Race, Class, and Transit Oriented Development

Examining high-income demographic change after light rail transit

Thelonious Goerz
Dept. of Sociology
Johns Hopkins University

PHI Applied Research Fellowship
Center for Studies in Demography and Ecology

July 22, 2021

Outline

- Background and prior research
- Seattle case study
- Methods and data
- Research notes about working with these data
- Descriptive and statistical results
- Conclusion

Motivation

- How and where people move have been a core questions in urban sociology and poverty research for years.
- Moves and their associated neighborhood contexts are important for wellbeing, educational attainment, and development over the life course (Bergman et. al. 2020; Chetty et. al. 2016)
- So it is important to understand the whole picture of mobility: Both high and low income mobility.

But, does it makes sense to study the most vulnerable populations?

Motivation

Yes and No.

- I argue that an asymmetric focus on studying the movement patterns of low-income residents in changing neighborhoods has left open theoretical and empirical gaps for researchers.
  - We know little about the movement of high income individuals and households.
  - Often elite wealthy individuals have more power and sway over government and economic processes (Gilens and Page 2014).

Background: Theory

- Social scientists are interested in the effects of gentrification on urban demographic patterns.
    - In recent years, it has been linked to major urban re-investment projects, such as Light Rail Transit on the west coast.
    - So, transit development is a good proxy for gentrification, neighborhood change, and associated ideas.

Why does studying transit matter?

Background: Theory

Seattle and many other cities are increasingly turning to Light Rail Transit (LRT) as a way to manage growth, promote green travel initiatives, and reduce congestion.

- Manage tech-related in-migration in Seattle.
- Transit needs of low-income residents.
- Population growth.

The Present Study

In Seattle:

- The Link Light Rail has been in development since 1996 when it was approved.
  - Construction began in 2003 and a majority of stations opened in 2009.
  - As of 2021 there are 14 stations.
  - There are currently north and south expansions in development to 2036.

As a consequence:

- There are puzzling trends going on.
  - Hess (2020) finds dramatic increases in non-Hispanic White residents after LRT in greater Seattle area census tracts.
  - Declines in Asian and Hispanic residents after LRT.

How is this happening?

Background: Income and mobility

Conventional wisdom suggests that neighborhoods change through low-income displacement.

- But, low-income residents are often much less mobile than middle-income and higher-income residents (Freeman 2005).
- However, there is evidence to suggest that middle and upper income residents are far more mobile:
  - Ding et al. (2016): Increases in high credit score individuals' mobility in gentrified neighborhoods.
  - Bartholemew and Ewing (2017): Disamenity effect in neighborhoods with urban development, homeowners moving out.
  - Martin and Beck (2011): Higher status non-homeowners may be moving out of gentrified neighborhoods.

Background: Income and Mobility

- The demographic trends in Seattle are not consistent with patterns of socioeconomic mobility in changing neighborhoods.
  - Often low-income groups are declining.
  - But, statistically these groups are not as mobile.

Where is this demographic change happening on average?

Hypothesis

- **This study argues that middle and high income groups are the primary forces shifting neighborhood racial composition in LRT neighborhoods because of their capacity to move.**

Data

- Time series data for 135 census tracts (Seattle, N = 540) and 24 LRT treated tracts [1990-2015]:
  - Income (by race), demographic variables, and controls.
  - American Community Survey, Decennial Census Long Form, Hess (2020).

Data: A note on working with the ACS

- I assemble this panel dataset between 1990-2015 at 4 time periods.
  - The 1990 and 2000 are census long form data that are geographically linked to the 2010 re-draw of census tracts. ^[This is accomplished using the IPUMS geographic crosswalk files.[1]
- I create income quintiles by matching the income bins in the ACS and Census data at time t to the cutoffs for each quintile in that year.
  - This has some issues, given there is error in the cutoffs.
    - Thankfully in this case the error is at most $5,000.
  - The upper tail of the distribution is unknown so we have very little idea how much error there is.
- Data after 2009 can be accessed easily with the `tidycensus` package in R. This has excellent support and needs an API key![2]

[1] More info here: https://www.nhgis.org/geographic-crosswalks I am happy to discuss this in more depth too if it is of interest to the team.

[2] So get one if you need.

Methods

- Difference in difference (DID) (comparative counterfactual design)
- DID is a quasi-experimental research design borrowed from econometrics, that given thee assumption of “parallel pre-treatement trends” as an identification strategy, can determine a causal effect.
  - This means that we find some panel data where there is a pre and post-treatment stage, and compare pre-treatment states of both treatment and control groups.
  - The limitations and threats to identifcation are many, especially in this case.

Methods

- To specify the model, I use robust standard errors clustered at the tract level and formulate the model in a maximum likelihood regression framework.
- I specify the following model with the functional form:

$$Y_{it} = \alpha_i + \gamma_t + X_{it} + \beta\delta_{1990} + \beta\delta_{2010} + \beta\delta_{2015} + \epsilon_{it}$$
$$\epsilon \sim N(\mu, \sigma^2)$$

- Where, Y is the percent of a racial group in a census tract at time t and in the treatment group i, alpha is a group fixed effect and gamma is a time fixed effect, and X is a matrix of control variables for the 1980 composition and others. The deltas are interactions coefficients that correspond to pre-trend (1990), a reference category (2000), and a post-construction effect (2010) and a post link opening (2015) effect.

Methods: Income Quintile Computation Error

Table 1: **Error of Estimated Income Qunitiles Over Time (In Dollars)**

Quintile	1990	2000	2010	2015
Lowest (Q1)	0	2045	0	2,200
Second Lowest (Q2)	-1,162	1994	2000	1,489
Middle (Q3)	1,200	-2272	-1,500	2,999
Second Highest (Q4)	-205	-6,960	-29	12,738
Highest (Q5)	205	6,960	29	-12,738
Avg.. absolute dev	595	4,046	711	6,432

Summary Statistics

Table 2: Pooled Cross-Sectional Pre-Treatment Summary Statistics (2000)

Statistic	N	Mean	St. Dev.	Min	Max
Percent White	135	67.000	23.000	9.100	94.000
Percent Black	135	8.300	10.000	0.000	50.000
Percent Asian	135	13.000	13.000	0.880	58.000
Percent Hispanic	135	5.500	4.200	1.000	37.000
Percent Q1	135	20.000	12.000	4.500	71.000
Percent Q2	135	18.000	5.400	6.000	37.000
Percent Q3	135	16.000	3.900	4.200	27.000
Percent Q4	135	19.000	4.700	3.300	28.000
Percent Q5	135	27.000	13.000	2.400	66.000

Summary Statistics

Table 3: Pooled Cross-Sectional Post-Treatment Summary Statistics (2015)

Statistic	N	Mean	St. Dev.	Min	Max
Percent White	135	65.000	21.000	5.900	92.000
Percent Black	135	7.500	8.900	0.000	44.000
Percent Asian	135	14.000	12.000	2.400	63.000
Percent Hispanic	135	6.700	5.400	1.100	41.000
Percent Q1	135	19.000	12.000	2.500	67.000
Percent Q2	135	15.000	5.000	4.300	31.000
Percent Q3	135	19.000	5.300	6.800	33.000
Percent Q4	135	21.000	5.900	4.000	35.000
Percent Q5	135	26.000	13.000	1.000	63.000

Summary Statistics: Treatment

Table 4: Treatment Group Cross-Sectional Pre-Treatment Summary Statistics (2000)

Statistic	N	Mean	St. Dev.	Min	Max
Percent White	24	45.000	26.000	9.100	78.000
Percent Black	24	17.000	9.500	2.800	33.000
Percent Asian	24	24.000	18.000	5.000	58.000
Percent Hispanic	24	6.900	3.000	1.900	15.000
Percent Q1	24	35.000	14.000	19.000	71.000
Percent Q2	24	21.000	6.600	11.000	37.000
Percent Q3	24	14.000	5.300	4.200	21.000
Percent Q4	24	15.000	5.200	3.300	24.000
Percent Q5	24	15.000	8.400	2.400	37.000

Summary Statistics: Treatment

Table 5: Treatment Group Cross-Sectional Post-Treatment Summary Statistics (2015)

Statistic	N	Mean	St. Dev.	Min	Max
Percent White	24	48.000	21.000	12.000	75.000
Percent Black	24	14.000	10.000	2.900	35.000
Percent Asian	24	23.000	13.000	8.700	54.000
Percent Hispanic	24	8.000	5.100	2.700	25.000
Percent Q1	24	30.000	10.000	14.000	49.000
Percent Q2	24	17.000	5.300	7.600	31.000
Percent Q3	24	18.000	4.900	8.300	26.000
Percent Q4	24	18.000	4.900	9.000	25.000
Percent Q5	24	17.000	7.700	5.500	36.000

Statistical Analysis: DID of racial composition

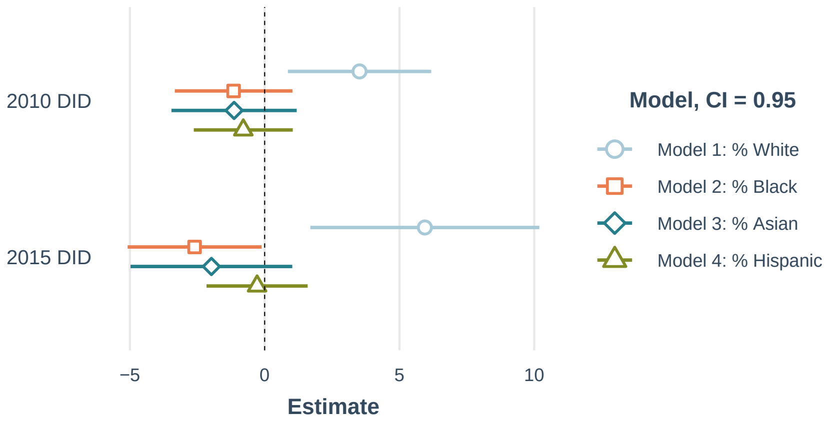

Figure 1: DID estimates of LRT effect on racial group percent

Statistical Analysis: DID for Income Composition

Table 6: Difference in Difference Estimates for Percent of Households in Each Quintile

	Q1 Model 1	Q2 Model 2	Q3 Model 3	Q4 Model 4	Q5 Model 5
1990	-0.380	0.350	4.300^{***}	2.100^{***}	-6.400^{***}
	(0.510)	(0.350)	(0.400)	(0.460)	(0.510)
2000	-3.300^{***}	-1.200^{*}	0.170	3.100^{***}	1.200^{*}
	(0.670)	(0.480)	(0.540)	(0.530)	(0.590)
2010	-1.400^{*}	-2.900^{***}	3.500^{***}	1.800^{***}	-0.950
	(0.680)	(0.460)	(0.490)	(0.540)	(0.600)
LRT Treat	4.900	0.005	-2.000	-2.200	-0.640
	(2.600)	(1.400)	(1.200)	(1.200)	(2.000)
1990 X LRT	6.200^{***}	-0.820	-2.500^{***}	-4.300^{***}	1.500
	(1.700)	(0.930)	(0.720)	(0.950)	(1.200)
2010 X LRT	-2.600	1.300	0.077	0.460	0.760
	(1.400)	(1.100)	(1.100)	(1.200)	(1.300)
2015 X LRT	-5.300^{*}	-1.700	-0.300	2.200	5.200^{**}
	(2.200)	(1.600)	(1.100)	(1.200)	(1.800)
N	540	540	540	540	540
Log Likelihood	$-1,886.000$	$-1,563.000$	$-1,595.000$	$-1,623.000$	$-1,881.000$
AIC	3,806.000	3,160.000	3,224.000	3,280.000	3,797.000

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$
Abbreviated model, other controls omitted.

Income and Race

- I estimate 20 models predicting the percent of households of each racial group at one of the five income quintiles (Not shown for brevity).[3]
  - These reveal statistically significant increases in the percents of high income Asian and white households equivalent to about 9 and 7 percent respectively.
  - For Hispanic and Black residents their distributions remain unchanged.
- But, as a major reminder – these are overall flows, not exactly causal estimates.

[3] But they are in the paper.

Conclusions

- 5 years after LRT, neighborhoods experience dramatic increases in white residents, and declining or stagnant non-white groups.
- 5 years after LRT, there is shift in the income distribution tending toward the two highest quintile earners.
- 5 years after LRT, there are increases in the percents of white and Asian households that are at the highest quintiles while Black and Hispanic groups do not have observable change.
- This suggests that income is an important factor in how demographics in Seattle are changing, but non-uniform.
- Income patterns are consistent with my hypothesis that dramatic shifts in income could be moving the composition.
- The big takeaway: There is a lot we do not know about high-income earners.
  - We stand to learn much about the social world from their movements and motivations.

Limitations

- The ACS and census report compositional estimates so understanding how distribution changes translate to in and out migration flows is tricky.
- Prediction of Black racial and economic trends can be subject to a lot of uncertainty.[4]
  - Small counts in ACS sample.
  - Low levels of Black population overall in Seattle.
- DID modeling assumptions may not be met in this case.[5]

[4] Data and full analysis provided on request. Email: tgoerz1@jh.edu

[5] Parallel trends and endogeneity are issues. I am happy to discuss these though.

Future Directions

- Examine LRT impact on just new in-movers using the ACS data.
- Look at the differences in compositions between people who moved from the same county and those who are moving from out-of-county.
- Look at the longer-term effect of LRT with the new 2020 ACS data.
- Full models and analyses are on my github `theloniousgoerz` free and open to the public.
  - If you have questions about software or data let me know.

References

Bartholomew, Keith, and Reid Ewing. 2011. "Hedonic Price Effects of Pedestrian- and Transit-Oriented Development." Journal of Planning Literature 26(1):18–34. doi: 10.1177/0885412210386540.

Bergman, Peter, Raj Chetty, Stefanie DeLuca, Nathaniel Hendren, Lawrence F. Katz, and Christopher Palmer. 2019. Creating Moves to Opportunity: Experimental Evidence on Barriers to Neighborhood Choice. w26164. National Bureau of Economic Research.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2003. "HOW MUCH SHOULD WE TRUST DIFFERENCES-IN-DIFFERENCES ESTIMATES?" 32.

Chapple, Karen, and Anastasia Loukaitou-Sideris. 2019. Transit-Oriented Displacement or Community Dividends?

Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment." American Economic Review 106 (4): 855–902.

References

Ding, Lei, Jackelyn Hwang, and Eileen Divringi. 2016. "Gentrification and Residential Mobility in Philadelphia." Regional Science and Urban Economics 61:38–51. doi: 10.1016/j.regsciurbeco.2016.09.004.

Understanding the Effects of Smarter Growth on Communities. Cambridge, MA: The MIT Press.
City of Seattle. 2019. Seattle 2035 Urban Growth Strategy. City of Seattle.

Freeman, Lance. 2005. "Displacement or Succession?: Residential Mobility in Gentrifying Neighborhoods." Urban Affairs Review 40(4):463–91. doi: 10.1177/1078087404273341.

Gilens, Martin, and Benjamin I. Page. 2014. "Testing Theories of American Politics: Elites, Interest Groups, and Average Citizens." Perspectives on Politics 12(3):564–81. doi: 10.1017/S1537592714001595.

Hess, Chris L. 2020. "Light-Rail Investment in Seattle: Gentrification Pressures and Trends in Neighborhood Ethnoracial Composition." Urban Affairs Review 56(1):154–87. doi: 10.1177/1078087418758959.

Martin, Isaac William, and Kevin Beck. 2018. "Gentrification, Property Tax Limitation, and Displacement." Urban Affairs Review 54(1):33–73. doi: 10.1177/1078087416666959.