Transit Usage in Seattle: A Spatial Investigation

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Final Project

GIS and Spatial Analysis

QMSS5070

Note that this is a truncated version prepared for an application to the NY State Office of the Attorney General

Contents

Introduction

Research Question:

1. How does transit usage percentage (percent of trips using mass transit / total trips per census tract) vary spatially in and around Seattle and Tacoma, Washington?
2. How does this variation relate to population density, median income, and median age at the census tract level?

Purpose of Study:

There are two purposes to this study. The first is to better understand where there are concentrations of high and low transit usage around the region. If there is clustering and we see hotspots and/or coldspots, further policy-focused questions can be asked.

The second research question is whether three independent variables (population density, median income, and median age) are related to the outcome of interest (percentage of commuter trips taken using public transit).

Hypotheses

1. I believe we will see transit hotspots close to urban centers (e.g., Seattle and Tacoma, the two biggest cities in the region of interest). Further, I believe the opposite will be true for coldspots–they should exist further outside urban centers.
2. I expect that transit use percentage is positively associated with population density and median income and negatively associated with age.

Data and Methodology:

Data Sources:

1. The **Puget Sound Regional Association (PSRC) Household Travel Survey (HTS) 2017-23** is a biennial survey of commuters done in the King, Kitsap, Pierce, and Snohomish counties of Washington state (the counties surrounding Seattle and Tacoma).
2. All **census tract-level ACS 2022 5-year estimates for demographic data and the associated geometries** were accessed via the R `tidycensus` package, which leverages an API connection to the US Census Bureau to provide US Census data for a specified geographic area.
3. Finally, **Stanford's Cities and Towns of the United States, 2014** dataset provided point data to allow me to add city labels to my maps for reference.

Data Preparation/Spatial Data Management:

Data Cleaning

1. *Mass Transit:* included in this category trips that used a metro bus, private bus or shuttle, urban rail/light rail, school bus, ferry, paratransit, and commuter rail. Essentially I included any multi-occupancy transit vehicle.
2. *Personal Vehicle:* trips including all single-occupancy motor vehicles. This includes personal cars, ride-shares, taxis, motorcycles, and car-share services.
3. *Active Transit:* included walking, running, biking, and skateboarding.
4. *Other:* included helicopter/plane, "other" responses.

GIS Methodology Overview

Manipulation/Analytical Methods Used

I counted the number of trips inside each census tract, then converted the total trip and mass transit trip counts to percentage. Finally, I used a simple join function to associate the counts with their respective geometries.

For the analysis in this project, I will perform a global cluster analysis (using Moran's I) and visualize any hot and cold spots using Getis-Ord Gi*. I will then run a Spatial Lag Model (SLM) regressing mass transit percentage on population density, median income, and median age.

Software Used

All data loading, cleaning, and manipulation, mapping (both choropleth and Getis-Ord Gi*), table-creation, regression modeling, and write-up were performed with R and RStudio.

Results and Analysis

Exploratory Data Analysis via Choropleth Mapping and Descriptive Tables

I will begin the analysis portion of this project with some simple choropleth maps in order to visualize some of the patterns I'm looking for will be apparent with a simple eye test.

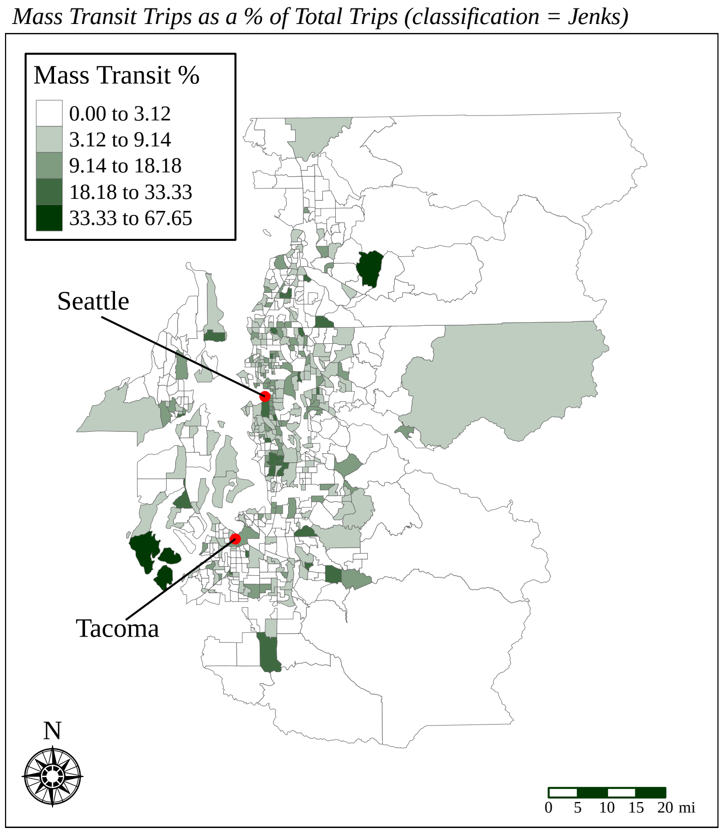


Figure 1: Sources: US Census ACS 2022 5-year estimates, Puget Sound Regional Countil, Cities and Towns of the US 2014, via Stanford University; Classification = jenks

Ignoring for a minute the top-end of the scale, it does seem that there are some clusters with higher transit usage and that these clusters tend to exist closer to the cities. Not only can we see that the apparent clustering occurs nearer to the two cities marked on the map, it also seems as though smaller census tracts tend to have higher mass transit percentages. As a general rule of thumb, smaller census tracts tend to be more urban, so this fits with my hypothesis that transit clustering will occur in more population dense areas.

For the final piece of exploratory data analysis, below is a table containing basic descriptive statistics for each of my variables. The only thing I will call out about this table is that it does show the high number of tracts with 0% mass transit trips. This is likely due to a low number of observations in those census tracts, since I only filtered out tracts with 0 observations. It is entirely possible there are tracts with a single observation and that the observation is for personal vehicles, active transit, or other.

Table 1: Descriptive Statistics Summary

	Mass Transit %	Population Density	Median Income	Median Age
mean	5.06	4,605.37	113,140.27	39.19
sd	6.94	4,483.13	40,662.76	5.69
min	0.00	4.90	30,327.00	21.90
q25	0.00	1,779.03	84,682.75	35.60
median	2.78	3,907.93	107,472.00	38.70
q75	7.69	5,963.44	135,001.75	42.60
max	67.65	47,121.04	250,001.00	69.30

Cluster Analysis

In this section, I will apply two different methods to test and visualize the clustering of transit access in the region. First, I will run a Global Moran's I to determine if the clustering we can see visually is statistically significant. Then, I will run a hotspot analysis using the Getis-Ord Gi* statistic, primarily as a tool for creating a visualization of the clustering.

Moran's I Test of Global Clustering

```
##
##  Moran I test under randomisation
##
## data:  psrc_table_clean$masstransit_perc
## weights: weights_clean
##
## Moran I statistic standard deviate = 7.1199, p-value = 5.4e-13
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##      0.1928134937     -0.0016103060      0.0007456762
```

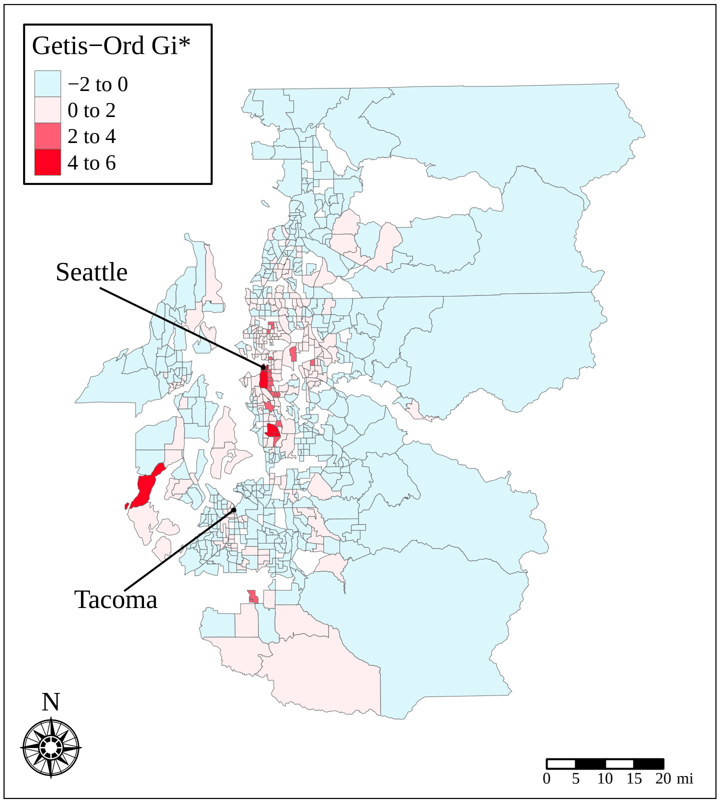
The Global Moran's I value of 0.193 indicates a moderate, positive clustering pattern. That is, tracts are somewhat likely to be similar to their immediate neighbors in terms of their mass transit percentage. High tracts are likely to be bordered by other high tracts, and low tracts are likely to be bordered by other low tracts. Given that the Moran's I statistic ranges from -1 to 1, the 0.193 value only indicates weak-to-moderate positive clustering.

While it is useful to know that there is statistically significant spatial clustering in our variable of interest with the region, these statistics alone do a poor job of helping us to understand where this clustering is happening and whether it fits with expectations. To that end, I will employ the Getis-Ord Gi* statistic and map its values across the region to visualize mass transit hotspots.

Hotspot Mapping with Getis-Ord Gi*

The Getis-Ord Gi* statistic evaluates each tract compared to its neighbors and finds "hotspots" (high-value tracts surrounded by other high-value tracts) and "coldspots" (low-value tracts surrounded by other low-value tracts). The output statistic, is a z-score associated with each tract. Roughly speaking, Gi* values between -2 and 2 represent areas with no significant clustering, while values outside that range (<-2 or >2), represent areas with significant clustering. A negative Gi* statistic indicates a coldspot, while a positive Gi* statistic indicates a hotspot. I am using the same spatial weights matrix as I used for the Global Moran's I.

Puget Sound Mass Transit Hotspot Tracts (Getis−Ord Gi)*



As can be seen in the map above, I chose to give the tracts with non-significant Gi* values directional coloration. Tracts with non-significant negative values are light blue and tracts with non-significant positive values are light pink.

Speaking of significant values, however, it is clear to see that the predominant occurrences of clustering are nearby Seattle, with most happening in South Seattle (noted earlier for having high population density and relatively lower median incomes). There are a couple of other instances of significant clustering towards the southwest corner of the map, but I do not have an intuitive explanation for why those are occurring there. More research on locations of transit lines and tract characteristics would have to be done in order to get a better understanding of what is happening.

In the next section, I will take my analysis further with a spatial model that regresses mass transit percentage onto the independent variables: population density, median income, and median age.

Regression using Spatial Error Model and Spatial Lag Model

Spatial Lag Model

A spatial lag model essentially includes the value of mass transit percentage in surrounding tracts as defined by the spatial weights matrix. This allows the model to take into account the spatial clustering we saw in the Moran's I test and produce coefficients for the other predictor variables that are more efficient and accurate. For this testing, I will use the `lagsarlm()` function from the `spatialreg` package. I will log both population density and median income, which is a common practice for variables that are always above 0 and can theoretically increase without limit.

```
##
## Call:
## lagsarlm(formula = masstransit_perc ~ log(pop_per_sqmile) + log(medincomeE) +
##     medageE, data = psrc_table_clean, listw = weights_clean)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.7888 -4.1372 -2.0656  2.3349 61.9643
##
## Type: lag
## Coefficients: (asymptotic standard errors)
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          0.906643   8.856855  0.1024  0.91847
## log(pop_per_sqmile)  0.491216   0.229086  2.1442  0.03201
## log(medincomeE)     -0.250715   0.777386 -0.3225  0.74707
## medageE              0.038179   0.053273  0.7167  0.47358
##
## Rho: 0.32971, LR test value: 37.7, p-value: 8.2494e-10
## Asymptotic standard error: 0.049143
##     z-value: 6.7092, p-value: 1.9574e-11
## Wald statistic: 45.013, p-value: 1.9574e-11
##
## Log likelihood: -2055.995 for lag model
## ML residual variance (sigma squared): 42.829, (sigma: 6.5444)
## Number of observations: 621
## Number of parameters estimated: 6
## AIC: 4124, (AIC for lm: 4159.7)
## LM test for residual autocorrelation
## test value: 2.519, p-value: 0.11248
```

As can be seen in this output, there are two predictors for which the coefficient is statistically significant. These are the lag term (Rho), as expected given the clustering already seen above, and the log(pop_per_sqmile) term. The positive coefficient on log(pop_per_sqmile) indicates that greater population density is associated with greater mass transit percentage. This was hypothesized. I will not directly try to interpret the values of the coefficients because the spatial lag term makes direct interpretations inaccurate. The other predictors are non-significant.

I will also calculate a pseudo R^2 value for this regression model using the formula $1 - \frac{SSE}{TSS}$.

```
## Pseudo R-squared: 0.1069
```

This indicates our model explains approximately 10% of the variation seen in the dependent variable, mass transit percentage.

From the relatively low r-squared values and the lack of statistical significance in most of my predictors, it is clear to me that this analysis would benefit from a new selection of predictor variables. A simple first step in this direction would be to do a more thorough analysis with the ACS demographic variables, but there are richer extensions beyond this. There are a plethora of built-environment and transportation-relevant variables that could be summarized per tract, such as land use percentage (industrial, residential, commercial, etc.), parking availability/price, and traffic congestion (particularly relevant in Seattle, where buses and at-grade light rail are common), among others. I believe the more model complexity is the answer here, rather than simplicity. This is particularly true as the goal of the analysis is to better understand what impacts transit usage, rather than whether a single variable does or does not impact transit usage.

Discussion and Interpretation

Key Findings

This investigation put into statistical terms a pattern that was (a) probably easy to intuit and (b) visually apparent from the initial mapping: high values of transit usage clusters close to city centers (particularly for Seattle) in the Puget Sound region. A further corroborating relationship was revealed with the SLM: that population density is positively associated with mass transit usage.

The other predictor variables (median income and median age) were not statistically significantly related to my outcome variable. The analysis did not present me with any surprising or counterintuitive results, merely a lack of significance for some of my variables.

Implications/Areas for Future Inquiry

With statistical evidence in favor of urban clustering of transit usage, I can now confidently ask the question: "what is it about urban areas that encourages transit ridership?" I believe this can be decomposed into two pieces. First, there are likely certain pro-transit characteristics of urban areas. A high density of stops and transfer options mean transit is more convenient for riders, as does better walkability and a lower distance between likely origin and destination. On the other hand, some characteristics of urban areas have a more anti-car flavor. Limited and expensive parking options are a good example. If increasing transit adoption and usage is a priority (and it should be, for sustainability and equitability reasons), further research should investigate these characteristics to better understand how to design desirable transit in areas with low usage rates.

This sort of investigation could remain a spatial one. I imagine a survey of people in the region, each linked to a census tract, and would imagine that their public transit usage considerations might vary with geography. People in urban areas might consider transfer reliability, walkability, or anti-car factors more than suburban or rural respondents, who might be more interested in things like overall speed. Seattle, in particular, has a big suburban population that commutes either to the city or nearby tech campuses and, as we can see from the initial choropleth mapping, tends to do so by car. A better understanding of their reasons for this would allow for better policy and infrastructure design to increase transit usage and adoption.

Conclusion

This report can be thought of as a jumping-off point for my personal research interests. Having this sort of statistical and spatial understanding of how transit usage is distributed in the region gives me a concrete foundation off of which to build further analyses. Although I did not find much in the way of interesting regression results, the analysis has given me pause to consider what other types of variables (especially outside of basic ACS demographics) might be useful and/or interesting to consider adding to future work. Finally, I think the number of questions that this analysis provokes within me will be helpful for thinking about future research directions and how the relate to policy decisions.

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