Is free and reduced-price lunch a valid measure of educational disadvantage?

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Abstract

Students in the United States whose household income is less than 130 percent of the poverty line qualify for free lunch, and students whose household income is between 130 percent and 185 percent of the poverty line qualify for reduced-price lunch. Education researchers and policy-makers often use free and reduced-price lunch (FRPL) status to measure socioeconomic disadvantage. But how valid is this measure? Linking IRS income tax data to school administrative records for all 8th graders in one California public school district and in Oregon public schools, we examine how well FRPL enrollment captures student disadvantage. We find that FRPL categories capture relatively little variation in household income. However, FRPL captures elements of educational disadvantage that IRS-reported household income data do not.

Introduction

Founded in 1946, the National School Lunch Program (NSLP) serves free or reduced-price meals to over 30 million students at a cost of nearly $12.6 billion annually (USDA 2017). The program provides free lunches to students whose household income is less than 130 percent of the poverty line, and reduced-price lunches to students whose household income is between 130 percent and 185 percent of the poverty line. Nearly 99 percent of all public schools offer meals via the NSLP, and close to 60 percent of school-aged US children regularly receive meals through the program (IOM 2008; Snyder et al. 2016).

As NSLP free and reduced-price lunch (FRPL) participation is often the sole available indicator of student socioeconomic status available in K-12 school administrative data, the program also plays a central role in educational research and in the allocation of school finances. Income information used by this program is typically based on student, parent, or guardian reports of total household income in the month prior to program application. Educational researchers routinely use NSLP enrollment as a proxy for economic disadvantage (c.f. Hill, Bloom, Black, & Lipsey 2008; Reardon, Kalorides & Shores 2017) and represent peer socioeconomic status based on classroom or school-level free and reduced-price enrollment rates (Hanushek et al. 2003; Kim & Sunderman 2005). Likewise, school finance policies – including federal Title I funds as well as state and local weighted student funding formulae – use NSLP enrollment data to target supplemental funds to poor students.

In this paper, we investigate how well FRPL designations measure household income and educational disadvantage. We draw on a unique link between Internal Revenue Service (IRS) records of students' annual household income and student administrative records from 8th graders in a mid-sized California public school district and in Oregon public schools. The resulting data provide an unprecedented look at the relationship between NSLP enrollment categories, the economic resources in students' homes, and students' educational achievement.

Our analyses suggest that school data on students' NSLP enrollment do not do a good job of capturing students' socio-economic resources as measured by IRS-reported annual household income. Interestingly, however, school-reported measures of student FRPL enrollment correlate more strongly with test scores than do similar measures that we generate using IRS-reported annual household income. This finding suggests that NSLP data may better capture student educational disadvantage than annual household income data. Further, we find that school NSLP enrollment data predict test scores independent of other measures of household income, suggesting that FRPL categories may capture income volatility, educator perceptions of family resources, and other dimensions of disadvantage beyond annual household income. Finally, we show that the degree to which FRPL classification captures student poverty varies across schools, so that school-level FRPL enrollment rates provide an imprecise measure of school-level economic disadvantage.

Background

The NSLP's primary aim is to address the substantial and well-documented developmental challenges associated with childhood malnutrition (c.f. Adolphus et al. 2013, Brown & Pollitt 1996, Frisvold 2015, Glewwe et al. 2001, Hinrichs 2010, Victora et al. 2008) by ensuring that poor and near-poor students in American schools have access to at least one nutritious meal during school days.

But the NSLP has also come to occupy a central place in educational research. School administrative data provide unprecedented opportunities for the study of education, since they provide repeated measures of academic progress and educational contexts for the universe of students in many states and large districts. However, NSLP enrollment is often the only indicator of student home economic resources available in K-12 administrative data. While scholars acknowledge the coarseness and limited purview of this measure of family background, they regularly use FRPL enrollment categories as an individual-level control or stratifying variable, and use school-level variation to characterize the concentration of poverty in schools. Indeed, of the 82 articles published in *Educational Researcher* from 2006 to 2017 that include any empirical measure of student or school socioeconomic status, nearly 70 percent (57 articles) use FRPL measures (author's calculations). Prominent examples in related disciplines include Chetty, Friedman, & Rockoff (2014), Dobie & Fryer (2010), Figlio & Hart (2014), and Morris & Perry (2016).

The NSLP also plays an instrumental role in the provision of funds targeted at schools that educate economically disadvantaged youth. The Elementary and Secondary Education Act allocates Title I funds to districts and schools based on the proportion of students enrolled in the free or reduced-price lunch program. Likewise, 34 states allocate supplemental educational funds to districts based on free or reduced-price lunch enrollment rates (Verstegen 2011).

Threats to measurement validity

FRPL data measure student program enrollment (Hauser 1994; Cruse & Powers 2006; Harwell & LeBeau 2010; Michelmore & Dynarski 2016). Analyses using these data inevitably confound several factors, including income eligibility, program participation, and program effects.

Income eligibility as a proxy for socioeconomic disadvantage

Scholars and policy-makers use FRPL as a measure of socioeconomic disadvantage because, in most cases, families must report relatively low income to qualify for the program. However, several factors potentially undermine the match between FRPL enrollment and socioeconomic disadvantage. First, FRPL data are based on largely unverified family reports of household income. The accuracy of family-reported income is not clear. Second, FRPL eligibility rules are built around the federal poverty line, a measure that is based on dated ideas about the relation between food costs and total expenditures, neglects the role of taxes and non-cash transfers in family budgets, and overlooks important geographic variation in the cost of living (Hauser 1994). Third, as Michelmore and Dynarski (2016) point out, FRPL data obscure important variation in household resources at both the top and bottom of the income distribution since they reduce a continuous underlying variable (household income) to a rough categorical variable. Fourth, income-based eligibility requirements capture just one element of socioeconomic disadvantage, and provide no information on parental education, neighborhood resources, residential stability, and other family background characteristics associated with educational experiences and outcomes (c.f. National Forum on Education Statistics 2015).

Unmeasured variance in program participation

FRPL data are not collected for research purposes, and thus are likely not collected using scientific best practices. District offices enroll students in FRPL for the academic year based on student, parent, or guardian reports of household income in the past month, collected in varying ways in different contexts. The USDA provides detailed guidance to schools about how to solicit and validate applications for NSLP data. Districts are required to publicize the program's existence via local media, encourage participation by sending letters home with children, solicit standardized information about students' household size and current income from all household earners, directly verify income reports from a small sample of applicants, and retain records for potential audits. However, schools may vary in the encouragement and assistance they provide to potential NSLP applicants. Accordingly, some students who are income-eligible likely do not apply for FRPL.

Furthermore, verification studies suggest that family income reports may be inaccurate (Bass 2010).[4] Indeed, Harwell & LeBeau (2010) compile evidence from multiple verification studies conducted between 1990 and 2005 suggesting that a considerable proportion of students who enroll in free or reduced-price lunch are income ineligible and a considerable proportion of students who are income eligible do not enroll. In an attempt to boost free lunch program enrollment and reduce the bureaucratic burden on schools and school districts, the U.S. Department of Agriculture (USDA) authorized local educational authorities (LEA) to directly certify students whose families participate in SNAP and TANF enrollments for free lunch in 1986 and LEAs slowly rolled out direct certification through the 1990s and early 2000s. However, little information is available about the extent to which direct certification has improved the match between student income and FRPL status.

Other recent changes to the legislation governing the NSLP may render the measure increasingly problematic for research purposes and for governmental programs that use NSLP enrollment data in funding formulae. A series of provisions authorized by the U.S. Department of Agriculture (USDA) in 2002 make it possible for schools in which many students are enrolled in the free lunch program to renew students' program registration for up to four years without collecting updated information on students' household incomes (USDA 2002). Further, the Healthy, Hunger-Free Kids Act of 2010's Community Eligibility Provision (CEP), implemented nationwide in the 2014-15 school year, allows schools or districts in which 40 percent or more of students are directly certified for enrollment in the NSLP based on their participation in other federal nutrition programs to offer free lunch and breakfast to all students without collecting data

[4] Federal guidelines regarding verification of NSLP eligibility are available at https://fns-prod.azureedge.net/sites/default/files/cn/EligibilityManualFinal.pdf.

on other students' household income. In the 2015-16 school year, more than 15 percent of U.S. students attended a school or district that participated in the CEP (Segal et al. 2016). As this program becomes more widely adopted, it will likely create new challenges for educational researchers using school-reported NSLP participation rates as a proxy for economic disadvantage.

Unmeasured program effects

Finally, students who enroll in FRPL receive an educational intervention – one or more free or subsidized meals on school days. Analyses using FRPL to measure disadvantage inevitably confound the effects of this meal subsidy with the consequences of income eligibility and enrollment. When researchers use FRPL as a proxy for socioeconomic disadvantage, they implicitly assume that the meal subsidy has no appreciable effect on student outcomes. If, however, existing evidence suggesting that FRPL has a positive effect on student outcomes is accurate (c.f. Hindrichs 2010), FRPL measures may understate the consequences of family socioeconomic disadvantage.

Research Questions

In this study, we investigate the validity of FRPL as a measure of student socioeconomic disadvantage. Following Messick (1987, p. 6) we think of validity as an evaluative judgment of the degree to which inferences based on a measure are justified. We approach this task via two sets of analysis.

First, we investigate the *convergent validity* of FRPL enrollment data, asking: What is the relationship between IRS-reported annual household income and school-reported free or reduced-price lunch program enrollment? This analysis is predicated on the assumption that a valid measure of socioeconomic disadvantage should correlate with the income that a student's household reports annually to the IRS.

Second, we explore the measure's *predictive validity,* asking: What is the relationship between school-reported FRPL enrollment and student test scores? How does this relationship compare to the relationship between IRS-reported annual household income and test scores? This analysis proceeds from the empirical observation that socioeconomic disadvantage is strongly associated with low levels of academic achievement. A valid measure of socioeconomic disadvantage should correlate negatively with academic achievement, as measured by 8^{th} grade English Language Arts test scores. If FRPL measures correlate less strongly with academic achievement than IRS-validated household incomes, these analyses might indicate measurement error in the FRPL measures.

Data and Methods

To facilitate our analyses, we have linked student-level educational administrative data from one mid-size California public school district and from the state of Oregon with IRS tax records stored at the U.S. Census Bureau. The resulting merged datasets provide unique opportunities for assessing the measurement properties of FRPL data, since they provide the basic student demographic and annual test score data that are routinely included in educational administrative data as well as continuous student-level measures of household income as reported on 1040 forms filed annually during the students' elementary school career.

We have student-level administrative records from all 8th graders enrolled in one mid-sized California public school district for the 2008-09 through 2013-14 school years,[5] as well as similar records from all 8th graders enrolled in Oregon public schools during the 2004-05 to 2013-14 period. As is typically the case in school administrative data, these records provide little information about students' family background beyond a categorical variable describing students' free or reduced-price enrollment status. Both datasets provide annual data on students' end-of-grade test score achievement, as well as indicators of students' gender, race/ethnicity, English Language Learner status, and identifiers for the schools in which students were enrolled.

We examine the relationship between student poverty, FRPL enrollment, and 8th grade English Language Arts achievement. In California, during this time period, students were tested annually with the California Standards Test (CST) in grades 2 through 11.[6] In Oregon, students in grades 3 through 8 and in grade 11 took the Oregon Assessment of Knowledge and Skills (OAKS) in English Language Arts each spring.

Students whose household income is less than 130 percent of the poverty line[7] are eligible for free lunch, and students with household incomes between 130 and 185 percent of poverty are eligible for reduced-price lunch.[8] The California district data include indicators flagging students who were listed by the district as enrolled to receive free lunch, reduced-price lunch, or no support under the NSLP in each academic year.[9] In this district, the NSLP application asks for the current income, which is defined as pre-tax income from a wide variety of sources in the last month. The application specifies that the definition of income should include earnings from all sources (including work, pensions, public assistance, child support, and interest) from all members of the household (defined as "related or non-related individuals who are living as one economic unit and sharing living expenses.")[10] None of the schools in the California district participate in the USDA's Provision 1, Community Eligibility Provision, or

[5] The California district is an immigrant enclave in the inner-ring suburbs of a major metropolitan area. The district enrolls an ethnically diverse mix of approximately 4,000 eighth graders each year.
[6] We examine student performance in English Language Arts because all 8th grade students take the same exam in this subject. By contrast, student mathematics course-taking in California, and in this district, begins to differentiate in 8th grade, such that some students are tested in pre-algebra and others in algebra.
[7] The poverty line is defined annually by the U.S. Department of Health and Human Services and is the threshold used to determine who is officially considered to be living in poverty (defined as having less than the amount of income necessary for a family to pay for a minimum level of food, clothing, transportation, shelter, and other needs). In 2017, the poverty line for a family of four in the continental U.S. was $24,600 (US DHHS 2017).
[8] Note, however, that students in households receiving benefits from certain assistance programs (e.g. Supplemental Nutrition Assistance Program) are directly enrolled in the NSLP program.
[9] It would also be useful to examine the district's designation for students' program enrollment status over multiple years and at other ages (as in Dynarski and Michelmore 2016); however, we unfortunately only have NSLP data from 8th grade in the California district.
[10] The NSLP application states that if the household income in the past month was unusually high or low, the applicant should report the household's usual monthly income.

any other program designed to allow all students in a given school to enroll in free or reduced-price lunch independent of income eligibility.

The Oregon data provide information on a much broader array of schools and a longer time period. However, our Oregon administrative data provide less detailed FRPL enrollment data, combining students who enrolled in free or reduced-price lunch in a single category. Further, NSLP application and enrollment processes vary across Oregon schools.

We link these student-level records with IRS tax records stored at the U.S. Census Bureau. Most notably, IRS records include income information for the students' households, as reported on 1040 forms filed during each year of the students' elementary school and early high school careers. IRS-reported income measures provide unprecedented insights into the economic resources available in students' homes. The IRS-reported income data are continuous, include a wide range of income sources, and are collected in a context in which respondents have scaffolds (in the form of W2s and similar statements) as well as strong legal incentives to report accurate information.

The student records were processed at the Census Bureau using the Person Identification Validation System (PVS), which employs record linkage techniques using personal information such as Social Security Number, name, date of birth, and address to assign each student, when possible, an anonymized unique Protected Identification Key (PIK).[11] Approximately 94 percent of students in the California district administrative records and 93 percent of students in the Oregon administrative records were assigned a PIK. These students' PIKs were matched to their household's IRS 1040 tax records. Approximately 99 percent of all IRS 1040 records filed across the United States were assigned a PIK. As not every household files taxes in every year and not all students received a PIK, 8th grade household income is available for 87 and 88 percent of the students from California and Oregon, respectively, for whom we also have school NSLP enrollment data.[12] We exclude students who are missing IRS household income data, as well as a very small number of students whose families report income greater than roughly 20 times the poverty line (approximately $500,000 annually in 2017 dollars) from the analysis. In both samples, excluded students due to missing IRS household income data are disproportionately low-performing, receive free and reduced lunch at a higher rate than non-excluded students, and include a high proportion of racial and ethnic minorities.

[11] Once the PIK is assigned, personal information is removed from the file to protect the student's confidentiality. For more information on the linking process used in this study, see Wagner and Layne (2014).

[12] As assessment of the potential impact of missing 8th grade income information on our findings, we re-ran our models using a measure of 8th grade income that uses IRS reported income from the immediately succeeding and preceding tax years, in that order, as a proxy for 8th grade household income for students that lived in a household without 1040 income data for 8th grade (e.g. no one in the household filed). Overall, the results from the supplementary analyses (where we are able to link roughly 92 percent of students with NSLP information to IRS information) were very similar to those presented in the paper. Results are available upon request.

We use the IRS 1040 tax records to create measures of the household income to poverty ratio and predicted FRPL eligibility following the NSLP enrollment thresholds.[13] We use a unique address identifier to indicate a student's household, and our measure of household size is based upon the total number of primary, secondary, and dependent exemptions claimed on all 1040s filed in a household.

As multiple persons in a household may file a 1040, we follow USDA-Food and Nutrition Service guidelines and define household income as the sum of all total money income reported on all filed 1040s in a student's household. An important limitation is that tax years and school years are not aligned. We use students' household income from the IRS tax records for the calendar year that coincides with the beginning of the school year (e.g. for the 2008-09 school year we use 2008 tax records) since schools typically ask students to complete NSLP applications at the beginning of the school year. We are unable to account for short-term income volatility and its implications for student NSLP enrollment. Recent data suggest that this volatility is substantial, such that the average family spends several months each year with a monthly household income that is at least 25 percent lower than their average monthly household income for that year (Morduch & Schneider 2017). Under NLSP guidelines, students can enroll in NSLP based on household income during a period of unemployment or underemployment and remain on the program throughout the school year.[14]

Our analyses proceed in two steps. First, we consider the *convergent validity* of FRPL as a measure for student socioeconomic disadvantage by investigating the degree to which these widely-utilized measures account for variation in students' household income. We use household income and size to create a measure of household income relative to the poverty line, dividing students' household income by the poverty threshold for a household of their size. We also create annual indicators of household poverty from kindergarten through 8th grade for students in the California district and from 4th to 8th grade for students in Oregon. These variables indicate whether students came from households with incomes less than 130 percent of the poverty line (corresponding to the free lunch threshold), between 130 and 185 percent of the poverty line

[13] We note, however, that IRS records and FRPL applications operationalize household, household size, and household income somewhat differently. Due to these differences, we re-estimated the models presented below with varying samples of students to examine whether the results were robust to changes in the sample based upon various household size and number of 1040s filed per household inclusion thresholds (e.g. limit the sample to households in which only one 1040 was filed or to households with 7 or fewer people). Although the specific point estimates and p-values varied, the general patterns were consistent.

[14] Since our data cannot address short-term income volatility, and NSLP eligibility guidelines do not prohibit students from enrolling in the NSLP based on short-term dips in household income, our findings cannot speak to which students are or are not eligible for the NSLP. Likewise, our data do not permit us to examine the extent to which students actually receive or consume free or reduced-price lunches via the NSLP participation. Gleason (2008) and others (for example, Ponza, Gleason, Hulsey, & Moore 2009; USDA 2004, 2015) seek to address questions around NSLP under- and over-enrollment, and several studies indicate that children discard between 10 and 45 percent of the food served via the NSLP (c.f. Buzby & Guthrie 2002; Byker et al. 2014; Cohen et al. 2013).

(corresponding to the reduced-price lunch threshold), and whether the student lived in a household with an income below the poverty threshold.[15]

We further examine the extent to which the convergent validity of FRPL enrollment measures varies across schools and with student demographics. Investigating the school-level relationship between IRS-reported household income and FRPL category data provides important information about the extent to which these measures capture socioeconomic variation across schools. After a preliminary descriptive analysis in the California data, we use the Oregon data to estimate a series of models investigating cross-district and cross-school variation in FRPL enrollment and the extent to which IRS-reported household income, as well as other demographic controls, explain that variation.

We then examine the *predictive validity* of FRPL enrollment measures by estimating the relationship between NSLP enrollment, IRS-reported household income, and student English Language Arts (ELA) achievement. In a series of OLS regression models, we compare the extent to which NSLP enrollment and IRS-reported annual household income each explain variation on ELA achievement net of controls for student race/ethnicity, U.S. nativity, language status, and various measures of students' prior exposure to poverty and family composition.

Findings

Convergent validity

NSLP enrollment data reduce continuous variation in students' household income to poverty ratio into three discrete categories: Free lunch enrollees, reduced-price lunch enrollees, and non-FRPL students. As such, these data inevitably result in the loss of information and obscure important differences among students within each category. In these data, the estimated 1.5 million U.S. children who live on less than $2 a day (Schafer, Edin & Talbert 2015) might look no different from classmates whose household income is just below 130 percent of the poverty line (approximately $32,000 for students in a family of four.) Likewise, students from relatively modest backgrounds whose family incomes are just above 185 percent of the poverty line (approximately $45,000 for a family of four) look no different in FRPL data than their wealthy peers.

In analyses reported in Appendix Tables 1a and b, we consider the extent to which these categories capture the continuous variation in student household income. These analyses predict the continuous measure of the household income to poverty ratio using FRPL categories, as well as categories constructed around free lunch eligibility and reduced-price lunch eligibility thresholds with IRS-reported household income data.[16] Appendix Table 1a demonstrates that

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[15] See https://www.fns.usda.gov/school-meals/income-eligibility-guidelines for details on NSLP eligibility and https://aspe.hhs.gov/poverty-guidelines for details on poverty status. Poverty status (and NSLP threshold indicators) were not computed for small handful of cases (between .5 and 1 percent of all cases) due to extreme values for household size or number of 1040s filed at an address.

[16] For these analyses, we code students from households with IRS-reported income less than 130 percent of the poverty line as free lunch eligible, and students from households with IRS-reported income between 130 and 185 percent over the poverty line as reduced-price lunch eligible.

IRS-validated income categories account for approximately twice as much of the within-school, within-year variation (51 percent) in the continuous household income to poverty ratio as FRPL categories (28 percent) in our California school district. Appendix Table 1b demonstrates that IRS-validated income categories account for approximately 1.5 times as much of within-school, within-year variation as FRPL categories in Oregon (43 percent vs. 30 percent).

Figures 1a and 1b plot household income-to-poverty ratios for students separately by NSLP enrollment categories and illustrate the information lost by using free or reduced-price lunch status as a proxy for annual household income. These figures make it clear that there is substantial variation in household income among students in the same NSLP participation category. This variation is particularly pronounced among FRPL non-enrollees, a category that includes students from middle-income families, a considerable number of more affluent students, and many students who have household incomes below the 185 percent of poverty threshold. For example, in the California district, approximately 13 percent of students who are not enrolled in free or reduced-price lunch appear to be income-eligible based on their household's IRS records. We note this figure likely understates the degree of under-enrollment, since these data exclude students from families who do not file income tax returns.

FIGURE 1a AND 1b AROUND HERE

Considerable variation in household income also exists among FRPL recipients. Figure 1a illustrates that most free lunch recipients in the California district come from households with incomes near or below the poverty line. However, the left tail of the income-to-poverty distribution for free lunch recipients includes a group of extremely poor students. In the California district, 26 percent of free lunch recipients come from households with household incomes below the poverty line. Likewise, a substantial number (35 percent) have incomes that are greater than two times the poverty line. The statewide results from Oregon presented in Figure 1b are consistent with these California findings.

Figure 2 examines whether school-level aggregated NSLP enrollment rates capture school-level differences in household income in our California district. We plot the percent of students who 1) are enrolled in the free or reduced-price lunch program, 2) were below the poverty line according to IRS household income information from the relevant tax year, 3) were ever below the poverty line in kindergarten through 8th grade, based on IRS records, 4) and were below the threshold for free or reduced-price lunch according to IRS information from the relevant tax year. Figure 2 reveals substantial school variation in the degree to which the NSLP information aligns with other indicators of poverty. Schools 7 and 8, for example, have similar NSLP enrollment rates (74 and 75 percent of students respectively) but vary considerably on other measures of poverty, while schools 8 and 10 vary on NSLP enrollment rates (75 and 84 percent of students) but are similar in their other measures of poverty.

Table 1 reports the results of a series of multilevel models that extend these analyses using Oregon data. The results reported in the first column regress continuous IRS-reported income, centered at 185 percent of poverty, on FRPL enrollment, controlling for secular changes and school-level random effects.

FRPL enrollment in Oregon is substantial and increasing over time. The results reported in Model 1 suggest that 37 percent of Oregon 8^{th} graders enrolled in free or reduced-price lunch in 2005. That enrollment rate increased throughout the study period to more than 50 percent by 2014. This increase is evident in models with additional controls for student and family background.

FRPL enrollment rates also vary substantially across contexts. The results reported in Model 2 indicate that this is the case even after controlling for IRS-reported household income. The interclass correlations demonstrate that districts account for 4.5 percent of residual variation in FRPL enrollment while schools account for an additional 14 percent of the residual variation.

TABLE 1 AROUND HERE

The results reported in Model 3 suggest that students of color are substantially more likely to be enrolled in FRPL than white students with similar IRS-reported household income. Migrant students and special education students also have elevated rates of free or reduced-price lunch enrollment net of controls. While student demographics vary substantially across schools, controlling for student demographics explains very little of the district- and school-level variation we observe in FRPL enrollment rates. However, as Model 4 indicates, including richer measures of student family background reduces the racial and ethnic differences in FRPL enrollment.

Predictive validity

Tables 2 and 3 present results from OLS regression models examining the degree to which NSLP status and household income explain student ELA achievement in the California district and in Oregon, respectively. Perhaps surprisingly, the results of these analyses indicate that school-reported FRPL status variables are *more closely* associated with student achievement on standardized tests in ELA than parallel categories constructed using IRS-reported household income.

Results from the first model reported in Table 2 indicate that compared to non-FRPL students, students in the California district who are flagged as free lunch recipients score nearly 0.4 standard deviations lower on 8^{th} grade ELA tests and students who are flagged as reduced-price lunch recipients score 0.2 standard deviations lower than students who are not enrolled in FRPL. The R-square on this model is 0.098. Model 2 reports results predicting ELA achievement with IRS-validated income FRPL measures yielding a smaller R-square and coefficients than Model 1. Taken together, these results indicate that school-reported FRPL indicators explain more variation in ELA achievement than parallel variables constructed using IRS-reported household income. Interestingly, Model 2 also shows that students whose IRS-reported household income is less than 130 percent of poverty experience similar levels of educational disadvantage as students whose IRS-reported household income is between 130 percent of poverty and 185 percent of poverty (both score roughly 0.15 points lower than students who appear to be ineligible for FRPL based on their IRS-reported income).

TABLE 2 AROUND HERE

The third and fourth models in Table 2 indicate that, rather than being a simple but imprecise proxy for household income, FRPL enrollment appears to provide information about students that is unavailable in IRS-reported household income. We see in Model 3 that FRPL enrollment categories significantly predict ELA achievement after controlling for the IRS measures. Indeed, free lunch enrollment continues to predict ELA achievement even after controlling for linear and quadratic measures of IRS-reported household income to poverty ratios in Model 4.

Given that school-reported FRPL categories appear to contain information that is predictive of test scores above and beyond IRS-reported household income, we examine whether this might be explained by other student characteristics. Model 5 in Table 2 indicates that controlling for student race/ethnicity and language status substantially mitigates the relationship between school-reported FRPL categories and ELA achievement. However, even after including these demographic controls, as well as controls for prior years of poverty from IRS records in model 6, FRPL categories continue to predict ELA achievement.[17]

Table 3 presents parallel models for the state of Oregon. The results of these models are strikingly consistent with the California district models. The ODE-reported FRPL enrollment flag accounts for 16 percent of student-level variance in 8th grade ELA scores, compared to just 13 percent of the variance for parallel flags constructed from IRS data. Further, FRPL enrollment continues to predict ELA achievement even after controlling for continuous measures of household income and other indicators of family background.

TABLE 3 AROUND HERE

Discussion

Our analyses provide new evidence regarding the relationship between FRPL enrollment and socio-economic and educational disadvantage. We find that while schools' administrative FRPL category data are at best imperfect proxies for the household income of students in a given year, these data appear to capture additional aspects of disadvantage not captured by IRS income measures.

Before discussing the implications of these findings, we note several important data limitations. The most of obvious of these is generalizability. Although we have consistent results from two distinct locations, future analyses should continue to investigate the extent to which the correspondence between NSLP participation and household income varies across schools, districts, and students' grade level.

[17] Supplementary models, reported in Appendix Tables 2a and 2b, indicate that these results are robust to the inclusion of multiple years of IRS-reported household income using linear and quadratic terms in order to control for longer-term income volatility. Additionally, we re-estimated the models in Table 1 using average IRS-reported income over a longer period of time in place of 8th grade income (we use Kindergarten through 8th grade in California and 4th through 8th grade in Oregon). As expected, the measure of average income showed a stronger association with test scores than the 8th grade income measure alone. However, the general patterns were consistent with those presented in Tables 2 and 3.

A second set of limitations involves measurement. Our IRS-validated household income measure captures income in a continuous fashion for all earners in a household from a broad array of sources including employer W2 earnings reports, investment returns, business income, and other sources. However, while the NSLP eligibility requirements are designed to extend nutrition support to students who are experiencing relatively short-term income fluctuations, our IRS income measure is not sensitive to month-to-month income volatility. Further, the calendar year covered by IRS data captures only a portion of the fall-to-spring school year. Additionally, we compute IRS household income based upon all tax units in a household in an attempt to match the NSLP household definition, which includes all people that live together and share living expenses. However, this decision may lead us to overstate household income in cases in which individuals live in housing units without sharing living expenses. Finally, IRS data may undercount cash income and other informal income sources. In light of these measurement issues, it is important to recognize that our analyses cannot speak to questions around NSLP eligibility.

That said, these data provide previously unavailable information about the validity of FRPL data as a measure of socioeconomic disadvantage. In sum, our findings suggest that the quality of widely-utilized FRPL enrollment variables depends on what, precisely, analysts want these data to measure.

Our analyses of the convergent validity of FRPL enrollment measures suggest that it may be inappropriate to think of FRPL as a proxy for household income. FRPL data do not capture student-level differences in household income-to-poverty ratios well. Likewise, school and district-level aggregate measures of FRPL enrollment obscure important cross-school variation in school poverty and other school-level income measures. Our analyses raise important questions about the extent to which researchers and educators understand students' household income and its relation to educational experiences.

At the same time, our predictive validity analyses indicate that FRPL enrollment predicts academic achievement more effectively than IRS-reported income data, and that it continues to robustly predict achievement after controlling for household income. One potential explanation for this surprising finding is that enrolling in the FRPL program is itself an educational intervention. While it unlikely that this nutritional intervention has unintended negative average effects on student achievement, the available evidence on this question is limited (see Hindrichs 2010 for estimates of the educational consequences of FRPL in 1960s schools; Frisvold 2015, Imberman & Kugler 2014, Leos-Urbel et a. 2013, and Schanzenbach & Zaki 2014 for estimates of the effects of school breakfast programs). However, there is some evidence to suggest that FRPL carries a social stigma in certain settings (Poppendieck 2011).

We believe a more likely explanation for the strong and robust negative association between FRPL enrollment and student test scores is that these measures tap into aspects of educational disadvantage that more precise IRS income data elide. Income volatility could be one such aspect. If students enroll in free or reduced-price lunch during periods in which their household incomes dip and if these income dips have long-term consequences for student achievement, NSLP enrollment may provide information that IRS-reported annual household income data – even over multiple years – do not. Additionally, educators may encourage students to apply for FRPL and may provide families with application assistance based on their perceptions of student need. Consistent with this idea, we find that racial and ethnic minorities, special education students, and migrant students in Oregon enroll in free or reduced-price lunch at higher rates than expected based on their IRS-reported household income. Regardless of the precise cause, NSLP enrollment categories appear to reflect educational disadvantages that simple household income data and poverty line calculations overlook.

Our findings thus raise many questions for future analyses. Further research – both qualitative and quantitative – is needed to better understand the formal and informal processes that determine which children do and do not enroll in FRPL and the ways in which these enrollment processes vary across schools and districts. Future research should consider the ways in which FRPL enrollment patterns vary as students advance through school. Finally, we lack strong evidence regarding the consequences of FRPL for student school experiences and achievement outcomes.

In light of our findings, we believe that educational researchers and policy-makers need to reflect on what they mean by disadvantage and what they intend to measure when they use FRPL data. These data clearly capture important aspects of educational disadvantage. However, the nature of the disadvantage that FRPL captures is amorphous and may not be a simple function of family resources. From a policy perspective, federal and many state educational finance systems identify “high need” schools for targeted resources and other interventions based, in part, on the proportion of students in these schools who qualify for free or reduced-price lunch. If these criteria imprecisely distinguish poor and non-poor schools, they may impede efforts to provide educational opportunities for students from highly economically disadvantaged homes.

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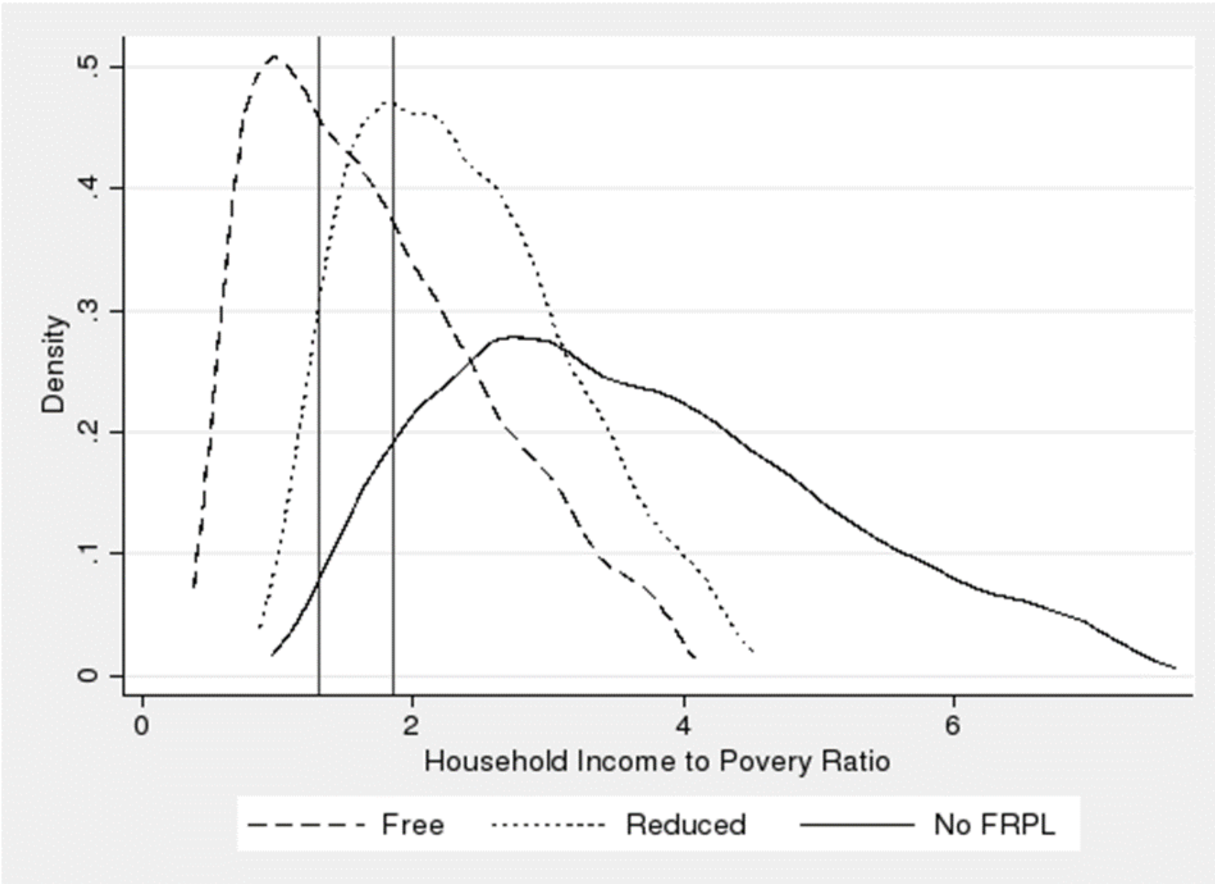
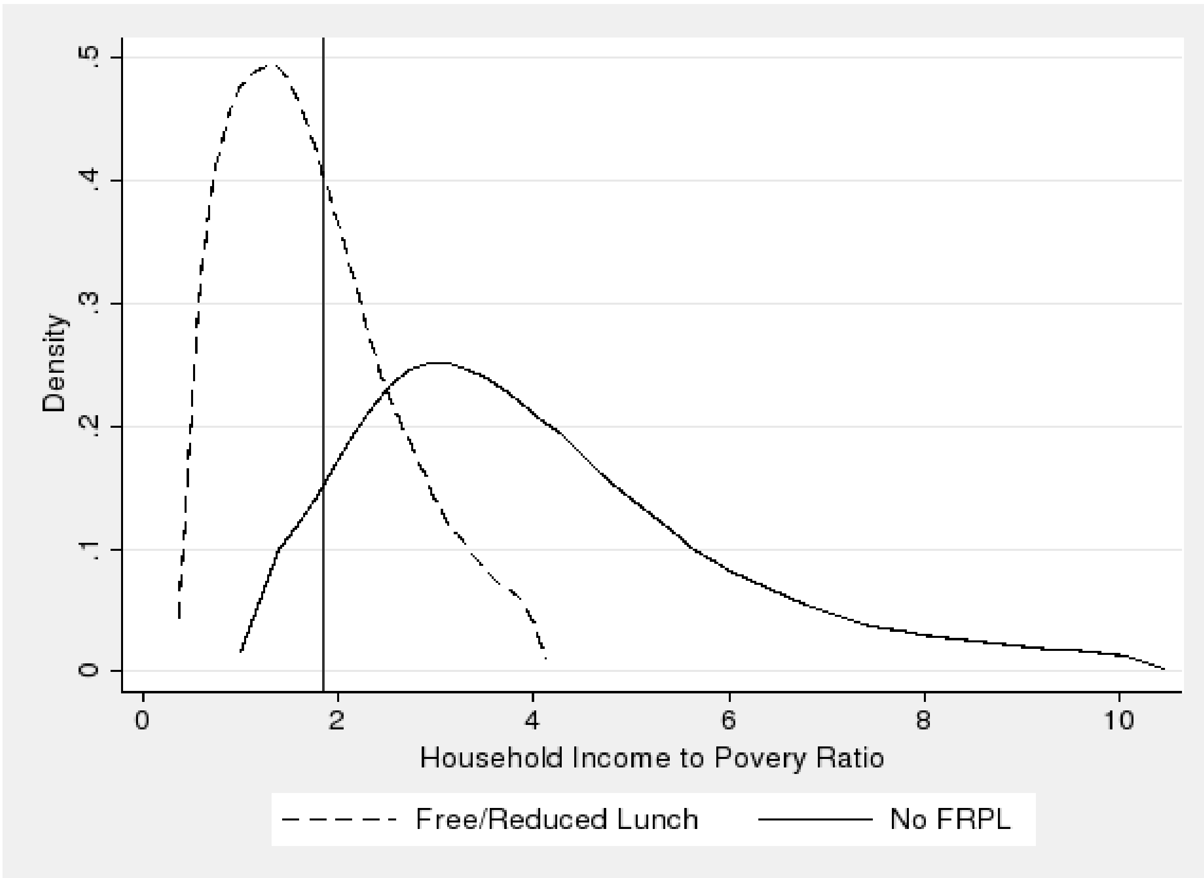
Figure 1a Distribution of IRS-reported household income-to-poverty ratio by 8th grade NSLP enrollment in one California school district for academic years 2008-09 through 2013-14 (N =12,500).



Note: Sample size, distributions, and density bandwidths have been adjusted to comply with Census Bureau disclosure requirements.

Source: Linked school district administrative records, for academic years 2008-09 through 2013-14, and Internal Revenue Service 1040 Tax data, from 2008 through 2013.

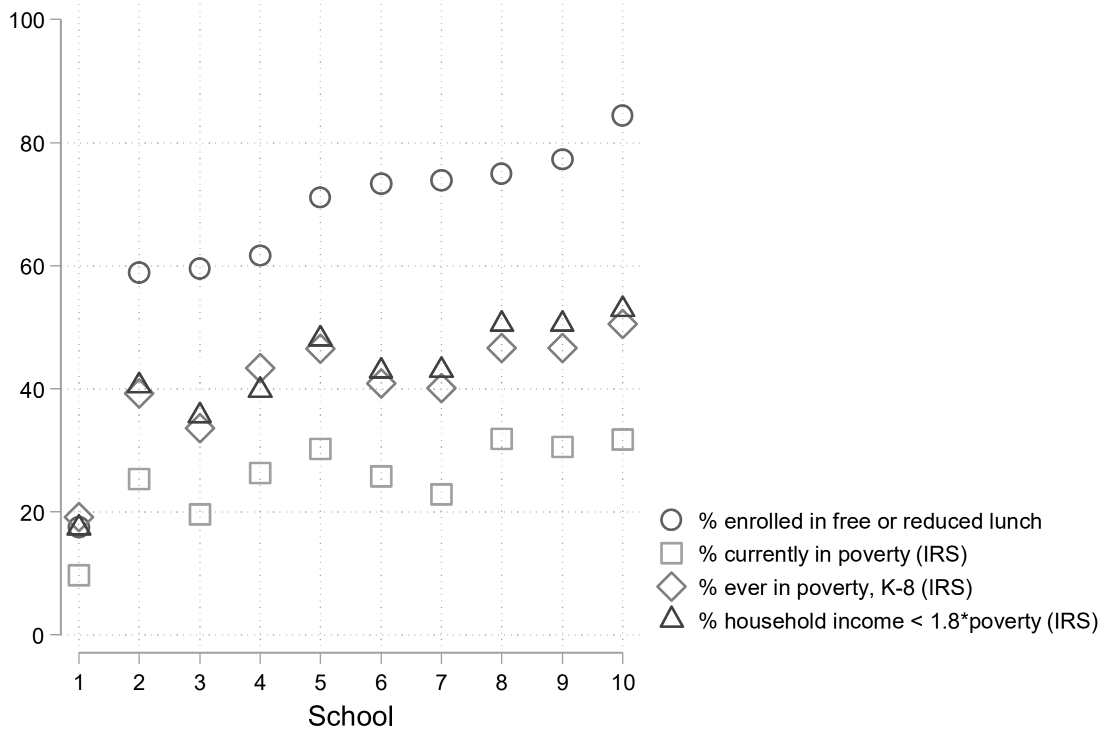
Figure 1b. Distribution of IRS-reported household income-to-poverty ratio by 8th grade NSLP enrollment in Oregon schools for academic years 2004-05 through 2013-14 (N= 315,000).



Note: Sample size, distributions, and density bandwidths have been adjusted to comply with Census Bureau disclosure requirements.

Source: Linked Oregon Department of Education school district administrative records, for academic years 2004-05 through 2013-14, and Internal Revenue Service 1040 Tax data, from 2004 through 2013.

Figure 2. 8th grade NSLP enrollment and IRS-validated household income and poverty rates (averaged at the school level for all 8th graders in one California Public School District, 2008-09 through 2013-14) (N=14,000)



Note: Sample size has been rounded to comply with U.S. Census Bureau disclosure requirements.

Source: Linked school district administrative records, for academic years 2008-09 through 2013-14, and Internal Revenue Service 1040 Tax data, from 2000 through 2013.

Table 1. Mixed level linear probability model predicting free or reduced price lunch enrollment using academic year, household income indicators, and demographic measures using data from the Oregon Department of Education (2005-2015) and Internal Revenue Service 1040 Tax Data (2000-2014). N ≈ 358,000

Indicators	Model 1 Coef./ SE	Model 2 Coef./ SE	Model 3 Coef./ SE	Model 4 Coef./ SE
Year began 8th (2005 ref.)	--	--	--	--
2006	.012 ***	.012 ***	.010 ***	.006 *
	.003	.003	.003	.003
2007	.025 ***	.028 ***	.018 ***	.013 ***
	.003	.003	.003	.003
2008	.035 ***	.034 ***	.023 ***	.019 ***
	.003	.003	.003	.003
2009	.064 ***	.053 ***	.041 ***	.041 ***
	.003	.003	.003	.003
2010	.106 ***	.070 ***	.054 ***	.063 ***
	.003	.003	.003	.003
2011	.110 ***	.085 ***	.067 ***	.066 ***
	.003	.003	.003	.003
2012	.131 ***	.105 ***	.085 ***	.082 ***
	.003	.003	.003	.003
2013	.131 ***	.109 ***	.088 ***	.078 ***
	.003	.003	.003	.003
2014	.135 ***	.113 ***	.090 ***	.079 ***
	.003	.003	.003	.003
Household Income		-.170 ***	-.156 ***	-.075 ***
		.000	.000	.001
Household Income Squared		.011 ***	.010 ***	.005 ***
		.000	.000	.000
Female			.001	-.001
			.001	.001
(Ref: Male)			--	--
Asian			.040 ***	.036 ***
			.003	.003
Black			.161 ***	.135 ***
			.004	.004
Hispanic			.218 ***	.181 ***
			.002	.002
Race: Other			.060 ***	.052 ***
			.003	.003
(Ref: White)			--	--

Table 1 (cont). Mixed level linear probability model predicting free or reduced price lunch enrollment using academic year, household income indicators, and demographic measures using data from the Oregon Department of Education (2005-2015) and Internal Revenue Service 1040 Tax Data (2000-2014). N ≈ 358,000

Indicators	Model 1 Coef./ SE		Model 2 Coef./ SE		Model 3 Coef./ SE		Model 4 Coef./ SE	
Limted English in G8					.088	***	.054	***
					.004		.004	
Special Education					.079	***	.069	***
					.002		.002	
Migrant Education					.108	***	.067	***
					.005		.005	
Household Size 3 or Fewer People							.044	***
							.002	
Household Size 4 People							--	
Household Size 5-6 People							.042	***
							.002	
Household Size 7-plus People							.123	***
							.002	
% Years in Poverty (Grades 4-8)							-.043	***
							.003	
% Years FRPL (Grades 4-8)							.411	***
							.003	
Constant	.372	***	.468	***	.424	***	.193	***
	.012		.010		.009		.009	
Random Effect Param.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
District	.115	.012	.090	.009	.086	.009	.083	.009
School	.175	.006	.132	.005	.118	.005	.118	.005
Residual	.457	.001	.390	.000	.381	.000	.364	.000
Inter-Class Corr. Coef.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
District	.052	.010	.045	.009	.044	.009	.044	.009
School | District	.174	.010	.143	.009	.128	.009	.136	.009

Various specifications of household were examined, including a linear measure and a linear measure and a squared measure. The results were similar to the results presented above.

Note that there are roughly 800 schools and 200 districts with average 8th grade enrollments of sizes roughly 450 (per school) and 1700 (district).

Note that the sample sizes have been rounded to comply with Census Bureau Disclosure review board guidelines.

*** $p<0.001$ ** $p<0.01$ * $p<0.05$

Table 2. Linear Regression on standardized 8th grade English Lanaguage Arts scores with IRS income measures, free and reduced price lunch indicators, and demographic indicators using California school district and IRS administrative records with school and year fixed effects (N= 14,000).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE
NSLP Free Lunch	-.392 ***		-.384 ***	-.348 ***	-.145 ***	-.146 ***
	.019		.021	.022	.018	.019
NSLP Reduced Price Lunch	-.200 ***		-.192 ***	-.155 ***	-.066 **	-.069 **
	.027		.027	.028	.023	.023
IRS Free Lunch		-.153 ***	-.002	.085 *	.046	.049
		.020	.021	.034	.028	.029
IRS Reduced Price Lunch		-.160 ***	-.056 *	.007	.032	.022
		.023	.023	.028	.023	.024
HH Income to Poverty Ratio				.032	.024	.025
				.018	.014	.015
HH Income to Poverty Ratio Squared				.001	.001	.001
				.002	.001	.001
Female					.146 ***	.146 ***
					.013	.013
(Reference: Male)					--	--
Black					-.230 **	-.232 **
					.076	.076
US Born Hispanic					-.266 ***	-.268 ***
					.028	.028
Foreign Born Hispanic					-.235 ***	-.235 ***
					.062	.062
US Born Asian					.264 ***	.265 ***
					.029	.029
Foreign Born Asian					.214 ***	.218 ***
					.038	.038
Unk POB Hispanic					-.313 ***	-.315 ***
					.048	.048
Unk POB Asian					.225 ***	.228 ***
					.050	.050
(Reference: White)					--	--
English Only					.759 ***	.761 ***
					.022	.022
Intially Fluent in English					1.013 ***	1.014 ***
					.070	.070
Reclassified Fluent in English					1.169 ***	1.169 ***
					.017	.017
Multiple Language Statuses					.922 ***	.923 ***
					.036	.036
(Reference: English Learner)					--	--
% Years in Poverty (Grades K-8)						-.067
						.044
% Years NSLP Eligible (Grades K-8)						.040
						.032
Constant	.282 ***	.122 ***	.286 ***	.133 **	-.673 ***	-.678 ***
	.022	.019	.022	.051	.060	.060
Adj. R^2	0.098	0.077	0.099	0.102	0.409	0.409

Note: School and year fixed effects covariates are not shown. Sample size has been rounded to comply with U.S. Census Bureau Disclosure Requirements

Source: Linked California school district administrative records, from 2008-09 through 2013-14, and Internal Revenue Service 1040 Tax data, from 2000 through 2013.

*** $p<0.001$ ** $p<0.01$ * $p<0.05$

Table 3. Linear Regression on standardized 8th grade English Lanaguage Arts scores with IRS income measures, free and reduced price lunch indicators, and demographic indicators using Oregon Department of Education and IRS administrative records with school and year fixed effects (N= 363,000).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE
NSLP Free/Reduced Price Lunch	-.362 ***		-.305 ***	-.260 ***	-.160 ***	-.147 ***
	.003		.004	.004	.004	.004
IRS Free/Reduced Price Lunch		-.263 ***	-.115 ***	.021 ***	.023 ***	.070 ***
		.003	.004	.005	.005	.006
HH Income to Poverty Ratio				.071 ***	.054 ***	.045 ***
				.002	.002	.002
HH Inc:Poverty Ratio Squared				-.002 ***	-.002 ***	-.001 ***
				.000	.000	.000
Female					-.077 ***	-.077 ***
					.003	.003
(Reference: Male)					--	--
Asian					.146 ***	.146 ***
					.008	.008
Black					-.293 ***	-.290 ***
					.010	.010
Hispanic					-.152 ***	-.151 ***
					.005	.005
Other					-.036 ***	-.035 ***
					.006	.006
(Reference:White)					--	--
Special Education Flag					-1.037 ***	-1.036 ***
					.008	.008
Migrant Education Flag					-.039 ***	-.036 **
					.011	.011
Limited English Proficiency (Grade 8)					-.239 ***	-.236 ***
					.009	.009
% Years in Poverty (Grades 4 to 8)						-.025 **
						.008
% Years NSLP Eligible (Grades 4 to 8)						-.090 ***
						.007
Constant	.179 ***	.130 ***	.195 ***	-.055 ***	.132 ***	.165 ***
	.005	.005	.005	.008	.008	.008
Adj. R^2	0.124	0.111	0.127	0.132	0.265	0.266

Note: School and year fixed effects covariates are not shown. Sample size has been rounded to comply with U.S. Census Bureau Disclosure Requirements.

Source: Linked state of Oregon school district administrative records, from 2004-05 through 2014-15, and Internal Revenue Service 1040 Tax data, from 2000 through 2014.

*** p<0.001 ** p<0.01 * p<0.05

Appendix Table 1a. Linear regression of free and reduced price lunch indicators on 8th grade household income to poverty threshold ratio with school and year fixed effects using linked IRS and California school district administrative records (N=19,000).

	Model 1 Coef./ SE	Model 2 Coef./ SE
NSLP Free Lunch	-1.76 ***	
	0.03	
NSLP Reduced Price Lunch	-1.15 ***	
	0.04	
IRS Free Lunch		-2.53 ***
		0.02
IRS Reduced Price Lunch		-1.81 ***
		0.03
Constant	3.73 ***	3.53 ***
	0.03	0.02
Adj. R^2	0.280	0.510

Note: School and year fixed effects covariates are not shown. Sample size has been rounded to comply with U.S. Census Bureau Disclosure Requirements.

Source: Linked California school district administrative records, for academic years 2008-09 through 2013-14, and Internal Revenue Service 1040 Tax data, from 2008 through 2013.

*** p<0.001 ** p<0.01 * p<0.05

Appendix Table 1b. Linear regression of free and reduced price lunch indicators on 8th grade household income to poverty threshold ratio with school and year fixed effects using linked IRS and Oregon Department of Education school administrative records (N=366,00).

	Model 1	Model 2
	Coef./ SE	Coef./ SE
NSLP Free or Reduced Lunch	-2.12 ***	
	0.01	
IRS Free or Reduced Lunch		-2.87 ***
		0.01
Constant	4.01 ***	4.13 ***
	0.01	0.01
Adj. R^2	0.300	0.430

Note: School and year fixed effects covariates are not shown. Sample size has been rounded to comply with U.S. Census Bureau Disclosure Requirements.

Source: Linked state of Oregon school district administrative records, for academic years 2004-05 through 2014-15, and Internal Revenue Service 1040 Tax data, from 2004 through 2014.

*** p<0.001 ** p<0.01 * p<0.05

Appendix Table 2a. Linear Regression on standardized 8th grade English Lanaguage Arts scores with IRS income measures, free and reduced price lunch indicators, and demographic indicators using California school district and IRS administrative records with school and year fixed effects (N=13,000).

	Model 1	Mode 2	Model 3	Model 4	Model 5	Model 6
	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE	Coef./ SE
NSLP Free Lunch	-.388 ***		-.405 ***	-.310 ***	-.126 ***	-.126 ***
	.020		.022	.023	.019	.019
NSLP Reduced Price Lunch	-.201 ***		-.201 ***	-.117 ***	-.052 *	-.053 *
	.028		.028	.028	.023	.023
IRS Free Lunch		-.150 ***	-.087 **	.019	.024	.021
		.020	.028	.029	.024	.024
IRS Reduced Price Lunch		-.166 ***	-.103 ***	-.031	.001	-.011
		.024	.027	.027	.022	.023
One Year Lag IRS Free Lunch			.071 *	.126 ***	.023	.018
			.031	.031	.026	.026
One Year Lag IRS Reduced Price Lunch			.016	.063 *	.048 *	.035
			.029	.029	.023	.024
Two Year Lag IRS Free Lunch			.032	.102 **	.047	.041
			.032	.032	.026	.027
Two Year Lag IRS Reduced Price Lunch			.026	.085 **	.053 *	.038
			.031	.031	.025	.026
Three Year Lag IRS Free Lunch			.086 **	.170 ***	.062 **	.050
			.029	.029	.024	.027
Three Year Lag IRS Reduced Price Lunch			-.001	.041	.005	-.015
			.035	.035	.029	.031
Avg. HH Income to Poverty Ratio				.198 ***	.087 ***	.095 ***
				.019	.016	.018
Avg. HH Income to Poverty Ratio Squared				-.010 ***	-.002	-.003
				.002	.002	.002
Female					.149 ***	.149 ***
					.013	.013
(Reference: Male)					--	--
Black					-.177 *	-.178 **
					.078	.078
US Born Hispanic					-.260 ***	-.261 ***
					.029	.029
Foreign Born Hispanic					-.209 ***	-.204 ***
					.063	.063
US Born Asian					.258 ***	.260 ***
					.030	.030
Foreign Born Asian					.219 ***	.227 ***
					.038	.039
Unk POB Hispanic					-.307 ***	-.307 ***
					.049	.049
Unk POB Asian					.220 ***	.223 ***
					.051	.051
(Reference: White)					--	--

Appendix Table 2a (continued). Linear Regression on standardized 8th grade English Lanaguage Arts scores with IRS income measures, free and reduced price lunch indicators, and demographic indicators using California school district and IRS administrative records with school and year fixed effects (N=13,000).

	Model 1 Coef./ SE	Mode 2 Coef./ SE	Model 3 Coef./ SE	Model 4 Coef./ SE	Model 5 Coef./ SE	Model 6 Coef./ SE
English Only					.740 ***	.741 ***
					.023	.023
Intially Fluent in English					.943 ***	.941 ***
					.073	.073
Reclassified Fluent in English					1.167 ***	1.165 ***
					.018	.018
Multiple Language Statuses					.915 ***	.914 ***
					.037	.037
(Reference: English Learner)					--	--
% Years in Poverty (Grades K-8)						-.062
						.054
% Years NSLP Eligible (Grades K-8)						.095
						.050
Constant	.283 ***	.128 ***	.281 ***	-.298 ***	-.838 ***	-.866 ***
	.022	.020	.022	.052	.060	.065
Adj. R^2	0.096	0.08	0.1	0.112	0.41	0.41

Note: School and year fixed effects covariates are not shown. Sample size has been rounded to comply with U.S. Census Bureau Disclosure Requirements.

Source: Linked California school district administrative records, for academic years 2008-09 through 2013-14, and Internal Revenue Service 1040 Tax data, from 2000 through 2013.

*** p<0.001 ** p<0.01 * p<0.05

Appendix Table 2b. Linear Regression on standardized 8th grade English Lanaguage Arts scores with IRS income measures, free and reduced price lunch indicators, and demographic indicators using Oregon Department of Education and IRS administrative records with school and year fixed effects (N=308,000).

	Model 1 Coef./ SE	Mode 2 Coef./ SE	Model 3 Coef./ SE	Model 4 Coef./ SE	Model 5 Coef./ SE	Model 6 Coef./ SE
NSLP Free/Reduced Lunch	-.354 ***		-.267 ***	-.225 ***	-.138 ***	-.138 ***
	.004		.004	.004	.004	.004
IRS Free/Reduced Lunch		-.260 ***	-.038 ***	.004	.005	.007
		.004	.005	.005	.005	.007
One Year Lagged IRS FRL			-.035 ***	.008	.007	.009
			.006	.006	.005	.007
Two Year Lagged IRS FRL			-.042 ***	.006	.006	.008
			.006	.006	.005	.007
Three Year Lagged IRS FRL			-.072 ***	-.007	.001	.004
			.005	.005	.005	.008
Avg. Household Income (Grades 4 to 8)				.095 ***	.071 ***	.071 ***
				.004	.003	.004
Avg. HH Income Squared (Grades 4 to 8)				-.003 ***	-.002 ***	-.002 ***
				.000	.000	.000
Female					-.078 ***	-.078 ***
					.003	.003
(Reference: Male)					--	--
Asian					.157 ***	.157 ***
					.008	.008
Black					-.274 ***	-.274 ***
					.010	.010
Hispanic					-.147 ***	-.147 ***
					.005	.005
Other					-.031 ***	-.031 ***
					.006	.006
(Reference:White)					--	--
Special Education Flag					-1.037 ***	-1.037 ***
					.005	.005
Migrant Education Flag					-.048 ***	-.048 ***
					.013	.013
Limited English Proficiency					-.209 ***	-.209 ***
					.009	.009
% Years in Poverty (Grades 4-8)						.008
						.008
% Years NSLP Eligible (Grades 4-8)						-.013
						.025
Constant	.211 ***	.164 ***	.237 ***	-.088 ***	.113 ***	.113 ***
	.005	.005	.005	.011	.011	.011
Adj. R^2	0.123	0.11	0.127	0.134	0.266	0.266

Note: School and year fixed effects covariates are not shown. Sample size has been rounded to comply with U.S. Census Bureau Disclosure Requirements.

Source: Linked state of Oregon school district administrative records, for academic years 2004-05 through 2014-15, and Internal Revenue Service 1040 Tax data, from 2000 through 2014.

*** p<0.001 ** p<0.01 * p<0.05