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Measures of Economic Disadvantage Explain Outcomes Differently Across Geographies

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Abstract

Alternative poverty measures have been proposed in response to the emerging insufficiencies of the National School Lunch Program (NSLP) eligibility data. The analysis presented here involves seven poverty measures. Using outcome measures as a yardstick, we can assess how poverty measures explain these outcomes and note variations between geographical locales (assessing predictive validity). An analysis of 2019 data from Montana revealed that no poverty measure emerges as consistently meeting or exceeding the results found with the NSLP on the state level. Results are mixed based on locale (size) and distance from an urban centre, and within school communities.

Résumé

En réponse aux insuffisances relevées dans les données sur l'éligibilité au National School Lunch Program (NSLP), certains objectifs pour diminuer la pauvreté ont été proposés. L'analyse présentée ici comprend sept mesures de la pauvreté. En utilisant des critères d'évaluation spécifiques comme guide, on peut estimer comment ces mesures de la pauvreté peuvent expliquer les résultats obtenus et, en jaugeant la valeur prédictive de ces mesures, on peut observer des variations entre lieux géographiques. Une analyse de données de 2019 provenant du Montana indique qu'aucune des mesures de la pauvreté se distingue comme ayant rencontré ou dépassé les résultats observés par le NSLP à l'échelle de l'état. Les résultats diffèrent selon le lieu

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(surtout sa population) et sa distance par rapport à un centre urbain. Les résultats diffèrent aussi au sein même des communautés scolaires..

Keywords / Mots cles : economic disadvantage, free and reduced lunch, poverty, Montana / désavantage économique, dîner gratuit ou à prix réduit, pauvreté, Montana

Introduction

In Montana, we expect variation in relative income and poverty, and that variation occurs in an environment with strong geographic and educational differences. How poverty measures explain differences in income and student outcomes differs between geographic areas and between poverty measures. The focus of comparison is the predictive validity that each measure has on a student outcome and in relation to other poverty measures for the same outcomes. This predictive validity can be analyzed across geographic locales to gauge the relevance, strength, and parsimony of each measure in different contexts.

One poverty measure may be sensitive in one geographic context whereas other measures are not. Importantly, this variation highlights differences between how we measure poverty and the impact that this has on applied research and government programs. It provides a yardstick to assess differences between the measures and a benchmark to define consistency across locales. These differences are reflected in how we compare alternative poverty measures to the established proxy of economic disadvantage—National School Lunch Program (NSLP) eligibility data. Research into the inefficiencies of NSLP is emerging and gaining traction in research and public policy (e.g., Domina, Pharris-Ciurej, Penner, Penner, Brummet, 2018; Geverdt & Nixon, 2018; Doan, Diliberti, & Grant, 2022; Fazlul, Koedel, & Parsons, 2023). To date, there are alternative poverty measures that have not been employed in these analyses and the impact of geographic differences on measures of economic disadvantage is currently limited.

In rural areas it is difficult to analyze educational differences since many of the demographic variables in rural communities are homogenous. This calls for alternative ways to analyze variation in rural communities by describing internal factors. Income and poverty in rural areas are not homogenous. When using alternative poverty measures, we can acknowledge differences within communities and student groups. Some poverty measures are more consistent than others in explaining this variation and accounting for differences.

This study investigates differences in educational outcomes and assessments of economic disadvantage prior to the pandemic (2019) on the state level, in multiple locales (size), and between different kinds of rural locations (distance from an urban centre) and discusses trends within small rural communities (measured by the distance a student lives from their school). There are important differences in how poverty measures relate to each other and the degree they explain student outcome measures. Students in Montana are roughly equally dispersed between cities, towns, and rural areas, making this analysis even more important. Policymaking in Montana merits a poverty measure that is sensitive across locales to a degree that explains economic disadvantage and its association with student outcomes. The State of Montana uses NSLP data for Title 1-A allocations to school districts for communities with less than 20,000 inhabitants (Skinner, 2020). Over time, all states will have to reassess program allocations, research, and evaluations considering the relevance of different poverty measures.

This variation is seen in education policy when policymakers and researchers use poverty measures to better understand economic disadvantage in a community. The author's assumption is that poverty measures account for variation based on geography in different ways and these trends differ from what is seen with NSLP. Understanding what happens both on the macro (state) and micro (within small communities) broadens our perspective of what it means to be educated in a rural state. This perspective is important when directing scarce resources or assessing the effectiveness of education programs in situations that are unique to the West. Recognizing consistency of poverty measures is important in the way that they explain student outcomes in different geographies. This entails that a poverty measure, when applied to different locales, would predict this variation similarly across locales. At the national level, research indicates that few poverty measures have the same or greater predictive validity than NSLP eligibility (Domina et al., 2018; Doan et al., 2022).

There is a need for reliable and consistent poverty measures that can be used in multiple geographies, as has been seen in the past with NSLP. This is apparent at the locale (size of community) and distance from an urban centre level. An alternative poverty measure introduced by the U.S. Department of Education—the Spatially Interpolated Demographic Estimate (SIDE)—provides data on a student level. An example of a SIDE measurement on a school level is the School Neighborhood Poverty (SNP) estimates. Statewide Longitudinal Data Systems have access to a U.S. Department of Education pilot application that geolocates any address in the United States and provides an income-to-poverty ratio (IPR) for that address, not just the school address as used in the SNP (BlindSIDE). This yields a unique IPR for a geolocated student address. Aggregations of these data to the student group or to the school level show promise indicating that this measure may supplement NSLP eligibility data even when factoring in geographic differences (Geverdt & Nixon, 2018).

Problem definition

This article asks three questions that address whether there is variation by state, locality, distance from an urban centre, and within rural communities in how poverty measures account for economic disadvantage. It is evident that there is variation in how poverty measures account for income in diverse contexts; however, we do not know how alternative poverty measures are related to NSLP (historical standard) in each context and how the various poverty measures may explain student outcomes. Addressing historical continuity when making criticisms of NSLP is a necessary but not sufficient requirement when framing alternatives to NSLP. Continuity is important in public policy and is achieved in this study by comparing the predictive validity of NSLP with that of the alternative poverty measures. In this study, it is sufficient to address this continuity and predictive validity by incorporating multiple alternative poverty measures in the analysis. For this reason, this article focuses on the year before the pandemic when the insufficiencies of NSLP eligibility due to policy constraints were made clear in the policy literature. The study's questions are:

1. What is the relationship between the alternative poverty measures and NSLP data?
2. When explaining student outcomes, are poverty measures consistent across geographies?
3. When using a model to predict satisfactory attendance, are there differences when poverty measures are separately used as controls?

These questions compare NSLP eligibility and the alternative measures to establish the degree to which policy measures align with historical standards using data prior to the pandemic.

This article considers seven alternative poverty measures, including the two SIDE measures (based on school address and student address). Results are compared with more established poverty measures (SNP index, Small Area Income Poverty Estimate [SAIPE], NSLP eligibility, NSLP participation, years a student has been in NSLP program, and Direct Certification) and focuses narrowly on variation between NSLP and the SIDE measures between locales and within rural communities based on how close a student lives to their school.

This analysis adopts the methodology of a RAND study that focused on the comparability of certain poverty measures to the NSLP standard. Doan, Diliberti, and Grant (2022) conclude that these alternative measures add little value and recommend that policymakers continue to use the NSLP eligibility standard for lack of better alternatives. This conclusion is problematic. The NSLP standard has been the school level proxy poverty measure of choice for the last 40 years, but that may be coming to an end due to errors in data collection and policy constraints. In this case, policy regarding alternative poverty measures should be informed by the research applications of NSLP. This addresses policy alternatives and data use of the measures. The current study looks to establish variation between the alternative poverty measures and NSLP eligibility, and to a degree compare their validity. Alternative poverty measures may interpret data differently; however, they should match the predictive validity of the NSLP eligibility data.

Background

The most recent authorization of the *Elementary and Secondary Education Act* (ESEA) addresses the needs of economically disadvantaged students. The Act requires that the National Assessment of Educational Progress (NAEP) reports on students with economic disadvantage. Relationships between poverty measures are unclear. For example, it is unclear whether a poverty measure is fixed to a family income of 75 percent of the poverty level (Temporary Assistance for Needy Families [TANF]), the poverty level (e.g. Title 1 status, SAIPE), or 130 percent of the poverty level (e.g. NSLP-free, Supplemental Nutrition Assistance Program [SNAP]). The socio-economic status of school communities has been debated in academia and in policy since 1920 with Taussig's seven-part classification of parental occupational status (National Forum on Education Statistics, 2015). Socio-economic status and its proxies have guided education policy since the 1960s, even before the development of the ESEA (Harwell

& LeBeau, 2010). For the last 50 years, the most widely used proxy in education policy and research for socio-economic status has been the NSLP eligibility measure.

There are a variety of criteria that the NSLP data intends to fulfill (Geverdt & Nixon, 2018). Most districts and schools participate in the U.S. Department of Agriculture (USDA) program. The NSLP program uses poverty data from the U.S. Department of Health and Human Services (DHHS), which publishes guidance each school year. The NSLP eligibility data is updated every year, and these updates are largely transparent to both administrators, policymakers, and the research community. The NSLP measure is sensitive to many student outcomes including student achievement. The data collection is rigorous at the student, school, and district levels.

Poverty measures are often used in conjunction, for example, in Title 1 allocations. Since the enactment of ESEA, Title 1 local and state formula grants have been calculated based on one or more poverty measures. This program uses SAIPE to allocate formula-based funding to districts and has been historically supported by NSLP data to assist districts in school-level allocations. There are many issues with the use of SAIPE in this way. The estimate of the number of children in poverty does not consider geographic variation, the impact of government programs on income, and regional variations in inflation. In Title 1 allocations, SAIPE provides a focus on relative poverty rather than trends in family income occurring within a school district.

The NSLP measure has its own set of challenges. First, NSLP eligibility data is aggregated into three categories: free (< 130% of the poverty level), reduced (< 185% of the poverty level), and not participating/paid. The data targets 130 percent of the poverty level for free lunch ($33,475 for a family of four in 2020) and 185 percent of the poverty level for reduced lunch ($47,638), well above the established poverty level ($26,200) (Skinner, 2020; Department of Health and Human Services, 2020). This has created a condition where the ability to identify and target high-need areas and disadvantaged students is limited (Geverdt & Nixon, 2018). Furthermore, the data is self-reported by parents/guardians, approximately 20 percent of eligible students do not apply or receive services, students ineligible because of income sometimes receive services due to errors in reporting, and incomes can vary during a typical school year, meaning the number of disadvantaged students may be overestimated (Harwell & LeBeau, 2010; Fazlul, Koedel, & Parsons, 2023). Eligibility is not necessarily determined by economic disadvantage. In addition to data collection issues, there are issues with school-level implementations in that many rural schools do not participate in the program.

Although highly correlated, participation rates in NSLP schools do not correspond directly with eligibility rates. This occurs acutely in the upper grades where students opt out of the system, or families do not submit applications for eligible students. In addition, participation rates vary by locality, subgroup, and age levels, not just by income (Skinner, 2020). One way to account for these situations is to take the longevity (years) a student has participated in the NSLP program. Michelmore and Dynarski (2017) explore the effect of years in the NSLP program and conclude that it is an effective alternative poverty measure without the shortcomings of annual NSLP eligibility data collection,

In Community Eligibility Program (CEP) schools, rates are calculated through direct certification (Cookson, 2020). This involves records of students and families who receive public benefits (in Montana, SNAP or TANF) or are automatically certified due to their family, immigration or housing status (e.g., foster, migrant, homeless). To be eligible for SNAP benefits, families must have a gross income of under 133 percent of the poverty level and limited financial resources (Skinner, 2020). To be eligible for TANF, families must have an income less than 75 percent of the poverty level. In school lunch programs, the number of identified students due to direct certification is multiplied by 1.6 to calculate the claim rate (the difference between those that received services and those that are eligible but did not receive services) (Cookson, 2020; Skinner, 2020). This multiplier is based on research at the time of a 2010 statute (*Healthy, Hunger-Free Kids Act*). There has been no change to the multiplier since, although the Act outlined that potential revisions would lie on a 1.2–1.6 continuum. The spread of the CEP program since 2010 masks the true number of economically disadvantaged students by not directly collecting data about family income (Domina et al., 2018). It also masks the number of students who may not be normally eligible, but who are eligible in CEP districts. In 2019, this is seen acutely in schools that have less than 40 percent of students directly certified when the district is considered CEP eligible (more than 40% of the students are directly certified). In Montana, this happens in 11 schools.

The American Community Survey (ACS) is a focus of many alternative poverty measures (an annual data collection that samples 1–3% of the U.S. population each year). Aggregated into a vintage (a span of five years), this survey collects data on income and household and neighbourhood characteristics, something that is missing in the NSLP data. This is important since the sample of ACS data points are refined each year. An example of a measure that uses ACS data is the School Neighborhood Poverty (SNP) index, which takes a granular look at IPRs for point estimates based on a school address. These estimates rely on a nearest neighbour approach in which the nearest 25 responses (points) of a certain vintage of the ACS are tabulated to create a unique IPR. In the case of these estimates, a least squares statistical interpolator uses the weighted sum of values from measured locations to predict values at non-measured locations (Geverdt & Nixon, 2018).

The SNP relies on unique customizations of ACS data and is an example of a SIDE estimate. Currently the ACS publishes data to local areas; however, tabulations of neighbourhoods are limited since geographical boundaries of neighbourhoods are hard to identify except through point estimates. By approximating neighbouring data for each point, in this case students, a school can be seen as consisting of multiple student-based neighbourhoods based on the point estimate for each student address. It is a migration from the polygon orientation used by most census data (Geverdt, 2019). The focus on neighbourhoods changes this orientation and refines calculations of small areas. In the case of this study, student addresses are used in the point estimates, which serve to anchor the geographical boundary based on the 25 nearest neighbours. A collection of these point estimates based on the addresses of students in a school serves as the "neighbourhood" for the school and can provide a school-level indicator based on the mean and standard deviation of student point estimates. An IPR value of 100 indicates that the average income is at the poverty line. A value of 200 would indicate that the value is 2x the poverty line. The median value for school-level estimates for the state of Montana is 264.

Based on national analyses, we know that SIDE estimates are only moderately correlated to free and reduced-price lunch data (Doan et al., 2022; Skinner, 2020). Nonetheless, the predictive validity of the SIDE measures should be as robust as the NSLP eligibility data in different geographies. The SIDE measure may be used to understand disadvantaged students who qualify for free and reduced lunch; however, the results would not be matched to economically disadvantaged families with children in the neighborhood since many of the neighboring estimates would consist of families without children. At the same time, SNP estimates tend to underestimate poverty when compared with NSLP data (Fazlul, Koedel, & Parsons, 2021). Recognizing the need to better understand both the SIDE estimates and potential complications in the use of the estimates (for example, in rural locales), the U.S. Department of Education launched a competition among grantees of the 2019 Statewide Longitudinal Data System program to encourage the testing of a school-level poverty measure (Skinner, 2021). The Montana Office of Public Instruction is a grantee.

Three studies address the predictive validity of NSLP eligibility data with alternative poverty measures. Domina, Pharris-Ciurej, Penner, Penner, Brummet, Porter, and Sanabria (2018) describe predictive validity as defining the relationship of eligibility with student test scores and comparing that association with the outcomes found with other poverty measures, in this case IRS income tax records. If, for example, the eligibility measure correlates less strongly with academic achievement than alternative poverty measures, this comparison may show measurement error in the eligibility measures. The study found that eligibility predicts variation in student outcomes more effectively than the alternative poverty measures. Fazlul, Koedel, and Parsons (2023) conclude the opposite when comparing two alternative poverty measures with eligibility (SNP and direct certification), finding value in direct certification and SNP data. Doan et al. (2022) report mixed results when analyzing the predictive validity of eligibility and income measures from the ACS.

Data

Montana has a Statewide Longitudinal Data System (SLDS) that has been fully operational since 2009. This is part of a National Center for Education Statistics grant program. It has an important public presence that fosters dissemination, reporting, and transparency. It also serves to consolidate data for the Office of Public Instruction's (OPI's) internal use. The data for this study was taken from the SLDS. This includes data behind two poverty measures (eligibility and longevity). Table 1 describes these poverty measures and the source of the data.

Student outcome variables (2019) include event dropout rate, dropout probability used in Early Warning System schools, cohort graduation rate, college enrollment rate by high school, discipline data from 21st Century Community Learning Centers schools (student with an Individualized Education Plan or section 504 status), elementary proficiency rates based on the Smarter Balanced summative assessment (math and English Language Arts – ELA) proficiency rates on the Smarter Balanced interim assessment (math and ELA), and the mean scale score by high school with the American College Test (ACT) Composite assessment measure (grade 11).

Table 1: Poverty measure description

Label	Variable description	Source
Direct certification CEP	Identified student percentage for CEP schools	Montana Department of Public Health and Human Services (DPHHS)
Direct certification	Identified student percentage for all schools	DPHHS
Longevity	Calculation using SLDS data of the numbers of years each student has participated in NSLP (grade five)	SLDS/Districts
NSLP eligibility	Count in the SLDS of students eligible for free or reduced-price lunch (FRPL)	SLDS/Districts
NSLP participation	Count number of students receiving NSLP meals	OPI School Nutrition Program
SAIPE	Percentage (district) of estimated students in poverty by total child and youth population.	U.S. Census Bureau
SNP	IPR for geolocated school address (US-ED address data)	U.S. Dept. of Education's Education Demographics and Geographic Estimate Program (EDGE)
SIDE school	IPR for geolocated school address (SLDS address data)	SLDS | EDGE Program
SIDE student	IPR for geolocated student address	SLDS | EDGE Program

Methods

Quartiles of NSLP eligibility schools were used in the analysis if there was variation between schools that are predominantly eligible and those that are not predominantly eligible, meaning that the alternative poverty measures may be more sensitive at different quartiles of eligible students. The author classified each poverty measure by quartile of NSLP eligibility to create a count of schools whose poverty measure falls within the same quartile of NSLP and within one quartile.

The degree of variation in the student outcome is also examined and explained by each poverty measure. Each student outcome data is separately regressed by each poverty measure. There are eight student outcome measures. This step identifies the magnitude of the contribution of the alternative poverty measures when explaining variation in the dependent variables. Analysis also can contribute to the understanding of the sensitivity of the alternative poverty measures by comparing the degree to which eligibility explains variation in a student outcome to results found with the alternative poverty measures.

To further probe the relationship between student outcomes and poverty measures as a yardstick to understand the consistency of alternative poverty measures across locales, this study focuses on a model in which selected predictors (student outcomes) are controlled by different poverty measures to explain satisfactory attendance rates (a similar analysis is seen in Doan et al., 2022). Satisfactory attendance applies to all grade levels and schools. We individually regress the satisfactory attendance rate by a student outcome variable with each covariate (poverty measures).

$$Satisfactory\ Attendance_i = \beta_0 + \beta_i X_i + \delta Poverty + \epsilon_i$$

Where Satisfactory Attendance$_i$ is the ratio of students who achieved a 95 percent attendance rate in each school, is regressed on X_i, a school level student outcome, and *Poverty*, the poverty level at the school using one of the seven poverty measures used by this study. For a given X_i, we compare estimates of β_i and how they may differ when controlling for school-level NSLP eligibility or the alternative poverty measures. Analyses are provided as to the sign, significance, and magnitude of the differences when comparing NSLP eligibility, the naïve condition (no control), and a measure created when all poverty measures are used as controls together. Differences in the contribution of the control to the analysis, the coefficient and standard errors, and data on sign and significance are explored, as well as if all things are held equal and how much each poverty measure lends to the model. The analysis focuses on variation in significance, magnitude, and direction between alternative poverty measures and if this variation compares with eligibility data or the naïve condition.

Empirical evidence

What is the relationship between the alternative poverty measures and NSLP data?

This article asks if there are strong relationships between alternative poverty measures and NSLP eligibility at the state level, in certain locales, between types of rural communities, and within rural communities, and finds that there is indeed variation among poverty measures in the degree they are related to NSLP. There is variation based on the level of analysis (between quartiles of NSLP eligibility or within geographies). Relationships that may be strong in certain contexts may not be as strong in others. Moreover, poverty measures may more closely align with NSLP eligibility at different rates at the state level, in locales, and within rural communities. The main trait to capture is which poverty measures are consistent across these levels of analysis (see Table 2).

To measure the fidelity of each poverty measure with the NLSP data, the quartiles of the NSLP eligibility data were compared with the quartiles of each poverty measure. This shows whether a poverty measure quartile (for example schools with more students closest to the poverty level) corresponds with an eligibility Quartile 4 (most students participate in NSLP). The strongest matches were with Community Eligibility Provision (CEP) schools (direct certification) and NSLP participation rates (Quartile 4).

Based on this analysis, the count of schools for each poverty measure that aligns with the same quartile of NSLP eligibility is much lower in Quartiles 2 and 3 of NSLP eligibility. This signals that some poverty measures align with NSLP eligibility in ways that favour either income (Quartile 1) or poverty (Quartile 4); however, when analyzing the other quartiles, there is much less alignment. The exception is NSLP participation, which aligns with eligibility more closely in Quartiles 2 and 3. Longevity proved to provide the most alignment within one quartile compared with the remaining poverty measures. The strength of the relationship was > 93.182 percent across all quartiles; SAIPE, SNP, and SIDE estimates all ranked within 80 percent of their schools matching the eligibility quartile.

Table 2: Comparison poverty measures to FRPL (dispersion by quartile)

School poverty measure	Count	Percent exact match	Percent within one quartile
Quartile 1			
CEP direct certification	—	—	—
Participation	168	89.29%	100.00%
Longevity	44	77.27%	93.18%
SAIPE	165	55.15%	80.00%
SNP estimate	164	55.49%	86.59%
Student address SIDE	152	58.55%	86.18%
School address SIDE	168	51.19%	84.52%
Quartile 2			
CEP direct certification	3	—	—
Longevity	78	41.03%	93.59%
Participation	167	100.00%	100.00%
SAIPE	161	34.16%	88.20%
SNP estimate	159	32.08%	88.05%
Student address SIDE	156	29.49%	85.26%
School address SIDE	167	28.74%	86.23%
Quartile 3			
CEP direct certification	8	100.00%	100.00%
Longevity	87	55.17%	93.18%
Participation	169	100.00%	100.00%
SAIPE	164	34.15%	85.98%
SNP Estimate	155	25.16%	85.16%
Student Address SIDE	152	35.53%	94.08%
School Address SIDE	169	33.73%	86.98%
Quartile 4			
CEP Direct Certification	126	100.00%	100.00%
Longevity	85	77.27%	97.65%
Participation	168	83.93%	100.00%
SAIPE	167	53.89%	80.24%
SNP Estimate	165	62.42%	81.82%
Student Address SIDE	129	62.79%	86.05%
School Address SIDE	167	62.87%	83.83%

This study also focused on how correlated each measure is to NSLP eligibility. This included a comparison of differences within communities based on the distance a student lives from their school. Based on the geolocation of student addresses, the author identified students who live in town versus out of town and the relative IPRs for each address. This allows for comparisons within rural communities based on the distance a student lives from their school. Within rural areas, rural remote communities have few correlations among the poverty measures that are strong. When comparing SIDE measures based on student addresses, we see that within rural remote communities the school aggregate and the population of students who are near to school are highly correlated with NSLP, meanwhile students who live out of town have poverty ratios that are moderately correlated. This may signal that data relevant to out-of-town students is more difficult to capture or that there are socio-economic differences when comparing distant students SIDE estimates with school-level FRPL data. In comparison, cities, towns, and rural fringe/distant areas have correlations that are strong between all three groups (in town, out of town, and whole school aggregate).

When explaining student outcome measures, are poverty measures consistent across geographies?

This study looks at the ways that poverty measures explain variation in student outcome variables. This provides a yardstick to assess the relative effectiveness of the alternative poverty measures to explain variation in context where the NSLP eligibility data has proven to be strong. At the state level, alternative poverty measures are mixed to the degree to which they meet or exceed the magnitude of the NSLP eligibility. Differences are apparent in the range of r^2 values by poverty measure when the student outcome variables are separately regressed by each poverty measure. Relationships that may be strong in one geographic context can vary in other geographic locations. The same is true when comparing one student outcome with another in the same locale. Differences for satisfactory attendance are similar across poverty measures based on size; however, other student outcome measures vary widely in the range of variance explained by the poverty measures when looking at schools at different distances from an urban centre, as seen in the difference between rural fringe/distant communities and rural remote.

Among all measures there is also variation by student outcome. For example, high school graduation varies to a greater degree than satisfactory attendance when each poverty measure separately regresses the outcome measure. Trends for NSLP eligibility vary less than the alternative poverty measures. The SIDE measures exhibit the smallest range of r^2 between geographic areas when compared with the other alternative poverty measures as seen in Table 3.

Relationships that may be strong in one geographic context can vary in other geographic locations. This is seen in the magnitude of the strongest and weakest association for direct certification. Smaller ranges reflect associations that are more consistent. The SIDE measures reflect these differences.

In the analysis within communities, in cities the magnitude of the regressions is high with all three SIDE analyses in comparison with NSLP eligibility. These differences did not continue in other geographical areas. In these areas, attendance and suspension data were the only outcomes that exceeded eligibility in comparison with the SIDE measures. When comparing SIDE measures, both in-town and out-of-town students had associations with magnitudes higher than the whole school SIDE measure. Student groups in town tended to have associations with the student outcome measures that had greater magnitude than out-of-town students. In only a few instances, the SIDE estimates exceed the NSLP measure. This occurs primarily in cities. All three SIDE estimates were stronger than eligibility with high school graduation rates, satisfactory attendance rate, and suspension/expulsion data in cities. The student far measure and the student near measure have higher r^2 values than the eligibility data for the satisfactory attendance and suspension/expulsion variable in towns and rural areas.

Table 3: Range in variance explained between geographical areas

	Eligibility	SAIPE	School address SIDE	longevity	Student address SIDE	Direct certification	All poverty indicators
High school graduation rate	0.239	0.297	0.211	—	0.337	0.749	—
Post-secondary enrollment	0.230	0.310	0.159	—	0.279	0.287	—
Satisfactory attendance rate	0.184	0.175	0.203	0.127	0.269	0.146	0.262
Suspension-expulsion rate	0.388	0.344	0.300	0.301	0.097	0.173	0.547
Elementary ELA proficiency	0.198	0.473	0.328	0.209	0.279	0.436	0.350
Elementary math proficiency	0.224	0.458	0.349	0.394	0.301	0.352	0.303
High School ACT composite	0.358	0.409	0.320	—	0.276	0.278	—

There are a variety of instances when the r^2 values of the students at a distance group is higher than the r^2 values of the whole school. There are also more data points for the students near to school measure that exceeds the r^2 value of the whole school. Overall, the magnitude of the r^2 values for near students is higher in towns than in other locales, with the weakest associations occurring in rural remote contexts.

When using a model to predict Satisfactory Attendance, are there differences when poverty measures are separately used as controls?

The author constructed a model in which one dependent variable (satisfactory attendance rate) is explained by the predictor variables (other student outcome measures) while controlled by the different poverty measures (both separately and together). Satisfactory attendance is important since this data is present for all schools, and it is a marker of student success. This allows us to analyze differences between poverty measures (controls) when holding the dependent variable and predictor variables static. What we find is that when all things are held equal, when one poverty measure is exchanged for another, there are important differences in sign, sensitivity, and magnitude of the association. This is reflected in the contribution of the control to the analysis and the degree this contribution differs from what is found with NSLP eligibility.

Many values exceed the r^2 value of the analysis ran with NSLP eligibility. Participation, direct certifications, and longevity explain most of those values attributable to the control, which surpass the eligibility r^2 value (see Table 4).

SAIPE is the only poverty measure with an r^2 value that meets or exceeds the eligibility value for dropout rate, dropout probability, and discipline referral. Both the SIDE measures and SNP explain less of the variation than the eligibility measure for all student outcome variables.

There are differences at the state level based on the magnitude of the regression, meanwhile sensitivity and direction remain largely similar. This differs from the conclusions of Doan et al. (2022) where magnitude and direction remain similar across measures; however, there are differences in sensitivity. What the direct certification measures show is that among the schools with students who are mostly eligible for school meals, there is strong associations among those schools that are classified as Community Eligibility schools. The way NSLP gauges poverty is similar to how direct certification accounts for poverty in these schools. When analyzing direct certification across geographic locales or quartiles of NSLP eligible students, the relative strength of this measure diminishes. These mixed results point to the need to probe deeper into the construction of each poverty measure to inform policy choices.

Table 4: Contribution of control to the model (r^2)

	Eligibility	Participation	SAIPE	School address SIDE	School SNP	Direct certification	Longevity	Student address SIDE	All poverty indicators
High school dropout Rate	0.055	0.062	0.067	0.015	0.027	0.073	—	0.027	—
Dropout probability	0.082	0.062	0.095	0.027	0.027	0.227	0.087	0.052	—
High school graduation rate	0.055	0.078	0.025	0.013	0.018	0.051	—	0.009	—
Post-secondary enrollment	0.051	0.067	0.023	0.014	0.020	0.073	—	0.017	—
Discipline referral rate	0.103	0.062	0.154	0.048	0.040	0.239	0.086	0.056	0.828
Elementary ELA proficiency	0.090	0.095	0.027	0.041	0.041	0.088	0.083	0.040	0.050
Elementary math proficiency	0.090	0.095	0.027	0.043	0.410	0.088	0.083	0.039	0.050
High school ACT composite	0.056	0.078	0.026	0.016	0.021	0.051	—	0.019	—
Elementary interim ELA	0.247	0.195	0.102	0.111	0.102	0.065	0.272	0.180	0.202
Elementary interim math	0.252	0.224	0.224	0.103	0.106	0.038	0.299	0.146	0.205

The overall pattern across geographies is that no measures consistently meet or exceed NSLP eligibility in magnitude, level of sensitivity, or match in terms of direction. The NSLP data has been noted to be very sensitive to achievement outcomes (NCES, 2012; National Forum on Education Statistics, 2015). Table 5 focuses on elementary math proficiency disaggregated by locale.

By focusing on achievement outcomes, it becomes apparent which measures explain more of the variation in relation to eligibility data. For some measures, the sign and significance of the analyses are consistent across poverty measures and locale types. The SIDE estimates and SAIPE have associations with magnitudes greater than

NSLP in town and rural fringe/distant communities as seen in Table 5 when analyzing elementary math proficiency. Overall, there are more significant associations with the SIDE estimates based on student addresses than with the SIDE estimate based on school addresses. This is particularly true in cities and with rural areas (all distances from an urban centre).

Table 5: Sensitivity of estimated associations of poverty measures and elementary smarter balanced assessment consortium math on satisfactory attendance

	Naïve	Eligibility	SAIPE	Longevity	School address SIDE	Student address SIDE	Direct certification	All Poverty Indicators
City	0.3219***	0.350***	0.306***	0.194*	0.329***	0.334***	0.356***	0.580**
	(0.065)	(0.082)	(0.066)	(0.091)	(0.074)	(0.075)	(0.086)	(0.172)
Town	0.270***	0.077	0.158	0.138	0.145	0.106	0.099	0.319
	(0.062)	(0.081)	(0.081)	(0.110)	(0.080)	(0.073)	(0.078)	0.168
Rural	0.183***	0.180***	0.163**	0.015	0.120**	0.178***	0.097*	0.541***
	(0.040)	(0.055)	(0.041)	(0.056)	(0.042)	(0.047)	(0.040)	(0.130)
Rural Fringe/ Distant	0.189**	0.154	0.174**	0.053	0.113	0.228***	0.103	0.354*
	(0.063)	(0.079)	(0.065)	(0.087)	(0.064)	(0.066)	(0.065)	(0.169)
Rural remote	0.185***	0.192**	0.052**	0.009	0.128*	0.163*	0.100	0.673***
	(0.052)	(0.070)	(0.052)	(0.071)	(0.053)	(0.063)	(0.051)	(0.177)

Notes: ***significance level $p < 0.001$; **significance level $p < 0.01$; *significance level $p < 0.05$

Policy alternatives

This study of the impact of poverty measures in different geographical contexts found many differences between poverty measures and based on state trends, locale type, distance from an urban centre, and proximity to school (within communities). Overall, relations in cities and rural areas were stronger than in town locales. Moreover, rural fringe and rural distant areas proved to have stronger associations than in rural remote areas. State results were mixed between the seven poverty measures. This piecemeal variation may prove to be a problem.

The lack of consistency of the other alternative poverty measures is troubling. This reflects less the differences in socio-economic status between geographies. The key is predictive validity, the degree to which these measures predict student outcomes. What these yardsticks show is the degree to which the poverty measures vary in different contexts. It suggests that what may be relevant in a city context does not accurately describe variation in a town or rural context in the same way as NSLP eligibility. The value of the NSLP eligibility measure is that it is consistent across locale types. Lack of consistency occurs acutely with SAIPE and direct certification. With these variables there are large differences between r^2 values across different locales when explaining variation in all student outcome variables. The SIDE estimates had less variation, approaching the level of consistency as the NSLP eligibility measure.

The attraction of the geospatial tool is compelling on many levels, including the relevance of focusing the analysis on a school neighbourhood and basing estimates on the ACS, which contains data on income, poverty, demographic, and neighbourhood characteristics. An important point of correspondence is the impact that poverty measures have on student achievement variables. The strength of the association of student achievement outcomes in predicting satisfactory attendance is stronger with the SIDE student estimates. When the associations among student achievement variables are significant using NSLP eligibility as a control, SIDE student has significant findings of a greater magnitude than SIDE school.

Implications and recommendations

The SIDE student measure is consistent across locale and rural types in terms of sign, significance, and magnitude of the associations in which SIDE was used as a covariate. These measures may also be more appropriate to use in rural remote areas due to the relative strength of the associations in comparison with other poverty measures when analyzing student achievement. Consistency points to the fact that the SIDE student measure explains variation in the student outcome variables in a similar way across locale types and rural areas. The SIDE estimates, like NSLP eligibility, explain variation in the student outcome variables when disaggregated by locale, specifically student achievement. The NSLP eligibility measure proved to have the most cases of any poverty measure that met at least a moderate level (.200) of association among all poverty measures. Nonetheless, across rural types there were many findings that exceeded the NSLP standard, specifically the SIDE student variable.

The NSLP eligibility measure consistently explains more of the variation in the student outcome variables than all other poverty measures. The lack of consistency of the alternative poverty measures to meet or exceed NSLP eligibility in all contexts leads to the conclusion that decisions about use of alternative poverty measures depend on the various constructs, policy or otherwise, of the poverty measures. An example of a construct is the value added when analyzing student neighbourhoods by geolocating school or student addresses to derive an income estimate. By taking a granular approach, we can more readily identify differences and account for insufficiencies present in the NSLP data. This analysis of differences within rural communities would only have been possible with the BlindSIDE application.

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