

Education Demographic and Geographic Estimates (EDGE) Program

Sidestepping the Box:
Designing a Supplemental Poverty Indicator
for School Neighborhoods

Education Demographic and Geographic Estimates (EDGE) Program

Sidestepping the Box: Designing a Supplemental Poverty Indicator for School Neighborhoods

NOVEMBER 2018

Doug Geverdt
National Center for Education Statistics

Laura Nixon
U.S. Census Bureau

NCES 2017-039
U.S. DEPARTMENT OF EDUCATION



U.S. Department of Education

Betsy DeVos
Secretary of Education

Institute of Education Sciences

Mark Schneider
Director

National Center for Education Statistics

James L. Woodworth
Commissioner

Administrative Data Division

Ross Santy
Associate Commissioner

The National Center for Education Statistics (NCES) is the primary federal entity for collecting, analyzing, and reporting data related to education in the United States and other nations. It fulfills a congressional mandate to collect, collate, analyze, and report full and complete statistics on the condition of education in the United States; conduct and publish reports and specialized analyses of the meaning and significance of such statistics; assist state and local education agencies in improving their statistical systems; and review and report on education activities in foreign countries.

NCES activities are designed to address high-priority education data needs; provide consistent, reliable, complete, and accurate indicators of education status and trends; and report timely, useful, and high-quality data to the U.S. Department of Education, the Congress, the states, other education policymakers, practitioners, data users, and the general public. Unless specifically noted, all information contained herein is in the public domain.

We strive to make our products available in a variety of formats and in language that is appropriate to a variety of audiences. You, as our customer, are the best judge of our success in communicating information effectively. If you have any comments or suggestions about this or any other NCES product or report, we would like to hear from you. Please direct your comments to

NCES, IES, U.S. Department of Education
Potomac Center Plaza
550 12th Street SW
Washington, DC 20202

November 2018

The NCES Home Page address is <http://nces.ed.gov>.

The NCES Publications and Products address is <http://nces.ed.gov/pubsearch>.

This publication is only available online. To download, view, and print the report as a PDF file, go to the NCES Publications and Products address shown above.

Mention of trade names, commercial products, or organizations does not imply endorsement by the U.S. Government.

Suggested Citation

Geverdt, D., & Nixon, L. (2018). *Sidestepping the Box: Designing a Supplemental Poverty Indicator for School Neighborhoods* (NCES 2017-039). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved [date] from <http://nces.ed.gov/pubsearch/>.

Content Contact

Doug Geverdt
(202) 245-8230
Douglas.Geverdt@ed.gov

Foreword

The Research and Development (R&D) series of reports at the National Center for Education Statistics (NCES) has been initiated to

- share studies and research that are developmental in nature. The results of such studies may be revised as the work continues and additional data become available;
- share the results of studies that are, to some extent, the “cutting edge” of methodological developments. Emerging analytical approaches and new computer software development often permit new and sometimes controversial analyses to be done. By participating in “frontier research,” we hope to contribute to the resolution of issues and improved analyses; and
- participate in discussions of emerging issues of interest to education researchers, statisticians, and the federal statistical community in general. Such reports may document workshops and symposia sponsored by NCES that address methodological and analytical issues or may share and discuss issues regarding NCES practices, procedures, and standards.

The common theme in all three goals is that these reports present results or discussions that do not reach definitive conclusions at this point in time, either because the data are tentative, the methodology is new and developing, or the topic is one on which there are divergent views. Therefore, the techniques and inferences made from the data are tentative and subject to revision. To facilitate the process of closure on the issues, we invite comment, criticism, and alternatives to what we have done. Such responses should be directed to

Marilyn Seastrom
Chief Statistician
Statistical Standards Program
National Center for Education Statistics
Institute of Education Sciences
550 12th Street SW
Washington, DC 20202

Contents

	Page
Abstract	1
Introduction	1
Limitations of existing school poverty indicators	1
Limitations of existing neighborhood poverty indicators	4
Proposal	7
Estimating a regional poverty surface	9
Resulting strategy	12
Case study: Creating a SIDE-based neighborhood poverty indicator for NAEP assessments	13
Case study data	16
Model development	17
Results	19
Conclusions	25
Recommendations	28
References	31

List of Tables

	Page
Table 1. Percent of ZCTAs that satisfy Census Bureau disclosure rules by analytic group	14
Table 2. Cross validation results	19
Table 3. Income to poverty ratio for school neighborhoods by analytic group	20
Table 4. Neighborhood size	21

List of Figures

	Page
Figure 1: Empirical semivariogram model	11
Figure 2: Income-to-poverty ratio SIDE geostatistical surface: Columbus, OH	23
Figure 3: Median household income for census tracts: Columbus, OH	24

Abstract

School and neighborhood poverty indicators are a familiar feature in educational research, but the scope and specificity of available indicators is limited. As a result, researchers frequently rely on data from proxy neighborhood geographies out of operational necessity rather than analytic choice. This study examines common constraints of neighborhood data used for educational research and proposes the use of school-centered neighborhood poverty estimates based on data from the U.S. Census Bureau's American Community Survey (ACS) and estimation techniques borrowed from spatial statistics. This study tested the feasibility of producing the proposed indicator by developing neighborhood poverty estimates for 1,793 Ohio elementary schools. Initial results suggest that the proposed indicator may provide a useful supplement to existing school-level poverty indicators and offer additional clarity about economic conditions in neighborhoods where schools are located.

Introduction

The impact of poverty on student achievement, educational attainment, and other educational outcomes has been a concern for educators and federal policymakers since the passage of the Elementary and Secondary Education Act (ESEA) in 1965. Educational programs like Title I, Head Start, Promise Neighborhoods, E-Rate, and the National School Lunch Program (NSLP) target federal resources to help mitigate the effects of poverty on low-income students, families, and neighborhoods. These federal resources are combined with equally substantial investments at the state and local level, along with numerous compensatory programs sponsored by philanthropic foundations, religious institutions, and other concerned citizens. Although federal, state, and local education programs focus billions of dollars each year to improve educational opportunities for children in low-income schools and neighborhoods, the information available to identify and target high-need areas is limited. Most compensatory education programs use some type of poverty indicator to determine program eligibility and/or funding levels, but the development and accessibility of poverty data has not kept pace with the needs of these programs. The existing poverty thresholds do not fully reflect nonfood expenses needed to maintain household well-being, and they do not fully account for noncash in-kind benefits provided to individuals and families participating in federal need-based initiatives like the Supplemental Nutritional Assistance Program (SNAP) or the Women, Infants, and Children program (Citro and Michael 1995). Nor do they reflect important interactions between poverty status and other attributes like occupational prestige and educational attainment. More importantly, the structure and accessibility of poverty data is too limited. Carefully constructed measures of socioeconomic status (SES) provide little benefit if the resulting data are not available at the necessary geographic scale or for required analytic areas.

The purpose of this study was to develop a flexible neighborhood poverty indicator that could help educational programs identify schools located in low-income communities. This paper reviews the need for supplemental poverty data, investigates key constraints to data access, examines design issues and spatial statistical techniques, and discusses the results of a case study that produced a new neighborhood poverty indicator for a set of elementary schools in Ohio. The analysis concludes with an assessment of the proposed indicator and recommendations for future research and development.

Limitations of existing school poverty indicators

Official poverty thresholds and guidelines

The poverty thresholds widely used as statistical indicators in educational programs were originally developed by the Social Security Administration in 1964 based on data from the U.S. Department of Agriculture (USDA) about food expenditures needed to maintain basic levels of household nutrition

(Orshansky 1965). The thresholds were adjusted and expanded to reflect the needs of households of different sizes and structures and were officially adopted for federal statistical purposes in 1969. The poverty thresholds were incorporated into ESEA for Title I purposes in 1974 and their use as an educational program criterion has expanded ever since (Education Amendments of 1974; U.S. Department of Health, Education, and Welfare 1976). Although the poverty thresholds do not account for geographic differences in the cost of living, they are annually adjusted for inflation based on changes in the Consumer Price Index (Procter, Smega, and Kollar 2016).

The official poverty thresholds are developed each year by the U.S. Census Bureau based on updated family income reported in the Current Population Survey. The Department of Health and Human Services (HHS) creates a separate set of annually updated poverty *guidelines* (using approximations based on prior-year poverty thresholds) that are released about seven months earlier than the Census Bureau's poverty threshold to help support HHS program planning. Although the Census Bureau's poverty thresholds are the official national poverty rates and are used to construct the poverty guidelines, other federal programs (e.g., USDA's National School Lunch Program) have adopted the simplified HHS poverty guidelines as an administrative and budgeting convenience.

District-level and school-level indicators

Educational programs rely on a variety of indicators to assess student and community needs, but the following data sources are most common:

Census Bureau School District Poverty Estimates

The U.S. Census Bureau provides the Department of Education (ED) with annually updated school district poverty estimates to support the allocation of Title I basic grants and concentration grants. These data are developed by the Census Bureau's Small Area Income and Poverty Estimates program and include estimates of the number of grade-relevant related children ages 5 – 17 in families below the poverty level. The American Community Survey (ACS) also provides direct estimates of the Title I poverty universe and other poverty universes as part of the Census Bureau's standard ACS data products and through custom tabulations developed for the National Center for Educational Statistics (NCES) Education Demographic and Geographic Estimates (EDGE) program.

Although district-level poverty estimates provide the fundamental input for Title I program allocations, estimates based on district-level economic conditions may mask important variations within school districts in household income at the neighborhood or school level. Therefore, in addition to being cautious about the data quality of district-level poverty estimates, data users must also be careful of committing ecological fallacies by assuming that district-level poverty indicators are a reasonable representation for the conditions of individual schools or households within a district.

Title I school

The NCES Common Core of Data (CCD) provides school-level indicators that identify whether a school qualifies for Title I Targeted Assistance (TA) and whether it provides a TA program. The CCD also provides indicators to identify whether a school is eligible for a school-wide program (SWP) and whether a SWP is offered (U.S. Department of Education 2016). Whereas TA funding is intended to target resources to specific high-need students within schools, SWP funding provides flexibility to offer programs and resources to all students in schools that have at least 40 percent of its students from low-income families. These binary indicators provide limited information, but offer a basic way of screening for schools with potentially high concentrations of low-income students.

School Attendance Boundary Survey (SABS) tabulations

The NCES School Attendance Boundary Survey (SABS) was an experimental project to collect school attendance boundaries (also known as school catchment zones) that are designed and used by local school systems, along with student assignment policies, to assign children to local schools. The primary focus of the SABS experiment was to collect and publish geographic boundaries of school areas. A secondary focus of the SABS experiment was to integrate school attendance boundaries with data from the ACS to develop demographic estimates for individual school areas. Although the mechanics of creating school-level ACS poverty estimates proved possible, the average quality for these small geographic areas was too unreliable for NCES to create and release as a regular public data product. Additionally, the school areas were only updated biennially, and schools with open enrollment policies may not have neighborhood-level boundaries.

NSLP program counts (Free and reduced-price lunch)

The most common poverty indicator used for educational programs is the count of students eligible for a free or reduced-price lunch under the USDA's National School Lunch Program (NSLP). Students with a documented household income less than 130% of the poverty guidelines qualify for free lunch, and those between 130%-185% qualify for reduced-price lunch. Students who live in a household with a member who qualifies for other select federal means-tested programs like SNAP or Temporary Assistance for Needy Families (TANF) are categorically eligible for free lunch (U.S. Department of Agriculture 2016).

Although educational programs tend to use the NSLP lunch counts as a standard indicator for identifying school-level poverty, the administrative data have a variety of shortcomings. Validation studies of the NSLP applications found that one out of every five students were inaccurately deemed eligible or ineligible for meal benefits, and the certification error most often identified students who did not meet the qualifications as eligible for free lunch (Ponza et al. 2007). Studies have also found that the stigma of program participation leads to systematic underrepresentation of low-income students at higher grade levels (Glantz et al. 1994; Mirtcheva and Powell 2009). Not surprisingly, different schools also use different incentives and place different priorities on the collection of student eligibility documentation, which can lead to systematic differences in school-level participation.

In addition to these data quality concerns, the NSLP recently initiated the Community Eligibility Provision (CEP) that complicates the use of the lunch data for educational programs. The CEP allows schools with high concentrations of low-income students to bypass the task of collecting required eligibility documentation from students in exchange for providing a free lunch to all students in the school. Schools and Local Education Agencies (LEAs) that opt for CEP are reimbursed by the NSLP program based on the number of students who are directly certified for free lunch as a result of having someone in their household participating in other federally recognized means-tested programs. Because these automated checks of state-level databases are relatively quick and cost-effective, the CEP is an increasingly appealing option for schools, students, and NSLP program administrators (Healthy, Hunger-Free Kids Act of 2010). Unfortunately, the CEP inflates the number of participating students in the standard educational program data, and high-poverty schools that previously had a high rate of participation may now report an even higher rate (100%). Additionally, the adoption of CEP at the school level erodes the ability of educational surveys to identify free and reduced-price lunch status for individual students.

Despite these limitations and data quality issues, the NSLP free and reduced-price lunch counts continue to serve as the standard for identifying school-level poverty for educational programs and surveys

because they satisfy core conditions needed to serve as a useful program indicator (Harwell and LeBeau 2010). These include:

1. Universal participation—Almost all schools and school districts participate in NSLP. Therefore, the lunch data provide the necessary coverage needed for general comparisons within and between districts and states.
2. Uniform criteria—The NSLP relies on a measure of poverty used by other federal programs, and the processes for administering NSLP are codified in statute, regulations, and agency guidance. This contributes to the validity and reliability of the data and – when combined with near universal participation – helps to make the data more comparable across schools and districts.
3. Regular updates—NSLP requires annual verification of household income or verification of household eligibility for other federal programs, so the lunch data are updated each academic year. These regular updates provide a data series that allow for analysis of change over time.
4. Stable infrastructure—The NSLP is a well-funded, nondiscretionary, statutory program with a long history, substantial political support, and a broad constituency. As a result, educational policymakers and program administrators can confidently rely on the NSLP data for other educational program purposes.
5. Flexible application—NSLP lunch counts have been used as student-level, school-level, and district level indicators by educational surveys and programs. This flexibility and comparability at different scales makes them highly useful for a broad range of analytic activities.
6. Easy access—State departments of education publicly report annually updated school-level and district-level lunch counts, and NCES regularly posts national-level compilations of the lunch data as part of its administrative data collection for schools and LEAs. As a result, the NSLP school poverty indicator is easily accessible and widely available.
7. Cost-effective development—The cost of collecting new data from all schools in the U.S. to create a new school-level poverty indicator would be prohibitive, and it would require new statutory authority and substantial new program funding to implement. Instead, compiling and repurposing existing data is a convenient and cost-effective solution.

Limitations of existing neighborhood poverty indicators

Why neighborhood?

Researchers have given considerable attention to the ways that neighborhoods affect educational outcomes for students, as well as the impact that neighborhoods have on the climate and efficacy of schools. Whether the focus is poverty, violence, joblessness, health, or exposure to various other social ills or amenities, place-based investigations suggest that neighborhood conditions affect the expectations, aspirations, and outcomes of students and schools (Brooks-Gunn et al. 1993; Carlson and Cowen 2015; Connell and Halpern-Felsher 1997; Massey 2001; Massey and Denton 1993; Small 2006; Small, Jacobs, and Massengill 2008; Wilson 1987; Zenk et al. 2005). But there is also a well-established perspective of envisioning schools as institutions that help to change or preserve the social order, as institutions with the potential to impact or transform communities, and as institutions with a mandate to serve the neighborhoods around them (Counts 1932; Dewey 1915; Silverman 2014; Taylor, McGlynn, and Luter 2014). Unlike the neighborhood effects framework that identifies students and schools as the recipients of neighborhood influences, this alternate model posits schools as causal agents that

independently affect communities. They impact housing values; they serve as polling stations; they offer common space for civic events; they provide subsidized lunches to poor children; they initiate community outreach and educational opportunities; and they instruct and encourage students to apply their education outside the classroom. If schools did not impact communities, school closures and redistricting would not be such contentious events.

Schools and neighborhoods are symbiotic. Although the nature of this inter-relationship is complex and the direction and magnitude of the influences on each other are often unclear, there is general consensus that schools should not be examined in isolation. Neighborhoods matter for schools. And because they matter, researchers and administrators need to be mindful about how they define and measure these areas. Not simply the social or economic conditions that occur in neighborhoods, but the physical extent of the area itself.

What is a neighborhood?

Despite familiarity with the concept of neighborhood, there is little agreement as to how neighborhoods should be defined. This is partly because the concept involves a blend of social and spatial dimensions (Furstenberg and Hughes 1997; Galster 2001; Lee, Oropesa, and Kanan 1994). Neighborhoods are locations or spaces where social interactions occur, but the extent of the space and the nature of those interactions tend to defy operational consensus. Research examining the perception and delineation of neighborhoods suggests that these areas are not fixed geographies, but instead are highly individualized (Andersson and Malmberg 2015; Campbell et al. 2009; Coulton et al. 2001; Galster 2001; Lee, Oropesa, and Kanan 1994; Nicotera 2007; Raudenbush and Sampson 1999). Two people living in the same location may define the physical extent of their neighborhood differently. Suffice it to say, this inconsistency creates challenges for research and comparability.

The problem of defining and operationalizing neighborhood geography is further complicated by the availability (or lack) of data about social or economic conditions for the neighborhood unit researchers wish to study. For example, if researchers want to look at variation in the spatial distribution of poverty across neighborhoods, they not only need to define a common unit for neighborhood geography, they also have to ensure that poverty estimates are available for the proposed units. Unfortunately, this dependency often leads researchers to use proxy geographies based on operational convenience, rather than more meaningful units or definitions that may better fit analytic contexts (Hipp 2007; McWayne et al. 2007; Riva et al. 2008, Sampson, Morenoff, and Gannon-Rowley 2002). Because the Census Bureau's American Community Survey (ACS) is the only large-scale household survey that systematically measures poverty for small geographic areas throughout the U.S. and the ACS only publishes poverty estimates for limited types of small areas, the geographic options for systematically studying neighborhood poverty are limited.

Common neighborhood proxies

Census blocks

Census blocks are the smallest unit of geography that the Census Bureau uses to publish population characteristics, but the information available at the block level is limited to basic counts of population by age, race, sex, and household structure collected in the decennial census. The original concept was modeled after a city block, and the size of census blocks can vary from zero to several hundred people. More detailed information about the social, economic, and housing characteristics (i.e., the kinds of conditions that tend to be of interest for educational researchers and program administrators) are collected as part of the ACS sample survey and are only published for larger geographic areas.

Census block groups

Block groups (BG) are groups of census blocks that generally range from 300 to 6,000 people, with an average of about 1,500. The Census Bureau delineated more than 217,000 BGs for 2010 census operations. BGs are appealing to researchers because they are the smallest unit of geography for which data from the ACS are published. However, ACS BG data have three key features that limit their use for educational research. First, not all ACS characteristics are available at the BG level because the Census Bureau intentionally limits publication of some characteristics to avoid disclosing the identification of survey respondents. Second, estimates at the BG level tend to have large sampling errors and therefore are difficult to use for program purposes where a high degree of reliability is required. Third, BGs are statistical geographies primarily designed to support Census Bureau survey operations and data publication. They are not systematically designed to achieve social or demographic homogeneity, and they are not designed to reflect pre-existing neighborhoods. In fact, they can potentially misrepresent neighborhood boundaries that may have a high degree of local consensus.

Census tracts

Census tracts are clusters of block groups that generally include between 1,200 to 8,000 people, with an average of about 4,000. The physical size of 2010 tracts ranged considerably from hundreds of square miles to less than 1/10th of a square mile, with the median size about 1.86 square miles. Unlike the limitations imposed on block groups, all ACS characteristics are published at the tract level. Although tracts are larger than BGs and generally contain more ACS sample cases, the sampling error associated with tract-level estimates can still be quite high (Folch, et al. 2016; Spielman, Folch, and Nagle 2014). Like BGs, census tracts are statistical geographies that are primarily constructed to support the needs of survey operations. They are not systematically constructed to reflect neighborhood boundaries or to provide socially or economically homogeneous areas. Unlike BGs, the Census Bureau takes additional steps to support the stability of tract boundaries over time as a means of helping to provide comparable demographic data over time. This would be a useful feature if tract boundaries were good proxies for neighborhood boundaries, but – like BGs – tracts are geographies of convenience (Riva et al. 2008). The general rationale for using them in educational research is because the ACS (or decennial censuses prior to 2010) is the only source for the needed demographic data, it provides the necessary data at the tract level, and tracts are relatively small. As a result, tracts are often adopted as neighborhood proxies.

School zones and school districts

School boundaries are sometimes considered as neighborhood proxies because they are geographically bounded and often provide a shared social and functional relevance for households served within the school attendance area (Jencks and Mayer 1990; Perry 1929). Although the geographic properties of school attendance boundaries may be more useful than general statistical geographies like BGs and tracts, school boundaries are not routinely collected as part of a pre-existing program and would require substantial new program funding to provide annual updates. As noted earlier, the quality of school-level poverty estimates is not sufficient to support and justify large-scale, systematic collection, and increasing experimentation with school-choice arrangements makes the reliability of school-level boundaries less clear.

School district boundaries share some of the functional attributes of schools, but the spatial structure of school districts varies considerably throughout the U.S., making the unit untenable for use as a neighborhood proxy. District geography may work reasonably well for a one-school district in small-town Iowa, but it would not be credible to consider the five boroughs of New York City or the entirety of Miami-Dade County as a single neighborhood.

ZIP codes and ZCTAs

ZIP codes are a common option for defining neighborhoods largely because of their simplicity and familiarity. Unlike a cryptic census tract ID, most people know their five-digit ZIP code. But they do not necessarily know the physical extent of their ZIP code service area or make other decisions or affiliations based on an awareness of ZIP code.

The primary purpose of the USPS Zone Improvement Plan was and is to improve the efficiency of mail delivery – not to identify economically homogeneous neighborhoods or to support social research. ZIP codes were designed to help USPS deliver mail from point A to point B as quickly and as cheaply as possible. However, the ubiquity of ZIP code data in commercial transactions and business planning has produced a host of secondary demographic and economic data resources. Even the Census Bureau has converted the USPS ZIP-code street networks into ZIP-Code Tabulation Areas (ZCTAs) to meet the demand for demographic and economic data at the ZIP level. ZIP codes are used as neighborhood equivalents out of operational convenience, but they lack sufficient construct validity to be used as a proxy, and prior research suggests that ZIPs are not appropriate for neighborhood analysis (Coulton et al. 2001; Nicotera 2007).

Unfortunately, ZIP codes suffer from many of the same limitations that affect other neighborhood proxies. Although ZIPs may be large, there is no guarantee that they will include a sufficient number of sample cases needed to produce reliable, publishable poverty estimates. The large physical size of many ZIP codes also decreases the likelihood that average conditions calculated for an entire area are equally applicable across all locations within the area. Moreover, the Census Bureau only updates ZCTAs once a decade to prepare for the decennial census. New ZIP codes created during the decade are not included in the Census Bureau's collection, which means that poverty estimates would not be developed for these areas. Perhaps more challenging, USPS continuously updates the addresses and street segments associated with each ZIP code, so the physical coverage of a ZIP code can change throughout the decade even though the ID may be stable. As a result, the initial correspondence between Census ZCTAs and USPS ZIPs may degrade over the decade without the ability to detect this change in Census ZCTA estimates.

Proposal

The design constraints for a new neighborhood poverty indicator are considerable. Ideally, new indicators would be comparable, flexible, authoritative, geographically focused, and nationally comprehensive, yet also valid, reliable, cost-effective, and operationally feasible to produce as part of an annual development cycle. Given these design requirements and their occasional contradictory aims (e.g., the desire for smaller neighborhood size conflicts with the desire to increase the reliability of survey estimates), it was clear from the outset that simple alternatives were not available. The lack of alternate solutions to-date was not due to a lack of domain expertise or a lack of awareness about off-the-shelf options. It was also clear that that our solution would need to be developed through custom tabulations of ACS poverty data. The ACS is the only data source that fits all of the basic design requirements, and it provides a collection of other household characteristics (e.g., race/ethnicity, age, etc.) that can be used to support research and production. Data from IRS tax returns were not considered as a reasonable option due to significant restrictions in data access and also due to known limitations in the geographic data quality and lack of other characteristics like child age. Custom tabulations are similar to estimates developed from the ACS Public Use Microdata Sample, except they are based on the full collection of weighted sample responses that are used to create estimates for standard ACS data products. However, all ACS custom tabulations must satisfy disclosure-avoidance requirements before the estimates can be released for public use, therefore the strategy and methods used to create new demographic estimates can have a direct bearing on whether the estimates will

ultimately be accessible and useful for their intended purposes. Lastly, it was clear that the most productive path forward would be to reconsider the traditional geographic assumptions used for defining neighborhood demographic data. If estimates could be decoupled from standard geographic boundaries, then a new set of data options may be available.

Spatially interpolated demographic and economic estimates

The crux of our design strategy was to shift analytic focus from polygons to points – to move away from demographic estimates that are based on the spatial extent of predefined geographic areas and toward estimates that are optimized for specific point locations. Instead of thinking about social and economic conditions as if they were contained and constrained by geographic boundaries, we assume that these conditions behave as continuous characteristics across a landscape. As a result, our primary analytic need is to develop methods and indicators that help us understand and characterize conditions at specific points on an overall social or economic surface. We refer to these location-centric results as spatially interpolated demographic and economic (SIDE) estimates.

Our focus on point-specific estimates is not new. One of the drivers for the rapid expansion of address geocoding over the past few decades has been a desire to link the resulting address point locations with census tract, block group, or ZIP-level demographic estimates so that the area-level characteristics could be associated to individual households. This interest in point-level or address-level conditions is further evidenced by data users' general unfamiliarity and disinterest in tract and block group boundaries. Most data users give little attention to the geographic boxes used to create their estimates. These areas are simply the closest approximation to get what they truly want – address-level or point-optimized characteristics.

In order for us to embrace this point-based paradigm and develop SIDE-based poverty estimates, we needed estimation methods that explicitly accounted for geographic location. But, before that, we first needed to shift our focus from neighborhoods to neighbors.

Inside the box: Geographically defined neighborhoods

Neighbors are the defining feature of a neighborhood. Traditional neighborhood proxies – whether ZIP codes or tracts or block groups – are simply geographic boxes that define a set of neighbors (i.e., the survey respondents who live within a given geographic box and are associated with the ID assigned to that area). The ID is the key for aggregating, summarizing, and calculating statistical estimates for survey responses from households living in the box. Therefore, in a traditional Census Bureau processing and estimation environment, the only way to develop neighborhood estimates is to define the neighborhood box first. But this masks a bigger problem. Assigning neighborhood IDs to survey respondents allows us to identify neighbors located within the same geographic box. However, the system is not easily able to identify neighbors across different geographic areas, even though the true social and economic conditions that the Census Bureau attempts to measure do not usually respect the boundaries that the Census Bureau uses to measure them. In other words, if two neighbors live on opposite sides of a street and the street centerline is used as a tract or block group boundary, the two neighbors will be assigned to different tracts or block groups and used for separate estimates. The typical work-around for this type of artificial separation is to use a larger geographic unit that spans a wider area, but this approach invites the modifiable areal unit problem (MAUP) where demographic conditions vary depending on the type of geography selected for analysis (Clark and Avery 1976; Fotheringham and Wong 1991; Hipp 2007).

Sidestepping the box: School-centered neighbors

Rather than define neighborhoods based on predetermined geographic boundaries, SIDE-based neighborhoods are defined by a predetermined number of neighbors (i.e., a collection of households in the ACS survey). Moreover, the collection of neighbors is determined by their geographic proximity to a selected anchor point. Because the primary goal of our experiment was to design neighborhood poverty estimates, we used school locations as the anchor point to identify collections of nearest neighbors. The notion of a school-centered neighborhood, while limiting for some applications, has a number of advantages: it explicitly acknowledges the role of schools as significant institutions that impact the areas around them (Silverman 2014; Taylor, McGlynn, and Luter 2014); it is consistent with the general expectation and practice that school-age students living close to a grade-appropriate school are very likely to attend that school; it follows the precedent of state and federal guidelines that explicitly consider proximity to school location when determining sentences for legal violations (Controlled Substances Act 1970; Porter and Clemons 2013); and it recognizes that neighborhood boundaries are individually-constructed perceptions developed from specific points of reference.¹

Point-based estimates could provide a variety of benefits for researchers, and conceptualizing neighborhoods as collections of neighbors is a reasonable approach that bypasses many of the problems with current neighborhood proxies. But, these theoretical shifts pose a pragmatic question: how do we create school-based neighborhood estimates? What estimation approach could we use that would account for location and proximity of neighbors (with sensitivity to the magnitude of their responses), instead of simply tabulating and estimating based on who is inside the geographic box? The operational core of our proposed solution required the use of spatial statistics.

Estimating a regional poverty surface

Unlike traditional statistical techniques, spatial statistics explicitly attempt to account for the influence of location and distance, and most spatial and geostatistical techniques are based on a fundamental assumption expressed as Tobler's first law of geography: Everything is related to everything else, but near things are more related than distant things (Tobler 1970). This simple premise is easily observed in nature and in social arrangements. For example, the level of elevation or rainfall from two measured locations relatively close to each other are likely to be more similar than the measurements from two locations significantly further apart. Similarly, the age and value of two single-family residences located down the street from each other are likely to be more similar than the age and value of two units on different sides of a city. Unfortunately, this tendency is observable with poverty as well. Low-income households tend to be located near to other low-income households, and the subsequent impact of this condition on schools helps to explain why policymakers eventually added the need for concentration grants as part of ESEA Title I reauthorizations.

Researchers from the environmental sciences and disciplines like geology and geography regularly need to make predictions about expected conditions at particular locations. Soil scientists need to know the level of lead present in order to properly manage public health responses; agricultural scientists need to predict arability and crop yields; and mining companies need to predict the likelihood of finding deposits before they commit costly resources for more substantial exploration. Unlike social scientists who had the luxury of large scale censuses and social surveys systematically constructed with geographic sampling or tabulation units, researchers in the natural sciences had to develop statistical techniques to handle location-specific estimation. These techniques are collectively referred to as kriging (named after South African mining engineer Daniel Krige who originally pioneered the method).

Kriging

Kriging is a least squares statistical interpolator that uses the weighted sum of values from measured locations to predict values at nonmeasured locations (Cressie 1989; Cressie 1993). In the same way that a weather map developed from temperature readings at select locations can be used to infer potential temperature for interstitial areas elsewhere on the map, a kriging model produces a prediction surface for an entire study region and can produce a poverty surface to predict the likelihood of low-income households in nonmeasured locations. The general interpolation function can be represented as:

$$\hat{Z}(s_0) = \sum_{i=1}^N \lambda_i Z(s_i)$$

where the predicted value at a new nonmeasured location ($\hat{Z}(s_0)$) is the product of the sum of all individually measured locations ($Z(s_i)$) conditioned by their individual weights (λ_i). Kriging assumes that data are spatially autocorrelated, meaning that the value of sample cases partly depends on their distance to other cases. Generally, the closer a sampled location is to a nonsampled location, the more weight it will have on the final predicted value of the nonsampled location. However, kriging weights are not solely a function of individual distance. They incorporate prior information about the covariance structure across the full set of measured points. In other words, kriging uses the data twice (Cressie 1989). It first examines the spatial relationships in the data to quantify spatial dependence and formalize a covariance function, and then it applies that function back to the data to enable prediction. Therefore, individual weights are informed by what is known about the relationship between cases with a similar distance elsewhere in the data. This relationship is modeled with a semivariogram.

Semivariogram

The goal of a semivariogram is to quantify Tobler's law and measure the spatial dependence within a dataset. It accomplishes this by modeling the interaction between the semivariance of all potential pairs of cases (y-axis) against the distance of all potential pairs of cases (x-axis). The semivariance can be represented as:

$$\gamma(h) = \frac{1}{2N_h} \sum_{i=1}^{N_h} \left[(Z_i - Z_{(i+h)})^2 \right]$$

where $\gamma(h)$ is the semivariance of lag (h), N is the number of potential pairs, Z_i is the value at location i , and $Z_{(i+h)}$ is the value at location j . For example, to model the spatial dependence in income among ACS sample households, the process would first determine all potential pairs of ACS households in a defined study area and then calculate the squared difference in income level between all potential pairs. The cases are then binned by distance lags and the average variation is determined for each bin. These results are then plotted as a two-dimensional point cloud (the semivariogram) that identifies the distribution of distance-difference relationships, and a least squares model is fitted to the resulting points. The resulting semivariogram function has three key parameters: the nugget, the range, and the sill (Cressie 1993) (see figure 1).

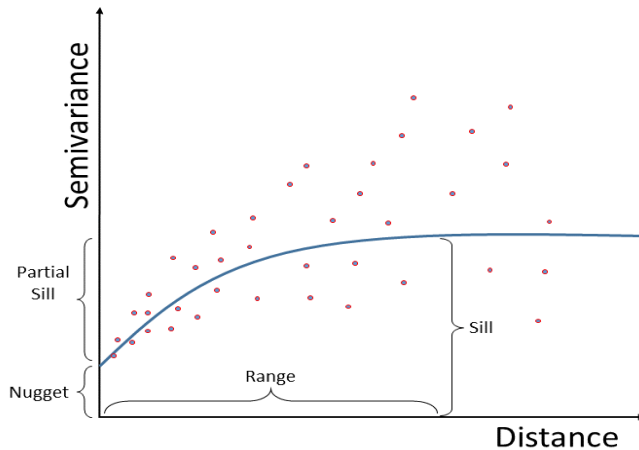
Nugget

The nugget identifies the level of semivariance when distance = 0 (i.e., where the model curve meets the y-axis). In theory, two measurements at the exact same location should be identical, and therefore the semivariance should be zero. However, real data may include measurement errors or differences that produce a discontinuity.

Range

The range is the extent to which the measured condition maintains an identifiable relationship with distance (i.e., the area within which spatial autocorrelation matters). This means that the household income for ACS households living within the range provides useful information to help predict income of nonsampled households, whereas the weights of sampled households outside the range would have no appreciable effect.

Figure 1. Empirical semivariogram model



Sill

The sill is the value at the extent of the range and represents the point at which additional distance produces no additional change in the semivariance. For example, the sill would indicate the point at which the likelihood of finding a low-income household vs. a high-income household is random.

Weights and prediction

The resulting empirical semivariogram model provides the weights that are applied to each neighbor in a kriging model based on the known distance between the unmeasured location (the prediction point) to each of the neighbors (i.e., ACS sample households) and based on the known income measurements of those neighbors. Again, the data are used twice. First, they are used to identify existing spatial dependence in the overall dataset and to construct the semivariogram model, and then they are used directly (adjusted with weights from the model) as neighbors to predict values for unmeasured locations.

Benefits and limitations of kriging

One of the key benefits of kriging, aside from the general advantage of producing a prediction surface that can provide estimates at all locations within a study area, is that the process provides an explicit measure of error for each predicted location. The prediction standard error allows the quality of the estimates to be evaluated at any given location. The general flexibility of kriging has spawned a family of variants to address unique conditions (e.g., simple kriging and cokriging) (Cressie 1993).

Despite the various benefits and advantages, kriging also has limitations as a design solution due to some of its fundamental assumptions and requirements. Ordinary kriging assumes that the resulting empirical semivariogram model is indeed the correct model and that the resulting parameters would be stable under repeated samples. This may not be the case, and – as a result – the model may not calculate the standard error correctly (Pilz and Spock 2007). More importantly, kriging assumes that the underlying structure of the data is stationary. In other words, it assumes that the relationship between

variance and distance is consistent across all portions of the study area. Unfortunately, this is frequently not the case, and the fundamental design requirements of our study ensure that this assumption will be violated. In order for the SIDE approach to provide a practical solution for neighborhood poverty estimation, it would need to be applied to large, statewide study areas with a broad mix of urban and rural territory that would certainly violate the assumptions of a stationary model.

Empirical Bayesian kriging (EBK)

Fortunately, spatial statisticians and commercial Geographic Information System (GIS) developers have been working on solutions to address these concerns, including a relatively new technique referred to as empirical Bayesian kriging, or EBK (Krivoruchko 2012; Krivoruchko and Gribov 2014). EBK provides a number of advantages over traditional kriging techniques and helps to address key concerns.

EBK provides a relatively robust response to the problem of nonstationarity by dividing large study areas into smaller regional subsets and then developing a unique model for *each* individual subset. This computational strategy produces a collection of local models that reflect the unique spatial dependencies of each region. The harmonized effect of these local models allows EBK to provide better predictions and more accurate standard errors than are usually achieved through classical kriging methods that rely on a single model of the study area. Also unlike traditional kriging, EBK does not assume that the default empirical semivariogram model is the true function. Instead, EBK relies on restricted maximum likelihood and subsequent simulation to develop a distribution of semivariogram models for each region. The process develops an initial model and uses it to simulate new data at each of the originally measured locations. The simulated data are then used to produce a new semivariogram model, and the process is repeated to produce a distribution of empirical semivariograms. This refinement produces a more accurate measure of the standard error.

Resulting strategy

EBK provided the final piece to our overall design puzzle by providing a way to create location-specific estimates over large regions while still maintaining sensitivity to regional differences in spatial dependency. Moreover, by reframing neighborhoods as collections of neighbors who are proximate to schools, we are not only able to use the native framework and strength of kriging to develop neighborhood estimates anchored on school locations, we are also able to provide an indicator that reflects the centrality of schools as neighborhood institutions. Lastly, this strategy may offer a useful solution for concerns about ACS data quality and the restrictions related to data disclosure because it allows developers to determine the number of neighbors used for estimation. This ensures that neighborhoods can always have sufficient sample size to satisfy the Census Bureau's disclosure requirements and will not be restricted from release due to an insufficient number of sample cases. More importantly, the results do not compromise the Census Bureau's disclosure requirements because the estimates are model-based coefficients derived from the independently weighted contributions of multiple neighbors to school locations.²

SIDE-based neighborhood poverty indicators appeared to provide a good solution for most of our basic design needs. The approach could potentially produce indicators based on official poverty thresholds from an authoritative source and provide annually updated estimates for all school locations in the U.S. The design could produce cost-effective value-added data by leveraging existing investments in ACS data collection, and it offered a flexible approach to produce similar estimates anchored on other points of interest. Although the approach has important limitations, the SIDE strategy appeared to have many potential advantages. However, it was not clear whether the design could be operationalized and implemented successfully in the Census Bureau's data processing environment, and we did not know whether the resulting indicators would be useful for analysis. This required a test.

Case study: Creating a SIDE-based neighborhood poverty indicator for NAEP assessments

SES problem

The U.S. Department of Education's National Assessment of Educational Progress (NAEP) (also known as the Nation's Report Card) is the largest continuing assessment of what our country's students know and can do in subjects such as mathematics, reading and writing. NAEP measures a broad set of educational outcomes for 4th, 8th, and 12th graders, and collects a variety of indicators about school conditions and student characteristics. Socioeconomic status (SES) has been a key element of NAEP since the survey was first implemented in the late 1960s, and NAEP regularly uses SES indicators to analyze and report results. These indicators attempt to assess the income and education level of students' households through indirect measures about the number of books in the home, the availability of large appliances, access to a computer, and exposure to various other amenities (National Forum on Education Statistics 2015). However, the quality of these data poses significant challenges due to the limited scope of the items measured and the unreliability of student responses. Unfortunately, direct responses by fourth graders to questions about the occupation and education level of their parents are too unreliable for NAEP to collect from students as part of the regular survey (National Center for Education Statistics 2012). Collecting these data from parents may yield more accurate responses, but these items are not regularly pursued because the potential intrusiveness of the questions could create nonresponse problems, which would then require costly follow-up procedures (National Assessment Governing Board 2003).

NAEP is required by statute to disaggregate and report assessment data by SES and has primarily used the NSLP lunch counts as a SES proxy for reporting purposes, though it has also disaggregated and reported assessment data by parental education (for 8th and 12th graders) as well (National Assessment of Educational Progress Authorization Act 2002). As discussed earlier, the reliability of the lunch data, coupled with potential reporting artifacts from high-poverty schools participating in CEP, poses on-going concerns for analysis and reporting of NAEP data.

Supplement NAEP with data from the ACS

To better understand how to improve SES measurement, NCES convened an expert panel to explore alternative options for identifying SES for NAEP through additional survey items and data sources (Barton 2002; National Center for Education Statistics 2012). As part of its overall guidance, the panel recommended that NAEP explore potential ways of using Census ACS data to help supplement NAEP's SES needs. Despite the influence that neighborhood conditions may have on educational outcomes, neighborhood-level SES indicators have not been included in NAEP because of the difficulty in collecting this information as part of the survey. The panel suggested that ACS content related to family income, educational attainment, occupation, and other household conditions may be assembled into useful neighborhood-level SES indicators. Once constructed, the ACS neighborhood-level SES indicators could potentially contribute to a composite SES measure when combined with the school-level SES conditions already identified and included in NAEP (National Center for Education Statistics 2012).

Although the ACS provides a host of potentially useful neighborhood-level social and economic characteristics, the panel recognized that NAEP lacks a good mechanism for effectively linking ACS information to NAEP records. Privacy and data quality concerns prevent NAEP from collecting student addresses and geocoding them to precise locations, so NAEP's only potential for linking with ACS is through a student-reported ZIP code. The panel acknowledged that ZIP codes lack demographic homogeneity and are not well suited as neighborhood units. However, given the potential value of the ACS data to help address NAEP's SES concerns and the lack of other useful data sources, the panel recommended that NAEP explore ways of linking and using ZIP-level ACS data.

Initial ZIP test

Fortunately, NAEP was able to leverage on-going work between NCES and the Census Bureau as part of NCES's Education Demographic and Geographic Estimates program (EDGE), and EDGE staff began to explore potential estimation and integration of ZCTA-level estimates. NAEP initially requested a custom tabulation of basic population disaggregated by race/ethnicity and household type for 5-year ZCTA-level estimates (2007 – 2011 ACS). This tabulation did not include SES characteristics and was intended as an initial exploratory exercise to help determine the quality and potential applicability of ZCTA-level ACS estimates for NAEP. The EDGE program provided these data to NAEP in early 2013, but the results were not promising for future use.

The ZCTA-level custom tabulations of ACS households with school-age children (5 – 18 year olds who were not high school graduates) by household type and race/ethnicity revealed that significant portions of ZCTAs lack sufficient sample size for these groups to satisfy the Census Bureau's disclosure requirements for public release. Most groups had insufficient sample size for the majority of ZCTAs. This was before any additional socioeconomic conditions were considered that would further reduce the number of sample cases available for estimation (see table 1). These findings led NAEP staff to consider aggregating ZCTAs into larger geographic units to achieve sufficient sample size, but this was not pursued for a variety of reasons. First, ZIP codes are not good representations of neighborhoods; therefore, aggregating ZIP codes would exacerbate an already known problem. Second, ZIP codes vary considerably by shape, size, perimeter length, and the number of adjacent neighbors. This variation would pose significant challenges for developing consistent aggregation rules, which would be necessary for implementing an automated process. Third, the quality of student-reported ZIP codes in NAEP is uncertain, which could create potential for inappropriate matching. Fourth, the lack of systematic update and management of ZCTA boundaries could create potential for mismatches and nonmatches that may introduce data errors and require time-consuming ad hoc fixes for each NAEP collection cycle.

Table 1. Percent of U.S. ZCTAs that satisfy Census Bureau disclosure rules by analytic group, 2007-2011

Analytic group	Percent of ZCTAs that satisfy disclosure
All households	96
Single-parent households with school-age children	
Household race composition is Hispanic	34
Household race composition is Non-Hispanic White	81
Household race composition is Non-Hispanic Black	31
Household race composition is Non-Hispanic All Other Single Race	25
Household race composition is Non-Hispanic Multi-Race/Ethnicity	54
Two-parent households with school-age children	
Household race composition is Hispanic	38
Household race composition is Non-Hispanic White	90
Household race composition is Non-Hispanic Black	30
Household race composition is Non-Hispanic All Other Single Race	31
Household race composition is Non-Hispanic Multi-Race/Ethnicity	67

NOTE: *Other Single Race* categories include: Non-Hispanic American Indian or Alaska Native alone, Non-Hispanic Asian alone, Non-Hispanic Native Hawaiian or Pacific Islander alone, Non-Hispanic Some other race alone, Non-Hispanic Two or More Races. *Multi-Race/Ethnicity* Household Composition includes households with at least one individual reporting a different race group than the householder, where race groups are: Hispanic, Non-Hispanic White alone, Non-Hispanic Black alone, Non-Hispanic American Indian or Alaska Native alone, Non-Hispanic Asian alone, Non-Hispanic Native Hawaiian or Pacific Islander alone, Non-Hispanic Some other race alone, Non-Hispanic Two or More Races. SOURCE: U.S. Census Bureau, American Community Survey 2007 – 2011.

Proposal for a SIDE-based neighborhood poverty indicator

Given the ZCTA results and the similarity of NAEP's request with the general design that EDGE staff had already been considering, we proposed that NAEP instead pursue SIDE-based estimates. This approach, as discussed earlier, would provide multiple benefits for NAEP. First, it offered a direct means of linking ACS data with NAEP records through the use of school location. All NAEP student records have an associated school ID, and schools can be integrated with SIDE prediction surfaces by means of school location (latitude/longitude). Second, SIDE would provide a means of leveraging ACS sample responses in a way that could satisfy the Census Bureau's disclosure requirements for all schools and allow the data to be released and integrated with NAEP. Third, SIDE could provide a reasonable neighborhood construct, arguably as reasonable as traditional neighborhood proxies. Fourth, SIDE-based estimates are systematically more reliable than conventional neighborhood units because the sample size (i.e., number of neighbors) can be set to a consistent level. And finally, the approach could provide estimates for all schools in the NCES administrative universe and offer a common metric of neighborhood poverty for all schools, regardless of their inclusion in the NAEP sample. Given the limitations of a ZIP-based approach and the potential benefits of the SIDE approach, the NAEP team agreed to pursue a case study to prototype the SIDE design. The study was framed by five core design criteria:

Poverty

Given the novelty of the experiment and the lack of a clear operational definition for SES, the EDGE design team decided to focus on developing poverty estimates. Although poverty is less encompassing than SES, the data were available, the definition was clear, it served as the central component of the NAEP panel's proposed SES construct, and the end result – if successful – could provide a directly usable indicator. In the same way that NAEP primarily relied on a poverty indicator (NSLP counts) as a SES proxy at the school level, it could potentially use ACS poverty as a SES proxy at the neighborhood level.

Ohio as the study area

Because the SIDE approach is processing intensive and processing is directly related to the size of a study area, we decided to limit the scope of analysis and selected the state of Ohio for our case study. Ohio provided a sufficiently large state to test processing requirements and options; it provided a wide range of geographic, economic, and social diversity; it included major cities like Cleveland, Cincinnati, and Columbus, as well as sparsely populated remote rural areas; and it allowed the authors to compare the experimental results with prior knowledge of local demographic conditions. An additional bonus of selecting Ohio was that Cleveland is a participant in the NAEP Trial Urban District Assessment (TUDA) program, which meant that NAEP staff could potentially compare the SIDE results with a larger collection of schools in the Cleveland area.

Elementary schools

Rather than create estimates for all schools, we decided to limit our focus to public elementary schools because they tend to serve smaller, more focused geographic areas, and they are the subset of institutions most commonly considered as "neighborhood" schools. Therefore, elementary schools seemed to offer the best conceptual match for experimental neighborhood poverty indicators.

Analytic groups

NAEP was interested in developing group-specific indicators to examine potential differences between race/ethnic groups by household structure. Because EBK models are based on a single indicator, this required that a different model be designed for each subgroup.³

Estimates and errors

One of the goals of the experiment was not only to develop a useable prediction surface, but also to develop a corresponding standard error surface to help assess the reliability of the resulting estimates. Each group-specific prediction surface needed a group-specific error surface as well. Each predicted value would receive an estimated measure of error to help assess data quality.

Case study data

The analysis required a blend of demographic, geographic, and administrative data from the ACS, the Census Bureau's Topologically Integrated Geographic Encoding and Referencing system (TIGER), and the NCES Common Core of Data (CCD). Although the resulting estimates were designed as a test for NAEP, the analysis did not require direct use of NAEP data.

ACS

The ACS is a continuous household survey that collects social, demographic, economic, and housing information from the population in the United States each month. Survey characteristics include race, ethnicity, sex, language and ability to speak English, ancestry, educational attainment, industry, occupation, income, household type, and various other conditions for individuals, families, households, and housing units. The ACS was originally designed as a replacement for the decennial census 'long form' sample survey and was designed to provide rolling estimates each year using five years of accumulated sample (Torrieri 2014).

Vintage and region

Data for the test file were collected between 2009 and 2013.⁴ Like most federal elementary and secondary education programs, NAEP is most interested in households with school-age children. Therefore, the ACS sample cases were limited to households with children (ages 5 – 18) related to the householder that were located in Ohio and adjacent states (PA, MI, IN, KY, WV). Although case study estimates were limited to schools in Ohio, ACS sample data from the adjacent states were included to produce more accurate model predictions near the state border.

Income-to-poverty ratio

The outcome variable used for prediction was the income-to-poverty ratio (IPR), also referred to as the poverty index (POVPI) on ACS files. The Census Bureau calculates the IPR based on money income reported for families relative to the poverty thresholds for the reported family size. Noncash benefits (such as food stamps and housing subsidies) are excluded, as are capital gains and losses. The value of the IPR ranges from 0 to a top-coded value of 999.

Analytic groups

Given the potential income variation for different race/ethnic groups or family structures, we developed separate models for nine different household types. Children were grouped into two race and ethnicity categories: (1) White and/or Asian who are not Hispanic or (2) all other race/ethnicity combinations. A household contributed to the race/ethnicity household group prediction surface if it contained a child in those race/ethnicity categories. Each household was also identified as either a single parent or two-parent family. Family type was determined by the relationship of household residents to the householder. A household was identified as two-parent if the householder was married and had 'own children' in the household. The relationship of unmarried partners to children in the household cannot be determined from the ACS questionnaire so some two-parent households may be classified as single parent. Our analysis focused on models, estimates, and standard errors for nine groups

1. All households with children;
2. Households with children who are White and/or Asian (non-Hispanic);
3. Households with children who are non-White and non-Asian (and/or Hispanic);
4. Households with children in a single parent family;
5. Households with children in a single parent family who are White and/or Asian (non-Hispanic);
6. Households with children in a single parent family who are non-White and non-Asian (and/or Hispanic);
7. Households with children in a two-parent family;
8. Households with children in a two-parent family who are White and/or Asian (non-Hispanic); and
9. Households with children in a two-parent family who are non-White and non-Asian (and/or Hispanic).

CCD

Model estimates were based on the location of 1,793 Ohio public elementary schools in the 2012 – 2013 Common Core of Data (CCD) that reported serving 4th grade. This collection allowed the experimental SIDE file to provide coverage for all potential schools in the NAEP 4th grade sample from Ohio. The physical locations were determined by the latitude and longitude values (LATCOD, LONCOD) representing a school's reported physical address.

Additionally, school enrollment (MEMBER) and counts of students eligible for free and reduced-price lunch (FRELCH, REDLCH) were used to create a percentage of students eligible for NSLP that could be compared with the experimental school-based neighborhood poverty estimates. Lastly, the school locale code (LOCALE) was included to help examine the variation in neighborhood size in different types of geographic areas.

TIGER

Census ACS operational files assign block identifiers to sample cases, but these cases require additional location information to be used for spatial interpolation. ACS records were linked with 2013 TIGER Ohio face data to identify the longitude and latitude (x,y values) of internal block points, and those points were then imported into a GIS and projected to a US equidistant conic projection. The resulting projected point locations with poverty indices (z values) were used as the input for the modeling process.

Model development

Given the unusual application of this technique to ACS data, we experimented with a variety of options before settling on the final parameters and conditions used for the final model estimates. These included:

Data transformation

Data transformations attempt to bring data closer to a normal distribution and may improve stationarity in the data model. We examined the impact of using an empirical transformation and found that standard errors (SEs) from models using an empirical transformation tended to be smaller than SEs from models with data that were not transformed. Median SEs ranged from 64 to 71 for transformed data, depending on semivariogram type, whereas nontransformed data produced median SEs over 85. Consequently, we opted to apply an empirical transformation for the final models.

Semivariogram type

Given our decision to transform the data, we compared the effects of three different semivariogram functions – Exponential, Whittle, and K-Bessel. Model results based on the Whittle semivariogram function tended to have lower maximum SEs than the Exponential or K-Bessel functions. Models based on Whittle and K-Bessel semivariograms were further examined for stability by comparing predictions using surfaces made from ACS 2009 – 2013 and ACS 2008 – 2012. Models based on the Whittle function were more stable than K-Bessel models using the same number of neighbors. Comparatively, fewer schools had a change of more than 100 poverty index points and the mean difference was slightly lower with the Whittle semivariogram. Based on this preliminary testing, we opted to rely on a Whittle function for the final semivariogram models.

Regional size, overlap, and distribution of semivariograms

The default parameters for the size of the regional subsets and number of semivariograms implemented by the developer of our EBK algorithm (ESRI) was a maximum of 100 for both conditions. We experimented with regional sizes that varied between 50 and 200 cases using 50 to 100 simulations per region, but the benefits of adjusting the default thresholds were not appreciable. In addition to selecting 100 points as a sub-region size, we experimented with a range of overlap factors to help create a smoother surface. The overlap factor specifies the average number of sub-regions that include each point. For example, an overlap factor of 1.5 means that about half of the points in a sub-region will also be included in another sub-region. We tested models with overlap factors ranging from 1.0 to 3.0, and although increasing levels of overlap produced slightly smoother surfaces, an overlap factor of 1.5 appeared reasonable for our analytic purposes.

Number of neighbors in neighborhood

We applied a standard circular search neighborhood to identify potential neighbors and experimented with group sizes of 15, 25, and 50 nearest neighbors, and the influence of each neighbor is weighted based on Euclidean distance from the predicted location. Although the availability of more sample cases tends to produce more reliable estimates in some analytic contexts, the semivariogram curve shows that more neighbors – if located relatively far away from an unmeasured location – may contribute more noise than signal to a predicted value.

Based on the group sizes we tested, models with 25 neighbors had lower mean and median SEs than groups with 15 or 50 neighbors. Therefore, we opted to use 25 nearest neighbors as the neighborhood group size for the final models. Overall, we found the model that was most stable and had the best prediction errors at school locations relied on empirical data transformations, Whittle semivariograms, 25 neighbors, 100 points in each sub-region, 1.5 overlap factor, and 100 simulated semivariograms.⁵

Coincident points

The ACS sample included some blocks that contained more than one household with school-age children, and those block centroids may have different IPR measurements at the same location. Interpolation models can treat coincident points as averages or as independent points, so we tested the impact of both options based on incidents for all households with children and explored potential effects on models that relied on empirical transformations and Whittle functions. Block averages provided 277,352 location instances to use for model inputs, whereas treating each household as an individual point provided 414,504 location instances for use as model inputs. Cross validation results were very similar for both methods, which suggested that the treatment decision would not affect the predictive quality of the models. Therefore, we chose to treat coincident events as separate points rather than as averages, based on the principle that each sample case should have the same influence and contribution in constructing the model.

Model performance

Cross validation (i.e., the comparison of each measured value with the predicted value at the same location when the measured value is omitted) produced relatively low Mean Predicted Error, a measure of potential bias in model prediction that ideally sums to zero. Values suggest that the models slightly under-predicted some population groups (e.g., non-White/non-Asian) and over-predicted others (e.g., Two-parent family, White/Asian). Relative to the Standard Deviation of the original IPR measured values, the Root Mean Square Errors (RMSE) suggest that the predicted estimates were somewhat improved by accounting for spatial autocorrelation. Although the impact of location varied by analytic group and the overall benefit from the model appeared to be modest (a 17% improvement for all households with children), the RMSE is a summary statistic that is sensitive to large errors which are more prevalent in the types of sparsely populated areas with low spatial autocorrelation that account for the majority of the study region. As a result, the global RMSE indicator may obscure the effect that location has on prediction in specific areas where spatial autocorrelation is more pronounced. Fortunately, EBK's use of local models helps to ensure that estimates in areas with strong spatial autocorrelation are able to take advantage of this additional local information.

Table 2. Cross validation results for Ohio by analytic group, 2009-2013

Analytic group	Mean error	Root mean square error	Sample standard deviation¹
All households with children	-.62	197.12	236.70
White/Asian	.34	202.09	238.34
Non-White/non-Asian	-4.01	172.54	197.27
Single-parent family	-2.50	152.76	167.82
White/Asian	-1.10	161.23	175.89
Non-White/non-Asian	-2.99	131.65	140.09
Two-parent family	1.58	203.16	238.71
White/Asian	2.11	204.30	239.03
Non-White/non-Asian	-2.35	196.24	222.41

¹NOTE: Standard deviation values reflect the distribution of IPR measurements across the original ACS sample cases for each analytic group.
SOURCE: U.S. Census Bureau, American Community Survey 2009 – 2013.

Results

Final models for each of the nine analytic groups were based on ACS sample cases that satisfied the group criteria. Values were then created for the 1,793 Ohio elementary schools using group-specific nearest neighbors. In addition to producing predicted values and standard errors for each analytic group at each school location, we took the added step of investigating the geographic dimensions of the nearest neighbors used to produce these estimates. The results of both components were encouraging.

Estimates and group variation

General results for the analytic groups matched expectations based on what was previously known about general group-level poverty conditions. Average IPR values for two-parent households were higher than average IPR values for single-parent households, and the average IPR for white/Asian student households was higher than average IPR for non-White/non-Asian households. Two-parent White/Asian households had the highest overall median predicted value (308), which was about 2.5 times higher than the median IPR for non-White/non-Asian single-parent households (see table 3).

On average, households with children had incomes about 2.38 times higher than the poverty threshold (or 238%). However, compared to the NSLP free and reduced-price lunch thresholds (130 and 185 respectively), the median income-to-poverty ratio of non-White/non-Asian single-parent household

(119) was low enough to qualify for free lunch, whereas the median income-to-poverty ratio of single-parent households (150) was low enough to qualify for reduced-price lunch.

Table 3. Income to poverty ratio for school neighborhoods in Ohio by analytic group, 2009-2013

Analytic group	Median	Mean	Median coefficient of variation
All households with children	238	258	26
White/Asian	260	282	25
Non-White/non-Asian	189	202	40
Single-parent family	150	163	31
White/Asian	163	177	29
Non-White/non-Asian	119	128	36
Two-parent family	291	314	21
White/Asian	308	332	20
Non-White/non-Asian	258	274	29

SOURCE: U.S. Census Bureau, American Community Survey 2009 – 2013; National Center for Education Statistics, Common Core of Data 2012 – 2013.

Neighborhood size

SIDE-designed estimates were based on weighted information from the 25 nearest sample cases, rather than based on explicit neighborhood boundaries. The spatial footprint of this collection of nearest neighbors may vary considerably from school to school and for different demographic groups, but the size and shape of census tract and block group boundaries can vary significantly as well. Given the common use of tracts and block groups and their acceptance as neighborhood proxies primarily due to their small geographic size, we were curious to know how the spatial footprint for groups of neighbors compared with the average geographic dimensions of tracts and block groups.

Neighborhood size by analytic group

Not surprisingly, the group with the largest number of potential sample cases (all households with children) produced the smallest neighborhood footprint. These groups of neighbors produced a median neighborhood size of 0.59 square miles (see table 4). In other words, if the locations of neighbor households were placed like pins on a map and a string was stretched around the collection of pins to create a polygon (with the pins functioning as vertices), the median size of these school-based neighbor polygons was slightly more than half a square mile. Median size of neighborhoods based on two-parent households with children was approximately 1.4 square miles, while median size for neighborhoods based on single-parent households with children was approximately 2.5 square miles. As expected, sub-setting household collections by race/ethnicity substantially changes the distribution of nearest neighbors used for estimation. The median neighborhood size for households with White/Asian children was about 1 square mile, whereas the area expanded to approximately 7 square miles for households with non-White/non-Asian children. Some parts of the state contain few non-White/non-Asian children, so the schools in those areas have fairly large neighborhoods for this demographic group. Comparatively, the median size of an Ohio census tract is about 2 square miles, and the median size of an Ohio block group is 0.5 square miles. In other words, not only is the physical size of school-based neighborhoods as small as and more targeted than standard neighborhood proxies, but they guarantee an adequate number of sample cases for estimation – a feature the proxy geographies cannot systematically provide. As table 1 suggests, even relatively large geographies like ZCTAs frequently lack a sufficient number of sample cases, and the collection of 1,197 Census ZCTAs with centroids located in Ohio had a median size of approximately 23 square miles.

Table 4. SIDE neighborhood size in Ohio by analytic group and locale, 2009-2013

Group	Schools	Median size (square miles)
Household group:		
All households with children	1,793	0.59
White/Asian	1,793	1.01
Non-White/non-Asian	1,793	6.96
Single-parent family	1,793	2.45
White/Asian	1,793	5.02
Non-White/non-Asian	1,793	13.03
Two-parent family	1,793	1.38
White/Asian	1,793	1.83
Non-White/non-Asian	1,793	15.18
Locale – All households with children:		
City—Large	379	0.32
City—Medium	66	0.53
City—Small	85	0.55
Suburb—Large	563	0.60
Suburb—Medium	29	0.56
Suburb—Small	51	1.39
Town—Fringe	69	0.73
Town—Distant	146	0.62
Town—Remote	8	0.78
Rural—Fringe	167	4.56
Rural—Distant	227	7.13
Rural—Remote	3	26.21

SOURCE: U.S. Census Bureau, American Community Survey 2009 – 2013; National Center for Education Statistics, Common Core of Data 2012 – 2013.

Neighborhood size by locale

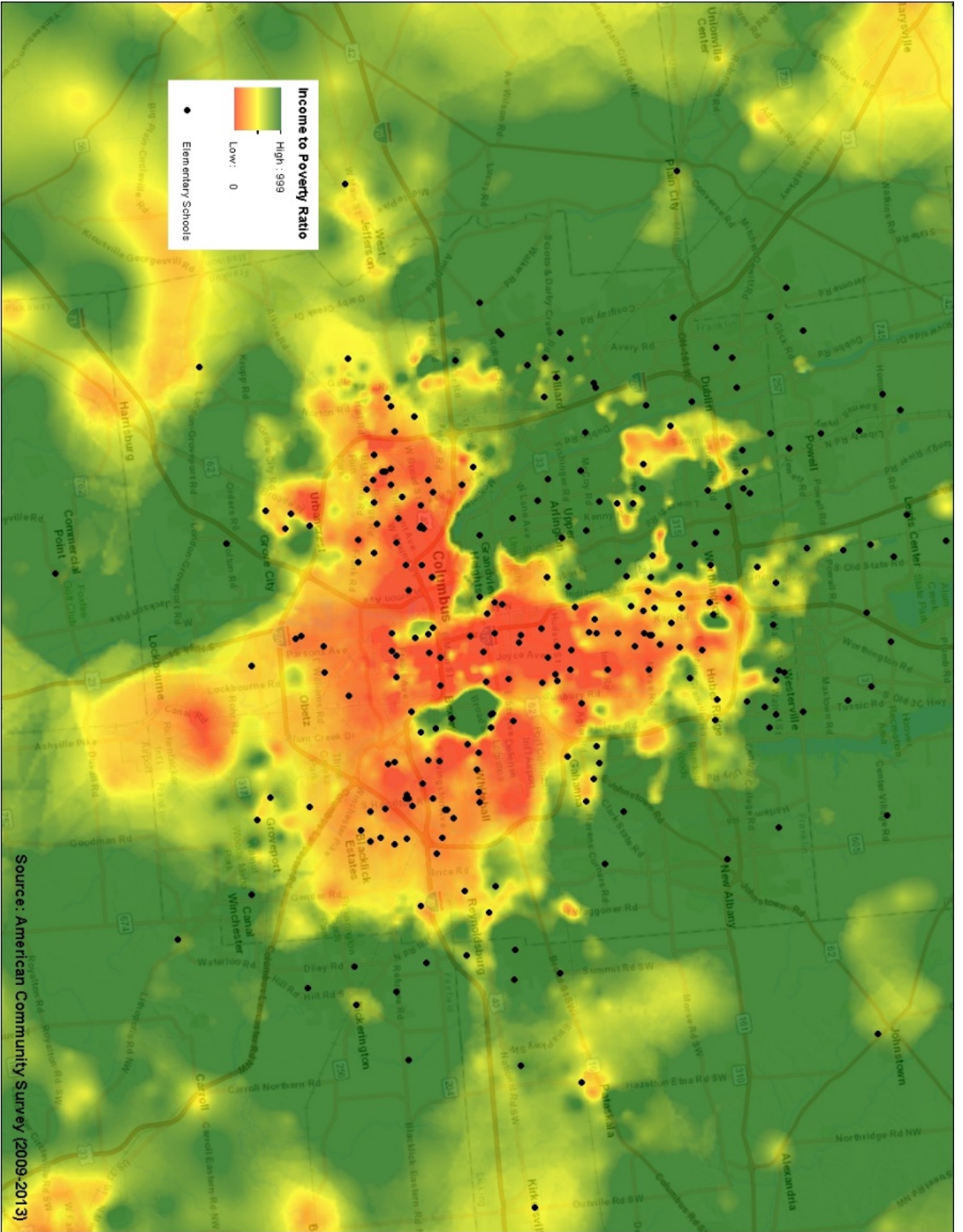
The median size of school-based neighborhoods varied depending on geographic location. Schools located in cities with a population of 250,000 or more had the smallest average footprint with neighborhoods spanning only 0.32 square miles, while schools in smaller cities and large and medium suburban areas had median neighborhood sizes between 0.53 – 0.60 square miles (see table 4). As expected, school neighborhoods in towns (urban cores with populations less than 50,000 but greater than 2,500) were somewhat larger with an average size between 0.62 – 0.78 square miles. Neighborhoods for rural schools were bigger. Schools located in the rural fringe (within 5 miles of an urban core with a population of 50,000 or more, or within 2.5 miles of a town) had a median neighborhood size of 4.56 square miles, while schools located in more distant rural areas had median neighborhood size of more than 7 square miles. At the extreme, the few schools in remote rural areas (more than 35 miles from an urban core with a population of 50,000 or more and at least 25 miles away from a town) had a median neighborhood size of about 26 square miles. Recall that the locale indicators reflect the location of the school and not necessarily the location of all the nearest neighbors used to construct the neighborhood. This is why, for example, the neighborhood size for schools in small suburban areas (1.39 square miles) is much larger than the neighborhood size for schools in larger suburban areas. The latter provides a physically larger area with greater opportunity to find a potential neighbor, whereas schools in smaller suburban areas have a greater likelihood of including nearest neighbors located in the rural fringe.

Spatial distribution

As expected, the resulting geostatistical prediction surface provides much more granularity than typical tract-level or block group-level maps, and the more nuanced landscape offers greater clarity as to the demographic and geographic context of individual schools relative to the distribution of household income (see figure 2). The prediction surface for households with school-age children was consistent with conditions of the area validated by external sources, including observations from one of the authors familiar with the area. For example, the island of green in the center of figure 2 highlights the suburb of Bexley, an affluent enclave of historic and high-end homes ranked by Business Insider as one of the top 50 suburbs in the U.S. (Fowler and Avakian 2015). Bexley's high school has been identified as one of the best schools in the state, and it ranked in the top 200 best high schools in the country (U.S. News and World Report 2016). Similarly, the high IPR finger encroaching toward the center of Columbus from the west reflects the high income suburbs of Upper Arlington, Marble Cliffs, and Grandview. The low IPR area sandwiched in-between is a corridor containing downtown Columbus, the Ohio State University campus, and a substantial amount of student housing.

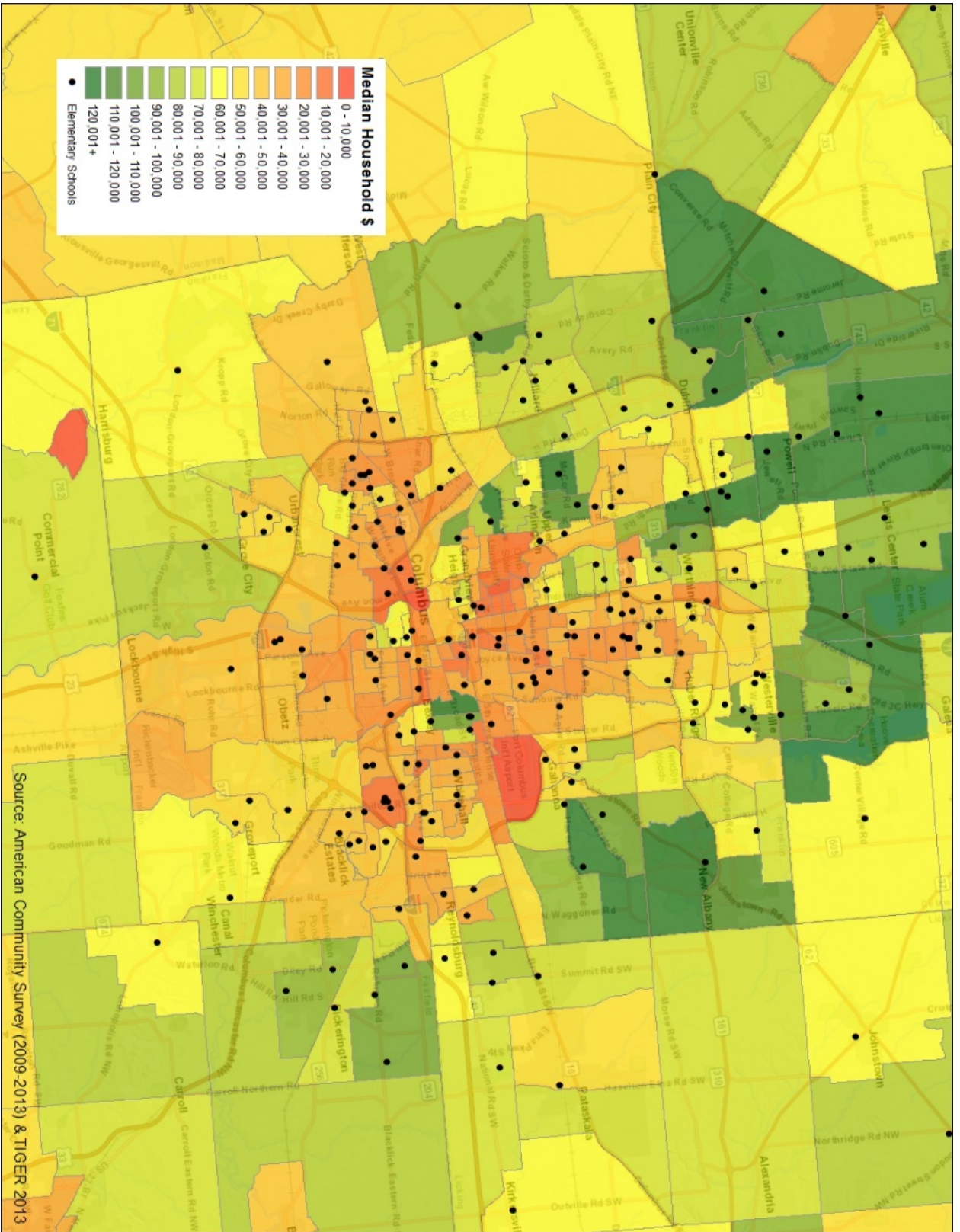
Investigations of neighborhood effects and community conditions make frequent use of census tract-level estimates, but figure 3 illustrates important limitations with this approach. First, although most ACS characteristics are included at the tract level, they are not necessarily available in the manner that researchers may need. For example, standard ACS IPR tract-level estimates are binned into predetermined categories (e.g., 1.00 – 1.24, 1.25 – 1.49) and are not directly available as a continuous measure. As a result, researchers may have to opt for a surrogate like median household income as a work-around for a more preferred indicator like the income-to-poverty ratio. Second, census tracts are not systematically constructed with school locations in mind, and many schools are located close to tract boundaries. As a result, assigning tract-level characteristics to schools through a basic point-in-polygon association invites two forms of ecological fallacy: it assumes that the area around a school is similar to areas in other portions of the tract, and it assumes the area around a school is independent of conditions that may exist in portions of nearby adjacent tracts that may even be coterminous with the boundary of the school parcel. Figure 3 displays many cases where schools are located near tract boundaries and where the adjacent tracts are assigned to different income class breaks. Changes to classification thresholds can change the visual appearance of this relationship on a map, but it would not alter the underlying tract-level estimates that researchers use for analysis, and it would not capture the unique conditions for specific school locations. Although the pattern of income distribution in figure 2 is generally detectable in figure 3, the tract-level boundaries make it difficult to clearly identify the spatial extent of these conditions, which – not surprisingly – may compromise a researcher's ability to detect potential neighborhood effects. This problem is somewhat like a spatial cousin of statistical power analysis. The geographic unit used to measure a phenomenon needs to be sufficiently aligned with the true extent of the spatial phenomenon to properly detect an effect. If an analyst lacks a sufficient number of properly aligned units, they will lack sufficient spatial power to detect a real effect and will therefore increase the chance of making a Type II error.

Figure 2. Income-to-poverty ratio SIDE geostatistical surface: Columbus, OH



NOTE: School locations based on National Center for Education Statistics, Common Core of Data 2012 – 2013.

Figure 3. Median household income for census tracts: Columbus, OH



NOTE: School locations based on National Center for Education Statistics, Common Core of Data 2012 – 2013.

Comparison with free and reduced-price lunch

Despite the limitations of NSLP lunch counts and the significant conceptual differences between the NSLP data and the experimental SIDE IPR indicator, we nonetheless expected the predicted poverty level of school-based neighborhood estimates to be correlated with the percentage of students in schools receiving free and reduced-price lunch. Indeed, the comparison confirmed the expected relationship. As the IPR value increased, the percentage of students eligible for free or reduced price lunch tended to decline. The correlation was approximately $r = -0.46$. This moderate relationship suggests that the SIDE IPR reflects a portion of the low-income household conditions identified by school lunch participation, but the lack of a stronger relationship indicates that the two measures have important differences as well. Most importantly, NSLP counts are based on school enrollment rather than sampled households, and they represent an aggregation of a binary measure – students are either eligible for free or reduced-price lunch or they are not. The SIDE IPR provides a direct measure of income from sampled households and provides a more nuanced indicator of the depth of individual need.

Conclusions

Thomas Jefferson, the nation's original advocate and architect for national-level data collections to serve the public good, believed that education was a primary means of ameliorating poverty (Jefferson 1817). Nearly 150 years after Jefferson's observation, President Johnson identified poverty as America's greatest barrier to progress and proposed a variety of measures through the Elementary and Secondary Education Act to help support schoolchildren (Johnson 1965). Yet, more than a half century after the introduction of the ESEA, educational researchers and program administrators still lack robust information about the level of poverty affecting the nation's schools. Fortunately, NSLP administrative data has provided a useful surrogate to address this need, even though it was not originally designed to be a school-level poverty indicator. However, educational programs and research would benefit from having a more robust collection of measures about the socio-spatial conditions of local schools, and the SIDE-based poverty estimate described and tested here shows promise as a possible addition to that collection.

Benefits

Many of the general features of the SIDE approach would support a broad set of data users. The neighborhood estimates can be created for all schools (or other entities with point locations); the basic poverty concept is a well-known and widely used standard; and the data originate from a reliable, authoritative source that uses a consistent method of measuring income and poverty across the country. The neighborhood estimates could be annually updated to help identify changing conditions, would be relatively cost-effective to produce, and would prevent disclosure concerns that typically restrict the release of small area poverty estimates. In addition to these general features, the approach may also offer unique advantages for specific analytic needs.

Advantages for research

The moderate correlation between the school neighborhood IPR and the NSLP lunch counts suggests that the SIDE-based poverty indicator reflects additional conditions that are not fully captured by the lunch data. Because the lunch data are the de facto standard for statistically controlling socioeconomic differences between schools, this suggests that including the SIDE IPR indicator as an additional covariate in statistical models may provide additional control for economic variation and consequently allow researchers to see the effects of other model components more clearly. SES often has a significant effect on model outcomes and the behavior of other covariates, and the lunch data have served as a standard SES proxy in a broad range of research models for many years, so the potential improvements offered by a combination of internal and external poverty indicators (NSLP and SIDE IPR) may impact the findings of a wide range of existing research.

The SIDE-based estimates may also provide researchers with new opportunities to explore potential spatial discrepancies between school neighborhood conditions and student economic conditions (i.e., situations where lower income students attend schools in higher income areas or where higher income students attend schools in lower income neighborhoods). This type of inside-outside discrepancy is currently difficult to identify and assess due to a lack of systematic data about school neighborhoods.

As a practical matter, school point locations are already developed and available as part of existing NCES data collections so the SIDE approach does not require additional effort or expense for new data collection. The NCES school point location files include the federal ID for each school, which is a common identifier shared across federal and state agencies and included in many commercial datasets. As a result, school-centered neighborhood poverty indicators could be easily shared across a variety of school-based programs and added as a supplemental context variable to large-scale NCES school-based sample surveys.

Advantages for administration

As mentioned at the outset of this discussion, educational program criteria typically depend on indicators that are available for all schools, measured consistently for all areas, based on authoritative sources, updated to reflect potential changes, easily accessible and available, and incur minimal cost to the program to acquire and use. In other words, programs need indicators that are fast, good, and cheap – without the trade-off of having to pick only two. Suffice it to say, the SIDE-based IPR estimates appear to satisfy many of these core program needs.

One potentially interesting application would be to explore the use of SIDE-based school neighborhood IPR estimates as a proxy for school attendance area poverty estimates in helping to rank and determine the intra-district distribution of Title I funds to high-need schools. Although ESSA and its predecessor NCLB identify Census poverty estimates for children ages 5 to 17 in school attendance areas as a primary data source for ranking and prioritizing intra-district Title I allocations, those data have never been systematically available and cannot be produced on an annual basis with an acceptable level of reliability. Additionally, some LEAs do not create attendance areas for some schools and instead operate open-enrollment programs that accommodate grade-appropriate children throughout the LEA. These types of school-choice arrangements have increased substantially over the years and the trend is likely to continue for the foreseeable future. As a result, a Census-based school attendance area poverty estimate is not a viable option for operationalizing intra-district Title I allocations.

In the absence of a Census-based indicator, most local education agencies typically rely on NSLP lunch counts for ranking Title I allocations to schools because the data are available and used for other purposes. LEAs are also free to use school-specific counts of children participating in the Social Security Assistance program or Medicaid, but access to school-level counts from these sources is more challenging to obtain. From an analytic perspective, these alternatives also pose challenges for broader comparisons because of state-specific differences in the way these programs may be administered.

However, ESSA provisions suggest that LEAs may use “a composite of such indicators, with respect to all school attendance areas in the local education agency” (Title I, Section 1113[a][5][A]). The primary intent of the provision is to ensure that LEAs use a fair and consistent method to assess and rank their schools and that the method relies on a reputable, authoritative data source – preferably administrated and collected consistently at the federal level. The order of the data sources listed in the provision suggests that, ideally, the school-level poverty indicator would rely on Census data so that it complements similar use of Census data for the school district-level poverty estimates. More importantly, the concluding option – “a composite of such indicators” – appears to offer the flexibility

for LEAs to use other indicators that may help to achieve the legislative intent. After all, it would not make sense for policymakers to present these data sources as the exclusive or exhaustive option set for decision-making when the primary recommended source (Census-based school attendance area poverty estimates) has never been available. Instead, it appears that these sources are recommended as potential solutions to address the fundamental need for data and assessment. This interpretation appears to be supported by program guidance that LEAs could use counts of students certified for SNAP to provide a common poverty metric for all schools – even though SNAP is not explicitly identified as one of the data sources in Title I, Section 1113(a)(5) (U.S. Department of Education 2015). The operating principle is simply that LEAs must use a common poverty metric to rank their schools.

SIDE-based IPR estimates could be measured and produced consistently for all schools in an LEA and the estimates can be based on households with school-age children. The National Center for Education Statistics (with support from the Census Bureau) has the capacity to produce these estimates annually, so it is reasonable to consider whether they may offer an acceptable supplement to assist with intra-district allocations. Regardless, SIDE-based IPR estimates may provide a new criterion or indicator to assist with other types of program administration.

Advantages for general geographic analysis

Aside from potential use in educational applications, SIDE-based prediction surfaces may offer a variety of potential benefits for general spatial analysis as well. First and foremost, they provide point-specific estimates to address point-specific questions instead of depending on estimates produced for polygons that may or may not adequately reflect the point of interest. Second, they bypass traditional statistical and administrative boundaries and therefore may provide a useful work-around for many applications that may otherwise be affected by the modifiable areal unit problem. Third, they help to avoid ecological fallacies by eliminating the requirement and expectation for a single estimate to represent all portions of a geographic box equally. Fourth, they explicitly account for spatial autocorrelation – a condition inherent in Census small area demographic estimates, but seldom addressed or accounted for when the estimates are used for analysis. Finally, predictive social surfaces offer a potential option for identifying true demographic change that would be undetectable for estimates in geographic areas if there were concurrent geographic changes in those areas. For example, if a city annexes territory between Time1 and Time2 and the percent of children in poverty also changes during the same period, was the change simply a consequence of the new boundaries (and the introduction of new sample cases), or is it a genuine shift in the condition of the population? If analysts had a full poverty surface for Time1 and another full poverty surface for Time2, they could use raster-based map algebra to identify differences between the two surfaces and essentially control for spurious differences in demographic conditions resulting from boundary changes. Suffice it to say, the availability of rasterized statistical surfaces with the flexibility to provide an optimized IPR (and standard error) at any specific location within a large analytic region would open up a host of new analytic possibilities.

Advantages for Census Bureau estimates

The Census Bureau considers spatial proximity when imputing values for incomplete or inconsistent survey responses, but the operational process for producing standard estimates is unable to detect spatially relevant neighbors. As a result, it cannot make use of this information for estimation. However, if spatially-sensitive estimation processes could be developed and integrated into the current estimation process, it could effectively increase the ACS sample size by allowing the Census Bureau to use existing cases multiple times. This potential for repurposing existing sample may be useful as the Census Bureau searches for new options to increase ACS sample size amid threats of declining response rates.

Limitations

SIDE-based estimates offer new potential for addressing some types of location-specific questions, but they have important limitations as well. First, they do not provide estimates of social or economic conditions for legal jurisdictions, so data users looking for estimates of county, city, or congressional district characteristics will continue to need traditional estimates that rely on sample cases aggregated within the specified geographic area. Second, unlike traditional education indicators, SIDE-based estimates do not provide population-based characteristics like the number of children who are English language learners or the percent of children in poverty, because they lack a defined area in which to estimate a population. Kriging was not designed to address these types of questions, so this criticism is somewhat out-of-scope; however, it is reasonable to highlight this as a limitation because SIDE indicators will not match many of the traditional assumptions, expectations, and use-cases that data users may have for a neighborhood poverty indicator. Third, although SIDE-based estimates could be developed for any set of geographic points, the utility of the resulting estimates would depend on the local context and the specific nature of the anchoring entity or institution involved. The concept of a school neighborhood works reasonably well for most public schools because most children continue to live relatively close to the school they attend (particularly in the elementary grades) and because there is general consensus that schools both affect and are affected by the community around them. However, this rationale works less well for schools of choice that have a highly distributed student population, or in nonpublic settings where the location of the school may be less indicative of the location where students live and where the school's engagement with the surrounding community may be less pronounced. That said, many private schools are operated by religious institutions that may intentionally engage with the neighborhood around them as a matter of religious belief and practice. Fourth, the specific poverty measure used for the test study is based on a standard definition that relies on money income and does not fully account for other important sources of income, program services, or other in-kind benefits. The Census Bureau's work on supplemental poverty measures suggests that a more nuanced definition may moderate the overall level of child poverty (Renwick and Fox, 2016). Fifth, although the ACS is the largest continuous household survey operated by the federal government, the number of sample cases is still rather limited in many areas, even with five years of cumulative sample. As a result, many SIDE-based estimates have relatively large standard errors, particularly in more sparsely populated areas. Sixth, the SIDE approach relies on accurate locations for schools. If a school's longitude and latitude are incorrect, the estimate may not be based on the sampled neighbors nearest to the true location of the school. Efforts are being made to improve and verify school locations, but this will remain a limitation until all school points are confirmed to be on their school building footprint.

SIDE-based IPR estimates will not address all the needs that data users have for supplemental neighborhood poverty indicators. They have significant limitations and are designed to address location-specific questions that may not be related or aligned with many research and program needs. But they may offer new opportunities to explore questions that have not previously been addressed due to the lack of location-specific data.

Recommendations

Initial efforts to produce a SIDE-based school neighborhood poverty indicator have offered useful and promising results, but more investigation is necessary to explore additional issues related to access, content, concept, and use.

Access

The Ohio case study provided a useful proof-of-concept, but similar estimates will need to be developed for the complete public school universe in order to fully examine the relationship between school neighborhood income-to-poverty ratios and NSLP school lunch counts (and other social context

indicators) and whether the new indicator could address requirements needed to support program purposes. A national level file would also be required in order for NCES school-based surveys like NAEP, the National Teacher and Principal Survey (NTPS), or Early Childhood Longitudinal Study (ECLS) to pilot the indicator as an additional social context variable on their restricted use data licenses.

Additionally, one of the lessons learned from the case study exploration is that SIDE-based estimates need to be supported with base maps that enable data users to visualize the spatial distribution of IPR in context with the built environment. Estimates in tabular data files may be useful for statistical models and administrative spreadsheets, but NCES data users also need to see results of socio-spatial conditions in a spatial context. Therefore, the NCES-Census EDGE design team should work to develop robust maps to help users understand the concept and conditions. Base maps – rasterized versions of the statistical prediction surface – could provide an additional source for accessing IPR estimates. A raster base map would encapsulate an IPR value for each pixel of the raster, which could essentially provide a new public data source that allows GIS users to produce their own IPR values for a broader set of applications.

Content

Once a full set of IPR estimates is developed for the public school universe and NCES decides how to develop and apply those estimates in the future, the NCES-Census EDGE team should continue to take steps toward developing an SES indicator that could be tested for NAEP (which would also provide the necessary vetting for potential use with other NCES school-based surveys). This will require clear definitions for parental occupation and educational attainment informed by prior NCES survey use, as well as a significant amount of experimentation to ensure that the resulting SES construct can be operationalized within the SIDE-based estimation process.

It may also be useful for Census EDGE staff to explore the potential of adjusting the existing IPR indicator to help account for in-kind program benefits and geographic differences in the cost of living that are not currently incorporated into the standard poverty thresholds. Although prior research on supplemental poverty measures by the Census Bureau suggests that the adjustments would, on average, attenuate the level of child-poverty compared to the standard poverty threshold, it may be useful to explore whether such adjustments can be applied to SIDE-based estimates, and if so, whether the effects are consistent with the results of prior research.

Lastly, since most NCES school-based surveys are composed of public and private schools, NCES should consider developing a set of school neighborhood IPR estimates for private schools as well. Although the conceptual fit of a school neighborhood IPR for private schools is more tenuous, it may still provide a useful indicator of the immediate operating environment around a school.

Concept and use

As already suggested, once a complete set of estimates is available for all schools, it would be useful to replicate pre-existing models of educational outcomes, particularly those that relied on the percentage of free and reduced-price lunch participation as the primary means of controlling SES variation, to see what effects (if any) the addition of the school neighborhood IPR has on other covariates and model outcomes. Given the use of NSLP lunch data as a proxy SES measure across a broad set of educational research topics, it would be useful to replicate models with the additional IPR indicator across a broad set of research areas to identify whether the neighborhood indicator affects some domains more than others. Similarly, it may also be useful to apply the school neighborhood poverty indicator in a multilevel modeling context.

¹ This study developed school neighborhood estimates based on neighbors (sample cases) that were close to schools. The economic conditions of neighborhoods around schools may be different from the economic conditions of neighborhoods where students live, therefore school neighborhood estimates may overestimate or underestimate school-level poverty.

² Unlike traditional Census population estimates where the number of sample cases available for estimation is determined by the extent of a geographic area, the number of neighbors used to inform kriging estimates is set as a model parameter and determined by analytic need. Therefore, SIDE-based estimates better address traditional concerns about data disclosure associated with areas with few sample cases.

³ Separate models for analytic subgroups were primarily created to address internal NCES research interests, but we included the results in this report to help demonstrate that SIDE IPR estimates behaved in a manner consistent with traditional Census poverty estimates for these groups.

⁴ The SIDE-based estimation strategy could produce estimates using ACS one-year data, but the distances between the available sample cases would be substantially larger than the distances between cases in the five-year data collection, and the estimates from the one-year data would produce larger standard errors. The primary purpose of this initiative was to create neighborhood-level estimates, therefore the use of five-year data was more appropriate.

⁵ Kriging assumes that data used for estimation are not independent, and it exploits the structure of spatial dependence as part of the estimation process. Although ACS sample cases can potentially be used as neighbors for more than one school estimate, they will likely function differently for each school estimate (in terms of its contributed weight) due to the varying distance of the neighboring case to each school.

References

- Andersson, E., and Malmberg, B. (2015). Contextual Effects on Educational Attainment in Individualized Neighborhoods; Differences Across Gender and Social Class. *Annals of the Association of American Geographers. Urban Studies*, 52(12): 2117–2133.
- Barton, P.E. (2002). *Perspectives on Non-Cognitive Questions in the National Assessment of Educational Progress*. Paper presented at workshop on NAEP background questions. National Assessment Governing Board, Washington, DC. Retrieved July 7, 2016 from: <https://nagb.gov/content/nagb/assets/documents/publications/reports-papers/assessment-design/consultant-papers-background-questions-barton.pdf>
- Brooks-Gunn, J., Duncan, G.J, Klebanov, P.K., and Sealand, N. (1993). Do Neighborhoods Influence Child and Adolescent Development? *American Journal of Sociology*, 99: 353–395.
- Campbell, E., Henly, J.R., Elliott, D.S., and Irwin, K. (2009). Subjective Construction of Neighborhood Boundaries: Lessons From a Qualitative Study of Four Neighborhoods. *Journal of Urban Affairs*, 31(4): 461–490.
- Carlson, D., and Cowen, J.M. (2015). Student Neighborhoods, Schools, and Test Score Growth: Evidence from Milwaukee, Wisconsin. *Sociology of Education*, 88(1): 38–55.
- Citro, C.F., and Michael, R.T., (Eds.). (1995). *Measuring Poverty: A New Approach*. Washington, DC: National Academy Press.
- Clark, W.A.V., and Avery, K.L. (1976). The Effects of Data Aggregation in Statistical Analysis. *Geographical Analysis*, 8: 428–438.
- Connell, J.P., and Halpern-Felsher, B.L. (1997). How Neighborhoods Affect Educational Outcomes in Middle Childhood and Adolescence: Conceptual Issues and an Empirical Example. In J. Brooks-Gunn, G. J. Duncan, and J.L. Abers (Eds.), *Neighborhood Poverty Volume I: Policy Implications in Studying Neighborhoods* (pp. 174–199). New York: Russell Sage.
- Controlled Substances Act (1970), 21 U.S.C. § 860 (2017).
- Coulton, C., Korbin, J., Chan, T., and Su, M. (2001). Mapping Residents' Perceptions of Neighborhood Boundaries: A Methodological Note. *American Journal of Community Psychology*, 29(2): 371–383.
- Counts, G.S. (1932). *Dare the School Build a New Social Order?* New York: John Day Company.
- Cressie, N. (1989). Geostatistics. *The American Statistician*, 43(4): 197–202.
- Cressie, N. (1993). *Statistics for Spatial Data*. New York: John Wiley & Sons.
- Dewey, J. (1915). *The School in Society*. Chicago: University of Chicago Press.
- Education Amendments of 1974, P.L. 93-380, 88 Stat. 484–613, Section 103(c)(1)(A).

- Folch, D.C., Arribas-Bel, D., Koschinsky, J., and Spielman, S. (2016). Spatial Variation in the Quality of American Community Survey Estimates. *Demography*, 53(5): 1635–1554.
- Fotheringham, A.S., and Wong, D.W.S. (1991). The Modifiable Areal Unit Problem in Multivariate Statistical Analysis. *Environment and Planning A*, 23: 1026–1044.
- Fowler, B., and Avakian, T. (2015). Ranked: The 50 Best Suburbs in America. *Business Insider*. Retrieved from: <http://www.businessinsider.com/ranked-the-50-best-suburbs-in-america-2015-10/>.
- Furstenberg, F.F., and Hughes, M.E. (1997). The Influence of Neighborhoods on Children’s Development: A Theoretical Perspective and a Research Agenda. In J. Brooks-Gunn, G.J. Duncan, and J.L. Abers (Eds.), *Neighborhood Poverty Volume II: Policy Implications in Studying Neighborhoods* (pp. 23-47). New York: Russell Sage.
- Galster, G. (2001). On the Nature of Neighborhood. *Urban Studies*, 38(12). 2111–2124.
- Glantz, F.B., Berg, R., Porcari, D., Sackoff, E., and Pazer, S. (1994). *School Lunch Eligible Non-Participants: Final Report*. U.S. Department of Agriculture/Food and Nutrition Service. Retrieved February 28, 2017 from: <http://www.fns.usda.gov/school-lunch-eligible-non-participants>.
- Harwell, M., and LeBeau, B. (2010). Student Eligibility for a Free Lunch as an SES Measure in Education Research. *Educational Researcher*, 39(2): 120–131.
- Healthy, Hunger-Free Kids Act of 2010, 42 U.S.C. § 1759a (a)(1)(F) (2017).
- Hipp, J.R. (2007). Block, Tract, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point. *American Sociological Review*, 72: 659–680.
- Jefferson, T. (1817). Thomas Jefferson to M. Correa de Serra. In A.A. Lipscomb and A. E. Bergh (Eds.) (1903-1904), *The Writings of Thomas Jefferson Memorial Edition, Volume 15*. (p. 153 – 157). Washington, DC: Thomas Jefferson Memorial Association.
- Jencks, C., and Mayer, S. (1990). The Social Consequences of Growing up in a Poor Neighborhood. In L. Lynn (Ed.), *Inner-city Poverty in the United States* (pp. 111–186). Washington, DC: National Academy Press.
- Johnson, L.B. (1965). Remarks Following Enactment of the Elementary and Secondary Education Bill: April 9, 1965. In *Public Papers of the President of the United States: 1965 (Book1)* (pp. 407–408). Washington, DC: U.S. Government Printing Office.
- Krivoruchko, K. (2012). Empirical Bayesian Kriging – Implemented in ArcGIS Geostatistical Analyst. *ArcUser*, 15(4): 6–10.
- Krivoruchko K., and Gribov A. (2014) Pragmatic Bayesian Kriging for Non-Stationary and Moderately Non-Gaussian Data. In E. Pardo-Igúzquiza, C. Guardiola-Albert, J. Heredia, L. Moreno-Merino, J. Durán , and Vargas-Guzmán J. (Eds.), *Mathematics of Planet Earth: Proceedings of the 15th Annual Conference of the International Association for Mathematical Geosciences (Lecture Notes in Earth System Sciences)* (pp. 61–64). Berlin: Springer-Verlag.

- Lee, B.A., Oropesa, R.S., and Kanan, J.W. (1994). Neighborhood Context and Residential Mobility. *Demography*, 31(2): 249–270.
- Massey, D.S. (2001). Segregation and Violent Crime in Urban American. In E. Anderson and D. E. Massey (Eds.), *Problem of the Century: Racial Stratification in the United States* (pp. 317–345). New York: Russell Sage.
- Massey, D.S., and Denton, N. (1993). *American Apartheid: Segregation and the Making of an Underclass*. Cambridge, MA: Harvard University Press.
- McWayne, C.M., McDermott, P.A., Fantuzzo, J.W., and Culhane, D.P. (2007). Employing Community Data to Investigate Social and Structural Dimensions of Urban Neighborhoods: An Early Childhood Education Example. *American Journal of Community Psychology*, 39: 47–60.
- Mirtcheva, D.M., and Powell, L.M. (2009). Participation in the National School Lunch Program: Importance of School-Level and Neighborhood Contextual Factors. *Journal of School Health*, 79(10): 485–494.
- National Assessment Governing Board. (2003). *Background Information Framework for the National Assessment of Educational Progress*. Washington, DC: U.S. Department of Education, National Assessment Governing Board.
- National Assessment of Educational Progress Authorization Act (2002), 20 U.S.C. § 9622(b)(2)(G) (2017).
- National Center for Education Statistics. (2012). *Improving the Measurement of Socioeconomic Status for the National Assessment of Educational Progress: A Theoretical Foundation*. Washington, DC: U.S. Department of Education.
- National Forum on Education Statistics. (2015). *Forum Guide to Alternative Measures of Socioeconomic Status in Education Data Systems*. (NFES 2015-158). U.S. Department of Education. Washington, DC: National Center for Education Statistics.
- Nicotera, N. (2007). Measuring Neighborhood: A Conundrum for Human Services Researchers and Practitioners. *American Journal of Community Psychology*, 40: 26–51.
- Orshansky, M. (1965). Counting the Poor: Another Look at the Poverty Profile. *Social Security Bulletin*, 28(1): 3–29.
- Perry, C.A. (1929). City Planning for Neighborhood Life. *Social Forces*, 8(1): 98–100.
- Pilz, J., and Spock, G. (2007). Why Do We Need and How Should We Implement Bayesian Kriging Methods. *Stochastic Environmental Research and Risk Assessment*, 22: 621–632.
- Ponza, M., Gleason, P., Hulseley L., and Moore, Q. (2007). *NSLP/SBP Access, Participation, Eligibility, and Certification Study – Erroneous Payments in the NSLP and SBP, Vol. I: Study Findings*. (CN-07-APEC) U.S. Department of Agriculture, Food and Nutrition Service, Office of Research, Nutrition and Analysis. Retrieved from: <http://www.fns.usda.gov/sites/default/files/apecvol1.pdf>.

- Porter, N.D., and Clemons, T. (2013). *Drug-Free Zone Laws: An Overview of State Policies*. Washington, DC: The Sentencing Project.
- Procter, B.D., Smega, J.L., and Kollar, M.A. (2016). U.S. Census Bureau, Current Population Reports, P60-256(RV), Income and Poverty in the United States: 2015. Washington, DC: U.S. Government Printing Office.
- Raudenbush, S.W., and Sampson, R.J. (1999). Ecometrics: Toward a Science of Assessing Ecological Settings, With Application to the Systematic Social Observation of Neighborhoods. *Sociological Methodology*, 29: 1–41.
- Renwick, T., and Fox, L. (2016). The Supplemental Poverty Measure: 2015. *Current Population Reports*. Washington, DC: U.S. Census Bureau.
- Riva, M., Apparicio, P., Gauvin, L., and Brodeur, J.M. (2008). Establishing the Soundness of Administrative Spatial Units for Operationalizing the Active Living Potential of Residential Environments: An Exemplar for Designing Optimal Zones. *International Journal of Health Geographics*. 7(43): 1-13.
- Sampson, R.J., Morenoff, J.D., and Gannon-Rowley, T.G. (2002). Assessing “Neighborhood Effects”: Social Processes and New Directions in Research. *American Review of Sociology*, 28: 443–478.
- Silverman, R.M. (2014). Anchoring Community Development to Schools and Neighborhoods: A Renewed Tradition of Putting People First. In K. L. Patterson and R. M. Silverman (Eds.), *Schools and Urban Revitalization: Rethinking Institutions and Community Development* (pp. 14–27). New York, NY: Routledge.
- Small, M.L. (2006). Neighborhood Institutions as Resource Brokers: Childcare Centers, Inter-Organizational Ties, and Resource Access among the Poor. *Social Problems*, 53: 274–292.
- Small, M.L., Jacobs, E.M., and Massengill, R.P. (2008). Why Organizational Ties Matter for Neighborhood Effects: A Study of Resource Access Through Childcare Centers. *Social Forces*, 87(1): 387–414.
- Spielman, S.E., Folch, D.C., and Nagle, N.N. (2014). Patterns and Causes of Uncertainty in the American Community Survey. *Applied Geography*, 46: 147–157.
- Taylor, H.L., McGlynn, L., and Luter, D.G. (2014). Back to the Future: Public Schools as Neighborhood Anchor Institutions – The Choice Neighborhood Initiative in Buffalo, New York. In K.L. Patterson and R.M. Silverman (Eds.), *Schools and Urban Revitalization: Rethinking Institutions and Community Development* (pp. 109–135). New York, NY: Routledge.
- Tobler, W. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*, 46(2): 234–240.
- Torrieri, N. (2014). *American Community Survey Design and Methodology (January 2014), Version 2.0*. Washington, DC: U.S. Census Bureau. Retrieved from: <https://www.census.gov/acs>.

- U.S. Department of Agriculture, Food and Nutrition Service. (2016). *Eligibility Manual for School Meals: Determining and Verifying Eligibility, School Year 2016-2017*. Washington, DC. Retrieved from: <https://www.fns.usda.gov/2016-edition-eligibility-manual-school-meals>.
- U.S. Department of Education (2016). *Supporting School Reform by Leveraging Federal Funds in a School-wide Program: Non-Regulatory Guidance*. Washington, DC. Retrieved from: <https://www2.ed.gov/policy/elsec/leg/essa/essaswpguidance9192016.pdf>
- U.S. Department of Education. (2015). *Guidance: The Community Eligibility Provision and Selected Requirements under Title I, Part A of the Elementary and Secondary Education Act of 1965, as Amended*. Washington, DC: Office of Elementary and Secondary Education. Government Printing Office. Retrieved from: <https://www2.ed.gov/programs/titleiparta/13-0381guidance.doc>.
- U.S. Department of Health, Education, and Welfare. (1976). *The Measure of Poverty: A Report to Congress as Mandated by the Education Amendments of 1974*. Retrieved from: <https://www.census.gov/content/dam/Census/library/publications/1976/demo/measureofpoverty.pdf>
- U.S. News and World Report. (2016). *Best High Schools Rankings*. Retrieved from: <http://www.usnews.com/education/best-high-schools/ohio/districts/bexley-city/bexley-high-school-15114>
- Wilson, W.J. (1987). *The Truly Disadvantaged: The Inner-City, the Underclass and Public Policy*. Chicago: University of Chicago Press.
- Zenk, S.N., Schulz, A.J., Israel, B.A., and Sherman, A.J. (2005). Neighborhood Racial Composition, Neighborhood Poverty, and the Spatial Access of Supermarkets in Metropolitan Detroit. *American Journal of Public Health*, 95(4): 660–667.