Analysis of Alternative Poverty Measures Applied to the Case of Montana

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Executive Summary

Poverty measures are used in the field of education to promote public policy and enable research and evaluation activities. The question remains which poverty measures to choose in what context. Since the 1970's researchers have been using free and reduced priced lunch eligibility (NSLP Eligibility) as a measure of proxy and choice. NSLP Eligibility data has many emerging insufficiencies, including over identification of students, inaccurate income information, and inaccurate accounting of economically disadvantaged students in Community Eligible Provision schools (Geverdt & Nixon, 2018). The arrival of Covid and constraints placed on schools made these insufficiencies more apparent. Nonetheless, any alternative poverty measures would need to consider policy continuity and historical precedence. There are eight poverty measures under consideration in this study. An example of an alternative poverty measure is the Spatially Interpolated Demographic Estimates (SIDE) provided by the US Department of Education and the Census Bureau. In this study we use three SIDE measures: the School Neighborhood Poverty index, a school level measure created for this study, and a measure based on the geolocation of student addresses.

By comparing alternative poverty measures to the free and reduced meal data, the Montana Office of Public Instruction asks how correlated are measures of school poverty to the NSLP measures for March 2019 (policy continuity)? Second, are the same schools classified relatively similarly as the NSLP measure? Third, understanding the impact of poverty measures on the analysis of student outcome and institutional variables is also important to policy continuity. It allows an analysis of the relative strength of a poverty measure and enables comparisons between measures. Fourth, the study also looks to better understand how much variation in satisfactory attendance is explained by each poverty measure and whether there are differences in the direction, significance, and magnitude of the estimates. By holding all factors equal, we can use the model to make further comparisons between poverty measures. In short, all things held equal, do the alternative poverty measures meet or exceed the values found with the NSLP Eligibility data and confirm based on sign and significance.

Overall, the most highly correlated poverty measures are NSLP Participation and Longevity. The Longevity measure is construct from the number of years a student has participated in NSLP. SIDE measures are highly correlated in a similar grouping. Participation is the count of those students actually participating in the school meals program, which as research notes is different from NSLP Eligibility. Of these, the SIDE estimates based of student address show the highest correlation. SAIPE and Direct Certification data are moderately correlated. To further measure the fidelity of each poverty measure with the NLSP data, we analyzed the quartiles of the NSLP eligibility data in comparison to the quartiles of each poverty measure. This looks at whether a poverty measure quartile (for example schools with more students closest to the poverty level) corresponds with an eligibility quartile 4 (mostly participating in NSLP). Not surprisingly, the strongest matches were with Direct Certification and Participation rates (Quartile 4).

When regressing student outcome measures and institutional variables by each poverty measure, we found that the NSLP eligibility data explained the variation with many student outcomes and

institutional variables to a greater degree than the alternative poverty measures. By and large direct certification matched the magnitude of Eligibility more reliably than Participation and the other alternative poverty measures. Most Direct Certification analyses explained at least 30% of the variation in the student outcome and institutional variables. SAIPE and Longevity proved to explain little of the variation in student outcome or institutional variables.

In a model, we analyzed the degree to which variation in Satisfactory Attendance is predicted by student outcome measures while controlled by the poverty measures. We then separately regressed each combination of measures by exchanging the values for each poverty measures (all things held equal). Nearly all poverty measures showed stronger associations than seen with the naive condition (no control). Participation, Direct certification, and Longevity showed the most regression values that met or exceeded those found with Eligibility.

We then look to the sign, significance, and magnitude of the regression coefficients. The magnitude of the β coefficients were similar with the alternative poverty measures compared with the magnitude of the NSLP eligibility and the naïve condition. This confirms the finding of a RAND study which found similar variation. (Doan, S., Diliberti, M., Grant, D, 2022, p. 18). There are important differences based on significance. For example, for the Superintendent salary measure, the significance is stronger with the student SIDE measures than with either the Eligibility condition or the naïve condition. The signs remain the same with the student point estimates and Eligibility or naïve conditions.

By noting differences in the same context, for example by adding/removing an alternative poverty measure from the model, the study concludes that use of a poverty measure is a choice dependent on policy factors. There are differences between how the measure correlate with NSLP Eligibility, explain variation in student outcome and institutional variables, and function in a model where all things are held equal except for the poverty measures (controls). Nonetheless, no single alternative poverty measures have consistent values that meet or exceed the magnitude of the NSLP Eligibility measure. In fact, NSLP eligibility consistently explains more of the variation in the student outcome and institutional variables. The lack of consistency of the alternative poverty measures to meet or exceed NSLP eligibility values, leads to the conclusion that decisions about use of alternative poverty measures depend on the various constructs, policy or otherwise, of the poverty measures.

Introduction

The Elementary and Secondary Education Act (1965) was based on scientific rigor of the era that sought to address trends in child poverty as part of a larger effort to improve living standards and disrupt inequities in the delivery of education. This rigorous approach to making policy choices and funding was further refined in the 1970's when the hallmark of the ESEA, Title 1, began to use free and reduced lunch measures as a proxy for economic disadvantage. The use of this data from the National School Lunch Program (NSLP) soon became the norm in education policy and academic research. In addition to allocating billions of dollars in funding, NSLP measures are used in understanding the effectiveness of programs and institutions. NSLP eligibility data has long been held to be imperfect, however alternative poverty measures have come and gone (Fazlul, Koedel, & Parsons, E., 2021). Moreover, in recent years the insufficiency of the NSLP standard has grown acute as the proxy tends to overcount students at disadvantage (often identified students are above the poverty level) and has important methodological constraints such as being based on self-reports of income, is collected using different data collection instruments, possibly undercounts some demographic groups while inflating numbers for others, and is reliant on an opt in strategy in which some parents apply to the program meanwhile other parents may not apply or supply their income data.

By looking at data trends in Montana we are better able to understand the viability of the use of alternative poverty measures in a small western state and understand how it applies to our education system. The data in this study is based on trends in 2019. With the pandemic, all students became eligible for pandemic assistance with school meals. By taking the year prior to the pandemic, we hope to identify trends in NLSP data that shed light on its policy course. This emphasis on policy continuity and historical trends is important. If an alternative poverty measure were to gain traction and use in public policy, the measure would need to be sensitive to these historical trends in the NSLP data.

This analysis adopts 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). The purpose of this study was to see if the alternative poverty measures more accurately explained variation present in selected survey measures of school principals about achievement and related school data points. The study found that the sign, significance, and magnitude of the variation was like that when using the NSLP standard as with the alternative poverty measures. The authors conclude that there is little value added from the use of these alternative measures and recommended that policymakers continue to use the NSLP eligibility standard. However, the complications are two-fold. The authors do not explore the idea of policy continuity and longevity. NSLP has a forty-year track record of being the school level proxy poverty measure of choice that may be coming to an end due to policy constraints. While this is important, variation between poverty measures would indicate that some measures are unable to replicate the NSLP standard, meanwhile others chart different courses. Our study looks to establish that variation between the alternative poverty measures and NSLP eligibility, and to a certain degree compare their effectiveness to one another. 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. Moreover, any available data about the use of the alternative poverty measures, such as which ones are appropriate in what context, is highly important when making policy choices or decision-making.

What enters into question is how suitable and sensitive the measure is to future trends. For example, point based estimates may define a school neighborhood more reliably, or census data, which rely on the actual count of children in poverty may, more accurately define what economic disadvantage means. By adopting a stance that the measures explain variation similarly, and reverting to the NSLP standard, the authors may have missed the understanding of viability, suitability, and sensitivity.

Refining the research questions in the RAND study, we look to differences with the conclusions of the authors. Although the research design is similar, it is important to also outline how our studies differ. We focus on variants of the RAND research questions:

- How correlated are measures of school poverty to the NSLP measures (policy continuity)? Are the same schools classified relatively similarly as the NSLP measure (with a quartile of NSLP schools)?
- How much variation in the dependent variables (student outcome and institutional) is explained by each measure of school poverty, both separately and jointly?

- Does use of the school poverty measures (as control variables) change the understanding of the variation in attendance explained by the predictor variables? Do different school poverty measures generally create estimates in the same direction, significance, and magnitude?

To respond to these questions, we incorporate eight poverty measures, three of which are the same poverty measures used for the RAND study (NSLP eligibility, SAIPE, and School Neighborhood Poverty). The remaining poverty measures involved in the RAND study are income-based variables originating in the American Community Survey (ACS). This Montana study considers free and reduced participation (something noted in the research literature as being potentially different from eligibility), neighborhood poverty measures based on student address, poverty measures based on school address (a different vintage than the School Neighborhood Poverty measure), identified student percentages (direct certification) from Community Eligibility Provision (CEP) schools, and a measure of the longevity of the student participation in the NSLP measured with the fifth-grade cohort in 2019.

Background

The most recent authorization of the ESEA Act placed emphasis on addressing the needs of students with economic disadvantage. A practical example of how it is unclear is whether a poverty measure is pinned to the poverty level, or 130% of the poverty level. Socio Economic Status (SES) 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). In education policy, SES and its proxies have guided policy since the 1960s, even before the development of the Elementary and Secondary Education Act (ESEA). Essential components of SES are parental occupation, parental education, and common poverty measures. Other aspects of SES that may be considered are household and neighborhood characteristics to build a larger universe of factors that consider a child's human, social, and cultural capital in the calculation of SES.

Data from NSLP and the US Census Bureau has been used for decades to allocate funding and are commonly used in research and among practitioners. There are a variety of criteria which use of the NSLP data intends to fulfill (Geverdt & Nixon, 2018). Most districts and schools participate in the USDA program. The NSLP program uses poverty data from the US Department of Health and Human Services which releases guidance in a frame that aligns with the school year. FRPL data is commonly updated every year and these updates are largely transparent. Other criteria which seem to be absent from alternative poverty measures is that the NSLP program is established, reliable, and has a proven track record that is present in research literature and policymaking. NSLP data is also seen as applicable to the student, school, and district levels when framing the data.

Poverty measures are often used in conjunction, for example in Title 1 allocations. Since the enactment of ESEA, Title 1 local and state grants have been calculated based on one or more poverty measures. This program uses measures (e.g., income tax data from the Department of the Treasury or survey responses from the American Community Survey) such as the Small Area Income Poverty Estimate (SAIPE) to allocate 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. This estimate of the number of children in poverty does not consider geographic variation, may not consider the impact of government programs on income, and may not account for regional variation in inflation. In Title 1 allocations It may also provide a better understanding of relative poverty rather than income. SAIPE is widely used for district level calculations combined with NSLP data used by districts to allocate funding to schools. NSLP data is used by the State of Montana for Title 1-A allocations to school districts, with the permission of the US Department of Education, for communities with less than 20,000 inhabitants (Skinner, 2020).

NSLP eligibility has its own set of challenges. NSLP data has come to be used more broadly as a proxy for economic disadvantage. However, it is used in ways that the NSLP eligibility data was not intended. This has created a condition where the ability to identify and target high need areas and disadvantaged students is limited (Geverdt & Nixon, 2018).[1] Other reasons for the insufficiency of NLSP eligibility data is that data is self-reported by parents/guardians, incomes commonly vary during a typical school year, and may be overcounting the students considered to be disadvantaged. Although highly correlated, participation rates in NSLP schools are different than eligibility rates. This occurs acutely in the upper grades where students opt out of system, the families do not submit applications in situations where the student would be otherwise eligible. In addition, participation rates vary based on locality, subgroup, and age levels, not just by income (Skinner, 2020). One way to account for this overcounting 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 conclude that it is an effective alternative poverty measure.

In Community Eligibility Program schools (CEP), rates are calculated through direct certification (Cookson, 2020). This involves records of students and families that receive public benefits (e.g., SNAP, TANF, and Medicaid) or are automatically certified due to their family status (e.g., foster, migrant, homeless). To be eligible for SNAP and Medicaid benefits, families must have a gross income of under 130% of the poverty level and have limited financial resources (Skinner, 2020). 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 otherwise eligible but did not receive services) (Cookson, 2020; Skinner, 2020). This multiplier is based on research at the time of the 2010 statute. There has been no change to the multiplier since, although the Act outlined those potential revisions would lie on a 1.2 – 1.6 continuum. The spread of the CEP program since 2010 (National Forum on Education Statistics, 2015), mask the true number of students with economic disadvantage by not directly collecting data about family income. And it masks the number of students that may not be normally eligible, but who are eligible in CEP districts. This is seen most acutely in schools that have less than 40% of the student directly certified in cases where the district is considered eligible.

The American Community Survey is a focus of many alternative poverty measures (an annual data collection that sample 1-3% of the population each year). Aggregated into a vintage (a span of five years), this survey seeks to collect data on income and household and neighborhood 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 this level of analysis occurs with the US Department of Education, Education Demographic and Geographic Estimates (EDGE) program which provides a granular look at income to poverty ratios for point estimates based on address. These estimates rely on a nearest

[1] NSLP eligibility data in commonly aggregated into three categories: ‘free’ (< 130% of the poverty level), ‘reduced’ (< 185% of the poverty level), or not participating. NSLP data targets 130% of the poverty level for free lunch in ($33,475 for a family of 4 in 2020) and 185% 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).

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 ratio. 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).

EDGE relies on unique customizations of ACS data. Currently the ACS publishes data to local areas, however tabulations of neighborhoods are limited since geographical boundaries of neighborhoods are hard to identify except through point estimates. Neighborhoods and schools have long been linked in policy and practice. Although neighborhood schools have declined in the past decades due to student mobility and consolidation of schools, by approximating neighboring data for each point, in this case students, a school can be seen as consisting of multiple student-based neighborhoods based on the point estimate for each student address. These estimates have been in use by the EDGE program since 2016 (Fazlul, Koedel, & Parsons, 2021). It is a migration from the polygon orientation used by most census data. The focus on neighborhoods changes this orientation and refines calculations of small areas. In the case of this study, the student addresses are the point estimates which serve to anchor the geographical boundary based on the twenty-five nearest neighbors. A collection of these point estimates based on the addresses of the student in a school serves as the 'neighborhood' for the school and can provide a school level indicator based on the mean and standard deviation of student point estimates. Location centric results are known as SIDE: Spatially Interpolated Demographic Estimates (Geverdt & Nixon, 2018). 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 (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 (Fazlul, Koedel, & Parsons, 2021). The median 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, Diliberti, & Grant, 2022; Skinner, 2020). SIDE may target disadvantaged students that qualify for free and reduced lunch; however, their results would not be matched to economically disadvantaged families with children. One attributable factor to this difference is that NSLP data is dependent on student enrollment, whereas SIDE estimates use sampled households. This produces a challenge since any supplemental poverty indicator would have to consider historical and demographic trends (policy continuity). Not all students that live in a certain area attend the nearest public schools leading to systematic discrepancies on who is in a school neighborhood (Fazlul, Koedel, & Parsons, 2021). Moreover, SIDE estimates tend to under count in terms of poverty when compared to 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, use in rural locales), the US Department of Education launched a competition among grantees of the 2019 Statewide Longitudinal Data System program to encourage the testing of this student level poverty measure (Skinner, 2021). The Montana Office of Public Instruction is a grantee.

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 four poverty measures (eligibility, participation, student addresses, and longevity). Data on direct certification was provided by the OPI School Nutrition Program. The student addresses were geolocated by OPI using a US Census Bureau application. Analysts used the BlindSIDE tool to mine the American Community Survey (2013-2017) data and derive a SIDE estimate.

Table 1: *Cut Points for Quartiles for Each Poverty Measure*

		Percent Total Eligible for Free Reduced NSLP	**Percent Students Participating in NSLP**	**Percent Students in Poverty**	**School SNP**	**School Address SIDE**	**Student Address SIDE**	**Direct Certification (CEP)**	**Longevity (0-5 years)**
N	Valid	673	699	816	689	815	682	157	359
	Missing	149	123	6	133	7	138	683	481
Quartiles	25	0.318	0.303	0.100	213	214	237	0.456	1.000
	50	0.441	0.430	0.151	264	265	279	0.591	2.033
	75	0.618	0.688	0.207	315.5	314	320	0.701	3.333

To get a nuanced look at the data, the median percentage of student that qualify for Free and Reduced lunch in Montana (2019) is 44.1%. This count is for all schools that participate in both the NSLP and federal E-Rate programs. Schools that lie in the upper quartile of schools eligible for NSLP have a median of 61.8%. This is important to place in context since CEP districts have 100% of their students who are eligible. The percent of children in poverty (SAIPE) is a district wide indicator. Since disaggregation below this level is held to be unreliable by the Census Bureau, this study uses a proxy for each school that gives the same value as other schools that reside in the district by dividing the population of students in poverty by the total number of children aged 5-17 in the district. This is enabled by the fact that the majority of Montana's school districts have few schools. Using this indicator, schools that have 20.7% of their students in poverty lie in the upper quartile of schools throughout the state. The School Neighborhood Poverty (SNP) measure is provided by the US Department of Education. This vintage of the point-based estimates differs from what is available on the SIDE application (2013 – 2017). Moreover, the coverage of schools is limited. Data on school district boundaries is not readily available on the federal level leading to the absence of SNP data for some schools. [2]

Student point-based estimates are used by this study. It is assumed that the collection of point-based estimates for a student would more accurately depict income and poverty information within the school community. This is especially true as the size of the community increases when income estimates of the school address may be drastically different from the collection of data points where the student resides. Student address points contain more and different measures than school address-based points. In the Montana OPI Statewide Longitudinal Data System, there are 88,362 unique addresses of student contacts (parent and guardian). That compares to a student population of 147,785 (PK – 12). 14,807

[2] While SNP and School Address point-based measures do not differ substantially, it is important to note these issues with coverage and the vintage of the ACS survey (the SNP has data that is a year older than the SIDE tool) when better understanding how the tool may be refined in the future (reliability of the data).

addresses were removed since contact information only contained a PO Box address. This is not surprising since in many rural communities physical address is not collected by the school. After geolocating the remaining addresses, 64,790 student locations were identified and given an income value based on American Community Survey (SIDE estimate), or, 43.4% of the student population. 682 schools had at least 10% of their students with an identified SIDE estimate. In 2019, there were 821 schools in Montana. All the schools (139) that are not included are small rural schools (Rural Remote). This compares to 426 rural remote schools in the state, or 608 rural schools overall. For purposes of this analysis, pairwise deletion is used in the dataset and missing data is indicated as system missing. We do not impute missing data. This creates complications especially when we analyze all poverty measures together. Since, pairwise deletion is used, the 139 schools are not considered. When you combine this with the constraints on the Longevity variable, a fifth-grade measure, the n for these analyses is small.

Overall, there are significant difference between the student address SIDE estimates and the SNP data. Mean SIDE estimates for student address data is higher than the SNP estimates ($p<.001$). There are clear differences based on locale. In cities, SNP estimates are higher, although the difference is insignificant. In towns and rural areas, the student address SIDE estimates are higher. For towns, the difference is +12.27 ($p<.001$). Similarly, the difference with rural areas is +11.45 ($p<.001$).

Direct certification is calculated based on the percent of students identified whose families participate in the SNAP or TANF programs divided by the total number of students enrolled. We focus on CEP districts to shine light on the correspondence between NSLP eligibility and CEP status.

The variable for longevity is based on the number of years (1-5) that a fifth-grade student in 2019 was eligible for NSLP. There are 359 schools that contain a grade 5. Kindergarten data was not used due to the complication of half day versus full day kindergarten. The median school in Montana had students that averaged 2.033 years in the NSLP program (including the population of students that normally are not eligible for the program). It is hoped that by using the longevity variable that there would be a more accurate accounting of the poverty level of students over time. Moreover, as a school level measure, variation is seen when the mean number of years that students have been in the program, establishing greater reliability of the NSLP data.

Methods

As indicated above, there is variation in the *n* of schools encompassed by each poverty measures. The goal of the OPI analysis is universal coverage (participation, SAIPE, and school level SIDE estimates). Some measures had a smaller *n* of schools (eligibility, school SNP, direct certification in CEP schools and student SIDE). For each poverty measure we provide a pairwise correlation. Quartiles of NSLP eligibility schools were used in the analysis since there may be important 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. Moreover, when comparing how the alternative poverty measures exhibit stronger correlations at certain eligibility quartiles, we can better measure suitability.

We also compared whether schools that are in a NSLP Eligibility quartile rank in the same, or nearby, quartile of a different poverty measure. In this step we describe how each poverty measure may or may not be matched with the NSLP standard. We look at quartiles of NSLP school and compare alternative poverty measures to the same group of schools. This allows for us to investigate whether some poverty measures are more sensitive among schools whose students are mostly eligible, meanwhile others may only be sensitive for those schools in which students are mostly not eligible. The process investigates simply if there is a difference in how alternative poverty measures identify income versus how poverty is identified.

We also look to understand how much of the variation in the student outcome and institutional data is explained by each poverty measure. In this task we separately regress each student outcome and institutional data by each poverty measure. There are eleven student outcome measures and four institutional variables. This step identifies the magnitude of the contribution of the alternative poverty measures to explaining variation in the dependent variables. Analysis also can contribute to the understanding of the sensitivity and appropriateness of the alternative poverty measures by comparing the degree to which eligibility explains variation in a student outcome or institutional variable to results found with the alternative poverty measures.

For Research Question 3, we individually regress the median attendance grouping by student outcome / institutional variable with each covariate (poverty measures)[3].

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

Where $\text{SatisfactoryAttendance}_i$ is the median grouping of attendance by school, is regressed on X_i, a school level student outcome or institutional measure, and Poverty, the poverty level at the school using one of the eight poverty measures used by this study. For a given X_i, we compare estimate of β_i differ when controlling for school level NSLP Eligibility (the focus of comparison, versus those obtained with alternative poverty measures). 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 r^2, the contribution of the control to the analysis, and the coefficient and standard errors that provide data on sign, significance, and magnitude.

We explore if all things are held equally, how much each poverty measure lends to the model. 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. Our dependent variable is whether a school is in the top 50% of schools on the satisfactory attendance measure. This measure aims to promote comparability between schools and includes data for all Montana's schools. In most schools in Montana at least 50% of their students attend school at least 95% of the time. By taking the median of Montana schools and creating a dichotomous indicator we seek to analyze whether the predictor variables explain whether the school is in the top 50% of schools (closer to meet attendance expectations). The independent variables are each student outcome or institutional factor with a covariate of the selected poverty measures. Student outcome variables (2019) include event dropout rate, drop out probability used in Early Warning System schools, cohort graduation rate, college enrollment rate by high school, discipline data from 21st Community Learning Centers schools (IEP and 504 students), elementary proficiency rates on the Smarter Balanced summative assessment (math and

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

ELA), proficiency rates on the Smarter Balanced interim assessment (math and ELA), and the mean scale score by high school with the ACT Composite (11th grade). [4]

Results

Research Question 1: How correlated are measures of school poverty to the NSLP measures (policy continuity)? Are the same schools classified relatively similarly as the NSLP measure (with a quartile of NSLP schools)?

Overall, the most highly correlated poverty measures are Participation and Longevity. The Longevity measure is constructed from the number of years a student has participated. The point estimate measures are highly correlated in a similar grouping. Of these, the SIDE estimates based of student address show the highest correlation. SAIPE and Direct Certification are moderately correlated. Since we are only considering the population of CEP schools, this is expected since variation would most likely occur in the 4th Quartile of NSLP schools.

As we can see in the result in the eligibility quartile 1 (mostly nonparticipating), there is strong correlations with participation and longevity. This is repeated in quartile 3, and 4. This variation is important since the poverty measures are more sensitive at some quartiles of Eligibility than others. Seen below, in schools that have a moderately low proportion of their students that are eligible, the relationship between eligibility and longevity is not as strong. This is also seen in Eligibility Quartile 2, where the participation measure is moderately correlated, meanwhile in other quartiles it is highly correlated.

Table 2: *Correlations Alternative School Poverty Measures to Quartile of NSLP Eligibility*

		Correlation	Count	Lower C.I.	Upper C.I.
All Schools	CEP Direct Certification	0.562	673	0.508	0.611
	Eligibility	1.000	673	--	--
	Participation	0.926	653	0.914	0.936
	Longevity	0.855	298	0.822	0.883
	SAIPE	0.592	671	0.541	0.639
	School Address	-0.623	671	-0.667	-0.574
	SNP Estimate	-0.621	643	-0.667	-0.571
	Student Address	-0.682	599	-0.723	-0.637
Eligibility Quartile1	*CEP Direct Certification*	--	0	--	--
	Eligibility	1.000	169	--	--
	Participation	0.794	164	0.730	0.845
	Longevity	0.513	70	0.316	0.668
	SAIPE	0.205	169	0.056	0.345
	School Address	-0.455	168	-0.567	-0.326

[4] When controlling for all poverty measures in the same analysis, the population of schools is limited since Longevity is a fifth-grade measure and direct certification data is only with CEP schools.

		Correlation	Count	Lower C.I.	Upper C.I.
	SNP Estimate	-0.471	164	-0.582	-0.343
	Student Address	-0.545	155	-0.647	-0.423
Eligibility Quartile2	*CEP Direct Certification*	--	3	--	--
	Eligibility	1.000	167	--	--
	Participation	0.413	161	0.276	0.533
	Longevity	0.120	65	-0.128	0.353
	SAIPE	0.110	167	-0.043	0.257
	SNP Estimate	-0.279	159	-0.417	-0.129
	Student Address	-0.252	158	-0.392	-0.100
	School Address	-0.238	167	-0.376	-0.089
Eligibility Quartile3	*CEP Direct Certification*	--	8	--	--
	Eligibility	1.000	169	--	--
	Participation	0.523	162	0.401	0.627
	Longevity	0.497	74	0.302	0.651
	SAIPE	0.224	168	0.075	0.363
	School Address	-0.223	169	-0.361	-0.074
	SNP Estimate	-0.239	155	-0.382	-0.084
	Student Address	-0.194	157	-0.340	-0.039
Eligibility Quartile 4	*CEP Direct Certification*	0.869	127	0.819	0.906
	Eligibility	1.000	168	--	--
	Participation	0.450	166	0.320	0.564
	Longevity	0.482	89	0.304	0.627
	SAIPE	0.367	167	0.228	0.491
	School Address	-0.380	167	-0.503	-0.242
	SNP Estimate	-0.357	165	-0.484	-0.216
	Student Addresses	-0.491	155	-0.602	-0.361

The point estimate variables were moderately correlated across quartiles in a consistent fashion. Regardless of whether the point estimates undercount income relative to Eligibility, this trend is occurring at all quartiles. Direct certification was highly correlated in Quartile 4 (mostly participating) and is a reminder that we are only considering CEP schools.

SAIPE is moderately correlated with the eligibility data for Quartiles 3 and 4. SAIPE is more sensitive to community poverty than with income whereas in Quartiles 1 and 2 the relationship is not as strong. What we can see is that for some variables there are differences in the degree of correlation by the eligibility quartile, with the strongest relationships occurring among the schools where students are mostly eligible. Furthermore, data most affiliated with school lunch (participation, longevity, and direct certification) showed the strongest relationships in Quartile 4 in the relationship to poverty. However, data affiliated with poverty level (SAIPE) did not have relationships that were highly correlated across all quartiles, a difference with the RAND study.

To further measure the fidelity of each poverty measure with the NLSP data, we analyzed the quartiles of the NSLP eligibility data in comparison to the quartiles of each poverty measure. This looks at whether a poverty measure quartile (for example schools with more students closest to the poverty level) corresponds with an eligibility quartile 4 (mostly participating in NSLP). Not surprisingly, the strongest matches were with CEP schools and participation rates (Quartile 4).

Table 3: *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%

Longevity proved to provide the most matches within one quartile in comparison to the remaining poverty measures. The strength of the relationship was > 93.182% across all quartiles. SAIPE, SNP, and SIDE estimates all ranked within 80% of their schools matching the eligibility quartile.

Research Question 2: How much variation in the dependent variables (student outcome and institutional) is explained by each measure of school poverty, both separately and jointly?

The student outcome and institutional variables were regressed by each poverty measure to explain the proportion of variance with each school student outcome and institutional variables. With few exceptions, there were relatively weak relationships. Although, when compared with the results of the RAND study, we show stronger relationships across the board (as a percent explained by the poverty measure). The strongest occur with dropout probability, graduation, ACT Composite score, discipline referral rate, and math achievement on the Smarter Balanced assessment.

The strongest occurred with eligibility, participation, and direct certification in CEP schools. For example, 44.5% of the variation in the ACT Composite variable was explained by the direct certification measure. The NSLP eligibility data explained the variation with many student outcomes and institutional variables more frequently than the alternative poverty measures. By and large direct certification matched the magnitude of eligibility more reliably than participation and the other alternative poverty measures. Most CEP analyses explained at least 30% of the variation in the student outcome and institutional variables. SAIPE and longevity proved to explain little of the variation in student outcome or institutional variables.

Table 4: *Variance Explained by Poverty Measures for Each Dependent Variable*

	Eligibility	**Participation**	**SAIPE**	**School Address SIDE**	**School SNP**	**Direct Cert (CEP)**	**Longevity**	**Student Address SIDE**	**All Poverty Indicators**
HS Dropout Rate	0.327	0.229	0.101	0.105	0.108	0.247	--	0.130	--
EWS Dropout Probability	0.224	0.192	0.152	0.093	0.105	0.683	0.202	0.040	--
HS Graduation Rate	0.247	0.175	0.059	0.057	0.045	0.334	--	0.055	--
Post-Secondary Enrollment	0.184	0.19	0.02	0.05	0.038	0.353	--	0.044	--
Satisfactory Attendance Rate	0.082	0.111	0.029	0.056	0.067	0.208	0.113	0.059	0.274
Discipline Referral Rate	0.147	0.136	0.346	0.153	0.165	0.057	0.008	0.154	0.900
ELEM SBAC ELA Proficiency	0.358	0.307	0.059	0.097	0.166	0.318	0.143	0.083	0.588
ELEM SBAC Math Proficiency	0.348	0.295	0.066	0.107	0.179	0.309	0.15	0.104	0.441
HS ACT Composite	0.33	0.261	0.143	0.251	0.265	0.445		0.281	--
ELEM SBAC Interim ELA	0.145	0.121	0.072	0.08	0.096	0.199	0.187	0.062	0.608
ELEM SBAC Interim Math	0.257	0.235	0.07	0.146	0.17	0.151	0.175	0.131	0.615
Superintendent Salary	0.004	0.003	0.028	0.058	0.06	0.003	0.012	0.053	0.448
Teacher Salary	0.007	0.003	0.021	0.029	0.053	0.024	0.029	0.042	0.372

	Eligibility	Participation	SAIPE	School Address SIDE	School SNP	Direct Cert (CEP)	Longevity	Student Address SIDE	All Poverty Indicators
Teacher Longevity	0.02	0.025	0.002	0	0.01	0.027	0.002	0.001	0.185
Per Pupil Expenditures	0.113	0.053	0.061	0.03	0.055	0.134	0.016	0.061	0.317

(blue)	$r^2 < .100$	(red)	r^2 between .1 and.199	(green)	$r^2 > .20$

The point estimate measures explained the least about the variation in the student outcome and institutional variables. R^2 values were < 0.281, with the strongest results showing the degree to which the student address estimates explained the variation in the student outcome and institutional variables. Most of the results involving institutional variables were weak, including the eligibility measure. R^2 values are consistent with eligibility findings and the remaining poverty measures. When using all controls together we showed that the measures explain the variation to the greatest degree, although the analysis is limited to CEP schools with a fifth grade (the proportion of students that are directly certified coincides with the schools with the most eligible students).

Research Question 3: Does use of the school poverty measures (control) change the understanding of the variation in attendance explained by the predictor variables? Do different school poverty measures generally create estimates in the same direction, significance, and magnitude?

What we see is that the r^2 values of the model are weak. For example, 23.9% of the variation in attendance is explained by the discipline referral rate and the direct certification poverty measure. Nearly all poverty measures showed stronger relationships than seen with the naive condition (no control). However, when all controls are considered, the associations appear stronger. Most poverty measures showed weaker relationships than with the eligibility control. Participation, direct certification, and longevity showed the most regression values that met or exceeded those found with eligibility (as highlighted below in green).

Table 5: *Proportion of Variance of Model Explained by the Model (r^2): Dependent Variable Above 50% Median Attendance Rate*

	No Controls	Eligibility	Participation	SAIPE	School Address SIDE	School SNP	DC	Longevity	Student Address SIDE	All Poverty Indicators
HS Dropout Rate	0.042	0.061	0.081	0.084	0.046	0.054	0.154	--	0.031	--
EWS Dropout Probability	0.279	0.105	0.098	0.125	0.088	0.084	0.227	0.179	0.075	--
HS Graduation Rate	0.276	0.092	0.104	0.085	0.079	0.077	0.057	--	0.066	--
Post-Secondary Enrollment	0.067	0.083	0.093	0.081	0.071	0.075	0.215	--	0.060	--
Discipline Referral Rate	0.007	0.105	0.062	0.187	0.048	0.041	0.239	0.155	0.088	0.832
ELEM SBAC ELA Proficiency	0.026	0.117	0.115	0.043	0.050	0.094	0.124	0.086	0.059	0.057

	No Controls	Eligibility	Participation	SAIPE	School Address SIDE	School SNP	DC	Longevity	Student Address SIDE	All Poverty Indicators
ELEM SBAC Math Proficiency	0.037	0.120	0.115	0.051	0.058	0.090	0.094	0.091	0.068	0.058
HS ACT Composite	0.042	0.058	0.085	0.050	0.043	0.047	0.178	--	0.027	--
ELEM SBAC Interim ELA	0.062	0.253	0.202	0.131	0.136	0.116	0.026	0.278	0.197	0.216
ELEM SBAC Interim Math	0.145	0.272	0.252	0.252	0.180	0.176	0.038	0.288	0.206	0.205
Superintendent Salary	0.003	0.090	0.088	0.041	0.049	0.050	0.174	0.128	0.045	0.123
Teacher Salary	0.018	0.098	0.105	0.052	0.062	0.076	0.077	0.080	0.075	0.052
Teacher Tenure	0.002	0.076	0.088	0.032	0.040	0.039	0.071	0.080	0.039	0.066
Per Pupil Expenditures	0.001	0.076	0.087	0.029	0.038	0.039	0.071	0.085	0.039	0.050

Point estimate measures such as school level SIDE or SNP have no values which meet or exceed the r^2 values with eligibility as the covariate. When viewed comparatively, the Eligibility estimates are stronger than the student address SIDE estimate. SAIPE has four values which meet or exceed Eligibility as the covariate. These include dropout rate, dropout probability, discipline referral rate, and teacher tenure. Dropout Probability and discipline referral rates most often have poverty measures values that meet or exceed the r^2 values of eligibility. Longevity has five values which exceed the r^2 values of the Eligibility condition, including with teacher tenure and per pupil expenditures.

Another way to look at this variation is to note the contribution of the control to the model (how much the variation of the satisfactory attendance measure is explained by the control condition). In this case, the dependent variable remains whether the school is in the top half of schools ranked based on satisfactory attendance. Highlighted in green are those values which exceed the r^2 value of the analysis ran with NSLP eligibility as the independent variable. Participation, direct certifications, and Longevity explain most of those values attributable to the control which surpass the Eligibility r^2 value. This is likely because participation is highly correlated to Eligibility, direct certification is measured in CEP schools, and Longevity is based on years in the NSLP program. Of the remaining alternative measures, SAIPE is the only poverty measure whose r^2 meets or exceeds the eligibility value for dropout rate, dropout probability, and discipline referral. Both SIDE and SNP explain less of the variation than the eligibility measure for all student outcome and institutional variables. Point estimates based on student address align most closely with the contribution of all control conditions considered, apart from the discipline referral category.

Table 6: *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
HS Dropout Rate	0.055	0.062	0.067	0.015	0.027	0.073	--	0.027	--
EWS Dropout Probability	0.082	0.062	0.095	0.027	0.027	0.227	0.087	0.052	--
HS Graduation Rate	0.055	0.078	0.025	0.013	0.018	0.051	--	0.009	--

	Eligibility	Participation	SAIPE	School Address SIDE	School SNP	Direct Certification	Longevity	Student Address SIDE	All Poverty Indicators
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
ELEM SBAC ELA Proficiency	0.090	0.095	0.027	0.041	0.041	0.088	0.083	0.040	0.050
ELEM SBAC Math Proficiency	0.090	0.095	0.027	0.043	0.410	0.088	0.083	0.039	0.050
HS ACT Composite	0.056	0.078	0.026	0.016	0.021	0.051	--	0.019	--
ELEM SBAC Interim ELA	0.247	0.195	0.102	0.111	0.102	0.065	0.272	0.180	0.202
ELEM SBAC Interim Math	0.252	0.224	0.224	0.103	0.106	0.038	0.299	0.146	0.205
Superintendent Salary	0.085	0.083	0.034	0.037	0.036	0.099	0.126	0.034	0.035
Teacher Salary	0.070	0.081	0.027	0.037	0.037	0.069	0.079	0.040	0.052
Teacher Tenure	0.074	0.087	0.030	0.038	0.039	0.069	0.080	0.039	0.050
Per Pupil Expenditures	0.076	0.087	0.029	0.038	0.038	0.069	0.085	0.039	0.050

Taken a different way, these differences can be understood through reference to the regression coefficients and standard errors of the model. The dependent variable is again the median attendance grouping, the independent variable is the student outcome and institutional variables, and the control condition is the poverty measures. What we see is that few of the variables correspond to the same significance of the eligibility models. This is in stark contrast to the RAND study which found many of these trends. Taken at the $p < .05$ level, eligibility aligns with the sign and significance of the naive condition for graduation rate, post-secondary enrollment, elementary ELA assessment, elementary math assessment, and teacher salary. Only with the elementary ELA and math assessments was there an exact match based on significance level. SAIPE and the School Neighborhood Poverty measure match eligibility on the math and ELA elementary assessments. However, with no student outcome or institutional variable was there a 100% match rate when factoring in different poverty measures (to Eligibility or the naïve condition). The ELA and math elementary assessment analyses show that most of the poverty measures match sign and significance, apart from direct certifications and longevity.

There are other important differences based on significance. For the Superintendent salary measure, the significance is stronger with the student point estimates than with either the Eligibility condition or the naïve condition. The signs remain the same with the student point estimates and Eligibility or naïve conditions.

Table 7: Sensitivity of Estimated Association of School Poverty Measures and Student outcome/ Institutional Measures to Attendance Rate

	No Controls	Eligibility	Participation	SAIPE	School Address SIDE	School SNP	DC	Longevity	Student Address SIDE
	-3.54 *	-1.692	-1.766	-2.364	-3.202	-2.958	-2.683	--	-2.486

	No Controls	Eligibility	Participation	SAIPE	School Address SIDE	School SNP	DC	Longevity	Student Address SIDE
HS Dropout Rate	(1.643)	(2.006)	(1.852)	(1.703)	(1.742)	(1.748)	(1.887)	--	(2.129)
EWS Dropout Probability	0.899**	-0.559	-0.676*	-0.603*	-0.825**	-0.813*	-0.010	-1.200*	-0.572
	(0.283)	(0.318)	(0.312)	(0.300)	(0.296)	(0.299)	(0.804)	(0.590)	(0.347)
HS Graduation Rate	0.012***	0.009*	0.008*	0.011***	0.011***	0.011	0.002	--	0.012**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	--	(0.004)
Post-Secondary Enrollment	0.624***	0.487*	0.428*	0.583**	0.590**	0.571**	1.302	--	0.511*
	(0.185)	(0.212)	(0.204)	(0.186)	(0.190)	(.189)	(0.651)	--	(0.201)
Discipline Referral Rate	-0.766	0.428	0.087	2.050	0.019	0.161	-0.056	-3.050	2.602
	(1.097)	(1.136)	(1.156)	(1.237)	(1.176)	(1.175)	(1.000)	(2.019)	(1.884)
ELEM SBAC ELA Proficiency	0.369***	0.548***	0.449***	0.291**	0.216**	0.670***	0.471	0.135	0.371***
	(0.090)	(0.142)	(0.132)	(0.093)	(0.096)	(0.112)	(0.225)	(0.136)	(0.115)
ELEM SBAC Math Proficiency	0.441***	0.563***	0.436***	0.364***	0.304**	0.649***	0.220	0.232	0.452***
	(0.091)	(0.138)	(0.130)	(0.093)	(0.097)	(0.124)	(0.262)	(0.135)	(0.117)
HS ACT Composite	0.048**	0.013	0.044*	-0.528	0.044*	0.044*	0.065	--	0.027
	(0.018)	(0.023)	(0.021)	(0.448)	(0.021)	0.021	(0.034)	--	(0.023)
ELEM SBAC Interim ELA	0.001*	0.000	0.001	0.001	0.001	0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ELEM SBAC Interim Math	0.002 ***	0.001	0.001	0.001	.002*	0.002*	<-0.001	0.002 *	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.020)	(0.001)	(0.001)	(0.001)
Superintendent Salary	< -0.001	< 0.001	< 0.001*	<.001*	<0.001**	<.001**	<0.001***	<0.001	<0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Teacher Salary	< 0.001***	< 0.001***	< -001***	<0.001***	<0.001***	<0.001***	<0.001	<0.001	<0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Teacher Tenure	-0.24	-0.033	-0.034	-0.028	-0.023	-0.014	0.026	-0.003	-.002
	(0.020)	(0.029)	(0.028)	(0.020)	(0.020)	(0.029)	(0.046)	(0.027)	(0.025)
Per Pupil Expenditures	< 0.001	< 0.001***	< 0.001	<0.001	<0.001	<.001	<-0.001	<-0.001	<0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.00)	(0.590)	(0.000)	(0.000)

The β coefficients show consistent strong associations between the median attendance grouping, dropout probability and poverty measures. There was moderate associate with HS ACT composite and ELA and math assessment proficiency for all poverty measures, indicating agreement with the research literature that there is a moderate to strong association between attendance and achievement (Liu, 2022). Post-secondary enrollment rates also proved to have moderate associations across all poverty measures. The magnitude of the β coefficients were similar with the alternative poverty measures compared with the magnitude of the NSLP eligibility and the naïve condition. This confirms the finding of the RAND study which found similar variation.

Conclusions

This study explores the viability of alternative poverty measures to be used in the context of a rural state with a variety of student outcome and institutional variable and shows whether the alternative poverty measures promise an avenue of policy continuity with the NSLP standard. What we found is that different poverty measures generally show similar magnitude when compared to the NSLP eligibility standard. This confirms the RAND study that found different measures lead to finding relationships between predictor and outcome variable in with coefficients of the same magnitude, but with differing levels of precision (Doan, S., Diliberti, M., Grant, D, 2022, p. 18). Our study noted issues with the direction and precision of the findings. The results are not consistent across all poverty measures. In our study (Research Question 2 & 3), the r^2 values were substantially stronger than with the RAND study with many variables meeting or exceeding the r^2 values of the eligibility data. There are important differences between alternative poverty measures. This variation occurred in different patterns. For example, direct certification and Longevity showed the most findings that met or exceeded the NSLP standard, whereas the point-based estimates showed the least. The point estimates showed much weaker associations. This points to the conclusion that use of these poverty measures is context dependent, in this case highly associated with achievement factors. Moreover, some measures more accurately explain variation in the same way as Eligibility in certain contexts. Stating our finding above a little differently, school level SIDE and SNP explain variation in different ways than the eligibility variable. It should be noted that even when different, the SIDE and SNP values display more consistency across groups. We see this variation with the student address estimates in Interim Math, Interim ELA, and ACT Composite exceed the magnitude of the Eligibility condition however match the magnitude of the naïve condition.

We found differences between the results of the NSLP findings and those of the naive condition. The alternative poverty measures tend to align with the naïve condition more closely. This lends to the conclusion that some poverty measures may be more suitable in certain contexts than others.

There are a variety of policy choices that have been made about the poverty measures, such as a definition of the level in which a student is economically disadvantaged, that would test how suitable a measure is in what contexts. Do we want economic disadvantage to measure poverty level or 130% of poverty level as in the case of SNAP certification? Participation and Longevity are reliant on USDA data collection and subject to the same limitations and standards hence the assumption can be made that results (β, standard error, and significance) would not be different. However, that proves not to be the case. Another example of a policy choice occurs with the SAIPE data and whether disaggregation can be reliably offered. A similar policy challenge can be found with the data collection involved with the American Community Survey which only surveys 1-3% of the households in the US each year and has complication arising from response rates that impact the validity of the survey results. Approximately 18,000 Montanans are contacted each year.

The RAND study is reliant on a small nationally normed sample of principals. Our study attempts to work from a census of schools in a small western state. It relies on data from the SLDS and student information systems. Data is vetted multiple times prior to annual release and analysis. Data is released according to common standards and practices to the federal government, state policy makers, researchers, and educators throughout the state. Moreover, few predictive analyses have been conducted on the RAND dataset. Montana has been responsive to researchers; facilitating data requests and promoting research. For each of the student outcome and institutional variables there is track record of reporting and research. The RAND study is reliant on ACS poverty metrics, primarily self-reported. The SAIPE is based on income reported to the IRS, state, and county. The longevity construct, which seeks to look at income over time, is reliant on the same survey that is filled out in most NSLP schools (or a survey designed by districts for that purpose).

The longevity measure may be aged out due to the CEP program. Although the Longevity measure accounts for consistency in the self-reports of income on the NSLP questionnaire, it does not account for those students who are not directly certified in CEP schools. We may still have the threshold limitation to years eligible, for example all students in CEP schools would be eligible for all years. The Longevity measure is meant to consider variation in students eligibility year over year (for example due to reports of income). In these schools it would be beneficial to take the percentage of identified students that receive public benefits; however, the 1.6 multiplier merits scrutiny. The poverty measures in the RAND study themselves only differ slightly in construct. Hence, it would be predictable for a similar poverty measure to behave the same. Our study faces similar constraints. The School Neighborhood Poverty data, the school point-based estimates, and the student address-based estimates are dependent on data from the ACS. However, when comparing these measures there were few point-based datapoints that met or exceeded the magnitude of the NSLP standard.

Taking a closer look at the point-based poverty measures, we found that less of the variation of the outcome variable were explained by the independent variable and co-variates (poverty measures). There were also few associations that were significant involving SNP or SIDE values. This raises important questions about policy continuity. It is quite likely that this may be attributable to the fact that the twenty-five nearest neighbors to the school differ substantially from the mean of the twenty-five nearest neighbors of its students (neighbors being respondents to the ACS survey). In fact, throughout our analysis the student point-based estimates appeared more robust than the school-based estimates, although overall trends in sign, significance, and magnitude occur in the same direction.

This Montana OPI study faces several additional limitations with its poverty measures. The issue of the income of the families of students that do not fill out the NSLP form or do not participate in SNAP or TANF, is relevant. In this context that the NSLP Eligibility data may be undercounting students in poverty, meanwhile as research has shown in other contexts it may be overcounting.

SAIPE data is a district level measure. The same measure was applied to all schools in the district in this study, in some cases generating inaccuracies. The occurs in larger LEAs where there is more variation than in communities in which there is only one school. The SNP value and the SIDE values are highly correlated and differences between are attributable to vintage, differences in school address, and the number of schools covered by the poverty measure. Direct certification only represents those schools in the CEP program in our study. Further research will investigate the numbers of directly certified students in all schools. We were also unable to capture the physical address of all students.

What is clear is that the NSLP program has changed since 2010 with fewer families self-reporting income data. Alternatives such as direct certification and measures created about a student's tenure in the school lunch program show promise. More research is needed about the point-based income estimates and what they may or may not tell us. This includes analysis across communities, whether they are rural, town, or small city, to see the validity of alternative poverty measures.

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