JOINT CENTER FOR HOUSING STUDIES OF HARVARD UNIVERSITY

The Geography of Gentrification and Residential Mobility

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Kristin L. Perkins Georgetown University

- This research was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau at the Boston Research Data Center and the Georgetown University Research Data Center. Results and conclusions are those of the authors and do not necessarily reflect the views of the U.S. Census Bureau. The results shown in this draft have been reviewed by the US Census Bureau's Disclosure Review Board, authorization numbers CBDRB-FY20-128 and CBDRB-FY21-POP001-0012.

Motivation and Background

Gentrification and Displacement: Prior Work

Does Gentrification Cause Displacement?

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- Yes. It displaces low-income residents (Brown-Saracino 2017; Aron-Dine and Bunten 2019; Brummet and Reed 2019)

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Why do we have inconsistent results?

- Different measures of gentrification? No. Many report their results are robust to alternative measures of gentrification
- Different neighborhood processes across cities? Probably.
  - Growing regional divergence and inequality across cities (Ganong and Shoag 2017; Manduca 2019)
  - Greater heterogeneity across disadvantageous neighborhoods across cities (Small, Manduca, and Johnson 2018)
  - Spatial heterogeneity in the pattern of neighborhood ascent (Owens 2012)

Gentrification and Displacement: This Work

Association between Gentrification and Residential Mobility

- Comparing residential mobility out of gentrifying neighborhoods with mobility out of similar gentrifiable but non-gentrifying areas

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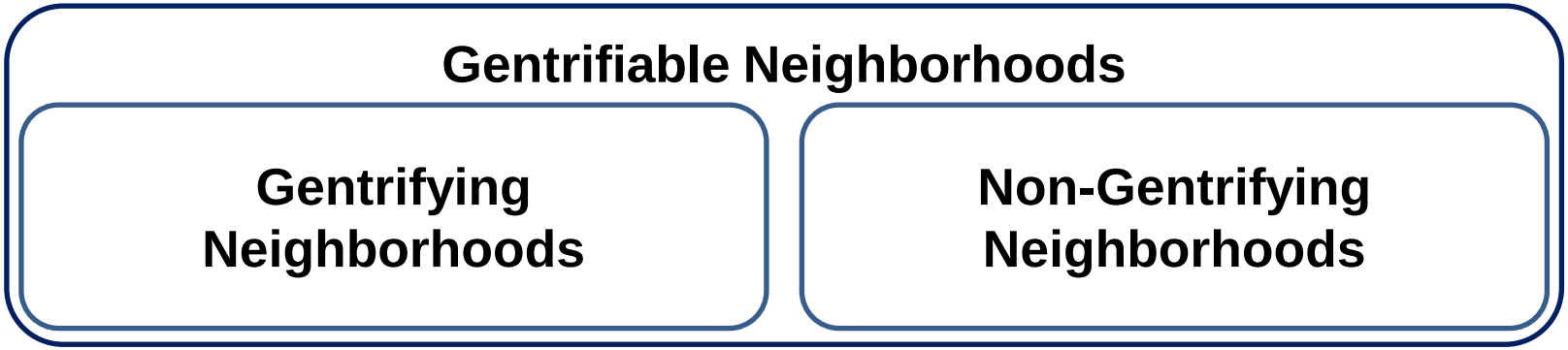

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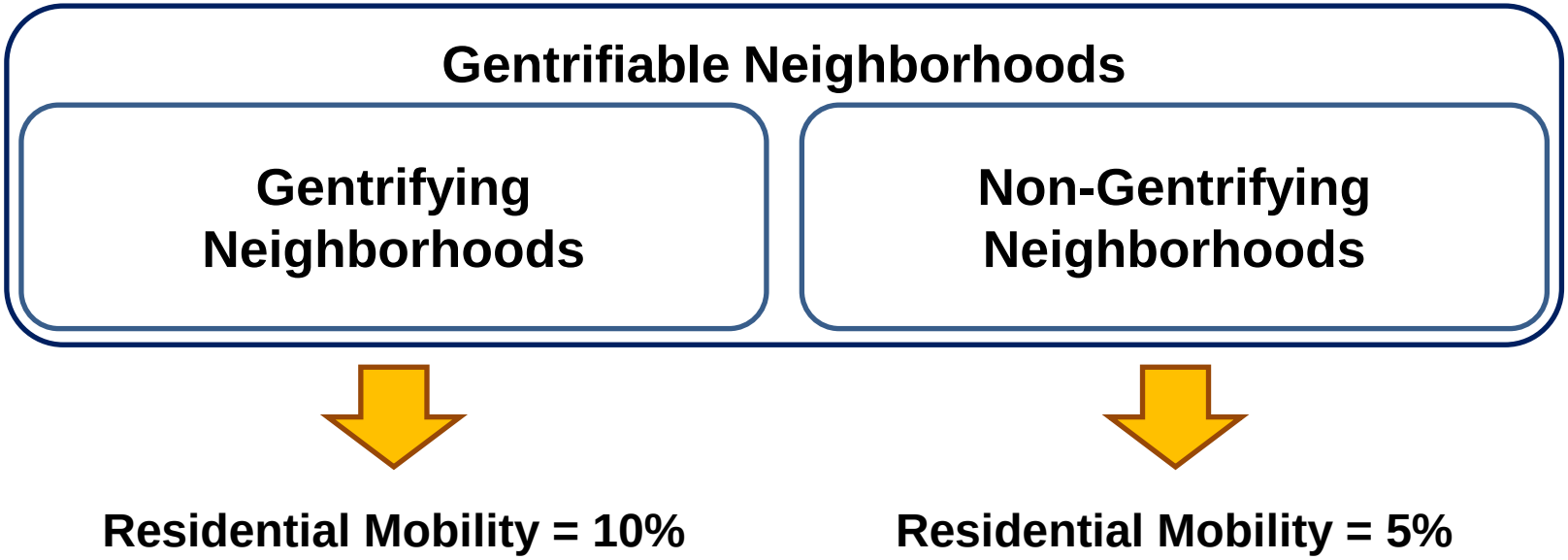

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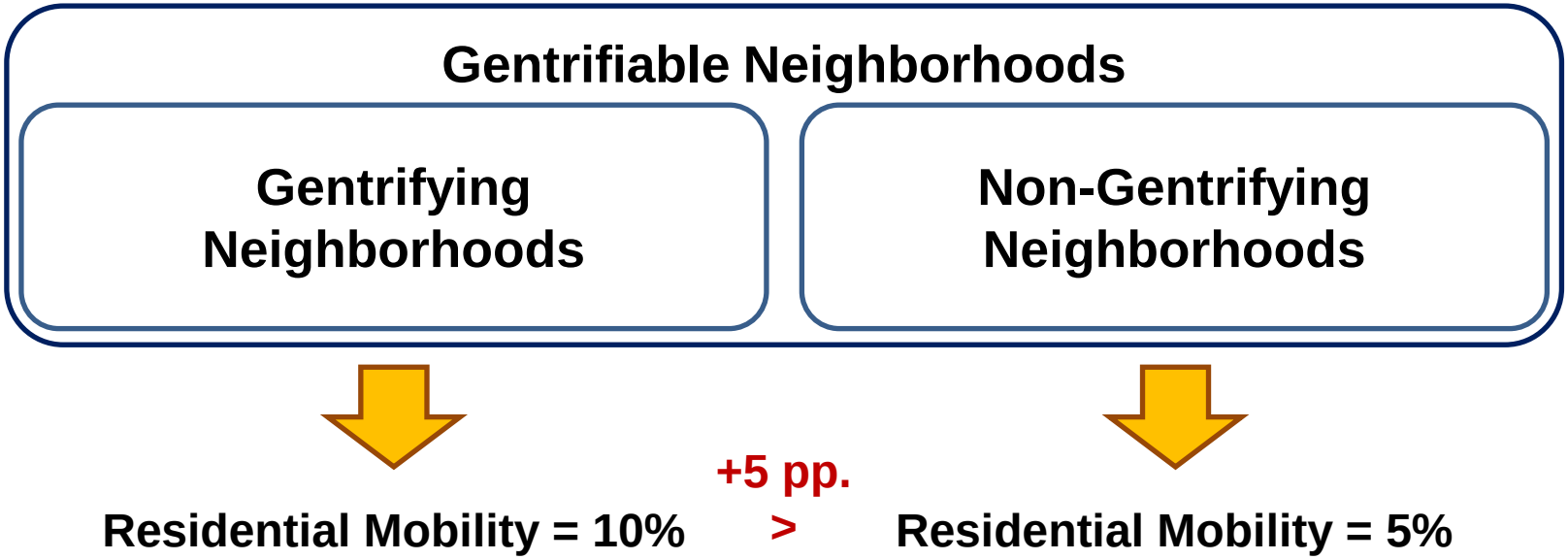

➔ **Interpretation: Gentrification is associated with residential mobility**

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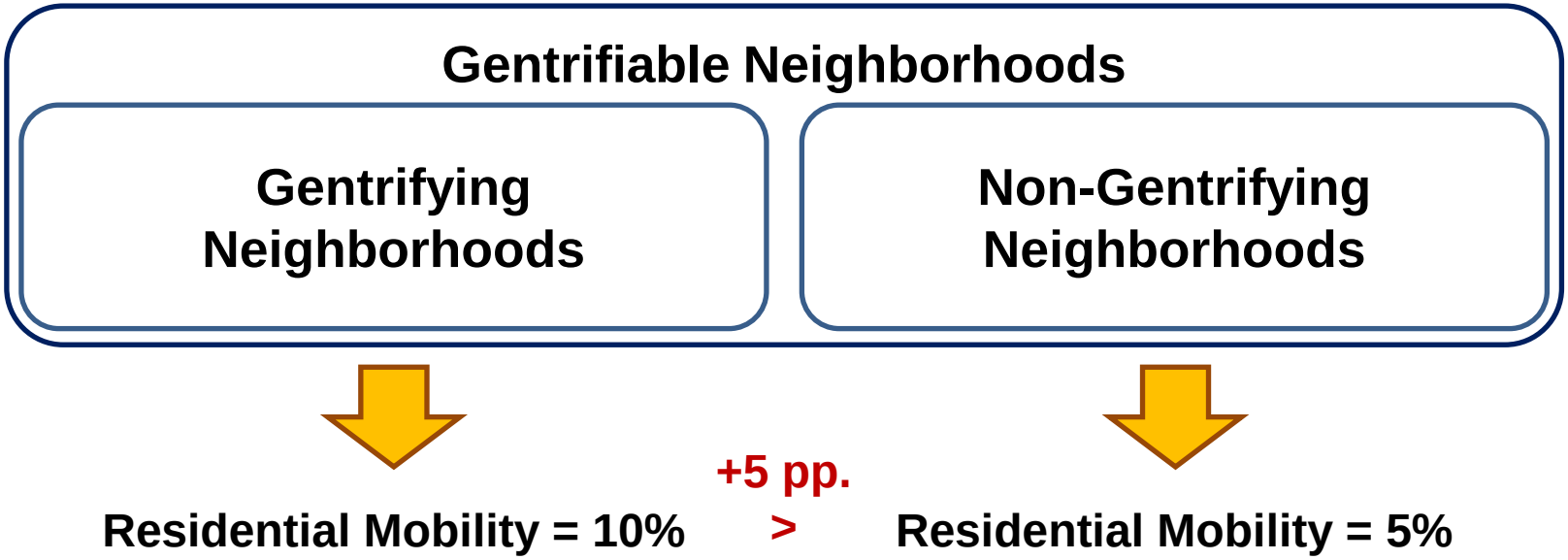

➔ **Interpretation: Gentrification is associated with residential mobility**

- Examining the differences in the association across MSA clusters

Gentrifiable, Gentrifying, and Non-Gentrifiable Neighborhoods

Definition of Gentrifying Neighborhoods

Gentrifiable Neighborhoods

Central/Urban: within principal cities of the top 100 Metropolitan Statistical Areas (MSAs)

Low-Income: with a median household income less than 80% of the MSA's median income

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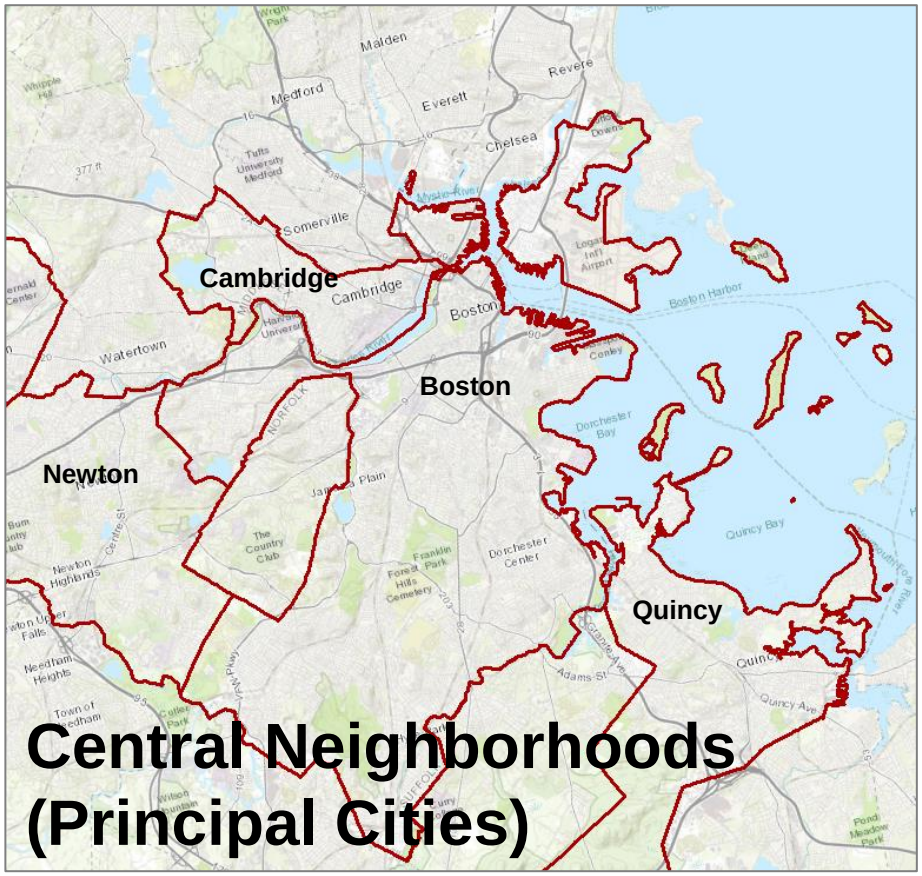

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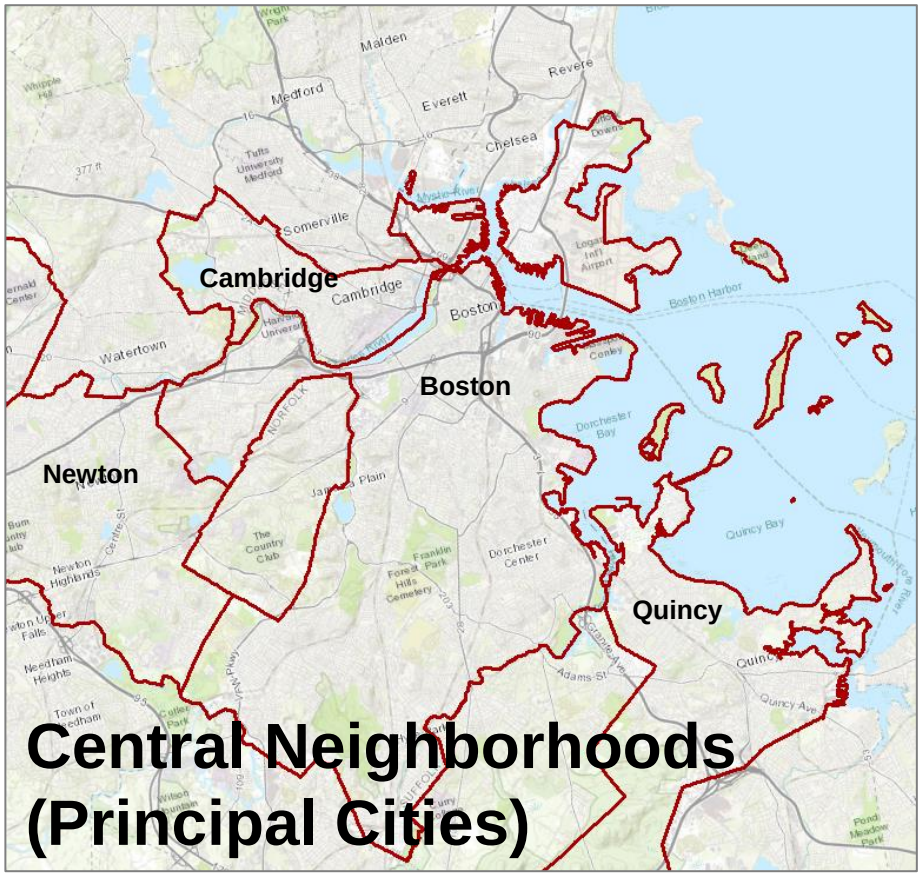
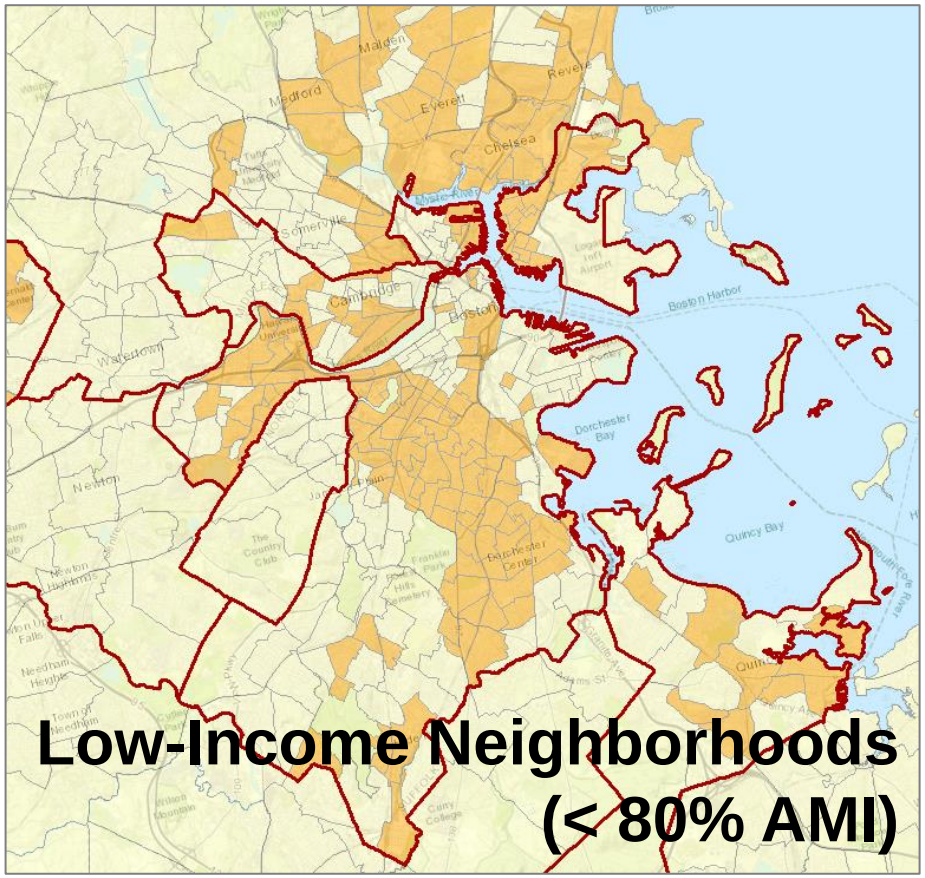


Central Neighborhoods (Principal Cities)



Low-Income Neighborhoods (< 80% AMI)

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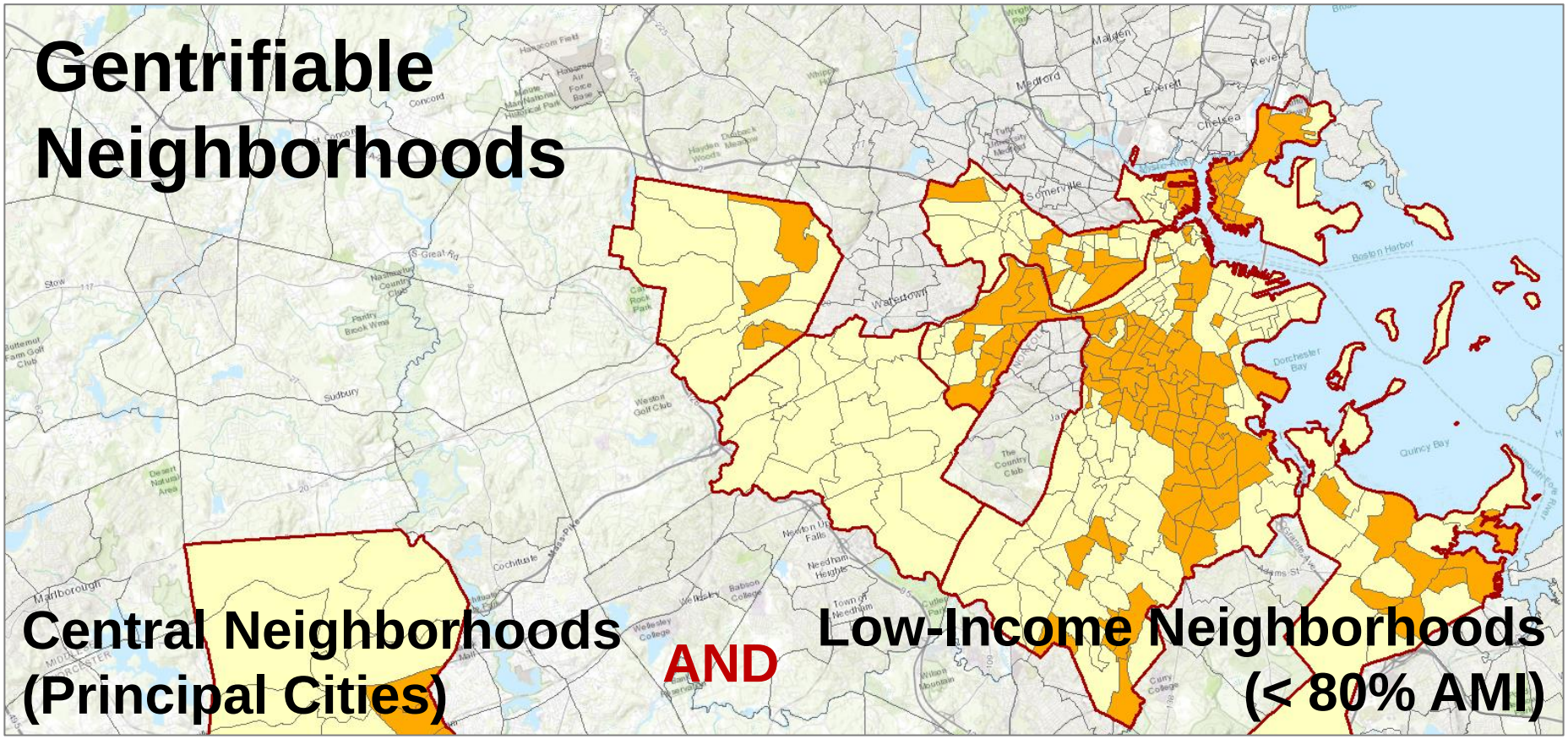
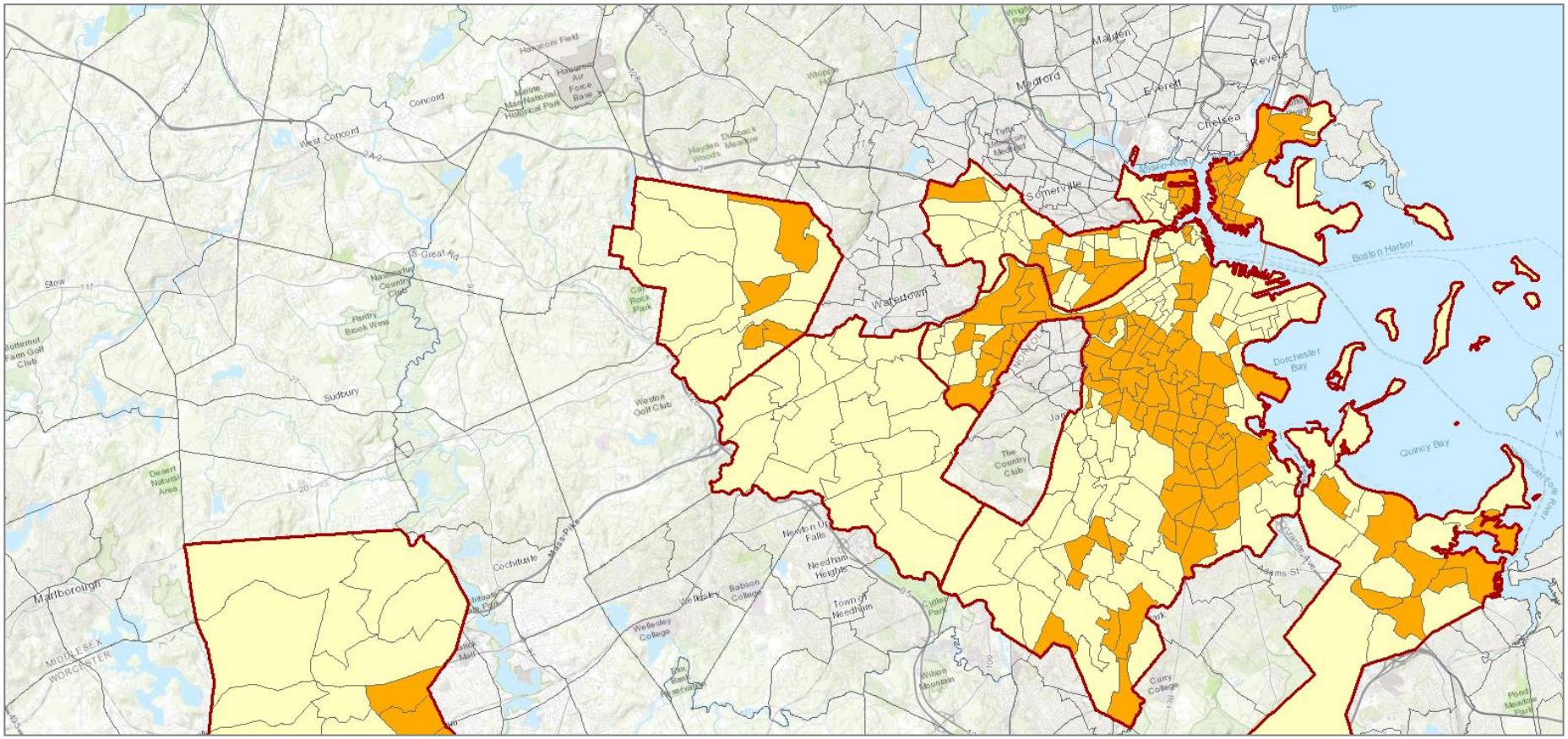


Definition of Gentrifying Neighborhoods

Gentrifying Neighborhoods

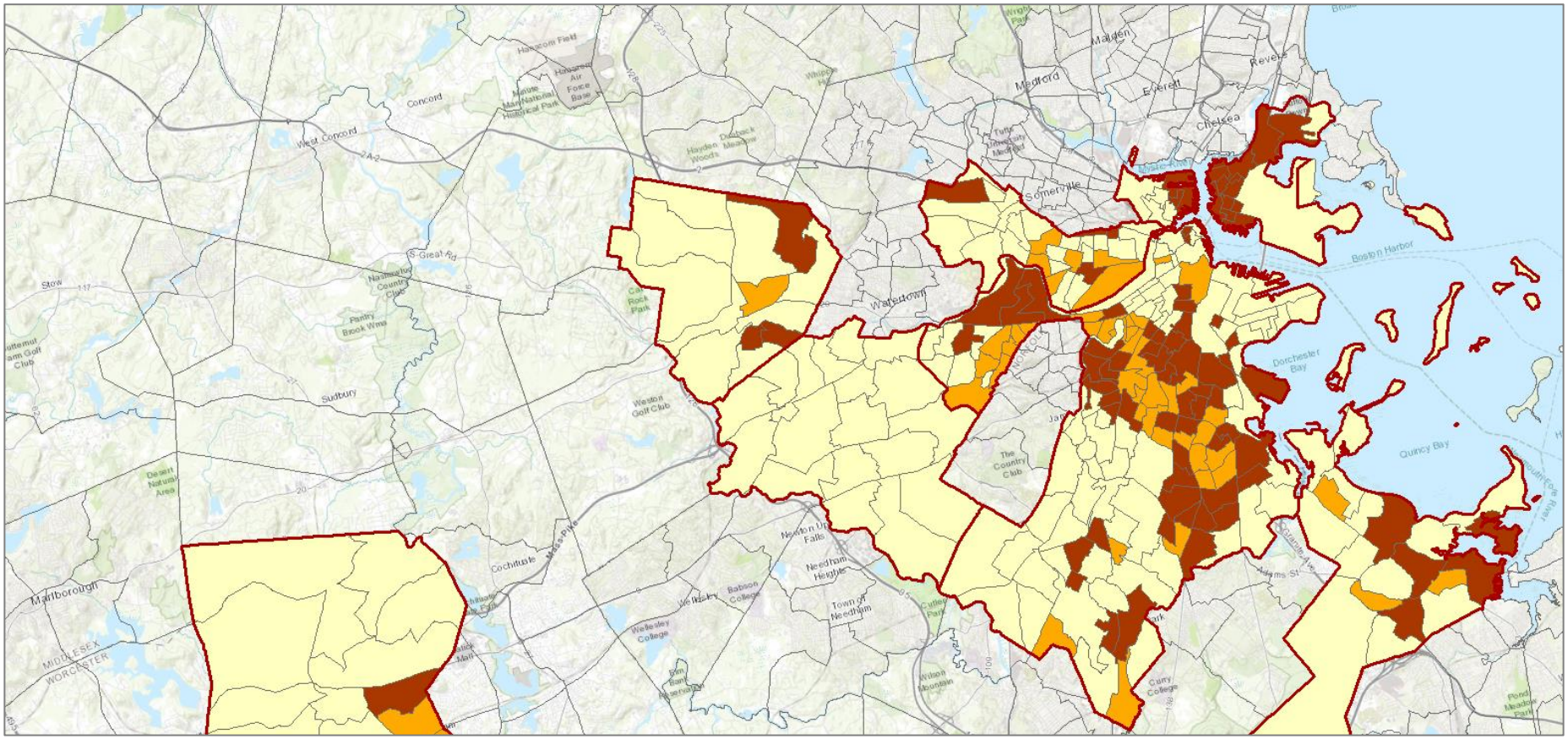
- A "gentrifiable" neighborhood



Definition of Gentrifying Neighborhoods

Gentrifying Neighborhoods

- A "gentrifiable" neighborhood that experiences (a) an above metro increase in college graduate share



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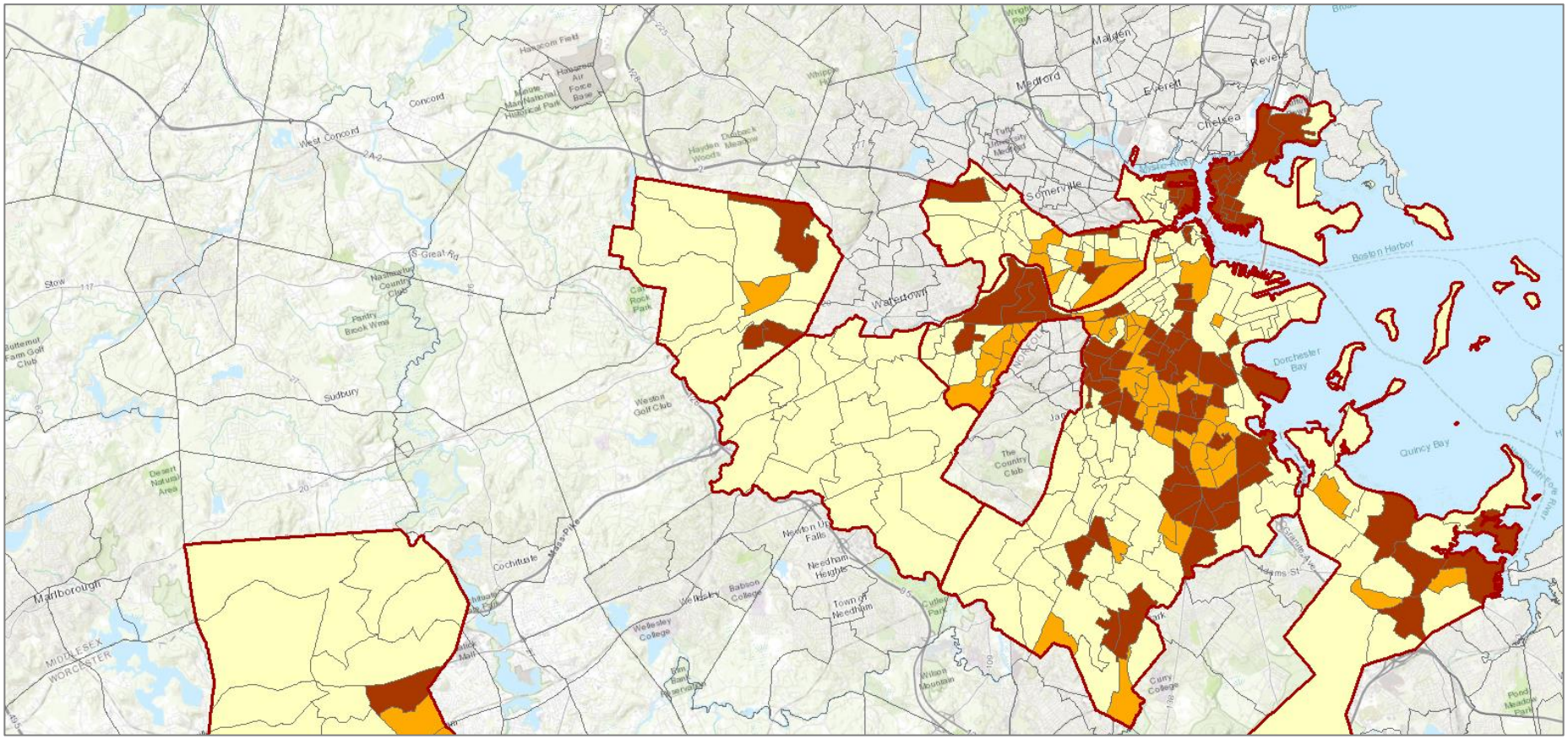
- A "gentrifiable" neighborhood that experiences (a) an above metro increase in college graduate share AND (b) an above metro increase in median housing prices (house value or gross rent)



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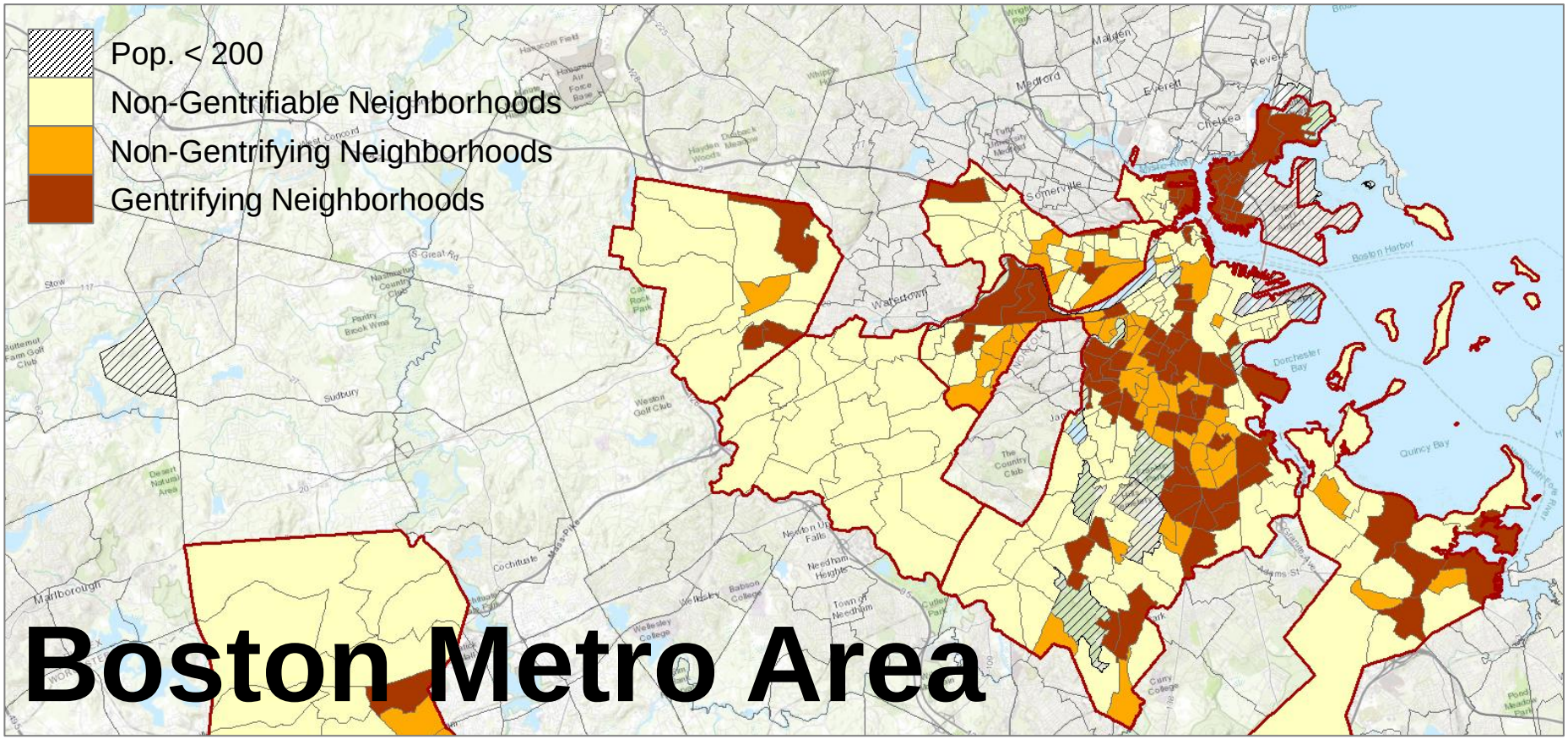

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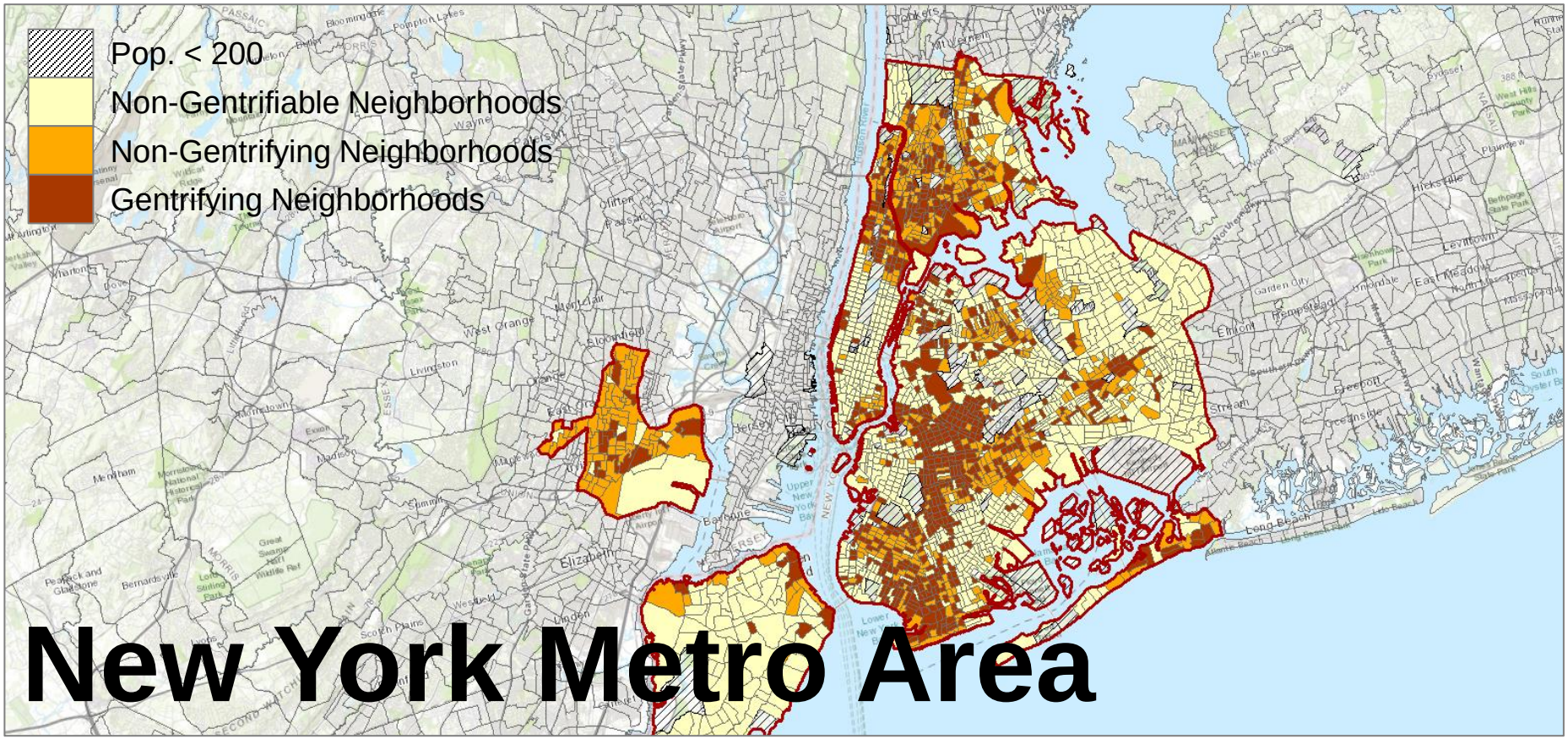

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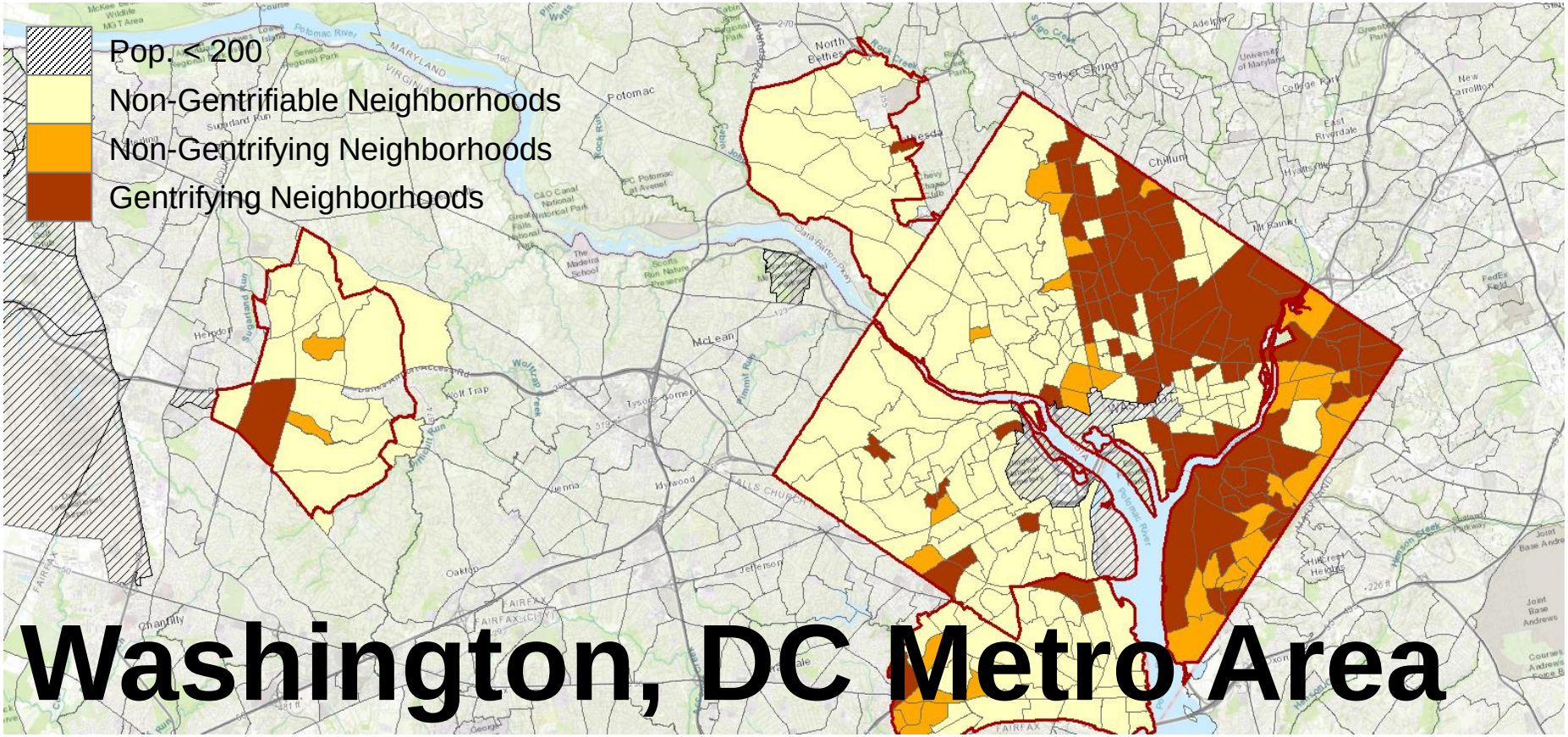

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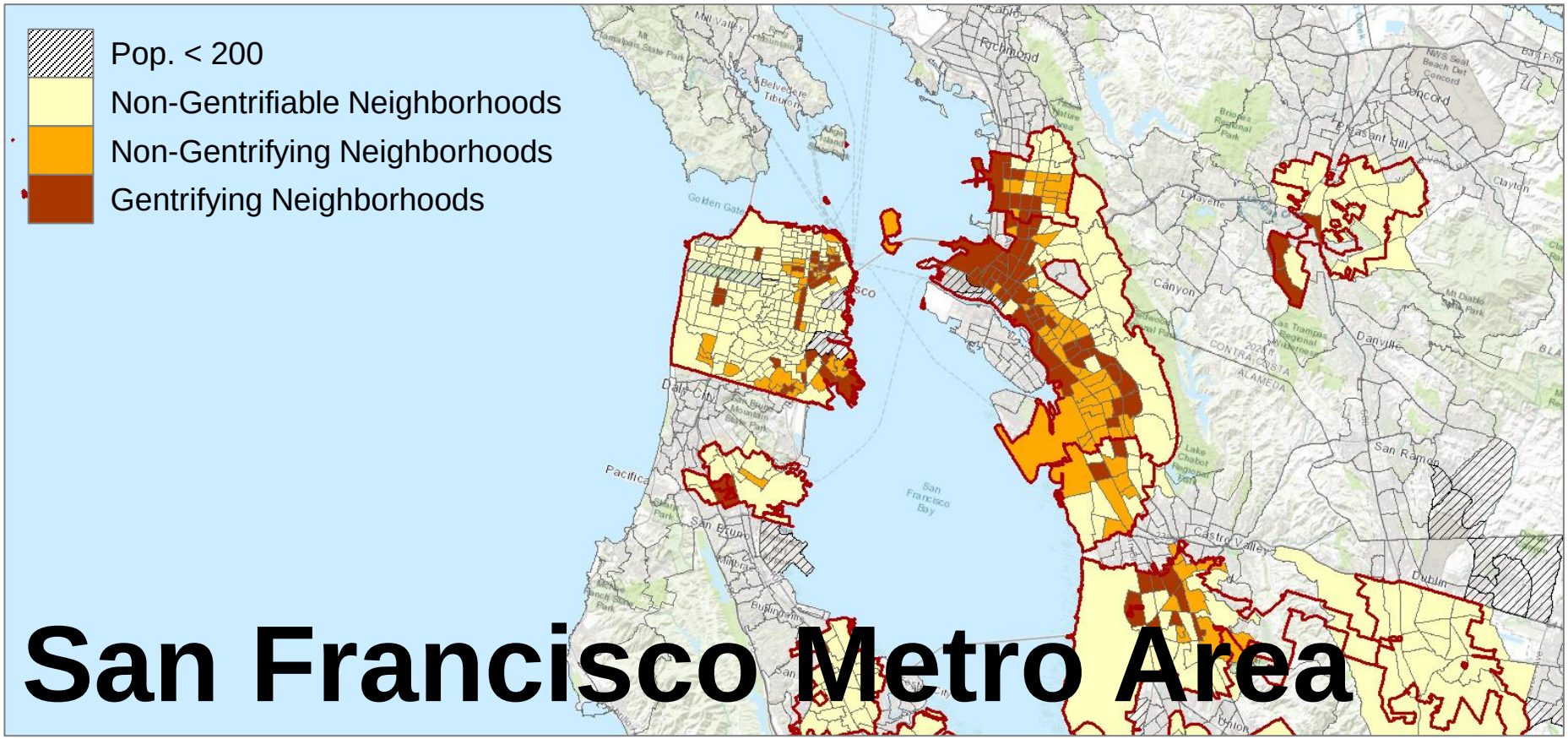

Classification of MSAs: PCA and Cluster Analysis

Classification of MSAs

(1) Principal Components Analysis (PCA)

- Conducting PCA on 25 metro-level variables that reflect population, socio-economic, and housing characteristics of the top 100 MSAs

Categories	Variables	
Population	Total Population (in 000s)	Total Households (in 000s)
	% Under 18	% NH-White
	% 65 and over	% Black
	% Recent Immigrants	% Asian and PI
	% Long-term Immigrants	% Hispanic
Socio-economic	Median Household Income	% Poverty
	% < High School	% Married-Couple HHs
	% BA+	% Single-Mom HHs
	% Unemployment	% Recent movers
	% High-Status Occupation	
Housing	% Owners	Median Value
	% Occupancy	Median Gross Rent
	% Multifamily Units	% Units Built After 2000

➔ Six principal components that have an eigenvalue over one

Classification of MSAs

(1) Principal Components Analysis (PCA)

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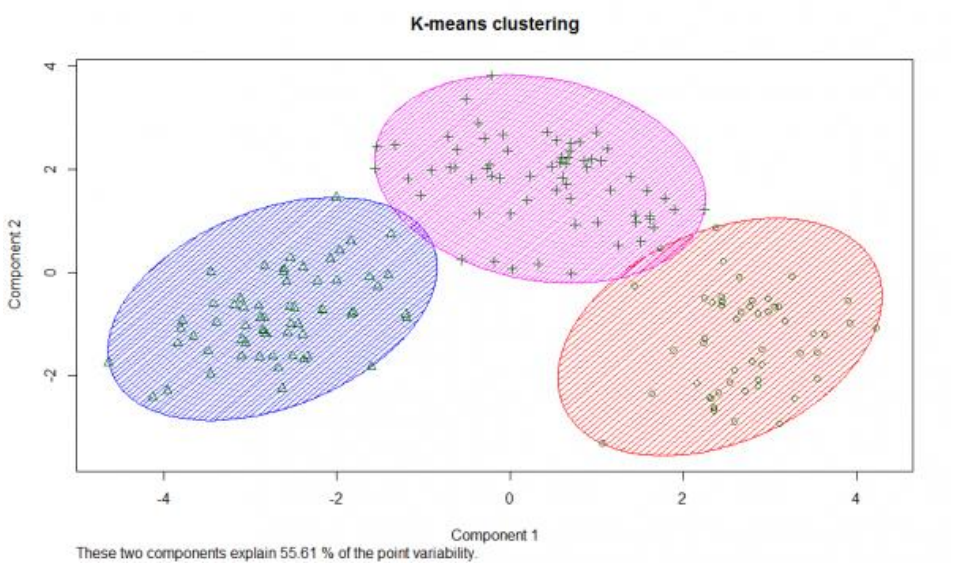
(2) Cluster Analysis

- Grouping those MSAs that have similar characteristics (minimizing Euclidean distances between them in terms of the principal components)



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MSA Clusters	Key Features	
Coastal and Tech (9)	• Large % BA+ and high-status occupation • High median income and housing costs	• Relatively greater % Asian and PI • Low %unemployment
Immigrant Gateways (4)	• High % recent and old immigrants • Low % married couples and recent movers	• High % old and MF buildings • Low % recent movers and % owners
Southern and Mountain (23)	• % Newcomers and newly built buildings • Relatively affordable housing prices	• Relatively high %kids and low %65+ • Low % single-mon households
Formerly Industrial (53)	• Large % NH-White and % African American • Affordable housing prices	• Low % immigrants, % Asian and PI, and % Hispanic
Florida Retirement (4)	• Large % 65+ and NH-White • High homeownership and recently built units	• High % vacancy • Mostly single-family homes
Inland Empire /TX Border (7)	• Large % Hispanic and single-mom HHs • High poverty and unemployment rates	• High % married couples and % kids • Mostly single-family homes

Classification of MSAs

Coastal and Tech

- Boston, MA
- San Francisco, CA
- San Diego, CA
- Seattle, WA
- Washington, DC

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Classification of MSAs

Large Immigrant Gateways

- New York, NY
- Los Angeles, CA
- Chicago, IL
- Miami, FL

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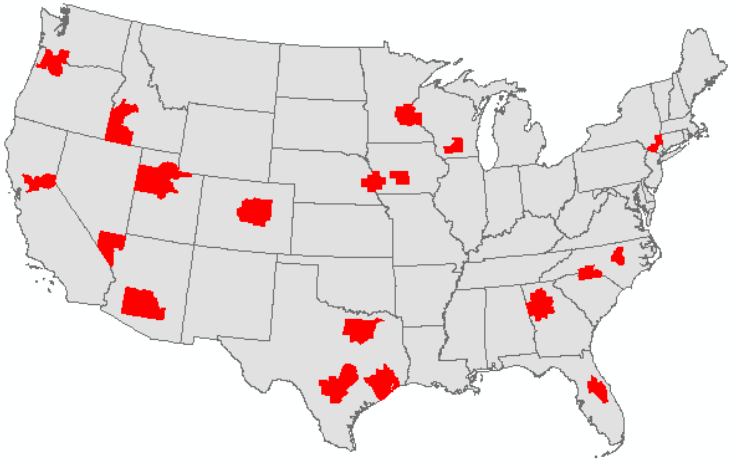

Southern and Mountain

- Atlanta, GA
- Dallas, TX
- Houston, TX
- Denver, CO
- Phoenix, AZ

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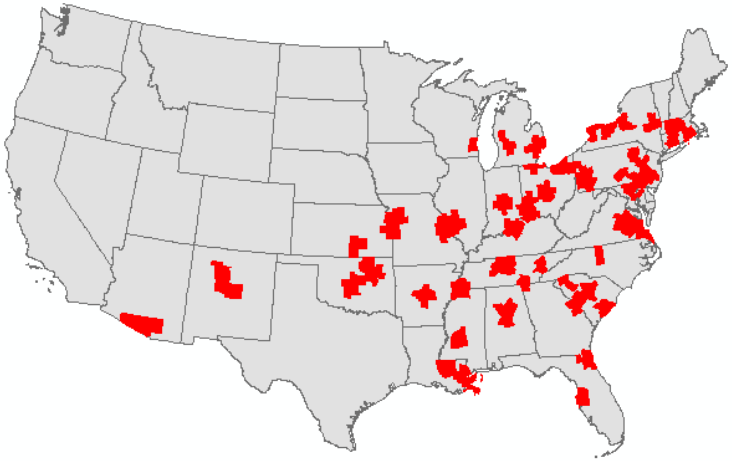

Formerly Industrial

- Philadelphia, PA
- Detroit, MI
- St. Louis, MO-IL
- Baltimore, MD
- Pittsburg, PA

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Classification of MSAs

Florida Retirement

- Cape Coral, FL
- Lakeland, FL
- North Port, FL
- Palm Bay, FL

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Inland Empire/TX Border

- Riverside, CA
- Fresno, CA
- Bakersfield, CA
- El Paso, TX
- McAllen, TX

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Method, Data, and Regression Results

Confidential American Community Survey

ACS Public-Use Microdata

- Demographic and socio-economic characteristics of households
  - Age, sex, race/ethnicity, education, marital status, income, household composition, etc.
  - Current residence (PUMA)

- Migration-related variables
  - Mobility status (lived here 1 year ago)
  - Previous residence (PUMA-level)

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Sample Selection

- 2011-2019 ACS 1-year microdata sample
- People 25 years old and over in the census tracts within gentrifiable tracts (urban and low-income neighborhoods)

Residential Mobility Decisions

Regression Model

$$y_{ijk,t+1} = \beta gentrifying_{jk} + \boldsymbol{\gamma X_{ijk,t}} + \boldsymbol{\delta N_{jk,2006-10}} + \sigma_k + \tau_t + \varepsilon_{ijk,t}$$

Dependent Variable

- Residential mobility outcome in year t+1 of individual person i who was in neighborhood j in MSA k in year t
  - 1 = move to different neighborhood
  - 0 = stayers and within neighborhood movers

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Gentrification Identifier Variable

- Gentrification dummy for a neighborhood j in MSA k
  - 1 = gentrifiable and gentrifying between 2010 and 2019
  - 0 = gentrifiable but not gentrifying between 2010 and 2019
- Non-gentrifiable neighborhoods were excluded from the sample

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Origin Neighborhood Characteristics in 2006–10

- Demographic and socio-economic characteristics of neighborhood j in MSA k before gentrification (i.e., 2006–2010)
- % racial/ethnic minority, % college grad+, median household income, median housing value, and median gross rent

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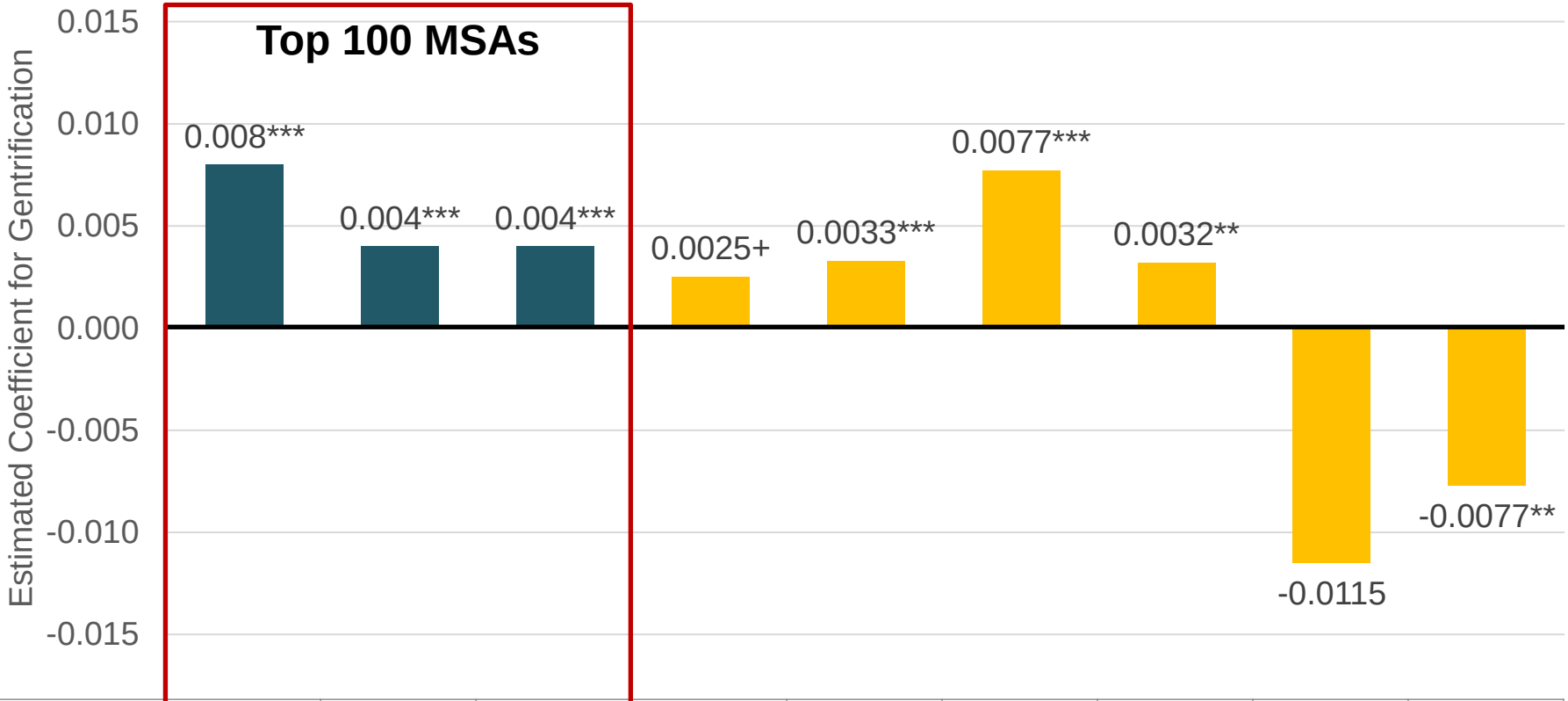
Metro (σ_k) and Year Fixed-Effects (τ_t)

Gentrification and Residential Mobility in the 2010s



	Base Model	Individual Char.	Full Model	Coastal and Tech	Immigrant Gateways	Southern & Mountain	Formerly Industrial	FL Retire-ment	CA IE /TX border
Ind Char.	X	O	O	O	O	O	O	O	O
Nbhd Char.	X	X	O	O	O	O	O	O	O
MSA FEs	O	O	O	O	O	O	O	O	O
Year FEs	O	O	O	O	O	O	O	O	O

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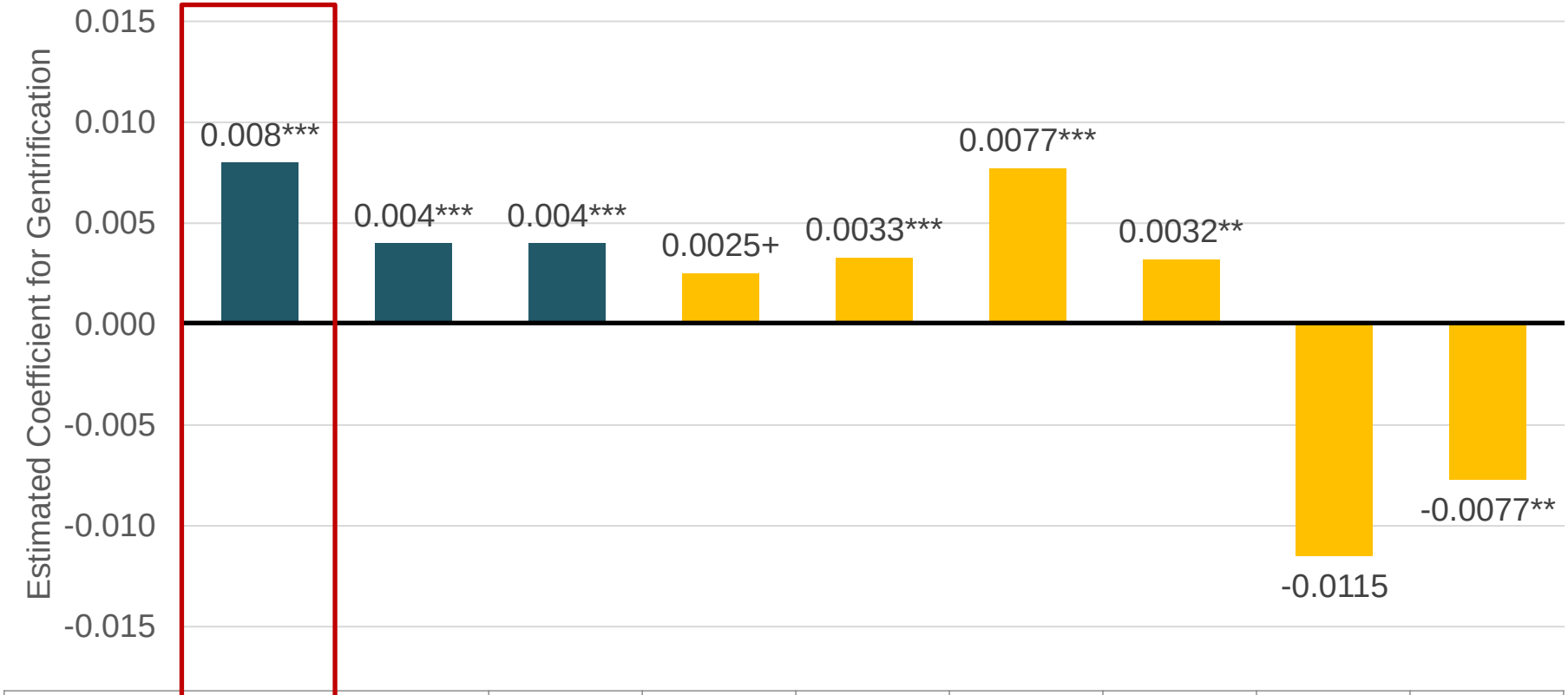
Gentrification and Residential Mobility in the 2010s



	Base Model	Individual Char.	Full Model	Coastal and Tech	Immigrant Gateways	Southern & Mountain	Formerly Industrial	FL Retire-ment	CA IE /TX border
Ind Char.	X	O	O	O	O	O	O	O	O
Nbhd Char.	X	X	O	O	O	O	O	O	O
MSA FEs	O	O	O	O	O	O	O	O	O
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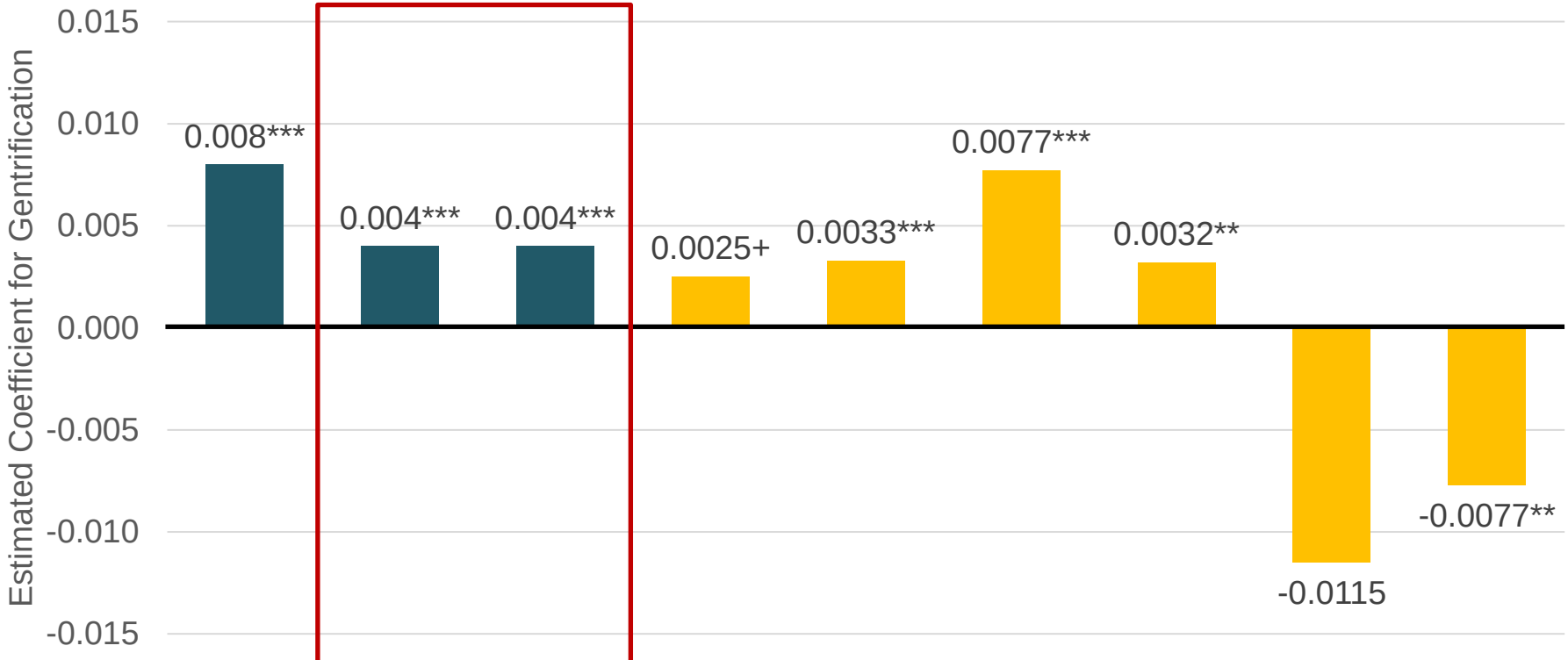

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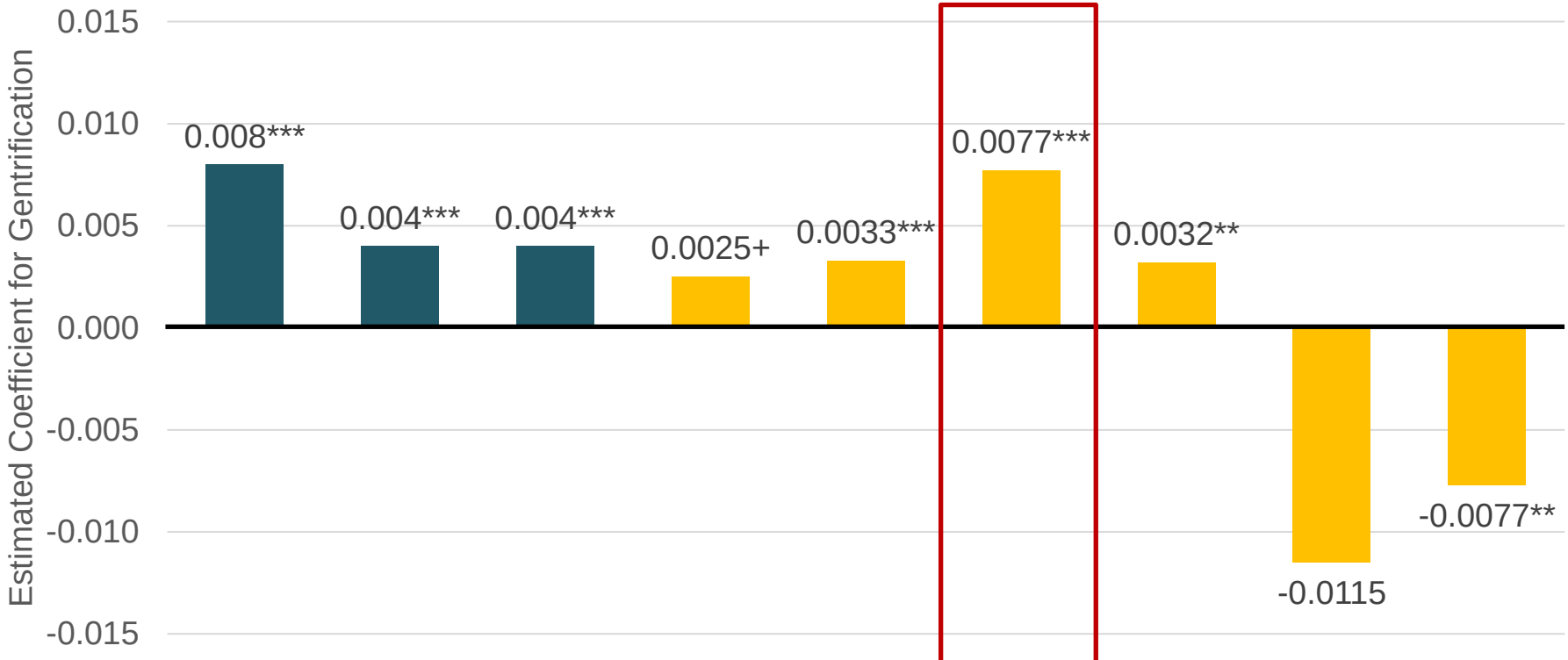

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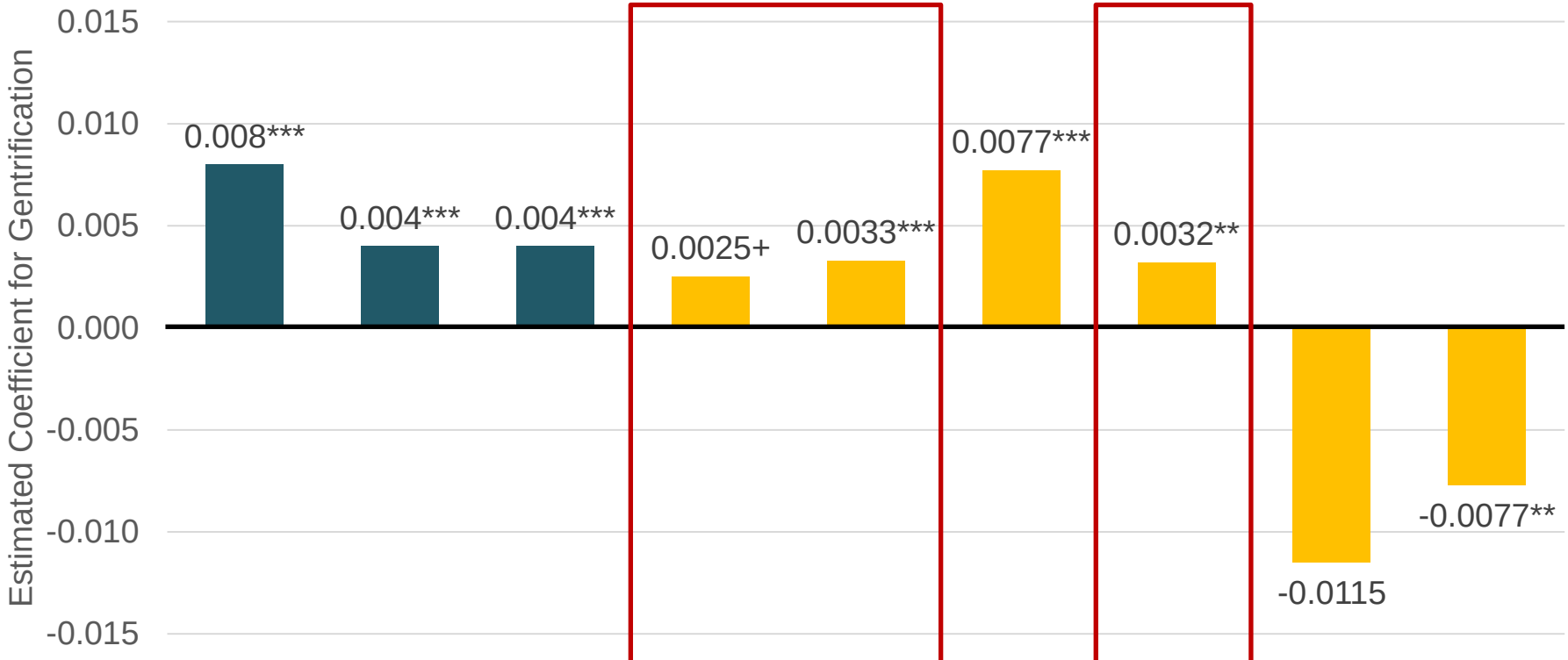

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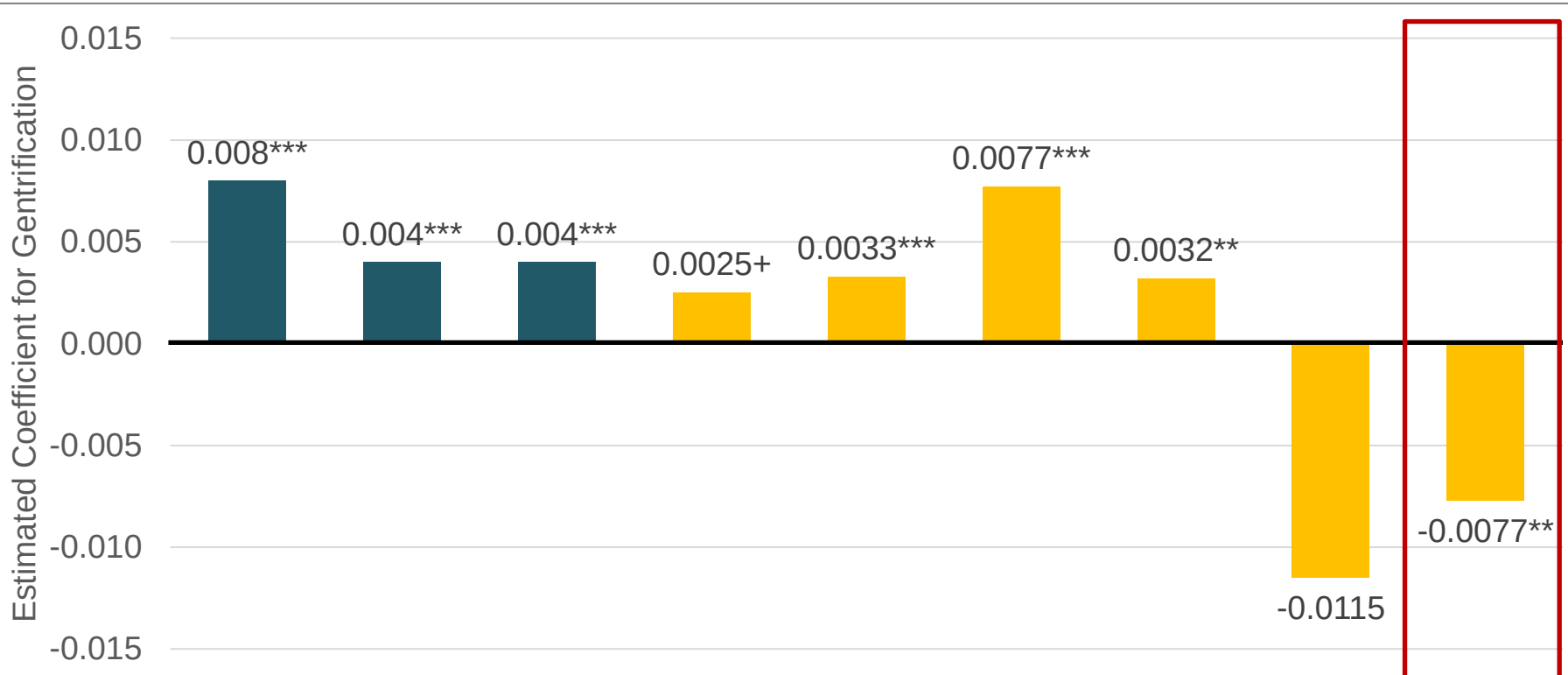

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Discussion and Next Steps

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- Gentrification as a mechanism connecting MSA characteristics to mobility outcomes
  - The process of neighborhood change, including gentrification, unfolds differently across different types of neighborhoods (Hwang and Sampson 2014; Owens 2012)
  - The between-city heterogeneity in neighborhood poverty has increased over time (Small, Manduca, and Johnston 2018)
  - Residential mobility is at least partially determined by metro-level characteristics (Crowder, Pais, and South 2012; South, Pais and Crowder 2011)

Discussion and Next Steps

… And what we have done since then

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Mobility rate (out of the neighborhood)

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Mobility rate (out of the neighborhood, out of the city, out of the MSA)

Destination neighborhood quality (%poverty, median household income)

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… so please stay tuned

Thank You | hyojunglee@vt.edu