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How Poverty Measures Account for Differences Between “In-Town” and “Out-of-Town” Students

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Research Article

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Rurality in education research is a function of the size of the school, the distance of a school in relation to urban areas, and factors within each school that may differentiate the school community based on geography. Distance matters. This study finds variation between rural communities at different distances from an urban center and differences based on analysis of student groups and student outcomes within a locale. By taking a granulated geographic approach to rurality we can better compare differences within locales. This analysis of the distance a student lives from school highlights socioeconomic differences between student groups. One related measure is the degree to which income estimates explain variation in student outcomes. Out-of-town students in rural areas have lower family incomes. These income data explain fewer school-level student outcomes than for students who live near to school. Use of data pertinent to students who live near to school reflects a certain bias in poverty measures and may not include variation in family income of students at a distance from school.

Montana is diverse in its geographic expanse, the characteristics of its schools, and the relative economic standing of its communities. These factors are localized and can show differences in what it means to live and be educated in a rural, town, or city community. Geographic analysis can be used to better understand these contexts, analyze the way geography impacts the education system, and compare variation in student outcomes between schools of different sizes and distances from an urban center. The National Center for Education Statistics' (NCES) locale classification frames these differences when comparing size and distance from an urban center for all U.S. schools (Burrola et al., 2023; Geverdt, 2019). For example, rural remote school communities have less than 2,500 inhabitants and are more than 25 mi from an urban area.

In Montana roughly equal proportions of people live in rural areas, towns, and small and medium cities. There are very few suburbs. Many small communities are close to Montana's cities, but due to the relative size, density of the population, and rural characteristics of the locale they are classified as rural fringe, which suggests variation between what may be classified as rural fringe, distant, or suburb. Burrola et al. (2023) noted that definitions of rurality outline differences in population size or density, geographic isolation, distance from metropolitan areas, or land use. Other researchers have focused on the size of a school community and what it may show about the rurality of a school. Drescher et al. (2022) observed that analyses of enrollment rooted in state education agencies' specific definitions of "small," "sparse," or "isolated" provide a reliable lens on rurality. Burrola et al. (2023) argued that gaps exist in our understanding of education opportunities, family income, and relative poverty that become magnified when we use the NCES locale classification, rather than school enrollments, to highlight differences. To date, research about family income and poverty in rural education communities is underdeveloped in the case of Montana. This study's framework of rurality is grounded in the Montana model and how it highlights similar traits as other states in the Northern Rockies or Northern Plains regions.

These classifications and commentary are helpful, yet certain factors may be ignored, such as differences in education factors within a locale classification, within a school community, or between rural schools. Often these differences are defined by distance. The analysis of state-specific definitions paints a picture of rural areas as more diverse in their racial, ethnic, and economic makeup. The goal of this study is to take one aspect of education research and its intersection with geography in rural areas one step further by focusing less on variation that is happening between schools and more on what may be happening among student groups or individual students. The core of the argument is economics, in that family incomes differ between student groups in a school.

This study is based on the school community and focuses on differences within these communities by defining where students live in relation to the school. It focuses on differences within school attendance zones. It is based on the hypothesis that economic and educational differences exist based on how far out of town a student lives. It is an extension of how the NCES considers distance. The NCES classification relies on the urban-centric definition of the distance a rural community may lie from an urban center (macro-level analysis of distance) to frame differences between locales. This study of the proximity of students to school focuses on differences within locales and within school communities (micro-level analysis of distance). Current approaches to the analysis of locale/region are not sufficient when describing variation in student outcomes that may be occurring in many small communities (e.g., Burrola et al., 2023; Clausen, 2022). This study starts with differences within rural schools and defines them within the NCES classification (what may be said to focus on the rural community at a distance from an urban center).

In rural areas, distance matters. Educational factors also differ between locales. For example, trends in student outcomes seen in rural remote out-of-town students may be quite different from out-of-town students in cities and towns. This trait is evidenced by variation in the predictive validity of each group's mean family income in relation to variation in student outcomes (Domina et al., 2018). This difference focuses attention on what population size and enrollment both may tell us about rural schools. The focus of this study is on distance and variation in how poverty measures may explain student outcomes that may occur within "fringe," "rural," and "remote" locales and how this may impact student groups.

Often, especially in rural areas, we hear of differences between those residing in small communities and those living in the countryside. In fact, this distinction came up in conversation with a community member prior to writing this article. It may manifest in school policy in larger rural communities by limiting enrollment by students from outlying communities whose families do not pay local property tax in these larger rural communities (e.g., the county seat). It creates a difference once students from both groups go to the same county high school. Students in the outlying areas who attended the local elementary school may not have the same access to resources as students in the larger community where the county high school is located. These differences may be seen in access to library resources or course offerings, among other factors, while in many cases both areas are classified as rural remote. Over half Montana's school districts are rural remote, each with students who live close to school and those who live out of town.

By differentiating relative income between students living in town and out of town, it may be possible to find a more accurate accounting of economic disadvantage within a locale. This approach provides a basis to differentiate school communities based on geographic, educational, and economic factors (Burrola et al., 2023). For example, it is possible that income data from one group are more consistent in explaining variation in student outcome measures than other groups. This difference can provide evidence of the income profile of the rural communities in comparison to much larger town and city communities. It also focuses on the relative effectiveness of each measure of income/poverty to explain variation in these outcomes.

Added complexity emerges when investigating differences that are apparent within a locale on the municipal level, specifically in rural school communities. At first sight, in many rural areas of Montana, demographic differences, especially race-ethnicity, are localized. In most Montana rural communities, many of the students are White. Significantly large minority populations live in or near reservation communities, but rural minority populations statewide do not exceed 20%. Few students are non-White non-Native, making up less than 5% of the rural population in many rural Montana communities.

Family income is not homogenous. Income can be used as one of many factors to explain variation in student outcome measures. This belief focuses on the use of an economic indicator (poverty measure) to conduct applied education research. In situations in which few differences exist between groups in a school, such as we see in Montana based on race/ethnicity, differences are found between students who are comparatively well off and those who are economically disadvantaged. As this study finds, important differences also exist between student groups based on geography. The trick is to find valid and reliable means to measure these differences.

Variation exists between poverty measures in that some poverty measures predict student outcomes to a greater degree than do others (Doan et al., 2022; Fazlul et al., 2021; Spiegel et al. 2022). Differences can be found on each level of analysis: relative size of the school, locale in which the school is located, distance from an urban center, and differences within schools among student groups.

This study analyzes two poverty measures and compares the degree to which each explains variation in a student outcome within a set of schools (e.g., Domina et al., 2018, in the case of the School Neighborhood Poverty [SNP] estimate). These measures include the Spatially Interpolated Demographic Index (SIDE) from which we construct three measures: a measure for whole school, a measure based on the in-town student group, and a measure based on the out-of-town student group (e.g. Geverdt & Nixon, 2018). The study compares this measure with the National School Lunch Program (NSLP) eligibility measure, and the degree variation in this measure explains a student outcome (e.g., Doan et al., 2022).

The NCES, in its partnership with the U.S. Census Bureau, developed the SIDE measure in response to demand for tools to analyze small area geographies through income estimates that are rooted in the school neighborhood. Analysis based on disaggregation of SIDE estimates within a school (student groups) is an emerging area of research. SIDE offers a granular view of income with student-level data based on student address, which may be aggregated for any group of students, including in-town and out-of-town (Gervardt & Nixon, 2018). The address provides the anchor for the point estimate of the nearest 25 responses to the American Community Survey (ACS), a mid-decennial survey collected by the U.S. Census Bureau. A weighted sum of these survey responses provides a unique income-to-poverty ratio (IPR) for each point. By defining which students live in town and which live out of town, we get an approximation of the school neighborhood and differences within. For purposes of this study, students who live within 3 mi of a school are considered in-town. For students who live more than 3 mi from a school, they are considered out-of-town. Three mi was chosen since this is the typical size of many rural communities in Montana (the average size of a Montana municipality is 8.7 sq mi).

Geography is a common element between schools. The NCES classification is useful in comparing data points within communities where options to compare educational trends are limited. This point is important when investigating which alternative poverty measures are reliable in different contexts by explaining variation in student outcomes, for example, in a manner that is consistent across locales and to the greatest degree meets or exceeds established NSLP measurements. This goal is achieved by comparing for each locale the two student groups.

These standards are compared for in-town and out-of-town students within each locale category (rural, town, city) and based on distance from an urban center (less than 25 mi from a city and more than 25 mi from a city). We compare what is happening in rural remote communities (the variation between in-town and out-of-town student groups) and compare it to what is happening in rural fringe and distant populations. We benchmark differences between these measures and between locales by discussing poverty's relationship to student outcomes. This strategy enables these kinds of comparisons: how these poverty measures relate to a student outcome, how this predictive validity may differ between poverty measures, and the differences between in-town and out-of-town student groups by locale. Drescher et al. (2022) noted that robust research literature exists on neighborhood effects in densely populated areas. However, analysis of these socioeconomic or demographic effects is currently underdeveloped as it pertains to nonurbanized locales. Variation also exists in the ways we measure a school neighborhood in terms of both size and distance. This investigation is completed by responding to three research questions:

- Do differences exist between those students who live less than 3 mi from a school (in town) and those who live more than 3 mi (out of town) based on size and distance of the community?
- To what degree do the student SIDE estimates in in-town and out-of-town communities correlate with NSLP eligibility data based on locale and rurality?
- How much of the variation present in the student outcome data do the poverty measures explain when disaggregating the SIDE student measure into whole-school, in-town, and out-of-town groups by locale and distance?

We measure how reliable and sensitive the measure is to historical trends and, in comparison, to other poverty measures. For example, SIDE estimates may more reliably define a school neighborhood than other alternative poverty measures (such as direct certification). Indeed, with a granular view of income we may be able to explain differences in such student outcomes as satisfactory attendance, graduation, postsecondary enrollment, proficiency in math and ELA, and ACT composite assessment outcomes. We can use these comparisons to comment regionally (Northern Rockies or Northern Plains states) on variation in these outcomes for student groups—in this case the characteristics of in-town and out-of-town rural student groups for each locale.

Background

Since the 1970s researchers have been using NSLP eligibility as a proxy measure of socioeconomic status, and this use reflects policy choices (Skinner, 2020). NSLP eligibility is commonly used in policy communities (for example, resource allocations) and in applied education research as a covariate in quantitative analysis to proxy socioeconomic status. Therefore, policy, such as Title I allocations, is frequently determined by NSLP eligibility data, often at the state or district level (allocations between schools). It is one of the most accessible indicators of economic disadvantage. Researchers often use NSLP eligibility data for reasons of accessibility and reliability (Cookson, 2020; Doan et al., 2022; Domina et al., 2018; National Forum on Education Statistics, 2015; Spiegel et al., 2022). The predictability of use and track record of scholarship are the basis of its reliability. Nonetheless, NSLP eligibility data have many emerging insufficiencies, including overidentification of poor students, inaccurate income information (which may vary over a school year), insufficient coverage in rural areas, and inaccurate accounting of poor students in Community Eligible Provision districts (Fazlul et al., 2021; Geverdt & Nixon, 2018; Skinner 2020). The arrival of COVID-19 and the constraints and opportunities regarding the expansion of school meals programs made these insufficiencies of eligibility data more apparent. Participation in NSLP became decoupled from income.

Poverty measures are used to allocate billions of dollars in Title I funds and for research and evaluation activities. While most districts and schools participate in NSLP, the number of schools which do not participate in the program is not insignificant (approximately one-eighth of schools, primarily small rural remote schools, in Montana did not have claims data in March 2019). A reason cited for nonparticipation is the size of the school community (i.e., the school is too small for a lunch program).

Any alternative poverty measures would be framed in the policy continuity and historical precedent of the NSLP eligibility standard. However, measures could vary in unique ways in that a suitable poverty measure would not have the same constraints as NSLP. Central to meeting the need for alternative poverty measures is the focus on level of analysis. The more granular and accurate the analysis, the better opportunity to gain a more exact account of student poverty (Fazlul et al., 2021). We can analyze student groups or the school community based on the income profile of the neighborhood in which a student lives. Complications emerge when the data are not granular, as is seen when comparing NSLP eligibility with the U.S. Census Bureau's Small Area Income Poverty Estimate , which cannot be reliably disaggregated to the school level (one notable effort is from the Urban Institute). Our study goes two steps further, using a granular measure by differentiating what is occurring within a locale, in rural school communities within that locale, and among student groups in these communities.

This research study focuses on rural areas and acknowledges that differences exist in poverty measures between rural areas, and towns and small to medium-sized cities. There are many reasons to focus on rural areas, particularly those with small school populations, including the competing definitions of rural areas. The U.S. Census Bureau has adopted an urban-centric model for the last 150 years. It defines rural as what is not urban, although the model notes nuances based on population thresholds, density, land use, and distance (Ratcliffe et al., 2016). This definition obscures differences between identified urban areas, such as differences between towns and cities. It also blurs the differences between rural schools of different distances from an urban center and differences in the income profile of their rural communities. Both factors suggest localized differences based on distance.

This research literature illuminates fixed urbanized categorizations provided by the U.S. Census Bureau and NCES (e.g. Burrola, 2023. Adding to this set of literature, the present study identifies differences within a locale classification and within rural schools in comparison to schools in towns or cities. This study assumes that variation exists based on a community's size and distance from a town or city and a student's proximity to school. It explores the null hypothesis that there is no variation. Reasons to expect that there may be variation include the following. Typical school enrollment differs by locale. The average 2019 enrollment in Montana in city (569.31), town (429.66), rural (96.24), rural fringe and rural distant (159.47), and rural remote (71.79) areas differs in the expected direction. Per pupil expenditure in Montana differs by locale and rurality in that federal, state, and local spending on average per student in cities is the least ($11,867.46) and is higher in towns ($13,142.64), rural areas ($17,769.95), rural areas within 25 mi of an urban area ($14,738.04), and rural remote areas ($18,979.90). These differences stem from the economies of scale found in larger institutions. Rural schools have additional costs per student that are often calculated in relation to smaller enrollments (costs are more difficult to spread out across the school), including pupil transportation, staffing costs, course offerings, services for special education students, and operational costs (Gutierrez & Terrones, 2023).

The fact that as school size decreases, per pupil expenditures increase is often not reflective of the relative income in each locale. An Organisation for Economic Cooperation and Development (OECD, 2021) study found that it is more expensive to educate a student in a rural area than in a suburb or city. The power of the resources available to schools is more efficient in larger school communities. The OECD (2021) noted that these resources include access to high-quality teachers and availability of curricular opportunities.

Approximately one-fifth of public-school students live in rural locales. In Montana, it is about a third. More than half of operating public school districts in the US are in rural locales (Provasnik et al., 2007). In schools in OECD countries, around 15% of teachers and 25% of principals work in rural communities of fewer than 3,000 students (OECD, 2021). The authors outlined some of the current conditions in common among rural schools in OECD countries, including fewer resources for local administration and schools, dwindling rural populations, lack of scale for viable service provision in proximity to where the student lives, decline of access to quality employment for teachers and administrators, and lower levels of achievement and educational attainment.

Rural areas are diverse in terms of variation in family income. The SIDE measure that uses school address to identify income using ACS data includes significant income differences based on locale category in Montana between cities (301.70, or three times the poverty level), towns (281.46), and rural areas (276.05). A ratio of 100 benchmarks the income profile for that community based on poverty thresholds from the U.S. Census Bureau. Provasnik et al. (2007) noted a trend among rural students in the US. Fewer rural students (38%) than students in towns (46%) or cities (47%), but more than students in suburban areas (28%), receive free and reduced-price lunch.

Data

The NSLP eligibility data in this study originated from an October 2018 count of schools that elected to participate in the program. These counts vary month over month. NSLP eligibility data are commonly aggregated into three categories: “free’” (< 130% of the poverty level), “reduced” (< 185% of the poverty level), or not participating. NSLP data target 130% of the poverty level for free lunch ($33,475 for a family of four in 2020) and 185% of the poverty level for reduced lunch ($47,638), well above the established poverty level ($26,200) (Skinner, 2020; U.S. Department of Health and Human Services, 2020).

The BlindSIDE tool is based on a vintage from the ACS. A vintage is revised annually and reflects a five-year time interval that is adjusted given the collection of the most recent data. This survey contains many income-related questions, some of which are used to construct the SIDE poverty measure. The span of the neighborhood when using school address differs from the span of the neighborhood estimates constructed from its students. Variation is seen particularly in town and city locales where the closest 25 responses to income questions on the ACS encompass an area much smaller than the school attendance zone (Fazlul et al., 2021). This difference is important because it can be expected that the larger size of the area in which the SIDE draws its estimates in rural communities would cause there to be few differences between in town and out-of-town students in rural areas.

The NCES SNP index is based on school addresses and is a proxy for income data from the school neighborhood. It uses the same methodology as the SIDE estimates. In the case of SIDE, a least-squares statistical interpolator uses the weighted sum of values from measured locations to predict values at nonmeasured locations (Geverdt & Nixon, 2018). This IPR is defined for each point (geolocated coordinates of a physical address) based on these measurements. These geolocations were also used to calculate a student’s distance from school.

The SNP index is highly correlated to the results from the SIDE application that used school address data from the state education agency (.923). The correlation between the SNP and the whole-school measure built from student addresses collected by the Montana Office of Public Instruction (OPI) is weaker but still highly correlated (.843). The annual sample size for the ACS in Montana is approximately 11,000 respondents, which yields a sample size for the vintage of approximately 55,000 responses statewide.

The 2019 address points were identified using the SIDE application from the 2013–2017 vintage.

Student addresses were collected by the Montana OPI. Approximately 15% of addresses could not be geolocated. Common reasons included the presence of a post office box and rural route information that does not provide a physical address. The longitude and latitude of each address were run through the NCES BlindSIDE system. A benefit of the tool is that it does not hand over address information collected by the state education agencies to the NCES. It is blind, and the state departments of education that field tested the tool could ensure privacy and confidentiality of the data for students and families. States participating in the 2019 NCES grant for the Statewide Longitudinal Data System program were asked to beta test the system and the use of the SIDE estimates. Montana is a grantee.

Analysis of student outcomes in rural areas is limited (Drescher et al., 2022), leading to turbulence regarding education policy as analysis is emergent, and policymakers may not be familiar with this emerging literature. This study uses seven unredacted student outcomes in Montana and analyzes differences in how poverty measures explain this variation. These student outcomes include satisfactory attendance, graduation, postsecondary enrollment, counts of in-school and out-of-school suspensions, counts of student proficiency on the Smarter Balanced math and ELA assessments, and mean scale scores for the 2019 ACT composite. Satisfactory attendance is the number of students who achieve a 95% attendance rate divided by the count of students enrolled. Graduation is calculated by the adjusted 4-year cohort graduation rate. The postsecondary enrollment rate is calculated by the count of students enrolled in the Montana University System divided by the count of students in the senior class. This calculation is completed by taking the count of students who enroll in college within three months of graduating high school. The count of in-school and out-of-school suspensions (discipline data) is divided by the enrollment count for the school. The number of students classified as proficient or advanced is divided by the population of students tested to record the proficiency rate. The mean scale score of students who take the ACT and have a composite score is calculated for each school. This 11th-grade ACT assessment is the high school test of math, ELA, and science proficiency.

Methods

To contrast the NSLP estimates and the three SIDE measures, we provide a breakdown of IPRs by locale and distance (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 variables, and the locale category and rural type are used as fixed factors to calculate variation in family income by geographic region. We also look at differences between in-town and out-of-town populations provided through paired sample *t*-tests broken down by locale size and distance. For each locale (e.g., rural remote) the paired sample *t*-test can be used when the same population of schools has two measurements, in this case in-town and out-of-town students. The resulting framework focuses on a region within the state (e.g., rural) and investigates variation within communities in that region based on the distance a student lives from school.

Variation in the degree to which poverty may differ based on this proximity is noted by mean differences of the student groups and whether the analysis was found to be significant. The goal is to understand whether differences exist between in-town and out-of-town groups based on SIDE IPRs for a certain locale category or rural area. We compare results found between in-town and out-of-town students in cities and towns with the results found with rural areas.

We analyze correlations of data comparing eligibility data with the SIDE point estimates. We look to establish how aligned each SIDE measure is to the NSLP measurements for Montana schools for 2019 Three different estimates are broken down by region/locale: the mean for all students within a school, the mean IPRs for students who live within 3 mi of a school (in town), and the mean of the estimates for students who live more than 3 mi from a school (out-of-town). 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, which represents the percentage of shared or explained variance by the square of the correlation coefficient ($p < .01$). Apparent differences can show how some alternative poverty measures align more closely with NSLP data in different locales and rural areas, which raises issues of policy continuity with the use of the SIDE estimates. To ensure that alternative poverty measures consider this policy continuity, our benchmark is the NSLP eligibility data. One measure of this alignment would be consistency and continuity of policy analysis across locale types and between the three SIDE measures.

We look at variation in school-level student outcome data (graduation, postsecondary enrollment, attendance, suspension and expulsion, proficiency in math and ELA assessments, and ACT composite) and the degree to which NSLP eligibility and the SIDE measures explain the variation. What it can tell us is that differences between measures may exist. The benchmark involves whether SIDE meets or exceeds the results found with NSLP eligibility (policy continuity). Moreover, we can assess differences between the three SIDE populations—whole school, in-town students, and out-of-town students—by locale. We separately regress each student outcome by each poverty measure and compare R^2 values in relation to NSLP eligibility and between SIDE measures. In doing so, we compare in-town and out-of-town groups with the whole-school measure. The goal is to have evidence of the consistency of the SIDE measures and at the same time the differences between the in-town and out-of-town populations. The difference in R^2 values between students who are close to school and those who are at a distance can show some groups are more closely aligned with measurements for NSLP eligibility. It may be true that in some contexts, income is higher with one group, and this assumption relates to the ability of the measure to explain variation in common school level student outcome variables.

Results

Of the four measures, variation exists with the poverty measures based on locale and distance from an urban center, meaning that the average count of students in a school who receive free lunch and the mean SIDE estimates for each of the SIDE measures (whole-school, in-town, out-of-town) differs between locales (city, town, rural) and between rural communities at a distance from an urban center (rural fringe/distant compared to rural remote). The difference with NSLP eligibility based on locale category shows higher rates of economic disadvantage for in-town locations in Montana (52% eligible) over city (48%) and rural areas (44%) ($p <$ .05). The significant difference seen with rural areas comment less on the relative poverty that students in a school may experience and more on structural differences in the lunch program in that many schools do not participate in NSLP. 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 level (size of the community). When considering distance, important differences exist between rural remote (262.50), or more than twice the poverty level, and rural fringe and rural distant communities (306.25) ($p = .000$). A ratio of 100 indicates that that point has an estimate that aligns with the poverty level.

These findings give evidence of the consistency and relevance of the SIDE measure in a context determined by community size, distance from an urban center, and factors within a community such as the distance a student lives from school. Overall, the whole-school student mean SIDE estimates are strongly correlated with the NSLP data for FY 2019. Correlations by locale and measure are in Table 1 (online only https://scholarsjunction.msstate.edu/ruraleducator/vol45/iss3). This strong correlation with NSLP data is repeated for the population of students who are in town. Variation exists with the students residing at a distance from school in the degree that this measure relates to NSLP eligibility. With out-of-town students, the correlation is weaker. The relationship for all schools (statewide) and city locales is moderate, whereas in the rural locales the magnitude of the relationship is stronger. Overall, the fidelity of the SIDE measures to the NSLP proxy is strong in rural areas, particularly as seen with in-town student groups in rural remote schools. The statewide values represent the correlation between NSLP eligibility and SIDE estimates for all schools in the state regardless of locale.

The magnitude of the association between the poverty measures and the student outcomes are seen in Table 2 (online only https://scholarsjunction.msstate.edu/ruraleducator/vol45/iss3). By assessing the magnitude of the linear regression analyses, we can analyze the degree to which variation within a student outcome is predicted by variation in a poverty measure. The variance explained of the graduation rate, for example, is analyzed separately for the four poverty measures. This analysis is conducted for each locale category. Relatively few associations emerge for the student outcome variables that have a magnitude at $R^2 > .600$ (strong). The NSLP measure has an R^2 value of .614, indicating a strong association in cities for the ACT composite variable. A strong association also exists in cities with the measure created for students at a distance in cities for the graduation rate (.703). The NSLP eligibility measure has six moderate associations. For the SIDE ratios, very few moderate associations exist (seven between the three measures). In only a few instances did the SIDE estimates exceed the NSLP measure, occurring most often in cities. All three SIDE estimates were stronger than eligibility with graduation rates, satisfactory attendance rates, and suspension/expulsion data in cities. The in-town student measure and the out-of-town student measures have higher R^2 values than the eligibility data for the satisfactory attendance and suspension/expulsion variables in towns and rural areas. When disaggregating rural areas based on distance from an urban center, no values met or exceeded the values for NSLP eligibility.

In a variety of instances, the R^2 values of the in-town group are higher than the R^2 values of the whole school. Overall, the magnitude of the R^2 values for in-town students are lower in town locales 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 mi from an urban center) are relatively robust. The out-of-town group also closely contributes to the variation in student outcome data in different contexts than the whole-school values, although fewer incidences occur where the R^2 value meets or exceeds the whole-school measure and fewer yet in which it did meet or exceed the NSLP value.

Discussion and Conclusions

Variation exists between the in-town and out-of-town SIDE groupings, and this variation occurs differently in cities and towns vs. in rural areas. In cities and towns, approximately two-thirds of the population of the state, out-of-town students have higher IPRs than in-town students. In rural remote communities, the difference in IPRs between out-of-town students and in-town students favors the students who live in town and have higher incomes. Clear income differences are visible between in-town and out-of-town students, and these differences are acute in rural communities. Income estimates based on school address using the SIDE or SNP school-level data may be biased for in-town students since the nearest neighbor approach takes the points closest to schools. Due to its reliance on points closest to school, the SNP index may be picking up more in-town students and neglecting those with lower income who live out of town and away from school.

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, few SIDE R^2 values exceeded the magnitude of the values for NSLP eligibility, indicating differences between how the measures explain variation in the student outcome variables—specifically, the relative ability of the NSLP measure to explain that variation. We saw very few moderate and strong associations with towns and rural remote areas, which differs from cities and rural fringe/distant areas, where we found robust associations.

What we found by investigating the relationship between the SIDE variables and NSLP eligibility shows differences. With town and city locales, the Pearson correlation was weaker with out-of-town students. For rural areas, the correlation was much stronger for both the in-town and out-of-town populations, presumably because of the higher income of out-of-town students in cities in relation to the variation in the school-level NSLP indicator.

When comparing the in-town and out-of-town populations, many values exceeded the magnitude of the whole-school variable. The most data points to exceed the whole-school SIDE values were with the in-town population. Differences between in-town and out-of-town populations did occur in different patterns across locales. Overall, when analyzing student outcomes, 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 pattern occurred across all four measures, indicating the relative sensitivity of these measures in certain contexts.

Size may be a factor here, although the differences between town and cities are negligible and go in the same direction. Moreover, income differences exist between rural remote and rural fringe and rural distant communities. Distance from an urban center appears to be a factor. This study has focused on analyzing differences within one micro conception of rurality based on distance, including the distance from an urban center or the distance within school communities based on proximity to school. The measures created based on student proximity to school showed higher magnitudes in the degree to which the city measures explain variation in student outcomes compared to rural areas. For in-town and rural fringe and rural distant student populations, regressions approximated the variation found with NSLP eligibility. Meanwhile, out-of-town rural remote populations differ.

This study takes the analysis of distance one step further by focusing on the "micro" involved in the effect of family income on school level outcomes. This study's approach to micro-level variation is this benchmark: how a poverty measure may explain student outcomes. Measures of family income are robust, and we see many differences based on in-town and out-of-town student populations by locale. We also see variation in how student outcomes are explained in that there are more differences based on satisfactory attendance and discipline data across the locale categories (size of communities).

Trends with in-town rural students are clear, and poverty measures for in-town student groups explain with higher magnitudes variation in school-level outcomes. The contribution of the SIDE measures to an analysis of the rural remote out-of-town student group is less well known. Differences exist in the degree to which these student populations' income estimates explain student outcome measures. The lower income of the out-of-town student group in rural communities explains to a lesser degree the variation in school-level student outcome measures than in-town student groups. In-town student populations align more closely with the school-level NSLP results.

By analyzing in-town and out-of-town student groups we can differentiate the poverty measure and its impact on how we understand student outcomes in rural schools. This analysis of measurements for in-town and out-of-town students by locale found that there is variation by locale, and this variation can occur according to distance. Through framing issues that impact income and poverty in rural contexts, we can comment on the success of the SIDE application in providing reliable IPRs. BlindSIDE helps us make these comparisons. This student-level measure enables comparisons across student groups within a geographic area. Yet, as noted, the SIDE measures seldom meet or exceed the degree to which NSLP eligibility explains school-level student outcomes, and when it does occur, it occurs primarily in cities or with satisfactory attendance and discipline variables. This pattern raises important issues for the prospect of ensuring policy continuity. We conclude that using SIDE derived from a school address or SNP IPRs in cities tends to underestimate income in cities since more affluent out-of-town students' income data may not be factored in. Conversely, in rural areas IPRs are overestimated since the SNP may not factor in the lower IPRs for students who live at a distance from school.

In the absence of a census of student addresses we are left with our main limitation: coming to an understanding of the randomity of student responses. Is the sample of student addresses that were collected (43% of student addresses) sufficient to the generalizability of the income-to-poverty estimates? Did the process of parents' providing contact information or the number of students at an address occur (or not) in a random fashion? The number of students by physical address varies, so the capture rate of students is higher than that suggested by student addresses alone. However, there is no known systematic bias in the data. Given these factors, the missing data from the population of students for which income estimates were derived are completely at random using Harwell and LeBeau's (2010) classification of missing data.

Our study suggests the SIDE ratios should be weighted by locale, rural area, and counts of students in town and out of town to obtain a generalized number for school-level poverty. Reliance on in-town or out-of-town estimates alone would be insufficient. Rather, a weighted factor established by locale, rurality, and proximity to school would benefit the protocol. This process can use SIDE estimates gathered from student addresses, achieving better results than using school address alone to define the school neighborhood.

Framing this relationship of proximity to school may be crucial in accounting for the viability of the SIDE measures in rural contexts. Complexity is seen when factoring in the out-of-town students, such as missing data and small school size. Approaches that classify economic disadvantage in rural schools based on a school address may be inappropriate due to reliance on those data points in town. Data pertinent to points in town in remote rural contexts are not sufficient to explain school-level poverty and student outcome trends.

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