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Direct certification as a measure of student poverty: Comparisons to other alternative poverty measures (Montana)

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Abstract

Direct certification has been described by policymakers and academics as a tool which may replace National School Lunch Program (NSLP) eligibility data (Douglas Geverdt, National Center for Education Statistics, personal communication, August 28, 2023). It suggests a policy future in which we change the metric of how we identify disadvantage. On the state level, this impacts allocations, program evaluations, and sponsored research by research institutions. Historically, NSLP eligibility data has been an effective predictor of student outcomes such as achievement and attendance. Little is currently known if direct certification will continue the policy legacy of NSLP eligibility data by accounting for differences in student level outcomes in the same way. Using student level data, this study finds that direct certification meets or exceeds the predictive validity of Montana eligibility data. This means that how direct certification explains student outcomes is like how NSLP eligibility data does, most notably in areas of student achievement. Direct certification does carry its own limitations, for example, comparability between states and systems. Measures for SNAP, TANF, and student statuses that are categorically eligible also differ in the predictive validity of each measure. Due to the differences between these component measures, it may be said that the overall construct is "accidental." Between states, there is no set formula for the percentage of students that come from SNAP, TANF, Medicaid, or categorically eligible groups. This study establishes that there are differences between these groups in the degree to which the poverty measure predicts variation in a student outcome.

Keywords

FRPL, direct certification, poverty measure, School Neighborhood Poverty, economic disadvantage

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Introduction

How we measure the economic disadvantage of student populations is important in public policy as noted in the Every Student Succeeds Act in which policymakers call for new and more exacting definitions of child poverty and how we measure disadvantage. In the post-pandemic era, this occurs in the context of a changing landscape of economic disadvantage. During the pandemic, child poverty fell to its lowest level in 2021, declining 46% from 2020 to 5.2% in 2021 (Burns et al., 2022). This decline is largely due to pandemic relief in the form of stimulus payments, increased enrollment in SNAP and Medicaid, and increased child tax credits. Yet, part, if not all, of this progress is transitory. Measures of child poverty may indeed change in the upcoming years as the effect of the stimulus payment wanes and enrollments in SNAP and Medicaid decline. What this variation tells us is that we need exacting measures of child poverty, especially in the field of education. The longstanding proxy of student economic disadvantage in use for both policy and analysis is the National School Lunch Program (NSLP) eligibility data. NSLP eligibility data has faced recent challenges due to the validity of the data (does it measure accurately) and are all students who receive free lunch indeed eligible for the program (does coverage change with the Community Eligibility Provision districts). Faced with these challenges, policymakers and analysts have turned to direct certification data (a tally of students that receive a public benefit) whose identified student percentage may be a replacement for NSLP eligibility at the school level (Fazul et al., 2021; Spiegel et al., 2022).

This study uses a yardstick to compare how different measures of economic disadvantage explain student outcomes. With this yardstick, we have a basis to comment on education policy in one state (Montana) and the use of direct certification as an analytical tool. This process is enabled by using unredacted student level poverty data and student level outcomes. It is built on the premise that analysis of student level data may yield different statewide results than an analysis of direct certification's identified student percentage (ISP) alone (school level).

NSLP eligibility has a 40-year track record as the proxy poverty measure of choice in education policy and research. It is the largest child nutrition program in the United States and provides more than 30 million students meals (Gothro et al., 2020). As an analytical tool, there are five general ways the NSLP eligibility has been used: to frame the demographics of a student population (economic disadvantage), to compare educational outcomes of disadvantaged and advantaged student populations (e.g., NAEP), as a covariate in models of educational outcomes (e.g., attendance, progression, and graduation), to match students for experimental studies, and as a basis for comparing performance of schools (e.g., Taylor, 2018). An alternative poverty measure would make possible each of these uses without facing the policy constraints of NSLP eligibility. It would be available at the school and student levels. Its application in research and policy would have the same relevance as we find with NSLP eligibility.

Policy alternatives

Poverty statistics are essential for both identifying the population of economically disadvantaged students for compensatory program (such as NSLP eligibility) and for identifying the size and composition of the population whose needs are unmet and tracking this condition over time (National Academy of Science, 2023). Poverty statistics are essential for identifying the economic disadvantage population in relation to students who are more privileged and to evaluate programs that are designed to ameliorate persistent disadvantage. This may involve a focus on school quality for schools that have large populations of economically disadvantaged students. Programs such as

Title 1 which are designed to address student poverty in schools should also address the unique characteristics of the economically disadvantaged student group (Ladd, 2012). Unfortunately, our understanding of this subgroup is limited as evident by the prospects and challenges of each poverty measure. Many programs do not address the unique needs of the economically disadvantaged student group. According to Ladd (2012), “current policy initiatives are misguided because they either deny or set to the side a basic body of evidence documenting that students from disadvantaged households on average perform less well in school than those from more advantaged families.” In fact, in 1940 the gap in reading achievement between children in high- and low-income families was about 0.60 standard deviations. By 2000, that gap doubled to 1.25 standard deviations by 2000 (Ibid).

Policy continuity is a factor since NSLP eligibility has a long track record in policy and research applications. For this reason, we look to data prior to the pandemic (2019) to assess if direct certification shows promise to continue this policy course. This avoids temporary changes in each measure caused by the expansion and contraction of SNAP and Medicaid rolls. There are a variety of policy level implications at the state level. For example, Montana uses NSLP eligibility in its Title 1 allocations for communities with populations less than 20,000 inhabitants. There are also important implications for research and evaluation within state agencies in which NSLP eligibility is the proxy measure of choice for a school level poverty measure.

That is not to say that there is a lack of alternatives; however, there are few alternatives that can be disaggregated to the school and student levels. For example, without manipulation, the Small Area Income Poverty Estimates are not disaggregated to these levels. By matching inclusion in a poverty measure with a certain student outcome on the student level, we are better able to gauge the predictive validity of the poverty measure (Domina et al., 2018; Spiegel et al., 2022). One of these measures, identified student percentage, is an aggregate at the school level. This measure is the count of students that receive a public benefit divided by the total enrollment in the school; in the case of Montana in 2019, this included SNAP recipients, TANF eligible, and students with certain statuses (e.g., foster, homeless, and migrant). Public benefit records are matched with student records so that students automatically become eligible for free meals.

As seen in this study, direct certification can be linked to outcomes on the student level. Title 1 and the Spatially Interpolated Demographic Estimates can also be disaggregated to the student level, but what these measures lack is the direct correspondence to a means test. The application process for public benefits such as SNAP and TANF provides evidence for that means test conducted by a state agency (Montana Department of Public Health and Human Services). That means test signifies that direct certification can be objective (the same rules and procedures are consistently used for all applicants), documentation is verified consistently, participation in the program is not unduly biased by schools recruiting students/families to participate in the NSLP, and eligibility for the NSLP for students directly certified does not require additional paperwork or time commitments by administration, staff, or families of the students in schools where students receive services.

When direct certification is used as a poverty measure, the ingredients to the measure are not similar between states as evidenced by the expansion/contraction of SNAP and Medicaid rolls. Also, in different states the process for applying for and receiving benefits varies, with some states having more stringent criteria than other states (Spiegel et al., 2022). This leads to conditions where poverty rates can be understated when enrollment processes place heavy burdens on recipients. There are also different thresholds in how direct certification may define poverty, versus how SNAP, Medicaid, TANF, or NSLP eligibility defines poverty. This includes the count of states that have included TANF and special student statuses for accountability purposes. In 2019, 45 states used TANF participation, 15 states use Food Distribution Program on Indian Reservations, and 15 states include in the accountability system students experiencing homelessness, living in foster care (26), or having migrant status (14 states) (Greenberg et al., 2019). Moreover, there is variation between states to the degree that students remain uncounted, for example, students with undocumented parents or guardians (Greenberg, 2018). There is also variation between states about work requirements for parents or guardians that impact the participation of potential beneficiaries. According to Greenberg et al. (2019), "states that have more expansive safety nets or use more programs for direct certification may identify more students than states with weaker safety nets or limited direct certification procedures." There is also variation based on the uses of established poverty measures that directly assess family income versus new neighborhood poverty measures (e.g., Maryland Department of Education, 2023).

Research questions (purpose)

This study analyzes 2019 data (prior to the pandemic-related turbulence in school meals programs) for seven poverty measures including NSLP eligibility, direct certification (Montana), SNAP eligibility, TANF eligibility, categorical eligibility, Title 1 enrollment, the Spatially Interpolated Demographic Estimates (SIDE), and a measure of longevity of a student in the NSLP in 5th grade, 8th grade, and 11th grade. How these different measures of poverty explain student level trends is underdeveloped in the research and policy literature. Free meals data has proven to have a strong association to educational achievement on standardized assessments (National Forum on Education Statistics, 2015; Taylor, 2018). Research is emerging as to whether direct certification follows suit. To date, analyses have explored student achievement but have not addressed other measures of student performance including attendance, progression through the grade levels, discipline, and graduation (e.g., Domina et al., 2018; Spiegel et al., 2022).

This study focuses on two research questions: (1) what is the relationship between direct certification and other alternative poverty measures in Montana and (2) what is the contribution of direct certification and the other poverty measures to an analysis of student outcomes? By investigating the contribution of the poverty measures to student outcomes, we have a yardstick to assess differences between measures of poverty, for example, by employing direct certification as a covariate in an analysis of student achievement. We can assess the relationship of different poverty measures to direct certification and assess the goodness of fit of how analyses may show differences between different sets of poverty measures. We look at the magnitude of the analysis in which direct certification or the other poverty measures were used as covariates. This allows us to add/remove poverty measures in the analysis while keeping all other inputs static. This provides evidence of the relative strength/weaknesses of direct certification when compared to the other poverty measures.

Background

Direct certification programs have been in effect since the early 1980s. The primary reason for the program was to ensure that the most vulnerable students receive free school meals. These programs were seen to lighten the paperwork burden with the NSLP application for both parents and schools. It is seen as reducing the program error by schools with the NSLP applications. Direct certification is seen as a reliable estimate of student poverty in that there was more scrutiny on the means test and related paperwork in assessing eligibility for public benefits. There was also less variation in reported family income than seen with the NSLP self-reported application. Many state direct certification programs are successful due to renewed attention placed on improving efficiencies of matching the public benefit records to student records (USDA Food and Nutrition Service, 2021).

Broad-based categorical direct certification is an effective way to increase participation in the NSLP (Kim and Joo, 2020). Categorical avenues include the inclusion of foster, homeless, and migrant students. It can also include children from households receiving SNAP or TANF. This is direct certification's very purpose, to assist disadvantaged students to access free school meals. In its early years, the scope of the program was limited. Prior to the expansion of direct certification to include SNAP participants, only 60% of districts used direct certification. A substantial number of students that could have been directly certified were missed by the system (Ibid). The impact of direct certification was greater for SNAP participants (more students newly enrolled in the NSLP) than with TANF students who experienced little change in enrollment in the NSLP.

Implementation of direct certification programs at the state level faces many challenges most notably in the matching process of student records to public benefit records (in the case of Montana in 2019 matching records from SNAP, TANF, or students that are categorically eligible—foster, homeless, and migrant) (Levin and Neuberger, 2014). Probabilistic matching has been shown to be a promising approach. In this approach, the likelihood of a match between two records is found to have a certain probability when matching multiple data sources. Montana uses a points-based probabilistic method with a threshold-based classification to identify high-confidence exact matches (USDA Food and Nutrition Services, 2021). By using these robust algorithms, Montana achieved a 100% match rate in FY 2019.

There are questions whether students who recently became newly eligible for the NSLP took advantage of the program. When SNAP became incorporated into direct certification, students were found to be less likely to participate (access free meals) than they were previously when applying for the NSLP. This started with the number of newly eligible students due to the SNAP expansion 15 years ago. This is also found with those students directly certified by the recent Medicaid expansion in other states (Fazlul et al., 2021). Evidence indicates that there is a difference between direct certification for the NSLP and actual participation.

Montana has begun to expand the direct certification program to include Medicaid participants. One criticism of this inclusion is that the criteria for enrollment in Medicaid are different from the NSLP free eligibility threshold (130% of the poverty level). However, in the case of Montana that difference is negligible when compared to other states (138% of the poverty level). The poverty thresholds for many states' direct certification programs range from 130% of the poverty level to 200% (Fazul, Koedel & Parsons, 2021). This causes differences in how Medicaid authorization impacts NSLP enrollment in states with different policies. Some students from Medicaid families may be eligible for free lunch in cases where they would only be eligible for reduced lunch had they filled out the NSLP application. In Montana, this occurs with relatively few households. In a study of 14 states that implemented this direct certification program, the increase in enrollment from Medicaid participants was offset by those students already TANF or SNAP eligible (Gothro et al., 2020). Many of those students eligible through Medicaid would have already applied and received free lunch status or received it automatically since their school is a Community Eligibility Provision school.

Direct certification has received attention from researchers who outline potential uses of the measure along with some of its limitations (Fazul et al., 2021; Spiegel et al., 2022). Fazlul et al. (2021) note that direct certification data provided by the State of Missouri and through the Common Core of Data is the most reliable income estimates that the researchers have assessed, but authors note it is no panacea. Different states may face distinct challenges to the implementation of direct certification as a measure in public policy or research. An example of these restrictions is that the income limits in some states may be higher.

As Spiegel et al. (2022) summarize direct certification may provide different pictures of socio-economic conditions in states with different income thresholds and from states that may recruit participants in public benefit programs in different ways. This creates a geographic and temporal variation in the characteristics of families whose data are captured by direct certification (Ibid). In some states, the administrative burden of enrolling in SNAP, TANF, or Medicaid by applicants is less pronounced than in other states. The opposite is said to occur in the context of immigrant communities in which there are greater barriers to enrollment (either by the program or perceived by the individual) in many states. Some states also started to incorporate Medicaid into direct certification earlier than others. This creates an uneven temporal component in which some states expanded quicker than others, or not at all (Fazlul et al., 2021). Hence, some may have a different composition to the school level ISP since some may include Medicaid while others do not.

This occurs in the context where there are a variety of inefficiencies of the NSLP, most notably the expansion of the CEP program. In this program, direct certification data is used to assign a school level percentage. In 2019, the ISP was calculated by the states to see if the district met the threshold for all students in the district qualifying for free meals (40% directly certified). This meant that often students would be assigned free status in cases in which family income did not make them economically disadvantaged according to NSLP criteria. Hence, the count of eligible students included all students in those schools and thus became an inaccurate measure of school level poverty for the most disadvantaged. Most recently that bar has been lowered to 25% (Final Rule-2023). To place this in context, the median for Montana's schools is approximately 23%, meaning that in Montana there has been a large expansion of CEP programs statewide.

In addition, eligibility faces challenges surrounding the application for free meals in that families often provide inaccurate income data, errors are introduced by how schools recruit parents and handle NSLP paperwork, and there are differences between who exactly may be eligible and who will apply. As noted by Harwell and LeBeau (2010), these errors have been longstanding. They note that 17% of students eligible for free or reduced meals were certified as eligible when they should not have been and 8% of students found to be ineligible did in fact meet the income criteria (this occurred prior to the CEP changes in 2015). For students that normally would be eligible if they had applied, there is a non-response bias that differs between educational systems.

The insufficiencies apparent in the NSLP data have called for policymakers to investigate alternative poverty measures, including direct certification. The National Center for Education Statistics as part of their Statewide Longitudinal Data Systems (SLDS) grant program provided supplemental funds to states to investigate the use of a school level neighborhood poverty metric, the Spatially Interpolated Demographic Estimates (SIDE). It is both a school level and a student level metric. As seen in the School Neighborhood Poverty estimates, SIDE's analyses can focus on any point estimate including a student or school address. Montana is one of the grantees. The main task of the grant was to geolocate student addresses and derive and use income estimates from the American Community Survey. One aspect of use of the estimates is the relevance for research use, such as how these measures may predict student outcomes.

Materials and methods

Montana has a SLDS that has been fully operational since 2009. This is part of a National Center for Education Statistics grant program. It has an important public presence that fosters dissemination, reporting, and transparency. It also serves to consolidate data for OPI internal use. The data from this study was taken from this data warehouse. It is census data, representing data on all students in the state (with exception of the SIDE estimates). This includes data behind three poverty measures (NSLP eligibility, Title 1, and longevity) and all the student outcomes. All poverty measures and student outcomes have data at the student level. As such, student counts may vary, for example, with the longevity measures there is only one grade per variable. For these variables, the student count of each variable is the statewide class size (e.g., all the 5th graders in the state). Table 1 describes these poverty measures and the source of the data.

Direct certification in Montana (2019) refers to students receiving SNAP, TANF, or qualify for direct certification based on their student status (foster, homeless, and migrant). SNAP notes that the student is from a family that receives federal supplemental nutrition benefits. TANF notes those students from families below 75% of the poverty level and receive federal temporary assistance for needy families' support. Foster, homeless, and migrant is noted for those students receiving direct certification because of their student/family status. These statuses are certified by the school/district.

SIDE is the Spatially Interpolated Demographic Estimates for each student that has a valid student address that we could geolocate and extract an income estimate based on the income of the 10 nearest respondents to the American Community Survey (a neighborhood estimate). Procedures for calculating the SIDE estimates are the same as used in the calculation for the School Neighborhood Poverty estimates (Institute for Education Sciences) and are presented in the BlindSIDE application (Geverdt, 2022). With the SIDE measure, there were difficulties obtaining a census of student addresses in Montana since many addresses that our student information system collects are PO Box, Rural Route, or unable to be geolocated. Non-inclusion of student addresses in the dataset occurred completely at random following Harwell and LeBeau's (2010) classification of missing poverty data.

Free NSLP status notes if a student receives free meals through the National School Lunch Program (less than or equal to 130% of the poverty level). Title 1 designates whether a student is classified as a disadvantaged student in a Title 1 school (less than or equal to 185% of the poverty level). Montana uses eligibility for free or reduced meals to assign students Title 1 statuses.

Table 1. Poverty measure description.

Label	Variable description	Source
Direct certification	Flag for direct certification regardless of program	Montana Department of Public Health and Human Services (DPHHS)
SNAP	Flag for student whose family participate in SNAP	DPHHS
TANF	Flag for student whose family participate in TANF	DPHHS
Homeless, migrant, and foster	Flag for selected student statuses (collected by school)	DPHHS
Title I	Flag for participant in Title I	SLDS/Districts
NSLP eligibility	Flag for student receiving free school meals	SLDS/Districts
SIDE student	Income to poverty ratios for geolocated student address	SLDS | EDGE Program
Longevity: 5	Calculation using SLDS data of the numbers of years each student has participated in the NSLP (5th grade)	SLDS/Districts
Longevity: 8	Calculation using SLDS data of the numbers of years each student has participated in the NSLP (8th grade)	SLDS/Districts
Longevity: 11	Calculation using SLDS data of the numbers of years each student has participated in the NSLP (11th grade)	SLDS/Districts

Longevity is the count of the number of years that a student was eligible for the NSLP (Michelmore and Dynarski, 2017). This measure has proven robust when comparing students that never participated in the NSLP, students that only participated a few years, and students that participated every year that they have been in the public school system. Authors note that the predictive validity of the population of students that has been participating in the NSLP every year is stronger than the other populations when looking at standardized achievement scores in the 8th grade. For purposes of our analysis, longevity is calculated at three grade levels (5th, 8th, and 11th).

For analysis purposes, all variables were coded into dichotomous variables. Most of the poverty measures were already dichotomous, but this impacted the two continuous variables in the poverty measure dataset: SIDE and longevity. For purposes of the SIDE variable, if a student scored below the median SIDE estimate for schools in the state (264), they were coded as a one. For the longevity variables, the criteria by which the dichotomous variable was created is as follows: 5th grade (a student had more than 2 years eligible for the NSLP), 8th grade (a student had more than 3 years in the NSLP), and 11th grade (a student had more than 4 years in the NSLP). This entails those students assigned with the longevity marker had spent more than 30% of their schooling receiving free meals.

Student outcome variables (2019) include student level satisfactory attendance flag (students that have a 95% attendance rate), graduation end status, dropout end status, progression flag (held back), college enrollment flag, discipline data flag (students with suspensions or expulsions), elementary proficiency based on the Smarter Balanced summative assessment (math and ELA), science proficiency on the MontCAS Criterion Referenced Test (CRT), and proficiency on the ACT (English, Math, and Science) assessment measure (11th grade). Satisfactory attendance is the dependent variable in the logistic regression analysis. This is because it is a variable of interest in the ESSA Act, the reauthorization of the Elementary and Secondary Education Act, and applies to all grades. All the student outcome variables were already dichotomous, for example, a student is either proficient on an assessment or not.

The focus is on 2019 data to gauge trends in the poverty measures before the pandemic. The SIDE estimates are based on estimates generated from a vintage (2013–2017). We also avoid issues with pandemic disruptions in school meals programs and sidestep issues surrounding the implementation of the USDA Final Rule in FY 2023. This rule expanded the scope of the implementation of Community Eligibility Provision schools such that schools are eligible for this program where all students receive free lunch if the total ISP is greater than 25% (USDA, 2023b). This factor and the capture of students from families receiving Medicaid likely inflated the count for NSLP eligibility in Montana (2023) (because of CEP policies) and direct certification in FY 2024 (because of Medicaid). The average ISP in Montana schools (2019) is 23%.

Three kinds of student level analysis are used in this study: pairwise correlation, chi square, and logistic regression. For the logistic regression, two displays are presented including the contribution of the control to the analysis (Nagelkerke r^2) and a display of the sensitivity of association of the estimates of poverty measures and a student outcome when explaining variation in satisfactory attendance (correlation coefficients and standard errors).

The Pearson correlation measures the linear correlation between two sets of data, in this case comparing direct certification counts with other poverty measures. It measures the strength and direction of the relationship between two variables. Along with the correlation, the probability is assessed. Most relationships in this study are significant at the $p < .01$ level, meaning the relationship had a less than 1% likelihood to have occurred by chance. Pairwise deletion was used to isolate those cases in which there were measurements for both poverty measures, for example, with 5th grade longevity only students in 5th grade were compared.

Chi square in this study is used to analyze the differences between two dichotomous variables. It compares observed results versus expected results (goodness of fit). It assesses whether differences occur by chance or whether there is a relationship between the two variables. In Table 3, frequencies are presented of those students whose data show a 1 (a flag for each poverty status) along with the significance level of the chi square analysis. For each student that is captured by direct certification, both conditions, for example, whether a student has satisfactory attendance are presented.

To probe this relationship between student level outcomes and poverty measures, we use the same yardstick to understand the consistency of other poverty measures (a similar analysis is seen in Doan et al., 2022). By swapping out one covariate for another within the same model, we can see variation between poverty measures, for example, the predictive validity of one poverty measure (the degree a measure explains a student outcome) may be greater than when other poverty measures are used. This is reflected in the magnitude of β or the Nagelkerke r^2. The baseline regression equation for this model is the following:

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

where $\mathrm{SatisfactoryAttendance}_{\mathrm{i}}$ is the count of students that achieved a 95% attendance rate in each school. It is regressed on X_{i}, a student outcome, and *Poverty*, the poverty level at the school using one of the ten poverty measures used by this study. For a given X_{i}, we compare estimates of β_{i} and how they may differ when controlling for student level direct certification or another poverty measures. Analyses are provided as to the magnitude of the differences when comparing direct certification, the naïve condition (no control), and a measure created when all poverty measures are used as controls together. We explore if all things are held equal, how much each poverty measure lends to the model. We compare each poverty measure to direct certification to see if the measures align closely with direct certification or the naïve condition.

Similarly, the Nagelkerke r^2 is a measure of goodness of fit. It provides a nuanced look using the same analysis as above. With smaller distributions, the Nagelkerke r^2 is typically between 0 and 1 with values closer to 1 indicating a strong relationship. When the sample size is large, the difference between expected adjusted r^2 and expected r^2 approaches zero. Small differences in r^2 in these cases can reflect stronger associations in how the variance in the dependent variable (satisfactory attendance) is explained by the predictor (student outcome) and different covariates (poverty measures). This measure is presented in Table 4 which focuses on the different components of direct certification.

Results

Research Question 1: What is the relationship between direct certification and alternative poverty measures in Montana?

To look at the relationship between direct certification and the other poverty measures, this study focused on unredacted student level data. The SIDE measure (based on a geolocated student address) and the longevity measures have student populations less than direct certification, for example, with the longevity measures there is a census of students within each grade. The correlational analysis below uses pairwise deletion to account for unequal numbers of students and to only focus on that grade. That means that for the SIDE measure only those students included in that population are analyzed in comparison to their direct certification status.

The strongest correlations with direct certification are the SNAP measure and the NSLP eligibility measure. This is not surprising since SNAP participation consists of most of the population of directly certified students in 2019. NSLP eligibility (free meals) thresholds for family income are highly like the thresholds for SNAP (130% of the poverty level versus 133%). The remaining correlations are less strong, as seen in Table 2.

The TANF population and students categorically eligible based on their student status have much weaker correlations than the SNAP population. Both populations are smaller than the direct certification or SNAP populations. The Title 1 and SIDE populations have moderate correlations when compared with direct certification. The longevity measures' correlations are much weaker even when pairwise deletion was used to account for difference in sample size and to isolate a single grade. This implies that the number of students that have been participating in the NSLP the longest bear little relationship to the count of students that are directly certified. These measures are also less than we find with the TANF population, or those students directly certified due to their student status. It also provides evidence that direct certification may be more sensitive to income ranges closer to 133% of the poverty level (the threshold for qualifying for SNAP benefits) than with incomes that are much lower, for example, with the TANF population at or below 75%.

When assessing the goodness of fit between students that are included in the direct certification populations, there are a variety of differences found in the significance level of the chi square analysis. The display in Table 3 provides data on direct certification, SNAP population, TANF population, and foster, homeless, and migrant populations. At the top of the display is labeled 1 which signals that students are flagged for receiving a benefit under that category. An example of a significant difference is that direct certification's analysis for attendance rate is significant at the $p < .001$ level; meanwhile, the significance for foster, homeless, and migrant is only significant at the $p < .05$ level. Contributing to this difference is the fact that, for example, 31.6% of students that are directly certified have satisfactory attendance in comparison to 42.2% of students categorically eligible due to the student status. We find differences with discipline data as well, where direct certification has a significance level of $p < .001$ and the remaining poverty measures have differences that are not significant. The percentage of students receiving a discipline referral is less for students categorically eligible due to student status (5.8%) than with TANF (7.2%) or direct certification (6.4%). As seen in Table 3, we can see a similar pattern for students that were held back.

Table 2. Pairwise correlations (comparison with direct certification).

	Pearson correlation	Sig (2-tailed)	*N*
Direct certification	1.00		139006
SNAP population	.944**	0.000	139006
TANF population	.149**	0.000	139006
Homeless, foster, and migrant	.207**	0.000	139006
Student level SIDE	.206**	0.000	58329
NSLP eligibility	.622**	0.000	139006
Title I population	.213**	0.000	139006
Longevity (5th grade)	−.040**	0.000	12421
Longevity (8th grade)	−.067**	0.000	11495
Longevity (11th grade)	−.036**	0.000	10719

Significance level **p < .01, ***p < .001

Table 3. Frequencies and significance of student outcome within poverty measure (chi square).

	Direct certification		SNAP		TANF		Foster, homeless, and migrant	
	1		1		1		1	
Attendance rate	0.316***	0.684	.309***	0.691	.340***	0.66	.422*	0.578
Graduation	0.904	0.096	0.901	0.099	0.902	0.098	0.924	0.076
Dropout	.024***	0.976	.023***	0.977	0.013*	0.987	0.034	0.966
Held back	.012***	0.988	0.012***	0.988	0.08	0.992	0.009	0.991
Discipline	0.064***	0.936	0.064	0.936	0.072***	0.928	.058***	0.942
College enrollment	0.151***	0.849	.153***	0.847	.126***	0.874	0.143***	0.857
ELA proficiency	.289***	0.711	.291***	0.709	0.2***	0.8	.307***	0.693
Math proficiency	0.218***	0.782	.221***	0.779	.144***	0.856	.211***	0.789
Science proficiency	.169***	0.831	.156***	0.844	.004***	0.996	.008*	0.992
Science ACT	.101***	0.899	0.099***	0.901	.122*	0.878	.120***	0.88
ELA ACT	.169***	0.831	.165***	0.835	.184*	0.816	0.211**	0.789
Math ACT	.114***	0.886	.113***	0.887	.102**	0.898	.134***	0.866

Significance level **p < .01, ***p < .001

For the student proficiency measure, we find that there is consistency among the four variables, with direct certification continuing to have highly significant differences ($p < .001$). Overall, the percentage of students with direct certification flags for proficient is higher on the proficiency measures than with TANF or students that are categorically eligible due to student status. With ELA proficiency (ACT) and Science proficiency (ACT, Smarter Balanced), we do see differences in significance levels with TANF populations having differences at the $p < .05$ level. For science proficiency (CRT) and ELA proficiency (ACT), the foster, homeless, and migrant population analysis differs in terms of significance with direct certification. They also differ in the percent of students that were proficient: CRT (direct certification: 16.9%, student status: 8%) and ELA ACT (direct certification: 28.9%, student status: 21.1%). Many of the differences occurred in the context where direct certification was highly significant; however, TANF was less so. This provides further evidence of the differences between the SNAP, TANF, and the foster, homeless, and migrant populations.

Research Question 2: What is the contribution of direct certification and the other poverty measures to an analysis of student outcomes?

In a model that assesses the degree to which a control (a poverty measure) and a predictor (a different student outcome) explain variation in satisfactory attendance (dependent variable). By adding and removing control and keeping the student outcome static, we can assess how much one control may contribute to the analysis versus another. When comparing direct certification with the other poverty measures, the contributions of the other controls to the analysis are negligible. As we see in Table 4, this contribution is much stronger with NSLP eligibility.

With every student outcome, the NSLP meets or exceeds the contribution of direct certification in the same model. However, the results are less than when we employ all poverty measures in the

Table 4. Contribution of the control to the multiple logistical regression model: dependent variable 95% attendance (Nagelkerke r2).

	Direct certification	SIDE: student	NSLP: free	Title I status	Grouped controls	Longevity: 5th grade	Longevity: 8th grade	Longevity: 11th grade
Graduation	0.027	0.012	0.027	0.009	0.046			
Dropout	0.035	0.010	0.047	0.009	0.048			0.001
Held back	0.034	0.006	0.060	0.008	0.033	0.000	0.000	0.001
Discipline	0.030	0.006	0.034	0.006	0.035	0.000	0.000	0.001
College enrollment	0.035	0.010	0.046	0.009	0.048			0.001
ELA proficiency	0.029	0.004	0.028	0.007	0.030	0.000	0.000	
Math proficiency	0.029	0.004	0.028	0.007	0.030	0.000	0.000	
Science proficiency	0.028	0.004	0.030	0.005	0.026		0.000	
Science ACT	0.029	0.007	0.043	0.006	0.046			0.001
ELA ACT	0.029	0.007	0.043	0.006	0.046			0.001
Math ACT	0.029	0.007	0.043	0.006	0.046			0.001

same analysis. The most pronounced difference in predictive validity between NSLP eligibility and direct certification is on the ACT assessment in which the r^2 of direct certification (0.029) is less than the magnitude of NSLP eligibility (0.043). Nonetheless, when comparing the poverty measures, direct certification's contribution is the closest to what we see with NSLP eligibility. We also see differences in the contribution of direct certification and TANF to the analysis. We expected TANF analyses to be just as strong, if not more so, as a covariate when predicting whether a person graduated or not. That proved to not be the case when, for example, the contribution of direct certification as a composite of different measures including TANF is pronounced in comparison to individual TANF findings.

Another way of assessing the magnitude of the contribution of the control to the analysis is to look at the β coefficients. As indicated above, TANF and the categorically eligible students align closely with the naïve condition. In most cases, this also occurs with Title 1. This is surprising since Title 1 draws from a population of free and reduced students and the fact that it aligns more closely with the naïve condition indicates that there are differences when the reduced category of students is included. Direct certification and SNAP are closely aligned in terms of magnitude. It also is closely aligned with NSLP eligibility, although with the ACT variables direct certification proves to have a higher magnitude. The same trend does not occur with the elementary and middle school assessments.

The SIDE estimates align with NSLP eligibility more frequently than they do with direct certification and Title 1 status. This occurs acutely with the ACT variables and college enrollment in which the SIDE estimate exceeds the predictive validity of NSLP eligibility. Table 5 provides the coefficients and standard errors of the logistic regression model predicting satisfactory attendance.

The longevity measures differ from both direct certification and NSLP eligibility. On the achievement measures, they align more closely with the naïve condition. These findings reinforce two pieces of evidence: the predictive validity of the measures involved in direct certification can differ in unexpected ways. Moreover, in many areas the β of the NSLP analyses are met or exceeded by the direct certification and SIDE coefficients, importantly in areas of student achievement.

Table 5. Sensitivity of estimated association of poverty measure and student outcome to count of student with a 95% attendance rate (multiple logistic).

	Grad	Held back	College enrollment	ELA proficiency	Science proficiency	Math prof	Science ACT	ELA ACT	Math ACT
No control (naive)	.656***	−1.232***	.843***	.496***	.706***	.587***	.885***	.849***	.943***
	(.086)	(.090)	(.022)	(.015)	(.023)	(.015)	(.046)	(.042)	(.025)
Direct certification	.652***	−1.107***	.766***	.391***	.630***	.495***	.805***	.772***	.858***
	(.087)	(.091)	(.022)	(.016)	(.023)	(.016)	(.046)	(.042)	(.044)
SNAP	−.648***	−1.108***	.775***	.396***	.637***	.490***	.810***	.777***	.864***
	(.087)	(.091)	(.022)	(.016)	(.023)	(.016)	(.046)	(.042)	(.001)
TANF	.656***	−1.231***	.840***	.494***	.703***	.703***	.585***	.884***	.941***
	(.085)	(.090)	(.022)	(.015)	(.001)	(.023)	(.016)	(.046)	(.044)
Foster, homeless, and migrant	.660***	−1.231***	.840***	.497***	.708***	.589***	.883***	.847***	.940***
	(.086)	(.090)	(.012)	(.015)	(.023)	(.016)	(.046)	(.042)	(.044)
SIDE: student	1.066***	−.923***	.771***	.426***	.596***	.524***	.806***	.730***	.912***
	(.188)	(.140)	(.036)	(.023)	(.035)	(.023)	(.083)	(.075)	(.079)
NSLP: free	.524***	−1.029***	.716***	.376***	.605***	.471***	.740***	.712***	.798***
	(.087)	(.091)	(.022)	(.016)	(.023)	(.016)	(.047)	(.043)	(.045)
Title 1 status	.618***	−1.228***	.815***	.462***	.684***	.554***	.858***	.822***	.917***
	(.086)	(.091)	(.022)	(.015)	(.023)	(.016)	(.046)	(.042)	(.044)
Grouped controls	1.082***	−.845***	.682***	.326***	.541***	.429***	.703***	.645***	.811***
	(.190)	(.141)	(.037)	(.024)	(.035)	(.024)	(.085)	(.077)	(.081)
Longevity: 5th grade		−1.557		.423***		.481***			
		(.775)		(.036)		(.037)			
Longevity: 8th grade		−1.503**		.646***	.748***	.763**			
		(.480)		(.039)	(.042)	(.040)			
Longevity: 11th grade		−2.118***	.761***				.882***	.847***	.937***
		(.522)	(.041)				(.046)	(.042)	(.044)

Significance level **p < .01, ***p < .001

Discussion

Fazlul et al. (2021) note that it is easier to describe the limitations of existing programs than to identify alternatives and reconcile both strengths and weaknesses of various poverty measures. Nonetheless, we are confronting the very real limitation that when we are addressing economic disadvantage, we may indeed be measuring the unmeasurable due to the sheer complexity of the issue (e.g., Unterhalter, 2017). Authors identified that the direct certification data in the case of Missouri is the most credible poverty data in comparison to NSLP eligibility and the School Neighborhood Poverty estimates (Institute of Education Sciences). Greenberg (2018) also claims that direct certification shows the most promise when compared to other poverty measures. The author also reiterates the challenges to the direct certification program which include technical challenges to program implementation and addressing privacy concerns by benefit recipients.

Yet this promise should be placed in context. It is an effort to find a replacement to NSLP eligibility. Is this effort producing more limitations than what the NSLP had in the past? We know that the standards and thresholds for the public benefits programs differ between states, as seen in differences in the efficiencies of matching protocols. Most of the inaccuracies of NSLP eligibility data occurred at the point of data collection, for example, if families chose to apply for the program there were often discrepancies due to the self-reported nature of the application. In addition, the NSLP eligibility measure is challenged by the Community Eligibility Provision, a policy which decouples family income and free school meals. This reflects a policy choice. Embedded in the direct certification measure are policy choices, such as those that determine the expansion/contraction of Medicaid. Poverty measures should be objective and not limited by policy constraints. Moreover, poverty measures should be multidimensional (e.g., Inter-American Development Bank, 2002). This leaves us to also question what exactly direct certification is meant to measure?

Due to a variety of factors, alternatives to the National School Lunch Program eligibility data seem necessary. Yet when framing alternatives, these questions come to mind about direct certification. It is a call to step back and reassess what goes into a poverty measure, does it measure what it is intended to measure, and does it have utility in multiple contexts? As UNICEF (2020) also notes, poverty is multidimensional. Any additional poverty measures may face opportunities and limitations, for example, the predictive validity seen when measures of poverty explain a student outcome. This is seen in differences in how participation in one program (SNAP or TANF) can yield very different results in the degree the measure predicts a student outcome. This occurs in the context in which the poverty measure is constructed, for example, the SIDE estimates are neighborhood poverty estimates based on a geolocated physical address. SIDE is a research-based tool that is less susceptible to policy limitations. The data behind the SIDE estimates (American Community Survey) has long been used to fulfill the research roles of NSLP eligibility outlined earlier. While there are many advantages to neighborhood estimates, the SIDE estimate lacks a clear correspondence to a means test or any verification of income (such as an IRS tax return). Yet, there is one outstanding benefit: accessibility. The research use of the School Neighborhood Poverty estimates, a school level neighborhood poverty measure, is enabled by public access to the school level data. There are questions whether direct certification data can be shared without redaction due to student privacy concerns, especially in small schools. One advantage of the SIDE estimates is that in the case of Montana student level SIDE data aligns closely with NSLP eligibility and to a lesser extent, direct certification. And, SIDE estimates do not store or transmit to US-ED private student and family data, an advantage of this neighborhood poverty tool (Gervedt, 2022).

Challenges and risks

Imaging an alternative poverty measure relies on assessing what aspect of disadvantage do we want to capture through use of the measure. This is seen acutely in discussion of socio-economic status in which certain qualitative indicators are used in conjunction with the alternative poverty measures (such as the number of books in the home or parental education). Taylor (2018) notes that using eligibility for free school meals with other socio-economic indicators to create combined measures is an area of research that is needed to understand contemporary dynamics of child poverty. There are many possibilities for reimagining the direct certification measure and many possible combinations to be made (see Fazlul et al., 2021). An example of an adaptation can be found in the work of the Urban Institute who created a school level metric using Small Area Income Poverty Estimate data. There are multiple contexts in which poverty measures are intended to be used impacting both policy and analysis. In so far as direct certification's ability to control for student achievement outcomes, it has proven to reliably meet or exceed magnitudes of the analyses involving NSLP eligibility. Nonetheless, direct certification main benefit as a poverty measure may be making sure the process of feeding economic disadvantaged students is streamlined and in assessing the ISP for a district when it is under consideration for the Community Eligibility Provision, purposes evident prior to 2019.

The future of direct certification's use as a measure of school level and student poverty is dependent on the implementation of the expansion/contraction of SNAP and Medicaid in Montana and other states. Similarly, the expansion of CEP programs, where all students are eligible for free meals, threatens the validity of the NSLP eligibility data as a measure of child poverty. This occurred in the FY 2024 school year in which the USDA Final Rule took effect (USDA Food and Nutrition Service, 2023). With this policy, the threshold for a school's eligibility for this free meals program changed. This results in a situation where an increasing portion of Montana's students are eligible for free meals regardless of whether their families' income may not normally qualify for free meals. This is a benefit for the school meals program and students, but as a measure of poverty it is sorely lacking. We are losing sight of how to identify the most disadvantaged of students in the data or those impoverished students for which we have no data. The concern this study addresses is less with who gets school meals, but which school receives more money in Title 1 funds (allocations), or which students are we tracking to see if the achievement is changing (NAEP) for the disadvantaged subgroup. While the expansion of the free meals program has outstanding benefits, it does question the utility of the NSLP eligibility as a measure of school and student poverty.

The implications of the study's findings can be parsed to include direct benefits to students and indirect benefits. An example of a direct benefit for students is the NSLP, which provides free and reduced meals to students. Direct certification provides paperwork and hassle-free access to this NSLP for students who come from families that receive public benefits. The remaining poverty measures are used as a tool for policymaking and research. In policymaking, a tool to allocate fundings and promote participation in public programs is necessary, but not sufficient, for addressing the needs of students that are economically disadvantaged. These tools are used, for example, in Title 1 school allocations which are meant to increase school quality in schools serving economically disadvantaged students. Participation in school programs often addresses the economically disadvantaged subgroup as seen in the 21st Century Community Learning Centers Program. These functional aspects of policymaking that are enabled using poverty measures increase policy efficiency however do lead to many downsides such as the shifting definition of what it means to be economically disadvantaged when different poverty measures are used.

Poverty measures are also used in applied research in a variety of capacities including to evaluate student achievement or to use as a covariate in analyses of how well the poverty measures identify the subgroup. Since the 1960s, the standard in educational research was free and reduced counts. While many still default to these counts, there is widespread recognition of the insufficiencies of the free and reduced measure in applied research. This stimulated the conversation regarding alternative poverty measures. No poverty measure under investigation in this study is a panacea; however, the set of measures does offer a portfolio of poverty measures to use for different purposes. It is the ability of the researcher to question that data at hand to determine which poverty measure to use out of this toolkit.

Direct certification does present its own challenges for use as a measure of research between states and federal policymaking. The ingredients to direct certification, for example, the percent of TANF student in each statewide measure, differ between states. As established in this study, the poverty measure derived from each program has different predictive validity of student outcomes. Moreover, direct certification may include some benefit programs and not others, such as the incorporation of Medicaid into direct certification rolls. Taken together, these factors highlight a course where a poverty measure derived from direct certification may be accidental, dependent on policy factors governing public benefit programs.

Conclusions

The conclusions of this study are that (1) there are differences in the predictive validity of analyses with the different student populations within direct certification and (2) some alternative poverty measure approximate the findings of direct certification and NSLP eligibility (free meals) while others do not. The predictive validity of SNAP enrollments is less than that of direct certification, NSLP eligibility, and SIDE estimates. TANF and the student group that is categorically eligible for free meals have less predictive validity than direct certification and these analyses are closer to the levels found with the naïve condition. This finding raises important concern about whether it would be beneficial to choose direct certification or to focus on SNAP benefits to account for the differences between program thresholds.

Second, although direct certification does approximate NSLP eligibility, it is unclear if use of this composite measure is measuring what it is intended to measure. Is the measure of family income at or below a certain level and if so, are there barriers to what this threshold may be in different states. This confusion may give credence to the use of neighborhood estimates such as seen with the BlindSIDE tool or the School Neighborhood Poverty estimates. SIDE estimates using student geolocated addresses approached or exceeded those found with NSLP eligibility and direct certification. Having a uniform and accessible measure, in this case responses to income questions on the American Community Survey, may support greater uniformity of reports of school level poverty than direct certification measures, apply to different contexts between education systems/states and in such diverse areas as allocations and research, be less dependent on policy choices such as the expansion/contraction of Medicaid rolls, and have less spatial and temporal variation in the use of the poverty measure.

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