Mapping Multidimensionality: Using Census Data to Understand Neighborhood Communities

Quantitative Histories Workshop

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Abstract

We explore how multidimensional measures of local communities – such as those provided by the Census Community Resilience Estimates (CRE) – can be used to frame and model dynamic changes in neighborhood communities using an intersectional lens.

We build on prior research inspired by work exploring nuances in the diversity of the United States as a "Patchwork Nation."

Quantitative Histories Workshop

`curriculum & software development collective`

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How have histories of segregation and isolation informed education, health, and political outcomes?

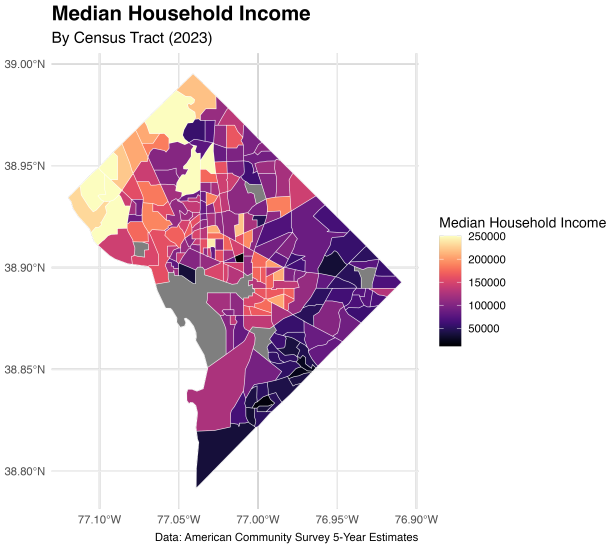
- Racial segregation
- Economic segregation
- Dynamic features of isolation

A History of Dividing Walls

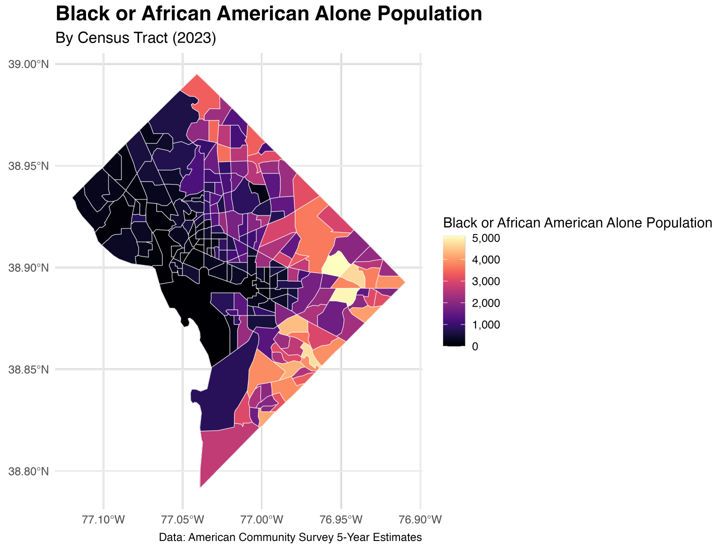
There are dynamic and complex historical structures that have segregated individuals based on a host of factors.

- Legacies of Jim Crow (e.g., highways)
- Redlining
- Gerrymandering
- Gentrification

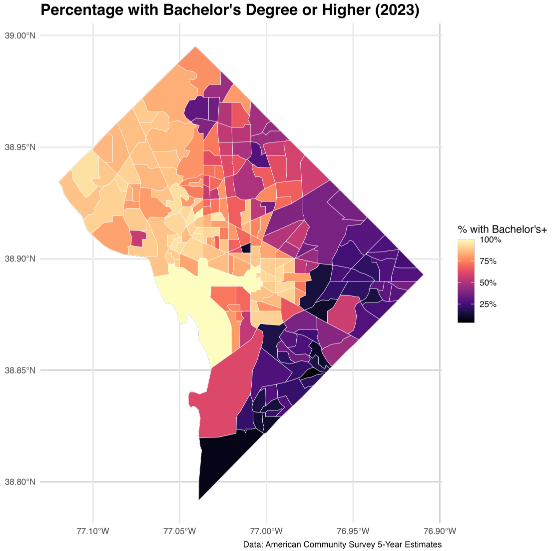
Single Dimension - Income



Single Dimension - Race



Single Dimension - Education



Considering Multiple Dimensions

How might we analyze the multidimensional patchwork of a city's fabric while retaining critical insights from theorists that challenge monolithic narratives of any single group?

Theoretical framework: A Patchwork Nation

"*If you pay attention to the complexity of the USA, its diversity and differences you soon realize that the ways we try to understand it – red and blue, Northeast and Midwest – are too simplistic. They are inadequate and misleading.*" -Patchwork Nation Project

Details of community types (national-level)

- **Boom Towns**: Rapidly “expanding” communities
- **Campus and Careers**: Areas with a significant presence of higher education institutions
- **Immigration Nation**: Areas with high concentrations of immigrant populations
- **Industrial Metropolis**: Large urban areas with a strong industrial base
- **Emptying Nests**: Communities with an aging population
- **Minority Central**: Areas with large minority populations
- **Monied Burbs**: Affluent suburban areas

Analytic Framework: Theory of Dividing Walls (city-level)

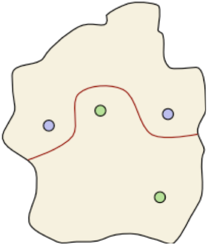
Consider a neighborhood as an “island” containing towns — the green tribe in two of the towns and the blue tribe in the other two.

Analytic framework

Using topology (mathematics) and topography (geology), we can formalize our analysis by attaching a few requirements:

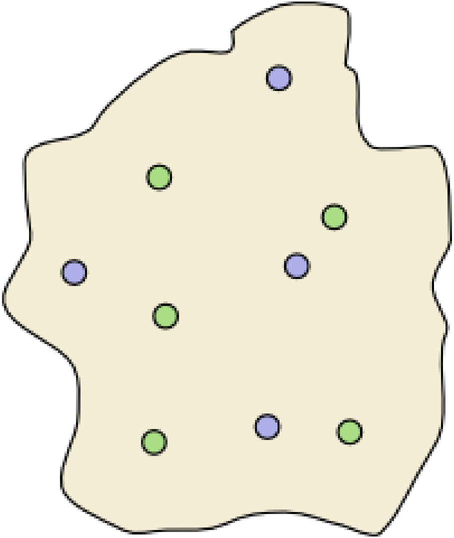
- The wall must be continuous, it must not intersect itself, it must not split, it must not pass through a town, and each end of the wall must be at the coast.
- Let us call such a wall a dividing wall.

Dividing Walls Theorem

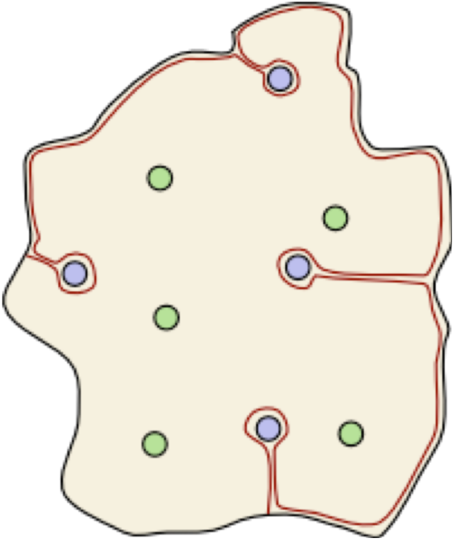


Theorem 1. Given any configuration of blue and green towns, there is a dividing wall that separates blue towns from green towns.

Is there a dividing wall?



A Dividing Wall



Measurement Model: Dissimilarity Index

$$D = \sum_{i=1}^{n} \left| \frac{b_i}{B} - \frac{w_i}{W} \right|$$

Where:

- b_i = Black population in tract i
- B = Total Black population in city
- w_i = non-Black population in tract i
- W = non-Black population in city

This census data model, however, only provides a single dimension of a neighborhood.

Community Resilience Estimates

- The CRE are a measure of the capacity of individuals and households within a community to absorb, endure, and recover from external stresses.
- The CRE data combine American Community Survey (ACS) and the Population Estimates Program (PEP) data to identify social and economic vulnerabilities by geography.
- There is a nice CRE Interactive Tool that allows for a quick overview of local contexts.

```r
cre_correlates_dc <- get_acs(
  geography = "tract", state = "DC",
  year = 2023, survey = "acs5",
  variables = c(
    median_income = "B19013_001",
    poverty_rate = "B17001_002",
    unemployment_rate = "B23025_005",
    no_health_insurance = "B27010_033",
    educ_less_than_hs = "B15003_002",
    median_age = "B01002_001",
    housing_cost_burden = "B25070_010",
    no_vehicle = "B08201_002",
    black_population = "B02001_003",
    median_rent = "B25058_001"),
  summary_var = "B02001_001",
  output = "wide", geometry = FALSE)
```

Spatial Model

– Base spatial model formulation:

$$\mathbf{y} = X\beta + \tau + \epsilon$$

- y is a n x 1 response vector
- X is a design matrix that contains explanatory variables
- β represents fixed effects coefficients
- τ denotes spatially dependent random errors
- ϵ represents independent random errors

Dimensionality in Spatial Models

Response vector structure ($\mathbf{y}$):

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

- Each element, y_i, represents the observed response at a neighborhood's location i
- These are ordered by adjacency relationships to preserve the geographical context
- Review of distributions, spatial autocorrelation (i.e., $Cov(y_i, y_j)$), and decomposition

Dimensionality in Spatial Models

Design matrix of explanatory variables structure (X):

$$X = \begin{bmatrix} 1 & x_{1,1} & \dots & x_{1,p} \\ 1 & x_{2,1} & \dots & x_{2,p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n,1} & \dots & x_{n,p} \end{bmatrix}$$

- First column is the intercept term
- Subsequent columns represent p explanatory variables
- Each row corresponds to a specific neighborhood's covariates

Dimensionality in Spatial Models

Sample design matrix of explanatory variables

$$X = \begin{bmatrix} 1 & 65,000 & 0.62 & 3,200 \\ 1 & 28,000 & 0.32 & 5,100 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 127,000 & 0.75 & 6,840 \end{bmatrix}$$

- Column 1 is the $E(\mathbf{y})$ when all other predictors are zero
- Variable 1 (col 2) as median income
- Variable 2 (col 3) as proportion of residents with HS diploma
- Variable 3 (col 4) as population density (residents/sq. mi)

Next steps: Information and spatial segregation

There are multiple models for consideration:

- Spatial regression using intersectional interactions
- Structural Equation Modeling (SEM) with CRE components
- Multilevel Analysis of Individual Heterogeneity and Discriminatory Analysis (MAIHDA)
  - Evans et al. (2024). A Tutorial for Conducting MAIHDA. *Population Health*, Vol. 26, 101664
  - Combines intersectional stratification with neighborhood-level clustering
  - Models individuals nested within: Intersectional strata (e.g., low-income Black men), community typologies from framework (e.g., Patchwork Nation) classifications

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References

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U.S. Census Bureau. (2024). Community Resilience Estimates. Retrieved March 26, 2025, from https://www.census.gov/programs-surveys/community-resilience-estimates/about.html.