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Employment Destination Accessibility by Car and Transit in the Buffalo-Cheektowaga-Tonawanda-Niagara Falls Metro Area

Defining Accessibility

During the past two weeks, the class has debated several competing – and at times conflicting – definitions of accessibility. Several scholars have attempted to pin down a working definition of the term. Levinson and Wu (2020) offer an exhaustive account of these efforts, and attempt to codify a general theory of access. As one might expect, this attempt yields complicated results:

$$A^{**}_{i,\cdot,\cdot,\cdot,e,t,\cdot} = \frac{\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{z=1}^{Z}\sum_{h=1}^{H}\sum_{p=1}^{P}\sum_{e=1}^{E} S_{i,p} U_h W_z V_{i,m}\, g(O_{j,z,h})\, f(C_{ij,h,m,e,t})}{\sum_{p=1}^{P} S_{i,p}}$$

Figure 1: Levinson and Wu's general theory of access.

It is worth spotlighting a few of these variables above. J/j is about destinations, P/p is the number of population subgroups, so on and so forth. This shows the sheer number of factors that have been/can be considered in any assessment of accessibility. As the above equation shows, quantifying an intangible feature like accessibility is incredibly difficult and could ultimately involve dozens of variables. Levinson and Wu also add another important dimension to their considerations: access is "a continuous flow of services provided over many years" (2020; pg. 148). With this in mind, they even go as far as quantifying the "discounted opportunity years" that an infrastructure project provides. Much like a capital investment, transportation infrastructure loses value over time and inevitably has decreasing utility for travelers.

Our definition determined that "accessible" places are those that could actually be reached over a continuous spectrum of time. Mobility factored far more into our definition than proximity, and we represented time through a log decay function. We tried to incorporate perceived transit time into our analysis; we weighed some factors to try and quantify the experience of travel (i.e. how long a trip takes or the inconvenience of it). This is embodied by the out of vehicle transit time variable. However, our model really doesn't touch upon other important elements of perception. For example, a traveler may be far more comfortable (and thus more likely) to wait ten minutes at a well-lit busy bus stop than they would at a dark bus stop on a quiet street. Even though the wait time is exactly the same, the traveler's willingness is different. Our accessibility definition of "places that can actually be reached over time" does not include the perception of safety and other psychological factors that define an individual traveler's universe of possible trips.

It is important to note that our analysis is measuring access to employment opportunities. We are using these jobs as a stand-in value for access to destinations. As discussed in class, this can be a deeply flawed metric. People frequently travel to employment destinations, but there are other types of destinations and trip attractions that go unobserved by our model. There are also administrative and data collection issues to consider. For example, the data we have may not represent actual jobs, but the number of total employees employed by firms that are headquartered in a place. In an ideal world, we would have more granular data.

Building the Model

Finding Travel Times

First we drew from compiled data on travel times to find the mobility of a driver or transit rider in the BCTNF MSA. Over the past few weeks we built both a road skim and a transit skim of the region measuring travel times between each census tract in the region to every other tract in a travel matrix. These skims used Open Street Maps data to plot road connections and public GTFS data from the NFTA Metro for transit routes and schedules. Our skims used the census tract as the traffic analysis and transit analysis zones and we made simplifying assumptions about average road speeds to calculate driving time and waits at transit stops to calculate time in transit. A full list of constraints and assumptions in the skims is included in the technical appendix.

We combined travel time information from our transit and road skims into one data set, the first few rows of which are included in Figure 2. As Figure 2 demonstrates, each row of the data set is a trip from one specific part of the Buffalo MSA to another part, using Census-designated geographic identifiers (GEOIDs) to track each location. Our transit skim provided the amount of time this trip would take via transit in minutes (total_time), the amount of that time in the vehicle versus waiting at a stop (IVTT) and the number of transfers needed to make the trip (n_transfers). Our road skim provided the amount of time in minutes it would take to drive the trip (car_time).

from_GEOID	to_GEOID	IVTT	n_transfers	total_time	car_time
36029002703	36029001602	1.765329	0	12.97375	1.376491
36029002703	36029016802	26.544277	1	105.84708	3.899925
36029002703	36029006801	12.425520	2	61.71854	4.486519
36029002703	36063022715	NA	NA	NA	27.053625

Figure 2. Selected rows from a combined car and transit travel skim of Buffalo

One key constraint in our accessibility metric reflected in the table is that we only included motorized trips and not biking, walking, or other human-powered forms of travel in our analysis. A fuller accessibility study might investigate whether adding non motorized travel meaningfully changes access within the region.

In comparing transit and car travel times, we adjusted for the perceived length of time waiting for transit. Our skim assumed that riders would use transit schedules to time their arrival at the stop and so would wait no more than 15 minutes for a bus, but this does not account for waits at transfer stops which can be very long. People perceive time passively waiting for the bus as about 50% longer than it actually is[1] and that perception is strong enough to create a psychological burden. To account for the effect waits have on riders, we weighted the time spent out of the vehicle in our model as 2.5 times its actual length. We added the time in minutes spent outside the vehicle (OVTT) and the adjusted time of the whole transit trip with the wait penalty (perceived_time) to our data set as seen in the excerpt in Figure 3.

from_GEOID	to_GEOID	IVTT	n_transfers	total_time	car_time	OVTT	perceived_time
36029002703	36029001602	1.765329	0	12.97375	1.376491	11.20842	29.78
36029002703	36029016802	26.544277	1	105.84708	3.899925	79.30280	224.80
36029002703	36029006801	12.425520	2	61.71854	4.486519	49.29302	135.65
36029002703	36063022715	NA	NA	NA	27.053625	NA	NA

Figure 3. Selected rows from a time-adjusted car and transit travel skim of Buffalo

Employment Destinations

Next we incorporated federal employment data for the Buffalo MSA from the Longitudinal Employer-Household Dynamics (LEHD) dataset in 2019 into our model. For our definition of accessibility, employment opportunities are all trip destinations. This is another constraint of the model, and another model could examine access to education, parks, or other attractions. We linked employment data to the GEOIDs in our existing data set to measure how many total jobs were available at the destination, as seen in Figure 4. The full data set is linked in the technical appendix.

from_GEOID	to_GEOID	IVTT	n_transfers	total_time	car_time	OVTT	perceived_time	total_emp
36029002703	36029001602	1.765329	0	12.97375	1.376491	11.20842	29.78	NA
36029002703	36029016802	26.544277	1	105.84708	3.899925	79.30280	224.80	NA
36029002703	36029006801	12.425520	2	61.71854	4.486519	49.29302	135.65	NA
36029002703	36063022715	NA	NA	NA	27.053625	NA	NA	NA
36029002703	36029000200	12.497892	1	49.25124	6.037798	36.75335	104.38127	637

Figure 4. Selected rows from a time-adjusted car and transit travel skim of Buffalo showing destination employment

[1]Kari Edison Watkins, Brian Ferris, Alan Borning, G. Scott Rutherford, David Layton *"Where Is My Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders"* Transportation Research Part A: Policy and Practice, V45, Issue 8, 2011/ https://www.sciencedirect.com/science/article/pii/S0965856411001030

Decaying Value of Employment by Distance

Our model then assigns a value to employment opportunities based on travel distance using a logistic decay function. In the aggregate, jobs that are closer are more valuable to a person than those further away. Or, in other words, a long commute lowers the value of the job. While individuals may have different preferences or make an exception for certain jobs, at a population level we assume closer jobs are higher value and more accessible. To estimate how much value an employment opportunity “loses” at further travel time distances, we set up a logistic decay function. We chose this function because a logistic trendline mirrors observed travel behavior, and does not have a “cliff” where jobs lose all value at a certain time threshold, which would not be an appropriate measure of real world travel for industries in Buffalo.

We assigned separate car and transit weights to jobs in this function, showing the decay of value by mode traveled. For car access we set an inflection point of 40 minutes and a standard deviation of 10 minutes, as seen in Figure 5. For transit access we set an inflection point of 30 minutes and a standard deviation of 10 minutes. This reflects our assumption that people are more willing to accept a longer car commute than a longer transit commute.

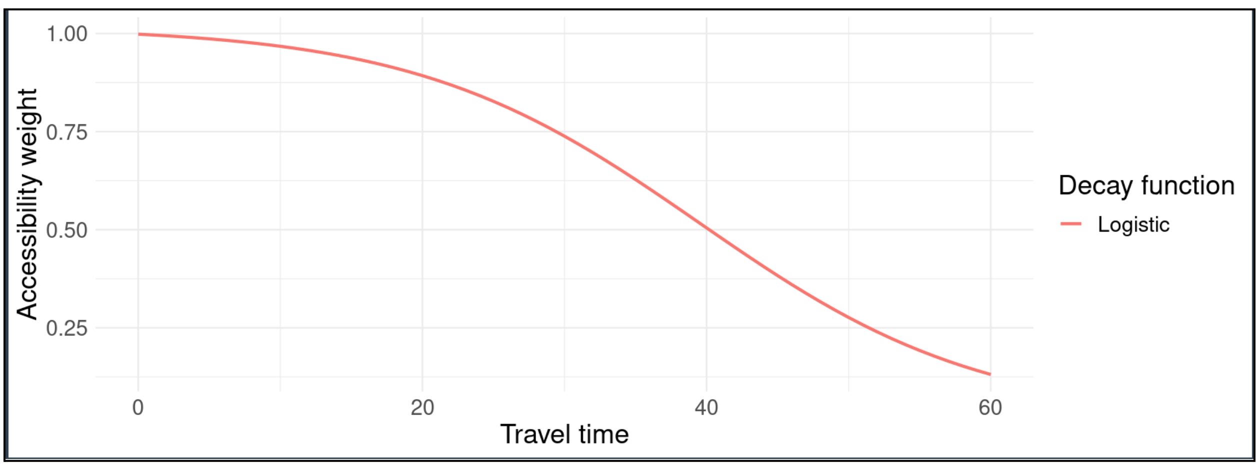

Figure 5. Logistic decay of value of job access at increasing travel times by car

After setting the decay function parameters, we re-ran our employment data to get the weighted value of the job opportunities accessible for each trip between GEOID pairs. There was a separate value for car and transit access. Since our function is nonlinear our results were not on an absolute scale, but a relative one. This meant that the data was not easy to compare at a glance, so we created an accessibility index to have a single, digestible, metric.

The accessibility index takes a ratio of the jobs accessible for each trip and the maximum possible jobs accessible on any trip within our study area to normalize the data for the Buffalo MSA. We then plotted this relationship on a 0 to 100 scale in order to make the data more legible to readers and assign the highest scores to the GEOID locations with the most jobs relative to the region. This index was calculated separately for car and transit access, so each trip has two index values representing employment opportunities for each travel mode. We used the indices to visualize the differences in accessibility throughout the MSA.

Our group also created a metric of total absolute accessibility in the data table by combining a weighted average of jobs accessible by car and by transit. This metric is separate from the index so is not normalized to the region. It also double counts jobs accessible by both car and transit, which is a drawback but does emphasize the value of zones that have both modes available. The weighting of the summary accessibility metric values a job accessible by transit at 1.5 times the amount as a job only accessible by car. We upweighted transit accessible jobs to value employment opportunities that are not reliant on cars since 60,523 households in the MSA do not own any cars.[2]

Analysis

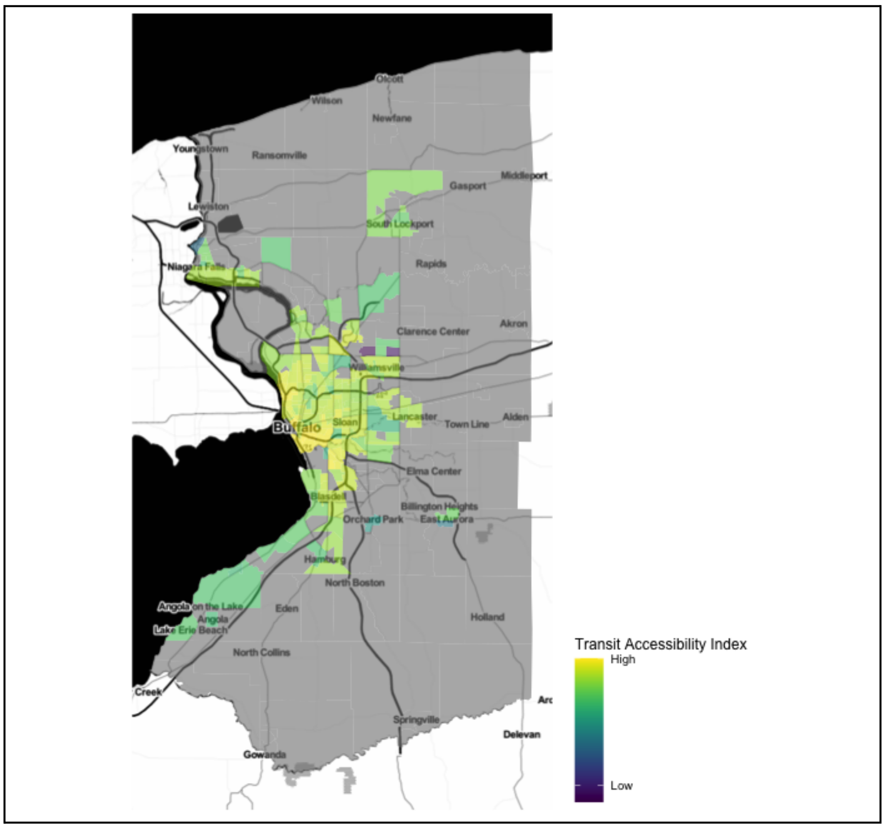

Figure 6: Transit Accessibility Index rankings across study area

Figure 6 visualizes the spatial breakdown of our transit accessibility index. Our index describes the accessibility of employment via transit normalized by the highest number of jobs available in the study area. As expected, accessibility to employment is at its highest in Buffalo, and radiates outward. Employment is a little bit less accessible in the areas immediately surrounding than the city. The coast of Lake Erie also has some accessibility to jobs according to our index. The area around South Lockport is also well-connected to employment via transit, even though it is spatially separated from the larger Buffalo transit network. There is another small oasis of

[2] US Census Bureau American Community Survey 5-Year Public Use, 2012-2017

employment accessibility via transit in the southeast of Buffalo around Billington Heights. These patterns indicate that these areas might be served by decent commuter bus service to Buffalo.

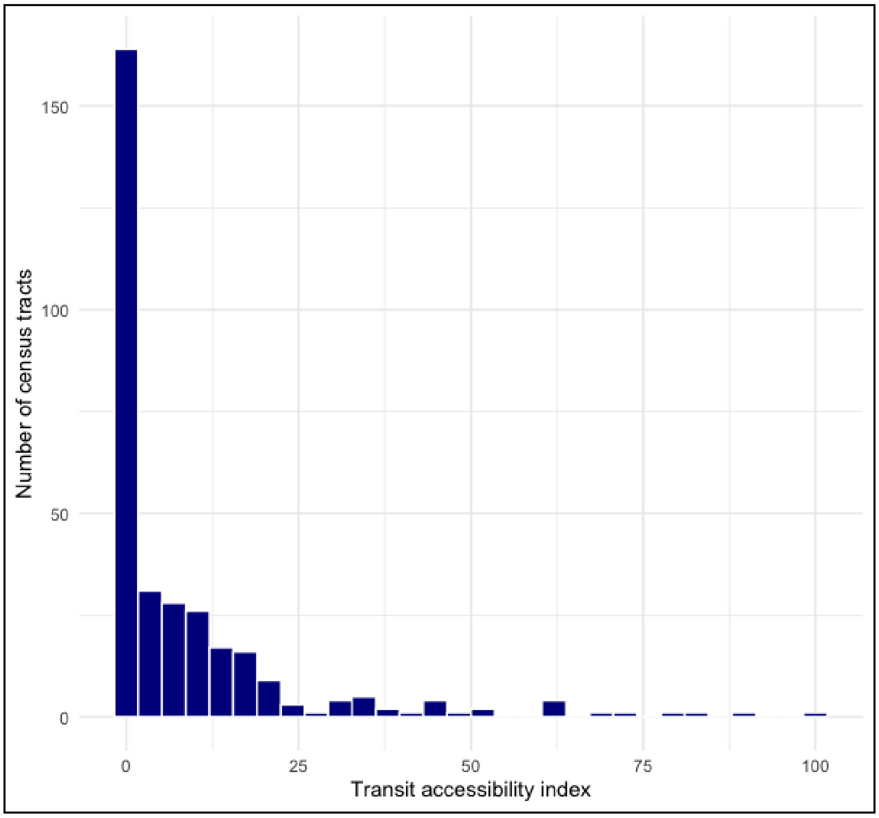

Figure 7: Transit Accessibility rankings for all TAZs across study area

In Figure 7, we see how transit accessibility to employment is distributed across our study area's traffic analysis zones. For the majority of our zones, a traveler cannot access employment via transit. This result was quite surprising. Numerically, we would expect that most TAZs would have some degree of transit accessibility to employment, since many TAZs are clustered around Buffalo and, by extension, Buffalo's transit network. However, this result certainly isn't outside of the realm of possibility. Like much of upstate New York, much of Erie and Niagara counties are largely rural by land area. While making our road network, we struggled to connect several TAZ centroids to the road network. One possibility is that the lack of major roads in some areas might make it quite difficult for transit vehicles to access many parts of the study area.

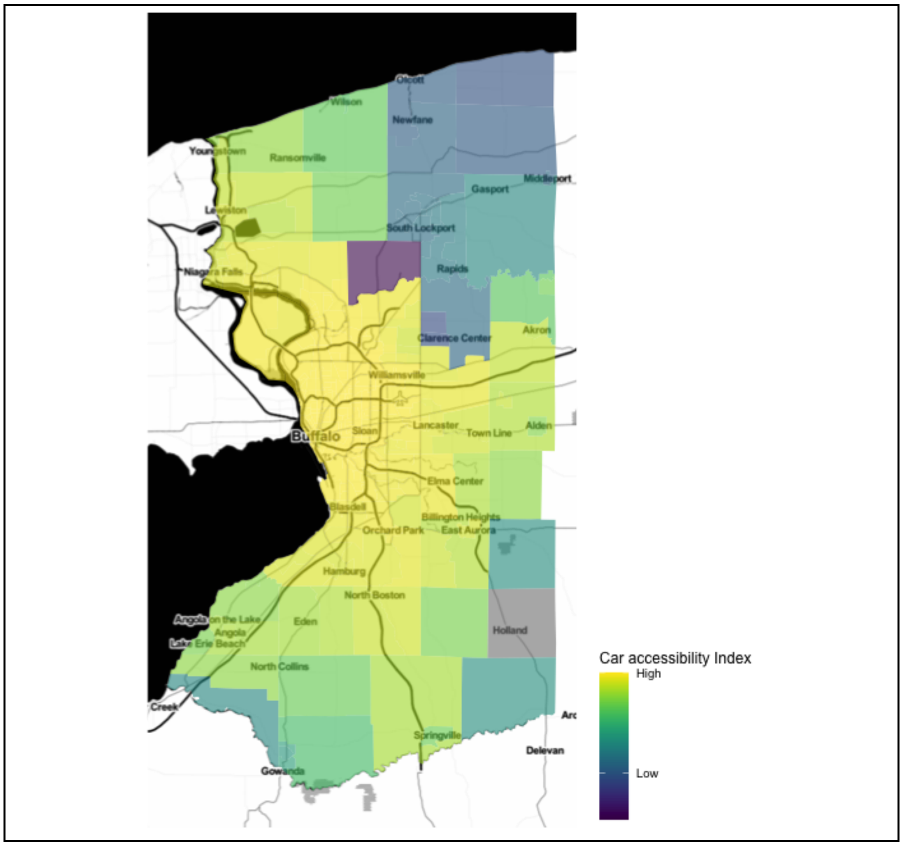

Figure 8: Car Accessibility Index rankings across Study Area

Figure 8 maps the car accessibility index to the region, showing the employment opportunities by car relative to the region as a whole. Unlike the transit index, much of this map shows high or moderately high access to jobs. Buffalo still has the highest employment access, but neighborhings metro areas like Lancaster, Williamsville and Niagara Falls have nearly identical values. More rural communities along the shore of Lake Ontario have less access, indicating more rural and less dense areas that are further away from employment centers. One zone lying between Buffalo and South Lockport has lower employment access than surrounding zones, likely the result of a sparse road network extending travel time from that area.

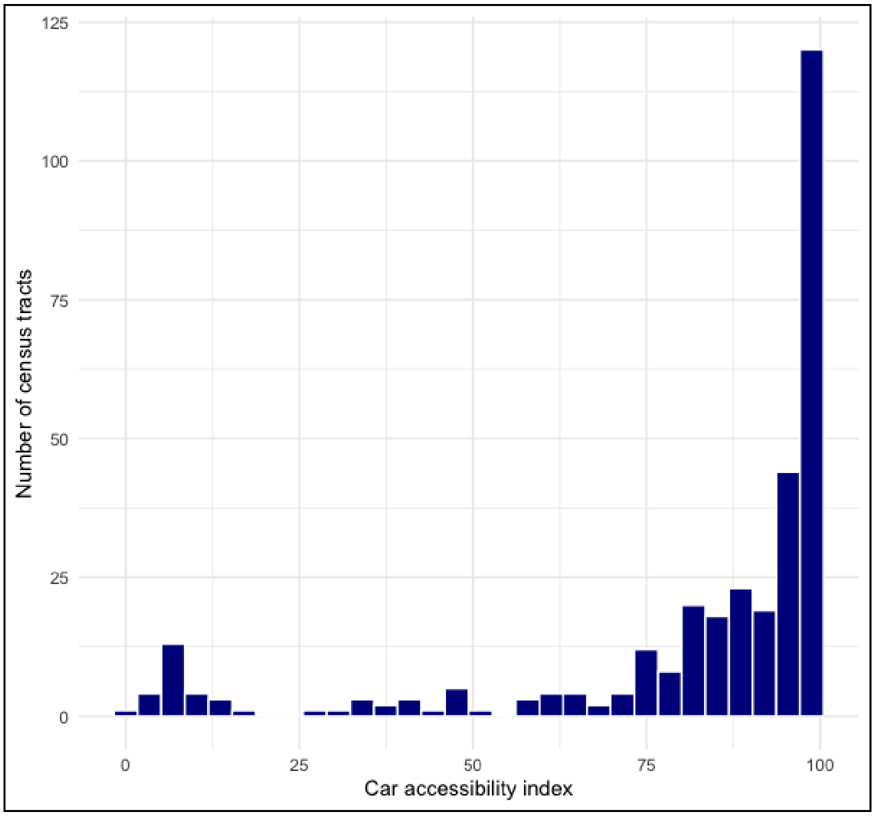

Figure 9: Car Accessibility Index rankings for all TAZs in study area

We then developed a car accessibility index. Like the preceding transit accessibility index, this measures the accessibility to jobs via personal vehicles. First, almost all TAZs register on our index. This was not the case for transit accessibility; there were many TAZs where a traveler could not access employment via transit. There is more variation in color for this index. It is useful to think about this in relation to our log decay function. The TAZs in dark blue are probably on the right side of the log decay function: one can access employment via car, but they may have very long commutes. Figure 9 also illustrates this fact. The majority of TAZs rank above 75 on our index. The main conclusion is that, for the most part, car ownership offers one decent access to employment. Even at the lower end of the index, you can access some employment, even though the commute may be long.

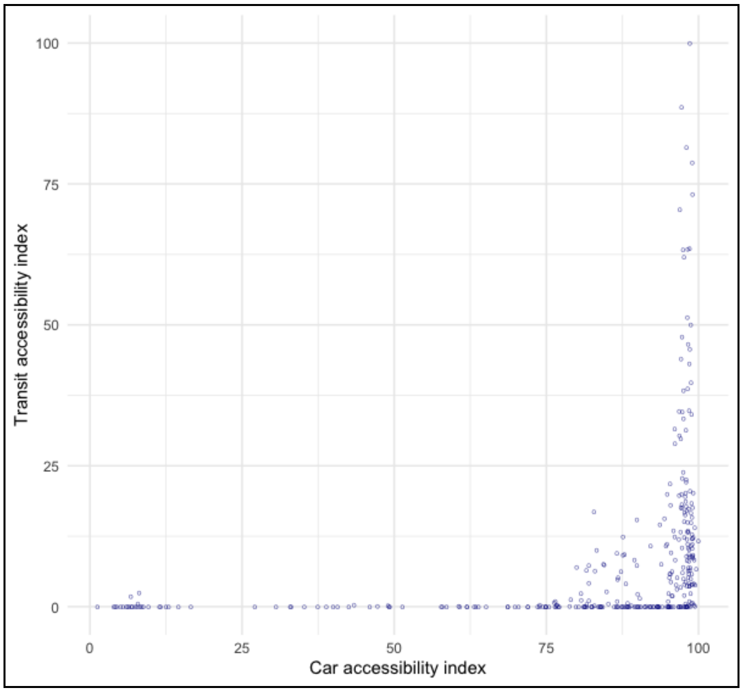

Figure 10: Comparative Accessibility Across TAZs (1 dot = 1 TAZ)

Lastly, we put our two indices in conversation with each other. Figure 10 visualizes each TAZs accessibility to employment by both car and transit. A few outliers show TAZs with either no transit accessibility to employment or no car accessibility to employment. The bottom right cluster reveals that most TAZs rank relatively low on transit accessibility but very high (75+) on car accessibility. There are almost no zones with high-transit accessibility/low-transit accessibility. Our model does not include parking or congestion, and we imagine this might change if we factored congestion into our analysis.

Technical Appendix

Assumptions and Constraints in the Skims

Road Skim
- Geographic constraints: Only includes roadways within the BCTNF MSA. The network excludes important state county roads that border the area and serve as regional connectors and excludes the neighboring Canadian city of Hamilton, Ontario   - The skim divided the region into traffic analysis zones coterminous with census tracts and plotted connectivity to a centroid in each zone. All travel is assumed to take place centroid to centroid, not to specific destinations within the zone   - Three census tracts were removed from the study area: GEOID 36029940100, 36029015003, 36063940100 for poor road connectivity   - Includes only roads coded as motorways and motorway links, primary, secondary and tertiary roads. Excludes residential roads   - Speed assumptions for each road exclude all congestion and traffic signals. Constant vehicle speed assumptions by functional road class are   - Motorway - 60 mph   - Primary - 50 mph   - Secondary - 45 mph   - Tertiary - 35 mph   - Centroid Connector - 15 mph

Transit Skim
- Geographic constraints: Dropped census tracts with GEOID 36029940100, 36029015003, 36063940100 as in the road skim   - NFTA Metro Bus and Rail GTSF data had 45 stops with milepost errors. We deleted in order to create a functional skim   - GTSF data produced 54 routes while NFTA Metro advertises 55 routes, the discrepancy is currently unknown   - Re coded light rail stops to metro to create a functional skim   - Time constraint: Weekday morning trips 7AM-11AM   - Fare assumption: $2 per ride and $0 transfer   - Stop wait time: riders use schedule information to plan stop arrival and wait for up to 15 minutes at the stop

Trip Time and Employment Data Set

Available at this link:
https://docs.google.com/spreadsheets/d/1G5bJx6ObH1rN-UI-2iTePQbbr0rPfLsmlKuH6Sm9t1U/edit?usp=sharing