibility is essentially identical, though as will be discussed later, there are small changes in the ratio of driving accessibility to transit accessibility. However, in order to see a larger impact of the alternative, for future chapters we will attempt a different approach. This will involve dramatically lowering the speed limit on Downtown's streets, rather than just prohibiting car use, which appears to route drivers around the CBD without accounting for additional walking time to their final destination.

Accessibility by Transit

Alternative

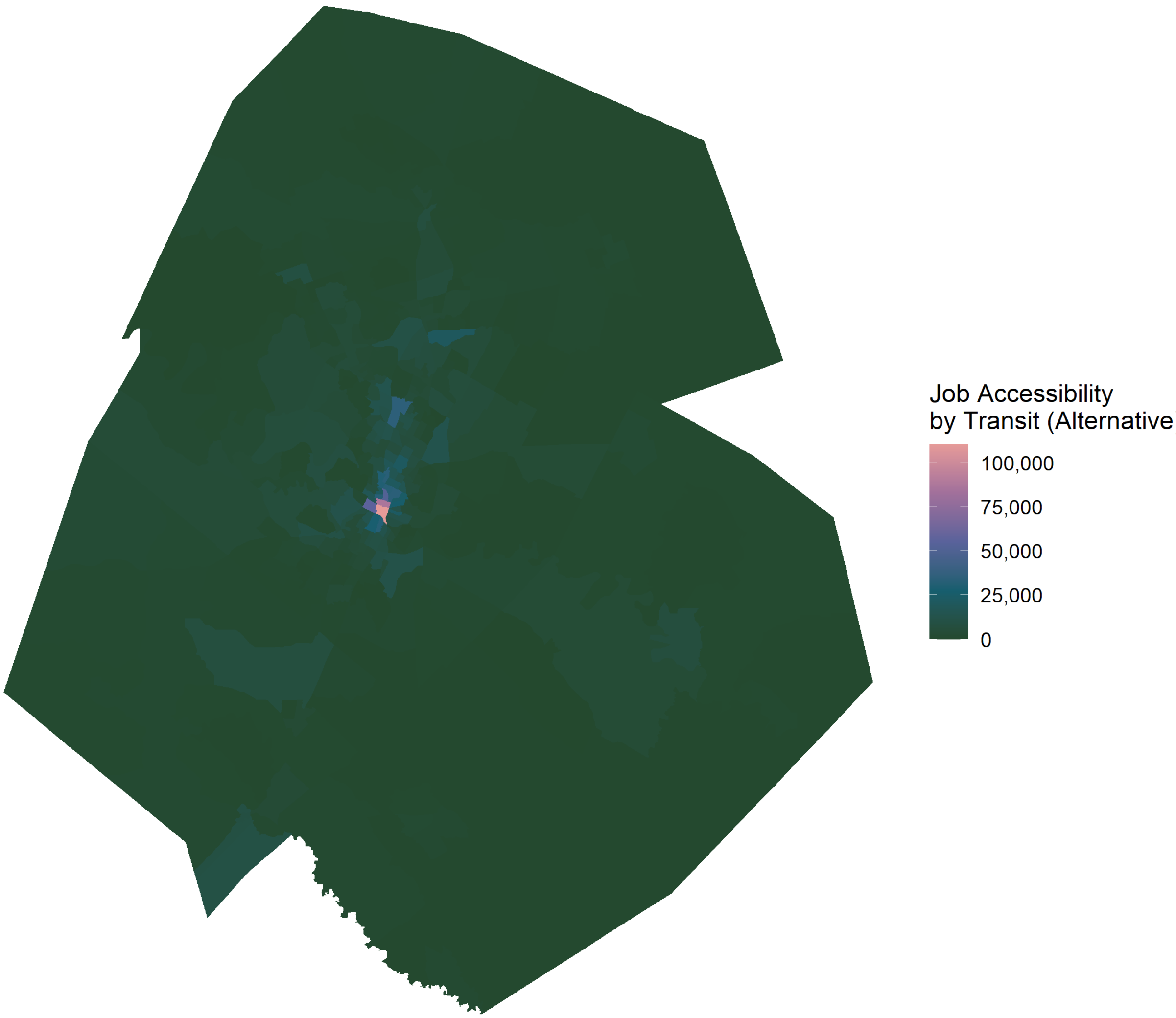


Figure 4-4

Figure 4-4 maps out job accessibility by public transit in the alternative scenario. Because the changes to the streets in Downtown Austin do not affect buses in any way, this is actually unchanged from the existing scenario. The maps on the following page compare the ratio of car and transit accessibility in the existing conditions and alternative (Figure 4-5 and Figure 4-6, respectively). As was the case with the differences in accessibility by car, it can be difficult to discern any meaningful change. However, it does exist!

Car/Transit Accessibility Ratios

Existing

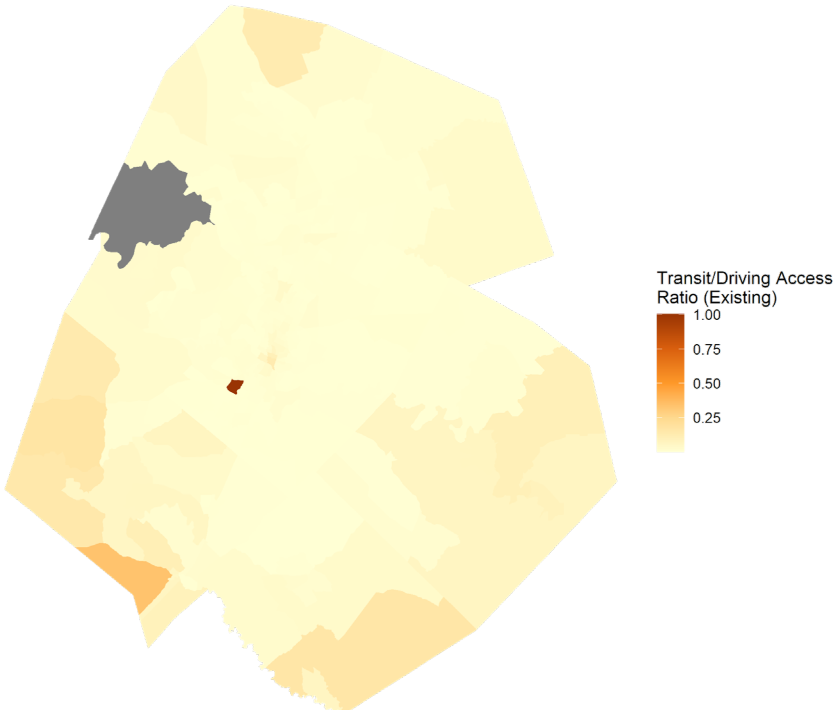


Figure 4-5

Alternative

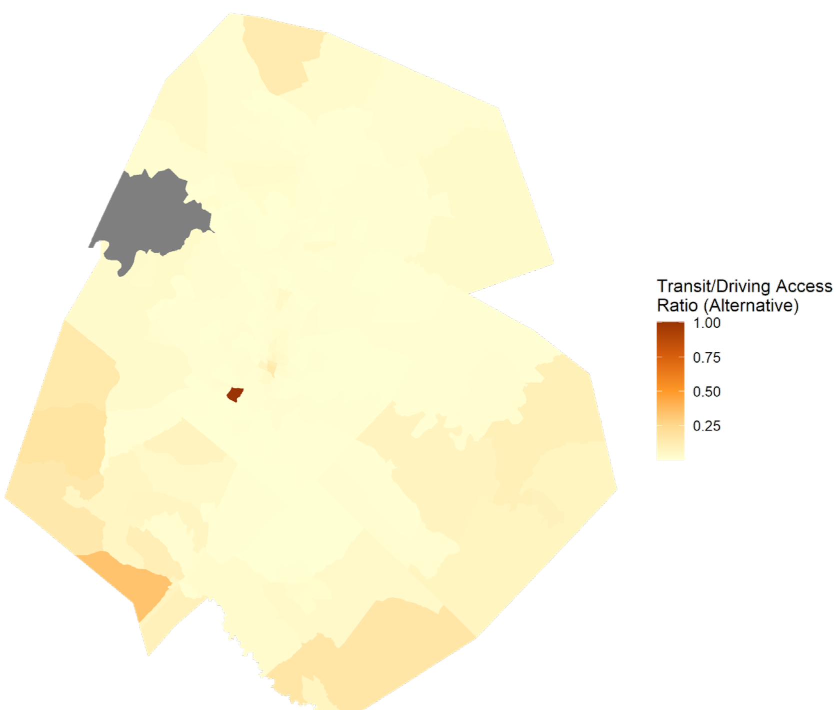


Figure 4-6

Car/Transit Accessibility Ratios

Percent Change

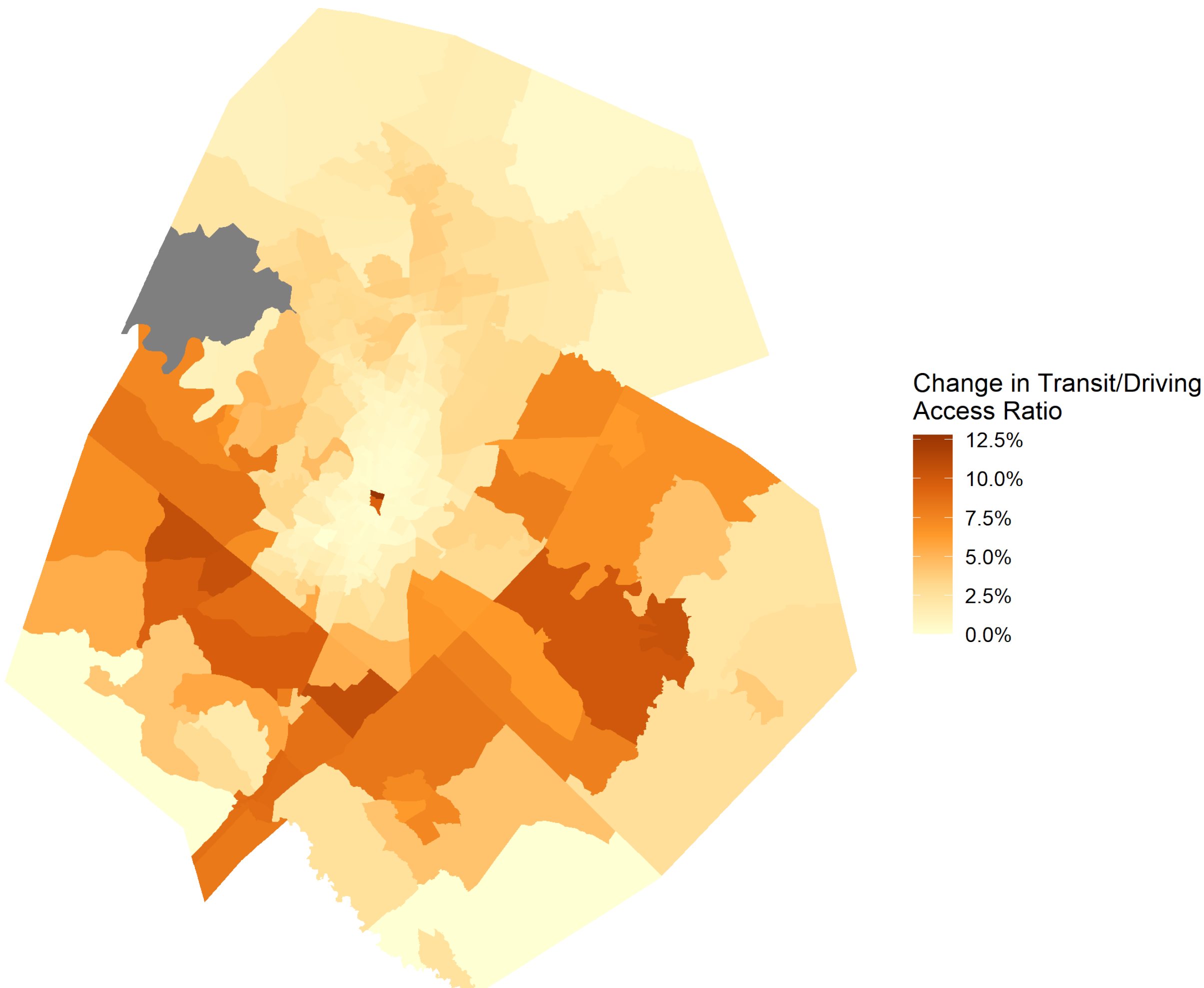


Figure 4-7

To better view the change in transit/car access ratio between existing conditions and the alternative, we calculate the percent change between the two scenarios. The largest changes in these ratios take on an interesting form, where the two tracts affected by street closures see some of the largest increases. This makes sense, as we are directly reducing accessibility for these two zones. Interestingly, a similar magnitude of change also takes place in a horseshoe-shaped pattern farther out in the region. This seems to be caused by these tracts losing access to the high concentration of jobs in Downtown, as they are on the cusp of a 30 minute trip by car.

Accessibility by Bicycle

Existing/Alternative

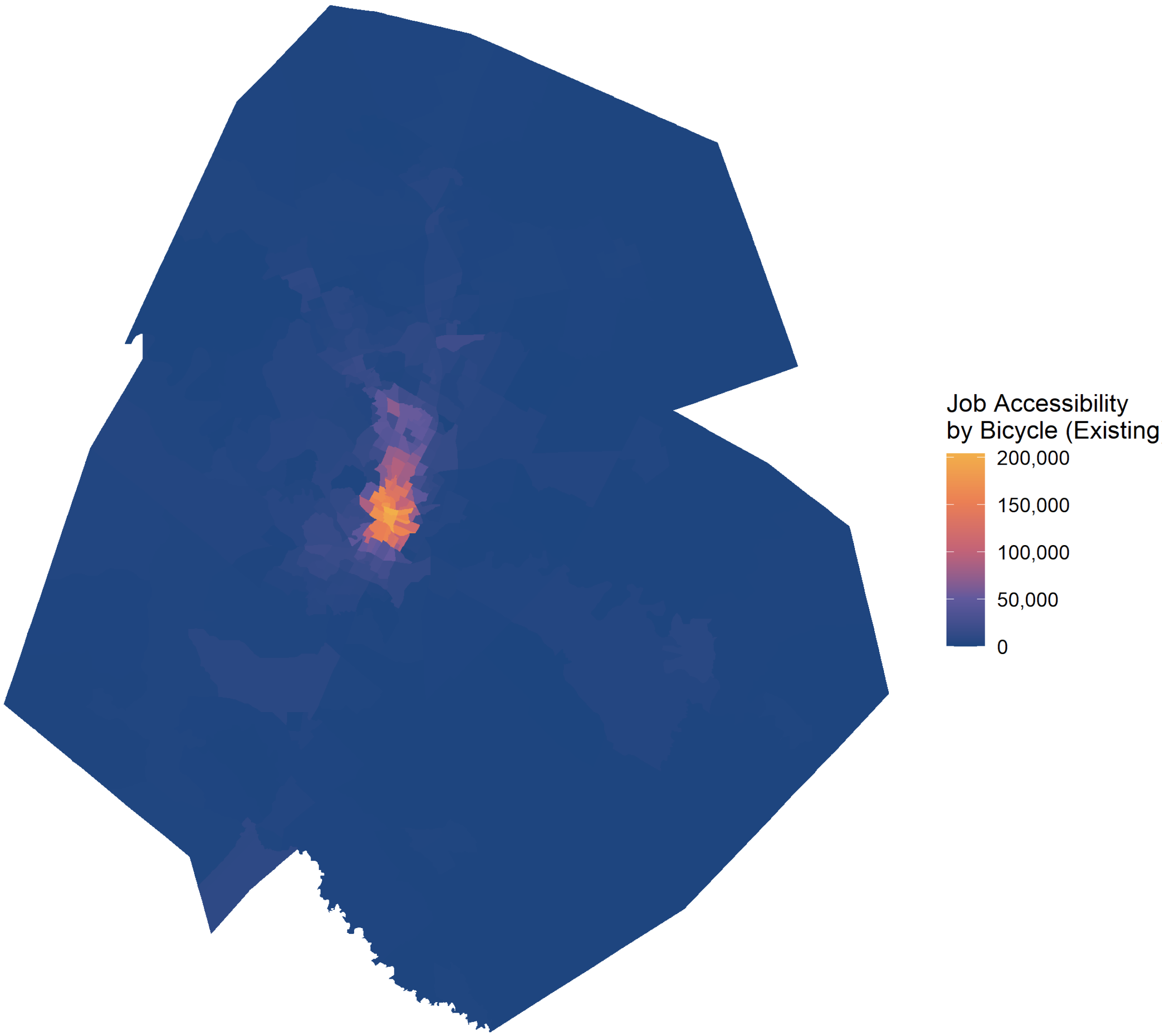


Figure 4-8

Figure 4-8 shows accessibility by biking. It is the same in both the existing conditions and the alternative. For our calculations, we increased the assumed travel speed to a more reasonable 10 mph (16 km/h). Additionally, this was performed with a steeper decay function, assuming a drop off of 50% in access after only 25 minutes of travel. This will be updated for future chapters with the same function across all mode, though the case can be made that travel is less tolerable on a bike than by car (mainly for weather-related reasons—Austin gets very hot in the summer, with heavy rain storms, yet also manages to have a cold climate in winter as well).

Accessibility by Walking

Existing/Alternative

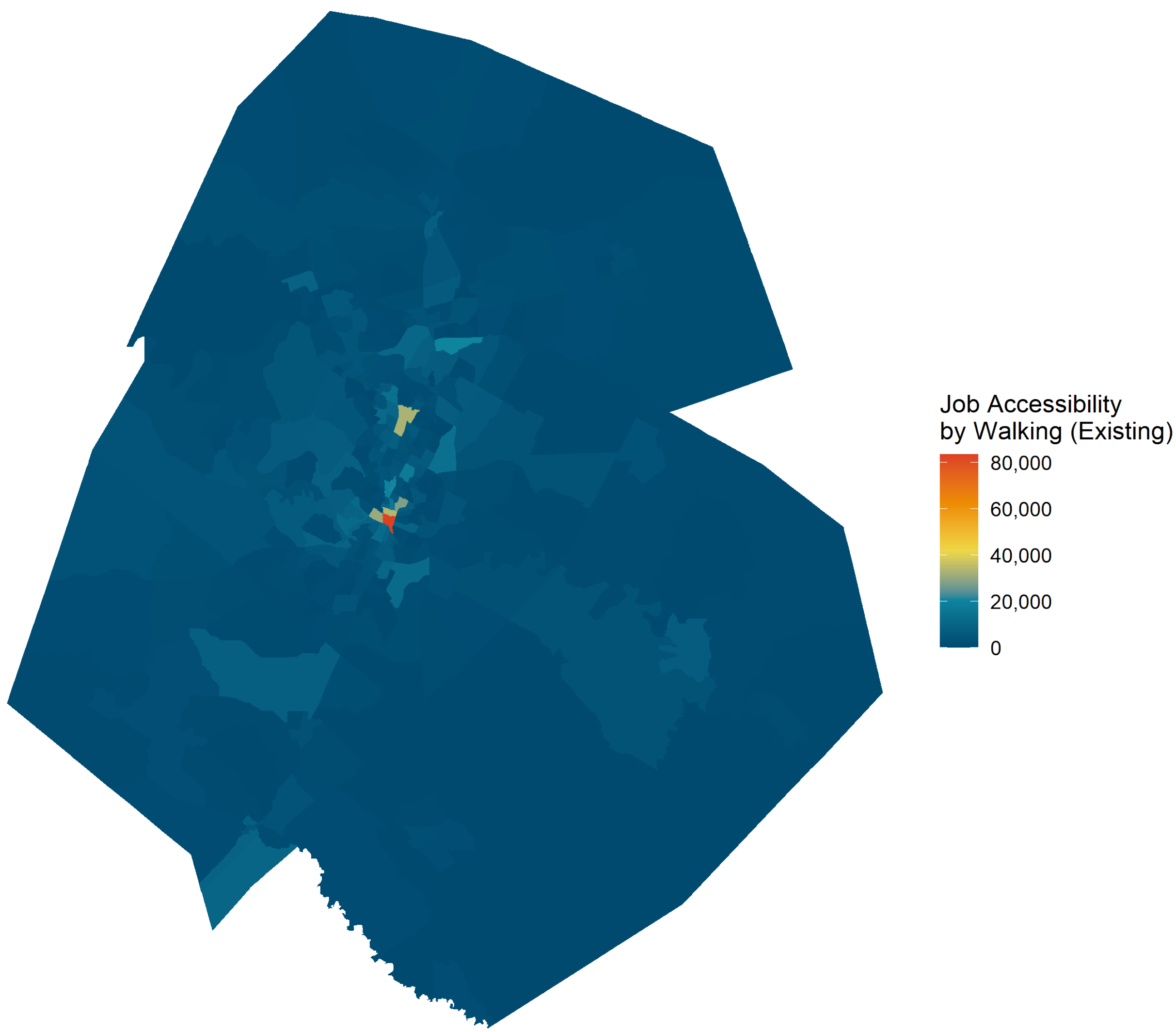


Figure 4-9

Finally, Figure 4-9 shows job accessibility by foot. As was the case with biking, this had a decay function assuming an access drop off of 50% at 15 minutes. After further reflection, this may not be a reasonable assumption. As a result, the accessibility calculations will be re-done with, at the very least, the same decay function as biking for future modeling assignments. Walking is assumed to have a travel speed of 3 mph (4.8 km/h). Like with biking, walking accessibility is unchanged by the effect of closing Downtown's streets to cars.

Chapter 5: Vehicle Access

Image source: Culture Map Austin

Introduction

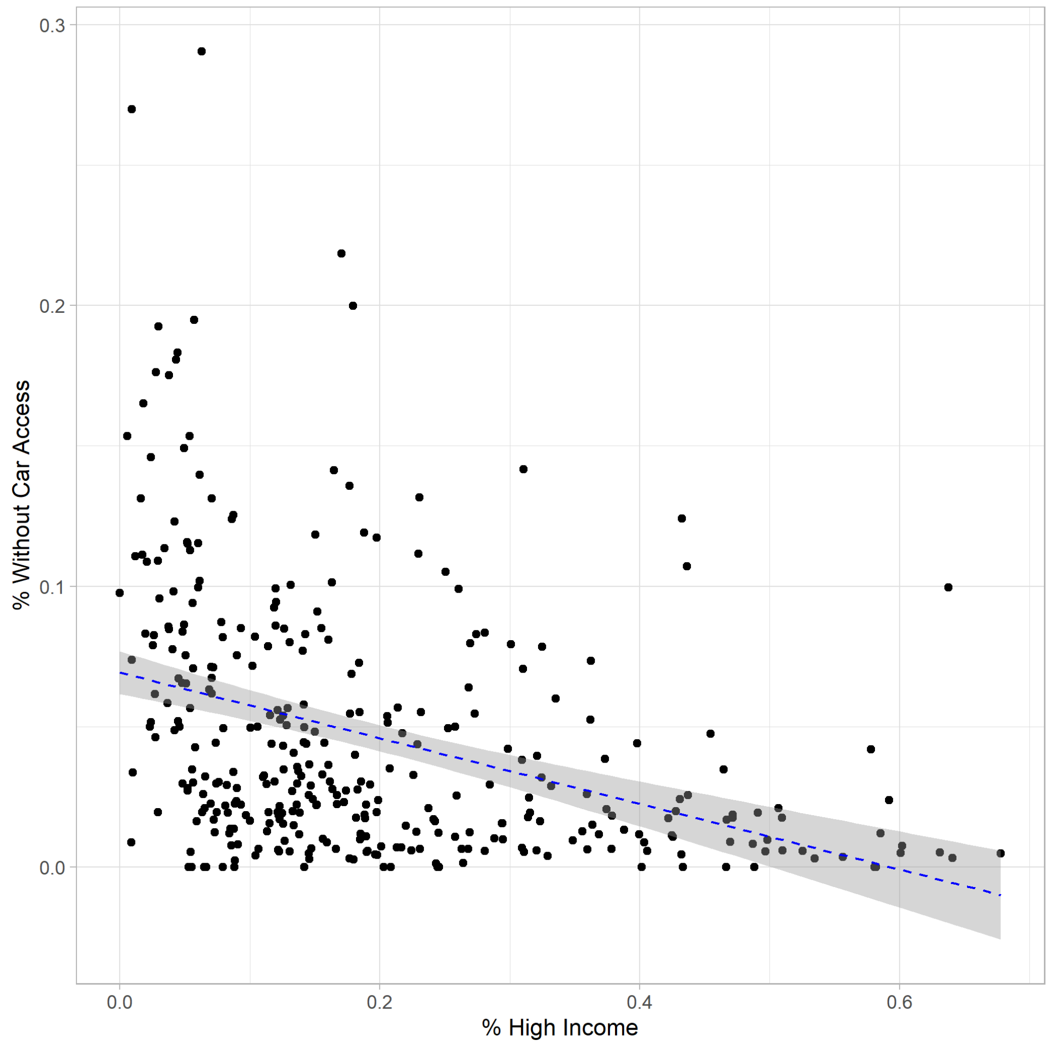


Figure 5-1

This chapter of the report will model the relationship between various characteristics of the Austin-Round Rock MSA and access to private automobiles. This model will be based on a number of demographic and economic factors, as well as certain aspects of the built environment. Using this model, we will predict the effect of downtown road closures on residents' access to vehicles. These estimates will be used in subsequent chapters of the report and the overall regional travel demand model.

Figure 5-1 highlights an example of such predictors of vehicle ownership: the percentage of households in a given census tract that are classified as high-income (they fall into the highest quintile for household income). As one may expect, there is a negative relationship between this and lack of car access, due to the financial requirements of car ownership.

A similarly strong relationship between the percentage of low-income households in a census tract and no vehicle ownership can be seen to the right in Figure 5-2. For the same reason the high-income households are more likely to be financially able to own a car, poorer households are more likely to be constrained in their ability to do so. Notably, the correlation between a high number of low-income households and lack of vehicle access is much steeper.

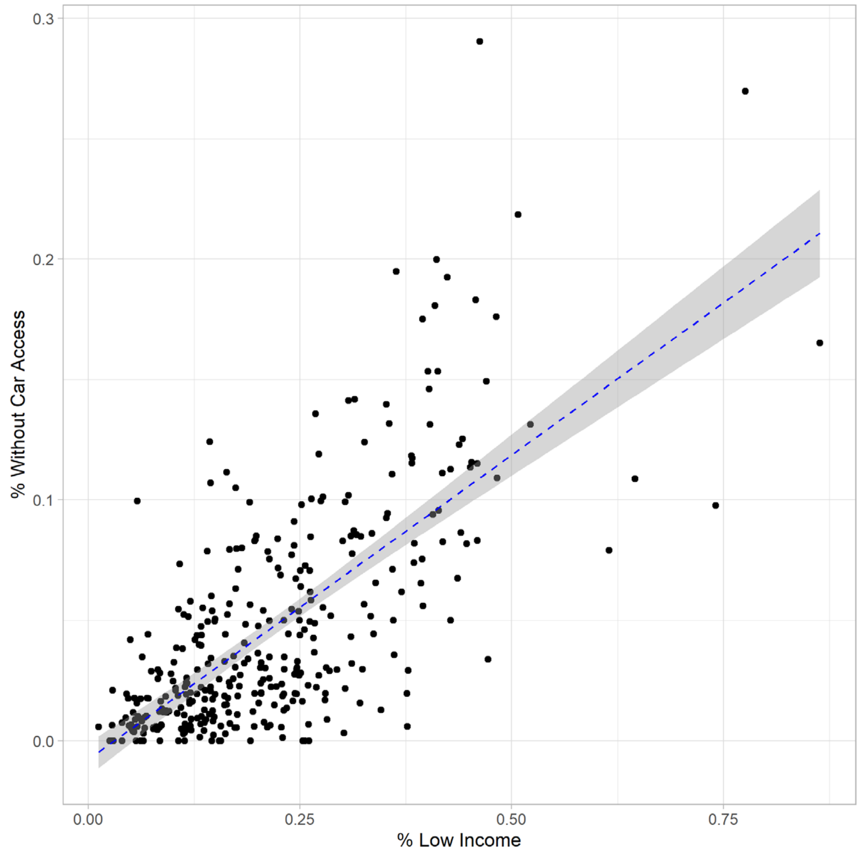


Figure 5-2

Another unsurprising trend in the MSA data is the negative correlation between the percentage of residents under the age of 18 and lack of car access. Figure 5-3 shows this statistical relationship. There are a couple possible explanations for this phenomenon. One is that younger people generally do not have a driver's license, so that is one fewer person in a household whose needs may drive decisions about car ownership. However, given that many residents under the age of 18 are in fact children living with their family, it is interesting that there is little indication of parents' travel needs in this plot (which would show up as increased car ownership in areas with more children).

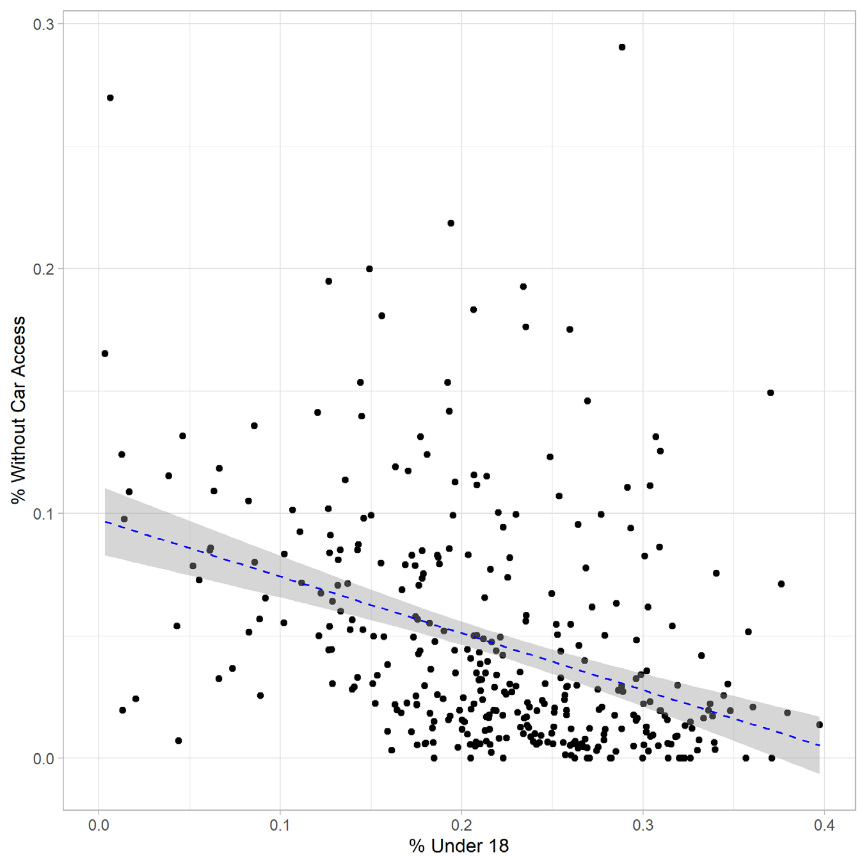


Figure 5-3

Other household characteristics are also good predictors of vehicle ownership, or lack thereof, shown in Figure 5-4. Larger households, meaning those with three or more members, are less likely to not have access to a car. Intuitively, the more people who live in a household, the volume and variation in travel needs increases, which are satisfied most easily by driving. This would show up when aggregated and averaged at the tract level.

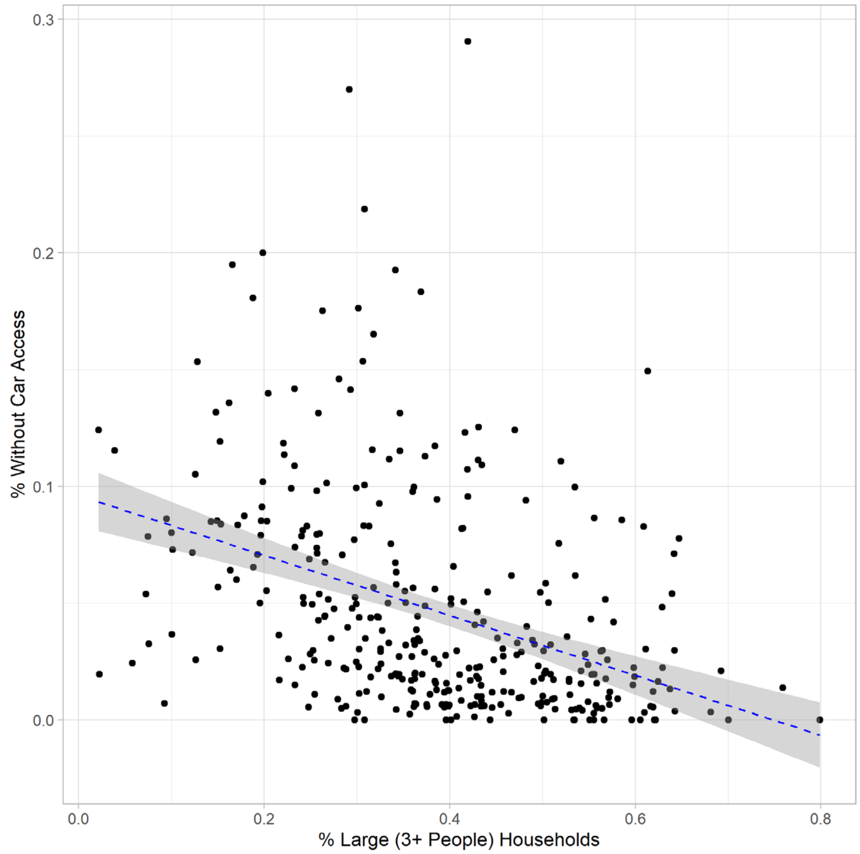


Figure 5-4

Beyond household characteristics, information about the build environment can be useful for understanding its effect on car ownership. Figure 5-5 plots the relationship between residential density and percentage of households without access to a vehicle. Denser areas are likely to have viable alternatives to driving to meet baseline mobility needs, or alternatively, may be more likely to have socioeconomic factors that contribute to lower rates of car access.

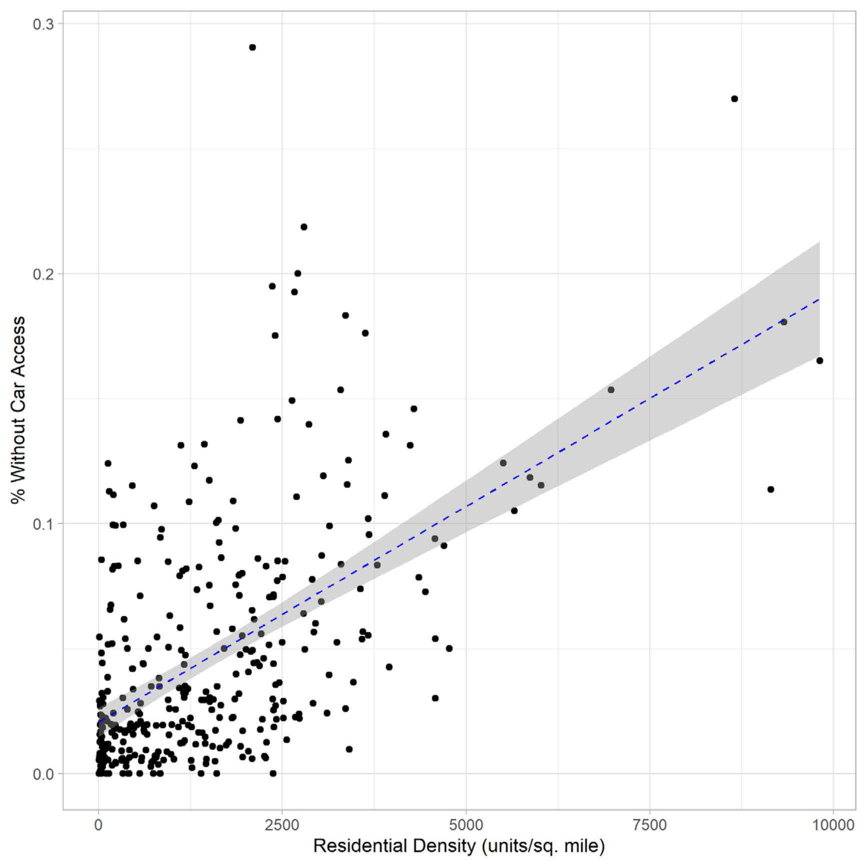


Figure 5-5

Not all information about the MSA necessarily tells us anything about the percentage of households with or without car access. Employment information, for example, was not a strong predictor (which will be the case in regression coefficients as well) of whether tracts have low rates of car ownership. Figure 5-6 shows the relationship between the percentage of employment in the retail sector and car access.

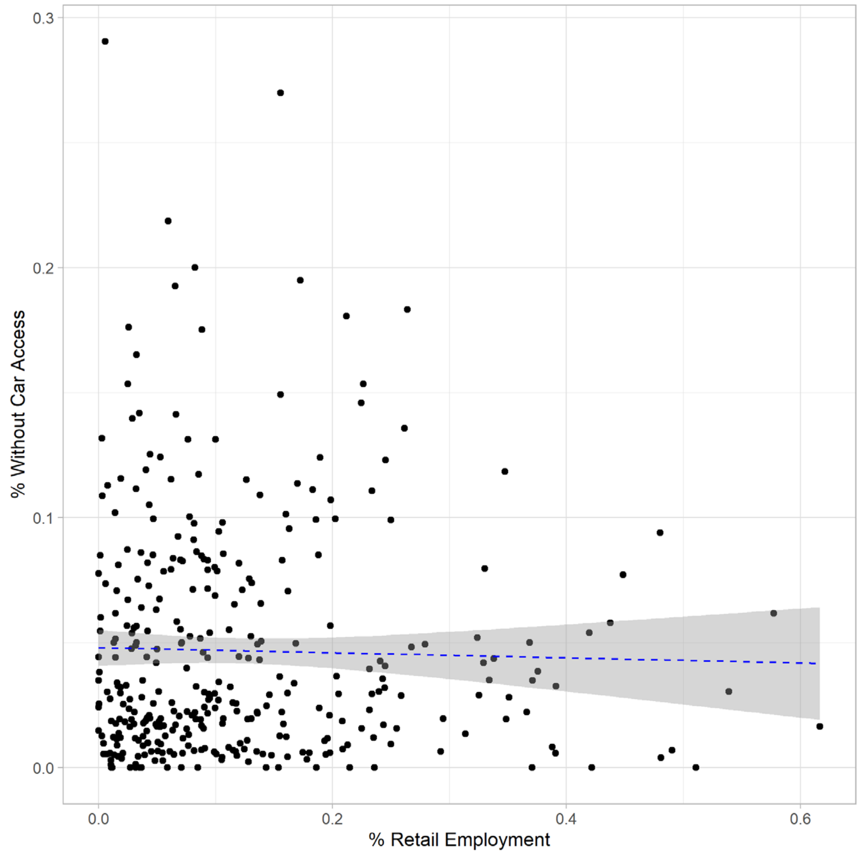


Figure 5-6

Shockingly, and mainly due to a single outlier (which is removed in the final regression dataset), the ratio of transit job accessibility to driving job accessibility is not strongly associated one way or another with vehicle access at the tract level. This is clear from Figure 5-7, which also illustrates how poor this accessibility ratio is for most tracts in the MSA, with a substantial grouping near zero.

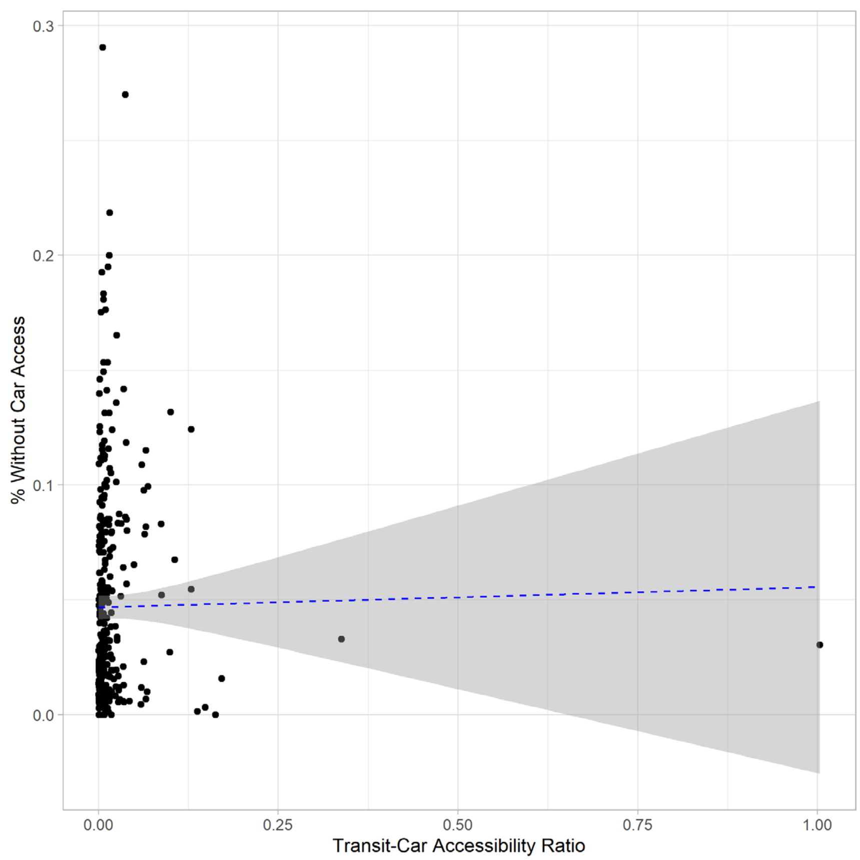


Figure 5-7

	Kitchen Sink		Refined		Just Land Use		Just Demo		Another Attempt		W/O Transit Ratio		Last Attempt	
(Intercept)	-0.00	(0.01)	0.02 **	(0.01)	0.02 **	(0.01)	-0.00	(0.01)	-0.01	(0.01)	-0.00	(0.01)	-0.01	(0.01)
pct_big_hh	-0.04	(0.03)					-0.11 ***	(0.02)	-0.10 ***	(0.02)	-0.04	(0.03)	-0.10 ***	(0.02)
pct_low_inc	0.23 ***	(0.02)	0.22 ***	(0.01)			0.26 ***	(0.02)	0.25 ***	(0.02)	0.24 ***	(0.02)	0.26 ***	(0.02)
pct_high_inc	0.02	(0.02)					0.06 ***	(0.02)	0.04 **	(0.02)	0.03	(0.02)	0.04 **	(0.01)
pct_under_18	0.08	(0.04)					0.08	(0.04)	0.12 **	(0.04)	0.06	(0.04)	0.11 **	(0.04)
pct_over_65	-0.15	(0.14)					-0.40 **	(0.14)	-0.24	(0.13)	-0.16	(0.14)		
transit_car_ratio	-0.65 *	(0.25)	-0.80 ***	(0.23)	-0.59	(0.32)			-1.18 ***	(0.22)			-1.32 ***	(0.22)
bike_car_ratio	0.02	(0.01)			-0.02	(0.02)					0.02	(0.01)		
walk_car_ratio	0.49 *	(0.25)	0.70 ***	(0.21)	0.64 *	(0.31)			1.03 ***	(0.20)	-0.12	(0.07)	1.15 ***	(0.20)
avg_commute_time	-0.00 **	(0.00)	-0.00 ***	(0.00)	-0.00	(0.00)					-0.00 **	(0.00)		
res_density	0.00 *	(0.00)	0.00 ***	(0.00)	0.00 ***	(0.00)					0.00 ***	(0.00)		
job_density	0.00	(0.00)			-0.00	(0.00)					0.00	(0.00)		
job_home_ratio	0.00	(0.00)			0.00 **	(0.00)					0.00	(0.00)		
pct_service_emp	0.01	(0.01)					0.03 **	(0.01)	0.02 *	(0.01)	0.01	(0.01)		
pct_retail_emp	0.00	(0.02)					0.00	(0.02)	0.01	(0.02)	-0.00	(0.02)		
N	346		346		346		347		346		346		346	
R2	0.64		0.63		0.36		0.57		0.61		0.63		0.60	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 5-1

The table above (Table 5-1) summarizes our various attempts at modeling the percentage of households without vehicle access, with the final specification ("Last Attempt") settling on six predictors: percentage of large households, percentage of low- and high-income households, percent of residents under the age of 18, transit-car accessibility ratio, and the walk-car accessibility ratio. All of the coefficients make sense, so to speak, with the exception of the transit-car job accessibility ratio. The reasoning for this is in line with what is discussed alongside the various scatterplots.

According to our model, areas where one can access a higher proportion of car-accessible jobs by public transit are less likely to have zero-car households. The best possible explanation for this is that there is something about the structure of the transit network that is correlated with unobserved variation between tracts, and this unobserved variation is the ultimate cause. Future assignments and chapters will attempt to resolve this confusing result.

On the following pages, existing and predicted percentages of households without vehicle access are mapped, as well as the change in these values between the existing conditions and the proposed alternative.

Figure 5-8 and Figure 5-9 show the existing percentage of households without vehicle access and predicted percentages, using our regression model. Figure 5-10, on the following page, shows the change between these two scenarios. The biggest difference is in the two tracts that make up Downtown Austin, where the alternative of closed streets has the largest impact on job accessibility by car, which makes sense.

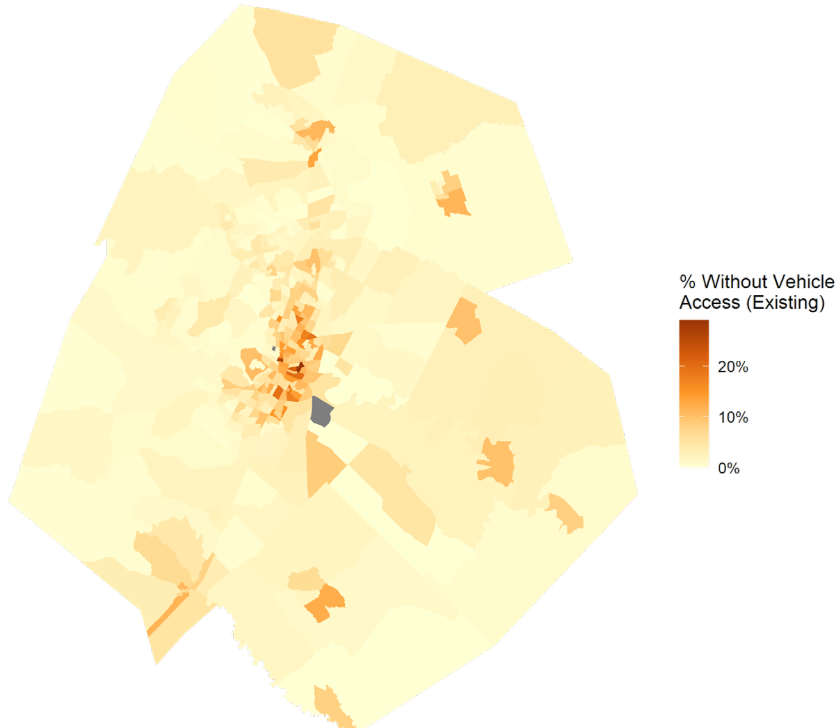


Figure 5-8

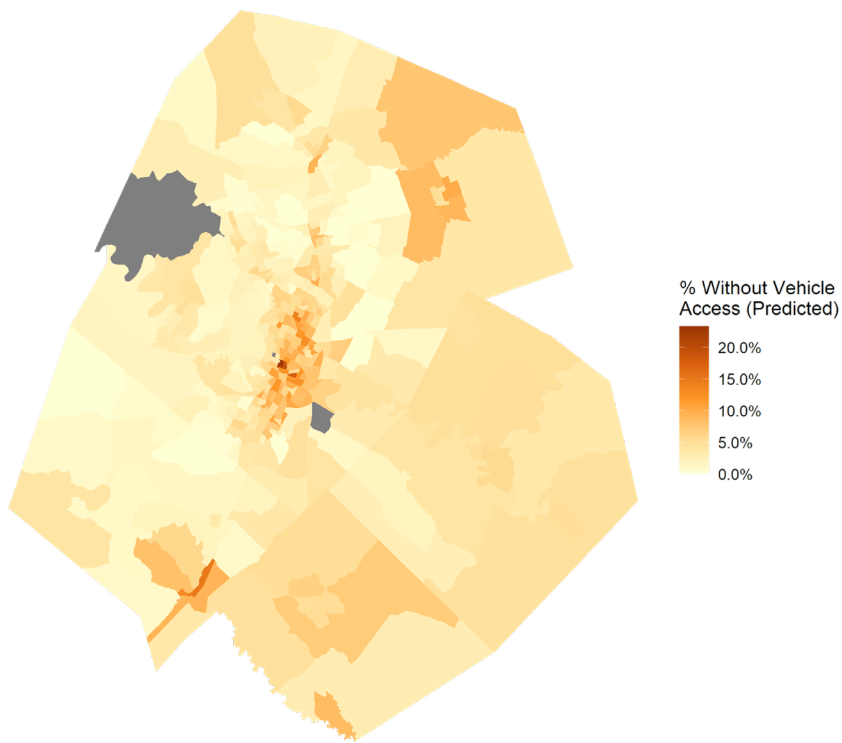


Figure 5-9

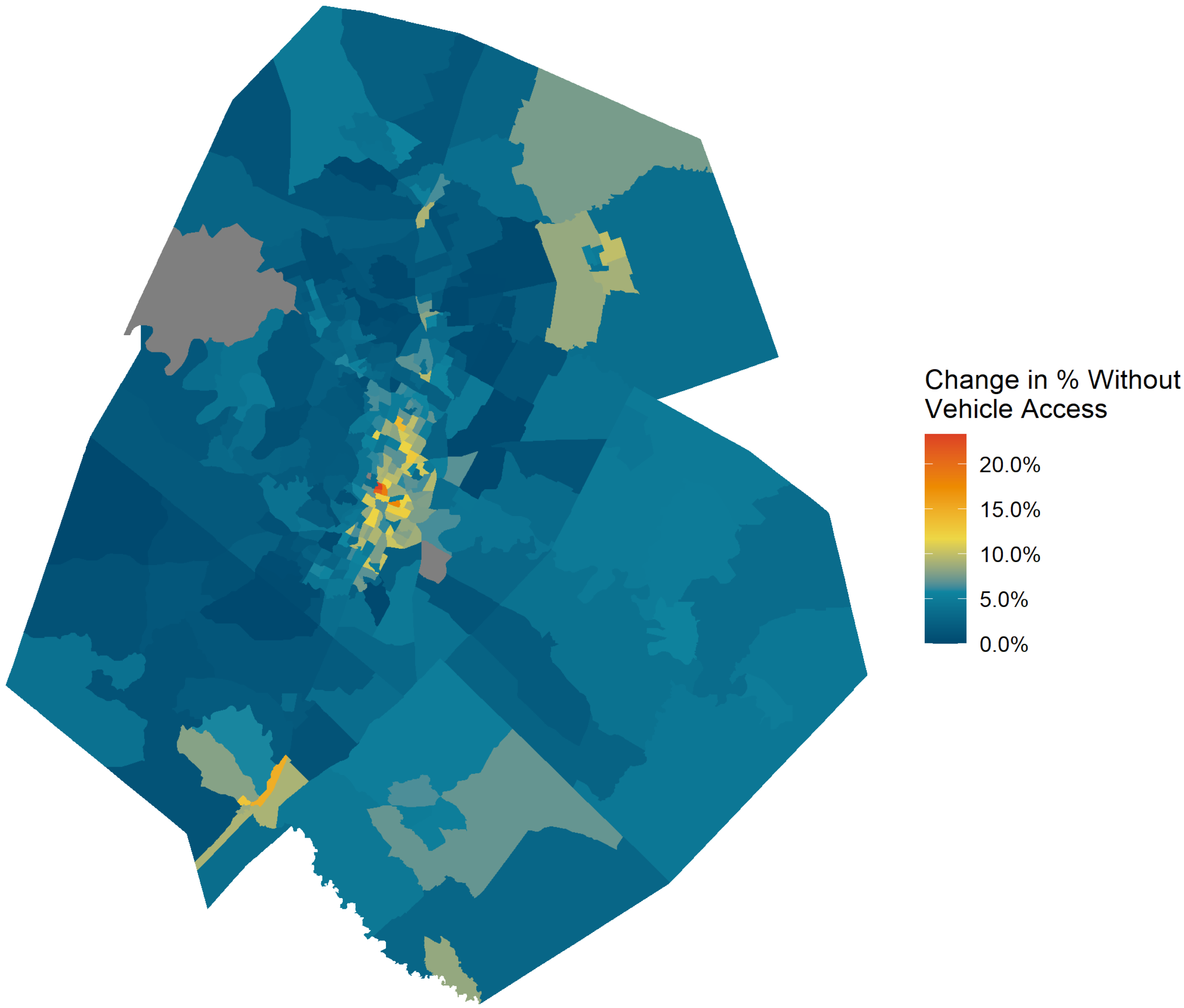


Figure 5-10

Chapter 6: Trip Generation

Image source: Culture Map Austin

Model Creation

We now move to the first step in building our four-step travel demand model, predicting trip generation. For this particular step, we are building a trip generation model based on the zonal demographic data we have previously obtained from the ACS, and travel survey data obtained from the 2017 National Household Travel Survey. Because there is no difference between the existing conditions and the alternative for trip production/attraction, we will only examine one set of these predictions.

The trip production model was based on running linear regressions between the NHTS data and the demographic data for the 350 tracts in the Austin MSA. Since NHTS data is categorized by trip purpose, we were able to build individual models for each of three trip types: Home-Based Work (Table 6-1), Home-Based Other (Table 6-2), and Non-Home Based trips (Table 6-3). All three relied heavily on household size, with larger households predicted more trips; the HBO model included presence of children, with a negative coefficient. This makes intuitive sense - households with children are more likely to have a parent staying at home, and not commuting to work. The Non-Home Based model included income quintiles, with higher incomes predicting more NHB trips. It's possible this can be explained in terms of work lunches - people with higher incomes are more likely to be in position to go out for lunch, and have the cash to do so.

Still, our model's predictive power is far from perfect, with an R^2 value of only 27%.

Home-Based Work Trips

	Full model		**Reduced model**	
(Intercept)	2.34 ***	(p = 0.00)	**2.26 *****	**(p = 0.00)**
zero_veh_TRUE	-0.04	(p = 0.85)		
size_one	-1.71 ***	(p = 0.00)	**-1.65 *****	**(p = 0.00)**
size_three	-0.49 **	(p = 0.01)	**-0.47 ****	**(p = 0.01)**
size_two	-1.18 ***	(p = 0.00)	**-1.15 *****	**(p = 0.00)**
inc_quint_2nd	-0.00	(p = 0.99)		
inc_quint_3rd	-0.02	(p = 0.90)		
inc_quint_4th	0.08	(p = 0.63)		
inc_quint_5th	-0.16	(p = 0.27)		
children_yes	-0.80 ***	(p = 0.00)	**-0.81 *****	**(p = 0.00)**
N	2127		**2168**	
R2	0.09		**0.09**	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 6-1

Home-Based Other Trips

	Full model		**Reduced model**	
(Intercept)	7.85 ***	(p = 0.00)	**8.15 *****	**(p = 0.00)**
zero_veh_TRUE	-0.66	(p = 0.13)		
size_one	-5.70 ***	(p = 0.00)	**-6.15 *****	**(p = 0.00)**
size_three	-2.87 ***	(p = 0.00)	**-2.97 *****	**(p = 0.00)**
size_two	-4.11 ***	(p = 0.00)	**-4.40 *****	**(p = 0.00)**
inc_quint_2nd	-0.34	(p = 0.51)		
inc_quint_3rd	0.01	(p = 0.99)		
inc_quint_4th	-0.13	(p = 0.82)		
inc_quint_5th	0.23	(p = 0.69)		
children_yes	0.26	(p = 0.64)		
N	2127		**2168**	
R2	0.27		**0.27**	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 6-2

For the other side of the trip generation model, trip attractions, we relied on a generalized model from NCHRP 716, building off of zonal employment data (Table 6-4). We were calculating all person trips, since our demand model includes active transportation. We used HBW Model 1, HBO Model 3, and NHB Model 1.

In a given region, the number of travel productions and attractions should match (since external-regional travel is negligible), but since our 2 models are built off of alternative approaches, it is natural they will not match. We therefore balanced our attraction predictions, maintaing proportionality, based on the absolute number of trip productions measured. (The production model is based off of survey measurements, and is therefore more reliable than the attractions model.)

Non-Home Based Trips				
	Full model		**Reduced model**	
(Intercept)	3.57 ***	(p = 0.00)	**2.99 *** **	**(p = 0.00)**
zero_veh_TRUE	-0.22	(p = 0.60)		
size_one	-2.64 ***	(p = 0.00)	**-2.10 *** **	**(p = 0.00)**
size_three	-0.91 *	(p = 0.01)	**-0.72 * **	**(p = 0.05)**
size_two	-1.73 ***	(p = 0.00)	**-1.21 *** **	**(p = 0.00)**
inc_quint_2nd	0.52	(p = 0.08)	**0.54**	**(p = 0.07)**
inc_quint_3rd	0.64 *	(p = 0.03)	**0.68 * **	**(p = 0.02)**
inc_quint_4th	1.15 ***	(p = 0.00)	**1.19 *** **	**(p = 0.00)**
inc_quint_5th	1.10 ***	(p = 0.00)	**1.13 *** **	**(p = 0.00)**
children_yes	-0.62	(p = 0.15)		
N	2127		**2127**	
R2	0.09		**0.08**	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 6-3

	Number of MPO Models Summarized	Households[a]	School Enrollment[b]	Employment			
				Basic[c]	Retail[d]	Service[e]	Total
All Person Trips							
Home-Based Work							
Model 1	16						1.2
Home-Based Nonwork							
Model 1	2	1.2	1.4	0.2	8.1	1.5	
Model 2	8	2.4	1.1		7.7	0.7	
Model 3	2	0.7		0.7	8.4	3.5	
Nonhome Based							
Model 1	5	0.6		0.5	4.7	1.4	
Model 2	8	1.4			6.9	0.9	
Motorized Person Trips							
Home-Based Work							
Model 1	8						1.2
Home-Based Nonwork							
Model 1	1	0.4	1.1	0.6	4.4	2.5	
Model 3	4	1.0		0.3	5.9	2.3	
Nonhome Based							
Model 1	6	0.6		0.7	2.6	1.0	

[a] The number of households in a zone.
[b] The number of elementary, high school, or college/university students in a zone.
[c] Employment primarily in two-digit North American Industry Classification System (NAICS) codes 1–42 and 48–51 [Standard Industrial Classification (SIC) codes 1–51].
[d] Employment primarily in two-digit NAICS codes 44–45 (SIC codes 52–59).
[e] Employment primarily in two-digit NAICS codes 52–92 (SIC codes 60–97).

Source: MPO Documentation Database.

Table 6-4

Results and Observations

A complete collection of maps displaying our predictions is available at the back of the chapter. First we'll present some highlights:

One important observation is that while trip productions are distributed consistently, if not evenly, throughout the built-up area of Austin, trip attractions are significantly more concentrated in the inner regions. The downtown tracts stand out way more on the attraction maps than any analog does on the production maps. The gradient maps in Figure 6-1 and Figure 6-2 compare the number of non-home based trips produced and attracted, respectively, with the number of trips normalized by area. Urbanized area in the MSA is outlined in both figures for reference.

The attraction/distribution maps appear similar to each other regardless of trip type. On the production side, the urban-rural divide is most pronounced when it comes to Non-Home Based trips. Again, this makes sense, as there are fewer clusters of nearby activity, where a traveler can make multiple stops.

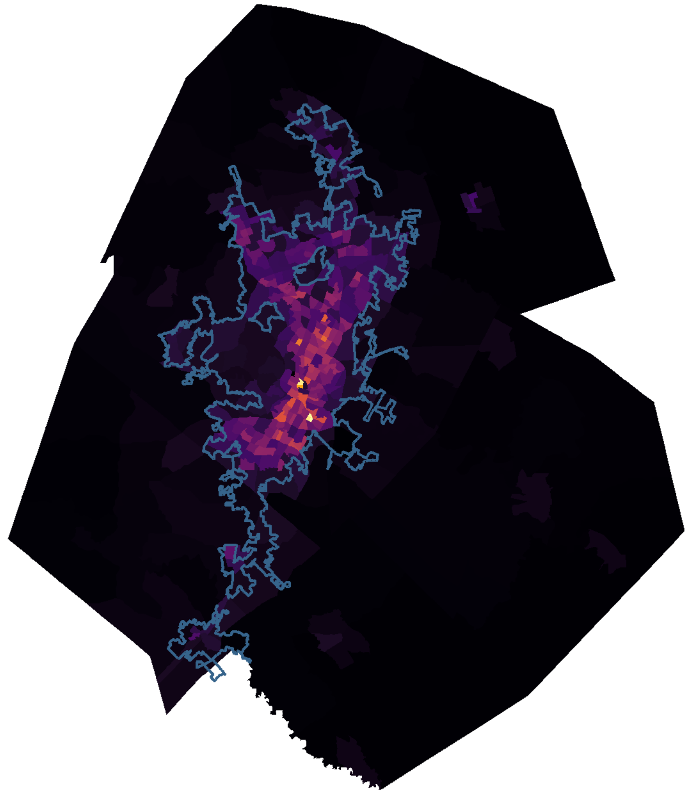


Figure 6-1

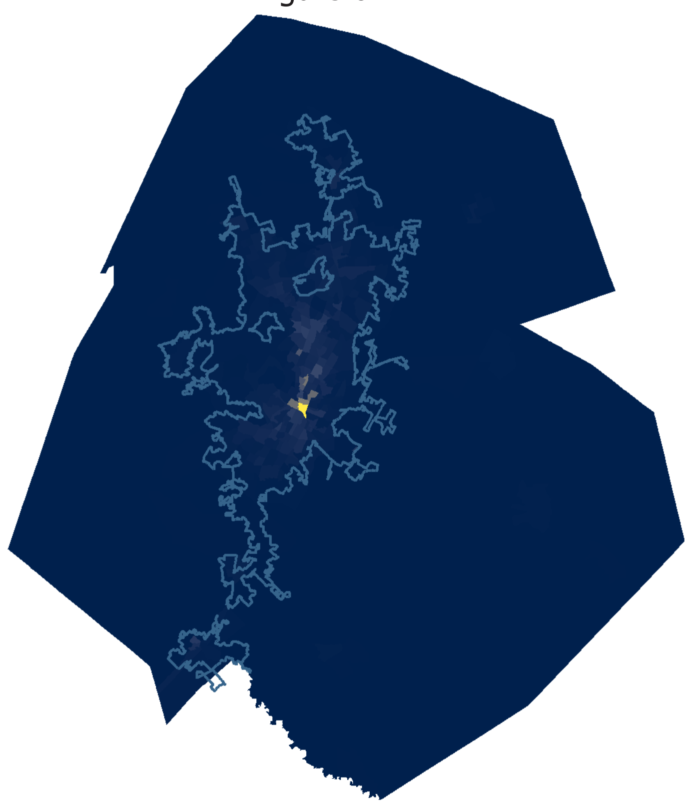


Figure 6-2

Also worth analyzing is how balanced each tract is between trip productions and attractions. In other words, these visualizations show where our trip production model's predictions differ from the trip attraction model. On the whole, our models' predictions for Home-Based Work trips appear to be more consistent throughout the region (Figure 6-3). On the other hand, the production and attraction models disagree greatly in both directions for HBO (Figure 6-4) and NHB trips (Figure 6-5).

There is also a pattern in the HBO and NHB balance maps that the more inner areas have lower ratios, implying either balance or more attractions than productions. This means that these areas have more commercial or retail activity, and the outlying suburbs are significantly more residential, which can be expected. Nevertheless it's interesting to see that this distribution is not entirely consistent, and where it does appear, the "centrality" is determined mostly according to east-west, with north-south less relevant. The major arteries of the MSA do run north-south, so perhaps development patterns have more to do with proximity to the highway than to downtown itself.

These ratio maps were produced using the Jenks Natural Breaks method. On revision, these should probably be modified slightly to include a break at 1 (so it is clear which areas have more predicted attractions than productions).

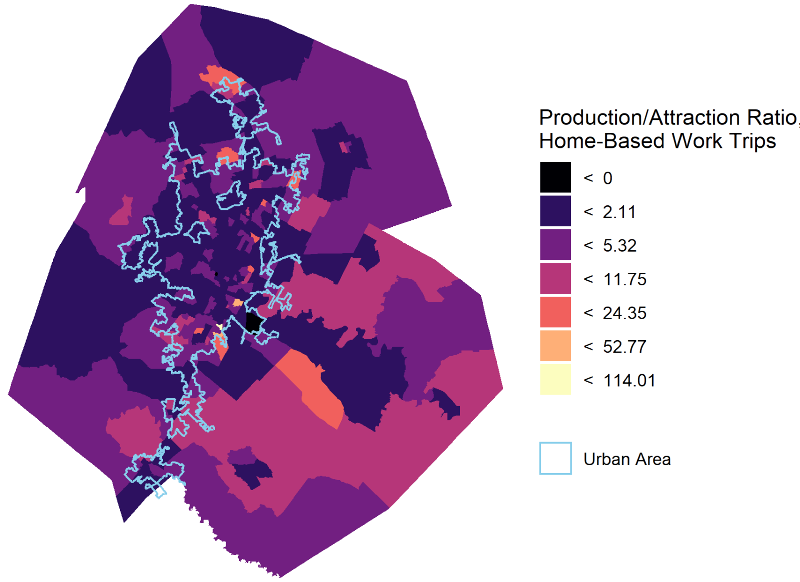


Figure 6-3

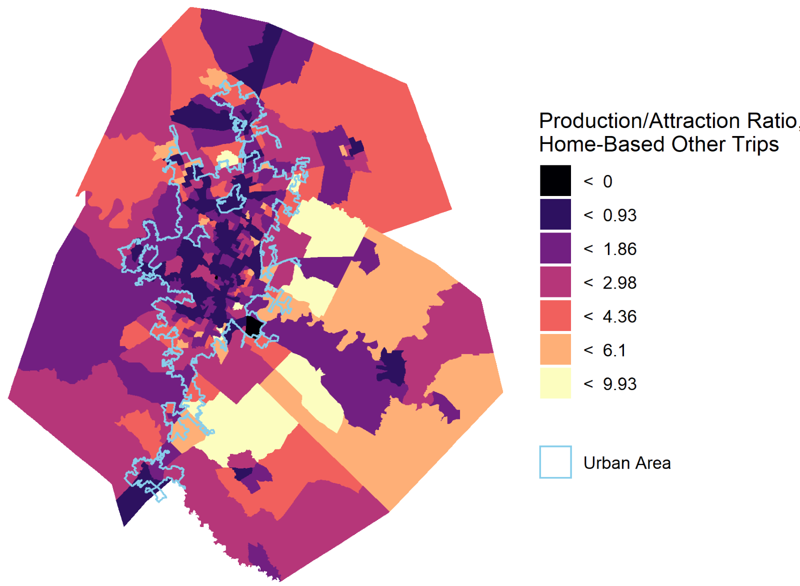


Figure 6-4

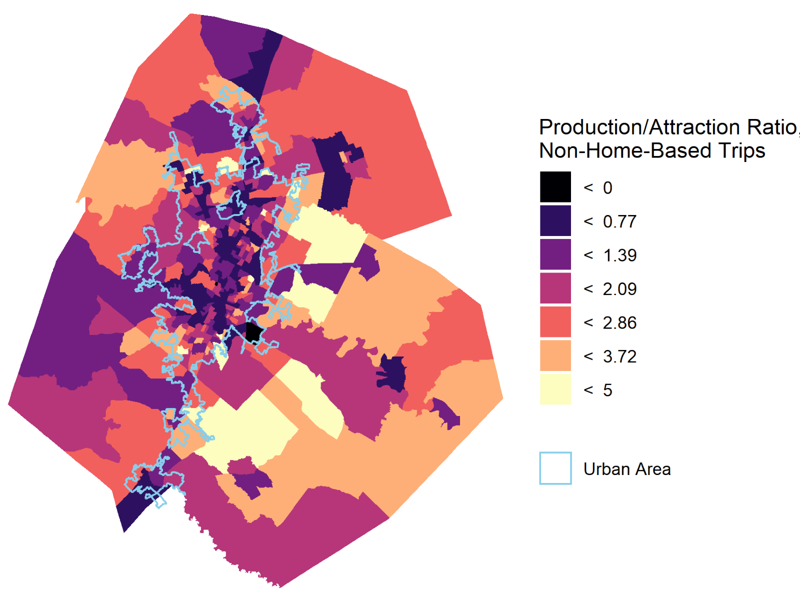


Figure 6-5

Maps: Trip Production vs. Attraction

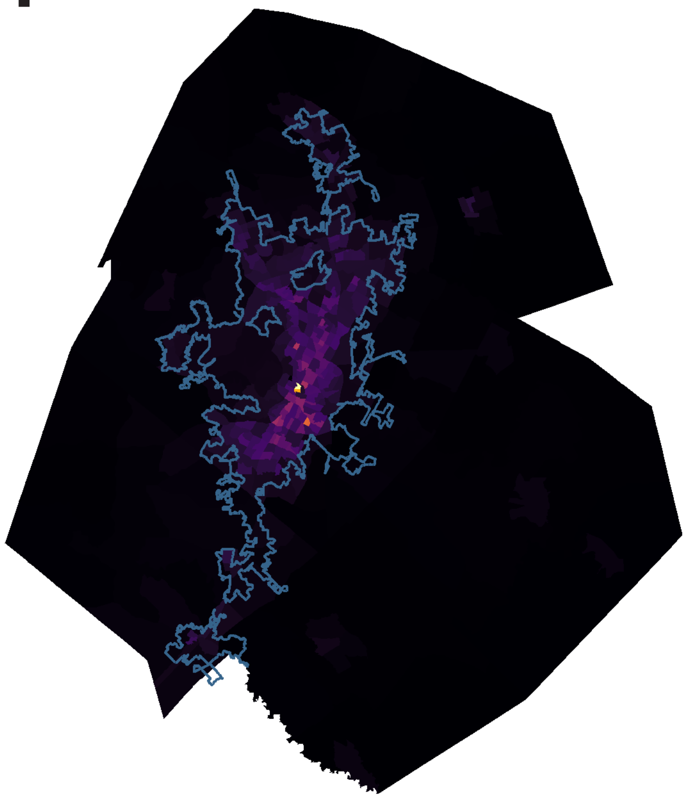


Figure 6-6: Modeled trip production for home-based work trips

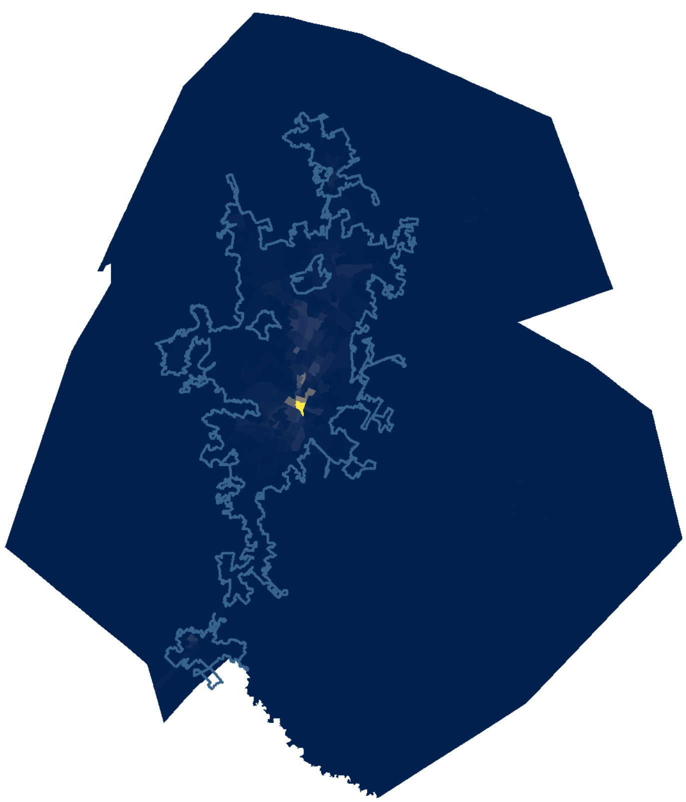


Figure 6-7: Modeled trip attraction for home-based work trips

Maps: Trip Production vs. Attraction

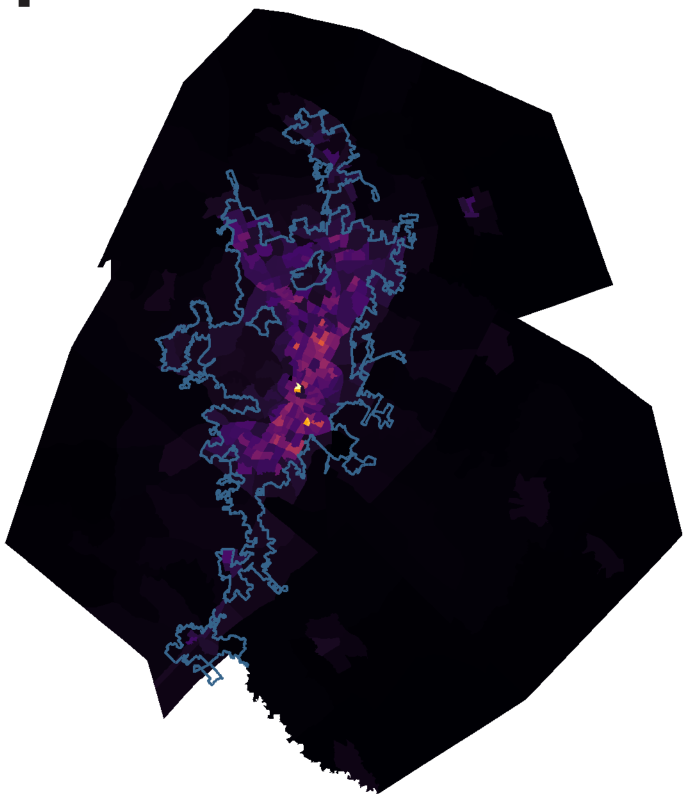


Figure 6-8: Modeled trip production for home-based other trips

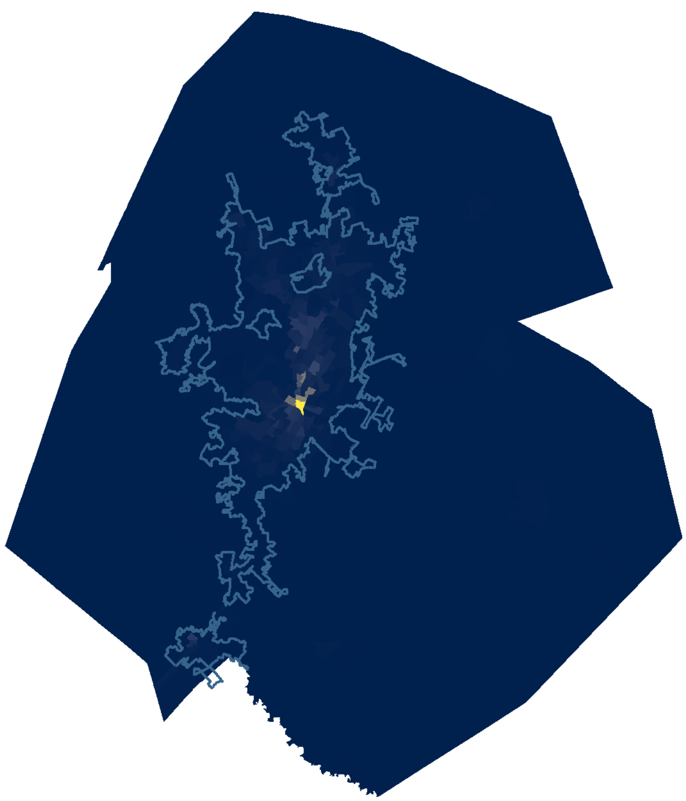


Figure 6-9: Modeled trip attraction for home-based other trips

Maps: Modeled Trip Type Share

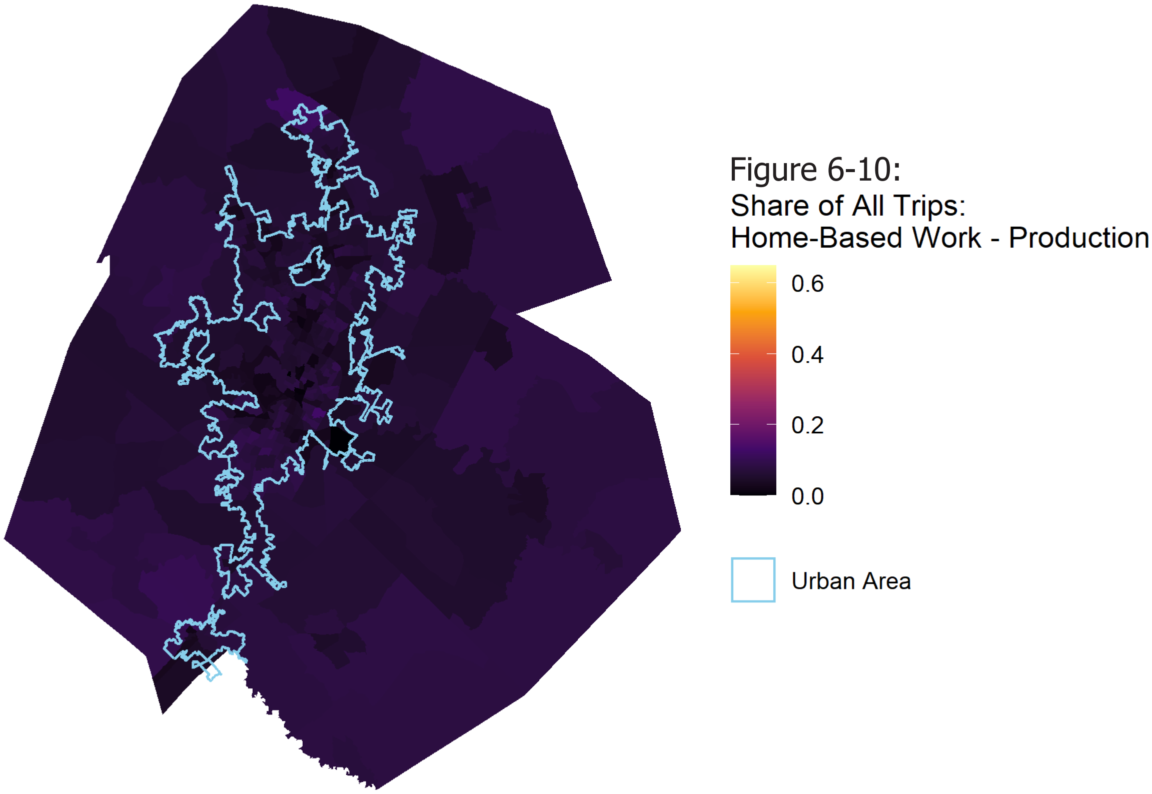


Figure 6-10:
Share of All Trips:
Home-Based Work - Production

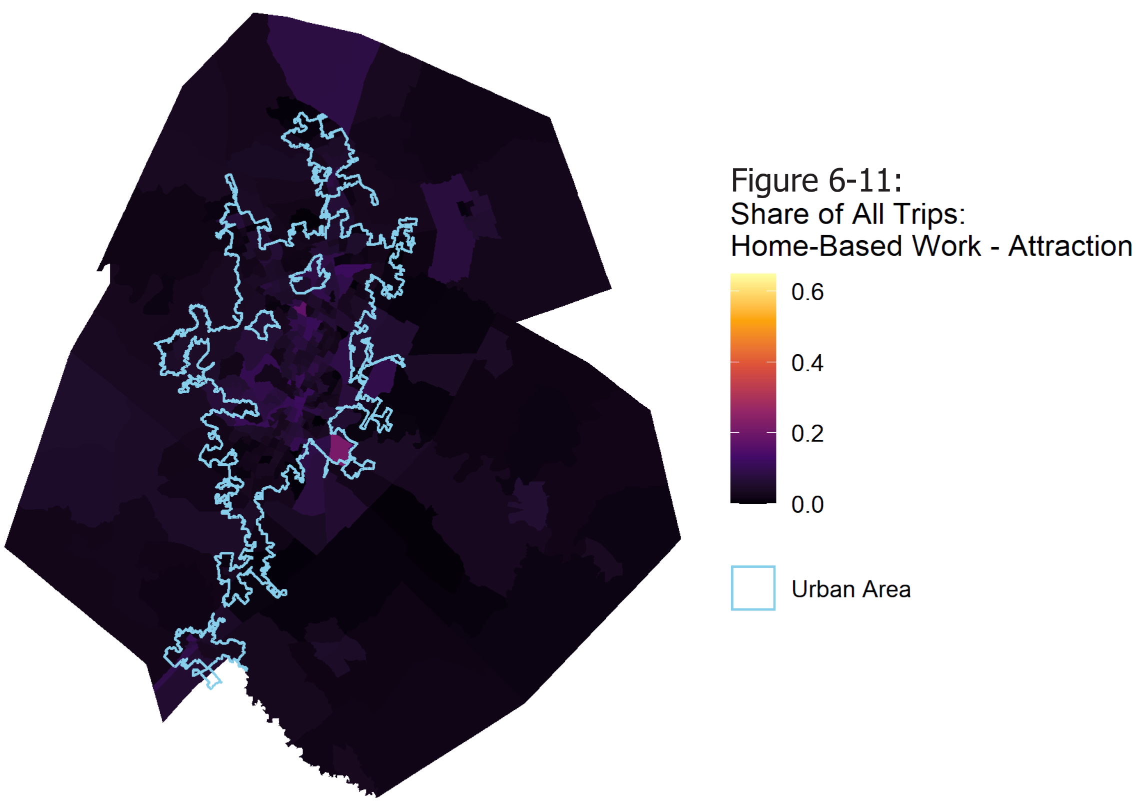


Figure 6-11:
Share of All Trips:
Home-Based Work - Attraction

Maps: Modeled Trip Type Share

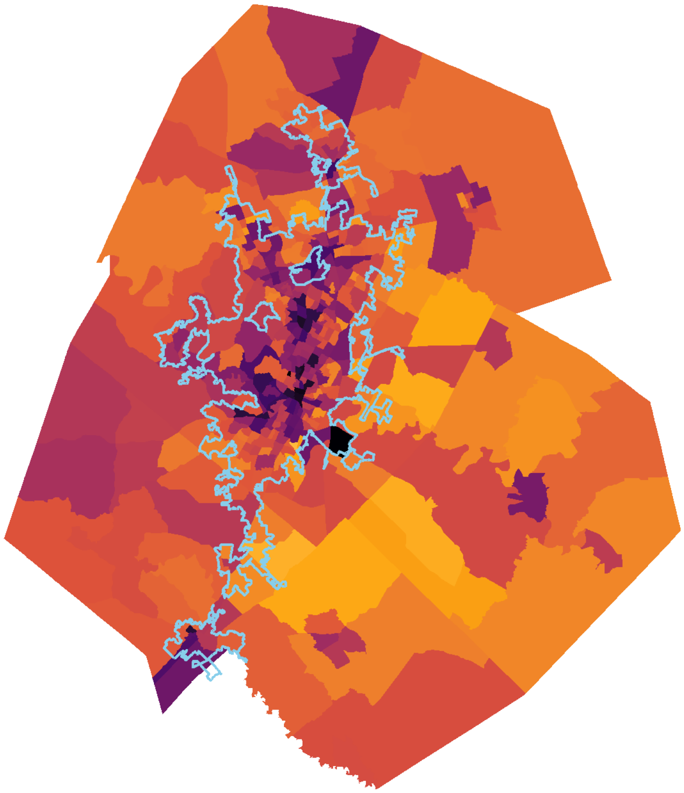


Figure 6-12:
Share of All Trips:
Home-Based Other - Production

Figure 6-13:
Share of All Trips:
Home-Based Other - Attraction

Maps: Modeled Trip Type Share

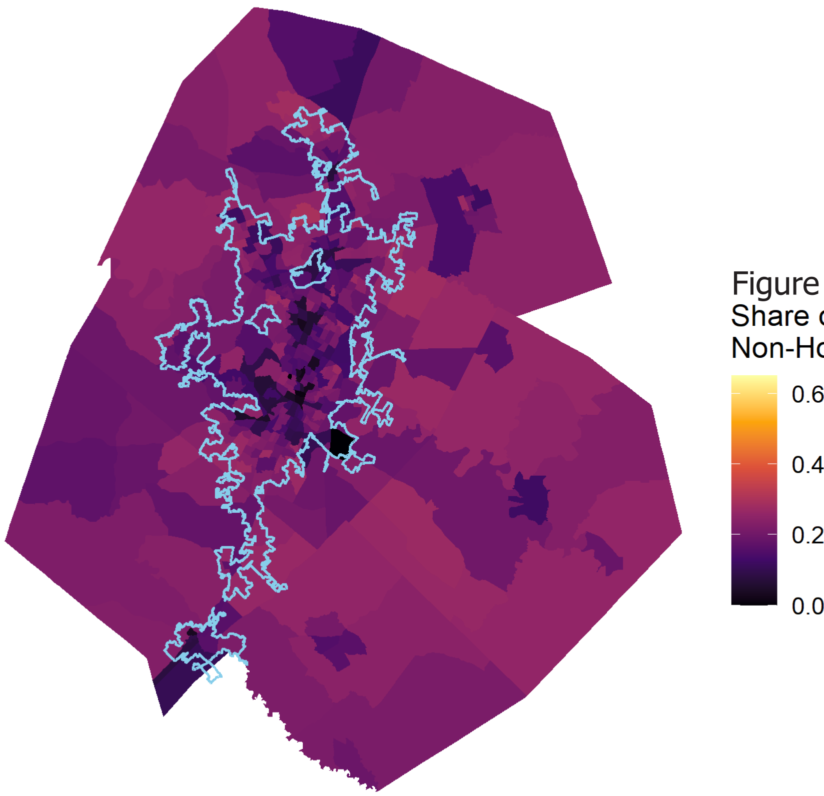


Figure 6-14:
Share of All Trips:
Non-Home Based - Production

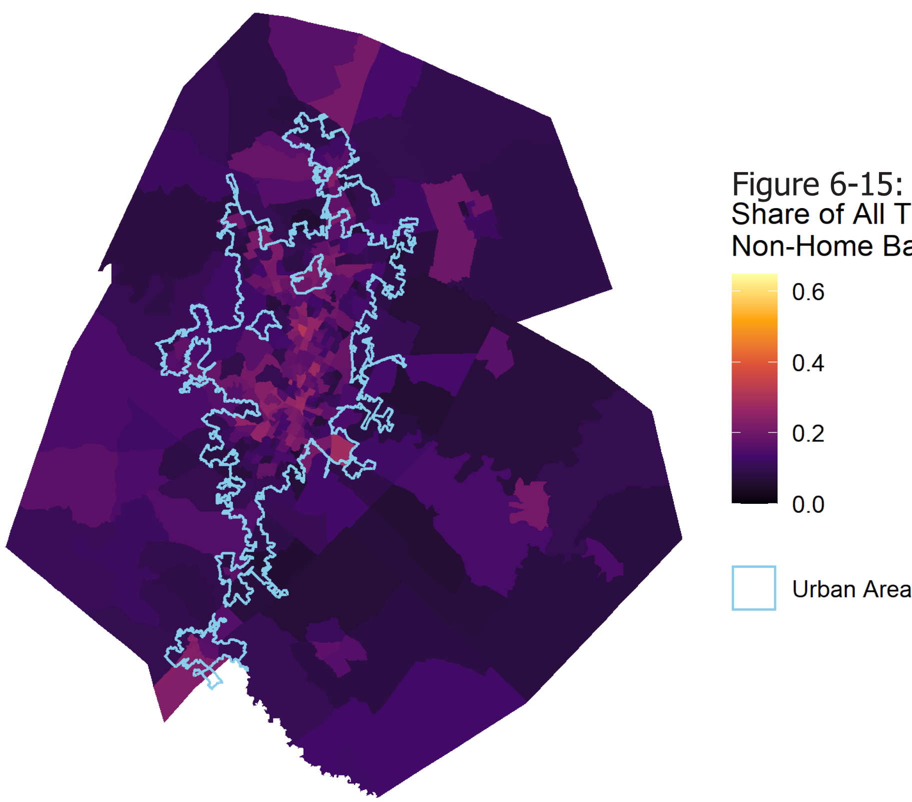


Figure 6-15:
Share of All Trips:
Non-Home Based - Attraction

Chapter 7: Destination Choice

Image source: Culture Map Austin

Calibrating the Gravity Model

Following our trip generation model, we can build a predictive model for how trips are distributed around the Austin area. We used the trip data from the NHTS and calculated average journey times. We then experimented with different gravity decay functions to allocate trips, and compared the resultant predicted average journey times with the surveyed average journey times (Table 7-2). We tweaked friction factors (Table 7-1) and repeated the process until the model matches the observed data very closely.

$$F_{ijp} = t_{ij}^{b} e^{c t_{ij}}$$

	b	c
HBW	-0.106	-0.035
HBO	-3.693	-0.015
NHB	-3.215	-0.002

Figure 7-1: Friction factor parameters

Several options are available to us for calculating friction factors between origin and destination pairs. We assessed three different functional forms, attempting to match observed travel time values as closely as possible. Exponential functions were prohibitively time-consuming during computation and failed to improve prediction accuracy over power or gamma functions. While friction factors calculated with the power function did not have this problem, the tuneability of parameters in the gamma function led to its selection. This ease of calibration is noted in NCHRP 716 as the reason why many transportation modelers prefer to use it.

	Avg. Journey Time – NHTS	Avg. Journey Time – Predicted	Avg. Journey Time – Predicted, Alternative Condition
HBW	28.70684	28.72249	29.16051
HBO	19.43281	19.4251	19.81491
NHB	21.37839	21.38919	21.77375

Figure 7-2: HBW Trips

Starting values for the gamma function parameters came from the Large MPO models in Table 4.5 of NCHRP 716, which are appropriate for MSAs of greater than 1 million residents. Home-based work trip times were best approximated by the parameters in Large MPO Model 3, while Large MPO model 1 performed best initially for home-based other and non-home based trips. From these starting values, they were then adjusted until predicted average travel times by type aligned with observed data in the National Household Travel Survey. After many iterations, we were able to get modeled average travel times to within a tenth of a minute of observed values.

Trip Distribution: Existing Condition

To the right are maps displaying the 500 most common trips for each trip type. We observe an incredibly strong attachment to downtown Austin in Home-Based Work trips. Even when we remove the 2 CBD tracts (Austin Tracts 35 and 7) from the analysis, an affinity toward central tracts is still present: People commute to the general center of town for work.

Home-Based Other trips and Non-Home-Based trips display very similar travel patterns to each other, though HBO trips are approximately 2.5 times as occuring as NHB trips. These trip patterns do display nodes of concentration, but are not nearly as centered on downtown as HBW trips. Multiple, smaller nodes are visible throughout the Austin urban area, and even cities outside the urban boundary reveal themselves as attractors for the surrounding towns and villages.

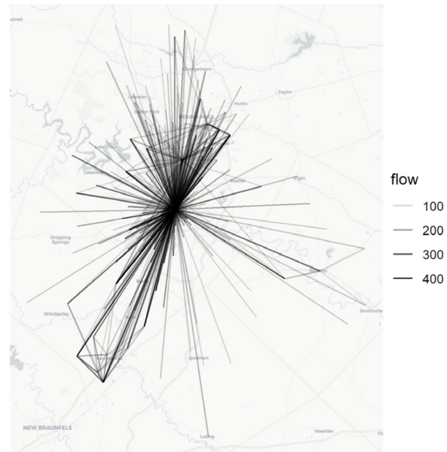


Figure 7-3: HBW Trips

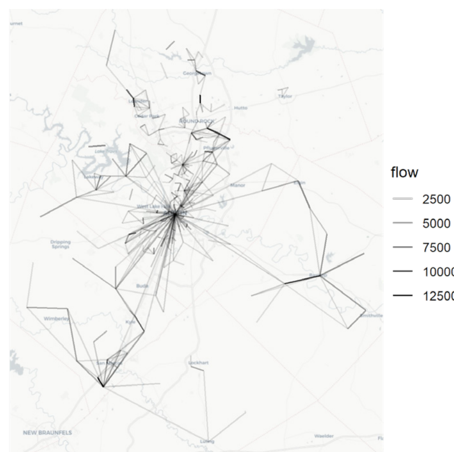


Figure 7-4: HBO Trips

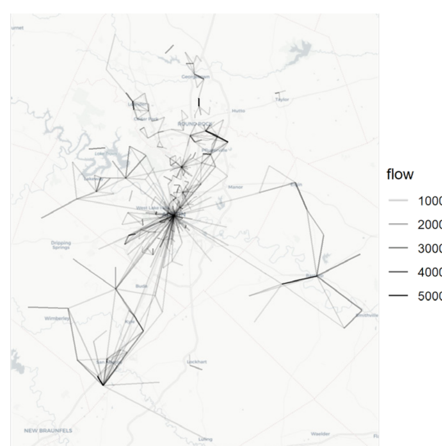


Figure 7-5: NHB Trips

Comparison: Alternate vs. Existing

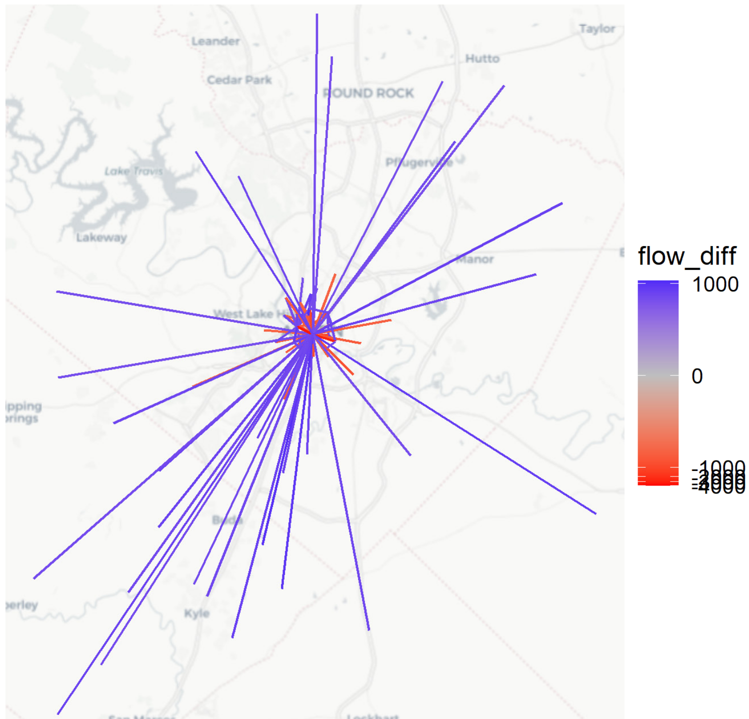


Figure 7-6: HBO Flow Differences

The next analysis compares the flows under the existing network to our alternative network (where the two downtown tracts are inaccessible to cars). These maps display the most extreme shifts in flows, whether positive or negative. All three trip types show that most changes are centered on downtown. This is to be expected, due to the outsized presence of downtown in total trips, as well as our alternative directly affecting access only to downtown.

Displayed above is the flow difference for HBO trips, since these are the majority of all trips in the Austin area. Interestingly, trips between downtown and far-reaching locales increase, whereas the decreases are concentrated in the core of the metropolitan area. We suspect this is because the cost effected by the change in network is less significant as overall travel time increases: the extra 15 minutes it takes to walk from the cordon is not a big deal if you're driving for 45, but it can fundamentally change an otherwise 10 minute door-to-door drive. Also apparent is an increase in ring trips around the core (it's difficult to see on this map; we will try to make it more apparent in an updated version), for people bypassing the downtown cordon.

Comparison: Alternate vs. Existing

Unsurprisingly, Home-Based Work trips are much less elastic, with the most extreme shifts two orders of magnitude less than the most extreme shifts in HBO trips. Since our model does not account for jobs relocating outside of the downtown cordon, workers still need to get there. Interestingly, the differential map shows an east-west divide. It is possible this is a fluke, or there is something about the western parts of the metro that are more elastic with their work trips.

The last two pages show the aggregate changes in flows for each census tract, for each trip type. This data is disaggregated to increased flows and decreased flows, because on balance the two mostly balance each other out (the largest aggregate shift in a single zone is 23 flows). By separately aggregating increases and decreases, we can see a measure of how much a given zone's travel patterns are different under the alternative condition, even if the total trip numbers are similar.

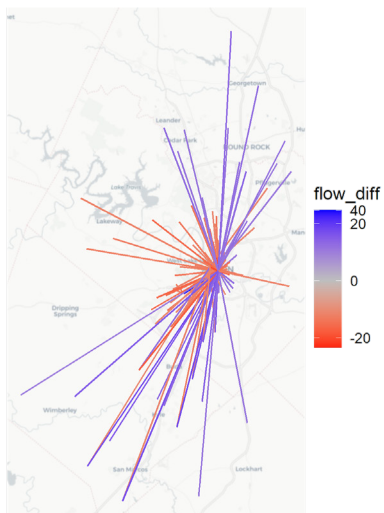


Figure 7-7: HBW Flow Differences

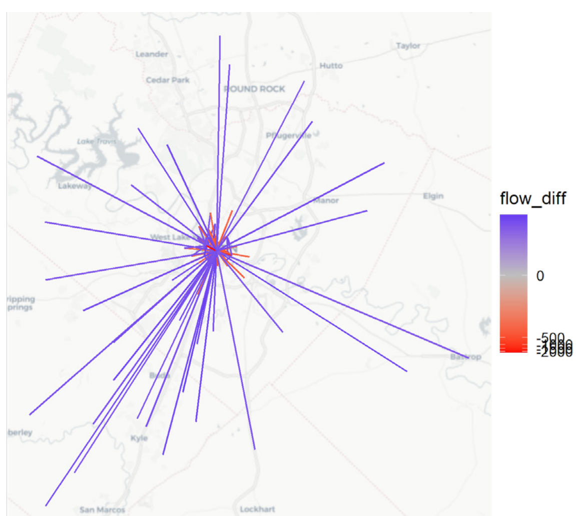


Figure 7-8: NHB Flow Differences

Aggregate Changes - Trip Origins

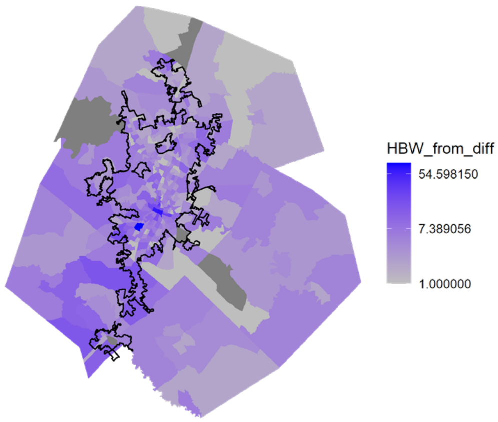


Figure 7-9: HBO Trip Decreases

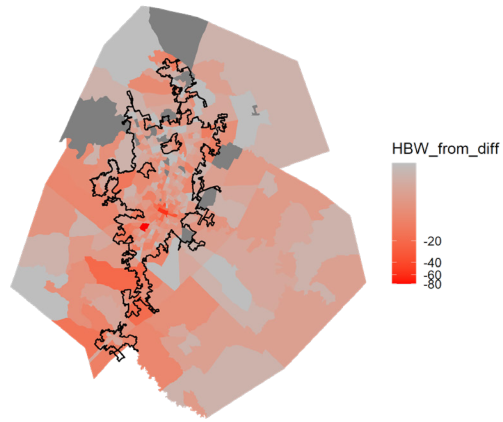


Figure 7-10: NHB Trips Decreases

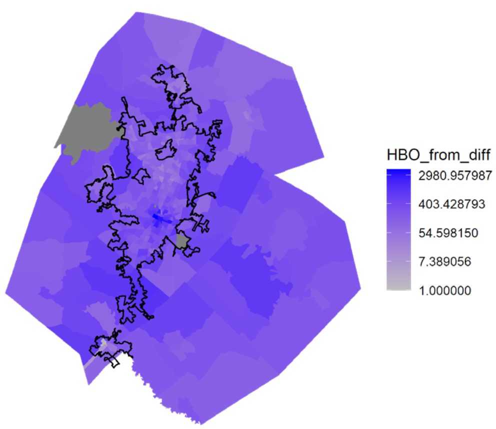


Figure 7-11: HBW Trip Decreases

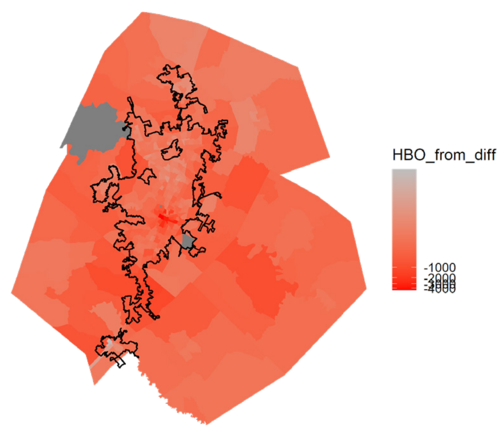


Figure 7-12: HBO Trip Increases

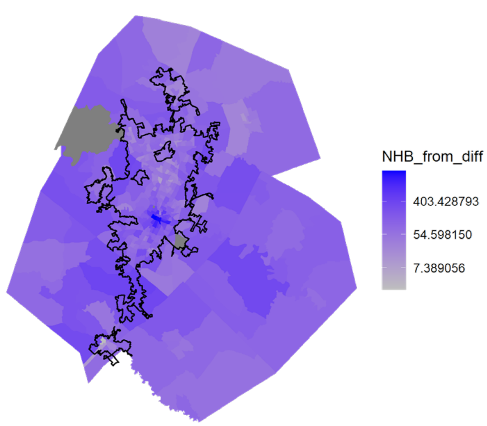


Figure 7-13: NHB Trip Increases

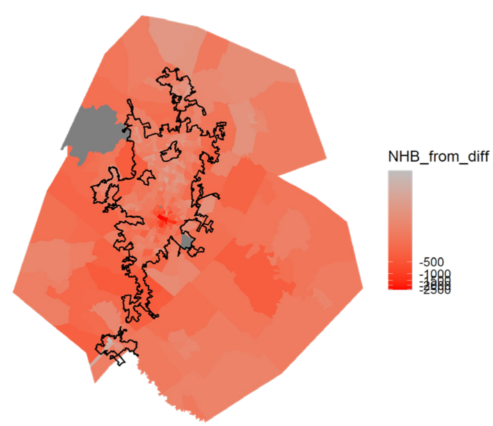


Figure 7-14: HBW Trip Increases

Aggregate Changes - Trip Destinations

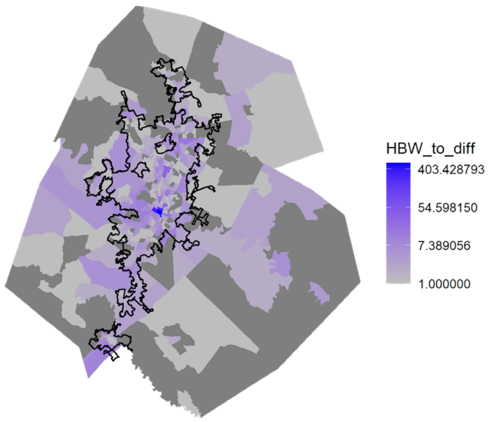


Figure 7-15: HBO Trip Decreases

Figure 7-16: NHB Trip Decreases

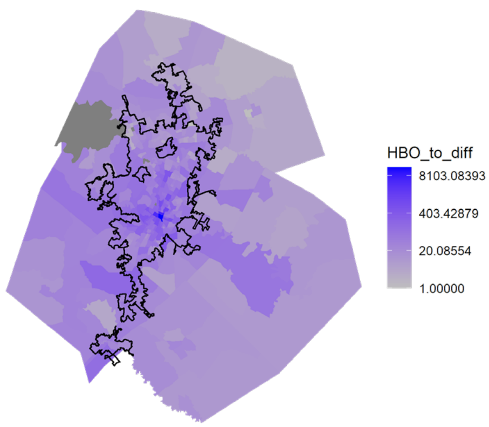


Figure 7-17: HBW Trip Decreases

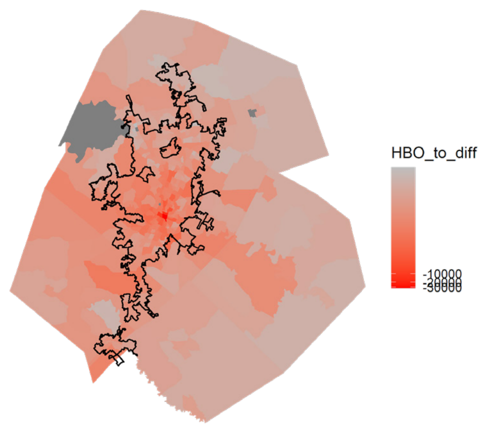


Figure 7-18: HBO Trip Increases

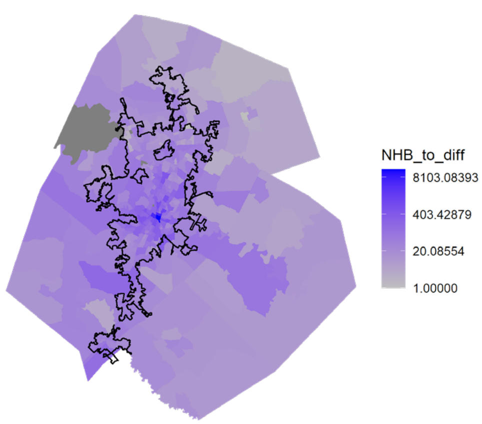


Figure 7-19: NHB Trip Increases

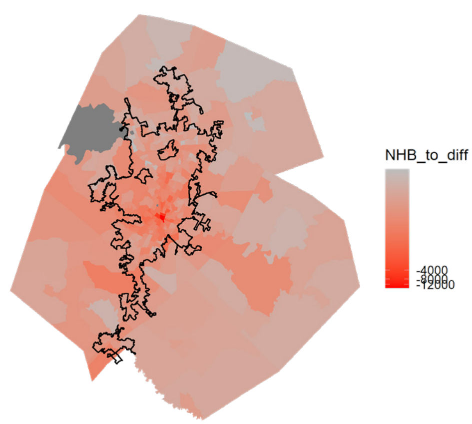


Figure 7-20: HBW Trip Increases

Chapter 8: Mode Choice

Image source: Culture Map Austin

Introduction

This chapter of the report estimates mode choice for trips in the region and compares the existing conditions to the alternative. At a regional level and for all trip types, limiting car access to Downtown Austin only has a small impact on the percentages for each mode's share of travel. As this restriction on access only affects private cars, SOV and HOV travel decrease slightly, while transit, walking, and biking all increase. The magnitude of this change is greatest for home-based work trips, but still small for all trip types.

Methods

We begin by calculating travel costs and utilities by mode. Using fare collection data from Capital Metro, we find the average local bus cost per trip to be $0.58, the per trip cost of express buses to be $2.70, commuter rail trips to cost $2.10, and driving to cost 5.2 cents per minute. A quick note about the discrepancy between commuter rail and bus trip costs—even though they have the same per-ride fare, we suspect the commuter rail users may be more likely to use a monthly pass, which comes out to a lower cost per ride in the end.

For high-occupancy vehicle trips, we use NCHRP Table 4.16 to establish how many people are in a vehicle, with 2.42 occupants on average. Due to a lack of network data on modes other than transit, private vehicle, and active transport modes, we also exclude forms of travel like paratransit, taxis/TNCs, or school buses. Excluding school bus travel is the most unfortunate omission we have to make, as a comparable number of trips to those taken on transit buses are present in the NHTS data. That said, all of these types of travel make modeling and counting trips difficult, as they do not begin and end trips with the same number of passengers.

We use the calculated travel costs to determine the utility of a given mode, and then from there, predict the probability of choosing that mode for a certain trip between zones. We start from model parameters in the NCHRP tables, then fine tune them until predicted mode shares in the existing condition match what is observed in the NHTS data. After several iterations, we were able to get relatively close.

These parameters are then applied to travel time skims for the alternative condition, and we calculate the probability of using each mode for each trip type. Overall, the changes are fairly minimal, and given the level of uncertainty in the modeling process, it would be difficult to conclude that there is any significant change (at least on the regional level).

Regional Mode Shares

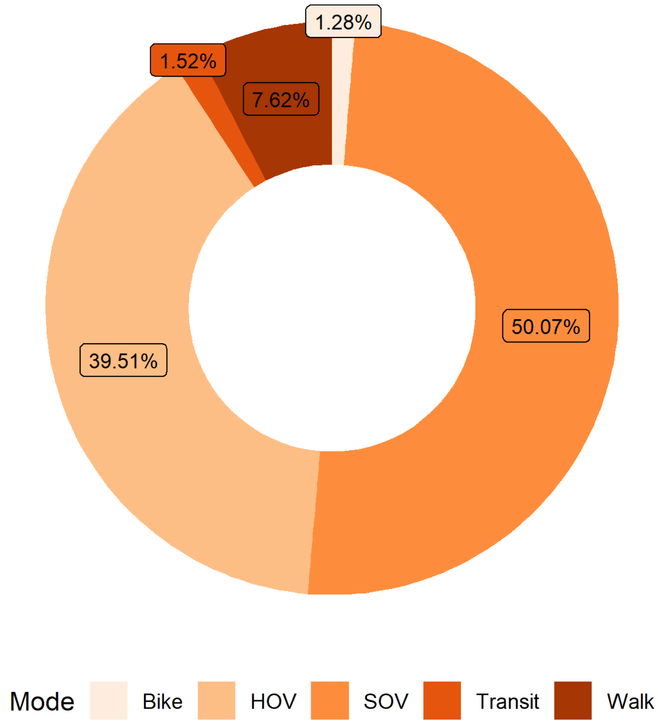


Figure 8-1: Existing Mode Shares

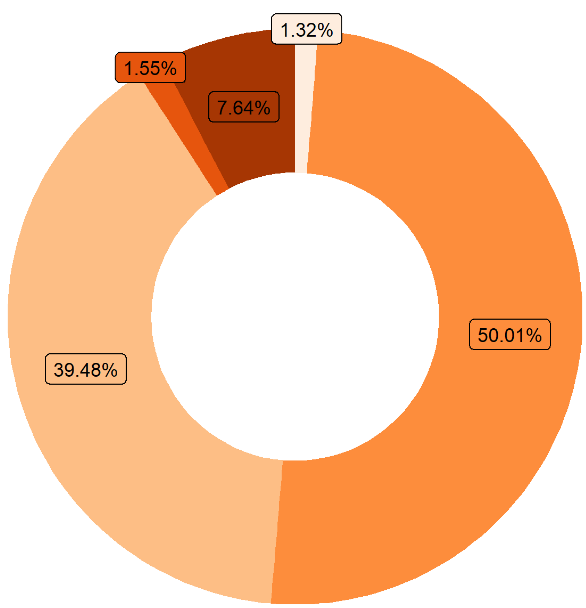


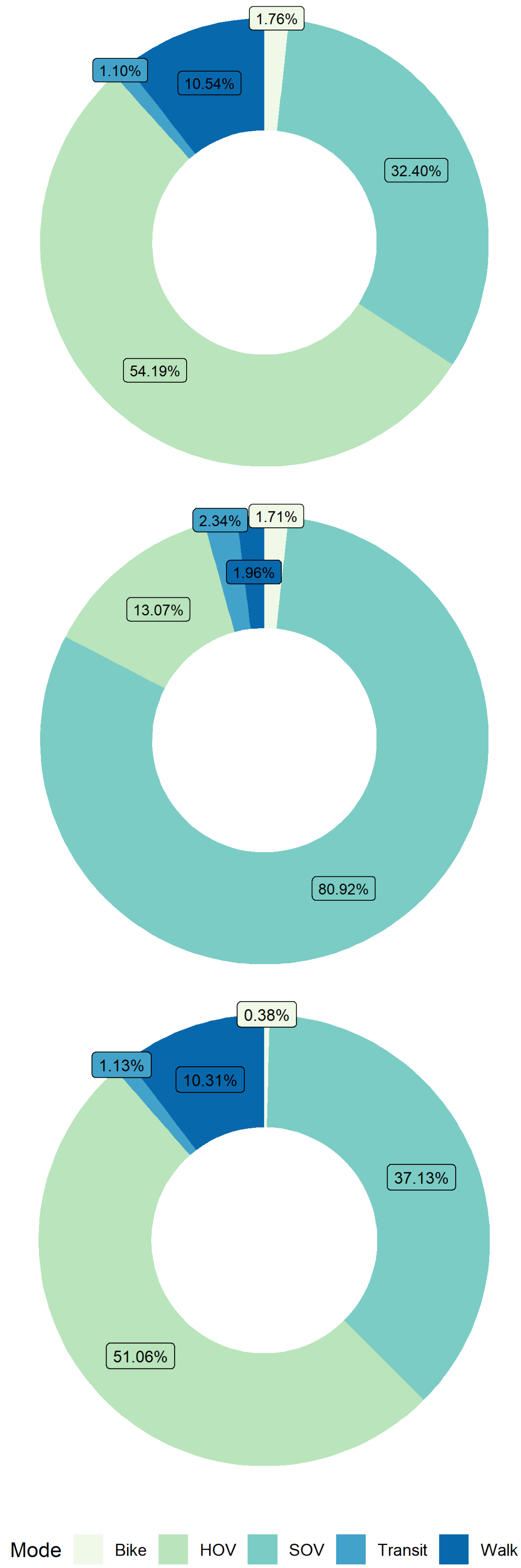
Figure 8-2: Alternative Mode Shares

This chapter of the report estimates mode choice for trips in the region and compares the existing conditions to the alternative. At a regional level and for all trip types, limiting car access to Downtown Austin only has a small impact on the percentages for each mode's share of travel. As this restriction on access only affects private cars, SOV and HOV travel decrease slightly, while transit, walking, and biking all increase.

By Trip Purpose

Only looking at average mode shares for the region obscures considerable variation by trip type. The figures to the right are for home-based other, home-based work, and nonhome based from top to bottom in the existing scenario. These values are ones generated from our mode choice model after significant efforts to calibrate the parameters so that predicted shares align with NHTS data. The modeled mode shares are all within approximately half a percentage point of observed values. Please note, that while these are reported to two decimal places, that is only because it is necessary to see any kind of change, not because we can decisively predict mode share with that level of precision.

Single-occupancy vehicle trips dominate commuting to work, with over 80 percent of all trips, while driving with others is most common for other trip types. People are also most likely to use transit for these home-based work trips, which considering the geography of employment in the region, makes sense. The transit network does a good job of serving employment centers downtown, making it more convenient than it might be for other trips. Walking is significantly less common as a mode choice for home-based work trips, with its mode share being roughly one fifth of the size of other trip types. Biking is most likely to be chosen for travel that begins at home, and only makes up a tiny fraction of nonhome based trips.



Comparisons

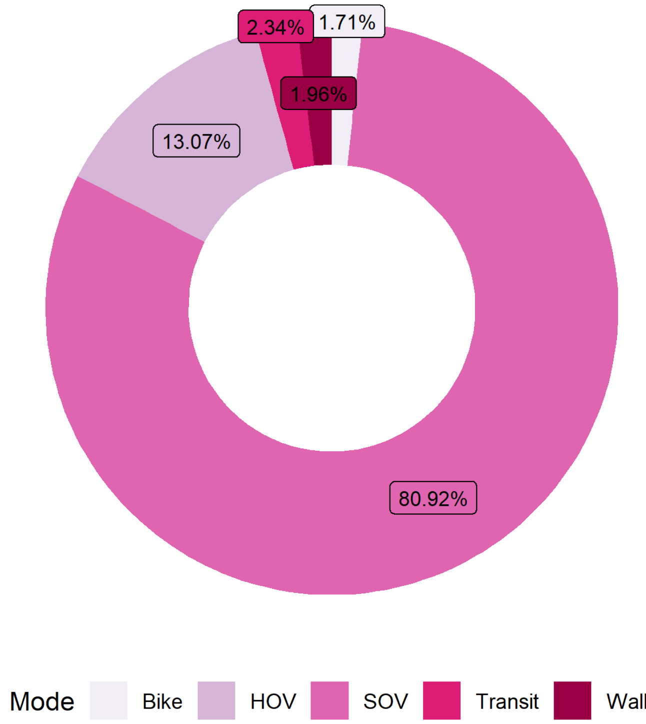


Figure 8-3:
Existing Mode Shares
(Home-based work)

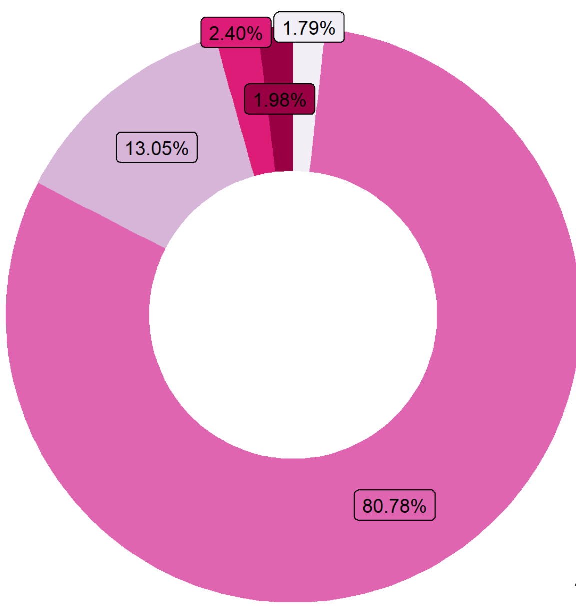


Figure 8-4:
Alternative Mode Shares
(Home-based work)

The figures on this page compare modeled mode share for HBW trips (which saw the largest changes) in the existing and alternative conditions. The magnitude of change is very small, but in line with what one would expect from making driving more difficult: SOV and HOV shares drop, and walking/biking/transit mode shares increase. Notable is the fact that biking sees the biggest gain by far with limited car access to Downtown.

Transit Mode Share Change

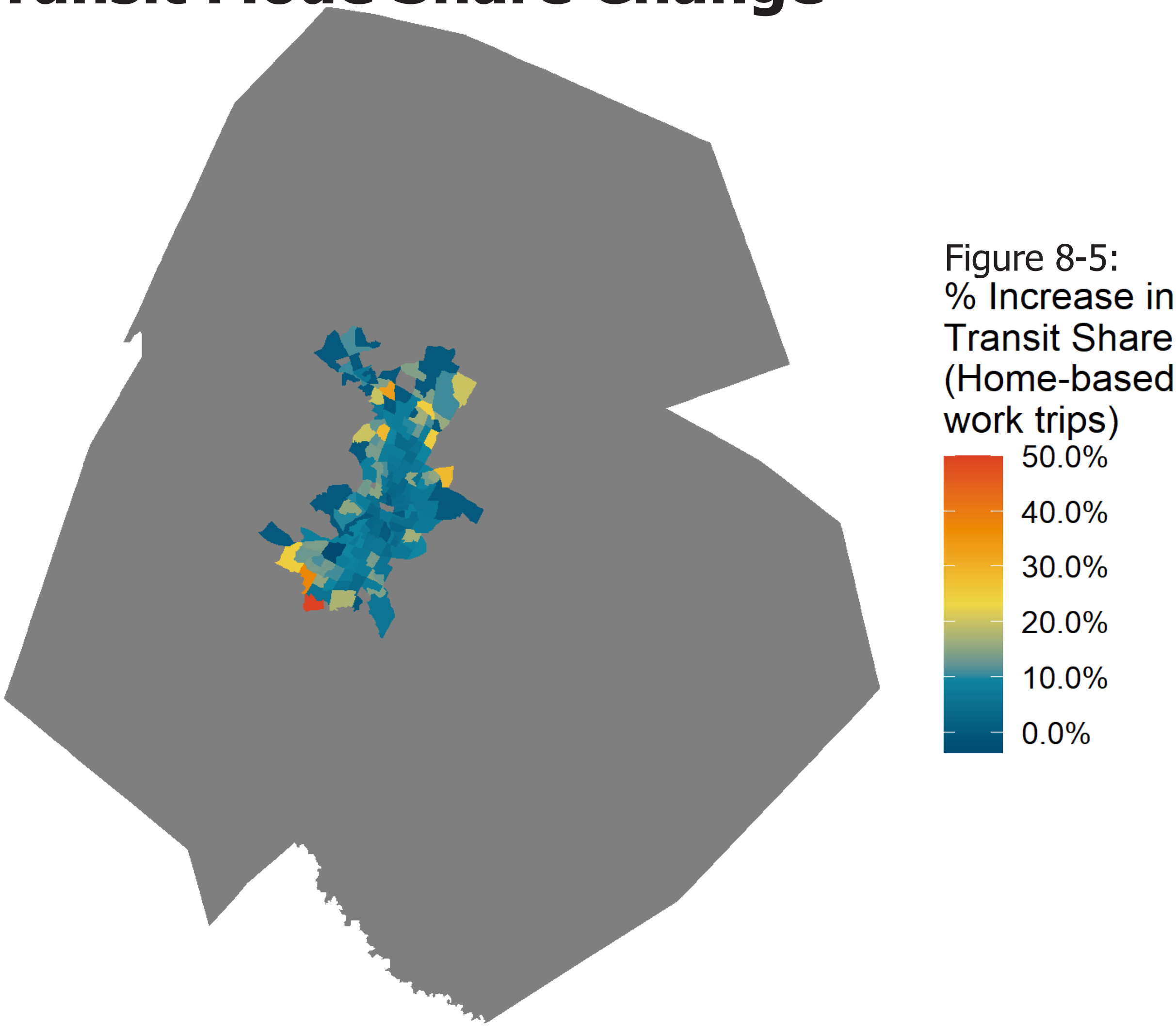


Figure 8-5:
% Increase in Transit Share (Home-based work trips)

The map in Figure 8-5 highlights where the transit mode share changes the most when comparing the existing and alternative conditions for trips with a destination in one of the Downtown Austin census tracts. These are both easiest to visualize, making this kind of trip convenient for the report (but not necessarily good transportation planning; most trips are not commutes!) and also most likely to be impacted by the street access limitations proposed for the alternative.

A couple factors likely drive these changes. The greatest change takes place farther out from the CBD, where transit ridership is likely lower. Any small increase in riders will seem bigger as a result, at least when viewed as a percentage. Additionally, the jump from zero to nonzero accessibility takes place at this periphery, as we limited transit trips to a maximum length. This, potentially in combination with other assumptions about the shape of utility/access functions, may make the marginal traveler more likely to switch to transit from private vehicles in this ring. We see a similar phenomenon with active travel modes on the following page, though at the distance that corresponds to their maximum travel time, instead.

Active Mode Share Change

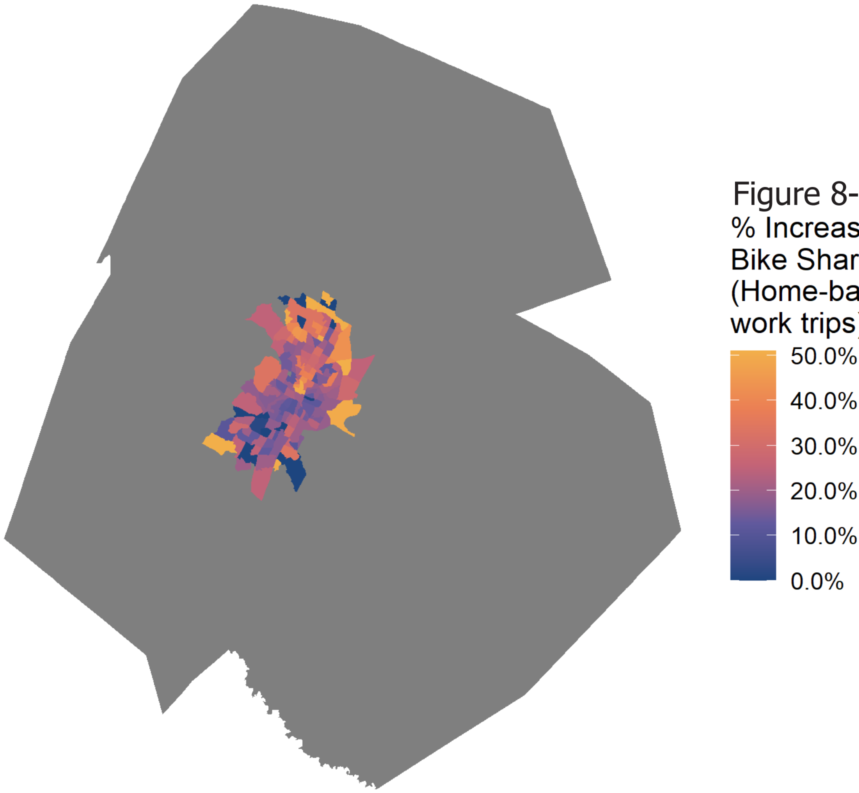


Figure 8-6:
% Increase in Bike Share (Home-based work trips)

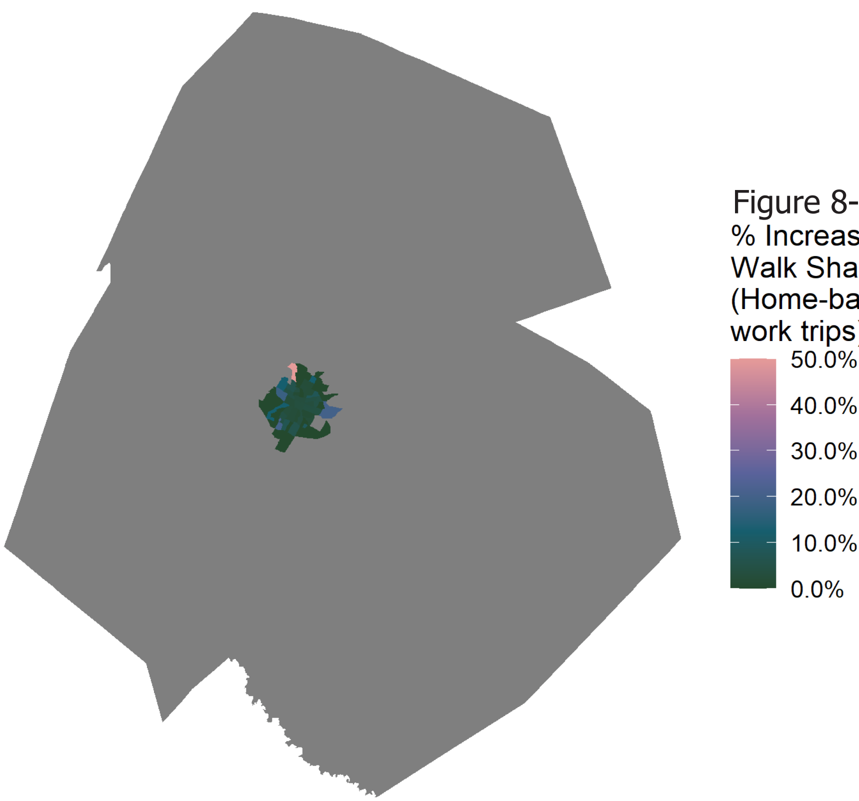


Figure 8-7:
% Increase in Walk Share (Home-based work trips)

SOV Mode Share Change

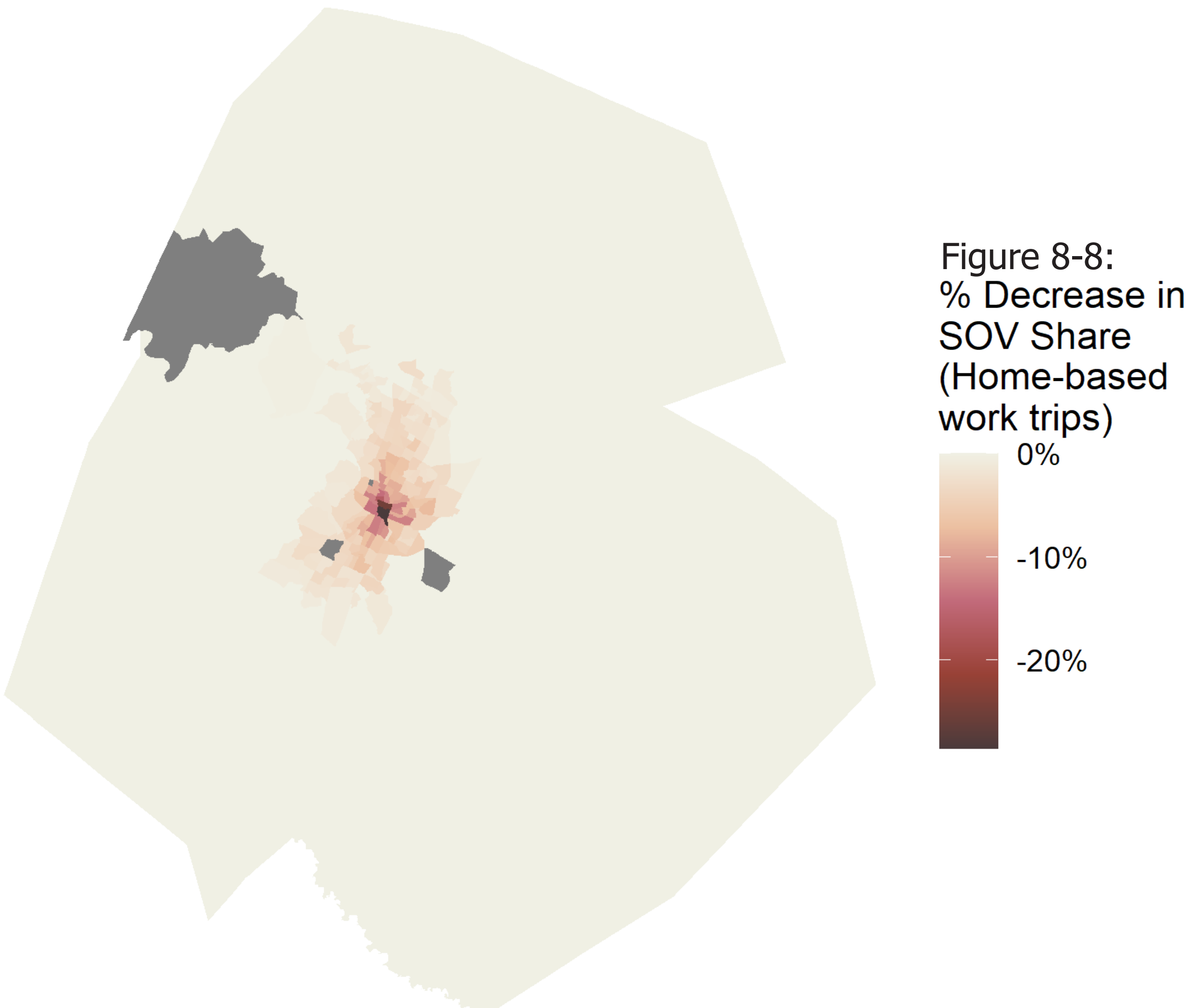


Figure 8-8:
% Decrease in SOV Share (Home-based work trips)

Intuitively, for the increases in active transportation and transit for home-base work trips ending in Downtown, we see a corresponding decrease in single-occupancy driving mode share. This is most pronounced for trips between the two zones that make up Downtown, which is a very unsurprising finding.

Chapter 9: Transit Ridership and VMT Effects

Image source: Austin Monitor

Introduction

This chapter of our report calculates the effect the alternative condition on regional vehicle miles traveled (VMT), transit ridership by route, and person miles traveled (PMT) for active travel modes. In previous sections, we have observed that our model predicts a small reduction in driving and small increases in other modes when the streets of Downtown Austin are closed. Though this aligns with our predictions of increased transit ridership and higher active transport PMT, our model also predicts a slight increase in regional VMT at the same time: an additional 30,811 VMT. In the context of an MSA where total VMT is over 51 million, however, this is ultimately a marginal change.

Methods

We use estimates of the number of trips between zones from skims produced for the existing and alternative conditions to create a production-attraction matrix. We then average this PA matrix with its transpose to create an origin-destination matrix. These trip flows are broken down by mode—drive alone, carpool, transit, walk, and bike—and trip purpose (home-based work, home-based other, and non-home based). We begin with route-level transit ridership. For each origin-destination pair with a nonzero number of transit trips between them, we break down the predicted ridership by route and trip purpose. This is done in both the existing and alternative conditions, allowing us to observe which routes see the change in ridership.

For driving, walking, and biking between each OD pair, we calculate the network distance for these interzone trips (for all modes, we are unable to estimate the number of intrazonal travel). While walking and biking trip distances are the same for both conditions, the access and speed limitations in Downtown Austin require recalculating trip distances for the alternative scenario. With biking and walking, we use the same length of trips for both conditions, but account for the change in number of trips taken. Because driving trips are split between single-occupancy and high-occupancy (2+), we also adjust estimates of PMT based on average vehicle occupancies by trip type. These are broken down for HBW, HBO, and NHB trips in NCHRP 716 Table 4-16.

The rest of this chapter consists of tables, maps, and other visualizations that highlight phenomena of interest.

Transit Ridership

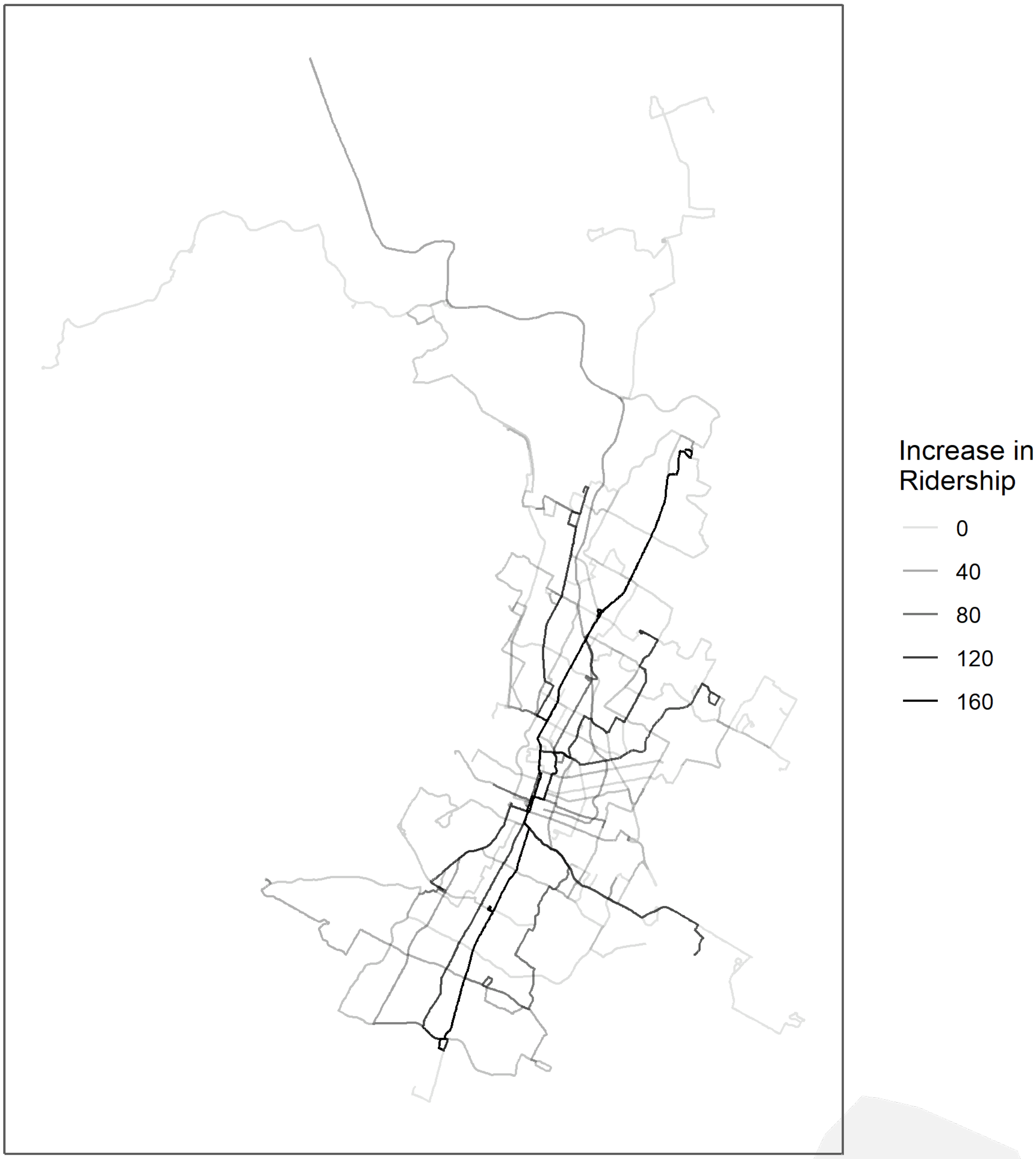
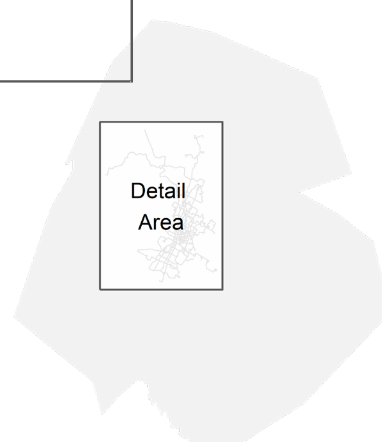


Figure 9-1



Transit routes that see the strongest gains in absolute ridership are those running generally north-to-south, through Downtown Austin, as shown in Figure 9-1. Due to the geography of the region, where the urbanized area is spread along this axis, this largely makes sense. One interesting exception to this is bus route 20, which takes a looping path from northeast Austin, through downtown, then back east towards the airport.

Transit Ridership

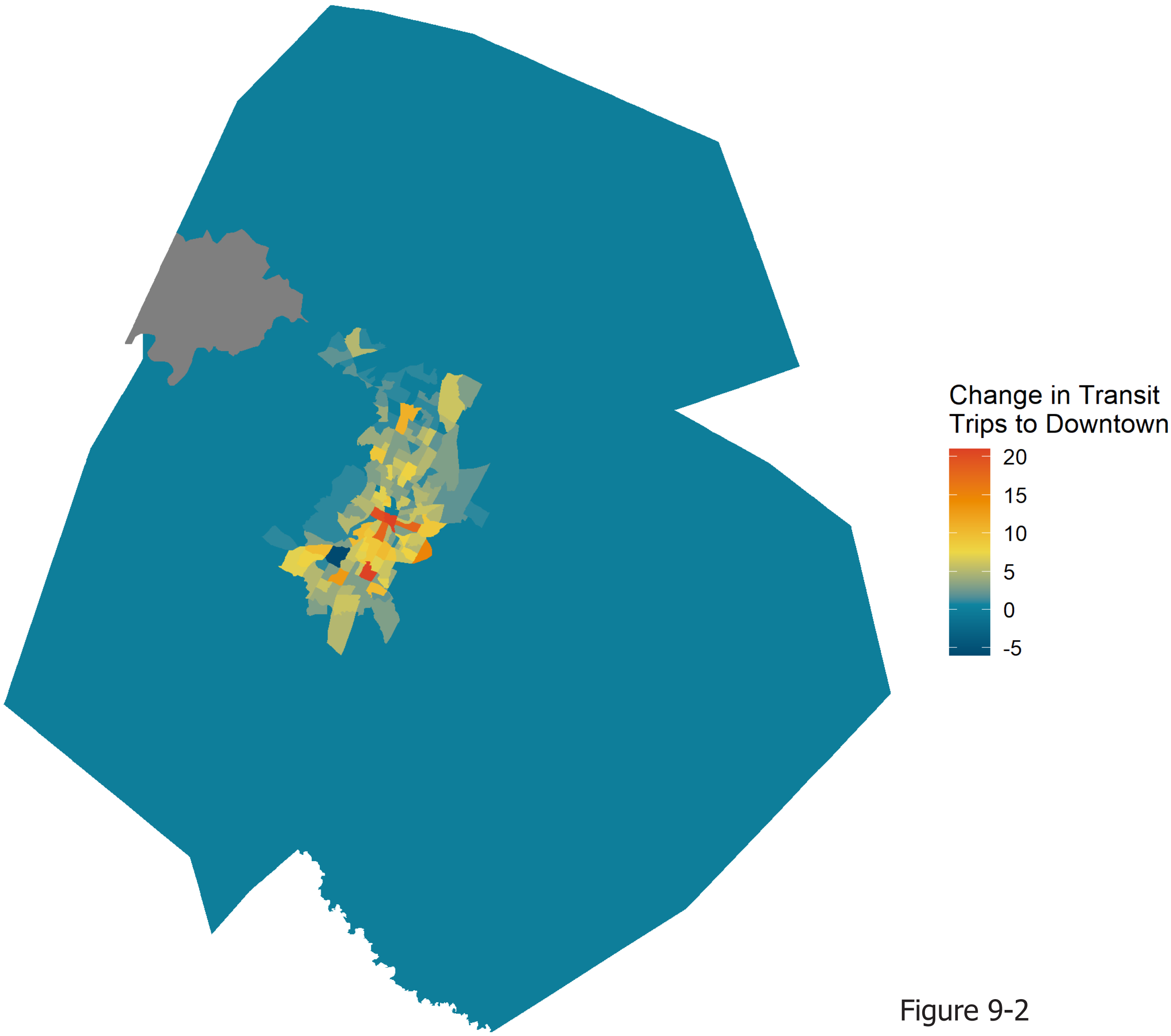
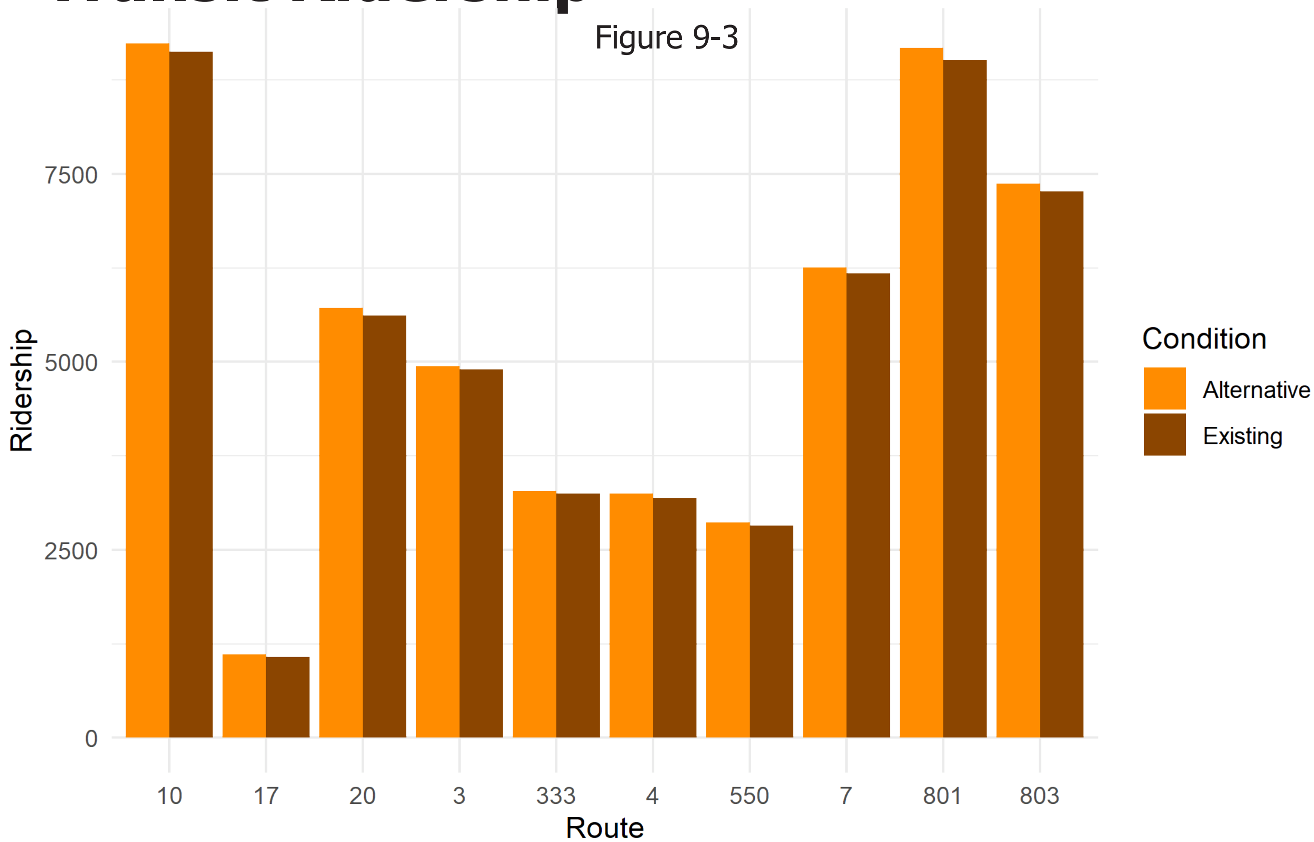
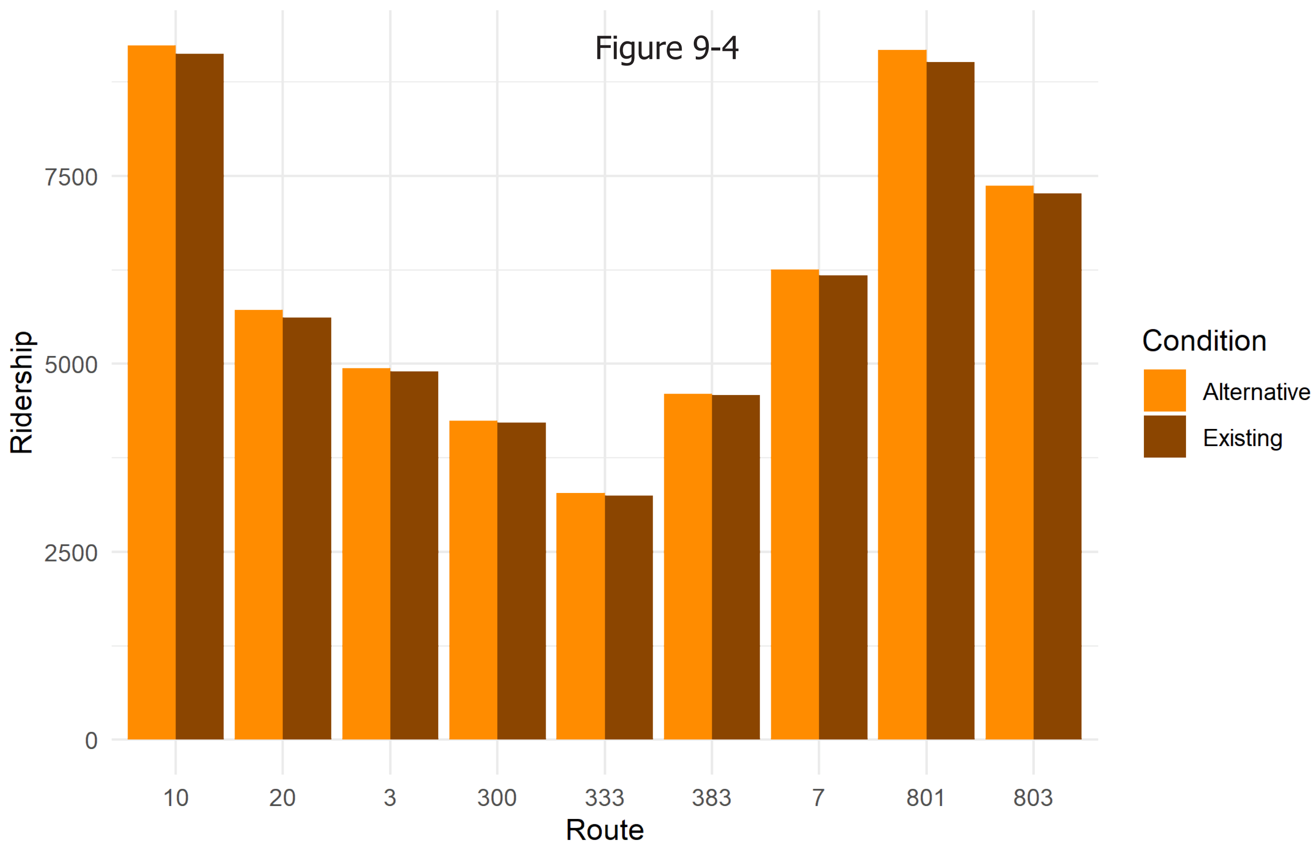


Figure 9-2

Though some routes see fairly significant gains in boardings, the actual number of trips from any one zone may not change that much. In Figure 9-2, we can see that trips with a destination in one of the two downtown zones do not increase by a huge number. However, depending on when these trips take place, this may be noticeable. If most people are boarding during rush hour, when buses might already be close to full, even an additional 20 people may justify an additional trip run by Capital Metro. Strangely, there are two bus routes that are each predicted to lose a single rider in the alternative condition, and neither of them serve the zone with fewer transit trips originating in it. On the following page, Figure 9-3 and Figure 9-4 show the routes with the greatest increase in ridership and the highest overall ridership, respectively.

Transit Ridership





VMT/PMT

	SOV PMT	HOV PMT	VMT	Walk PMT	Bike PMT
Existing	36318609	41155217	51499592	1146850	287664
Alternative	36340718	41178720	51530403	1149382	293672
Change	0.06%	0.06%	0.06%	0.22%	2.09%

Table 9-1

Table 9-1 summarizes the changes in regional PMT and VMT for all modes that we studied. Our model only predicts modest changes for driving VMT, as mentioned earlier. It seems most likely that some people would take circuitous routes to avoid the street closures downtown, making a given trip slightly longer. On the other hand, we would expect to see a larger percentage increase for walking and biking, partly due to the fact that a small shift in the very large number of driving trips is a proportionally larger increase for the active modes. Given that we do not account for intrazonal trips, these are likely an underestimate of how much more biking and walking might take place in the alternative condition, as they are better suited for shorter journeys. Given the lack of information on where transit riders board and alight on their trips, there is no easy way to compare it to VMT calculations. However, simply to note to regional change, predicted transit ridership would grow from 96,814 existing condition to 97,874 in the alternative, an increase of 1.09%. Considering that our model is focused on longer (interzone) trips, there is an intuitive logic to transit and biking seeing larger increases in use, since they are the closest substitute for car travel.