Differentiating Rural Economic Disadvantage: Poverty Measures and Student Outcomes

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Executive Summary

Understanding economic disadvantage in rural communities can prove challenging in the field of education due to missing data, the fact many schools do not participate in the National School Lunch Program (NSLP), or data originates from mid decennial US Census estimates which may underrepresent children and families that live in rural areas or tribal lands. The latter estimate is based on income data from the American Community Survey and uses geographic traits of a point (physical address) to triangulate income to poverty ratios calculated from the nearest 25 responses to income questions (Spatially Interpolated Demographic Estimate – SIDE). The process of accounting for variation in economic disadvantage in many Montana's communities is opaque due to the homogeneity of socio-demographic indicators such as race/ethnicity. This provides the warrant for our study which is to provide a lens on variation within locales based on geography.

We ask three questions that clarify the role that SIDE estimates have in calculating economic disadvantage in Montana's communities. First, are there differences in income to poverty ratios based on students that live near to school (less than 3 miles) and those that live far from school? Three miles was chosen since that is the typical diameter of a rural community or town in Montana.[1] This creates three measures based on student address: a value for the whole school based on student address, a value for the near students, and a value for the far students. Next, we look to how correlated these measures are to historical standards (NSLP). Finally, we triangulate differences between measures by looking to the degree to which they explain variation in common student outcome variables. This allows us to compare the degree to which different measures explain variation in student outcome variables.

First, there are important income-based differences between locales. The difference with NSLP Eligibility based on locale show higher rates of economic disadvantage in town locations (52% eligible) over city (48%), and rural areas (44%) ($p<.05$). This is repeated for rural areas in which Rural Remote communities are at a greater disadvantage than Rural Fringe and Distant communities ($p<.05$). The SIDE measure for the whole school is insignificant at the locale (size) level. When considering rurality (distance) there are important differences between Rural Remote (262.50) and Rural Fringe and Rural Distant communities (306.25) ($p=.000$). There are also important differences within rural locales on the relative distance from a community, in this case a school. These differences highlight that students residing at a distance from a rural school have lower incomes than students that are near to school. This differs from other locales (town, city) in which families residing at a distance from school have higher incomes in comparison to their peers.

[1] World Population Review. *Cities in Montana by Population*. Retrieved 12/3/2022 from https://worldpopulationreview.com/states/cities/montana. The average size of a Montana municipality is 7.58 sq nautical miles, slightly less than our three-mile diameter threshold.

Second, there are differences in how each measure are correlated to NSLP. Overall, the whole school mean student SIDE estimates are strongly correlated with the NSLP data for 2019. This is repeated for the population of students that are near to school. There is variation with the students residing at a distance from school. The relationship for all schools and city locales is moderate, whereas in the rural locales the magnitude of the relationship is stronger. Overall, the fidelity of the measures to the NSLP proxy is strong especially in rural areas. Nonetheless, this finding may pinpoint to a reason why the SIDE estimates may undercount student in poverty due to the reliance on data near to school rather than focusing on data far way.

Third, we look to differences in which selected student outcome measures are explained by the four measures. This allows us to benchmark among the four measure which measure tends to consistently explain the most variation. When analyzing the degree to which each measure explains with higher magnitude the variation in the student outcome variables, we witness the relative strength of the NSLP Eligibility measure in comparison to the SIDE measures. When looking at it from the standpoint of historical continuity, the SIDE measures were not able to consistently meet or exceed the r^2 values of the NSLP measure across community size and distance from an urban center when all things are held equal. When comparing the near and far populations, there were many values that exceeded the magnitude of the whole school variable. The most data points which exceeded the whole school SIDE value were with the near population, seen primarily in cities and towns. Overall, the r^2 values were most robust in Rural Fringe and Distant communities in comparison to the number of weak associations in cities. This occurred across all four measures indicating the relative sensitivity of these measures in certain contexts.

Understanding this relationship of proximity to school may be crucial in understanding the viability of the SIDE measures in rural contexts when understanding the students at a distance from school raises important challenges such as missing data and small school size. The way the School Neighborhood Poverty index approaches classifying economic disadvantage in rural schools based on a school address may be inappropriate due to reliance on 'near' factors rather than focusing on points at a distance. As we saw, near factors are more closely correlated to NSLP and explain to a greater degree variation in the student outcome data. As we indicate, this may be more of an issue with rural areas than with cities and towns since income to poverty ratios for far students are much lower than for near students in rural areas. Data pertinent to students near to school in rural contexts may not be sufficient in explaining school level poverty and student outcome trends.

Introduction

Montana is diverse in its geographic expanse and the relative economic standing of its communities. Geography has a profound impact. There are roughly equal proportions of people in rural areas, towns, and small cities with variation on community size and distance from an urban area.[2] In rural areas there may be differences seen in educational outcomes in comparison to towns or cities (size of population). There may also be differences in how far a locality is from an urban cluster (distance). However, this is not sufficient to understanding variation that may be occurring in many communities. There is added complexity when understanding what is happening within locales, specifically in rural areas. Many of the socio-demographic indicators in these areas are homogenous, as seen with race/ethnicity variables. One way to investigate variation within locales is to focus on differences based on geography.

Often, especially in rural areas, we hear of differences between those residing in small communities and those living in the countryside (proximity to school). Over half of Montana's school districts are Rural Remote each with students that live close to school and those that live far away. It is important to differentiate rural variation to seek a more accurate accounting of economic disadvantage. We developed a proxy measure to understand these differences by defining which students live near school and which students live at a distance. For purposes of this study, students that live within 3 nautical miles of a school are considered 'near' to a school. For students that live more than 3 nautical miles from a school, they are considered at a distance (far).[3]

This investigation is done in three steps. In the first step we look to differences between the near and far populations. Second, we place these differences in comparison to the historical standard (NSLP). This gauges the appropriateness of the fit of the SIDE measures. Third, we look to the degree these measures explain variation in student outcome data if all other factors remain equal. By asking these questions, we look to consistency of the ability of the SIDE measures to explain variation in common measures of student success. We ask the following research questions:

1. Are there differences between those students that live less than 3 nautical miles from a school (near) and those that live more than 3 miles (far) based on locale and rurality?
2. To what degree does the Student SIDE estimates in near and far communities correlate with National School Lunch Program eligibility data (NSLP) based on locale and rurality?
3. How much of the variation present in the student outcome data do the poverty measures explain when disaggregating the SIDE Student measure into near and far groups by locale and rurality?

It is hoped that by placing an emphasis on Rurality (relative size and distance) and placing these findings in context (proximity) between near and far students, we'll be able to draws out the nuances in SIDE estimates when applied to rural contexts. One would expect that the magnitude of the associations

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[2] There are six suburban school districts in the state. This study focuses on differences between rural, town, and urban locale categories based on size, distance, and proximity.

[3] Three miles was chosen since this diameter encompasses the diameter of most Montana's rural areas and towns. Nautical miles are chosen since it is easier to calculate this quantity of student addresses based on of the geographic coordinates rather than calculating distance traveled by car or foot. Since distance traveled by road is often greater than the nautical miles between two points, the actual distance traveled to school may be greater.

generated from the use of the SIDE estimates should meet or exceed the contribution of the NSLP Eligibility data if all other things are held equal.

Background

This study assumes that there is variation based on size, distance, and proximity to school and explores the null hypothesis that there is no variation. There are reasons to expect that there may be variation. The size of the typical school enrollment differs by locale. The average enrollment in City (569.31), Town (429.66), Rural (96.24), Rural Fringe and Rural Distant (159.47), and Rural Remote (71.79) differ in the expected direction. Per pupil expenditure differs by locale and rurality in that federal, state, and local spending on average in Cities is the least ($11,867.46), Towns ($13,142.64), Rural areas ($17,769.95), rural areas within 25 miles of an urban area ($14,738.04), and Rural Remote areas ($18,979.90). The fact that as school size decreases, per pupil expenditures increases, is not reflective of the relative income in each locale. There are significant differences based on locale category between Cities (301.70), Towns (281.46), and Rural areas (276.05) in the SIDE measure that uses student address to identify data from the American Community Survey (whole school).

We focus on the SIDE estimates since their design is compelling. The ability to define a school neighborhood based on the point estimates of where their students are located is a benefit. This may entail any configuration of students, for example, those students that live near and far from school. Next, the reliance on the American Community Survey (ACS) income data approaches the strength of the US Census in describing income and poverty. Also, by focusing on eligibility data, we can draw out comparisons to historical trends (2019).[4] What is in question is the reliability of these estimates in certain contexts such as town versus rural locale categories and among rural areas.

We analyze variation in the mean poverty ratios for three groups and which estimates may explain more closely variation in school level student outcome data. Poverty measures used in the field of education (primarily used in research and public policy) gauge relative economic disadvantage of students. The National Student Lunch Program's eligibility data has been the measure of proxy and choice for over four decades, however there are emerging insufficiencies to this measure which tends to undercount students in poverty and may not collect income data from all applicants (Geverdt, D., & Nixon, L., 2018; Skinner, R, 2020) These traits of the NSLP eligibility data have raised concerns by policymakers and opened avenues to explore alternative poverty measures.

Data

The data in this study originates in Spring of 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 making them directly certified to participate in the NSLP. By taking the year prior to the pandemic, we hope to identify trends in the SIDE measures that shed light on their potential and how they may be used in Montana (Clausen, R, 2022b).

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[4] 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 doesn't address appropriateness in different contexts, the insufficiencies of NSLP Eligibility data, and the need to replicate the historical trends.

Measures

In this study, we use two different poverty measures to better understand any variation and examine to which degree does each poverty measure contribute (NSLP Eligibility and SIDE based on student address) to the analysis of student outcome data. From the SIDE application, we constructed measures specific to whether a student lives less than 3 miles from a school, or more than three miles. The purpose behind this is to address socio economic differences between the two cohorts based on locale and rurality. We can contrast this variation with the SIDE measure created from all identified students in the school. It is believed that this will reveal variation between the two cohorts and that this variation will differ by locale and rurality. Moreover, it is important to note in which contexts data draws heavily from near communities and if it better explains variation in comparison to students at a distance from school about the school level outcome data. The School Neighborhood Poverty (SNP) index uses a school address to triangulate income estimates. These estimates may be biased towards those that are near to school and underestimate students that are far from school. When looking across locales, distance, proximity, and between poverty measures, the approach 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 (119 do not in March 2019) and these counts vary month over month. The SIDE application represents data aggregated into a vintage (a span of five years). The sample size for the ACS in Montana is approximately 13,000 year over year, however there are challenges as seen in response rates. The 2019 address points were identified using the SIDE application from the 2013 – 2017 vintage of the ACS. 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).[5] Student addresses largely consist of non-measured locations. Measured locations are triangulated to produce the unique income to poverty ratio for each unmeasured address. The mean of student point estimates is calculated for the whole school and those students that are near and far.

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 (IPR) to use student addresses to comprise a school neighborhood. Approximately, 43% of student contact addresses in Montana could be geolocated and a SIDE ratio assigned (Clausen, R, 2022b). This is because not all student contacts provide physical address information. Approximately 10% of addresses were removed from consideration since they could not be geolocated. (PO Boxes and Rural Routes). The remainder of the students for which we could not identify have addresses that could not be geolocated by the Census

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[5] The span of the neighborhood when using school address (for example with the School Neighborhood Poverty index) data is smaller than the span of the neighborhood estimates constructed from its students. This is important since the SNP may fall short in accounting for students that live at a distance from school. This variation is seen particularly in town and city locales (Fazlul, Koedel, & Parsons, 2021) when taking the mean of student point-based estimates as comprising a school community.[5] When using school address, the SNP index is highly correlated to the results from the SIDE application that were built from the SLDS school contact data although the number of schools differs (.923). The correlation between the SNP and the whole school measure built from student addresses is weaker, but still highly correlated (.843).

application, or had geolocations that were not recognized by the SIDE application. Means were calculated of student income to poverty ratios and used to generate 682 school values (whole school).

Mean income to poverty ratio was calculated for schools in which at least 10% of their student body had contact addresses that generated an IPR. Ninety-four of the remaining schools did not have any parent physical addresses data. These schools, plus the remainder that fell under the 10% threshold (42), are Rural Remote schools.[6] More than half of Montana's 821 schools are Rural Remote. The same threshold was used when constructing the measures for near and far students. Approximately, 60% of the student addresses were located less than three nautical miles from a school (the typical radius of a rural community or town). The remainder were greater than three miles. 10% of the identified addresses were removed since the contact address was greater than 60 miles from their school. This occurs particularly with noncustodial parent contact information.

The mean for NSLP schools which participate in the program and have eligible students is 51.71 % near the national average (52.11% in FY16).[7] The number of schools with missing NSLP Eligibility data is 119. This compares with the missing count for the whole school SIDE Student measure (136). With the whole school measure, the average student's family have income 2.8x the poverty level (100). Statewide, this compares to students at a distance from school (2.85x) and students near to school (2.72x).

Student Outcome

Seven student outcome variables were used in this analysis. The cohort graduation rate is calculated according to federal guidelines and consists of the precent of students who graduate divided by 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 pertains to the Montana University System (MUS). This rate is the count of students that enroll in higher education in a MUS 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.

Suspension and Expulsion data are from those schools participating in the 21st Community Learning Centers program. Suspension and Expulsion data is only reported to the state for special education or 504 students. The percentages of student scoring proficient or advanced are used for the Smarter Balanced ELA and math assessments. This is a school level rate. Proficiency levels are determined by the Montana Board of Public Education. The mean scale scores of students on the ACT composite are used for all high schools (11th grade assessment).

Methods

To address Research Question 1, we provide a breakdown of income to poverty ratios (IPR) by locale and rurality (the difference between Rural Fringe and Rural Distant communities in comparison to Rural Remote) by using a General Linear Model to note differences. The mean IPR values of each group are separately used as dependent variable and the locale category and rural type are used as fixed factors.

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[6] Schools were removed from the whole school measure if less than 10% of the school population was identified.

[7] National Center for Education Statistics. *Digest of Education Statistics*. Accessed 11/08/2022 from https://nces.ed.gov/programs/digest/d17/tables/dt17_204.10.asp

We also look to differences between near and far population provided through paired sample T tests broken down by locale size and rurality. The paired sample T test is used when the same population of schools has two measurements, in this case near and far. Variation is noted based on mean difference and whether the analysis was found to be significant. The goal is to understand whether there are differences between near and far groups based on SIDE income to poverty ratios for a certain locale category or rural area. Are differences more acute based on community size or distance from an urban center in rural areas?

Second, we analyze correlations of data comparing eligibility data with the SIDE point estimates. We look to establish how aligned is each SIDE measure to the NSLP standard for Montana. 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 the relevance of potential differences ($p < .01$). Apparent differences can show how some alternative poverty measure align more closely with NSLP data. This is established at each locale type and rural location. One measure of this alignment would be consistency across locale types and measures.

Finally, we look at variation in school level student outcome data and the degree to which NSLP Eligibility and the SIDE measures explain that variation. We separately regress each student outcome by each measure and compare r^2 values in relation to NSLP Eligibility (historical standard) and between SIDE measures comparing near and far groups with the whole school measure. It is hoped that by this way we'll have evidence to discuss the consistency of the SIDE measures and at the same time the differences between the near and far populations. The difference in r^2 values between students that are close to school and those that are at a distance indicates that variation could show some groups more closely aligned with values for NSLP Eligibility or the school SIDE measure based on student address. It may be true that in some contexts, income is higher among one group, and this relates to the ability of the measure to explain variation in common school level student outcome variables.

Results

Research 1: Are there differences between those students that live less than 3 nautical miles from a school (near) and those that live more than 3 miles (far) based on locale and rurality?

Of the four measures, we see a priori variation based on locale and rurality. The difference with NSLP Eligibility based on locale show higher rates of economic disadvantage in town locations (52% eligible) over city (48%), and rural areas (44%) ($p<.05$). This is repeated for rural areas in which Rural Remote communities are at a greater disadvantage than Rural Fringe and Distant communities ($p<.05$). The SIDE measure for the whole school is insignificant at the locale (size) level. When considering rurality (distance) there are important differences between Rural Remote (262.50) and Rural Fringe and Rural Distant communities (306.25) ($p=.000$).

We compared far versus near students by locale and rurality. What we found is that there are a variety of statistical differences between the two groups across locale and rurality. Statewide, students at a distance have higher mean IPR values (292.96) than students close to school (275.62) ($p=.000$). The pattern is consistent when looking at the mean difference in cities between far and near populations

(34.10) (p=.002). Town populations also exhibit the same variation with higher income to poverty ratios among far populations in comparison to near populations (+22.6) (p=.000). This trend reverses in rural areas in which students near to school have higher mean incomes than students at a distance. This is seen also in Rural Remote areas in which students who live far from school (250.80) having significantly lower IPRs than students who live near to school (262.50). Students that live in Rural Fringe and Rural Distant communities also exhibit a significant mean difference in the same direction (+13.07).

Research 2: To what degree does the Student SIDE estimates in near and far communities correlate with NSLP Eligibility based on locale and rurality?

Understanding how the SIDE estimates relate to NSLP data for Montana is important since it is necessary to note variation with established standards and ways in which different configurations of SIDE estimates may be suitable. These findings point to consistency and relevance of the SIDE measure in context determined by community size, distance from an urban center, and proximity to school. Overall, the whole school mean student SIDE estimates are strongly correlated with the NSLP data for 2019. This is repeated for the population of students that are near school. There is variation with the students residing at a distance from school. The relationship for all schools and city locales is moderate, whereas in the rural locales the magnitude of the relationship is stronger. Overall, the fidelity of the measures to the NSLP proxy is strong especially in rural areas.

Table 1: Bivariate Correlations Comparing NSLP Eligibility to SIDE Estimates

	Whole School SIDE	Students at a Distance	Students Near School
All School	-.722**	-.584**	-.724**
City	-.793**	-.324*	-.769**
Town	-.673**	-.609**	-.731**
Rural	-.753**	-.692**	-.743**
Rural Fringe/Distant	-.763**	-.682**	-.750**
Rural Remote	-.751**	-.707**	-.734**

** $p < 0.01$

Research 3: How much of the variation present in the student outcome data do the poverty measures explain when disaggregating the SIDE Student measure into near and far groups by locale and rurality?

There are relatively few associations that have a magnitude greater than .600 (strong). The NSLP measure has an r^2 value of .614 indicating a strong association in cities for the ACT Composite variable. There is also a strong association with the measure created for students at a distance in cities for the HS Graduation Rate (.703). The NSLP Eligibility measure has six moderate associations. For the SIDE ratios, there are very few moderate associations (7 between the three measures). In only a few instances did the SIDE estimates exceed the NSLP measure. This occurs primarily in cities. All three SIDE estimates were stronger than Eligibility with HS Graduation Rates, Satisfactory Attendance Rate, and Suspension/Expulsion data in cities. The student far measure and the student near measure have higher r^2 values than the Eligibility data for the Satisfactory Attendance and Suspension/Expulsion variable in towns and rural areas. When disaggregating rural areas into respective locales, these differences did not continue.

Table 2: Proportion of Variance Explained by Poverty Measures of Student Outcome Variables

		Eligibility	Whole School SIDE	Student Far	Student Near
City	*HS Graduation Rate*	0.219	0.394	0.703	0.234
	Post-Secondary Enrollment	0.161	0.363	0.152	0.452

		Eligibility	Whole School SIDE	Student Far	Student Near
	Satisfactory Attendance Rate	0.011	0.047	0.023	0.029
	Suspension/ Expulsion Rate	0.07	0.101	0.074	0.138
	ELEM SBAC ELA Proficiency	0.332	0.158	0.06	0.195
	ELEM SBAC Math Proficiency	0.396	0.277	0.114	0.265
	HS ACT Composite	0.614	0.229	0.057	0.181
Town	*HS Graduation Rate*	0.568	0.107	0.078	0.103
	Post-Secondary Enrollment	0.497	0.087	0.113	0.071
	Satisfactory Attendance Rate	0.195	0.17	0.256	0.221
	Suspension/ Expulsion Rate	0.079	0.004	0.098	0.087
	ELEM SBAC ELA Proficiency	0.483	0.291	0.303	0.385
	ELEM SBAC Math Proficiency	0.479	0.324	0.343	0.427
	HS ACT Composite	0.66	0.531	0.512	0.483
Rural	*HS Graduation Rate*	0.272	0.078	0.111	0.19
	Post-Secondary Enrollment	0.189	0.05	0.11	0.189
	Satisfactory Attendance Rate	0.098	0.055	0.142	0.144
	Suspension/ Expulsion Rate	0.158	0.059	0.141	0.209
	ELEM SBAC ELA Proficiency	0.322	0.056	0.126	0.146
	ELEM SBAC Math Proficiency	0.303	0.061	0.092	0.091
	HS ACT Composite	0.313	0.255	0.218	0.318
Rural Fringe/Remote	*HS Graduation Rate*	0.458	0.248	0.277	0.32
	Post-Secondary Enrollment	0.398	0.311	0.201	0.283
	Satisfactory Attendance Rate	0.157	0.125	0.103	0.135
	Suspension/ Expulsion Rate	0.498	0.451	0.344	0.451
	ELEM SBAC ELA Proficiency	0.385	0.109	0.133	0.145
	ELEM SBAC Math Proficiency	0.383	0.093	0.102	0.101
	HS ACT Composite	0.477	0.378	0.372	0.456
Rural Remote	*HS Graduation Rate*	0.248	0.057	0.083	0.138
	Post-Secondary Enrollment	0.168	0.032	0.116	0.163
	Satisfactory Attendance Rate	0.085	0.042	0.151	0.127
	Suspension/ Expulsion Rate	0.163	0.025	0.128	0.146
	ELEM SBAC ELA Proficiency	0.285	0.03	0.104	0.132
	ELEM SBAC Math Proficiency	0.255	0.023	0.078	0.073
	HS ACT Composite	0.302	0.256	0.235	0.299

>NSLP >SIDE Whole School Both

There are a variety of instances when the r^2 values of the students at a distance group is higher than the r^2 values of the whole school. This is important since the ability of the far group IPRs, for example, more closely contributes to understanding the variation in student outcome data in different contexts than the whole school values. This occurs less frequently in city locales. There are also more data points with the students near to school measure exceeds the r^2 value of the whole school. Overall, the magnitude of the r^2 values for near students are higher in towns than in other locales, with the weakest associations occurring in Rural Remote contexts. The r^2 values of fringe and distant rural communities (less than 25 miles from an urban center) are relatively robust.

Conclusions

There is variation between the near and far SIDE groupings and this variation occurs differently in cities and towns versus in rural areas. In cities and towns, approximately 2/3 of the population of the state, the students that live at a distance from school have higher income to poverty ratios than students that live near to their school. The trend is reversed in rural areas. Especially in Rural Remote communities the difference of IPR between students that live at a distance from school and those students that live nearby favors the student who live near to school who have higher IPRs. Correspondingly, the group of students that are near to school explain the variation in the student outcome variables more consistently, although these differences are sometimes negligible.

By introducing comparisons of the SIDE estimates to the NSLP Eligibility data for Montana we have evidence of the degree to which the SIDE estimates align with historical standards. Many of the Pearson Correlations were strong, indicating that there is a close relationship between the variation of the SIDE ratios and NSLP Eligibility. The whole school income to poverty ratios (IPR) values and the values for those students near to school exhibit consistency and strength, although the relationship does appear to be stronger in rural contexts. With students at a distance from school there are weaker relationships, especially in cities and with an analysis that considered all schools in the state.

When analyzing the degree to which each measure explains with higher magnitude the variation in the student outcome variables we witness the relative strength of the NSLP Eligibility measure in comparison to the SIDE measures. Apart from cities, there were few SIDE r^2 values that exceeded the magnitude of the values for NSLP eligibility. This indicates that there are differences between how the measures explain variation in the student outcome variables, in specific, the relative ability of the NSLP measure to explain that variation. When looking at it from the standpoint of historical continuity, the SIDE measures were not able to consistently meet or exceed the r^2 values of the NSLP measure across community size and distance from an urban center. When comparing the near and far populations, there were many values that exceeded the magnitude of the whole school variable. The most data points which exceeded the whole school SIDE value were with the near population, however differences between near and far populations are negligible. Overall, the r^2 values were most robust in Rural Fringe and Distant communities in comparison to the number of weak associations in Rural Remote schools. This occurred across all four measures indicating the relative sensitivity of these measures in certain contexts.

Size may be a factor here, however the differences between town and cities are negligible and go in the same direction. Distance from an urban center appears to be a factor as seen in the differences between Fringe and Distant Rural and Rural Remote communities. For example, the measures created based on student proximity to school showed higher magnitudes in the degree in which the rural measures explain variation in student outcome variables compared to cities. And these ratios are higher than the whole school measure.

Proximity to school in the context of neighborhood income to poverty ratios does have an impact and this impact is strongest in Rural Remote communities. What we see here is that what is occurring with the near students in Rural Remote schools is clear, however the contribution of the SIDE measures among students at a distance from school is less well known. By analyzing near and far grouping we can differentiate the poverty measure. By understanding issues that impact income and poverty in rural contexts, we can make comments as to the success of the SIDE application in providing IPR values that are reliable.

In the absence of a census of student address we are left with our main limitation (coming to an understanding of the randomity of student responses), i.e., was the sample of student address that we collected (43% of the student population) sufficient to the generalizability of the income to poverty estimates and did the process of parents providing contact information occur (or not) in a random fashion. We do believe that this process was random. What our study suggests is that results should be weighted by locale and rurality to obtain a generalized number for a school level poverty indicator. This may recover data from schools that had address data but did not meet our threshold of 10% of the student body with address data (42 schools for the whole school measure). Reliance on near or far alone would not be sufficient, rather a weighted factor established by locale, rurality, and proximity to school should be applied.

Overall, by segmenting into near and far populations, the magnitude of the r^2 values of these measures exceeded the values for the whole school when contributing to an understanding of student outcome data. Yet, in relatively few cases did the SIDE estimates more accurately explain the variation in the student outcome data more than the Eligibility measure. The strongest associations found with the near and far SIDE estimates were in the Rural Fringe and Distant category, and these tended to exceed the magnitude of the whole school SIDE estimates. Understanding this relationship of proximity to school may be crucial in understanding the viability of the SIDE measures in rural contexts when understanding the students at a distance from school raises important challenges such as missing data and small school size. The way the School Neighborhood Poverty index approaches classifying economic disadvantage in rural schools based on a school address may be inappropriate due to reliance on 'near' factors rather than understanding students at a distance. Data pertinent to students near to school in Remote Rural contexts is not sufficient in explaining school level poverty and student outcome trends.

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