Sidestepping the box: Designing a supplemental poverty indicator for school neighborhoods

Doug Geverdt  
National Center for Education Statistics

Laura Nixon  
U.S. Census Bureau

2018 Annual meeting of the Federal Committee on Statistical Methodology  
March 9, 2018 Washington, DC

This presentation is intended to encourage discussion and to inform interested parties of current research. The views expressed are solely those of the authors and are not necessarily those of the National Center for Education Statistics or the U.S. Census Bureau.
Poverty Data

• Poverty impacts a variety of educational outcomes
• Poverty data needed for programs - 1974 ESEA (Title I)
• Problem: Level of importance < > available indicators
• Common sources for educational programs:
  – School district Title I estimates (Census Bureau)
  – Title I school indicator (NCES-CCD)
  – National School Lunch Program (USDA/FNS; NCES-CCD)
NSLP program data

• Standard measure for school poverty (and SES proxy)

• Lunch data has many benefits for research/administration:
  – Near universal participation by school systems
  – Stable program infrastructure; regularly updated and accessible
  – Cost-effective (for education purposes)

• Lunch data also has limitations

• Community Eligibility Provision (CEP) and 100% eligibility

• We need multiple measures of poverty in/around schools
Neighborhood proxies in educational research

• How to define? How to operationalize?
• Source for all: American Community Survey (ACS)
• Census block groups, tracts, ZCTAs (ZIP)
• School districts
• Conclusions:
  – Proxies selected based on whether data are available
  – Proxies may provide a poor match (lack of construct validity)
  – Proxies pose difficulties for detecting neighborhood effects
Proposed solution: What if we...

- Re-frame problem to focus on point locations instead of polygons
- Use spatial statistics with ACS to create interpolated poverty surface
- Define neighborhoods as a set of neighbors nearest to schools
- Join school point locations to poverty surface to create estimates
- Result = poverty estimate for school neighborhoods
- Spatially interpolated demographic estimates (SIDE)
Linking outside the box

Estimates for non-sampled locations based on nearest neighbors instead of a default geographic container.

Traditional

ACS sample household

Predicted location (School)

Census Tract (or other geography)
Case Study Prototype

- Elementary schools in Ohio (n=1,793)
- ACS households from 5-year sample (2009-2013)
- Census block centroids for household locations (TIGER 2013)
- Model the income-to-poverty ratio (IPR)
- Empirical Bayesian kriging for estimation (ESRI)
- Neighborhoods based on 25 nearest neighbors
- School locations from NCES (2012-2013)
Kriging

- Least squares interpolator that uses the weighted sum of values from measured locations to predict values in unmeasured locations. The closer the location, the greater the weight. (Cressie, 1993)

- Based on Tobler’s first law of geography

- Kriging assumes data are spatially autocorrelated

- Kriging uses the data twice:
  - Modeled with a semivariogram to identify how differences vary by distance.
  - Applied to the data to predict values for unsampled locations

- Results in a continuous prediction surface across study region
Example: Poverty Surface

Source: American Community Survey (2009-2013)
Results

1. Estimates for household type by race followed the same pattern as general poverty estimates. No surprises.

2. Physical extent of SIDE neighborhoods tended to be smaller than census tracts, and estimates had a consistent sample size.

3. SIDE statistical prediction surface provided a more nuanced representation of school location vs. tract-level estimates.

4. Correlated with school lunch data ($r = -.46$)

5. Production was feasible (our server survived!)

6. SIDE estimates satisfied Census disclosure requirements
Potential benefits of SIDE IPR

• Leverage existing data sources (thus cost-effective)
• Provide a new covariate to help control for SES
• Create new poverty option for small areas (address-level)
• Avoid disclosure concern for small areas through modeling
• Avoid impact of boundary changes
• Identify mismatch between school and student neighborhoods
Potential benefits of SIDE IPR

- Leverage existing data sources (thus cost-effective)
- Provide a new covariate to help control for SES
- Create new poverty option for small areas (address-level)
- Avoid disclosure concern for small areas through modeling
- Avoid impact of boundary changes
- Identify mismatch between school and student neighborhoods
- Offer potential public SIDE IPR layer to create IPR estimates for other addresses or locations
Next steps

- R&D report – rationale and details of case study
- Experimental file of IPR estimates for all public schools
- Explore additional covariates
- Continue working on SIDE raster data product
- Explore potential internal applications for NCES programs.
- Gather feedback
Questions?

Doug Geverdt
National Center for Education Statistics
douglas.geverdt@ed.gov

Laura Nixon
U.S. Census Bureau

2018 Annual meeting of the Federal Committee on Statistical Methodology
March 9, 2018 Washington, DC

This presentation is intended to encourage discussion and to inform interested parties of current research. The views expressed are solely those of the authors and are not necessarily those of the National Center for Education Statistics or the U.S. Census Bureau.