WORKING PAPER

Measuring School Poverty Matters, but How Should We Measure It?

Comparing Results of Survey Analyses Conducted Using Various Measures of School Poverty

Sy Doan, Melissa Kay Diliberti, David Grant

RAND Education and Labor

WR-A168-1
May 2022

RAND
CORPORATION

For more information on this publication, visit www.rand.org/t/WRA168-1.

Published by the RAND Corporation, Santa Monica, Calif.

Abstract

Education researchers and policymakers have long used free or reduced-price lunch (FRPL) eligibility as a proxy for student, school, and district poverty. However, changes to eligibility requirements and increasing evidence that FRPL eligibility is not an accurate prediction of family income have led to growing concerns about whether FRPL-based measures can still be used reliably. In this paper, we seek to understand the relationship between school-level FRPL rates and alternative measures of school and community poverty and how these measures compare to one another as explanatory variables and covariates in analyses. As an illustrative example, we use data from a national survey of school principals to assess whether the selection of a specific school poverty measure over another has substantive implications on correlational analyses. We find that proxying school poverty using slightly different measures generally leads to finding relationships between predictor and outcome variables in the same direction with coefficients of approximately the same magnitude, but with differing levels of precision. Thus, we conclude that analyses that continue to rely solely on FRPL eligibility rates as a proxy for school poverty, despite known weaknesses, will generally uncover the same relationships as those that rely on alternative measures of school poverty.

Introduction

Decades of education research have highlighted the connection between a school's socioeconomic composition and students' opportunities to learn (e.g., Mickelson and Bottia, 2010; Mickelson, 2018; Kahlenberg, 2013; Reardon et al., 2019). Yet despite its centrality within education research, information on a school's socioeconomic status (SES)—which we refer to as the *school poverty level*—has historically been imprecisely measured. For decades, researchers have predominantly used the percentage of students eligible for free or reduced-price lunch (FRPL) through the National School Lunch Program (NSLP) as a proxy for capturing school poverty. Use of this measure has been largely a matter of convenience. These data are universally available, free, and easy to access, making them attractive for research and policy purposes. Despite its pervasiveness, there are well-documented problems with using student FRPL eligibility as a proxy for poverty. For one, the dichotomous indicator aligns poorly with data on students' family income (Domina et al., 2018). Complicating matters, state and federal policy changes over the past decade to how FRPL eligibility is determined have caused increasing concern about the suitability of these data as a continued proxy for school poverty (Greenberg, 2018; Chingos, 2016).

Given the critical need for school poverty data, researchers and policymakers have proposed alternative ways to measure school poverty levels, some of which center on reconceptualizing or augmenting existing FRPL data (e.g., Michelmore and Dynarksi, 2017; Greenberg, 2018; Cookson, 2020; Chingos, 2018; Center on Budget and Policy Priorities and Food Research & Action Center, 2017). These efforts coincide with those by statisticians at the U.S. Department of

Education and the U.S. Census Bureau to construct alternative school and community poverty indicators by mapping demographic data from other federal data collections onto school district attendance boundaries. While the retooling and expansion of school poverty measures is promising in that it could lead to more-reliable measures, we are presented with a new problem: which one to use.

In this paper, we examine whether use of different measures of school poverty (or economic disadvantage more broadly) in research settings has meaningful implications on inferences drawn from analyses. As an illustrative example, we replicate analyses using alternative school poverty measures using data from a nationally representative principal survey on the use of instructional materials and associated supports in K–12 schools. Although we acknowledge that alternative measures of school poverty might capture slightly different underlying concepts, if analyses consistently suggest that there is a relationship between two variables of interest after controlling for school poverty—regardless of how school poverty is measured—this would suggest that the selection of one school poverty measure over another does not substantively alter the conclusions drawn from the analysis.

Specifically, we seek to understand the relation between school-level FRPL eligibility rates and alternative measures of school poverty and how these measures compare to one another as explanatory variables and covariates in analyses. We focus on the following three research questions:

- **RQ1.** How correlated are measures of school poverty? Are the same schools consistently classified as "high-poverty" schools using various measures of school poverty?
- **RQ2.** How much variation in survey results is explained by each measure of school poverty, both separately and jointly?
- **RQ3.** Does use of different school poverty measures alter inferences regarding relationships between survey variables of interest? Do different school poverty measures generally create estimates of the same direction and magnitude?

Background and Literature Review

The NSLP was establsihed to help students from low-income families access nutritious meals. Historically, eligibility was determined through annual application processes that required households and schools to submit and verify information. This process imposed a great deal of administrative burden, leading some schools to limit efforts to ensure all eligible families properly applied and some to verify submitted FRPL applications automatically (Hauser, 1994; Gleason, 2008). Although the NSLP is means-tested and eligibility is tied to the federal poverty level, FRPL eligibility was not conceived with an intention to become a measure of student SES. Nevertheless, eligibility became a proxy for a student's SES and aggregation of student-level FRPL eligibility to the school level (that is, the percentage of students in the school who are FRPL eligible) has become the predominant way of defining and measuring school poverty.

The historical prevalence of student FRPL eligibility as the dominant proxy for school poverty has largely been a matter of convenience. Data on student FRPL eligibility are essentially universally available, free, easily accessible, and—until 2010—were uniformly defined, making them attractive data for research and policy purposes. Yet despite the measure's pervasiveness, problems with the measure have been well-documented. First, previous research has found that FRPL eligibility is not necessarily a reliable measure of a student's SES (Harwell and LeBeau, 2010; Michelmore and Dynarksi, 2017; Chingos, 2016; Cookson, 2020; Fazlul, Koedel, and Parsons, 2021). Several studies that attempted to validate student FRPL indicators against income data obtained through the U.S. Census Bureau (Cruse and Powers, 2006) or Internal Revenue Service (Domina et al., 2018) found that the dichotomous indicator does a poor job of tracking underlying differences in family income. Second, the measure likely misses some students who theoretically should be eligible. As noted by Chingos (2016), Cookson (2020), and others, schools might put in differential effort to help families enroll in the program, resulting in some families being unaware that they are eligible.

Finally, FRPL eligibility as a measure of school poverty has gotten less comparable in recent years due to state and federal policy changes to mechanisms through which FRPL eligibility is determined (Greenberg, 2018; Chingos, 2016). The Healthy, Hunger-Free Kids Act of 2010 allowed schools to begin using a "direct certification" process in which students are automatically qualified for FRPL if they are participating in such welfare programs as the Supplemental Nutrition Assistance Program (SNAP). Furthermore, the law expanded the "Community Eligibility Provision," meaning schools can categorize their entire student population as FRPL-eligible if more than 40 percent of students qualify via their participation in other public welfare programs. These changes introduce further ambiguity in the alignment between FRPL eligibility and family income. In addition, as these policy changes were not implemented uniformly across states, researchers face the additional concern of how comparable FRPL measures are over time and across jurisdictions.

Understanding the reliability of school poverty measures and how they are constructed is critical because researchers, practitioners, and policymakers use these measures for a variety of purposes. For example, local education agencies rely on measures of school poverty—most commonly counts of FRPL-eligible students—to assist them in targeting Title I funding to low-income students (Skinner and Rosenstiel, 2018). Some state agencies even use counts of FRPL eligibility directly in their school funding formulas (Greenberg, Blagg, and Rainer, 2019; Center on Budget and Policy Priorities and Food Research & Action Center, 2017).

As Fazlul et al. (2021) and Domina et al. (2018) both conclude, although FRPL eligibility might not be well suited to directly measure family income, it is likely still a meaningful measure of economic disadvantage. This begs the question of what exactly we want a school poverty variable to capture—whether we are solely concerned with capturing students' family incomes or more broadly interested in capturing the many disadvantages that likely affect students' opportunities to learn—and whether what the measure captures is appropriately aligned with how the measure is used.

Given FRPL's limitations and the critical need for data on school poverty, researchers and policymakers have proposed alternative ways to measure school poverty levels, some of which center on reconceptualizing or augmenting existing FRPL data (e.g., Michelmore and Dynarksi, 2017; Greenberg 2018; Cookson, 2020; Chingos, 2018; Center on Budget and Policy Priorities and Food Research & Action Center, 2017). Many of these ideas, such as the proposal by Michelmore and Dynarksi (2017) to use years spent eligible for subsidized meals instead of a binary, annual indicator of participation) are intended to make FRPL data a more-reliable proxy of family income. In addition, federal statisticians have been constructing alternative indicators by mapping existing demographic data onto school district attendance boundaries. Development of these indicators leaves open the possibility of abandoning FRPL-based measures entirely in favor of other school poverty measures. We explore how several of these alternative indicators compare to FRPL eligibility rates below.

School Poverty Measures Used in Analyses

Given our interest in identifying a uniform school poverty measure that is universally available and regularly updated for all K–12 public schools—essentially the minimum criteria a measure would need to meet to be a realistic alternative to student FRPL eligibility—we focus on six alternative school poverty measures published by U.S. Department of Education and the U.S. Census Bureau. Despite meeting the necessary minimum criteria, these measures have important differences, such as their definition of SES, their data collection timelines, and the geographic level at which they are constructed. We briefly describe each measure below.

- **School Neighborhood Poverty (SNP).** This annual school-level measure captures the average income-to-poverty ratio (IPR) in the school's local area. Unlike FRPL eligibility, this measure is not tied to a school's student population. Instead, it is constructed using income data from households in close proximity to the school, meaning it captures economic data from households potentially not affiliated with the school.
- **Percentage of 5- to 17-year-olds within the district attendance boundary who are in households with incomes below the federal poverty line.** Published annually by the U.S. Census Bureau as part of the Small Area Income and Poverty Estimates (SAIPE) Program, this district-level measure is constructed by dividing the count of school-age youth (5- to 17-year-olds) in poverty within a district attendance boundary by the estimated count of 5- to 17-year-olds within the same boundary. Like SNP, this measure does not directly capture economic data for students attached to the school, but instead focuses on the geographic area in which a school is located.
- **Median family income.** This measure is obtained from the American Community Survey (ACS)—Education Tabulation (ACS-ED), a data source that maps five-year ACS demographic data with school district attendance boundaries. This district-level measure captures richer detail about the entirety of the income distribution than the binary FRPL

measure. As with our other measures, it does not necessarily correspond directly to the student population that a district serves. Another significant drawback of this measure—and all of the measures obtained from the ACS-ED tabulation—is its delayed time reference (2014–2018).

- **Percentage of families with various income levels.** The ACS-ED tabulation also includes categorical variables for family income levels and income buckets ranging from less than $10,000 to $200,000 or more. This measure shares many of the same benefits and drawbacks as the ACS-ED median family income measure.
- **Percentage of all families below the poverty threshold.** Also obtained from the ACS-ED tabulation, this measure is very similar to the SAIPE measure, but it is constructed using all households, as opposed to focusing explicitly on the school-age population.
- **Percentage of households who received food stamps or SNAP benefits in the past 12 months.** Also obtained from the ACS-ED tabulation, this measure is likely best suited to capture data on the poorest families within a district attendance boundary.

Methods

To address our research questions, we first constructed a school poverty dataset with all seven of our measures (FRPL eligibility plus our six alternative measures) on all K–12 public schools in the United States. We used the 2020–2021 Common Core of Data (CCD) directory file as our frame. To address RQ1, we calculated pairwise correlations across these measures and across all schools in the CCD and conducted a classification analysis in which we used different definitions of school poverty to categorize schools and then examined the consistency of classifications.

We then linked our school-level dataset to survey data on 1,757 principals in the 2021 American Instructional Resources Surveys (AIRS). The AIRS are nationally representative surveys of K–12 educators that are conducted via the RAND Corporation's American Educator Panels (AEP). AIRS separately surveys teachers and principals; we use the principal survey for our analysis because education researchers often use principal surveys as a proxy for collecting school-level data. We matched 1,704 survey records (or 97 percent) to our school-level poverty dataset; 1,626 records had values for all available measures (93 percent).

The 2021AIRS principal survey was fielded in May 2021 and had an administration time of 30 minutes. Although AIRS focused primarily on schools' use and access to various curricula, other items addressed related topics, such as teachers' modification of instructional materials to address students' diverse learning needs, students' access to digital devices and the internet, and teachers' access to professional learning. We matched our school poverty data to the AIRS data to assess how the selection of a specific school poverty measure might affect the conclusions that researchers come to when conducting educational analyses. Specifically, to answer RQ2, we separately regressed survey items onto each school poverty measure, collecting the R^2 values from each regression, to examine how much variation in each survey item is explained by each of the school poverty measures. For RQ3, we examine whether the use of different school poverty measures as a covariate meaningfully affects inferences drawn from regression analyses.

These analyses, particularly the analysis for RQ3, come with an obvious but necessary caveat that a comprehensive examination of every survey item in the 2021 AIRS, much less the entirety of educational research, is not feasible within the context of a single paper. Thus, we make several restrictions to the analyses included in this paper to balance relevance and parsimony. First, we initially focused on 84 AIRS items nested in the following six broad categories:

- perceived importance of attributes of instructional materials
- learning environments during COVID-19
- use of and access to antibias education materials
- teacher use and need for professional learning (PL)
- school and district learning environments
- principal perceptions of student achievement.[1]

Second, we focused on how the selection of a specific school poverty measure affects estimates of the relationship between AIRS items and a single "outcome" variable. For our outcome variable, we used a binary indicator of whether a principal perceives that students are performing at or above grade level in English language arts (ELA) in 2020–2021. We focus on principals' perceptions of student achievement because this AIRS variable comes closest to capturing students' educational outcomes or opportunities to learn—a common outcome measure in educational analyses—and because principals' perceptions of student achievement are significantly correlated with school-level FRPL eligibility rates.

These analyses take the form of simple linear probability models:

$$GradeLevel_i = \beta_0 + \beta_1 X_i + \delta POVERTY_i + \varepsilon_i$$

where $GradeLevel_i$, whether principal *i* indicated that their students were at or above grade level in ELA in 2020–2021, is regressed on X_i , an AIRS item for principal *i*, and $POVERTY_i$, the poverty level at the school of principal *i*, using one of the measures listed in Table 1. For a given X, we compare how estimates of β_1 differ when controlling for school-level FRPL eligibility rates, our default school poverty measure, versus those obtained using alternative measures.

We further trimmed RQ3 analyses by including only survey variables that were statistically significantly correlated ($p < 0.05$) with both our outcome variable of interest (principals' perception of student achievement) and school-level FRPL eligibility rates. We placed this

[1] Survey variables included dichotomous indicators (e.g., whether instruction in 2020–2021 was in person), categorical items (e.g., whether principals (1) strongly disagree, (2) somewhat disagree, (3) somewhat agree, or (4) strongly agree with statements), and continuous measures (e.g., estimates of the percentage of students who have access to reliable high-speed internet). All categorical items were recoded as dichotomous indicators using the same cutoffs used elsewhere in AIRS reporting. This choice was made for simplicity in reporting results.

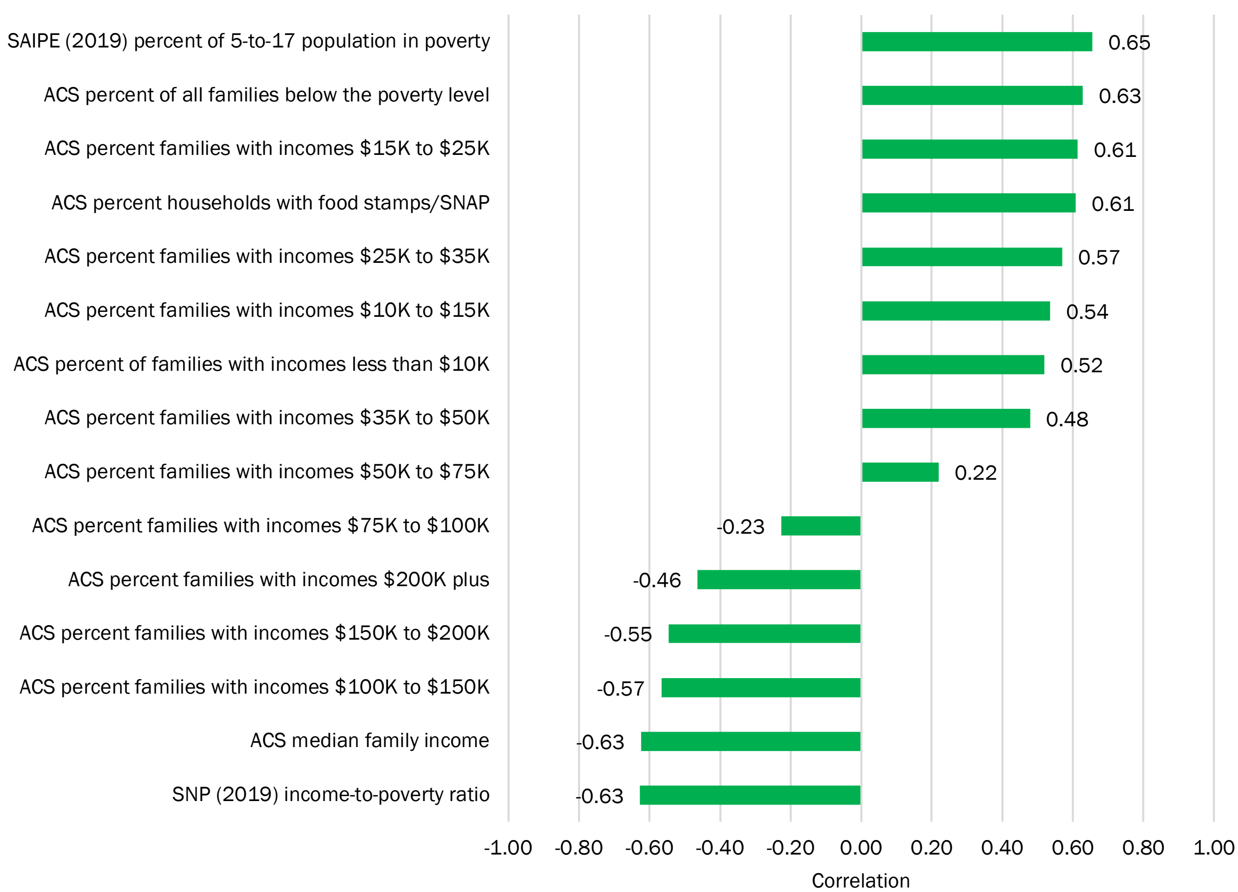
restriction on our sample because one would not plausibly include any school poverty variable in an analysis if it was unrelated to both the outcome of interest and the predictor variable. After placing this restriction, we identified 11 principal-reported AIRS items to include in our analysis as listed in Table 2.

Results

RQ1. How Correlated Are Measures of School Poverty? Are the Same Schools Consistently Classified as "High-Poverty" Schools Using Various Measures of School Poverty?

Using the full sample of K–12 schools in the 2020–2021 CCD, we present pairwise correlations between school-level FRPL eligibility rates and the other poverty measures (Figure 1).

Figure 1. Correlations Between School-Level FRPL Eligibility Rates and Other School Poverty Measures



NOTE: Figure 1 presents pairwise correlations between the measure of school poverty listed on the y-axis and CCD 2019–2020 school-level FRPL eligibility, estimated using all K–12 schools found in the 2020–2021 CCD (n = 94,240). ACS data are from 2014–2018.

Given that FRPL eligibility is determined in relation to the federal poverty level, the alternative school poverty measures that correlated most with school-level FRPL were, unsurprisingly, other measures defined in relation to the federal poverty line: the percentage of 5- to 17-year-olds in poverty (r = 0.65), the percentage of all families below the poverty line (r = 0.63), the average IPR (r = -0.63), median family income (-0.63), the percentage of families with incomes between $15,000 and $25,000 (r = 0.61), and the percentage of households with receipt of food stamps or SNAP (r = 0.61). Note that higher values of average IPR correspond to lower levels of school poverty, thus the negative correlation with school-level FRPL eligibility rates. These correlations are relatively high and in the expected direction, indicating either differences in the underlying construct of economic disadvantage and/or differences over time. The alternative school poverty measures least correlated with school-level FRPL eligibility rates are measures of the percentage of families falling into middle-income brackets: $50,000–$75,000 (r = 0.22) and $75,000–$100,000 (r = -0.23).

We next conducted a classification analysis to provide another manner of gauging similarities across measures. We categorized schools into quartiles for each school poverty measure and examined whether a school's quartile assignment is consistent across measures. In this classification, we used school-level FRPL estimates as the baseline against which to compare alternative classifications because we assume this is the school poverty measure researchers would choose by default.[2]

We examined schools that are in the top quartile of school FRPL eligibility rates (i.e., schools in which 73 percent of students or more are FRPL eligible) and, for all other poverty measures, calculate the percentage of schools that are

- *exact matches*—that is, the percentage of fourth quartile FRPL eligibility schools that are also in the fourth quartile of the non-FRPL school poverty measure
- *matches within one quartile*—that is, the percentage of fourth quartile FRPL eligibility schools that are in the third or fourth quartile of the non-FRPL school poverty measure.

Table 1. Classification Consistency of Schools with High FRPL Eligibility Rates

School Poverty Measure	Exact Matches (%)	Matches Within One Quartile (%)
ACS percent of families with incomes less than $10K	69	87
ACS percent families with incomes $15K to $25K	66	86

[2] When both "traditional" and "directly certified" rates are available for a given school, we follow National Center for Education Statistics's (NCES) guidance and use the traditional FRPL rate (Sinclair and Chen, 2020). As of 2019–2020, only four jurisdictions, Delaware, the District of Columbia, Massachusetts, and Tennessee, collected FRPL information solely through direct certification.

School Poverty Measure	Exact Matches (%)	Matches Within One Quartile (%)
ACS percent of all families below the poverty level	66	92
ACS percent families with incomes $25K to $35K	65	88
ACS percent households with food stamps or SNAP	60	83
ACS percent families with incomes $10K to $15K	60	96
SNP (2019) income-to-poverty ratio	60	85
SAIPE (2019) percent of 5- to-17-year-old population in poverty	59	88
ACS median family income	55	83
ACS percent families with incomes $100K to $150K	51	81
ACS percent families with incomes $35K to $50K	38	73
ACS percent families with incomes $200K plus	38	59
ACS percent families with incomes $75K to $100K	37	62
ACS percent families with incomes $150K to $200K	34	61
ACS percent families with incomes $50K to $75K	23	45

NOTE: Table 1 presents rates of classification consistency between school FRPL eligibility and each of the alternative poverty measures. The Exact Matches column shows the percentage of schools in the top quartile of FRPL enrollment that are also in the top quartile of the poverty measure listed in that row. The Matches Within One Quartile column shows the percentage of schools in the top quartile of FRPL enrollment that are in either the third or fourth quartile. ACS data are from 2014–2018.

Broadly, the measures most correlated with school-level FRPL eligibility rates shown in Figure 1 also tended to have the highest rates of classification consistency. At the top end, 69 percent of top-quartile FRPL schools were also in the top quartile of the percentage of families with incomes less than $10,000. Several other measures also had exact match rates at or above 60 percent, such as the percentage of families below the poverty line, the percentage of households receiving food stamps or SNAP, and the income-to-poverty ratio. When we loosen the match criterion to consider whether top-quartile FRPL schools fell in either the third or fourth quartile of an alternative poverty measure, we find that highest-correlated measures saw match rates exceeding 80 percent.

RQ2. How Much Variation in Survey Results Is Explained by Each Measure of School Poverty, Both Separately and Jointly?

Next, we estimated what proportion of variation in AIRS items is explained by each school poverty measure by regressing each survey measure on each of the school poverty measures and capturing the R^2 from each regression. Table 2 presents the R^2 values from each survey item-by-poverty measure regression and cells colored in proportion to the magnitude of the R^2 values. We also include the R^2 obtained from a fully saturated regression model that jointly controls for all of the individual school poverty measures.

We find several interesting patterns. Importantly, for all survey items except principal-perceived achievement, in which all poverty measures jointly explain 15.9 percent of the variation, the explanatory power (R^2) in all regression models is very small. The survey measures that are generally best explained by school poverty (i.e., have the highest R^2 values) are measures capturing attributes of students rather than of schools or teachers. Furthermore, unsurprisingly, the alternative school poverty measures that are most well-correlated to school FRPL eligibility rates (e.g., the percent of 5- to 17-year-olds in poverty) explain similar amounts of variation in survey items as school-level FRPL eligibility.

However, in survey measures such as the percentage of students who have access to reliable high-speed internet and whether principals consider it important to included content and approaches that are culturally relevant, we find some evidence that indicators of the percentage of families who fall within the middle income and upper-middle income brackets—poverty measures that were among the least correlated to school FRPL eligibility rates (Figure 1)—may be more predictive of these survey items than school FRPL eligibility and its most correlated measures.

Table 2. Proportion of Variation in AIRS Items Explained by School Poverty Measures

Survey Indicator	All Poverty Variables	School FRPL Eligibility	SNP IPR	SAIPE % Poverty 5-17	ACS % Family Poverty	ACS Family Income	ACS % SNAP	ACS % <10K	ACS % 10-15K	ACS % 15-25K	ACS % 25-35K	ACS % 35-50K	ACS % 50-75K	ACS % 75-100K	ACS % 100-150K	ACS % 150-200K	ACS % >200K
Principal reports students “at or above grade level” in ELA	**0.16**	0.15	0.07	0.05	0.05	0.05	0.05	0.03	0.03	0.04	0.04	0.03	0.01	0.01	0.03	0.03	0.03
Percentage of students with high-speed internet connection	**0.09**	0.05	0.05	0.04	0.03	0.05	0.03	0.02	0.04	0.04	0.05	0.06	0.02	0.00	0.05	0.06	0.03
Principal indicates supports for English learners are a “somewhat” or “extremely” important characteristic of instructional materials	**0.08**	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
Principal indicates cultural relevance is a “somewhat” or “extremely” important characteristic of instructional materials	**0.08**	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.01	0.00	0.02	0.03
Principal indicates teachers need “a little more” or “a lot more” PL for modification of curricula to meet needs of English learners	**0.07**	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.01	0.00	0.01	0.01
Percentage of students that pricinpals have not been able to contact	**0.06**	0.03	0.02	0.03	0.03	0.01	0.03	0.03	0.02	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00
Principal indicates school provides PL for coaching focused on ELA instruction	**0.05**	0.02	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00

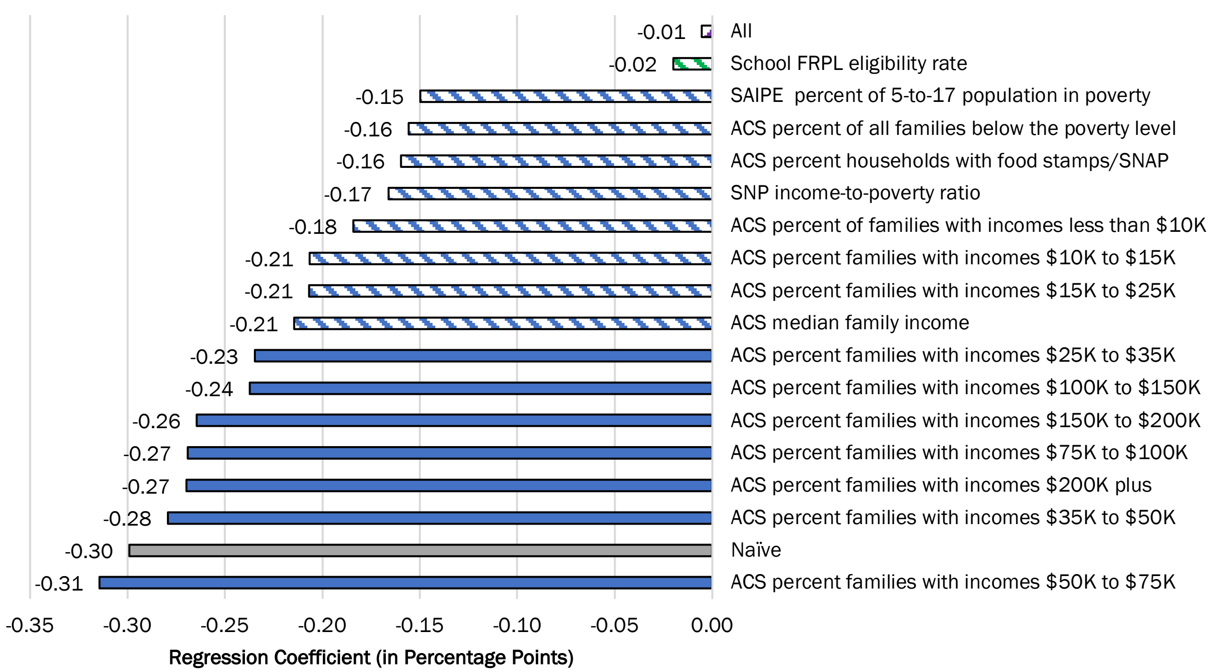
Survey Indicator	All Poverty Variables	School FRPL Eligibility	SNP IPR	SAIPE % Poverty 5-17	ACS % Family Poverty	ACS Family Income	ACS % SNAP	ACS % <10K	ACS % 10-15K	ACS % 15-25K	ACS % 25-35K	ACS % 35-50K	ACS % 50-75K	ACS % 75-100K	ACS % 100-150K	ACS % 150-200K	ACS % >200K
Percentage of students with access to digital device (e.g., tablet or laptop)	**0.03**	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.00	0.01	0.01	0.01
Principal indicates teachers need "a little more" or "a lot more" PL for provision of remote instruction	**0.02**	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00
Principal "somewhat" or "strongly" agrees that teachers at this school address antibias topics without the use of instructional materials	**0.02**	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Principal indicates teachers need "a little more" or "a lot more" PL for use of materials provided by school or district	**0.01**	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Principal indicates school has adopted new learning management system in response to COVID-19	**0.01**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

NOTE: Table 2 presents the R^2 values from ordinary least squares (OLS) regressions of the survey items (rows) regressed on the poverty measures (columns). All survey indicators are dichotomous variables with exception of the indicators beginning with "Percentage of students." All regressions are bivariate with the exception of the regressions in "All Poverty Variables," which regresses the survey item on all available school poverty measures. These regressions were run on a consistent sample of 1,626 AIRS respondents who have nonmissing values for all poverty measures listed in the columns. ACS data are from 2014–2018.

RQ3. Does Use of Different School Poverty Measures Alter Inferences Regarding Relationships Between Survey Variables of Interest? Do Different School Poverty Measures Generally Create Estimates of the Same Direction and Magnitude?

Last, we examined how the estimated relationship between principals' responses on 11 AIRS measures and principals' perceived student achievement differs depending on which school poverty measure is used as a covariate. We demonstrate our approach in Figure 2 in the context of one AIRS measure—the principal-reported percentage of students the school has *not* been able to contact during the 2020–2021 school year—and its estimated association with the likelihood a principal indicated that most students at their school were performing at or above grade level in ELA.

Figure 2. Estimated Association Between Principal Perception of ELA Achievement and Principal-Reported Percentage of Students Who Have Not Been Contacted After Controlling for Various School Poverty Measures



NOTE: Figure 2 presents the coefficient from a regression of an indicator of whether a principal indicated that their students performed at or above grade level in ELA on the principal-reported percentage of students at their school whom they have not been able to contact in 2020–2021. Each bar represents a separate regression, controlling only for the poverty measure listed in the row. Each coefficient has been multiplied by 100 to be expressed in percentage points. Solid bars mean that the coefficient is statistically significant at the $p < 0.05$ level. These regressions were run on a consistent sample of 1,626 AIRS respondents who have nonmissing values for all poverty measures. ACS data are from 2014–2018.

The gray bar in Figure 2 is the naïve "no controls" association between these variables, indicating that each additional reported percentage point of "uncontactable" students is associated with a 0.3 percentage point decrease in the likelihood that a principal reported that their students performed at or above grade level in ELA. When controlling for school-level FRPL eligibility rates (green bar)—what we consider to be the "default" covariate in educational analyses—the estimated association is attenuated to 0.02 percentage points and is no longer statistically significant at the p <0.05 level. The purple "All" bar shows the coefficient from a regression controlling for all available poverty measures.

The remaining blue bars show the estimated coefficient between the principal-reported percentage of uncontactable students and the likelihood of principal-reported ELA grade-level achievement, controlling for the specific school poverty measure next to the bar. Of the 16 school poverty measures included, seven would lead to a different inference than what would be obtained from controlling for all measures of school poverty. While neither is statistically significant, the point estimate obtained when controlling only for school FRPL eligibility rates (β = 0.2) is closest to the point estimate obtained from the fully saturated model. Regardless of what construct of school-level poverty is used, the coefficients consistently indicate an inverse relationship between the inability to contact students and principals' perceptions of student ELA achievement.

We conducted the same analyses depicted in Figure 2 for the remaining 10 AIRS variables and distilled the information obtained from those analyses. Table 3 shows

- the naïve coefficient obtained when not controlling for any measure of school poverty
- the coefficient obtained when controlling for school-level FRPL eligibility rates
- the coefficient obtained when controlling for all poverty measures
- the minimum and maximum coefficients obtained when controlling for the various non-FRPL school poverty measures individually
- the percentage of non-FRPL school poverty regressions in which the sign and significance of the regression coefficient match the sign and significance obtained when controlling for all measures
- whether the school-level FRPL-only regression matched the sign and significance of the all-measure estimate.

Because coefficient signs never changed due to the use of a specific school poverty measure, whether estimates "match" is based solely on alignment of statistical significance.

Table 3. Sensitivity of Estimated Associations with Principal-Perceived ELA Achievement to Selection of School Poverty Variable

Survey Variable	Reference Coefficients			Non-FRPL Coefficients			FRPL Only Match?
	No Controls	FRPL Only	All Measures	Min.	Max.	% Match All	
Principal "somewhat" or "strongly" agrees that teachers at this school address antibias topics without the use of instructional materials	**0.068** **(0.029)**	0.041 (0.027)	0.038 (0.027)	0.055	0.070	7	Yes
Percentage of students who principals have not been able to contact	**-0.003** **(0.001)**	-0.000 (0.001)	-0.000 (0.001)	-0.003	-0.001	53	Yes
Percentage of students with access to digital device (e.g., tablet or laptop)	**0.002** **(0.001)**	0.001 (0.001)	0.001 (0.001)	0.001	0.002	73	Yes
Percentage of students with high-speed internet connection	**0.004** **(0.001)**	**0.002** **(0.001)**	**0.002** **(0.001)**	0.003	0.004	100	Yes
Principal indicates school has adopted new learning management system in response to COVID-19	**-0.068** **(0.031)**	-0.045 (0.029)	-0.048 (0.029)	-0.072	-0.059	0	Yes
Principal indicates cultural relevance is a "somewhat" or "extremely" important characteristic of instructional materials	**-0.092** **(0.029)**	**-0.072** **(0.027)**	**-0.073** **(0.028)**	-0.131	-0.087	100	Yes
Principal indicates supports for English learners are a "somewhat" or "extremely" important characteristic of instructional materials	**-0.158** **(0.029)**	**-0.104** **(0.028)**	**-0.101** **(0.028)**	-0.172	-0.140	100	Yes
Principal indicates school provides PL for coaching focused on ELA instruction	**-0.096** **(0.037)**	-0.024 (0.035)	-0.022 (0.035)	-0.100	-0.073	7	Yes
Principal indicates teachers need "a little more" or "a lot more" PL for use of materials provided by school or district	**-0.076** **(0.031)**	-0.044 (0.029)	-0.047 (0.028)	-0.076	-0.064	0	Yes
Principal indicates teachers need "a little more" or "a lot more" PL for modification of curricula to meet needs of English learners	**-0.132** **(0.033)**	**-0.099** **(0.032)**	**-0.095** **(0.033)**	-0.161	-0.121	100	Yes
Principal indicates teachers need "a little more" or "a lot more" PL for provision of remote instruction	**-0.108** **(0.031)**	**-0.061** **(0.029)**	**-0.059** **(0.029)**	-0.108	-0.083	100	Yes

NOTE: Table 3 presents summary information on a series of OLS models that regress an indicator of whether a principal indicated that their students performed at or above grade level in ELA on the AIRS measure listed. For each row, point estimates and standard errors are provided for regression models that (a) do not control for measures of school poverty, (b) control only for school FRPL eligibility rates, and (c) control for all available poverty measures. Bolded values are statistically significant at the $p < 0.05$ level. In addition, we estimate regressions that control separately for each of the non-FRPL measures of poverty. The minimum and maximum point estimates obtained across these regressions are presented for each survey variable. "% Match All" refers to the percentage of all single poverty measure regressions, including school FRPL eligibility, in which the sign and significance of the regression coefficient of the survey variable match the sign and significance of the regression coefficient obtained when controlling for all measures of school poverty. These regressions were run on a consistent sample of 1,626 AIRS respondents who have nonmissing values for all poverty measures listed.

Several key patterns emerge. First, among our reference coefficients, we observe an attenuation of the estimated coefficients as we transition from controlling for no school poverty variables, to controlling only for school FRPL eligibility, to controlling for all poverty measures. By design, all measures are significantly related to principal perception of students' ELA achievement in naïve regressions. However, only five of 11 measures remain significantly related when all measures of school poverty are included in regression models. Second, the five measures that remain significantly related were also significantly related to perceived ELA achievement regardless of the specific measure of school poverty used, although the magnitude of the estimates varied. For example, while we would conclude that principal reports of teachers' need for more professional learning is negatively associated with the principals' perceptions of student ELA achievement after controlling for poverty—regardless of the school poverty measure(s) used—the magnitude of that association ranges from a 5.9 percentage point decrease when controlling for all poverty variables to a 9.3 percentage point decrease when controlling for only the percentage of families who make less than $10,000. Relatedly, inferences differed more substantially when the coefficient obtained when controlling for all poverty variables was not statistically significant. For example, only one of the 15 non-FRPL poverty measure regressions between teachers' use of antibias materials and perceived ELA achievement produced coefficients that matched the sign and significance of the all-poverty measures regression (not significant). Among the variables that were not significantly related to perceived ELA achievement, the percentage of students whom principals reported having not been able to contact and the percentage of students with a digital device appeared to be the most robust to the selection of school poverty measure—53 and 73 percent of regressions, respectively—producing the same non–statistically significant finding as the fully saturated model. Importantly, the only single poverty measure that consistently matched the sign and significance of the fully saturated model was school FRPL eligibility rates.

Conclusion

In this paper, we used data from a recent principal survey to investigate how sensitive analyses are to various methods of measuring school poverty. We found that most school poverty measures are fairly highly correlated and that the same schools are consistently categorized as high poverty regardless of which particular school poverty measure is used. We also found that proxying school poverty using slightly different measures generally leads to finding relationships between predictor and outcome variables in the same direction with coefficients of approximately the same magnitude, but with differing levels of precision (leading to some differences in what gets interpreted as statistically significant). Based on these results, we believe that if analysts were to select any single measure of school poverty among the measures of school poverty we compare here, analysts would generally uncover the same relationships between survey variables in their analysts.

Thus, given the timeliness and ease of FRPL data—and its long history as the dominant proxy for school poverty level—FRPL eligibility will likely remain the preferred measure. Despite the well-documented issues with FRPL, the school-level FRPL eligibility measure has substantial logistical advantages over the alternatives: It is annual, timely, and measured using actual student-level data. Comparatively, the available alternative measures are time-lagged or too geographically dispersed (i.e., district level or available only for the local community).

In the examples we presented, school-level FRPL eligibility performs favorably to other measures of school poverty and reasonably approximates the explanatory power and covariate functioning of more saturated models that control for the full set of poverty measures. Other measures that performed well in our comparisons were the SNP IPRestimates, SAIPE percentage estimates of 5- to 17-year-old populations in poverty, and ACS percentage estimates of families or K–12 aged populations living under the poverty level. These make intuitive sense because—like student FRPL eligibility—these measures are taken at the school level and/or focus specifically on the school-age population.

Our analysis has some limitations that readers should keep in mind. First, we use AIRS data for its national representativeness and the variety of survey items collected; however, these data cannot cover the full breadth of potential analyses that researchers might use as measures of school poverty. Prior AIRS analyses (e.g., Kaufman et al., 2020) largely use these data to examine descriptive relationships across survey items. The analyses we conducted in this paper suggest that the conclusions we draw from AIRS likely will not differ depending on which specific poverty measure we choose. However, other contexts and other research questions might be more sensitive to the selection of specific poverty measures. Other researchers can test how robust their findings are by conducting sensitivity checks using different constructs of school poverty (as we did in this paper), but we suspect that researchers will consistently find that their analyses are robust to whatever construct of school poverty they choose. Second, although the school poverty measures we examined in this paper are defined slightly differently, they share similar constructs, and many are built using the same data sources (which is why they correlate so well). Thus, all of the measures we examine in this paper might be flawed in similar ways. Although it has become clearer that student FRPL eligibility does not directly capture the family income levels among student populations, the alternative school poverty measures we examined in this paper might not be capturing the construct either. In choosing between imperfect options for proxies of povery, school FRPL eligibility is typically a preferable selection in comparison to its alternatives.

References

Center on Budget and Policy Priorities and Food Research & Action Center, "Alternative Approaches to Using School Meals Data in Community Eligibility (CEP) Schools," Washington, D.C.: Food Research & Action Center, June 2017. As of May 11, 2022: https://frac.org/wp-content/uploads/cep-state-education-data-policies.pdf

Chingos, Matthew M., "No More Free Lunch for Education Policymakers and Researchers," Brookings," June 30, 2016. As of May 11, 2022: https://www.brookings.edu/research/no-more-free-lunch-for-education-policymakers-and-researchers/

Chingos, Matthew M., "A Promising Alternative to Subsidized Lunch Receipt as a Measure of Student Poverty," Brookings, August 16, 2018. As of May 11, 2022: https://www.brookings.edu/research/a-promising-alternative-to-subsidized-lunch-receipt-as-a-measure-of-student-poverty/

Cookson, Peter W. Jr., "Measuring Student Socioeconomic Status: Toward a Comprehensive Approach," Learning Policy Institute, June 25, 2020. As of May 11, 2022: https://learningpolicyinstitute.org/product/measuring-student-socioeconomic-status-report

Cruse, Craig, and David Powers, (2006) "Estimating School District Poverty with Free and Reduced-Price Lunch Data," Suitland, Md.: U.S. Census Bureau, 2006. As of May 11, 2022: https://www.census.gov/content/dam/Census/library/working-papers/2006/demo/crusepowers2006asa.pdf

Domina, Thurston, Nikolas Pharris-Ciurej, Andrew M. Penner, Emily K. Penner, Quentin Brummet, Sonya R. Porter, and Tanya Sanabria, "Is Free and Reduced-Price Lunch a Valid Measure of Educational Disadvantage?" *Educational Researcher*, Vol. 47, No. 9, 2018, pp. 539–555.

Fazlul, Ishtiaque, Cory Koedel, and Eric Parsons, *Free and reduced-Price Meal Eligibility Does Not Measure Student Poverty*, Center for Analysis of Longitudinal Data in Education Research, working paper No. 252-0521, May 2021. As of May 11, 2022: https://caldercenter.org/sites/default/files/CALDER%20WP%20252-0521.pdf

Gleason, Philip, "Direct Certification in the National School Lunch Program Expands Access for Children," *Journal of Policy Analysis and Management*, Vol. 27, No. 1, 2008, pp. 82–103.

Greenberg, Erica, *New Measures of Student Poverty: Replacing Free and Reduced-Price Lunch Status Based on Household Forms with Direct Certification*, Washington, D.C.: Urban Institute, November 2018. As of May 11, 2022: https://www.urban.org/sites/default/files/publication/99325/new_measures_of_student_poverty.pdf

Greenberg, Erica, Kristin Blagg, and Macy Rainer, *Measuring Student Poverty: Developing Accurate Counts for School Funding, Accountability, and Research*, Washington, D.C.: Urban Institute, December 2019. As of May 11, 2022: https://www.urban.org/sites/default/files/publication/101430/measuring_student_poverty.pdf

Harwell, Michael, and Brandon LeBeau, "Student Eligibility for a Free Lunch as an SES Measure in Education Research," *Education Researcher,* Vol. 39, No. 2, 2010, pp. 120–131.

Hauser, Robert M., "Measuring Socioeconomic Status in Studies of Child Development, *Child Development*, Vol. 65, No. 6, 1994, pp. 1541–1545.

Kahlenberg, Richard D., "From All Walks of Life: New Hope for School Integration," *American Educator*, Winter 2012–2013, pp. 2–14, 40. As of May 11, 2022: https://files.eric.ed.gov/fulltext/EJ995900.pdf

Kaufman, Julia H., Sy Doan, Andrea Prado Tuma, Ashley Woo, Daniella Henry, and Rebecca Ann Lawrence, *How Instructional Materials Are Used and Supported in U.S. K–12 Classrooms: Findings from the 2019 American Instructional Resources Survey*, Santa Monica, Calif.: RAND Corporation, RR-A134-1, 2020. As of May 11, 2022: https://www.rand.org/pubs/research_reports/RRA134-1.html

Michelmore, Katherine, and Susan Dynarski, "The Gap Within the Gap: Using Longitudinal Data to Understand Income Differences in Educational Outcomes," *AERA Open,* Vol. 3, No. 1, 2017, pp. 1–18.

Mickelson, Roslyn A., and Martha Bottia, "Integrated Education and Mathematics Outcomes: A Synthesis of Social Science Research," *North Carolina Law Review,* Vol. 88, No. 3, 2010, pp. 993–1090.

Mickelson, Roslyn A., "Is There Systematic Meaningful Evidence of School Poverty Thresholds?" National Coalition on School Diversity, September 2018. As of May 11, 2022: https://files.eric.ed.gov/fulltext/ED603709.pdf

Reardon, Sean, Ericka S. Weathers, Erin M. Fahle, Heewon Jang, Demetra Kalogrides, "Is Separate Still Unequal? New Evidence on School Segregation and Racial Academic Achievement Gaps," Stanford Center for Education Policy Analysis, working paper No. 19-06, September 2019. As of May 11, 2022: https://edopportunity.org/research/

Sinclair, Beth and Chen-Su Chen, "Understanding School Lunch Eligibility in the Common Core of Data," *NCES Blog*, August 5, 2020. As of May 11, 2022: https://nces.ed.gov/blogs/nces/post/understanding-school-lunch-eligibility-in-the-common-core-of-data

Skinner, Rebecca R., and Leah Rosenstiel, *Allocation of Funds Under Title I-A of the Elementary and Secondary Education Act*, Washington, D.C.: Congressional Research Service, September 17, 2018.