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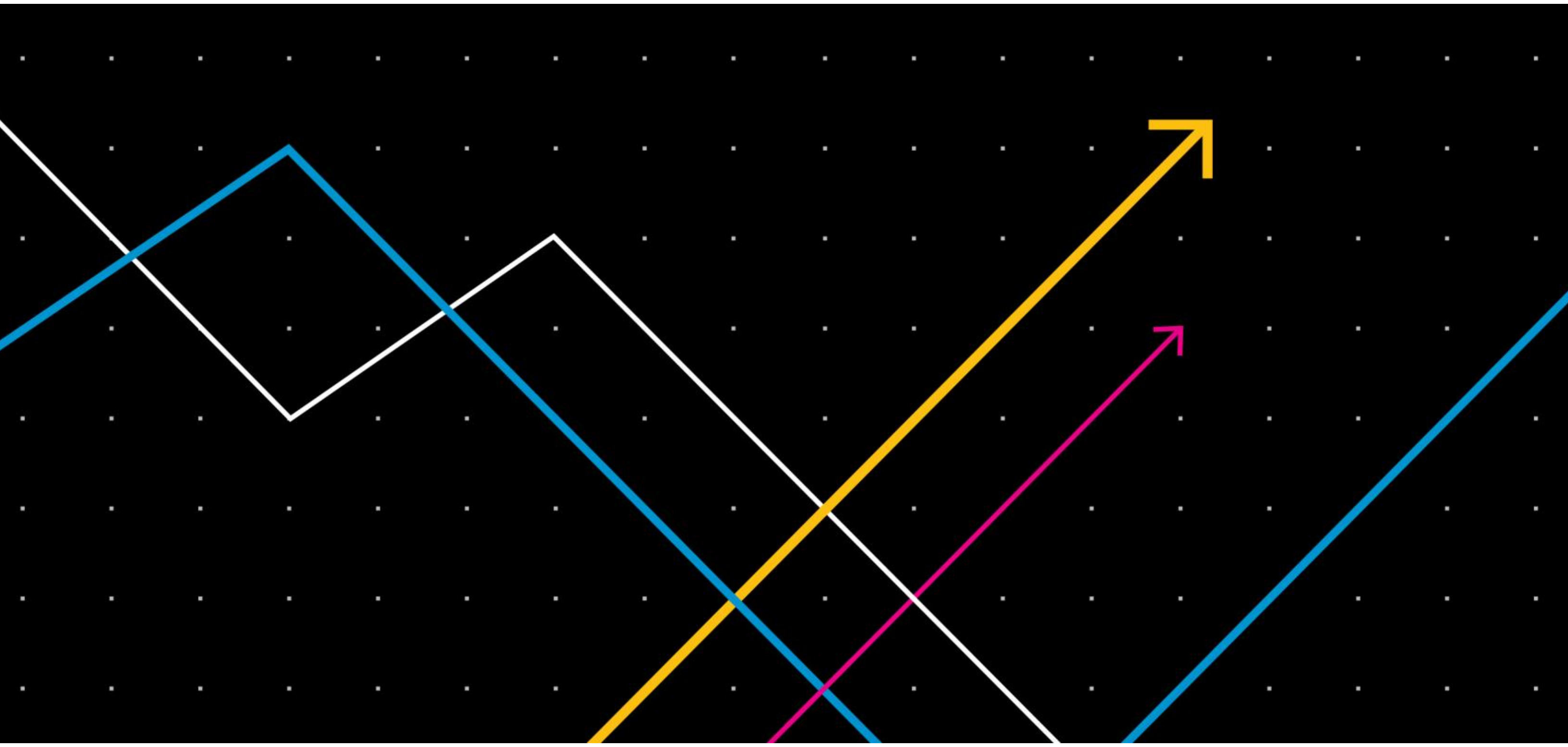

RESEARCH REPORT

Model Estimates of Poverty in Schools

A New School-Level Measure of Economic Need

Emily Gutierrez *Kristin Blagg* *Matthew M. Chingos*

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Model Estimates of Poverty in Schools

For years, policymakers and researchers have used the share of students eligible for free and reduced-price lunch (FRPL) via meal applications as a proxy for the share of students from low-income households at a school. But the recent adoption of universal meal programs, such as the Community Eligibility Provision (CEP), have given schools new options for reporting the low-income student share, making it difficult to consistently measure student poverty within and across states.

The goal of Model Estimates of Poverty in Schools (MEPS) is to create a school-level measure of the share of students living in poverty that is comparable across states and time and reflects, as closely as possible, the students who attend each school (i.e., the measure is distinct from a neighborhood measure). We focus on building a school-level poverty measure that aligns with the district-level estimates from the US Census Bureau's Small Area Income and Poverty Estimates (SAIPE).

To construct this measure, we estimate the district-level relationship between the share of students with household incomes up to 100 percent of the federal poverty level and the share of students eligible for free lunch or directly certified for free meals (i.e., the share of students from households earning up to 130 percent of the federal poverty level). We then take the parameters estimated at the geographic district level and apply them to school-level data to predict school-level poverty measures.

This model-based approach requires district-level student poverty rates (via SAIPE), as well as district- and school-level shares of students eligible for free lunch or direct certification (available at the school level via the US Department of Education's Common Core of Data, or CCD). The model also accommodates the inclusion of other regressors at higher levels of aggregation (e.g., neighborhood-, district-, or state-level characteristics) that may affect the estimated relationship between free lunch and direct certification rates and student poverty rates. School-level regressors are aggregated to the district level for the original estimation and disaggregated to the school level to predict school-level MEPS.

MEPS is an *estimate* of school poverty, not a perfect *direct* measure of student poverty. This measure is constructed for use in research with cross-state data, such as in combination with national school information available from the CCD. The measure may also be useful in research within a state across time (especially in states where school-level reporting may have changed). For example, a researcher who wants to examine the school-level relationship between state test scores and student poverty over time may want to use the MEPS measure.

MEPS is not appropriate for allocating resources within a state or district. The way student poverty is measured within state-specific formulas has direct and immediate consequences for schools and students. Because MEPS is a comparable estimate of poverty for all schools in all states and estimates poverty at a lower threshold than is typically used when allocating resources, we recommend states or localities assessing student economic need use measures that are generated as closely as possible from information provided by, or linked to, enrolled students and their families.

Background

The FRPL meal application proxy has been available for decades and is based on the National School Lunch Program's requirements. Families fill out meal application forms stating household income and family size. Students with household incomes up to 130 percent of the federal poverty level are eligible for free meals, whereas students with household incomes up to 185 percent are eligible for reduced-price meals. Students can also be categorically eligible for free meals if they have run away from home, are experiencing homelessness, or are migrants.[1]

Direct certification, a process for certifying students for free meals via school enrollment data linked to public benefit databases, has been an option for schools since 1986 (Levin and Neuberger, n.d.), but not until the 2004 Child Nutrition and WIC Reauthorization Act were local education agencies (LEAs) required to establish direct certification for the 2008–09 school year (FNS 2018). Since then, the direct certification process can identify students whose households participate in the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families, or Medicaid, depending on the state.[2] Direct certification generally identifies students on the low end of the income distribution (i.e., those with household incomes up to 130 percent of the federal poverty level), but the income eligibility thresholds and work requirements for these programs also vary by state. For example, states that implement broad-based categorical eligibility can have SNAP eligibility thresholds up to 200 percent of the federal poverty level (USDA 2022).

The Healthy, Hunger-Free Kids Act of 2010 authorized CEP, which enables schools, groups of schools, and districts to provide free meals to all students if at least 40 percent of students are either directly certified or categorically eligible (e.g., classified as being in foster care or Head Start, experiencing homelessness, or being a migrant or part of the Food Distribution Program on Indian

Reservations). Some states were authorized to pilot CEP beginning in 2011–12; CEP became a nationwide option in 2015. This greatly increased the use of direct certification for reporting purposes and decreased the use of FRPL forms, as one of the proposed benefits of CEP is to eliminate the administrative burden of FRPL form collection. Although schools use direct certification data as a component of their overall FRPL counts, schools and states inconsistently report direct certification counts, FRPL counts, or both over time, leading to an inconsistent measure of students living in poverty.

There are other differences in FRPL and direct certification measures beyond income eligibility thresholds. The FRPL measure relies on students returning meal application forms, but income-eligible students may not turn in these forms for various reasons, including stigma. Direct certification relies on household participation in means-tested programs, where participation among unauthorized citizens or families with mixed immigration status may be restricted.

There are differences in measures across school levels as well. Families of elementary school–age children are not only more likely to need public assistance but more likely to turn in FRPL forms (Haider 2021). Families with older students are less likely than families with younger students to need public assistance, and older students are generally less likely to turn in forms (Mirtcheva and Powell 2009). This results in differences in true poverty measures, as well as FRPL and direct certification measures, across school levels within a district.

The quest for a school-level poverty measure that improves on metrics from the federal school meals program is not new. For more than a decade, researchers have worked to identify new ways to characterize student socioeconomic status in a consistent way and improve upon the FRPL measure (Gleason 2008; Gleason et al. 2003; Harwell and LeBeau 2010). Some of these methods involve refining or statistically adjusting FRPL shares using other contextual data on students or schools (Blagg and Luetmer 2020).[3] Others involve new datasets, such as those containing tax data (Domina et al. 2018) or local family incomes, to build a school neighborhood poverty index (Fazlul, Koedel, and Parsons 2021; Geverdt 2018). Experts generally agree that FRPL eligibility and related measures, such as direct certification, do not fully capture the socioeconomic status of students in a school or district—family educational attainment, occupation, and income, as well as neighborhood and district characteristics, can also contribute to a measure of socioeconomic status (NCES 2012; NFES 2015).

Data

School-Level Data

We use school-level CCD data obtained via the Urban Institute's Education Data Portal[4] to build our estimates. We use data from the 2013–14 through 2018–19 school years, including the number of students certified eligible for free lunch, the number of directly certified students, and enrollment, as well as whether schools are charter or magnet schools, whether schools are eligible for the Title I Targeted Assistance Program or the Title I Schoolwide Program; school level (i.e., elementary, middle, or high school); and grades served.

In addition to CCD data, we use the school neighborhood poverty rate measured as the income-to-poverty ratio (IPR) from National Center for Education Statistics (NCES) Education Demographic and Geographic Estimates data from fall 2015 to fall 2018.

District-Level Data

We use district-level measures of student poverty (i.e., the share of students ages 5 to 17 with family incomes up to the federal poverty level) from SAIPE from 2013 to 2018. SAIPE is produced by the US Census Bureau and includes estimates of school-age children living in poverty. It is constructed using school district boundary data, federal tax data from the Internal Revenue Service (IRS), and population data from the American Community Survey (ACS).[5] To better measure the share of *public* school students living in poverty, we manually adjust SAIPE's number of students living in poverty for geographic school districts that enroll 10,000 or more students. To do this, we use the share of non–public school students and K–12 student population data from the ACS, matching Public Use Microdata Areas to geographic school district boundaries for each year (2013–18) and subtracting the number of non–public school students living in poverty from SAIPE's total number of students living in poverty.[6]

We use geographic LEA IDs from the Education Data Portal, which matches schools' latitude and longitude coordinates from the CCD and geographic school district boundaries from the NCES.[7] These data also provide information about whether a school is located in an elementary, secondary, or unified school district.

State-Level Data

States have discretion when determining whether they include Medicaid as a direct certification program. To better compare direct certification numbers across states, we collect data on states that participated in the Medicaid Direct Certification Demonstration Project (Husley et al. 2019).

Measures

School-Level Measures

We create the free lunch and direct certification shares of students by dividing the number of free lunch and direct certification students by school enrollment. We create binary indicators for whether a school is a charter or magnet school. These types of schools tend to attract students from a wider geographic area than traditional public schools, which may make neighborhood geographic descriptors less reliable. We also create indicators for whether a school is eligible for the Title I Targeted Assistance Program or the Title I Schoolwide Program. Schools are identified as Title I within district depending on school poverty levels relative to other schools in the district and help explain how district-level poverty rates might be distributed among schools within the district. Because the composition of free lunch and direct certification measures change depending on student age, we include binary indicators to reflect grades served at each school (i.e., elementary, middle, or high school). For similar reasons, we create another indicator variable equal to 1 if the school serves prekindergarten students.

We use the IPR measure as an indication of the federal poverty level of each school's neighborhood. This measure is based on the income responses of the 25 qualifying ACS sample households that are nearest to each school location. This reflects the federal poverty level of children who live in the school's neighborhood and not the school's student population, but 71 percent of students nationwide attend their assigned public school.[8]

District-Level Measures

We aggregate school-level measures to the geographic district level, weighting by school enrollment, to create the share of schools in each district that have each characteristic. We use binary indicators for whether the district is an elementary, secondary, or unified district to capture differences in the district average age of students (as students who are younger tend to have younger parents, who might, in turn, have lower incomes). We use the geographic district boundaries to include charter schools and other schools not tied to a typical LEA (Fahle et al. 2019).

State-Level Measures

We create a binary indicator equal to 1 for both Alaska and Hawaii. These two states have different poverty thresholds relative to the rest of the United States. Lastly, we create a binary indicator equal to 1 for years that states included Medicaid as a direct certification program to better reflect the composition of students directly certified in those states.

Sample

Our sample includes all open, nonvirtual schools serving grades K–12 in all 50 states plus Washington, DC, that report the number of free lunch or direct certification students. For district-level analyses, we aggregate school-level data using schools' geographic LEA IDs from the Education Data Portal.

Free lunch and direct certification data submission can be inconsistent across states and time. The CCD began collecting direct certification data in 2016–17, and schools could choose in any particular year which data to submit (either or both). To be included in our sample, schools must report either free lunch or direct certification data.[9] Because schools have flexibility in what they report, it is possible for a school within a district to report only free lunch while another school within the same district reports only direct certification. Therefore, we identify states as reporting free lunch if at least 90 percent of districts have free lunch data on at least 90 percent of students. These states are used in the free lunch model described below for the years where available. Similarly, we identify states as reporting direct certification if at least 90 percent of districts have direct certification data for at least 90 percent of students. These states are used in the direct certification model described below for years where available. Using this threshold means that we use virtually all states in the free lunch model, direct certification model, or both.[10] Table 1 shows the number of states we use in each model in each year.

TABLE 1

Number of States Used in Each Model, by Year

	Free lunch	Direct certification
2013	51	N/A
2014	51	N/A
2015	51	N/A
2016	45	19
2017	45	21
2018	44	23

Source: Urban Institute analysis of Model Estimates of Poverty in Schools data.

Notes: N/A = not applicable. This table shows the number of states with available data for the free lunch and direct certification models for each year. Several states that report sufficient free lunch and direct certification data (90 percent of districts for 90 percent of students) are included in both models. For an example of which states are included in each model for 2018, see table 4.

Methodology

We use a linear mixed effects model to produce comparable estimates and handle correlated and nonindependent hierarchical data from schools within school districts within states. We use aggregated, geographic district-level free lunch and direct certification shares to predict adjusted SAIPE poverty estimates in each available year.[11] We then apply the estimated parameters from this district-level model to the school-level data to predict school-level poverty. The model includes a state fixed effect and the free lunch or direct certification shares as a random effect. The state-level fixed effects allow us to identify the relationships for each state (individual intercepts) while allowing for the free lunch or direct certification share to be a random effect.

The outcome variable, Pct_Pov_{ds}, is our adjusted SAIPE share of public school students with family incomes up to 100 percent of the federal poverty level in geographic school district *d* and state *s*. At the district level, each β estimate for a particular state, β_{ns}, can be represented as a combination of a mean estimate for that parameter, γ_{n0}, and a random effect for that state, μ_{ns}, equal to the free lunch or direct certification shares, depending on the model. The intercept $\beta_{0\mathrm{s}}$ is allowed to vary across states because it is the only equation with a random effect term μ_{0s}. The other β_{ns} are constant across states, and $\boldsymbol{X'}_{\boldsymbol{ds}}$ is a vector of district characteristics we describe below.

$$Pct\_Pov_{ds} = \beta_{0s} + \beta_{ns}\boldsymbol{X'_{ds}} + \varepsilon_{ds} \tag{1}$$

where

$$\beta_{0s} = \gamma_{00} + \mu_{0s}$$

and

$$\beta_{ns} = \gamma_{n0}$$

Therefore,

$$Mixed\ Model\ Specification: \quad Pct\_Pov_{ds} = (\gamma_{00} + \mu_{0s}) + \gamma_{n0}\boldsymbol{X'_{ds}} + \varepsilon_{ds} \tag{2}$$

Continuous control covariates at the district level include the student-weighted aggregation of binary school-level data such as the share of schools that serve elementary and middle school grades (high school grades are the omitted group), offer prekindergarten, are charter or magnet schools, are eligible for the Title I Targeted Assistance Program, and are eligible for the Title I Schoolwide Program. An additional continuous control covariate includes the student-weighted average IPR.[12]

Binary control covariates include whether the district is a primary or secondary district (unified districts are the omitted group), whether the district is in a state that includes Medicaid in its measure of direct certification, and whether the district is in a state that uses a high federal poverty level (Hawaii and Alaska).

Mixed models typically measure dependent variables at the model's *lowest* unit of analysis (in this instance, the school), but it is still appropriate for measuring the dependent variable at a relatively higher unit (the district) because districts are nested within states, and the relationships between poverty and free lunch/direct certification are identified at the district level. The application of the parameters to the school-level data to predict school-level poverty is a secondary step that does not directly use a linear mixed effects method.

School-Level Predictions

We use the district-level relationships between the right-hand-side variables and adjusted SAIPE to predict the share of students from households earning below the federal poverty level at the school level. We do this by applying each estimated coefficient from the district-level model to the school-level data, which includes the original school-level covariates aggregated to be used in district-level regression (see appendix table A.1 for the coefficients).

School-level predictions of poverty are not dependent upon whether the state (or district) was present in the original estimation model. For example, we use only 19 states in the 2016 direct certification model, yet we predict MEPS for any school with direct certification data in 2016 in any state. If a state reports only free lunch data in 2016, we use the 2016 free lunch predicted MEPS values (and likewise for direct certification). Some states have schools that report free lunch *and* direct certification data in the same year and therefore have both free lunch–based and direct certification–based MEPS. In these cases, we use (for the entire state) the predicted poverty measure that most closely resembles the adjusted SAIPE measure when aggregated to the state level.

School-level predictions *are* dependent upon having all values for the covariates that were included at the district level. For example, if a single school in a district of 10 schools was missing data on whether it was a charter or magnet school, but the other 9 schools did have that information, we would still use the district in the district-level prediction (because aggregation from the school level to the district level would result in a nonmissing, district-level value for the charter or magnet variable). But it is not possible to predict MEPS for the school with missing charter or magnet data, because schools need nonmissing values for every covariate used in the district-level regressions.

Overview of MEPS

MEPS is expressed as the share of students with family incomes up to 100 percent of the federal poverty level. For context, this measure captures a family of four with an annual household income of $26,500 in 2021. This threshold is lower than typical definitions of student poverty (direct certification is generally up to 130 percent of the federal poverty level, and FRPL is up to 185 percent). Therefore, users should be aware that MEPS identifies a smaller number and share of students living in poverty, relative to other measures education audiences might be used to, and poverty among these students has not actually declined.

Of the more than 13,000 districts nationwide, at least 97.5 percent of districts had the data required for the free lunch models from 2013 to 2015. In direct certification models (i.e., for 2016 through 2018), we use 21 to 34 percent of districts, compared with 90 to 95 percent of districts in the free lunch models (table 2). Of the more than 94,000 schools nationwide, we predict MEPS for more than 94 percent of schools each year.

TABLE 2

Share of Districts and Schools Used to Estimate School-Level Poverty and for Which MEPS Are Estimated

	2013	2014	2015	2016	2017	2018
Free lunch (%)						
Districts	97.5	97.5	99.6	95.2	94.9	90.8
Schools	94.5	95.6	96.9	91.7	91.3	88.9
Direct certification (%)						
Districts	N/A	N/A	N/A	21.3	25.6	34.2
Schools	N/A	N/A	N/A	31.1	32.2	44.3
Schools with MEPS (%)	94.5	95.5	96.6	97.3	97.4	96.8

Source: Urban Institute analysis of MEPS data.

Notes: MEPS = Model Estimates of Poverty in Schools. Direct certification data become available in 2016. Schools missing MEPS are missing underlying school-level inputs we use in the model. The share of schools with MEPS is lower than the share of schools used to predict MEPS because of adjustments that rely on the availability of enrollment data.

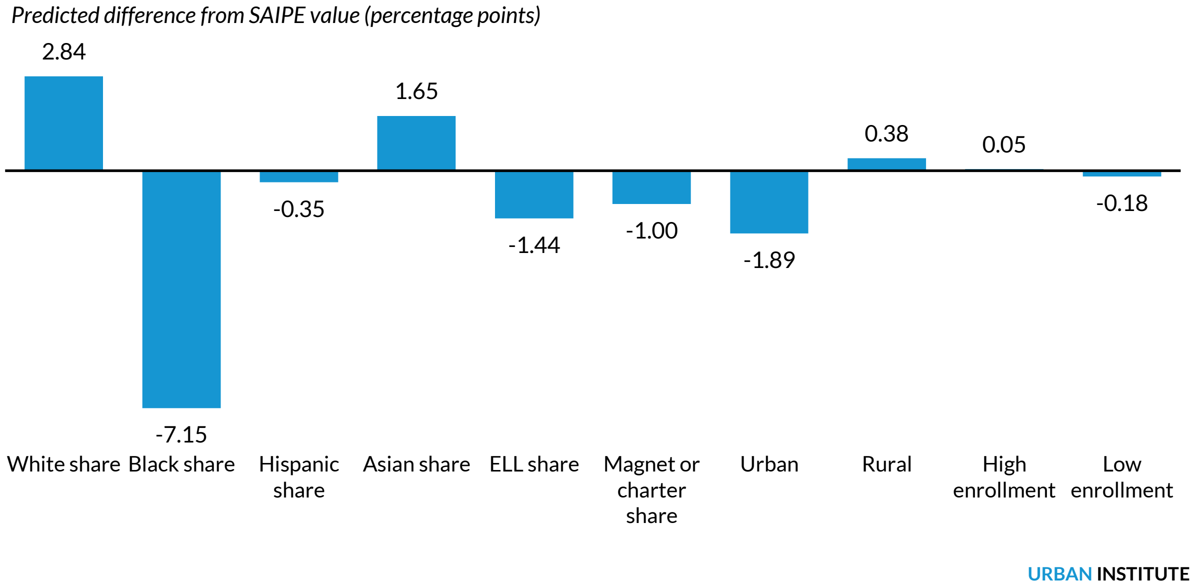
Bias Assessment

In assessing MEPS, we sought to understand how we may be systematically underestimating or overestimating poverty for different types of schools or districts before modifying our estimates to match adjusted SAIPE data. To conduct this analysis, we look at the aggregate share of students living in poverty, relative to the share of students identified in the adjusted SAIPE data. We test for bias (defined as a large under- or overestimate of poverty) along five dimensions: district racial and ethnic composition, share of students designated as English language learners, district geography (urban or rural, according to NCES locale classifications), share of students enrolled, and district size (high enrollment indicates more than 10,000 students; low enrollment indicates less than 500 students).

We find that, broadly, our method does not introduce substantial bias, except for enrollment by race and ethnicity. Using a regression model, we find that districts with very high or very low enrollment are estimated by our model to have poverty rates that are relatively close (within 1 percentage point) to the adjusted SAIPE value, on average, relative to districts that are not in the category (figure 1). Rural districts also have model values that are very close to the adjusted SAIPE value, on average, relative to nonrural districts. In our model, urban districts tend to have poverty estimates that are, on average, about 1.89 percentage points lower than the adjusted SAIPE value, relative to nonurban districts. And districts with high shares of English language learners tend to have estimates in our model that are also slightly lower than adjusted SAIPE measures, relative to districts with no English language learners, but to a small degree (with each 10 percentage-point increase in English language learners, our model underpredicts by about 0.14 percentage points).

FIGURE 1

Estimated Bias, by Race, Ethnicity, ELL Status, Geography, and Enrollment Size



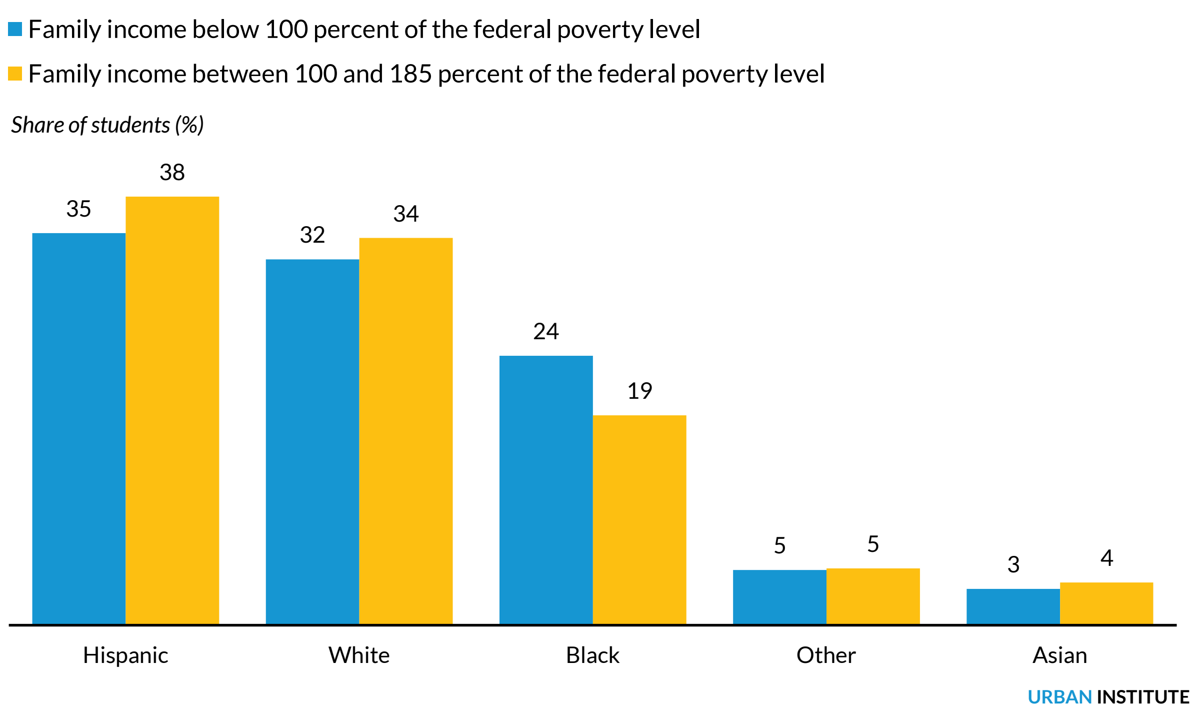
Source: Urban Institute analysis of Model Estimates of Poverty in Schools data.
Notes: ELL = English language learner; SAIPE = Small Area Income and Poverty Estimates. All shares range from 0 to 100 percent. We obtained the point estimates here using bivariate regressions where the reference category is either having no students of the given demographic or not having the given characteristic. In all regressions, the constant term (mean value is the reference category) has an absolute value of less than 1 percent, except for the white student share regression, where the constant is 1.4 percent.

Differences from the SAIPE measure are much larger when we look at districts by share of students from different racial or ethnic backgrounds. Districts with high shares of Black students are more likely to have a substantial underestimate of poverty in our model, relative to the adjusted SAIPE measure. For every 10 percentage-point increase in the Black student share in a district, our measure underestimates, on average, by 0.75 percentage points, relative to a district with no Black students. Aside from being the largest underestimate by district characteristic, this difference is particularly meaningful, as there are a significant number of districts with high shares of Black students.

We probe this bias further, adjusting variables and specifications to see if we can improve the estimates for districts with high shares of Black students, but we continue to find this bias. We conclude that this bias emerges from one of the underlying assumptions of our model—that the distribution of students at different thresholds of the federal poverty level is relatively consistent across different types of schools and districts. For example, our model might assume that in a school where 20 percent of students are directly certified, 10 percent of the students also have family incomes below 100 percent of the federal poverty level. But in some schools, this distribution could be different—all 20 percent of students could be below this lower threshold, or no students could be.

In this case, it appears that Black students who are eligible for free meals through direct certification (a threshold around 130 percent of the federal poverty level) or an FRPL application (a threshold of 185 percent of the federal poverty level) are more likely than students from other backgrounds to also have their earnings fall below 100 percent of the federal poverty level. To confirm this phenomenon, we look at individual-level data from the 2019 ACS on children ages 5 to 18 enrolled in public school. Black students make up 24 percent of students with family incomes below 100 percent of the federal poverty level and 19 percent of the students with family incomes between 100 and 185 percent of the federal poverty level (figure 2). In contrast, Hispanic and white students are less likely to be from households earning below 100 percent of the federal poverty level, relative to their representation among household earning between 100 and 185 percent of the federal poverty level. Asian students and students from other racial or ethnic backgrounds are evenly represented in both groups. To help resolve this issue, we modify school-level estimates such that the aggregate enrollment-weighted value matches the adjusted SAIPE value.

FIGURE 2
Share of Students Living in Poverty, by Race or Ethnicity



Source: Urban Institute analysis of 2019 American Community Survey data.

Modified MEPS

No model can perfectly match statistical estimates of poverty. Although our predicted school-level poverty measures aggregate up to a measure that is close to the reported share of students living in poverty in a given geographic district, the measures are not exact. Further, we identify at least one characteristic—student race or ethnicity—where our model systemically underpredicts poverty for certain groups. To remedy this, we modify our school-level estimates to match the geographic district poverty rates.

In districts where our total aggregated school estimates are lower than the adjusted SAIPE value, we allocate additional modeled students living in poverty to each school until we match the adjusted SAIPE rate. We conduct this allocation in a way that maintains the relative difference between each school. For example, in a district with two equally sized schools, one with a model estimate of 8 percent and the other with a model estimate of 14 percent, a modification to a goal-adjusted SAIPE average of 12 percent would move the schools to 9 percent and 15 percent, respectively. For districts that are overestimates relative to the SAIPE measure, we take the opposite approach. Less than 1 percent of schools are modified in ways that put the new MEPS measure above 100 percent or below 0 percent. In these cases, we place a realistic floor (0 percent) or ceiling (100 percent) on the measure. These realistic caps do not substantially affect the aggregate district averages.

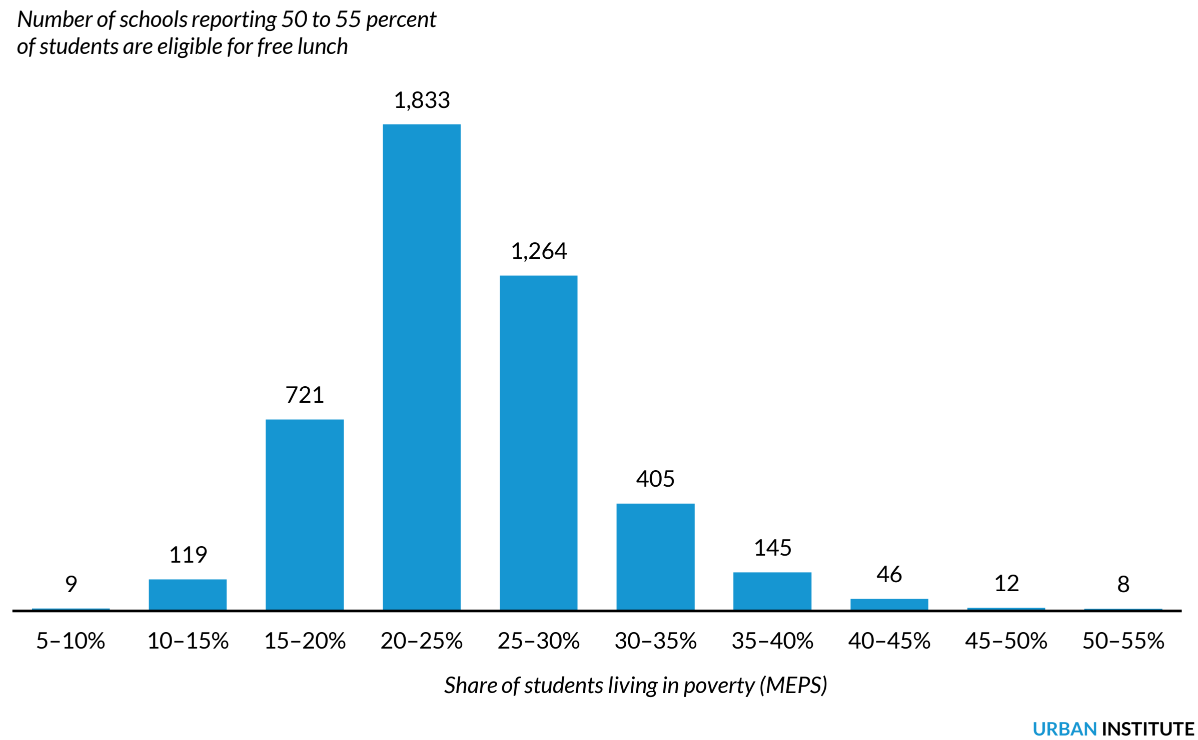
Modified MEPS are a subset of the original MEPS because the modified data rely on the availability of district-level SAIPE data. If a school is in a geographic district that does not have a SAIPE value in that year, we cannot produce a modified MEPS measure, even if the school has data sufficient to build an original MEPS value.

Understanding the Effects of Modified MEPS

One way to understand the effects of the modified MEPS measure is to look, nationwide, at schools that have similar shares of students identified as eligible for free meals via FRPL forms or via direct certification. These schools, which may appear similar in the data, can have wide-ranging modified MEPS values. Figure 3 shows the range of values for schools that reported between 50 and 55 percent of their students as eligible for free lunch in the 2018–19 school year. The mode of these schools has a corresponding modified MEPS value of 20 to 25 percent (indicating the share of students from households earning below the federal poverty level). But some schools are estimated to have much higher values; a small share of schools have a MEPS value of 40 percent or higher. And some of these schools are estimated to have lower poverty shares (as low as 5 or 10 percent in a small number of schools).

FIGURE 3

Distribution of Modified MEPS among Schools Reporting 50 to 55 Percent of Students Are Eligible for Free Lunch, 2018–19



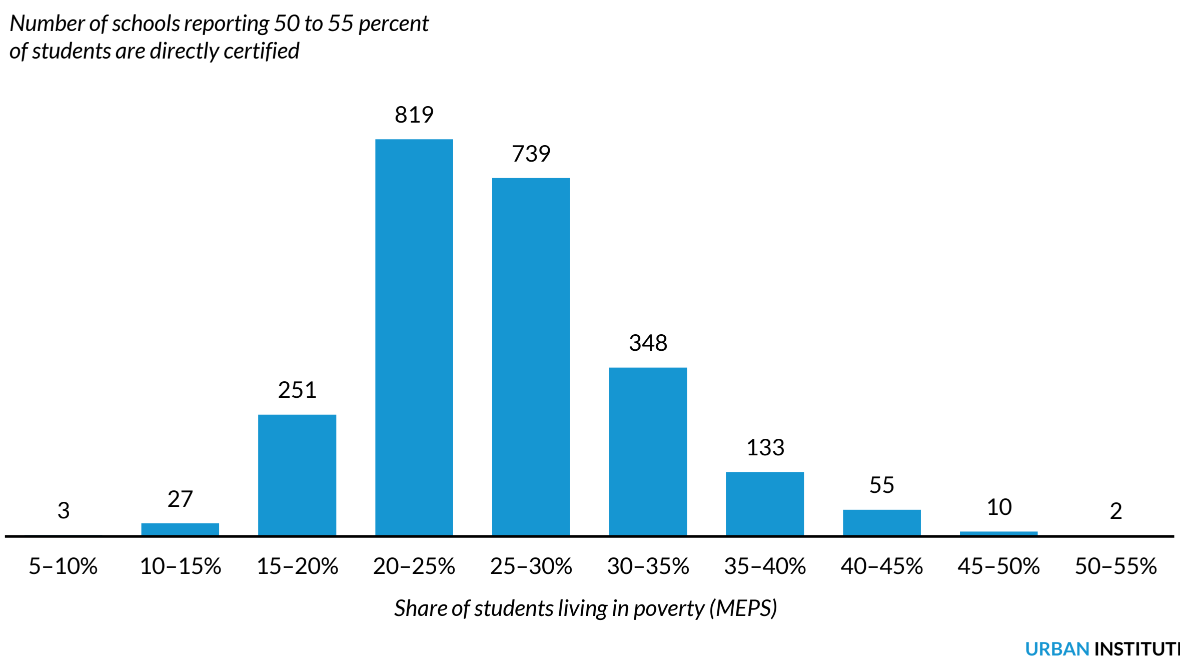
Source: Urban Institute analysis of MEPS data.

Notes: MEPS = Model Estimates of Poverty in Schools. The ranges on the horizontal axis are rounded for simplicity. For example, 5–10% means 5.00–9.99% and 10–15% means 10.00–14.99%.

Similarly, schools with 50 to 55 percent of students identified as eligible via direct certification in 2018–19 have a wide range of modified MEPS values (figure 4). Because direct certification tends to identify smaller shares of students, the modified MEPS values are, on average, a bit higher but still show a wide range of variation.

FIGURE 4

Distribution of Modified MEPS among Schools Reporting 50 to 55 Percent of Students Are Directly Certified, 2018–19



Source: Urban Institute analysis of MEPS data.

Notes: MEPS = Model Estimates of Poverty in Schools. The ranges on the horizontal axis are rounded for simplicity. For example, 5–10% means 5.00–9.99% and 10–15% means 10.00–14.99%.

Details on Original and Modified MEPS

Tables 3 and 4 demonstrate the differences between the MEPS measures, adjusted SAIPE measures, ACS poverty rates of public school students ages 6 to 17, and the typical free lunch and direct certification measures by year and state.

TABLE 3

Comparison of MEPS, SAIPE, ACS, Free Lunch, and Direct Certification, by Year

	Original MEPS	Modified MEPS	Adjusted SAIPE	ACS	Free lunch	Direct certification
2013	19.7%	20.7%	20.7%	21.1%	44.6%	N/A
2014	19.2%	20.2%	20.3%	21.7%	45.1%	N/A
2015	18.5%	19.3%	19.3%	21.8%	45.5%	N/A
2016	17.6%	18.2%	18.1%	21.1%	45.9%	32.9%
2017	16.8%	17.1%	17.1%	20.2%	46.8%	34.5%
2018	16.6%	16.7%	16.7%	19.4%	46.5%	32.8%

Source: Urban Institute analysis of MEPS data.

Notes: ACS = American Community Survey; MEPS = Model Estimates of Poverty in Schools; N/A = not applicable; SAIPE = Small Area Income and Poverty Estimates. All percentages are aggregated to the annual level and weighted by enrollment. The first four columns include all districts nationwide, whereas the free lunch and direct certification columns are calculated using data from the states we use in the free lunch model and direct certification model, respectively.

TABLE 4

Comparison of MEPS, SAIPE, ACS, Free Lunch, and Direct Certification, by State, 2018–19

	Original MEPS	Modified MEPS	Adjusted SAIPE	ACS	Free lunch	Direct certification
Alabama	20.4%	22.4%	22.4%	25.7%	49.1%	34.9%
Alaska	18.6%	12.9%	12.5%	22.2%	N/A	33.9%
Arizona	18.0%	18.7%	18.4%	23.9%	45.4%	N/A
Arkansas	20.9%	21.5%	21.4%	25.2%	55.1%	27.2%
California	18.1%	16.7%	16.6%	20.5%	52.5%	35.4%
Colorado	12.6%	11.1%	11.0%	13.1%	32.8%	19.8%
Connecticut	10.4%	13.0%	13.0%	13.6%	34.6%	N/A
Delaware	18.2%	16.0%	16.0%	18.7%	N/A	31.3%
DC	18.1%	27.3%	27.3%	26.9%	N/A	42.2%
Florida	17.4%	18.9%	18.9%	21.3%	49.5%	44.3%
Georgia	19.2%	19.6%	19.6%	23.0%	54.9%	26.2%
Hawaii	10.7%	10.6%	10.6%	14.0%	36.5%	25.3%
Idaho	15.1%	12.4%	12.4%	16.2%	31.2%	N/A
Illinois	16.5%	14.7%	14.7%	17.3%	46.5%	N/A
Indiana	16.1%	15.6%	15.6%	20.4%	40.6%	31.8%
Iowa	12.1%	11.9%	11.9%	14.1%	35.6%	N/A
Kansas	15.5%	13.2%	13.1%	16.3%	37.4%	N/A
Kentucky	20.1%	21.4%	21.3%	24.6%	52.7%	N/A
Louisiana	20.0%	25.9%	25.9%	29.7%	50.7%	N/A
Maine	15.4%	13.0%	13.0%	19.0%	37.3%	25.0%
Maryland	13.5%	11.1%	11.0%	12.4%	40.0%	N/A
Massachusetts	12.2%	11.4%	11.4%	13.4%	N/A	31.1%
Michigan	14.9%	16.4%	16.4%	19.7%	44.5%	N/A
Minnesota	12.1%	10.4%	10.4%	12.4%	28.0%	N/A
Mississippi	23.6%	26.0%	26.0%	32.1%	67.9%	N/A
Missouri	16.7%	16.5%	16.5%	20.2%	43.7%	23.9%
Montana	16.2%	14.4%	14.4%	18.7%	38.7%	N/A
Nebraska	12.7%	11.2%	11.1%	15.3%	36.6%	N/A
Nevada	20.4%	17.0%	16.9%	19.9%	55.2%	36.1%
New Hampshire	9.8%	8.7%	8.7%	10.0%	23.4%	N/A
New Jersey	11.5%	12.6%	12.6%	12.9%	32.2%	N/A
New Mexico	23.0%	23.1%	23.1%	30.3%	69.0%	39.4%

	Original MEPS	Modified MEPS	Adjusted SAIPE	ACS	Free lunch	Direct certification
New York	17.2%	17.2%	17.2%	19.3%	49.9%	N/A
North Carolina	18.9%	19.0%	18.9%	22.3%	52.1%	N/A
North Dakota	11.3%	8.9%	8.9%	13.0%	25.4%	12.9%
Ohio	16.5%	17.5%	17.5%	19.9%	30.1%	N/A
Oklahoma	19.2%	19.9%	19.8%	24.2%	N/A	28.9%
Oregon	15.4%	14.0%	14.0%	17.4%	41.2%	N/A
Pennsylvania	17.1%	15.8%	15.8%	16.2%	48.3%	N/A
Rhode Island	15.5%	17.1%	17.1%	17.5%	41.7%	N/A
South Carolina	20.1%	21.2%	21.2%	23.6%	57.5%	36.1%
South Dakota	13.6%	13.0%	13.0%	19.1%	30.0%	N/A
Tennessee	20.3%	20.2%	20.1%	22.9%	N/A	34.3%
Texas	17.9%	20.2%	20.2%	21.8%	55.2%	N/A
Utah	10.4%	8.5%	8.4%	10.6%	26.7%	N/A
Vermont	13.7%	11.2%	11.2%	13.5%	29.1%	N/A
Virginia	11.5%	12.4%	12.4%	14.0%	38.8%	N/A
Washington	12.0%	11.7%	11.7%	15.6%	35.4%	19.0%
West Virginia	20.4%	21.2%	21.2%	24.9%	N/A	46.5%
Wisconsin	12.2%	11.8%	11.8%	13.9%	34.3%	N/A
Wyoming	11.6%	11.3%	11.3%	12.6%	37.9%	10.9%

Source: Urban Institute analysis of MEPS data.

Notes: ACS = American Community Survey; MEPS = Model Estimates of Poverty in Schools; N/A = not applicable (comprehensive data are unavailable in 2018); SAIPE = Small Area Income and Poverty Estimates. All percentages are weighted by enrollment. The first four columns include all districts nationwide, whereas the free lunch and direct certification columns are calculated using data from the states we use in the free lunch model and direct certification model, respectively.

For consistency with measures historically used in the field of education, MEPS would ideally produce rates on a similar scale as FRPL rates (i.e., the share of students whose household incomes are up to 185 percent of the federal poverty level). But a definition more consistent with poverty outside the scope of education can provide stakeholders a more familiar understanding of students living in poverty. Moreover, research indicates that students living in deep poverty fare worse than their high-income peers, and a consistent measure that focuses on students in severe economic need can help policymakers understand variations of need within their community (Michelmore and Dynarski 2017).

Validity Evidence

Model Validity Assessment

We assess the validity of the original MEPS model and measure by aggregating MEPS to the district and state levels and comparing them with the adjusted SAIPE-reported share of students living in poverty.[13] Figure 5 demonstrates an example of state-level validity by comparing state-level SAIPE poverty rates with aggregated original MEPS, weighted by enrollment, for 2018. Original MEPS rates are generally within 2 percentage points of adjusted SAIPE values, with a few exceptions.

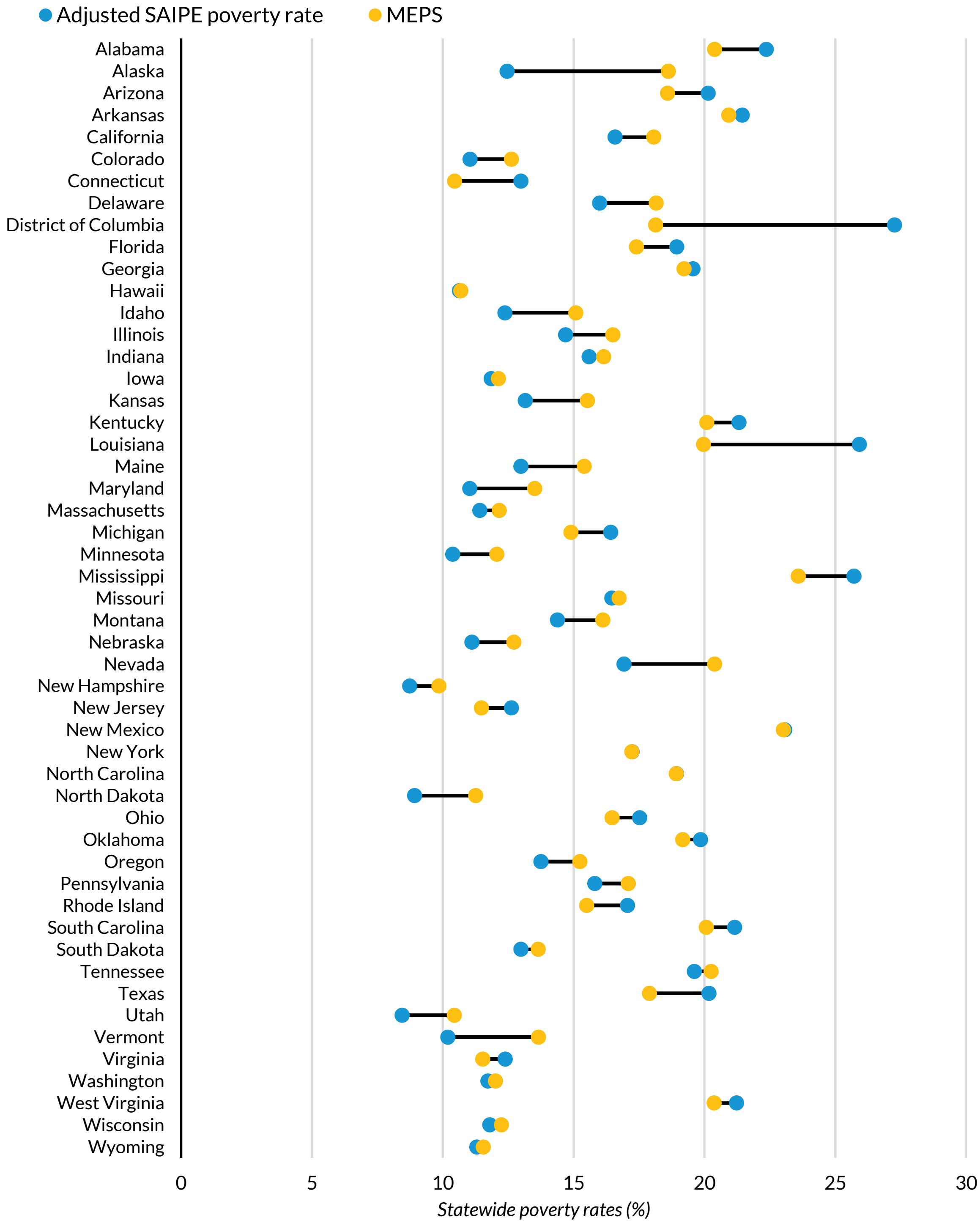
Predictions depend on the availability of free lunch and direct certification data. Direct certification predictions rely on fewer states and therefore a more limited set of data to predict the relationship between SAIPE poverty and direct certification rates compared with states that report free lunch. For example, the direct certification model relies on direct certification data for 23 states (about 4,500 districts) each year, whereas the free lunch model relies on data from 44 states (about 12,000 districts).

In a few instances, aggregated MEPS vary more than 2 percentage points from the adjusted SAIPE. Alaska reports direct certification in 2018 but results in an underestimation of 6 percentage points. Louisiana uses free lunch to predict poverty rates in 2018 and overestimates by 6 percentage points. We demonstrate state-level correlation between aggregated predicted poverty rates and adjusted SAIPE in figure 6.

District-level correlations between adjusted SAIPE values and the original MEPS rate using free lunch (figure 7) and direct certification (figure 8) indicate that the correlation coefficient for free lunch is equal to 0.80 and for direct certification is 0.78 in 2018. Some districts have predicted poverty levels equal to zero. These instances make up only 1.3 percent of the nearly 12,000 district observations in the free lunch model and 1.4 percent of the 4,500 districts in the direct certification model. These districts are smaller (they include an average of three schools) and serve smaller populations of low-income students (generally 4 percent of students are eligible for free lunch or are directly certified).

FIGURE 5

Comparison of Original MEPS and Adjusted SAIPE, Aggregated to the State Level, 2018



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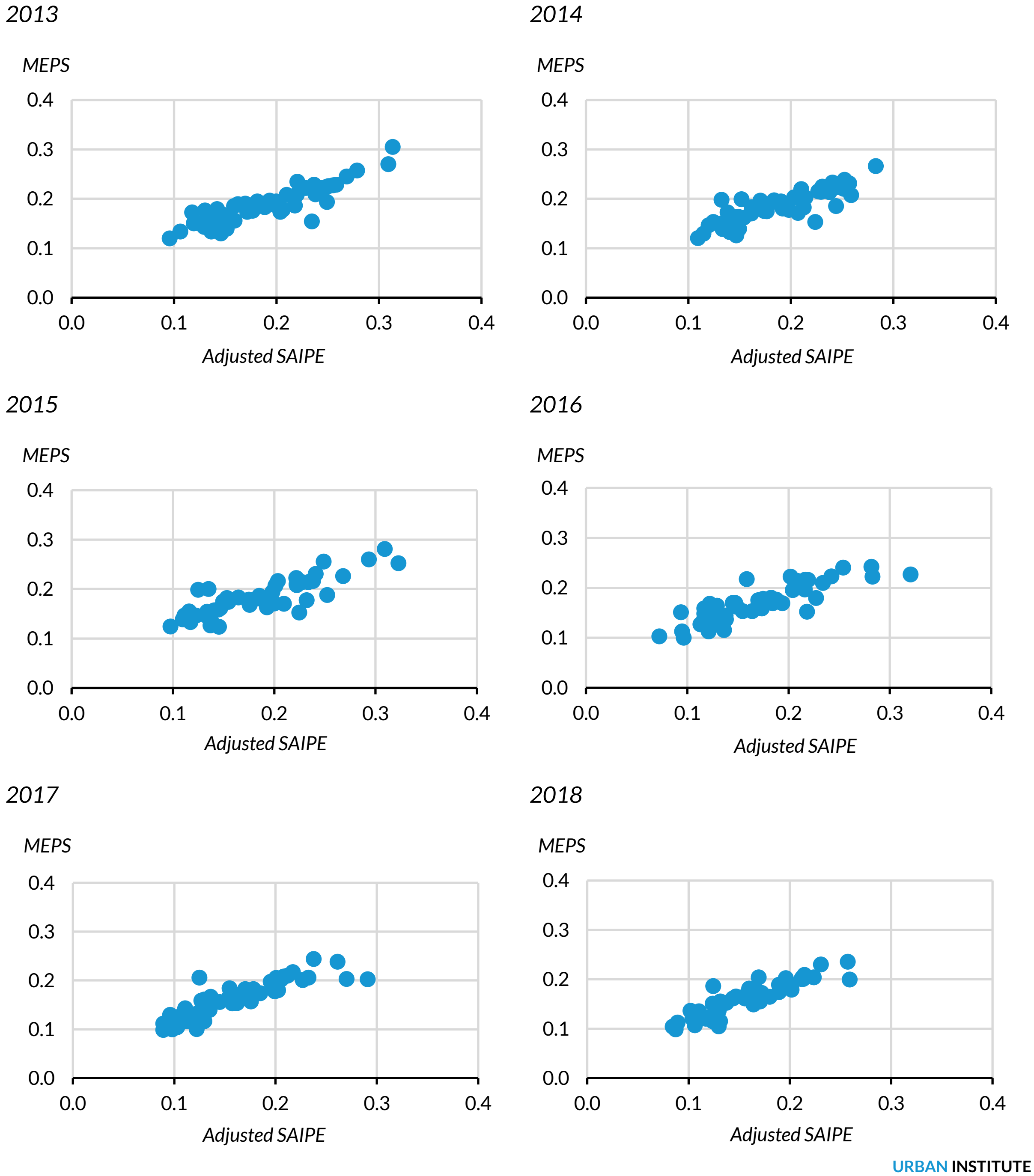
Source: Urban Institute analysis of MEPS data.

Note: MEPS = Model Estimates of Student Poverty; SAIPE = Small Area Income and Poverty Estimates.

FIGURE 6

Comparison of MEPS and Adjusted SAIPE, Aggregated to the State Level, by Year

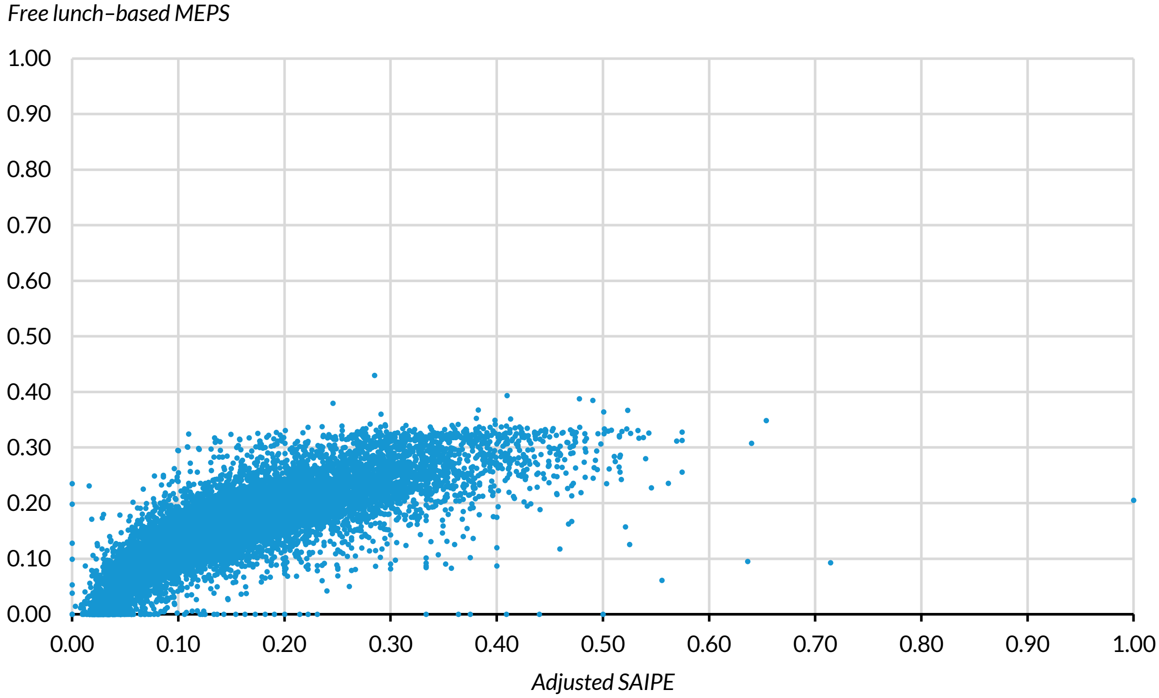


Source: Urban Institute analysis of MEPS data.

Note: MEPS = Model Estimates of Poverty in Schools; SAIPE = Small Area Income and Poverty Estimates.

FIGURE 7

Comparison of Free Lunch–Based MEPS and Adjusted SAIPE, Aggregated to the District Level, 2018



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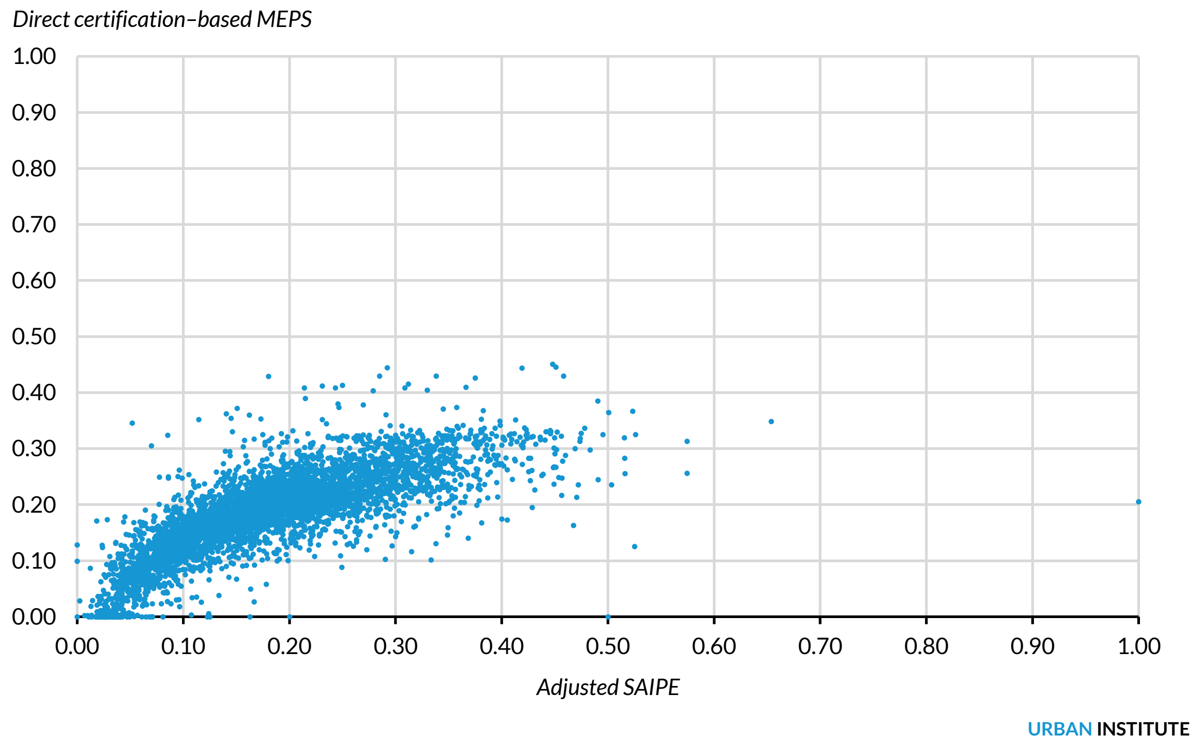
Source: Urban Institute analysis of MEPS data.

Notes: MEPS = Model Estimates of Poverty in Schools; SAIPE = Small Area Income and Poverty Estimates. Some districts have MEPS equal to zero. These instances make up only 1.3 percent of the nearly 12,000 district observations in the free lunch model. These districts are smaller (they include an average of three schools) and serve smaller populations of low-income students (generally 4 percent of students are eligible for free lunch).

FIGURE 8

Comparison of Direct Certification–Based MEPS and Adjusted SAIPE, Aggregated to the District Level, 2018



Source: Urban Institute analysis of MEPS data.
Note: MEPS = Model Estimates of Poverty in Schools; SAIPE = Small Area Income and Poverty Estimates. Some districts have MEPS equal to zero. These instances make up only 1.4 percent of the 4,500 districts in the direct certification model. These districts are smaller (they include an average of three schools) and serve smaller populations of low-income students (generally 4 percent of students are directly certified).

External Validity Assessment: Oregon

We further test the validity of MEPS against Oregon school-level measures of poverty created by Spiegel and coauthors (2022). These researchers use school-identifying data from the Oregon Department of Education and the US Census Bureau's IRS and SNAP data to determine how well existing or newly constructed measures capture school-level poverty. To do this, they construct a confidential "gold standard" measure that relies on more comprehensive and granular household-level data than do other publicly available measures of school poverty. The measure is defined as the share of students enrolled in SNAP or with documented family incomes below 185 percent of the federal poverty level by first determining whether students in each school are enrolled in SNAP, and then using IRS data to determine whether the remaining students have household incomes below 185 percent of the federal poverty level. The researchers found an early version of the original MEPS values (roughly 30 fewer Oregon schools per year) was highly correlated (0.92) with the gold standard measure of school poverty in Oregon.

Year-to-Year Stability

To ensure MEPS values do not vary widely from one year to the next, we first provide original MEPS year-to-year correlation measures (table 5). Measures are correlated at least 0.95 from one year to the next.

We then provide both the original and modified MEPS values as percentiles based on the national distribution of poverty rates across states for each year. We measure the absolute distance a school's poverty rate varies from one year to the next in the national distribution of poverty estimates. Table 6 shows the share of schools that move percentile ranks for all years in our sample. Eighty-eight percent of schools move between 0 and 9 ranks (either up or down) from year to year based on weighted original MEPS percentiles, compared with 9 percent of schools that move between 10 and 19 ranks and 2 percent of schools that move between 20 and 29 ranks. Weighted percentiles minimize the impact of large changes to poverty in schools with small enrollment numbers and are therefore the preferred percentile measures. Both tables demonstrate that year over year, there are not wide swings in the positions of schools, and the measure is reliable across time. Appendix tables A.3 and A.4 demonstrate that no particular state or year is responsible for any wide changes in percentile rank.

TABLE 5

Year-to-Year Correlation Matrix of Original MEPS

	2013	2014	2015	2016	2017	2018
2013	1.00					
2014	0.97	1.00				
2015	0.96	0.97	1.00			
2016	0.94	0.94	0.95	1.00		
2017	0.92	0.93	0.93	0.95	1.00	
2018	0.91	0.92	0.92	0.93	0.97	1.00

Source: Urban Institute analysis of MEPS data.
Note: MEPS = Model Estimates of Poverty in Schools.

TABLE 6

Share of Schools That Vary Rank, by Percentile Categories, 2014–18

	Original MEPS		Modified MEPS	
Percentile	**Unweighted**	**Weighted**	**Unweighted**	**Weighted**
0–9	86.9%	87.8%	83.3%	84.2%

10–19	10.0%	9.3%	13.9%	13.4%
20–29	1.8%	1.7%	2.1%	1.8%
30–39	0.6%	0.5%	0.4%	0.4%
40–49	0.3%	0.3%	0.2%	0.1%
50–59	0.2%	0.2%	0.1%	0.0%
60–69	0.2%	0.1%	0.0%	0.0%
70–79	0.0%	0.0%	0.0%	0.0%
80–89	0.0%	0.0%	0.0%	0.0%
90–100	0.0%	0.0%	0.0%	0.0%

Source: Urban Institute analysis of MEPS data.
Notes: MEPS = Model Estimates of Poverty in Schools. Percentiles are available for schools with predicted poverty rates. Values in weighted columns are weighted based on student enrollment.

Conclusion

Recent changes in how schools report the share of economically disadvantaged students has made it difficult to compare student poverty across time and states. MEPS is a measure of students living in poverty that is comparable across states and time and is distinct from the typical definitions of poverty in the education field. MEPS measures students in relatively deeper poverty (i.e., up to 100 percent of the federal poverty level).

Data Available via the Education Data Portal and Uses

MEPS measures are available via Urban's Education Data Portal, including original and modified poverty estimates, standard errors created using Stata 16's predict command, and enrollment-weighted percentile data for 2013–14 through 2018–19.

MEPS values are a statistical estimate of poverty and are best suited for use in education research. MEPS is intended to help policymakers and researchers understand the variation in needs across schools within and across state lines and over time. It is also constructed for researchers wishing to conduct cross-state or cross-time analyses. MEPS is not appropriate for allocating resources within a state or district. When allocating school resources or identifying schools in need of supports for students from low-income households, policymakers should use measures that are generated as closely as possible from information provided by, or linked to, enrolled students and their families. These measures could include direct certification counts, the number of students who are in foster care or experiencing homelessness, or through use of neighborhood socioeconomic status characteristics linked to student addresses.

Because the version of MEPS depends on the context of the research and comparisons, we make both the original and modified MEPS values available. We highlight that SAIPE values for areas with a small number of school-age children have a wider margin of error. For example, geographic districts with populations below 2,500 have a SAIPE value with an approximate 90 percent confidence interval of +/-110 percent. In contrast, a similar confidence interval for districts with populations of at least 65,000 is +/-25 percent.

Thus, modified MEPS values, which hew closely to the SAIPE value, are more appropriate for analyses that look only at schools within geographic school districts that have a large enrollment or student population. For example, the modified MEPS might be used for a comparison of schools in the largest 100 school districts by enrollment. For analyses that will incorporate districts with smaller student populations or enrollments, we suggest using the original MEPS values, as the estimations from the models further refine these predictions. Enrollment-weighted percentiles would be useful to those trying to understand the distribution of school poverty across the nation while accounting for school enrollment sizes.

Future Work and Data Considerations

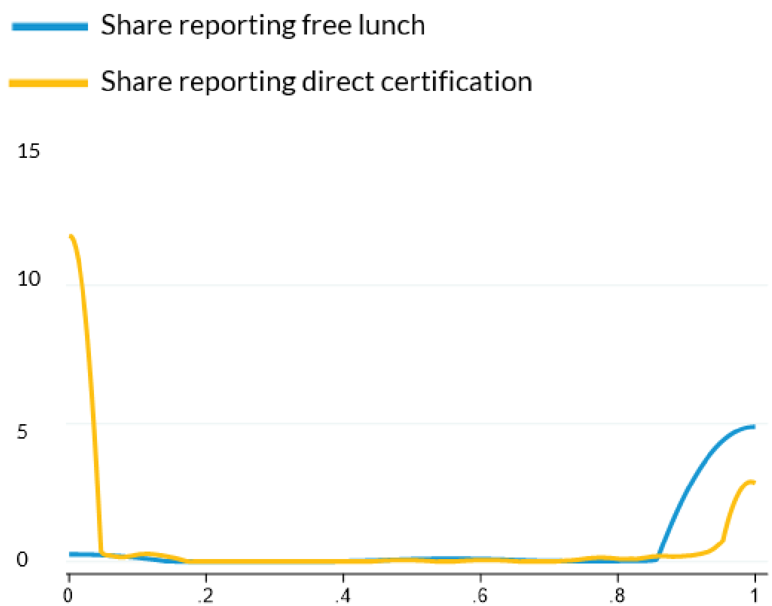
MEPS is currently produced for the 2013–14 through 2018–19 school years. We intend to update MEPS annually when possible and when the necessary inputs become available. We are aware that the data we use to estimate MEPS can change annually, particularly beginning in 2020–21 for pandemic-related reasons. We aim to address these concerns annually once data become available, using the knowledge we gained from the 2013–14 through 2018–19 estimates.

This is a foundational version of MEPS, and we welcome feedback as we refine and improve the measure going forward. Future iterations of MEPS could address such factors as cost-of-living differences.

Appendix

FIGURE A.1

Share of Districts Reporting Free Lunch versus Direct Certification Data, 2013–18



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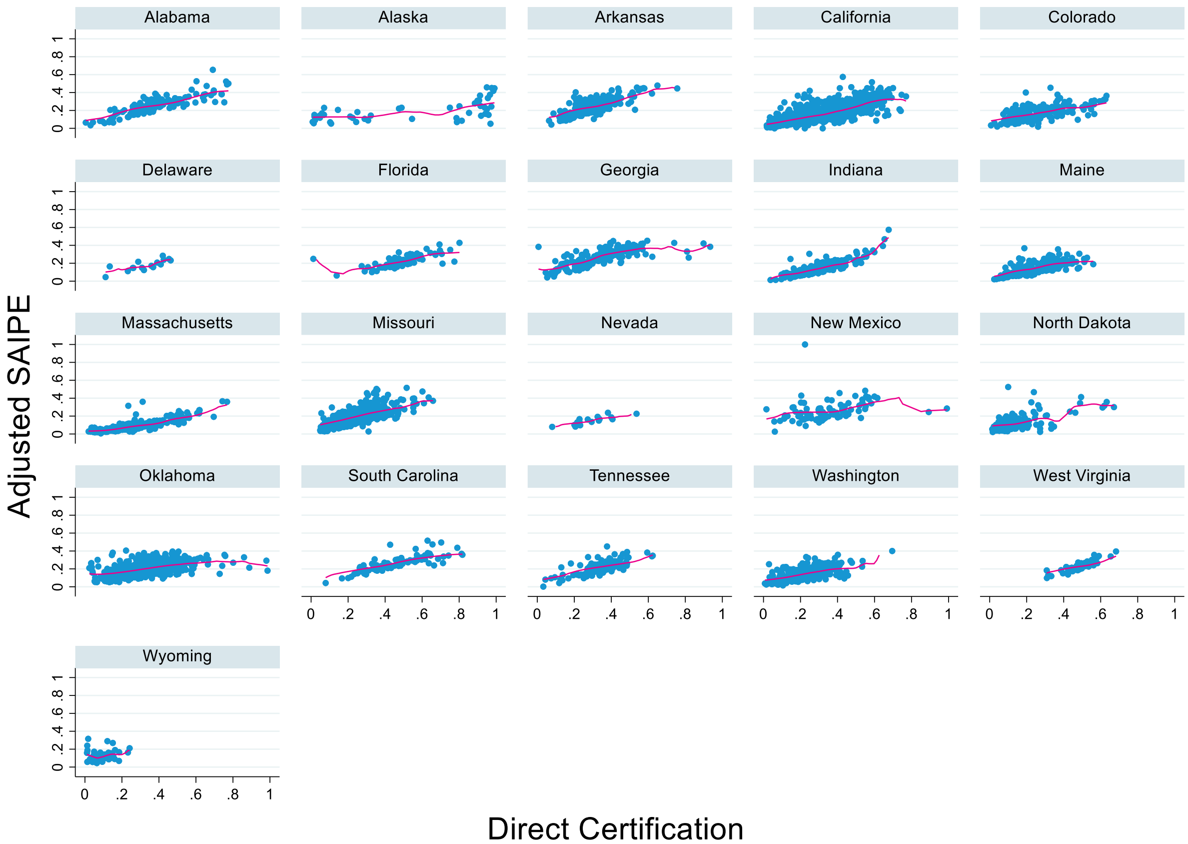
Source: Urban Institute analysis of Model Estimates of Poverty in Schools data.
Notes: The graph includes all districts from 2013 to 2018.

FIGURE A.2

Local Polynomials for States Used in the Direct Certification Model, 2018



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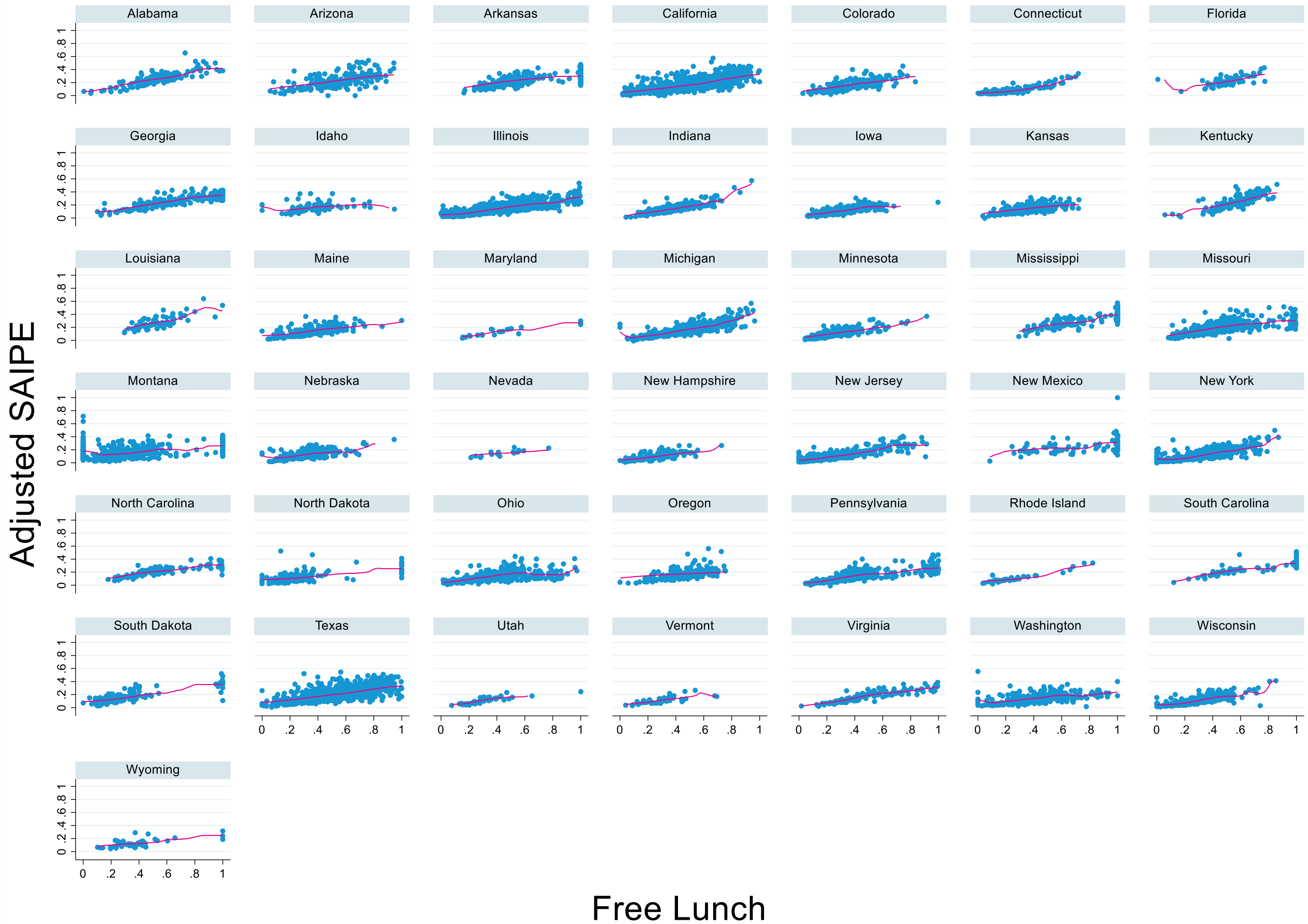
Source: Urban Institute analysis of Model Estimates of Poverty in Schools data.
Notes: SAIPE = Small Area Income and Poverty Estimates. The graphs plot the district-level direct certification share by the adjusted Small Area Income and Poverty Estimates for each state in 2018. We exclude DC and Hawaii, even though they report direct certification in 2018, because they each contain only one district.

FIGURE A.3

Local Polynomials for States Used in the Free Lunch Model, 2018



Source: Urban Institute analysis of Model Estimates of Poverty in Schools data.

Notes: SAIPE = Small Area Income and Poverty Estimates. The graphs plot the free lunch share by the adjusted SAIPE values for each state in 2018.

TABLE A.1

Estimated District-Level Parameters for Each Model and Year

	Free Lunch						Direct Certification		
	2013	2014	2015	2016	2017	2018	2016	2017	2018
Free lunch share	0.239***	0.220***	0.221***	0.201***	0.205***	0.212***	N/A	N/A	N/A
	(0.021)	(0.020)	(0.018)	(0.018)	(0.016)	(0.015)			
Direct certification share	N/A	N/A	N/A	N/A	N/A	N/A	0.245***	0.209***	0.288***
							(0.044)	(0.042)	(0.030)
Secondary district	0.004	0.003	-0.001	-0.004	-0.006	-0.004	0.004	0.002	-0.013*
	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)	(0.007)	(0.008)
Elementary district	0.009***	0.011***	0.006**	0.003	0.002	0.004	-0.016**	-0.012	-0.001
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.007)	(0.009)	(0.005)
Elementary grades	0.019***	0.015***	0.008	0.010	0.011**	0.010*	0.013	0.005	0.007
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.016)	(0.014)	(0.013)
Middle grades	0.006	0.001	0.007*	0.002	0.003	0.007	0.004	-0.001	0.010
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)	(0.009)	(0.008)
Charter or magnet	0.010	0.013	0.017*	0.013	0.008	0.018**	0.043***	0.026	0.009
	(0.008)	(0.011)	(0.010)	(0.011)	(0.008)	(0.007)	(0.015)	(0.022)	(0.015)
Title I Targeted Assistance	-0.006	-0.008	-0.007	-0.002	0.002	0.000	-0.001	-0.003	0.015***
	(0.008)	(0.008)	(0.007)	(0.006)	(0.004)	(0.005)	(0.010)	(0.009)	(0.004)
Title I Schoolwide Program	0.025***	0.024***	0.019**	0.023***	0.025***	0.021***	0.039***	0.037***	0.031***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.006)	(0.006)	(0.011)	(0.012)	(0.006)
Income-to-poverty ratio	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Medicaid pilot state	N/A	N/A	N/A	0.018	-0.016*	-0.019**	0.033**	-0.008	-0.031
				(0.036)	(0.008)	(0.008)	(0.017)	(0.023)	(0.019)
Poverty variable AK and HI	0.001	0.027*	0.032	-0.056***	-0.047***	-0.040***	-0.004	0.016	-0.002
	(0.015)	(0.016)	(0.020)	(0.005)	(0.004)	(0.004)	(0.014)	(0.019)	(0.014)
Serves prekindergarten	-0.004	-0.000	0.003	0.009**	0.006*	0.006*	0.015**	0.014***	0.007
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.007)	(0.005)	(0.006)
Constant	0.131***	0.137***	0.134***	0.128***	0.117***	0.109***	0.160***	0.186***	0.137***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.015)	(0.015)	(0.037)	(0.040)	(0.025)
Observations	12,923	12,934	13,018	12,465	12,408	11,869	2,789	3,344	4,473
Number of states	51	51	51	45	45	44	19	21	23

Source: Urban Institute's analysis of Model Estimates of Poverty in Schools data.

Notes: N/A = not applicable. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

TABLE A.2

District Means and Standard Deviations for Associations between Free Lunch/Direct Certification and Adjusted SAIPE

	2013	2014	2015	2016	2017	2018
Free lunch						
Mean	0.69	0.69	0.70	0.68	0.72	0.72
Standard deviation	N/A	0.23	0.22	0.22	0.15	0.14
Direct certification						
Mean	N/A	N/A	N/A	0.72	0.66	0.68
Standard deviation	N/A	N/A	N/A	0.14	0.21	0.18

Source: Urban Institute analysis of Model Estimates of Poverty in Schools data.
Note: N/A = not applicable; SAIPE = Small Area Income and Poverty Estimates.

TABLE A.3

Share of Schools That Vary Rank, by Percentile Categories, Using Original Model Estimates of Poverty in Schools, by Year

	0–9	10–19	20–29	30–39	40–49	50–59	60–69	70–79	80–89	90–100
2014	90.9%	7.0%	1.2%	0.5%	0.2%	0.2%	0.1%	0.0%	0.0%	0.0%
2015	91.5%	6.5%	1.0%	0.3%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%
2016	84.6%	11.3%	2.6%	0.8%	0.4%	0.2%	0.1%	0.0%	0.0%	0.0%
2017	83.6%	13.3%	1.8%	0.6%	0.3%	0.3%	0.2%	0.0%	0.0%	0.0%
2018	88.8%	8.6%	1.7%	0.5%	0.3%	0.1%	0.1%	0.0%	0.0%	0.0%

Source: Urban Institute analysis of MEPS data.
Notes: MEPS = Model Estimates of Poverty in Schools. Weighted by enrollment.

TABLE A.4

Share of Schools That Vary Rank by, Percentile Categories, Using Original Model Estimates of Poverty in Schools, by State, 2014–18

	0–9	10–19	20–29	30–39	40–49	50–59	60–69	70–79	80–89	90–100
Alabama	78.7%	16.2%	4.4%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Alaska	65.8%	17.0%	6.6%	3.8%	2.7%	2.3%	1.2%	0.5%	0.1%	0.0%
Arizona	80.0%	10.5%	3.0%	1.6%	1.4%	2.4%	1.1%	0.0%	0.0%	0.0%
Arkansas	83.2%	11.6%	3.6%	1.2%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
California	92.0%	6.8%	0.9%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Colorado	85.9%	11.8%	1.7%	0.4%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%
Connecticut	92.2%	6.6%	0.6%	0.4%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Delaware	71.3%	15.3%	9.2%	3.2%	0.6%	0.3%	0.0%	0.0%	0.0%	0.0%
DC	72.7%	15.1%	4.7%	3.1%	2.8%	1.0%	0.4%	0.0%	0.0%	0.0%
Florida	80.6%	15.1%	2.6%	0.8%	0.6%	0.3%	0.1%	0.0%	0.0%	0.0%
Georgia	94.4%	4.0%	0.9%	0.3%	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%
Hawaii	72.9%	8.4%	9.0%	9.3%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%
Idaho	90.0%	7.3%	1.3%	0.6%	0.2%	0.2%	0.5%	0.0%	0.0%	0.0%
Illinois	81.6%	16.3%	1.5%	0.4%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
Indiana	81.0%	15.2%	3.0%	0.5%	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%
Iowa	91.6%	7.9%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Kansas	93.0%	6.5%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Kentucky	91.4%	6.1%	1.3%	0.7%	0.3%	0.2%	0.0%	0.0%	0.0%	0.0%

	0–9	10–19	20–29	30–39	40–49	50–59	60–69	70–79	80–89	90–100
Louisiana	83.7%	13.5%	2.2%	0.4%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
Maine	91.9%	7.1%	0.8%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Maryland	94.5%	4.5%	0.6%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Massachusetts	79.0%	16.4%	3.7%	0.8%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Michigan	93.0%	6.2%	0.6%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Minnesota	92.2%	6.5%	1.0%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Mississippi	95.6%	3.6%	0.5%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Missouri	89.6%	7.7%	1.7%	0.6%	0.1%	0.1%	0.2%	0.0%	0.0%	0.0%
Montana	83.2%	10.9%	3.3%	1.1%	0.5%	0.4%	0.4%	0.1%	0.0%	0.0%
Nebraska	81.7%	17.0%	1.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Nevada	75.8%	15.3%	4.7%	2.0%	1.8%	0.3%	0.1%	0.0%	0.0%	0.0%
New Hampshire	94.5%	4.8%	0.5%	0.1%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%
New Jersey	93.6%	4.6%	0.6%	0.3%	0.4%	0.4%	0.1%	0.0%	0.0%	0.0%
New Mexico	72.8%	16.2%	6.7%	3.0%	0.9%	0.4%	0.1%	0.0%	0.0%	0.0%
New York	88.6%	8.2%	1.0%	0.5%	0.8%	0.6%	0.2%	0.0%	0.0%	0.0%
North Carolina	89.9%	6.3%	2.2%	1.0%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%
North Dakota	85.4%	11.9%	2.0%	0.4%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
Ohio	85.3%	10.6%	3.0%	0.5%	0.3%	0.1%	0.1%	0.0%	0.0%	0.0%
Oklahoma	82.1%	13.2%	2.5%	0.9%	0.6%	0.5%	0.1%	0.0%	0.0%	0.0%
Oregon	88.3%	10.7%	0.8%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Pennsylvania	91.0%	6.5%	1.3%	0.8%	0.2%	0.2%	0.1%	0.0%	0.0%	0.0%
Rhode Island	92.6%	6.3%	0.7%	0.2%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%
South Carolina	85.0%	9.2%	3.8%	1.4%	0.3%	0.2%	0.0%	0.0%	0.0%	0.0%
South Dakota	89.0%	8.3%	0.9%	0.2%	0.3%	0.5%	0.7%	0.1%	0.0%	0.0%
Tennessee	88.0%	10.0%	1.1%	0.4%	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%
Texas	93.4%	5.6%	0.6%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Utah	80.9%	17.5%	1.1%	0.3%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Vermont	89.8%	9.5%	0.6%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Virginia	89.7%	9.1%	0.9%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Washington	79.4%	16.8%	2.7%	0.6%	0.2%	0.2%	0.0%	0.0%	0.0%	0.0%
West Virginia	81.8%	7.7%	1.5%	1.2%	1.6%	2.7%	3.3%	0.1%	0.0%	0.0%
Wisconsin	93.1%	5.9%	0.7%	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
Wyoming	89.1%	8.4%	1.6%	0.2%	0.4%	0.2%	0.0%	0.0%	0.0%	0.0%

Source: Urban Institute analysis of MEPS data.

Notes: MEPS = Model Estimates of Poverty in Schools. Weighted by enrollment.

Notes

[1] Stanley C. Garnett, "Categorical Eligibility for Free Lunches and Breakfasts of Runaway, Homeless, and Migrant Youth," memorandum to special nutrition programs and others, July 19, 2004, https://www.fns.usda.gov/cn/categorical-eligibility-free-lunches-and-breakfasts-runaway-homeless-and-migrant-youth.

[2] Kristin Blagg, Macy Rainer, Erica Greenberg, and Emily Gutierrez, "Measuring Student Poverty: Dishing Up Alternatives to Free and Reduced-Price Lunch," Urban Institute, October 20, 2021, https://www.urban.org/features/measuring-student-poverty-dishing-alternatives-free-and-reduced-price-lunch?state=Alabama.

[3] See also sean reardon, Demetra Kalogrides, Andrew Ho, Ben Shera, Erin Fahle, Heewon Jang, and Belen Chavez, "Improving Educational Equity," Stanford Education Data Archive, accessed May 13, 2022, https://exhibits.stanford.edu/data/catalog/db586ns4974.

[4] School CCD Directory, Education Data Portal (Version 0.15.0), Urban Institute, accessed March 2, 2022, https://educationdata.urban.org/documentation/, made available under the ODC Attribution License.

[5] SAIPE is measured with error, but the methodology that creates the school district estimates is designed to minimize errors. SAIPE has continued to improve its estimates. For example, preliminary evaluation indicates that the ACS five-year estimate as an estimator of current-year poverty represents an improvement in relative error compared with using the 2000 Decennial Census estimate. See "Quantifying Relative Error in the School District Estimates," US Census Bureau, last updated December 1, 2021, https://www.census.gov/programs-surveys/saipe/guidance/district-estimates.html.

[6] For districts enrolling at least 10,000 students or are missing data from the ACS or the National Historical Geographic Information System, we use the original, unadjusted SAIPE values.

[7] Each year of CCD data is matched to the nearest available NCES shapefile (e.g., the shapefile for school year 2003–04 is matched to both 2003–04 and 2004–05 CCD data).

[8] "Fast Facts: Public School Choice Programs," US Department of Education, Institute of Education Sciences, National Center for Education Statistics, accessed May 13, 2022, https://nces.ed.gov/fastfacts/display.asp?id=6.

[9] Although schools with missing free lunch or direct certification numbers are generally random, most schools in the following states were missing both in each year: Maryland in 2016, Massachusetts in 2015, and Tennessee in 2014 and 2015. Year-over-year correlations of free lunch from 2013 to 2018 are at least around 0.93 and 0.86 for direct certification. Therefore, for 2013 through 2015, if a school is missing free lunch data, we replace it with the most recent year's data. For 2016 through 2018, we replace any missing free lunch data with data from the most recent available year as long as the school did not report direct certification data in that year. Also, some direct adjustments to FRPL and direct certification data were necessary. For example, according to CCD documentation, the fall 2016 and 2017 FRPL data for Arkansas did not include students who were directly certified for free lunch. Further, some schools reported high values for free lunch (at least 95 percent and often exceeding 100 percent). We adjust these values using each state's own probit-estimated relationship between direct certification and free lunch in non-CEP schools in each year. We then predict the share of free lunch students in schools with reported shares of free lunch students of at least 95 percent (in both CEP and non-CEP schools). We also find schools that are missing direct certification data in the CCD and match these schools to available 2016 Food Research and Action Center data to use identified student percentage (ISP) as a proxy for missing direct certification data. Individual state fixes include adjustments to FRPL data in Arkansas in 2016 and 2017 and in Wyoming in 2017 and 2018; Ohio FRPL data from 2013 to 2015 and direct certification data from 2016 to 2018. CCD lunch program data (participating, for example, in the NSLP, CEP, and Provision 2) are missing for Indiana, Texas, and West Virginia in 2016 and Massachusetts in 2017, among others.

[10] The decision to use a 90 percent reporting threshold was simple (see appendix figure A.1 for the justification). The range of reporting percentages spanned 0 to 80 percent and then 90 to 100 percent, with one exception. Ohio reported 52 to 54 percent of students had free lunch from 2016 to 2018, but only 10 to 12 percent of students had direct certification. To include Ohio, we use the best of the two options and use Ohio in the free lunch models from 2016 to 2018.

[11] We find the underlying relationship between free lunch/direct certification and the share of students living in poverty using adjusted SAIPE to be linear (appendix figures A.2 and A.3). Information on the associations between free lunch/direct certification and adjusted SAIPE measures can be found in appendix table A.2.

[12] We tested several combinations of control covariates and found that the inclusion of covariates improved the model by reducing the average difference between the state-level-adjusted SAIPE measure of student poverty and the state-level aggregate estimate of MEPS. We originally included census tract data from the NGHIS ACS, including Gini coefficient, the share of non-citizens, and the share of students ages 5 to 17 living in poverty. But we found that the impreciseness of these variables in smaller districts created MEPS that were less correlated with student-level Oregon validation measures and were removed.

[13] For states and years in which both free lunch and direct certification data are available, we compare each aggregated predicted measure with the SAIPE share of students living in poverty, by state and year, and use the prediction most closely resembling the SAIPE share.

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About the Authors

Emily Gutierrez is a research associate in the Center on Education Data and Policy at the Urban Institute, where her research focuses on K–12 education policies that aim to mitigate educational inequities, disparities, and external factors that affect student success. She received her BBA in economics, Spanish, and public administration and MS in economics from Baylor University, and she holds a PhD in public administration from Syracuse University.

Kristin Blagg is a senior research associate in the Center on Education Data and Policy. Her research focuses on K–12 and postsecondary education. Blagg has conducted studies on student transportation and school choice, student loans, and the role of information in higher education. In addition to her work at Urban, she is pursuing a PhD in public policy and public administration at the George Washington University. Blagg holds a BA in government from Harvard University, an MSEd from Hunter College, and an MPP from Georgetown University.

Matthew M. Chingos directs the Center on Education Data and Policy. He leads a team of scholars who undertake policy-relevant research on issues from prekindergarten through postsecondary education and create tools such as Urban's Education Data Portal. He received a BA in government and economics and a PhD in government from Harvard University.

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Washington, DC 20024

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