When Near Doesn't Compare with Far: Variation in Common Poverty Measures by Locale and Rurality

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Executive Summary

Geography determines educational opportunities and outcomes in Western states in diverse ways. Whether it is the advantages of increased school offerings in towns or cities, or the low pupil teacher ratios that we find in rural areas, differences are plentiful. Sometimes schools at a distance from an urban center experience relative advantages to those living in city environments. Other times, they may be at a disadvantage including resources and opportunities. Our study investigates differences in educational outcomes in multiple locales (size) and between different kinds of rural locations (distance from an urban center). Trends present in rural areas may not be present in towns or small cities. Moreover, trends in remote rural areas may be acute when compared to rural locales less than 25 miles from an urban cluster. This is seen in education policy when policymakers and researchers use poverty measures to better understand economic disadvantage in a community. Our assumption is that poverty measures account for variation between locale and rurality in different ways. Montana has roughly equal proportions of students residing in rural areas, towns, and small cities. Understanding this variation is important when directing scarce resources or better understanding the effectiveness of education programs. Moreover, recognizing suitability, sensitivity, and consistency of a poverty measure throughout these three kinds of communities is important.

In this study we ask four questions that address whether there is variation based on size and distance in how poverty measures account for economic disadvantage in a community. We consider six poverty measures in this study, including the Spatially Interpolated Demographic Estimates (SIDE). First, we look to a priori differences to establish if this variation is attributable to the use of the poverty measures or is the variation preexisting. We find three significant differences (suspension/expulsion rate, satisfactory attendance, and elementary Smarter Balanced math proficiency), however the remaining nine are not. This indicates that among the student outcome variables in this analysis, there is little a priori variation.

Next, we ask if there are stronger relationships between alternative poverty measures and NSLP Eligibility (National School Lunch Program) in certain locales. How do the poverty measures compare with NSLP data points based on locale and rurality? We find that there is indeed variation in that in certain contexts an alternative poverty measure may more closely align with FRPL. The main trait to capture is which poverty measures are consistent across locales and rurality. The SIDE measures are highly correlated and exhibit the most consistency by having the smallest range of Pearson values between locales.

Third, we also look to the ways that poverty measures explain variation in student outcome variables. Differences are apparent in the range of r^2 values by poverty measure when the student outcome variable is separately regressed by each poverty measure. Relationships that may be strong in one geographic context can vary in other geographic locations. Differences for Satisfactory Attendance are similar across poverty measures, however other student outcome measures vary widely in the range of variance explained by the poverty measures. For example, HS Graduation varies to a greater degree than Satisfactory Attendance. Trends for NSLP Eligibility vary less than the alternative poverty measures. However, the SIDE measures exhibit the least range of r^2 in comparison to the other alternative poverty measures. This again establishes the consistency of SIDE measures.

Finally, we construct 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 (separately). This allows us to analyze differences between poverty measures. 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. Common among poverty measures is the differences in the level of precision. For example, this is seen in Rural Remote areas with the ELA Proficiency outcome measure. The poverty measure with the least number of significant associations is the SIDE estimate based on school address. In most cases where NSLP Eligibility is significant, the magnitude of the finding from the SIDE based on student address value was significant and greater than NSLP Eligibility. Apart from Rural Remote areas, this point estimate's robustness carried across locale types, indicating that there is a greater level of consistency with this SIDE estimate (student) than the alternative poverty measures. This SIDE estimate may contribute to the analysis the same ways despite differences in geography.

By focusing in on achievement outcomes it becomes apparent which measures explain more of the variation. NSLP data has been noted to be very sensitive to achievement outcomes. (National Forum on Education Statistics, 2015; NCES, 2012). Commonly, the sign and significance of the analyses are consistent across poverty measures and locale types. Overall, there are more significant associations with the SIDE estimate based on student address than with the SIDE estimate based on school address. This is particularly true in Cities and the Rural area grouping.

This study of the impact of poverty measures in different geographical contexts found many differences between poverty measures and based on locale type and rurality. Overall, relations in Cities and Rural areas were stronger than in Town locales. Moreover, Rural Fringe and Rural Distant areas proved to have more stronger associations than in Rural Remote areas. However, this piecemeal variation may prove to be a problem. What is needed is a commonly held alternative proxy of economic disadvantage that is reliable across geographic locations. The SIDE estimates had the greatest level of consistency across locale types of the six poverty measures. Further investigation is warranted into aspects that may improve the SIDE application, for example, updating the vintage of the American Community Survey that is considered. This applies to the School Neighborhood Poverty dataset as well, which has outstanding issues with school addresses and the vintage of the application. As seen in this study, the SIDE Student estimates proved to be more consistent in understanding variation in the student outcome measures and is appealing based on being appropriate in multiple contexts such as with achievement outcomes.

Introduction

Montana is diverse in terms of education, economic opportunity, and demographic trends. One thing for certain is that there is a geographic variation common to many western states in that there are roughly equal proportions of people in rural areas, towns, and small cities. Geographic characteristics complicate the analysis of the impact of the economy on student outcomes. Trends present in rural areas may not be present in towns or small cities. This is seen with common poverty measures used in the field of education (primarily used in research and public policy). Some poverty measures do not account for geographic variation or variation in inflationary tendencies. Others are based on survey measures which can undercount individuals in rural areas and tribal lands.

These are common criticisms of the American Community Survey (ACS) of the US Census Bureau, a mid-decennial measurement of demographic and income characteristics. Data gleaned from the American Community Survey is used in alternative poverty measures. Some poverty measures are location based that seek to define a school neighborhood; however, in some rural areas this neighborhood may span school districts and counties. What is in question is the reliability of these estimates in certain contexts (city versus rural locales and among rural locales). The US Department of Education's Education Demographic and Geographic Estimates program (EDGE) promotes alternative poverty measures stemming from the ACS as seen in the School Neighborhood Poverty index (SNP) and the SIDE application.[1]

Scholars have sought to explore the fidelity of long held proxies for economic disadvantage with alternative poverty measures which have different purposes, are based on different methodologies, and may or may not have the same policy characteristics that enable policy continuity. Simply put, one poverty measure may more accurately describe a context or conform to historical reporting, in this case based on the size of the locality and distance from an urban center.

By looking at data trends in Montana we are better able to understand the impact of alternative poverty measures in a small western state and understand how it applies to our education system. Research indicates that there may be differences between rural, town, and city locations in student outcome variables such as achievement or attendance. This complicates the analysis of the impact of alternative poverty measures since differences based on locale/rurality for each student outcome measure may be preexisting to the use of the poverty measures as covariates. The poverty measures may only contribute part, or not at all, to understanding the variation.

The data in this study is based on trends in 2019. With the pandemic, all students became eligible for pandemic assistance with school meals. In addition, more families became eligible for SNAP, TANF, and Medicaid benefits, another alternative poverty measure. By taking the year prior to the pandemic, we hope to identify trends in alternative poverty measures that shed light on the SIDE estimates and how they may be used in Montana. This emphasis on policy continuity and historical trends is important. If an alternative poverty measure such as the SIDE estimates were to gain traction and use in public policy,

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[1] The SNP metric is a location-based estimate based on the American Community Survey. The SIDE tool (Spatially Interpolated Demographic Estimates), related to the SNP, triangulates point-based estimates from the ACS based on the geo location of an address. The SNP uses the geolocation of school address based on data from the US Department of Education. The SIDE tool enables geolocations based on school or student address.

the measurements would need to be sensitive to historical trends in the National School Lunch Program data (NSLP).

The National School Lunch Program (NSLP) eligibility measure has a forty-year track record of being the school level proxy poverty measure of choice. Eligibility is distinguished from participation as these counts may differ. While this is important, variation between poverty measures would indicate that some measures are unable to replicate the NSLP standard, while other are able to continue these historical trends. Thus, measures that are congruent with this policy continuity would be appropriate alternatives dependent on the policy choice of the purpose and methodology involved in the use of the alternative poverty measures.

The question remains how does this impact diverse Western states? Does use of alternative poverty measures in these contexts highlight differences based on location? How does this impact consistency and appropriateness of each poverty measure across locales and rural areas. This study investigates this possibility by looking at how selected poverty measures impact analyses of student outcomes based on locale.[2] It asks the following questions:

1. Are there variations in the student outcome data based on how large a community is and whether it is located at a distance from an urban center?
2. How do the poverty measures compare with NSLP Eligibility data points based on locale and rurality?
3. How much of the variation present in the student outcome data do the poverty measures explain when disaggregated by locale and rurality?
4. Is there variation in how an outcome variable (satisfactory attendance rate) may be explained by other student outcome variables and their covariates (poverty measures)? How is this evidenced by change in sign, significance, and magnitude between measurements when all things are held equal?

Background

Poverty measures that rely on income, poverty ratios, or participation in government programs are primary ingredients of Socio-Economic Status. Poverty measures focus on economic deprivation or having insufficient financial resources to achieve a specified standard of living (Congressional Research Service, 2022).[3] Used alone, they do not capture all the disadvantages that a student may face and challenges in their opportunity to learn. Moreover, statute directs attention to economic disadvantage, however that may be measured. For this reason, the EDGE program has focused on better understanding the poverty measures and small area geographies as a necessary step to understanding Socio-Economic Status (Gevert & Nixon, 2018). By statute, we must define economic disadvantage (or suitable proxies) for discretionary grants (Title 1) and achievement measures (NAEP). Measures of economic disadvantage are used to allocate funding to certain groups of people and to report on the

[2] This analysis draws from the research design and methodology of a RAND study that focused on the comparability of certain poverty measures to the NSLP standard (Doan, Diliberti, & Grant, 2022).
[3] Variation in poverty can occur quite differently from variation in income.

effectiveness of schools, programs, and services (National Forum on Education Statistics, 2015). By understanding income and poverty, policy makers and researchers are much closer to that goal.

The constraints of the use of NSLP data show the need for alternative poverty measures. The benefits of using the NSLP program show the criteria by which alternatives should be held to. The primary constraint on using NSLP data is that families in many schools are no longer required to submit income data. This is seen in Community Eligibility Provision (CEP) districts. Moreover, data collected is prone to inaccuracies as income may vary over the year, is based on self-reported income, and the program does not account for public benefits received.

There may be disagreement on the basic unit of analysis: the socio-economic conditions of the community. Alternative poverty measures take a geographic approach to understanding variation in self reports of income data and how this impacts communities. One effort to promote an alternative poverty measure was focused on Census Blocks and Block Groups. A Block Group contains between 300 and 6000 people (an example of an artificially defined polygon). Census tracts, school district attendance zones, and zip codes are also often used; however, boundaries of these polygons are at times arbitrary (do not conform to existing neighborhoods), are political (school districts), or are measures of convenience (based on how the postal service delivers its mail).

This is seen in many rural areas in which these levels of aggregation may be problematic as the local community is often obscured by the aggregation. This happens with localities on tribal lands and in other rural areas where a neighborhood may span school districts and counties. School districts are used as a unit of analysis by the Census Bureau (SAIPE - Small Area Income Poverty Estimate), however there are differences within school districts that may be ignored (such as in metropolitan or suburban areas)[4]. Moreover, according to current methods the SAIPE cannot be disaggregated to the school level. SIDE estimates have been promoted as a better way to identify a community and its impact on schools.[5]

It is important to place these point-based estimates in context with locale and with alternative poverty measures, including the standard of National School Lunch Program (NSLP) eligibility data.[6] Variation can be insightful since there are unique ways the poverty measures are sensitive to established standards even though they are based on different framing and constructs (reflecting different policy factors and choices). It is quite possible that some alternative poverty measures may be more sensitive in certain contexts and not others. By focusing on trends in the state of Montana, the Montana Office of

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[4] SAIPE is a district level measure. In the study we apply the same district estimated count of student whose families are below the poverty line and construct a percentage of these students divided by the population of student aged 5-17 in the district. This percentage is given to each school in the district. In rural areas this is not as problematic in method, since school districts often conform to a small number of schools residing in a geographic area.

[5] Nonetheless, there is difficulty in collecting spatial data about school districts and schools. This is evident in the SNP dataset which does not consider over 10% of Montana schools due to missing school address information.

[6] Scholars have studied the relative effectiveness of the poverty measures and conclude none are value added to the discourse and do not vary substantially from established standards as seen with the NSLP eligibility data. This includes the SNP index which is constructed in the same way as the SIDE application (Doan, S., Diliberti, M., Grant, D., 2022). However, this finding may be limited in that it does address suitability in different contexts, the need to replicate the historical trends, and the belief that alternative poverty measures rely on different assumptions, have different measurements, and may be suitable in some contexts and not others.

Public Instruction draws out these nuances and notes that similar results to established standards may also be beneficial in understanding ways to refine methodologies and seek a more accurate measure of child poverty. It is important to note differences in how a particular poverty measures explains variation across locales, and which poverty measures meet or exceed the NSLP Eligibility standard (may be more relevant in certain contexts). This process shins light on the history of the use of proxies, and the need to replicate to the greatest degree possible this long held proxy.

Data

Montana has had a Statewide Longitudinal Data System (SLDS) 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 OPI internal use. The data from this study were taken from this data warehouse. This includes data behind two poverty measures (Eligibility and Longevity). Data on Direct Certification was provided by the School Nutrition Program (OPI). School and student address data was collected in the SLDS. Addresses were geolocated by OPI using a US Census Bureau application and the income to poverty ratio was assigned using the SIDE application. Data for the student outcomes were accessed in the SLDS. Data was managed in SQL and SPSS.

Poverty Measures

In this study, we use six different poverty measures to better understand any variation and examine to which degree does each poverty measure contribute. It is believed that different poverty measures are suitable in some contexts; meanwhile in other contexts different poverty measures may be preferred. Or, when looking across locales and between poverty measures, the alternative poverty measure that is the most consistent and appropriate may be preferred.

The NSLP Eligibility data originates from a count done in March 2019 of schools that elect to participate in the program. Not all schools participate in the program (97 do not in March 2019) and these counts vary month over month. The SAIPE is used in this study to analyze the suitability of a measure which is benchmarked on the poverty level. SAIPE is based on data benchmarked on the poverty level gathered from county, state, and federal sources.

Using school address data inputted into the SIDE application, OPI was able to extract 813 SIDE estimates which are highly correlated to the SNP dataset (although there are fewer estimates with the SNP dataset) (Clausen, 2022). Aggregated into a vintage (a span of five years), the American Community Survey collects data on household and neighborhood characteristics, something that is missing in the NSLP data. These estimates rely on a nearest neighbor approach in which the nearest 25 responses (points) of a certain vintage of the ACS are tabulated to create a unique income to poverty ratios. In the case of SIDE, a least squares statistical interpolator uses the weighted sum of values from measured locations to predict values at non measured locations (Geverdt & Nixon, 2018). Thus, the responses are not only from the respondents to the survey, but missing data is tabulated in the application. The span of the neighborhood when using school address data is smaller than the span of the neighborhood estimates constructed from its students. This variation is seen particular in town and city locales (Fazlul, Koedel, & Parsons, 2021).[7]

The SIDE tool is designed to better account for geographic variation in income. One approach to understanding the effectiveness of SIDE income to poverty ratios is to use student addresses to comprise a school neighborhood. Approximately, 43% of student contact addresses in Montana could be geolocated. This is because not all student contacts provide physical address information. Approximately 10% of addresses were removed from consideration (PO Boxes and Rural Routes). The remainder of the students for which we could not collect a SIDE estimate have addresses that could not be geolocated by the Census application or had geolocations that were not recognized by the SIDE application. Mean scores of student address income to poverty ratios were tabulated to generate 682 school values. Mean IPR was calculated for schools in which at least 10% of their study body had contact addresses that generated an IPR. 94 of the remaining schools did not have any student addresses data. These schools, plus the remainder that fell under the 10% threshold (42), are Rural Remote schools.

Longevity is a measure used in this study that focuses on the number of years that a student has been in the NSLP in their district. Use of this measure addresses one insufficiency in NSLP data in that it does not effectively track income over time or variations in self-reported data. Thus, NSLP may be overcounting students at a disadvantage. In this study, Longevity is a school level measure for all schools that contain a fifth grade.[8] One way to account for overcounting in the NSLP data is to take the longevity (years) a student has participated in the NSLP program. Michelmore & Dynarski (2017) explore the effect of longevity in NSLP and poverty and how this measure is an alternative measure which better accounts for variation in family income.

Direct Certification is a measure of the count of students in families that receive a public benefit. In the case of SNAP benefits, the eligibility criteria are that a family must have an income within 130% of the poverty level as defined by the Department of Health and Human Services. Commonly, the identified student count (students from families that participate in SNAP or TANF) is used with a multiplier (1.6) to count those students normally eligible for free lunch more accurately (used specifically in the amount of a NSLP claim), including those that are identified and those who would normally be eligible if their families participated in the programs. Since this figure often yields results greater than 100%, the simple ratio of students identified divided by the total students enrolled is used in this study. Schools in the upper quartile of Community Eligibility Provision districts (high need) have over 70.1% of students that are directly certified. On average, each district in Montana has 24.3% of their students who are identified. We assume that the identified student percentage would vary in the same ways as with the use of the multiplier or without the threshold limitation.

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[7] One characteristic of these estimates is that the more populated the locale, the smaller the neighborhood imprint. Rural areas in Ohio are seen as having an 81x larger geographic imprint than a point estimates from a nearby city (Geverdt & Nixon, 2018). An Income to Poverty Ratio 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 (Fazlul, Koedel, & Parsons, 2021). The median for school level estimates for the state of Montana is 264.

[8] This measure can be replicated for all grades by creating a percentage of previous grades that a student has participated in the NSLP program.

Table 2 provides the basic descriptive statistics for each poverty measure. The mean for NSLP schools which participate in the program and have eligible students is 49.3 %. The SAIPE poverty measure identifies that on average 16.3% of students reside in families that live below the poverty line. In fifth grade (five years of participation counts) each student from a school has on average 2.2 years of participation per student in the NSLP program. The SIDE school measurements identify that school neighborhoods on average are at least 2.68x the poverty level. When using student addresses, this number is 2.80x the poverty level.

Table 1: Poverty Measures Compared

		March 2020 NSLP Eligibility	SAIPE	Longevity	SIDE School Level	SIDE Student Level	March 2020 Direct Certification
N	Valid	721	816	359	813	682	818
	Missing	97	2	459	5	136	0
Mean		0.493	0.163	2.281	267.601	280.007	0.243
Median		0.435	0.151	2.033	265.000	278.883	0.196
Std. Deviation		0.256	0.088	1.588	70.605	60.534	0.233

Student Outcome

Six student outcome variables were used in this analysis. The cohort graduation rate determines the precent of students who graduate in comparison to the number of students in the cohort that either started their studies in the 9th grade year or entered the cohort over time. Post-secondary enrollment is the count of students that enroll in higher education in a Montana University System program in the first three months after graduating from high school divided by the count of students in the high school's senior class. The satisfactory attendance rate is the percent of students in a school that have a 95% attendance rate during the school year. We identify satisfactory attendance as a variable of interest since attendance is prevalent in the research literature, is relevant to current ESSA requirements, and has coverage in all schools independent of grade level (Liu, 2022).

Suspension and Expulsion data are from those schools participating in the 21st Community Learning Centers program and are only counted for special education or 504 students. It is assumed that the balance of special education or 504 students would occur evenly across schools even though some schools have higher participation rates in these programs. The percentages of student scoring proficient or advanced are used for the Smarter Balanced ELA or math assessments. Proficiency levels are determined by the Montana Board of Public Education and proficiency is calculated for both Smarter Balanced and ACT assessments. In this study, the mean scale score of students on the ACT composite are used for all high schools (11th grade assessment). The 11th grade assessment is the statewide high school assessment of student proficiency.

Methods

In our first look at the data, we provide the outcome of 12 General Linear Model analyses to establish if there are apriori differences based on locale and rurality. There are many reasons to expect variation as seen in enrollment, per pupil expenditures, and median household income, among other institutional factors. The first set of analyses has a student outcome measure as the dependent variable and locale as the fixed factor. In the second set of analyses, we use rurality as the fixed factor. Rurality is defined as those rural schools that lie within 25 miles of an urban cluster (Rural Fringe and Rural Distant), whereas the Rural Remote locations lie at a greater distance from an urban cluster. In this manner we look for significant difference that are existing with the student outcome data. Our goal is to acknowledge prior differences as we discuss differences relevant with the use of the poverty measures.

Next, we analyze pairwise correlations of data comparing eligibility data with the other poverty measures. Each analysis uses pairwise deletion to account for missing data. We look to establish how aligned is each alternative poverty measures to the NSLP standard. Separate bivariate correlations are provided at each locale and rural area. Significance level of the correlation is noted with the magnitude of the Pearson value to establish potential differences ($p < .01$). It is hoped that apparent differences would show how some alternative poverty measure align more closely with NSLP Eligibility data. This is established at each locale type and rural location. One measure of this alignment would be consistency across locale types.

In Research Question 3, we identify the magnitude of the contribution of the alternative poverty measures to explaining variation in the dependent variables. Each student outcome variable is separately regressed by each poverty measure such that analysis is conducted across locales and rural areas. Analysis can contribute to the understanding of the sensitivity and appropriateness of the alternative poverty measures by comparing the degree to which NSLP Eligibility explains variation in a student outcome variable to results found with the alternative poverty measures. Thus, comparison is done in two directions. First, the magnitude of the r^2 value can be compared by locality and rurality to establish potential differences based on geography. In addition, each poverty measure can be compared to other measures, most important the Eligibility data.

Finally, by holding all thing equally, we compare the contribution of the poverty measures to an analysis of satisfactory attendance with attention paid to geographic differences. It is assumed that poverty measure would yield different findings based on locale type or rural area. We individually regress the satisfactory attendance variable by the other student outcome variables with each covariate (poverty measures) at each geographic level.[9]

$$SatisfactoryAttendance_{\mathrm{i}} = \beta_O \ + \ \beta_1 X_{\mathrm{i}} + \ \delta Poverty + \ \varepsilon_{\mathrm{i}}$$

Where $\mathrm{SatisfactoryAttendance}_i$ is the percent of students that attended school at least 95% of the time, is regressed on X_i, a school level student outcome, and Poverty, the poverty level at the school using one of the six poverty measures used by this study. For a given X_i, we compare how estimates of β_i differ from when controlling for school level NSLP Eligibility (the focus of comparison) versus those obtained with alternative poverty measures. Also, we look to variation by locale and rural type when satisfactory attendance, the predictor variables, and the poverty measure remain static.

We focus on variation in significance, magnitude, and direction between alternative poverty measures and if this variation compares with eligibility data or the naïve condition. We explore if all things are held

[9] Adapted from the Rand study research design (Doan, Diliberti, & Grant, 2022).

equally, how much each poverty measure lends to the model. We also conduct each analysis based on locale/rurality. Analyses are provided as to the sign, significance, and magnitude of the differences when comparing with NSLP Eligibility, the naïve condition (no control), and a measure created when all poverty measures are used as controls together. In three steps we look to differences in the magnitude of β values, in significance level, and in direction that impact differences established based on locale/rurality.

Results

Research Question 1: Is there variation in the student outcome data based on how large a community is and whether it is located at a distance from an urban center?

This research question is guided by the assumption that there are differences based on locality and rurality as found in the student outcome data. There were three significant differences found with the General Linear Models. Satisfactory Attendance data shows that there are differences found between city and rural areas in comparison to town locations. This difference is important to note since Satisfactory Attendance is the dependent variable in Research Question 4. Data may have a preexisting bias when describing town in comparison to city and rural areas that poverty measures themselves may not explain. The Suspension/Expulsion rate was highest in rural areas ($p < .001$) when comparing based on locale. Data may have a preexisting bias when describing rural in comparison to city and town areas. Elementary Smarter Balanced Math Results were higher in Rural Fringe and Rural Distant communities compared to Rural Remote communities ($p = .007$).

Table 2: Variation in Student Outcome Measures by Locality and Rurality

		Mean	Standard Deviation	N	df	Mean Square	F	Sig	Partial Eta Squared
Satisfactory Attendance Rate	City	0.480	0.088	66	2	0.159	4.489	0.012	0.011
	Town	0.424	0.131	133					
	Rural	0.477	0.206	605					
Suspension/ Expulsion Rate	City	0.016	0.009	11	2	0.017	7.667	0.001	0.184
	Town	0.028	0.032	25					
	Rural	0.067	0.061	35					
Elem SBAC Math	Rural < 25 miles	0.431	0.227	145	1	0.395	7.403	0.007	0.016
	Rural Remote	0.368	0.233	321					

The remainder of the results from the analysis were insignificant (9) indicating there are little a priori differences based on locale or rurality which impact the analysis. The significant findings occurred in a certain pattern. This variation happened with all three of the variables that were significant in one context (by locale category or rural area), but not the other.

Research Question 2: How do the poverty measures correlate with NSLP Eligibility data points based on locale and rurality?

To understand if variation is occurring based on locale and rurality, we conducted pairwise correlations of each poverty measure with NSLP eligibility. NSLP Eligibility has been the proxy poverty measure of choice in policy and research. By comparing how correlated an alternative poverty measure to Eligibility at each level we can identify differences among alternative poverty measures. Longevity proved to have the strongest correlations (> .827) with NSLP Eligibility across all schools, locales, and rural types. The range of values across locale types is also relatively small (.072). SAIPE proved to have only 1 strong correlation when comparing with Eligibility in Rural Fringe and Rural Distant communities. The range was larger (.300) with the SAIPE correlations. Direct certification also had strong correlations (3), however the range between the strongest correlation and the weakest correlation based on locale type was large (.461). The strongest correlation occurred with the city locale (.911).

Table 3: Correlations of Alternative Poverty Measures with NSLP Eligibility

	Longevity	SAIPE	SIDE School	SIDE Student	Direct Certification
All Schools	.853**	.545**	-.616**	-.673**	.554**
N	302	719	719	636	721
City	.892**	.367**	-.681**	-.787**	.911**
N	44	65	65	65	65
Town	.932**	.707**	-.621**	-.668**	.821**
N	55	132	131	124	132
Rural	.827**	.536**	-.621**	-.675**	.484**
N	197	511	512	436	513
Rural (within 25 Miles)	.851**	.667**	-.658**	-.781**	.622**
N	63	144	144	133	144
Rural Remote	.820**	.479**	-.592**	-.616**	.450**
N	134	367	368	303	369

** Relationship is significant at the p < .01 level

When comparing with Eligibility, SIDE estimates based on student addresses had strong correlations. The magnitude of the correlation was slightly stronger than SIDE based on school addresses. The range is relatively narrow for SIDE student (.171) and SIDE school (.089). This addresses issues about the consistency of the data across locale and rural type. Apparent in the data is that most alternative poverty measures vary by locale and rurality in the degree to which they correspond to how NSLP eligibility explains variation. The lone exception is the SIDE measures in which there is less variation by locale or rurality.

Research Question 3: How much of the trends present in the student outcome data do the poverty measures explain when disaggregated by locale and rurality?

This response is constructed by individually regressing each student outcome measure by NSLP Eligibility and the alternative poverty measures at each level (locale or rurality). There are only five measures that exhibit a strong association. Elementary Smarter Balanced Math has a strong association when all poverty measures are considered at the city level. Graduation rates has a .798 r^2 value with Direct

Certification at the City level. At the City level, the association between ACT Composite and NSLP Eligibility is strong (.614). It is also strong at the town level (.660). Suspension/Expulsion rates were highly associated when all poverty measures are considered at the Town Level (.630).

There are eight moderate associations ($r^2 > .400$). The fact that there are so few indicates that the power of all poverty measure to explain variation in the student outcome variables is relatively low. Apart from Cities, the explanatory power of the poverty measures proved to be relatively low. There are 36 analyses of the alternative poverty measures that proved stronger than the values found with the NSLP eligibility data. This indicates variation at different levels (locale/rurality) and across different measures. This number indicates that there is variation among poverty measures as to the degree which there is correspondence with the NSLP standard. This variation occurred primarily with SAIPE, Longevity, and Direct Certification. The values for the SIDE measures tended to be lower in comparison to NSLP Eligibility.

Amongst the highest r^2 values are found with ACT Composite. Compared to the other student outcome variables, more alternative poverty measures have associations greater than .200. There is also variation on the basis of locale where we can see when regressing ACT Composite by the NSLP Eligibility poverty measure in cities (.614) and rural areas (.398). With Elementary Math, this student outcome measure is moderately associated with SIDE student (.496), however in the other locales and with the rural areas the magnitude is much lower. The student outcome variable that consistently has weak associations is the Satisfactory Attendance measure (<.195) across all locales, rural areas, and poverty measures. The Suspension/Expulsion measure is weak with most locales and rural areas (< .163), except for Rural Fringe and Rural Distant communities where the magnitude is relatively strong (between .229 and .498).

These findings acknowledge differences based on geography. Table 4 provides the difference in r^2 when all things are held equal except geographic differences. For example, there is a .576 difference between how r^2 is measured in different locales/rural areas when regressing HS Graduation Rate by Direct Certification.

Table 4: Difference in Variance Explained by Poverty Measure for each Geographical Area

	Eligibility	**SAIPE**	**School Address SIDE**	**Longevity**	**Student Address SIDE**	**Direct Certification**	**All Poverty Indicators**
HS 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
ELEM SBAC ELA Proficiency	0.198	0.473	0.328	0.209	0.279	0.436	0.350

	Eligibility	SAIPE	School Address SIDE	Longevity	Student Address SIDE	Direct Certification	All Poverty Indicators
ELEM SBAC Math Proficiency	0.224	0.458	0.349	0.394	0.301	0.352	0.303
HS ACT Composite	0.358	0.409	0.320	--	0.276	0.278	--

This carries through the other alternative poverty measures where there is this difference based on rurality and with locale in which city and town locales have stronger associations than with rural areas. Differences are apparent in the range of r^2 values by poverty measure. Relationships that may be strong in one geographic context can vary in other geographic locations. Differences for Satisfactory Attendance are similar across poverty measures, however other student outcome measure varies widely in the range of variance explained by geography. HS Graduation varies to a greater degree than Satisfactory Attendance. Trends for NSLP Eligibility vary less than the alternative poverty measures. However, the SIDE measures exhibit the lowest variation in comparison to the other alternative poverty measures.

Nonetheless, there is variation in the overall magnitude of associations that are above a certain level favoring findings involving NSLP Eligibility. Eligibility has 23 associations that exceed an r^2 value of .200. The other poverty measures have fewer. For example, the SIDE estimates that are based on school address have 11 values that exceed .200. This compares to SAIPE (12), SIDE estimates based on student address (14), and Direct Certification (11). Taken together, Eligibility comparisons have greater strength despite this variation by geography.

SIDE estimates based on student address exhibit variation as well based on geography. When used to explain variation in the student outcome variables, there are relatively strong associations with Grad Rate and Post-Secondary Enrollment in the City category and favors Rural Fringe and Rural Distant areas. In town, rural, and rural remote areas these associations are relatively weak. When using SIDE estimates based on student address there are stronger associations with Rural Fringe and Rural Distant than with Rural Remote areas.

Research Question 4: Is there variation in how satisfactory attendance is explained by other student outcome variables and their covariates (poverty measures)? How is this evidenced by change in sign, significance, and magnitude between measurements?

In this analysis, we look at discrete variations when all things are held to be equal, apart from geography or the use of a poverty measures. For each student outcome variable, the alternative poverty measures are compared to the naïve conditions and NSLP Eligibility. Differences are noted in the ways a poverty measure may more closely align with Eligibility or the naïve condition. With the naïve condition, if results line closely, it is assumed that there is little contribution of the covariate to the analysis. Next, sign, significance, and magnitude are compared by locality and rural areas. Last, the analysis focuses on achievement outcomes. Historically, the NSLP Eligibility measures have aligned with student achievement variables (National Forum for Education Statistics, 2015). By highlighting three assessments, we can determine which poverty measure explains the most, in which context, and how this happens in different locales and rural areas.

Sign

By noting the direction of the different measures, patterns arise as to the degree of fidelity that alternative poverty measures have with NSLP Eligibility and the naïve condition. For example, with NSLP Eligibility (Post-Secondary Enrollment, City), has the opposite sign to the naïve condition. The remaining poverty measures align with the naïve condition. At the Town level, there is disagreement with the naïve condition for Graduation Rate and Post-Secondary Enrollment. Again, the alternative poverty measures align more closely with the naïve condition than with the Eligibility condition. ACT Composite shows an interesting trend (Town). There is disagreement between Eligibility and the naïve condition, however SAIPE agrees with Eligibility meanwhile other poverty measures differ in terms of direction.

It is common for Eligibility, the naïve condition, and the alternative poverty measures to agree. However, at times some poverty measures disagree. For example, in Rural areas, the Suspension and Expulsion rate for Student SIDE disagrees with the remaining measures. This happens also with Longevity for ELA Proficiency. The direction of Longevity is opposite that of the remaining poverty measures. This is also seen with SIDE student where the sign for Suspension/Expulsion is opposite the remaining poverty measures in Rural Remote locations.

Suspension/Expulsion and Eligibility is positive in Cities, however in the other locations it is negative. This happens also with Post-Secondary Enrollment and Eligibility. ACT Composite also shows similar variation in the direction is negative in the Cities and positive in the other locales. The measures for SIDE estimates are similar across locales with exceptions of rural locales (Suspension Expulsion Rate), Rural Remote locales (Suspension/Expulsion Rate), Rural Fringe and Rural Distant locales (Suspension Expulsion Rate), and the ACT composite variable in Cities.

Significance

The precision of the findings for each poverty measures differ from the other. For example, in Cities there are differences in the precision of the naïve condition and Eligibility (ELA proficiency). Four poverty measures have findings that are significant: SAIPE ($p<.01$), SIDE based on school address ($p<.01$), SIDE based on student address ($p<.05$), and the grouping of all poverty measures ($p<.01$).

Common among poverty measures is the differences in the level of precision. For example, this is seen in Rural Remote areas with the ELA Proficiency outcome measure. There are difference in the instance when the naïve condition may be significant, however NSLP eligibility is not (8). In such cases, some poverty measures more closely align with the naïve condition. The poverty measure with the least number of significant associations is the SIDE estimate based on school address.

By and large there are more significant association in Rural category (27), Cities (14), and Rural Remote areas (23). This is seen acutely with towns in that there are very few significant associations (3). There are also relatively few significant associations in the Rural Fringe and Rural Distant category (8). This is seen in Rural areas (combined) and Rural Remote categories where all poverty measures are significant for Graduation Rate, however, do not have significant findings at the other levels.

Magnitude

The SIDE estimates derived from student address has the most findings whose magnitude exceeded that of Eligibility (21), although as noted above the SIDE estimates have the least significant findings. This indicates that this SIDE measure may be more robust in explaining Satisfactory Attendance in conjunction with the predictor, however this is largely among findings that are insignificant. In most cases where NSLP Eligibility is significant, the magnitude of the finding from the SIDE Student value was significant and greater than NSLP Eligibility. Apart from Rural Remote areas, this point estimate's robustness carried across locale types, indicating that there is a greater level of consistency with this SIDE estimate than the alternative poverty measure.

In few cases where the Eligibility findings was significant did the other poverty measures have higher magnitudes. This finding agrees with RAND study which found that there were similarities in magnitude, however differences found with precision and direction (Doan, Diliberti, & Grant, 2022). In Rural Remote areas, only 4 poverty measure findings exceeded the magnitude of the Eligibility findings although most finding were insignificant.

Focus on Achievement

Much has been made about the relationship between Eligibility and achievement outcomes which has proven to be very sensitive (National Forum on Education Statistics, 2015; NCES, 2012). Commonly, the sign and significance of the analyses are consistent across poverty measures and locale types. The happens with ELA and Math Proficiency in Cities, ELA Proficiency and ACT in Rural areas, Math Proficiency and ACT in Rural Fringe and Rural Distant locales, and Math Proficiency in Rural Remote areas. Within Towns and Rural Areas within 25 miles of an urban area, there are few significant associations.

Overall, there are more significant associations with the SIDE estimate based on student address and the SIDE estimate based on school address. This is particularly true in Cities and the Rural area grouping. These estimates tend to agree with the NSLP Eligibility standard when they are present. When compared to Eligibility, the magnitude of the association is smaller with the point-based estimates. In those cases, the point estimates more closely align in magnitude with the naïve condition, except in the Town locale.

Differences are also seen when Eligibility and the naïve condition agree. For example, with ELA Proficiency in Rural Remote areas, both Eligibility and the naïve condition are significant and of similar magnitudes. However, in this analysis the alternative poverty measures findings are not significant and of lesser magnitudes. This trend is also seen with the Rural grouping. SAIPE is the alternative poverty measures which more closely align with NSLP Eligibility across locale types. Relatively few significant findings were found with Direct Certification and the SIDE measure of school addresses.

Table 5: Sensitivity of Estimated Associations of Poverty Measures, Student Achievement Variables, and Satisfactory Attendance

	Naïve	Eligibility	SAIPE	Longevity	School Address SIDE	Student Address SIDE	Direct Certification	All Poverty Indicators (Constant)
City								
ELEM SBAC ELA Proficiency	.221***	0.169	0.209**	0.096	0.208**	0.190*	0.163	0.613**
	(0.063)	(0.086)	(0.069)	(0.073)	(0.068)	(0.076)	(0.099)	(0.192)
ELEM SBAC Math Proficiency	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)
HS ACT Composite	-0.045	-0.042	-0.019	--	-0.023	-0.048	-0.064*	--
	(0.028)	(0.048)	0.028	--	(0.046)	0.034)	(0.024)	--
Town								
ELEM SBAC ELA Proficiency	0.255***	0.034	0.112	0.028	0.109	0.072	0.030	0.415*
	(0.065)	(0.084)	(0.089)	(0.109)	(0.081)	(0.074)	(0.088)	(0.167)
ELEM SBAC Math Proficiency	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
HS ACT Composite	0.021	-0.028	-0.011	--	0.007	0.006	0.017	--
	(0.019)	(0.035)	(0.027)	--	(0.022)	(0.029)	(0.022)	--
Rural								
ELEM SBAC ELA Proficiency	0.117**	0.180***	0.096**	-0.026	0.052	0.110*	0.018	0.417**
	(0.040)	(0.055)	(0.041)	(0.056)	(0.042)	(0.047)	(0.040)	(0.133)
ELEM SBAC Math Proficiency	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)
HS ACT Composite	0.032***	0.014	0.028***	--	0.025**	0.019*	0.022**	--
	(0.007)	(0.007)	(0.007)	--	(0.008)	(0.008)	(0.007)	--
Rural (Within 25 Miles)								
ELEM SBAC ELA Proficiency	0.139*	0.163	0.117	0.031	0.056	0.170*	0.013	0.277
	(0.067)	(0.086)	(0.070)	(0.751)	(0.068)	(0.070)	(0.071)	(0.167)
ELEM SBAC Math Proficiency	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)
HS ACT Composite	0.070***	0.059*	0.062**	--	0.069**	0.069**	0.041	--
	(0.018)	(0.025)	(0.020)	--	(0.023)	(0.023)	(0.022)	--
Rural Remote								
ELEM SBAC ELA Proficiency	0.111*	0.187**	0.092	-0.039	0.051	0.084	0.020	0.508**
	(0.050)	(0.069)	(0.050)	(0.068)	(0.051)	(0.060)	(0.049)	(0.182)
ELEM SBAC Math Proficiency	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)
HS ACT Composite	0.028***	0.010	0.025***	--	0.021	0.013	0.020*	--
	(0.007)	(0.008)	(0.007)	--	(0.008)	(0.009)	(0.010)	--

Conclusion

There are relatively few significant differences of the student outcome measures based on geography. This enables the analysis of when poverty measures are used to explain differences in the dependent variables. This analysis was constructed to find differences prior to the use of the poverty measure. It is believed that if there are differences with these would carry over in the analysis with Research Question 3 and 4. One finding that is significant is found with Satisfactory Attendance, particularly in Town locales with Town having a lower mean attendance rate than City or Rural areas. Hence, findings from Towns that indicates few differences may have already been biased by the preexisting difference in Satisfactory Attendance benefiting City and Rural locales.

This variation is found with Research Question 3 in the degree to which the poverty measures explain the variation in the student outcome variables is particularly minimal in Town areas. This proved to be the case; however, it is important to note that across the locale types the poverty measures explain little of the variation in the Satisfactory Attendance variable. This carries over to Research Question 4. Given this finding one would expect that relatively few of the analyses would be significant and vary in favor of the City and Rural areas. This proved to be not the case. There were many analyses that were significant, and variation did occur with the least number of significant differences happening in both Town and Rural Remote locales. We found many findings that had robust magnitudes in which some poverty measure did explain variation in a consistent fashion like NSLP Eligibility.

Longevity proved to be the poverty measure most highly correlated with NSLP Eligibility across all alternative poverty measure. Pearson values for Longevity were >.800. This is largely because Longevity is a measure based on NSLP data. SIDE student and SIDE school exhibited strong relationships that were also consistent across all locale types (>.600). This occurs even though one criticisms of the SIDE measures are that they focus on income rather than poverty and may tend to undercount poor students (Geverdt, D. & Nixon, L., 2018). SAIPE and Direct Certification exhibited weaker relationships that varied across locale types.

As expected, there is important variation between rural areas. Few of the finding in Rural Remote areas were significant, although when they do occur some poverty measures do explain variation to a greater magnitude than NSLP Eligibility. This compares with Rural Fringe and Rural Distant areas in which there were more significant findings. The ability to explain variation in the student outcome measures was less in Rural Remote areas than with Rural areas within 25 miles of an urban area. These trends highlight important differences based on rurality. Rural Fringe and Rural Distant areas tend to have values that align with NSLP, are significant in cases in which NSLP Eligibility is significant, and have values that are of a greater magnitude than Rural Remote areas. This lends to the conclusion that there are difficulties understanding Rural Remote areas in comparison to locale less than 25 miles from an urban area.

SIDE Student 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. Nonetheless, it should be noted that approximately a fifth of the Rural Remote schools did not have at least 10% of their students with address information that was identified. Nonetheless, this compares with the coverage of schools provided by NSLP Eligibility and the SNP measure.

This consistency of the SIDE measures, in particular the SIDE estimates based on student addresses, is seen throughout Research Question 3 and 4. 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. SIDE estimates also come near the degree to which NSLP Eligibility explains variation in the student outcome variables. NSLP Eligibility proved to have the most cases of any poverty measure that met a level (.200) of association. Nonetheless, across rural types there were many findings that exceeded the NSLP standard, specifically the SIDE Student variable.

The lack of consistency of the other alternative poverty measures is troubling. It suggests that what may be relevant in a city context, does not accurately describe variation in a town or rural context. The value of the NSLP Eligibility measure is that it is consistent across locale types and use of the measure to allocate resources or investigate the effectiveness of program benefits from this consistency. This 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 estimate had less variation, approaching the level of consistency as the NSLP Eligibility measure.

Appropriateness also carries through to Research Question 4 in which the SIDE Student estimates are on the whole of a greater magnitude, are significant when NSLP Eligibility is significant, and the direction of the analysis remains consistent. Appropriateness also addresses the design and common uses of a measure. The SIDE estimates have the benefit of targeting a school neighborhood rather than an abstract polygon that is often a matter of convenience. The SIDE estimate also draws from the American Community Survey which not only has data on income and poverty, but also neighborhood characteristics. As noted above, there are a variety of issues with the use of the ACS and the SIDE estimates. The ACS data may not be well representative of peoples in rural areas or tribal lands. The SIDE tool may undercount students in poverty. Nonetheless, the appropriateness and consistency of the SIDE findings gives credence to the SIDE estimates as an appropriate replacement to the NSLP Eligibility data.

SIDE estimates for student addresses align more closely with NSLP Eligibility than SIDE estimates based on school addresses. This is important since Montana is a state that has roughly equal proportions of its population that reside in City, Town, and Rural areas. A tool that can explain variation consistently in all contexts would be valuable. For example, there were few significant findings across all poverty measures in Towns and Rural Remote locales. In these cases, the SIDE estimates did align with NSLP Eligibility in a consistent fashion across all locale types. The findings are such that when NSLP was significant, the SIDE estimates had values that were significant and with greater magnitudes.

What this study found is that the SIDE application is the next best tool to understanding income and poverty in Montana. It does not have the same limitations of the NSLP Eligibility measure, particularly the lack and inconsistency of income data. In particular, the SIDE tool based on student address exhibited the closest alignment with NSLP Eligibility when explaining variation in Satisfactory attendance. When making comparisons to the degree that alternative poverty measures explained variation in a manner like Eligibility, the SIDE measures did appear to have the weakest relationships in comparison to other alternative poverty measures such as SAIPE. Nonetheless, SIDE findings remained consistent across the analyses conducted here based on locale type and rural area.

The attraction of the geo spatial tool is compelling on many levels including the appropriateness of focusing the analysis on a school neighborhood and basing estimates on the American Community Survey, which contains data on income, poverty, and neighborhood characteristics. An important point of correspondence is the impact that poverty measures have on student achievement variables. The strength of the association in predicting Satisfactory Attendance is stronger with the SIDE student estimates. Moreover, when the associations are significant, SIDE student has finding of a greater magnitude than SIDE school. In fact, the SIDE application would be invaluable in studies of student achievement since it is just as sensitive, if not more so, than NSLP Eligibility.

This study of the impact of poverty measures in different geographical contexts found many differences between poverty measures and based on locale type and rurality. Overall, relations in Cities and Rural areas were stronger than in Town locales. Moreover, Rural Fringe and Rural Distant areas proved to have more stronger associations than in Rural Remote areas. However, this piecemeal variation may prove to be a problem. What is needed is a commonly held proxy of economic disadvantage that is reliable across geographic locations. The SIDE estimates had the greatest level of consistency across locale types. Further investigation is warranted in aspects that may improve the SIDE application, for example, updating the vintage of the American Community Survey that is considered. This applies to the SNP dataset as well, which has outstanding issues with school addresses and the vintage of the application. As seen in this study, the SIDE Student estimates proved to be more consistent in understanding variation in the student outcome measures and is appealing based on being appropriate in multiple contexts.

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