

# **Have Income-Based Achievement Gaps Widened or Narrowed?**

by

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### **Abstract:**

Over the past three decades, policymakers and philanthropists have launched a series of efforts to close gaps in academic achievement by income and race (e.g. school finance reform, closing low-performing schools, charter schools) even as rising income inequality and income-based residential segregation have been threatening to widen them. Using school-level measures of the mean and variance in income and achievement, we reconstruct the student-level relationship between achievement and household income between 1990 and 2015 using the National Assessment of Educational Progress (NAEP). In contrast to Reardon (2011), who reported a sharp widening in the gap in achievement between high and low-income families, we estimate that achievement gaps *narrowed* substantially in 4<sup>th</sup> grade reading and math and in 8<sup>th</sup> grade math due to large increases in achievement for low income families, while the gaps remained stable in 8<sup>th</sup> grade reading. As a robustness check, we used the March Current Population survey to calculate mean income of dependent children by race, mother's education, urbanicity and state and then calculated mean achievement for those same groups in the NAEP. Again, we found gaps in achievement narrowing between groups with high and low mean household incomes. Our results challenge the prevailing understanding that income-based achievement gaps have widened in the United States.

## I. Introduction

In 1848, Horace Mann famously described public education as “the great equalizer of the conditions of men” and the “balance wheel of the social machinery.” In the face of rising income inequality and income-based housing segregation, policymakers and philanthropists have launched a series of efforts over the past three decades to preserve the balance wheel of schooling: raising educational standards, increasing school accountability, opening charter schools and increasing state aid to low-income districts. Yet, we know remarkably little about how the relationship between parental income and achievement has changed over time.

The chief obstacle has been the lack of data. In the United States, there is no nationally representative data source combining a consistent measure of academic achievement with the household income of individual students.

The best available evidence was provided in 2011, when Sean Reardon combined data from twelve nationally representative surveys, with different measures of academic achievement, administered to students at different ages, matched with different measures of student-reported or parent-reported income. After pooling the data for 12 cohorts of students, each with different measures of achievement and income, Reardon (2011) concluded that the income-based achievement gap had expanded substantially for the cohorts born between 1974 and 2001: the difference in mean achievement at the 90<sup>th</sup> and 10<sup>th</sup> percentiles of family income had risen by 40 to 50 percent in standard deviation units.

We take a different approach, supplementing the National Assessment of Educational Progress (NAEP) with neighborhood income measures from the U.S. Bureau of the Census. Specifically, we use the school-level measures of achievement and income to reconstruct the student-level relationships. In doing so, we rely on the fact that the student-level coefficient of achievement on household income is a

weighted average of the between-school and within-school relationships between achievement and income. We estimate the between-school coefficient of achievement on income directly, regressing school-level mean achievement on mean household income for families the surrounding census tracts. We then estimate the within-school slope by regressing the within-school variance in achievement on the variance in income. Intuitively, the schools with more unequal incomes should also have proportionally more variance in achievement (and the slope of that relationship should be equivalent to the squared value of the within-school slope). We then combine the within- and between-school coefficients with an estimate of the proportion of variance in income by school (a measure of the degree of income segregation by school) to estimate the *student-level* relationship between achievement and income.

Because census tract boundaries do not correspond with the boundaries of school attendance zones, our imputations of the mean and variance in income by school are subject to measurement error. However, because the correlation between our imputed income measure and school-reported measures of free and reduced price lunch receipt are stable over time, our finding of a declining slope is unlikely to be driven by measurement error.

As a robustness check, we use the March Current Population Survey to impute household income using the traits which are available for individual students in the NAEP: race/ethnicity, mother's education, urbanicity and state. We then investigate how the gaps in achievement associated with each of these traits compare with the changing gaps in family income corresponding to those same traits.

In contrast to Reardon (2011), we see no evidence of widening of achievement gaps in 4<sup>th</sup> grade or 8<sup>th</sup> grade math or reading. In fact, we see achievement gaps *narrowing* in 4<sup>th</sup> grade math and reading as well as in 8<sup>th</sup> grade math. For example, between 1990 and 2015, we estimate that the achievement

of students at the 10<sup>th</sup> percentile of income improved substantially: a full standard deviation in 4<sup>th</sup> grade math and .68 standard deviations in 8<sup>th</sup> grade math. Although achievement also rose for higher income families, the achievement gap between those at the 90<sup>th</sup> and 10<sup>th</sup> income percentile *closed* by .4 and .15 standard deviations respectively in 4<sup>th</sup> and 8<sup>th</sup> grade math. When we plot the mean achievement of each subgroup of students by race-ethnicity, mother's education, urbanicity and state against the mean income from the March CPS, we see consistent patterns of narrowing or stable achievement gaps between high and low-income groups. Our results challenge the prevailing view that gaps in achievement by family income have been widening. In fact, just the opposite appears to be true.

## II. **Prior Literature**

In a widely cited paper, Reardon (2011) combined survey data on parental income and achievement for multiple cohorts of children. He reports that reading and math achievement gaps at the 90<sup>th</sup> and 10<sup>th</sup> family income percentiles grew by 40 to 50 percent among cohorts born between 1974 and 2001.

However, each of the longitudinal used a different measure of achievement and a different measure of income. Thus, to make comparisons among the different surveys, Reardon was forced to make a number of adjustments:

- First, because each survey measured student achievement at different ages (some measuring students' at ages 1-6 and others measuring students at age 18) Reardon adjusted each survey for age differences.

- Second, the achievement measures had varying reliabilities, ranging from .75 to .96. As a result, Reardon standardized scores and adjusted by the estimated reliability for each assessment (multiplying scores by  $\frac{1}{\sqrt{r_{test}}}$ .)
- Third, each survey measured income differently. Some used parent-reported income; for others, the income measures were reported by students. Moreover, depending on the survey, the number of income categories respondents could choose ranged from five to fifteen categories. For each survey, Reardon estimated the mean achievement in each income category and then used the percentage of students in each income category to infer the estimated achievement gap at the 90<sup>th</sup> and 10<sup>th</sup> income percentile. Finally, he adjusted  $\frac{1}{\sqrt{r_{income}}}$ ).

Although the surveys prior to 1975 often included student-reported family income, all of the surveys for birth cohorts after 1975 (the period during which Reardon estimates a rapid growth in income-based inequality) rely on parent-reported income.<sup>1</sup> Reardon assumes that all the parent-reported income measures had a reliability of .86. For studies with student reported income, he used different reliabilities for students of different ages, assuming a reliability of 0.50 for 9th grade reports, 0.57 for 10th grade, 0.65 for 11th grade, and 0.72 for 12th grade.

In a recent paper, Hanushek, Peterson, Talpey, and Woessmann (2020) take a different approach, using achievement data from a different set of national and international tests (PISA, TIMMS, and the NAEP). Because none of the surveys include student-level measures of family income, the authors create an SES index-- using indicators of parental education and the number of home possessions as reported by students. Hanushek and colleagues find no change in reading or math

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<sup>1</sup> For the birth cohorts for whom Reardon finds widening gaps in achievement by income, the income measures are parent reported. Thus, it seems unlikely that the finding is driven by the shift from student-reported income measures (which tend to be less reliable) to parent-reported measures.

achievement gaps between top and bottom quartiles of the SES distribution for 13-17-year old students born between 1954 and 2001.

However, the findings in Hanushek et al. (2020) of stable gaps in achievement by SES are not necessarily inconsistent with Reardon's findings. Although Reardon focused primarily on income-based gaps, he also reported differences in achievement by parental education (the main factor in the Hanushek et al. SES index.) Like Hanushek et al., Reardon reported that achievement gaps by parental education have remained relatively stable over the same time period. (One of our contributions below is to reconcile the findings in Reardon and Hanushek et al., by rescaling achievement gaps associated with mother's education by the average household income for mothers of varying education levels and race-ethnicity.)

Lafortune, Rothstein and Schanzenbach (2018) investigate a related question, looking at the impact of school finance reforms (SFRs) on gaps in district spending and on achievement on the NAEP overtime. They focused on 64 major reform events across 26 states between 1990 and 2011. Leveraging the variation in timing of these reform events in an event-study framework, they find that SFRs were associated with an average total revenue increase of nearly \$700 per pupil in the lowest-income quintile school districts relative to top-income quintile districts. Moreover, they estimate that the impact of reform events on the test score gap between bottom and top-quintile districts was 0.008 standard deviations per year, which they extrapolate to mean that SFRs reduced between-district achievement gaps in those states by 10% within ten years.

As the authors emphasize, because the majority of the variance in income is within-districts and within-schools, district-level equalization does not necessarily translate to a narrowing of income-based achievement gaps. For instance, the authors find no impact of state SFR's on achievement gaps by student's free lunch status.

### III. Empirical Strategy

We employ two different strategies to estimate the student-level relationship between income and achievement. First, we use school-level aggregates to estimate the student-level relationship between income and achievement. Second, as a robustness check, we use the March Current Population survey in each year to impute household income by students' race/ethnicity, parental education and geographic location. In doing so, we essentially scale the gaps in achievement by race, mother's education, urbanicity and state of residence by the gaps in mean household income associated with those same characteristics. We then test whether gaps in achievement grew by imputed income. We briefly describe each of those two approaches below.

#### *Using School Level Aggregates to Estimate the Student-Level Parameters*

Our goal is to estimate the student-level relationship between achievement and income:

$$(1) \quad Score_{ij} = \beta_0 + \beta_1 Y_{ij} + v_{ij}$$

Where  $Score_{ij}$  is a student's scaled test score,  $Y_{ij}$  is a measure of log household income and  $i$  and  $j$  are subscripts for the student and the student's school respectively. ( $\beta_1$  is a descriptive relationship, not a causal one.)

It can be shown that the OLS estimator for  $\beta_1$  is a weighted average of the between-school relationship of mean achievement on mean achievement ( $\beta_{between}$ ) and the within-school relationship between an individual students' household income and achievement ( $\beta_{within}$ ):



$$(2) \hat{\beta}_1^{OLS} = \beta_{between} * ICC_Y + \beta_{within} * (1 - ICC_Y)$$

Where  $ICC_Y$  is the percent of the total variance in log household income that is attributable to school-level differences in mean log income ( $ICC_Y = \frac{\sigma_{\mu_j}^2}{\sigma_{Y_{ij}}^2}$ ). The statistic is also commonly known as the intra-class correlation in log income by school. With a value between 0 and 1,  $ICC_Y$  is a measure of the degree of income segregation by school. That is, if all of the variation in income was by school (every student in a given school had the same income) and different schools had different incomes, then the student level relationship between achievement and income would be equal to the between-school relationship. As implied by equation (2), the more segregated schools are by household income, the more the student-level relationship will reflect the between-school relationship.

With school-level measures of mean achievement and mean log income,  $\overline{Score}_j$  and  $\bar{Y}_j$ , we can estimate the between-school relationship:

$$(3) \overline{Score}_j = \beta_0 + \beta_{between} \bar{Y}_j + \varepsilon_j$$

Although we do not have the covariance of achievement and income at the student level, we can estimate the within-school slope using the school-level variance in achievement and income,  $\hat{\sigma}_{score_j}^2$  and  $\hat{\sigma}_{Y_j}^2$ :

$$(4) \hat{\sigma}_{score_j}^2 = \sigma_v^2 + \beta_{within}^2 \hat{\sigma}_{Y_j}^2 + \vartheta_j$$

The basic intuition behind equation (4) is that schools with higher income variance (i.e. more income inequality) should have proportionally higher variance in achievement-- with the proportion determined by the square of the within-school slope coefficient. In other words, although we do not see the covariance in income and achievement within schools, we can infer the within-school slope by

studying the changing relationship between within-school income variance and within-school achievement variance.

In estimating equations (3) and (4), we weight by the number of tested students in each school. We also allow the errors to be clustered by the geographic primary sampling unit used by NAEP. Given that the error terms,  $\varepsilon_j$  and  $\vartheta_j$ , could be related, we estimate equations (3) and (4) as seemingly unrelated regressions (SURE), thus estimating the covariance between  $\beta_{between}$  and  $\beta_{within}^2$ . Finally, as described in equation (2), the student level slope is a nonlinear function of the coefficients in equations (3) and (4),  $\beta_{between}$  and  $\beta_{within}^2$ . Thus, we use the delta method to estimate a standard error for our estimate of the student-level slope ( $\hat{\beta}_1^{OLS}$ ).

In equation (4), we express  $\beta_{within}$  as a scalar, assuming that the within-school slope is the same in all schools. However, the above model could be generalized to allow the slope to be a random coefficient, varying by school. If the within-school slope did vary by school, but was independent of log income, then the coefficient on  $\hat{\sigma}_{Y_j}^2$  in equation (4) would be interpreted as the sum of the expected value of  $\beta_{within}$  squared and the variance in  $\beta_{within}$  (that is,  $E[\beta_{within}]^2 + \sigma_{\beta_{within}}^2$ .) As long as the variance in  $\beta_{within}$  ( $\sigma_{\beta_{within}}^2$ ) is constant or rising, then any increase in the expected value of  $\beta_{within}$  should lead to an increase in the coefficient on  $\hat{\sigma}_{Y_j}^2$  in equation (4). It's only if the variance in within school slopes is declining that we might not detect an increase in the within-school slope using our method.

#### *Using Imputed Household Income for Individual Students*

As a validity check to our census-based income measures, we use student-reported race and mother's education as well as school location (urbanicity and state) to impute log household income using the March Current Population Survey. We then estimate the student-level slope, as well as the

between and within-school slopes, using imputed household income for each year. (We can estimate all three directly since we have imputed household income at the student-level.)

Unfortunately, the survey measures of maternal education were not available for all years for the 4<sup>th</sup> grade students in NAEP. However, respondents in 8<sup>th</sup> grade were asked to self-report race-ethnicity as well as level of education for both mother and father. Unfortunately, the NAEP did not consistently ask whether either parent lives in the same household with the student—which would have been helpful in imputing family income from the March CPS. Therefore, we assume that students in the NAEP lived in households where their mother was present in order to be able to impute household income by mother’s education. (We do not use information about the father’s education, given that we cannot know whether the father is present.) We estimate the following relationship for all households in the Current Population Survey with dependent children between age 5 and 18 with a mother present:

$$(5) Y_{it} = \sum_{\text{race/eth}} \sum_{\text{moth ed}} \pi_{\text{race,moth ed } t} + \gamma_{\text{urban}, t} + \delta_{\text{state}, t} + \varphi_{it}$$

Where  $Y_{it}$  is a measure of log household income,  $\pi_{\text{race,moth ed } t}$  represent a full set of interactions between four mother’s education categories and four categories for race/ethnicity,  $\gamma_{\text{urban}, t}$  reflects differences in income by four urban categories and  $\delta_{\text{state}, t}$  represents fixed effects by state and year. We assume that the student has the same race/ethnicity as the head of household.

Using the parameter estimates from equation (5), we generate a predicted household income for each 8<sup>th</sup> grade respondent with non-missing mother’s education,  $\hat{Y}_{it}$ . Since we are using imputed income,  $\hat{Y}_{it}$ , to substitute for actual household income, we would rewrite equation (1) as:

$$(1') \text{ Score}_{it} = \beta_{0t} + \beta_{1t}\hat{Y}_{it} + (\beta_{1t}\hat{\varphi}_{it} + v_{it})$$

Where  $Y_{it} = \hat{Y}_{it} + \hat{\varphi}_{it}$ . Note that as long as  $\hat{Y}_{it}$  is estimated by OLS, then  $\hat{Y}_{it}$  and  $\hat{\varphi}_{it}$  will be orthogonal by construction. In other words, as in two-stage least squares, even though imputed household income is an imperfect measure of true household income, our estimate of  $\beta_{1t}$  in equation (1') will not be biased due to measurement error (although we do not claim that it reflects a causal relationship). Many of the variables being used for imputation—mother's education, race, state, urbanicity—are likely to have their own direct effects on achievement beyond their influence on family income (that is,  $\hat{Y}_{it}$  will be correlated with the error term from equation (1),  $v_{it}$ .) For that reason, they are unlikely to be valid instruments. However, in order to infer the change in the descriptive relationship between income and achievement, we must assume that the correlation between  $\hat{Y}_{it}$  and  $v_{it}$  is constant over time and that any change in  $\hat{\beta}_{1t}$  is due to the effect of income and not to changes in the direct effects of the variables used for the imputation.)

Just as with the usual 2SLS estimate, equation 1' will estimate a LATE that may differ from that estimated by OLS. Recall from equation 2 that  $\hat{\beta}_1^{OLS}$  is a weighted average of the within-school and between-school slopes, where the weight on the between-school slope is  $ICC_Y$  (the intra class correlation in log income by school). Similarly, we can restate the estimate using from equation 1' using imputed log income (call this  $\hat{\beta}_1^{\hat{Y}}$ ) as:

$$(2') \hat{\beta}_1^{\hat{Y}} = \hat{\beta}_{between}^{\hat{Y}} * ICC_{\hat{Y}} + \hat{\beta}_{within}^{\hat{Y}} * (1 - ICC_{\hat{Y}})$$

If we assume that  $\bar{Y}_l$  and  $\bar{\varphi}_l$  (the school-level means of  $\hat{Y}_{it}$  and  $\hat{\varphi}_{it}$ ) are orthogonal (an additional assumption not guaranteed by OLS), then it can be shown that  $\hat{\beta}_{between}^{\hat{Y}} = \hat{\beta}_{between}$ ,  $\hat{\beta}_{within}^{\hat{Y}} = \hat{\beta}_{within}$  even when  $ICC_Y \neq ICC_{\hat{Y}}$ . In other words, if the error in equation (5) is uncorrelated with the proxy measure of income at both the individual level (true by construction) and at the school level (an

assumption), then the within and between slopes are the same for the true income data as for the imputed, proxy income measures. In this case, our estimate of the overall relationship between scores and log income using actual income (equation 2) differs from our estimate using imputed income (equation 2') because the two estimates put different weight on the between and within slopes (since in general  $ICC_Y \neq ICC_{\hat{Y}}$ ).

Therefore, although we estimate equation (1') with student-level data, we also estimate the between-school and within-school relationships and the ICC using imputed student level data for comparison to the estimates above. We then evaluate whether any difference in our estimates of  $\beta_{1t}$  between our two methods are due to differences in the within- and between-school estimates (which should be similar) or simply differences in the weighting places on within versus between estimates due to differences in the ICC (which are expected).

Our imputation using mother's education and race uses much of the same student-level information as that used by Hanushek et al. (2019). There are some important differences: in addition to mother's education and race, Hanushek et al. use several items reflecting household possessions (which we exclude given their absence from the CPS), while we use urbanicity and state. Moreover, while we scale the information on student-reported characteristics by the income differentials associated with those traits, Hanushek et al. (2019) scale the differences in student characteristics using loadings from a factor analysis. In doing so, they are focused on achievement differentials by socioeconomic status, a latent construct. Because the measures of household possessions they use to construct the SES index varies by year, that construct will have an unknown—and potentially changing—relationship to wealth and income over time. Since Reardon (2011) focused on differentials in achievement by income, our approach presents a more direct test of his conclusions.

#### IV. Data

To measure student achievement over time, we use student level data from the trial state assessments in 1990, 1992 and 1994, and from the state-representative samples in subsequent years. Known as “the Nation’s Report Card,” the main NAEP assessment provides a scaled score which is designed to be comparable over time. The samples are intended to provide a representative sample of schools and roughly 30 students in each school. Prior to 2002, states were able to opt into participating and the number of participating states ranged from 38 to 46, depending upon the subject and grade. Since 2003, the NAEP has been administered in every state, every other year, in both reading and mathematics.

Balancing the goal of maintaining a consistent sample of states with the goal of remaining as close to nationally representative as possible, we included states that missed at most one year of assessment scores in a given grade-subject combination. Thus, in 4<sup>th</sup> grade math and reading, that left us with 45 and 41 states respectively, and 43 and 46 states in 8<sup>th</sup> grade math and reading. We report the number of schools and students by grade/subject and by year in Table 1. For example, in 2015, we included scores from 108,290 students attending 5250 schools in 4<sup>th</sup> grade reading.

To add data on household income for public schools, we use information on school locations from the Common Core of Data. In 1990 and 2000, we rely on the decennial censuses. For 2007 and after, we use the American Community Survey. The NCES’s Common Core of Data (CCD) provides student enrollments as well as the latitude and longitude for each school. Using each school’s geographical coordinates, we rank the nearest block groups (as measured by block group centroid) by their distance from each school.<sup>2</sup> The census data report the number of related children attending

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<sup>2</sup>Overlaying school attendance zones and block group boundaries for a set of 21 of the largest 22 districts, Saporito and Sohoni (2007) found that 53 percent of census block groups in 2000 lay entirely within a school boundary in 2007.

public schools in grades 1-4 and in grades 5-8 in each block group. Combining the census data on number of children enrolled in various grade levels with data from the CCD on the enrollment of each school, we identify the  $K$  nearest block groups with a sufficient number of children to “fill up” the school’s official enrollment. In other words, if  $N_k$  is the number of students enrolled in public schools from block group  $k$  according to the census, and  $N_j$  is the number of students enrolled in school  $j$  according to the CCD, then we associate the nearest  $K$  block groups that satisfy the inequality  $\sum_{k=1}^{K-1} N_k < N_j \leq \sum_{k=1}^K N_k$  where block groups  $k$  are ordered in increasing distance from the school location.

In the census, detailed data on household income is only available at the census tract level—not the block-group level. As a result, we assume that the distribution of income in each block group matches the distribution in its associated census tract. We then weight the tract-level data by the counts of students in each of the  $K$  block groups associated with the school. Thus, the number of students in school  $j$  who come from a household with income in the  $i^{th}$  reported bin is given by

$$N_{ji} = \sum_{k=1}^K \frac{p_{ki}n_k}{n_j}$$

Where  $p_{ki}$  is the proportion of students in the corresponding census tract in income bin  $i$ . These counts can be thought of as a coarsened distribution of the household income for students in each school<sup>3</sup>. We merge our estimates for each school using a unique school identifier.

To infer the mean and variance in income from the binned income data, we assume the distribution of income for each school is approximately log normal. By definition, if the log of income,  $\ln(Y)$ , is distributed normally, and  $C_l$  is the upper range of the  $l$ th income bin (expressed in log 2016

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<sup>3</sup> To calculate the mean and variance of this distribution we use a method outlined by vonHippel, Scarpino, & Drown (2016), fitting the cumulative CDF of each school’s income bins to a log-Normal distribution

dollars), then the proportion of the school enrollment with income below  $C_l$  can be expressed as follows:

$$P_{C_l} = \Phi \left( \frac{\ln(C_l) - \mu_{Y_j}}{\sigma_{Y_j}} \right)$$

Where  $\mu_{Y_j}$  and  $\sigma_{Y_j}^2$  represent the mean and variance of log income in school  $j$ .

Accordingly, using for the top limit in each income bin ( $C_l$ , where  $l=1, \dots, 15$  corresponding to 16 income bins) and the proportion of households,  $P_{C_l}$ , in the school with incomes below  $C_l$ , we estimate the following regression for each school:

$$\ln(C_l) = \mu_{Y_j} + \sigma_{Y_j} \text{invnorm}(P_{C_{jl}}) + \vartheta_{jl}$$

Where  $j$  subscript the school and  $l$  subscript one of 15 income bins.

For inter-censal years and for the years between 2000 and 2009 (when the American Community Survey became available), we use a linear interpolation of the mean and variance of income from 1990, 2000 and 2009.

Our use of Census data to approximate the mean and variance in family income for individual public schools will suffer from two sources of measurement error: First, Census block group boundaries will not coincide with actual school attendance zones; second, not all children in a neighborhood will be attending public schools. According to the National Center for Education Statistics, 13.1 percent of students in grades Pre-K through 8 attended private schools in 1990 (the beginning of our period). The percentage had declined slightly to 10.8 percent by 2016.<sup>4</sup>

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<sup>4</sup> National Center for Education Statistics, *Digest of Education Statistics*, 2018, Table 105.20.



Nevertheless, the method performs reasonably well in replicating administrative data on race and income from the Common Core of Data (CCD). To check, we compare our Census-based estimates of poverty rates and race/ethnicity to the proportion of students receiving Free or Reduced Price Lunch (FRPL) and each race/ethnic group in the CCD. Those results are reported in Table 2. Unfortunately, the data on students receiving free or reduced price lunch was missing for more than half of schools in 1990 (52 percent). As a result, the first year we report the correlation is in 2000 (when 13 percent of schools were missing data). In 2000, the correlation between the poverty rates in nearby block-groups and the school's reported percentage of students receiving free or reduced price lunch was .715. By 2015, the correlation was roughly the same, .690.<sup>5</sup> The method performs even better for approximating a school's race-ethnicity; the correlation between our estimate of the percentage of students who are black in each school and the CCD report was roughly .9 in all years between 1990 and 2015. Although the census-based measure of school income is subject to error, there is no evidence that the relationship has diminished over time or that the reliability has gotten worse.

In order to impute household income for various student traits, we identify a subset of variables available in both the NAEP and the March Current Population Survey: mother's highest level of educational attainment, race-ethnicity, urbanicity (4 categories) and state. We limit the CPS sample in each year to households with a related child aged 5 through 18 and a mother present. Table 3 reports the  $R^2$  for each specification for each year. Although the traits account for a small share of the variance in household income in each year ( $R^2$  in the combined model is approximately .22), the proportion of variance explained is stable over time.

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<sup>5</sup> The imputation performs best in suburban areas, with an  $R^2$  of approximately .75 with respect to FRPL status, but  $R^2$  between .6 and .65 in the urban and rural areas as well as towns.

## V. Results Using School-Level Data to Estimate Student-Level Parameters

Before presenting parameter estimates, we start with a graphical summary of the between-school and within-school relationships in various years. Figure 1 reports the results of a locally weighted polynomial regression of school mean achievement on mean log income for 4<sup>th</sup> grade math and reading. The solid lines portray the relationship for the first year (1992) and the last year (2015) in our analyses; the dashed lines report the relationships for the years between 1992 and 2015. Upon inspection, the relationship is roughly linear in log income. Moreover, in both subjects—but especially in math—there has been a noticeable increase in the intercept and a decline in the slope. At least in terms of the differences in mean achievement between schools, there is no evidence of a sharp steepening of the relationship between mean achievement and mean income between schools.

Figure 2 reports similar relationships for 8<sup>th</sup> grade math and reading. In 4<sup>th</sup> grade and 8<sup>th</sup> grade math, there were sharp increases in mean achievement for schools at all levels of mean log income in math. Likewise, there were increases in achievement for schools all income levels in 4<sup>th</sup> grade reading. However, in 8<sup>th</sup> grade reading, the shift was much smaller than in the remaining three grade/subject combinations. In no subject-grade combination is there evidence of a steepening of the relationship mean achievement and mean log income at the school level.

Figure 3 reports the trend over time in the intra-class correlation in log income by school. Using the ICC metric, there's been a 20 percent increase in income-based school segregation over time (from .19 to .22.) Figure 3 is consistent with prior research on income-based residential segregation. Using a sample of the 100 largest metropolitan areas, Reardon and Bischoff (2011) find that income segregation grew rapidly between 1970 and 2000. (Watson (2009) finds consistent results using a different measure of income segregation.) Owens, Reardon, and Jencks (2016) find that between-district income segregation of families with children enrolled in public school increased by over 15% from 1990 to 2010.

They also find that within-district segregation based on students' free-lunch status increased by over 40% between 1990 and 2012.

Figure 4 uses school-level data to plot the relationship between the within-school variances in achievement and within-school variances in log income for grade 4 math. Under the assumption that the within-school slope is the same across schools, the slope of the relationship in Figure 4 should be equivalent to the square of the within-school slope of achievement on log income. Sample-based estimates of variances are inherently noisy, so to summarize the central tendency, we have calculated the average variance in achievement and the average variance in income for 20 equal-sized bins arranged by variance in log income. We have plotted the mean variance in achievement for each bin and then fitted a line. The relationship does appear to be roughly linear, with an increase in achievement variance being approximately proportional to the rise in log income variance. However, there is again no evidence of a steepening slope. If anything, the slope appears to be declining.

Figures 5 through 7 report analogous figures for 4<sup>th</sup> grade reading as well as 8<sup>th</sup> grade math and reading. In all cases, the relationship between the variance in achievement and the variance in income is either flat or declining.

As reported above, there is no evidence of a steepening of the between-school relationship between mean achievement and mean log income. It would still be possible for the student-level slope to rise, if there were a sufficient increase in the ICC (increasing the weight on the between-school slope which is larger than the within-school slope) or if the within-school slope were rising. However, equation (1) lets us bound the magnitude of the improvement one would have to see. If there has been no change in the between-school slope and the ICC is roughly .2, a 40 percent increase in the overall slope that Reardon (2011) infers would have required a 50 percent increase in the within-school

slope.<sup>6</sup> Even if we cannot estimate it precisely, we see no evidence of a 50 percent increase in the average within-school slope.

In Tables 4 through 7, we report our estimates of the between-school and within-school slope parameters and then use the estimated ICC to reconstruct the student-level relationship in each year. Table 4 contains our estimates for 4<sup>th</sup> grade math. As reported in column (1), between 1992 and 2015, our point estimates of the between-school slope decline from 27.9 to 20.9, approximately a 25 percent decline. That is a statistically significant difference. In column (2) we report estimates of the within-school slope parameter. The within school coefficient also declines from 14.7 to 7.2. This decline too is statistically significant. As reported in column (3), the intra-class correlation in ln income, which is a measure of income-based segregation, rises from .19 to .23. Because the between-school slope is larger than the within-school slope, an increase in the ICC would have led to a small increase in the student-level slope even if the between- and within-school coefficients had both remained constant. However, the rise in ICC was not nearly large enough to offset the declining between-school and within-school slope.

In column 4, we combine the ICC, the between-school slope and the within-school slope to estimate the student-level slope parameter. Our results imply that the student-level slope declined from 17.2 to 10.3 between 1992 and 2015, a statistically significant difference. In other words, a 10 percentage point difference in family income was associated with a 1.7 point higher score in 4<sup>th</sup> grade math (.05 standard deviations) in 1992.<sup>7</sup> By 2015, that had declined to 1 point or .03 standard deviations.

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<sup>6</sup> A 50 percent increase in the within-school slope with respect to log income would have required a more than doubling of the slope in Figures 4 through 7, since  $1.5^2=2.25$ .

<sup>7</sup> The standard deviation in 4<sup>th</sup> grade math was 32 points in the 1992 NAEP.

In the remaining columns of Table 4, we report the implied change in mean achievement at the 10<sup>th</sup> and 90<sup>th</sup> percentile of log household income. (Recall that we do not actually observe any individual student at either percentile. Thus, we are estimating these by plugging in the relevant percentiles of household income from Census data and using our student-level slope and intercept parameters to estimate mean achievement.) In column (5), we report the estimated mean achievement at the 10<sup>th</sup> percentile of family income. We estimate that there's been a 31.5 point increase in mean 4<sup>th</sup> grade NAEP scores at the 10<sup>th</sup> percentile of household income, from 198.4 to 229.9. That is equivalent to a full standard deviation in 4<sup>th</sup> grade math achievement in 1992.

In column (6), we report the difference in mean achievement between students at the 90<sup>th</sup> and 10<sup>th</sup> household income percentiles. In 1992, the gap in achievement from students from high and low-income families was 36.3 points or 1.1 standard deviations. By 2015, the implied gap at the 90<sup>th</sup> and 10<sup>th</sup> percentile of income had shrunk to 23.7 points—or .75 standard deviations.

Reardon (2011) makes a distinction between the student-level slope with respect to the level of log-income and the effect of rising inequality (that is, the widening gap in real incomes between those at the 10<sup>th</sup> and 90<sup>th</sup> percentiles.) He concludes that most of the change over time is due to a steepening in the slope rather than simply a widening gap in real incomes between those at the 90<sup>th</sup> and 10<sup>th</sup> percentiles. We too find that the declining slope was much more important than the widening income distribution.

In column (6), we report the combined effect of the change in slope and the change in income distribution. However, in column (8), we hold the income percentiles constant at their 1992 values. Thus, without a widening income distribution, the convergence would have been slightly larger, declining by an additional 2 points (.05 s.d.), from 36.3 to 21.8 points.

Tables 5 through 7 report similar estimates for 4<sup>th</sup> grade reading, 8<sup>th</sup> grade math and 8<sup>th</sup> grade reading. In 4<sup>th</sup> grade reading, we estimated that the variance in achievement had a small negative slope with respect to the variance in log incomes in the three latter years—2011, 2013 and 2015. We interpret that as a boundary constraint of zero. (Because the estimated slope was negative, the square root was not identified.) However, the between-school slope for 4<sup>th</sup> grade reading declined by 7 percent between 1992 and 2015 (from 26.0 to 24.2) and by 20 percent relative to its peak in 1994).

As reported in Table 6, both the between-school and within-school slopes declined by 11 percent in 8<sup>th</sup> grade math. We also estimate that mean 8<sup>th</sup> grade math achievement at the 10<sup>th</sup> percentile of household income increased by .7 standard deviations, from 240.1 to 264.8. Moreover, the gap in achievement between high and low income students declined from 42.9 to 37.5 points, or .15 standard deviations.

Reardon (2011) reports that size of the achievement gap at the 10<sup>th</sup> and 90<sup>th</sup> percentile of income rose sharply for those born between 1975 and 2001, eventually surpassing the black-white achievement gap for those cohorts. The results for the 8<sup>th</sup> grade cohorts in Tables 6 and 7 correspond with the 1977 to 2002 birth cohorts, so very close to the same period Reardon studied. In contrast to Reardon, we find that the income-based achievement gap (between the 90<sup>th</sup> and 10<sup>th</sup> income percentiles) in 4<sup>th</sup> grade math was equivalent to the black-white achievement gap in 1992 (1.12 standard deviations) and both the income-based gap and black-white fell by nearly .4 standard deviations by 2015. In 8<sup>th</sup> grade math, we see a similar pattern. The achievement gap at the 90<sup>th</sup> vs. 10<sup>th</sup> percentile of family income was similar to the black-white achievement gap in 1990 (1.19 standard deviations) and fell to roughly .88 standard deviations in 2015. While Reardon concluded that the racial gap and the income-based gaps were moving in opposite directions, we estimate that they were moving in tandem.

## VI. Results Using Imputed Household Income

Using the Census-based measure of schools' mean income and variance, our results above suggest that income-based achievement gaps have been narrowing or stable since 1990, even as mean achievement in 4<sup>th</sup> grade math and reading and 8<sup>th</sup> grade math have been rising. In this section, we investigate whether there has been any change in the achievement gaps associated with student-level characteristics available in the NAEP that are correlated with income: race/ethnicity, mother's education, urbanicity and state of residence. We use the March Current Population Survey to estimate mean family income for each combination of those traits (as described in equation (5)).

In Table 8, we report the coefficients on imputed income using each instrument separately (race/ethnicity, mother's education, urbanicity and state) and then combined (using interactions between race/ethnicity and mother's education.) Essentially, by instrumenting for income with the student level traits, we are scaling the differentials in achievement associated with each of these traits by the magnitude of the associated family income differential from the March CPS. Of course, if there is a direct effect of a given trait on achievement that operates outside of income, we will be overstating the impact of income on achievement in each year. (We are not claiming that these are valid instruments without a direct effect.) However, the trends over time should be consistent with the trends in underlying income effects as long as the direct effects of race, mother's education, urbanicity/state are constant. The implied slope with respect to log income for 8<sup>th</sup> grade math based on the race differentials declined by 18 percent between 1990 and 2015, from 51.1 to 42.1. Similarly, using mother's education as the instrument, the implied slope with respect to log income declined by 16 percent. Also, using state and urbanicity as the instruments, the implied slope declined by 30 percent, from .25.1 to 17.5—largely as many low-income states closed the gap with respect to higher income states. When we combine all of the measures, the implied slope declined by 13 percent, from 32.9 to

28.6. Recall from Table 6, the slope with respect to log income using our school-level measures of mean and variance in income, declined by 22 percent, from 20.9 to 16.4.

In Figure 8, we plot the mean 8<sup>th</sup> grade math score (from the NAEP) and the mean family income (from the March CPS) for each observed combination of race by mother's education by urbanicity by state. To provide a more concrete sense of what we are doing, we call out two specific points: children of Hispanic, high school drop-outs from rural New Mexico and children of white college-graduates from suburban New York. We then estimate the relationship between mean achievement and mean income for each of those subgroups. We report the same relationship in 1990 and 2015. Among 8<sup>th</sup> grade students, mean achievement rose at all income levels, but particularly for low income groups, with the implied relationship between achievement and income flattening.

In Figure 8, we also plot the points corresponding to mean achievement and mean income for black and white students as a whole. Reardon (2011) notes that the black and white achievement gap narrowed somewhat over the time period in which he estimated that the income slope coefficient rose sharply. He reconciles the two facts by noting that many black families have incomes below the median. In his estimates, the gap in achievement at the 90<sup>th</sup>-50<sup>th</sup> percentile of income increased more than the gap between the 50<sup>th</sup> and 10<sup>th</sup> income percentile. However, as we find in figure 8, the narrowing of gaps also seemed to occur between the highest income groups (e.g. the children of white, suburban college graduates in suburban New York) and the median household, as well as between the lower income groups (e.g. the children of Hispanic high school drop-outs in rural New Mexico.) There is no evidence that the slope increased within either income range.

In Figure 9, we report analogous results for 8<sup>th</sup> grade reading. The time span is somewhat different—the first year of 8<sup>th</sup> grade reading scores in the state trial assessment occurred in 1998.



Nevertheless, the results are similar to those reported earlier—the slope with respect to income remained fairly constant, with no evidence of a sharp widening.

## **VII. Comparing the Coefficients from the Two Methods**

In Figures 10 and 11, we report the trend in the student-level relationships for the two sets of estimates in 8<sup>th</sup> grade math and reading: using the census-derived school income measures and the imputed income measures, using race/ethnicity, mother's education, urbanicity and state. (Recall that the imputed income measures are only available in 8<sup>th</sup> grade.) The grey lines represent the trend in the overall slope (combining the within and between-school slopes). The slope estimates based on imputed income are larger than those based on the census-derived school income measures—possibly because the coefficients using imputed income are not attenuated by measurement error. However, the time trend is very similar: a stable slope during much of the 1990s, with a decline starting in 2005. Although the series for 8<sup>th</sup> grade reading does not start until 1998, the pattern is very similar, with the slopes based on imputed income exceeding those based on census-derived income, with both gradually declining over time.

Above, we highlighted the strong assumption required to estimate the within-school slope coefficient with the census-derived income measure, namely that schools have the same within-school slopes. As a robustness check, we estimated the between-school and within-school slope coefficients using the imputed family income measures. We wanted to know if we saw the same pattern of flattening in both the between school and within-school coefficients. We find a similar time trend in the within-school relationships using imputed income as we found with the variance on variance regressions: the within-school relationships between income and achievement were stable during the 1990's and declining after 2005.

## VII. **Private Schools**

Thus far, our analysis has been limited to public schools. Yet, as reported by Murnane and Reardon (2018), children in families at the 90<sup>th</sup> income percentile are roughly 4 times as likely to enroll in a private school than students at the 10<sup>th</sup> percentile of family income (roughly 18 percent versus 4 percent during the time period we are studying.) So, the question is, might the rise in the gap in achievement by income that Reardon (2011) reported be driven by a sharp widening of the gap in achievement between public schools and private schools?

There's little reason to believe that our conclusions would be any different if we had been able to include student-level data on income and achievement from private schools. In Figure 12, we report the trend in achievement for the average public school and the average private school for grade 4. We also report the achievement of the 90<sup>th</sup> percentile private school, recognizing that high-income families are unlikely to attend the average private school. For each grade-subject combination, the public-private gap in mean achievement has been narrowing over time. In addition, the gap between the average public school and the 90<sup>th</sup> percentile private school has also been narrowing.

Figure 13 reports similar results for 8<sup>th</sup> grade students. Again, there is no evidence of widening.

## VIII. **Conclusion**

The ideal data for measuring the change in income-based achievement gaps would combine a consistent measure of student achievement with a reliable measure of each student's parental income over a long period of time. Unfortunately, such data do not exist. Thus any effort to shed light on changes in income-based achievement gaps will necessarily involve compromises.

Reardon (2011) combined surveys from different time periods with different measures of academic achievement and different measures of income over time. Although the methods he uses are

reasonable, there are obvious hazards in trying to make comparisons over time with measures that are so different. The achievement measures varied in terms of content coverage, age group and reliability. The income measures varied as well, contain different numbers of categories, with some reported by students and some reported by parents.

Clearly, our approach to estimating the student-level relationship with school-level aggregates has its own shortcomings. For instance, we have had to rely on block-group boundaries and not actual school attendance zones to infer the mean and variance in income in each school. Although the reliability seems not to have changed over time, we know that the Census-based measures are subject to error. Moreover, we have assumed that the within-school relationship between income and achievement is the same across schools in any given year, although our evidence would be consistent with a declining mean slope with random coefficients.<sup>8</sup>

However, our two sets of findings-- first, using school-level aggregates from the Census to estimate the student-level relationship and, second, scaling the student-level traits by differences in household income (race/ethnicity, mother's education, urbanicity and state)—are consistent. In contrast, Reardon's finding of sharply widening achievement gaps must be reconciled with the narrowing gaps by race/ethnicity, mother's education, urbanicity and state.

Reardon (2011) offers a possible explanation. He finds that the steepening slopes with respect to income occurred primarily at the top end, for those with above-median income. He points out that most African American families have income below the median. However, that explanation cannot reconcile declining gaps for those with high and low levels of mother's education, or for those living in high and low-income states, whose mean incomes span the median. In contrast, the time trend in our estimates of the student-level relationships matches very well with the time trend for the imputed gaps

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<sup>8</sup> This would be true as long as there was not a more than offsetting decline in the variance in coefficients.

by race, mother's education, urbanicity and state. In our two approaches to measuring changes in income-based achievement differentials, there is no difference to reconcile. Using both methods, we find that the income-based gaps are narrowing in three out of four grade/subject combinations we study. In the remaining grade/subject, 8<sup>th</sup> grade reading, the income-based gap is constant.

In some grades and subjects, the implied achievement gains at the 10<sup>th</sup> percentile of the family income distribution have been remarkable: a full standard deviation in 4<sup>th</sup> grade math and .68 s.d. in 8<sup>th</sup> grade math. We cannot say how much of the improvement has been due to accountability reform, school finance reform or other changes, such as students becoming more comfortable with standardized testing. Although the previous literature has suggested that both accountability and school finance reforms have had an effect, they have been separate literatures—one focused on the effect of accountability laws (e.g. Dee and Jacob (2011), Hanushek and Raymond (2005)) and another focused on school finance reforms (Lafortune, Rothstein and Schanzenbach (2018) and Jackson, Johnson and Persico (2016)). However, many of the same states were implementing both school finance reforms and accountability at the same time. In fact, the accountability reforms and the school finance reforms were often explicitly linked as a way of ensuring that the additional dollars were to be spent well. In future work, we will be using the estimated shifts in intercepts and slopes of the student level-relationship between achievement and income to sort out the relative effect of different reforms in explaining the substantial increases in achievement since 1990.

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**Table 1: NAEP Administration Schedule and State Sample Size**

Year	Grade 4 Reading		Grade 8 Reading		Grade 4 Math		Grade 8 Math	
	Schools	Students	Schools	Students	Schools	Students	Schools	Students
1990							2,820	82,270
1992	3,930	97,470			4,200	105,030	3,170	95,240
1994	3,560	97,060						
1996					3,720	95,530	2,900	78,070
1998	2,980	75,930	2,840	77,110				
2000							2,560	67,170
2002	4,060	115,560	3,840	106,270				
2003	5,000	142,310	4,580	129,690	5,500	160,720	3,920	112,840
2005	6,280	126,340	5,280	133,870	6,880	143,100	4,570	118,330
2007	5,280	145,490	5,280	136,790	5,810	164,140	4,500	113,540
2009	6,460	136,640	5,330	137,730	7,080	140,560	4,500	118,800
2011	5,580	161,910	5,470	139,260	6,120	172,100	4,610	125,820
2013	5,500	147,070	5,160	148,880	6,050	156,990	4,410	127,630
2015	5,250	108,290	4,730	118,870	5,780	118,070	4,010	103,580
<i>States in our sample</i>		41		46		45		40

Note: School counts include District of Columbia but excludes Department of Defense Schools, as well as Bureau of Indian's Affairs schools. States were included if they opted out of no more than one available NAEP administration during the period between 1990 and 2002. All counts were rounded to the nearest 10, per IES reporting requirements.

Source: U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments.

**Table 2: Correlation Between Census-Derived School Characteristics and the Common Core of Data**

	1990	2000	2009	2011	2013	2015
<b>Percent of Students Receiving FRPL</b>						
Correlation between CCD and Estimate	N.A.	0.715	0.669	0.655	0.694	0.690
Coefficient on Estimate in Predicting CCD	N.A.	1.042	0.938	0.890	0.926	0.918
N		60860	74930	76400	76130	75820
<b>Proportion of Students Black (including Black-Hispanic)</b>						
Correlation between CCD and Estimate	0.853	0.903	0.900	0.899	0.901	0.898
Coefficient on Estimate in Predicting CCD	0.915	0.976	0.977	0.955	0.952	0.957
N	59,470	67,970	76,610	76,770	76,630	76,560
<b>Proportion of Students White</b>						
Correlation between CCD and Estimate	0.828	0.859	0.912	0.914	0.914	0.913
Coefficient on Estimate in Predicting CCD	1.006	1.053	0.982	0.966	0.963	0.967
N	60,796	67,972	76,607	76,773	76,630	76,564
<b>Total # Schools in CCD</b>	<b>68,300</b>	<b>69,790</b>	<b>76,610</b>	<b>76,780</b>	<b>76,630</b>	<b>76,560</b>

Note: 52% schools are missing FRPL information in the CCD in 1990, 13% are missing in 2000, and less than 2% are missing in 2009 and beyond. The CCD and Census handle race/ethnicity differently. For both datasets, the black category includes both black Hispanics and black non-Hispanics. In the CCD, the white category always includes both white Hispanics and white non-Hispanics. The Census data codes both white Hispanics and white non-Hispanics as "white" in 1990 and 2000. From 2009 on, our Census-based estimates include only white non-Hispanics, but are still compared to the CCD proportions which include white Hispanics as well.

**Table 3: R<sup>2</sup> for First-Stage Imputations of Household Income Using CPS**

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<b>Year</b>	<b>R<sup>2</sup></b>	<b>CPS Sample Size</b>
1990	0.268	32,826
1991	0.256	33,079
1992	0.267	32,230
1993	0.271	32,203
1994	0.287	31,879
1995	0.258	31,910
1996	0.250	28,287
1997	0.256	28,486
1998	0.259	28,513
1999	0.260	28,704
2000	0.255	28,695
2001	0.235	53,812
2002	0.246	53,339
2003	0.249	52,741
2004	0.243	51,707
2005	0.235	50,644
2006	0.247	49,797
2007	0.260	48,738
2008	0.256	48,067
2009	0.252	47,938
2010	0.261	47,689
2011	0.277	45,764
2012	0.261	44,794
2013	0.268	45,118
2014	0.243	44,154
2015	0.240	43,660

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Note: In columns 2 and 3, each row presents the R<sup>2</sup> and sample size for a separate regression predicting income in the CPS data in that year. 10th and 90th percentiles of log income are given for each subsample.



**Table 4: Reconstructing the Relationship Between Student Achievement and Income using School-Level Aggregates (4<sup>th</sup> Grade Math)**

Year	Between-School Slope (1)	Within-School Slope (2)	ICC <sub>y</sub> (3)	Implied Student Level Slope (4)	Using 1990 Income Percentiles		Using Actual Percentiles	Difference between (6) and (7) (8)
					Predicted Score at 10th Pctile (5)	Predicted Difference at 90th vs. 10th Pctile (6)	Predicted Difference at 90th vs. 10th Pctile (7)	
1990								
1992	27.898 (0.616)	14.671 (1.301)	0.191	17.204 (1.067)	199.761	35.313	36.314	1.001
1994								
1996	28.579 (0.669)	13.525 (1.442)	0.192	16.414 (1.184)	205.198	33.693	34.760	1.068
1998								
2000								
2002								
2003	25.626 (0.415)	10.274 (1.043)	0.211	13.517 (0.835)	218.966	27.746	28.338	0.593
2005	23.270 (0.364)	9.321 (1.221)	0.215	12.315 (0.971)	223.688	25.279	26.464	1.185
2007	23.182 (0.364)	6.715 (1.669)	0.222	10.364 (1.313)	227.766	21.274	22.420	1.146
2009	23.240 (0.339)	7.925 (1.174)	0.230	11.453 (0.911)	226.527	23.508	24.827	1.319
2011	21.834 (0.331)	7.438 (1.152)	0.229	10.736 (0.896)	228.796	22.036	24.282	2.245
2013	21.353 (0.325)	6.178 (1.346)	0.228	9.643 (1.045)	231.560	19.793	22.032	2.238
2015	20.861 (0.37)	7.179 (1.327)	0.230	10.326 (1.029)	229.830	21.196	23.663	2.467

Note: Income percentiles were calculated using US Census IPUMS data of families with school aged children.

Source: U.S. Department of Education, National Center for Education Statistics, Main State National. Mean Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. Mean and Variance of income were derived from 1990 and 2000 Decennial Censuses, and the American Communities Survey from the Bureau of the Census

**Table 5: Reconstructing the Relationship Between Student Achievement and Income using School-Level Aggregates (4<sup>th</sup> Grade Reading)**

Year	Between-School Slope (1)	Within-School Slope (2)	ICC <sub>y</sub> (3)	Implied Student Level Slope (4)	Using 1990 Income Percentiles		Using Actual Percentiles	Difference between (6) and (7) (8)
					Predicted Score at 10th Pctile (5)	Predicted Difference at 90th vs. 10th Pctile (6)	Predicted Difference at 90th vs. 10th Pctile (7)	
1990								
1992	26.024 (0.752)	18.734 (1.254)	0.191	20.130 (1.042)	192.806	41.320	42.490	1.171
1994	29.858 (0.858)	21.867 (1.692)	0.190	23.389 (1.413)	187.823	48.009	51.715	3.707
1996								
1998	29.774 (0.833)	18.770 (1.719)	0.197	20.934 (1.431)	191.683	42.970	44.751	1.780
2000								
2002	27.523 (0.506)	15.053 (1.154)	0.211	17.686 (0.937)	196.199	36.303	37.096	0.793
2003	29.623 (0.538)	13.060 (1.66)	0.211	16.560 (1.33)	197.616	33.991	34.717	0.726
2005	27.082 (0.461)	8.229 (2.338)	0.215	12.276 (1.858)	203.406	25.198	26.379	1.181
2007	26.603 (0.466)	5.576 (3.437)	0.222	10.236 (2.698)	207.788	21.011	22.142	1.132
2009	25.948 (0.421)	4.830 (3.523)	0.230	9.695 (2.731)	208.404	19.901	21.018	1.116
2011	24.819 (0.415)	0* (0)	0.229	5.685 (0.093)	213.664	11.669	12.858	1.189
2013	24.960 (0.413)	0* (0)	0.228	5.700 (0.092)	214.734	11.700	13.023	1.323
2015	24.236 (0.435)	0* (0)	0.230	5.574 (0.098)	215.478	11.442	12.774	1.332

Note: Income percentiles were calculated using US Census IPUMS data of families with school aged children.

\*Assigned to boundary of 0 because point estimate was negative.

Source: U.S. Department of Education, National Center for Education Statistics, Main State National. Mean Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. Mean and Variance of income were derived from 1990 and 2000 Decennial Censuses, and the American Communities Survey from the Bureau of the Census

**Table 6: Reconstructing the Relationship Between Student Achievement and Income using School-Level Aggregates (8<sup>th</sup> Grade Math)**

Year	Between-School Slope (1)	Within-School Slope (2)	ICC <sub>y</sub> (3)	Implied Student Level Slope (4)	Using 1990 Income Percentiles		Using Actual Percentiles	Difference between (6) and (7) (8)
					Predicted Score at 10th Pctile (5)	Predicted Difference at 90th vs. 10th Pctile (6)	Predicted Difference at 90th vs. 10th Pctile (7)	
1990	29.079 (0.78)	18.913 (1.5)	0.194	20.890 (1.217)	240.123	42.880	42.880	0.000
1992	32.067 (0.768)	20.441 (1.418)	0.191	22.668 (1.151)	242.290	46.529	47.847	1.318
1994								
1996	33.978 (1.035)	20.094 (1.709)	0.192	22.759 (1.411)	246.643	46.716	48.196	1.480
1998								
2000	33.439 (1.002)	19.709 (2.188)	0.209	22.579 (1.778)	247.884	46.347	47.201	0.853
2002								
2003	32.455 (0.661)	16.812 (1.448)	0.211	20.117 (1.155)	253.471	41.293	42.175	0.882
2005	30.370 (0.647)	18.997 (1.144)	0.215	21.439 (0.905)	253.475	44.006	46.069	2.063
2007	28.264 (0.609)	15.473 (1.469)	0.222	18.308 (1.147)	259.597	37.579	39.603	2.024
2009	28.728 (0.639)	16.170 (1.154)	0.230	19.063 (0.895)	260.289	39.129	41.324	2.195
2011	25.717 (0.642)	12.750 (1.381)	0.229	15.720 (1.064)	265.803	32.268	35.556	3.288
2013	25.890 (0.545)	13.253 (1.191)	0.228	16.139 (0.924)	266.919	33.127	36.873	3.746
2015	25.818 (0.588)	13.526 (1.229)	0.230	16.353 (0.952)	264.699	33.568	37.475	3.907

Note: Income percentiles were calculated using US Census IPUMS data of families with school aged children.

Source: U.S. Department of Education, National Center for Education Statistics, Main State National. Mean Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. Mean and Variance of income were derived from 1990 and 2000 Decennial Censuses, and the American Communities Survey from the Bureau of the Census

**Table 7: Reconstructing the Relationship Between Student Achievement and Income using School-Level Aggregates (8<sup>th</sup> Grade Reading)**

Year	Between-School Slope (1)	Within-School Slope (2)	ICC <sub>Y</sub> (3)	Implied Student Level Slope (4)	Using 1990 Income Percentiles		Using Actual Percentiles	Difference between (6) and (7) (8)
					Predicted Score at 10th Pctile (5)	Predicted Difference at 90th vs. 10th Pctile (6)	Predicted Difference at 90th vs. 10th Pctile (7)	
1990								
1992								
1994								
1996								
1998	24.526 (0.861)	15.025 (2.537)	0.197	16.894 (2.09)	243.757	34.676	36.113	1.437
2000								
2002	22.856 (0.609)	16.207 (1.16)	0.211	17.611 (0.944)	244.214	36.149	36.939	0.790
2003	27.241 (0.614)	12.816 (1.885)	0.211	15.864 (1.512)	245.441	32.562	33.258	0.695
2005	24.529 (0.57)	14.479 (1.469)	0.215	16.637 (1.17)	243.501	34.149	35.750	1.601
2007	24.176 (0.552)	10.047 (2.024)	0.222	13.179 (1.589)	248.053	27.051	28.508	1.457
2009	23.661 (0.53)	9.975 (1.766)	0.230	13.128 (1.367)	249.367	26.947	28.459	1.512
2011	22.435 (0.577)	8.975 (1.756)	0.229	12.058 (1.362)	252.224	24.751	27.273	2.522
2013	22.982 (0.501)	8.904 (1.566)	0.228	12.119 (1.221)	255.032	24.876	27.689	2.813
2015	22.292 (0.525)	6.915 (2.155)	0.230	10.452 (1.67)	254.835	21.453	23.951	2.497

Note: Income percentiles were calculated using US Census IPUMS data of families with school aged children.

Source: U.S. Department of Education, National Center for Education Statistics, Main State National. Mean Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. Mean and Variance of income were derived from 1990 and 2000 Decennial Censuses, and the American Communities Survey from the Bureau of the Census

**Table 8: The Relationship Between Achievement and Alternative Ways of Imputing Income (8<sup>th</sup> Grade Math)**

Year	Instruments Used			
	Race/ Ethnicity	Mother's Education	Urbanicity and State	Race*Mothers Education, Urbanicity, State
1990	51.091 (0.804)	28.458 (0.518)	25.156 (1.131)	32.883 (0.459)
1992	51.602 (0.892)	26.848 (0.560)	28.489 (1.607)	33.683 (0.543)
1994				
1996	47.946 (1.027)	26.010 (0.602)	27.243 (1.383)	33.778 (0.544)
1998				
2000	50.154 (1.446)	25.915 (1.120)	20.473 (1.607)	33.633 (0.963)
2002				
2003	48.341 (0.642)	23.664 (0.453)	16.696 (1.358)	31.144 (0.362)
2005	47.539 (0.569)	24.551 (0.391)	14.555 (1.123)	32.831 (0.364)
2007	43.961 (0.605)	24.093 (0.382)	9.497 (1.234)	29.417 (0.352)
2009	44.560 (0.617)	23.954 (0.460)	14.206 (1.053)	28.380 (0.394)
2011	39.734 (0.639)	22.796 (0.433)	16.332 (1.014)	27.399 (0.370)
2013	40.226 (0.532)	23.343 (0.391)	13.753 (1.061)	27.636 (0.309)
2015	42.141 (0.685)	23.999 (0.389)	17.552 (1.335)	28.606 (0.356)

Note: Each column reports the slope of a regression of student test score on income with income imputed using the variables indicated at the top of the column.

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Mathematics Assessments. Imputed income based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).

**Table 9: The Within- and Between-School Relationship Between Achievement and Imputed Income (8th Grade Math)**

Year	Between-School Slope	Within-School Slope	ICC <sub>y</sub>	Student Level Slope	Number of Students	Number of Schools
1990	37.388 (0.875)	27.129 (0.557)	0.464	32.880 (0.459)	69000	2630
1992	45.851 (0.848)	24.050 (0.467)	0.405	33.680 (0.543)	73770	2820
1994						
1996	46.691 (0.886)	23.155 (0.497)	0.416	33.780 (0.544)	62380	2670
1998						
2000	51.261 (1.123)	21.826 (0.650)	0.370	33.630 (0.963)	55140	2400
2002						
2003	52.476 (0.811)	21.679 (0.401)	0.336	31.140 (0.362)	93250	3640
2005	51.602 (0.768)	23.066 (0.322)	0.337	32.830 (0.364)	104890	4420
2007	44.317 (0.715)	21.027 (0.332)	0.353	29.420 (0.352)	97470	4230
2009	42.768 (0.649)	20.763 (0.391)	0.388	28.380 (0.394)	100940	4220
2011	42.161 (0.614)	19.770 (0.375)	0.376	27.400 (0.370)	106690	4350
2013	41.857 (0.623)	20.120 (0.371)	0.379	27.640 (0.309)	106600	4150
2015	43.788 (0.669)	19.544 (0.422)	0.389	28.610 (0.356)	88690	3840

Note: Column 1 was estimated using mean achievement and mean imputed income by school. Income was imputed based on the interaction between race and mother's education as well as dummies for urbanicity and stat. Column 2 was calculated regressing students' NAEP score on their imputed income and including school fixed effects. Column 3 was estimated with school random effects and imputed income as the outcome

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Mathematics Assessments. Imputed income based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).

**Table 10: The Relationship Between Achievement and Alternative Ways of Imputing Income (8<sup>th</sup> Grade Reading)**

Year	Instruments Used			
	Race/ Ethnicity	Mother's Education	Urbanicity and State	Race*Mothe d, Urbanicity, State
1990				
1992				
1994				
1996				
1998	36.667 (1.122)	21.220 (0.550)	16.504 (1.626)	26.354 (0.609)
2000				
2002	40.628 (0.869)	22.157 (0.497)	12.523 (1.213)	27.243 (0.499)
2003	40.576 (0.702)	22.290 (0.337)	13.460 (1.177)	27.711 (0.376)
2005	40.790 (0.503)	21.131 (0.279)	15.200 (1.177)	27.983 (0.284)
2007	38.972 (0.533)	21.535 (0.338)	8.372 (1.079)	25.969 (0.326)
2009	39.532 (0.606)	21.228 (0.367)	15.880 (0.931)	25.257 (0.379)
2011	34.939 (0.464)	20.642 (0.384)	19.220 (0.943)	24.302 (0.335)
2013	35.685 (0.553)	20.848 (0.350)	15.117 (1.028)	24.686 (0.328)
2015	37.828 (0.646)	20.912 (0.447)	16.746 (1.113)	24.648 (0.386)

Note: Each column reports the slope of a regression of student test score on income with income imputed using the variables indicated at the top of the column.

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Reading Assessments. Imputed income based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).

**Table 11: The Within- and Between-School Relationship Between Achievement and Imputed Income (8th Grade Reading)**

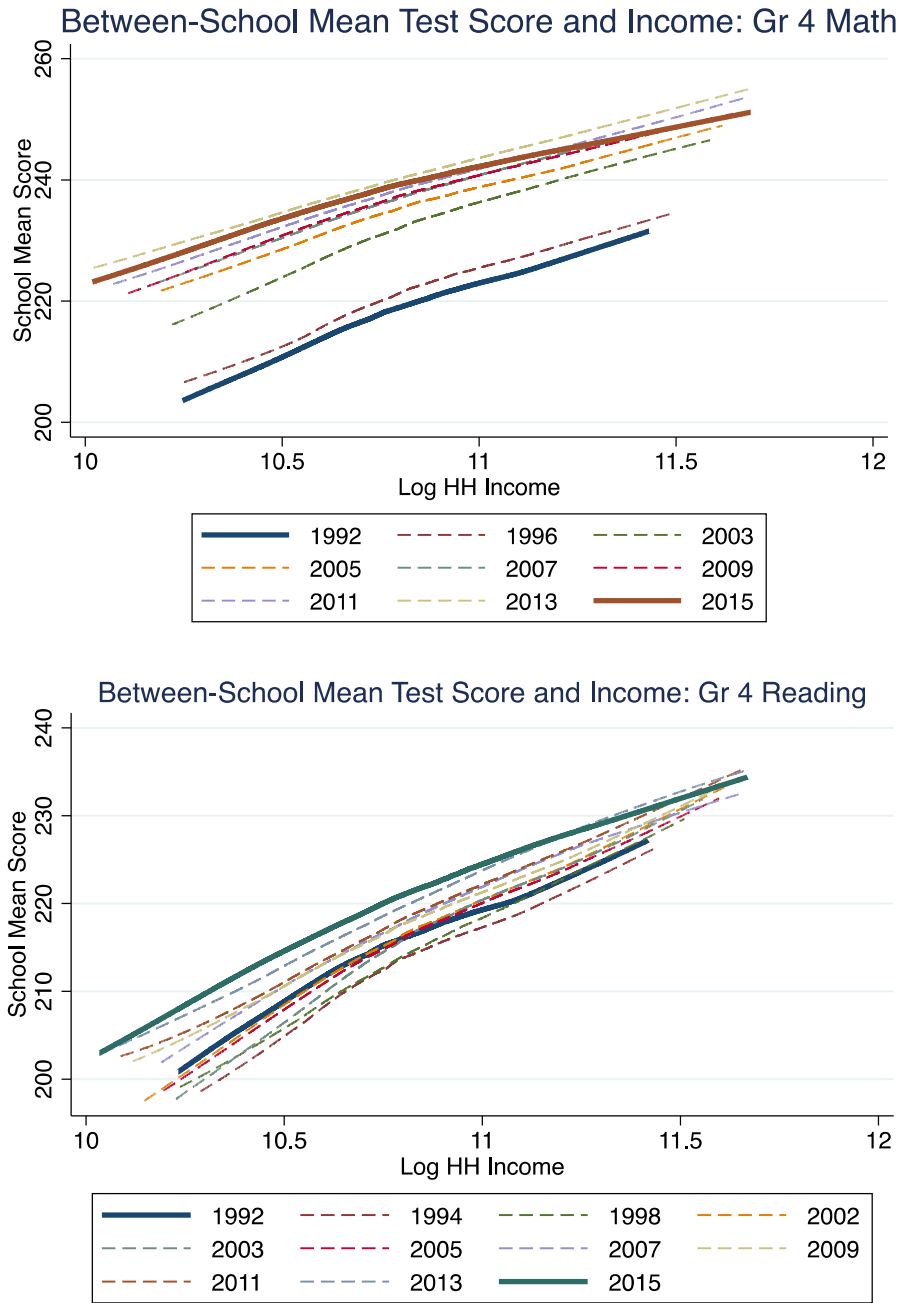
Year	Between-School Slope	Within-School Slope	ICC <sub>y</sub>	Student Level Slope	Number of Students	Number of Schools
1990						
1992						
1994						
1996						
1998	36.031 (0.823)	19.61 (0.466)	0.382	26.354 (0.609)	2620	62270
2000						
2002	41.873 (0.780)	19.31 (0.412)	0.332	27.243 (0.499)	3570	87460
2003	46.527 (0.740)	19.07 (0.367)	0.322	27.711 (0.376)	4290	108230
2005	43.912 (0.695)	19.47 (0.303)	0.324	27.983 (0.284)	5090	117880
2007	41.302 (0.648)	18.18 (0.301)	0.332	25.969 (0.326)	4990	117510
2009	38.054 (0.558)	17.82 (0.362)	0.375	25.257 (0.379)	5030	116330
2011	38.989 (0.534)	17.60 (0.341)	0.361	24.302 (0.335)	5170	117460
2013	39.283 (0.530)	17.47 (0.321)	0.364	24.686 (0.328)	4870	123650
2015	37.821 (0.588)	16.66 (0.365)	0.379	24.648 (0.386)	4530	101040

Note: Column 1 was estimated using mean achievement and mean imputed income by school. Income was imputed based on the interaction between race and mother's education as well as dummies for urbanicity and stat. Column 2 was calculated regressing students' NAEP score on their imputed income and including school fixed effects. Column 3 was estimated with school random effects and imputed income as the outcome

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Mathematics Assessments. Imputed income based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).



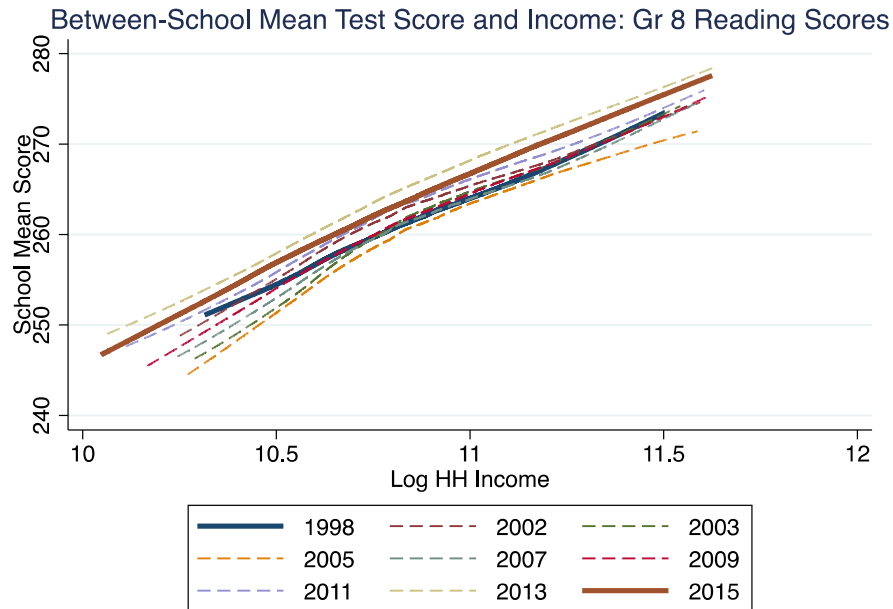
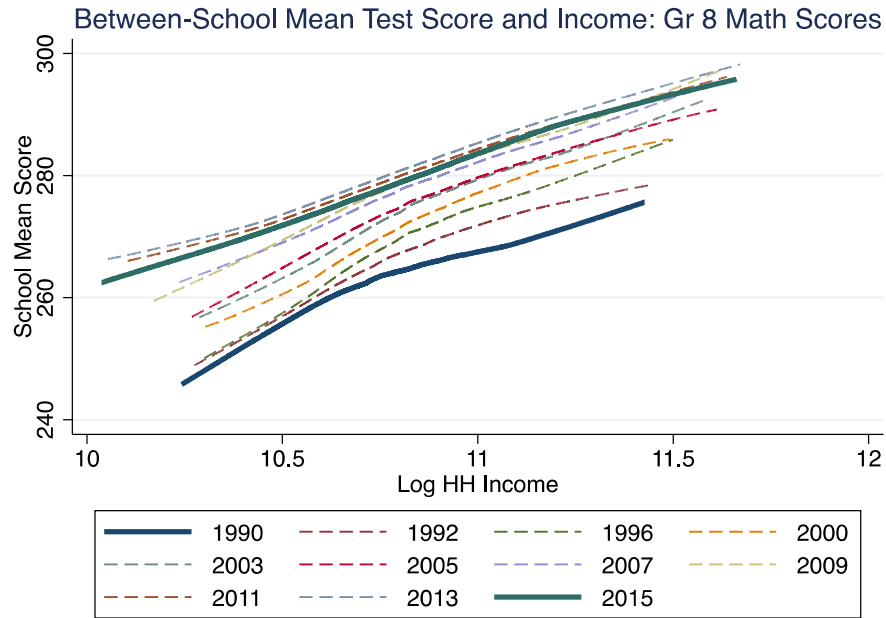
Figure 1: Non-Parametric Relationship Between School Mean Achievement and Mean Log Income By Year (4th Grade Math and Reading)



Note: Each line represents a separate lowess regression run at the school level. School-level weighted averages are calculated using NAEP's student-level weights. Schools with scores or estimated income in the top or bottom 5% of the distribution are excluded.

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. Mean household income data are constructed using data from the U.S. Bureau of the Census.

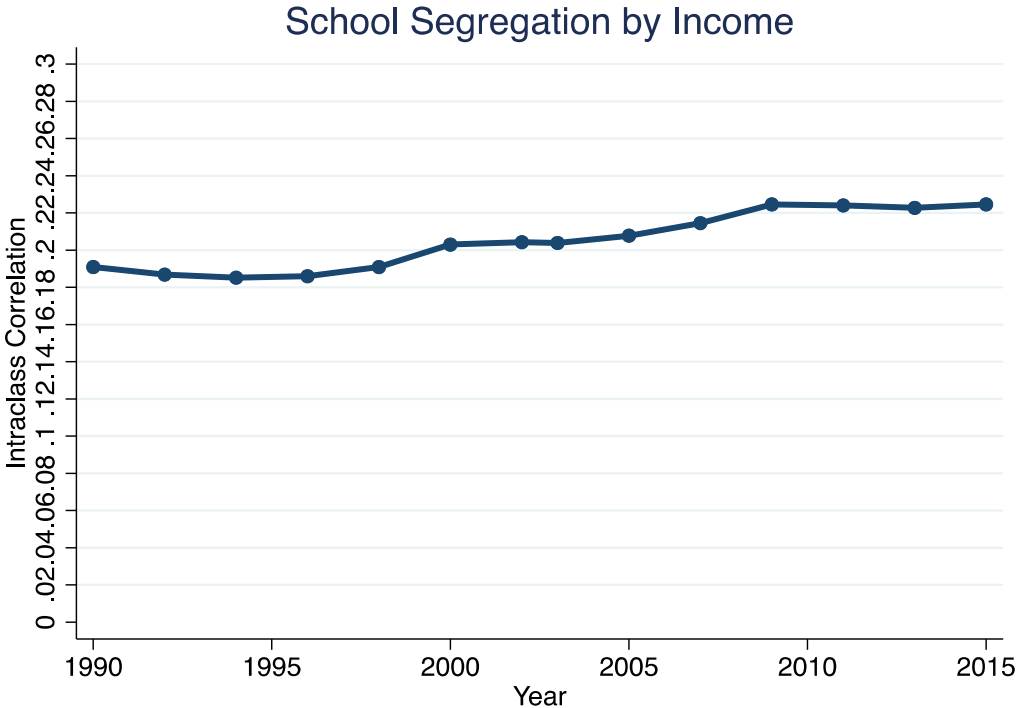
Figure 2: Non-Parametric Relationship Between School Mean Achievement and Mean Log Income By Year (8th Grade Math and Reading)



Note: Each line represents a separate lowess regression run at the school level. School-level weighted averages are calculated using NAEP's student-level weights. Schools with scores or estimated income in the top or bottom 5% of the distribution are excluded. Schools with estimated income variance in the top 5% of the distribution are also excluded. Sample is limited to consistent state sample (see Data section for details).

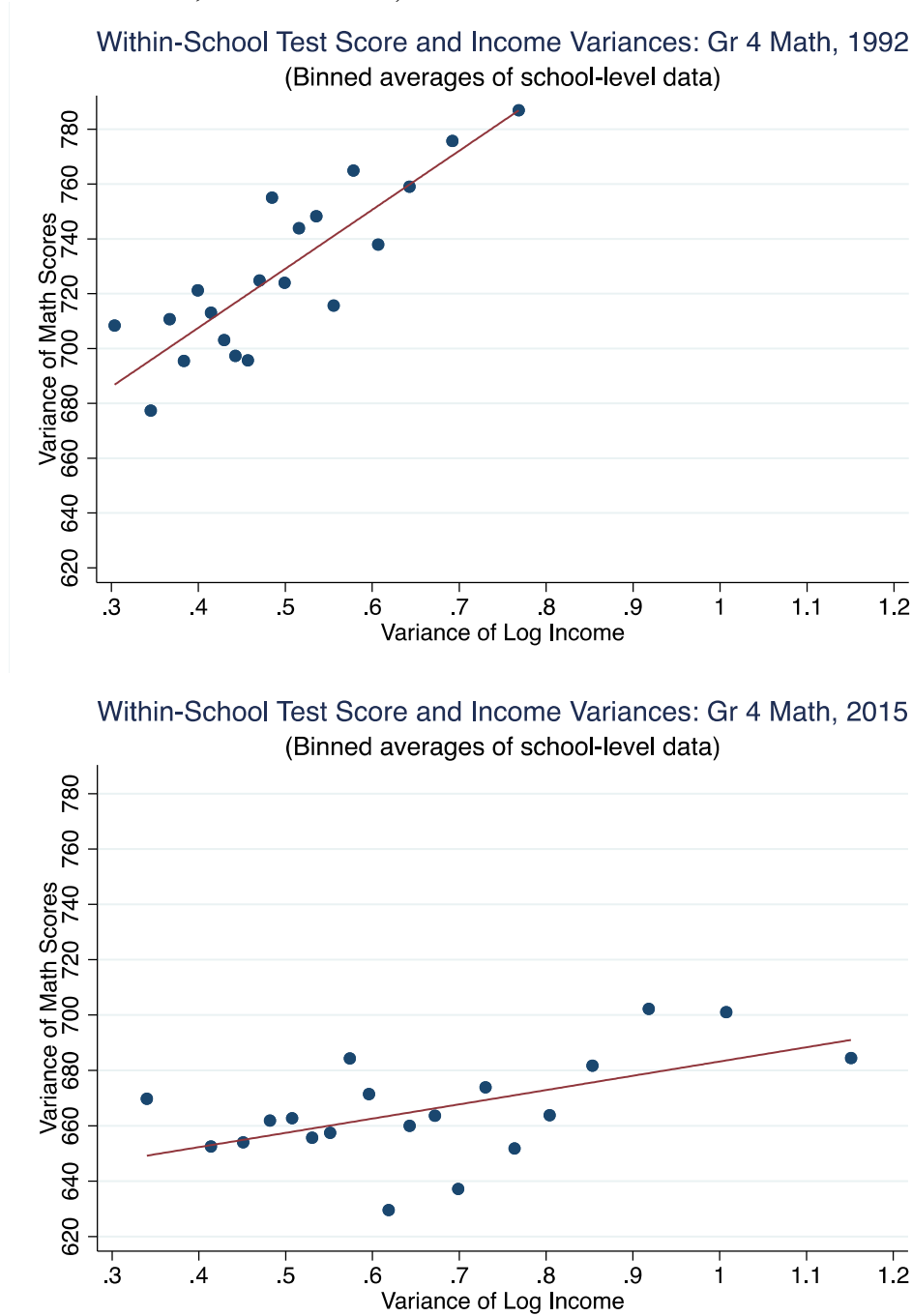
Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. Mean household income data are constructed using data from the U.S. Bureau of the Census.

Figure 3: Intra-Class Correlation in School Household Income by Year



Note: ICC is calculated using means and variances of school household income calculated from census data. Schools whose variance fell above the 97<sup>th</sup> percentile were excluded from this calculation.

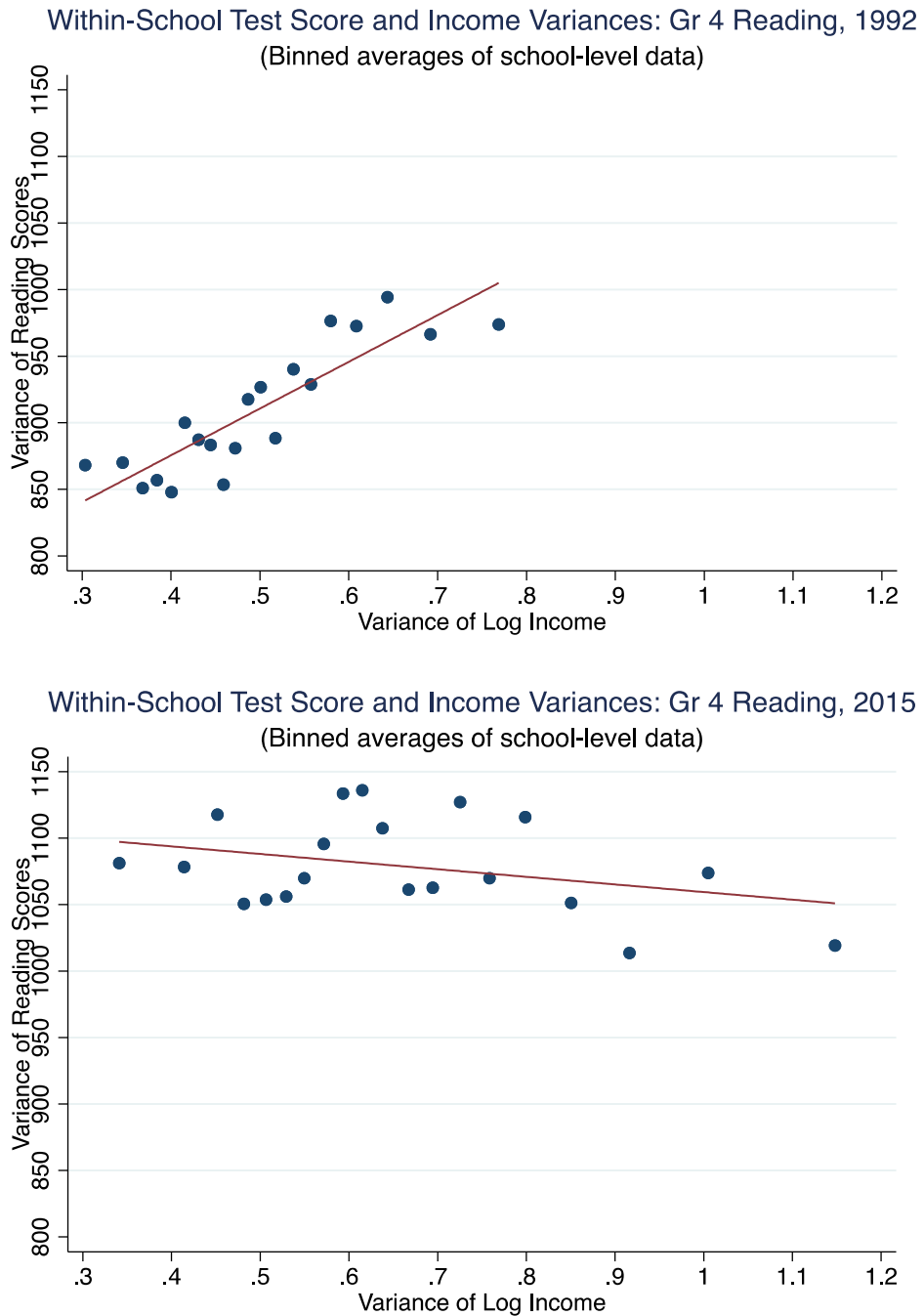
Figure 4: Within-School Variance in Achievement by Variance in Log Income By Year (Binned Averages, 4th Grade Math, 1992 and 2015)



Note: Each point is a binned average of school-level data. Bin averages were weighted by the number of student scores in each school. Schools with estimated income variance in the top 5% of the distribution are excluded. Sample is limited to consistent state sample (see Data section for details).

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. The variance in ln income in each school was estimated using data from the U.S. Bureau of the Census.

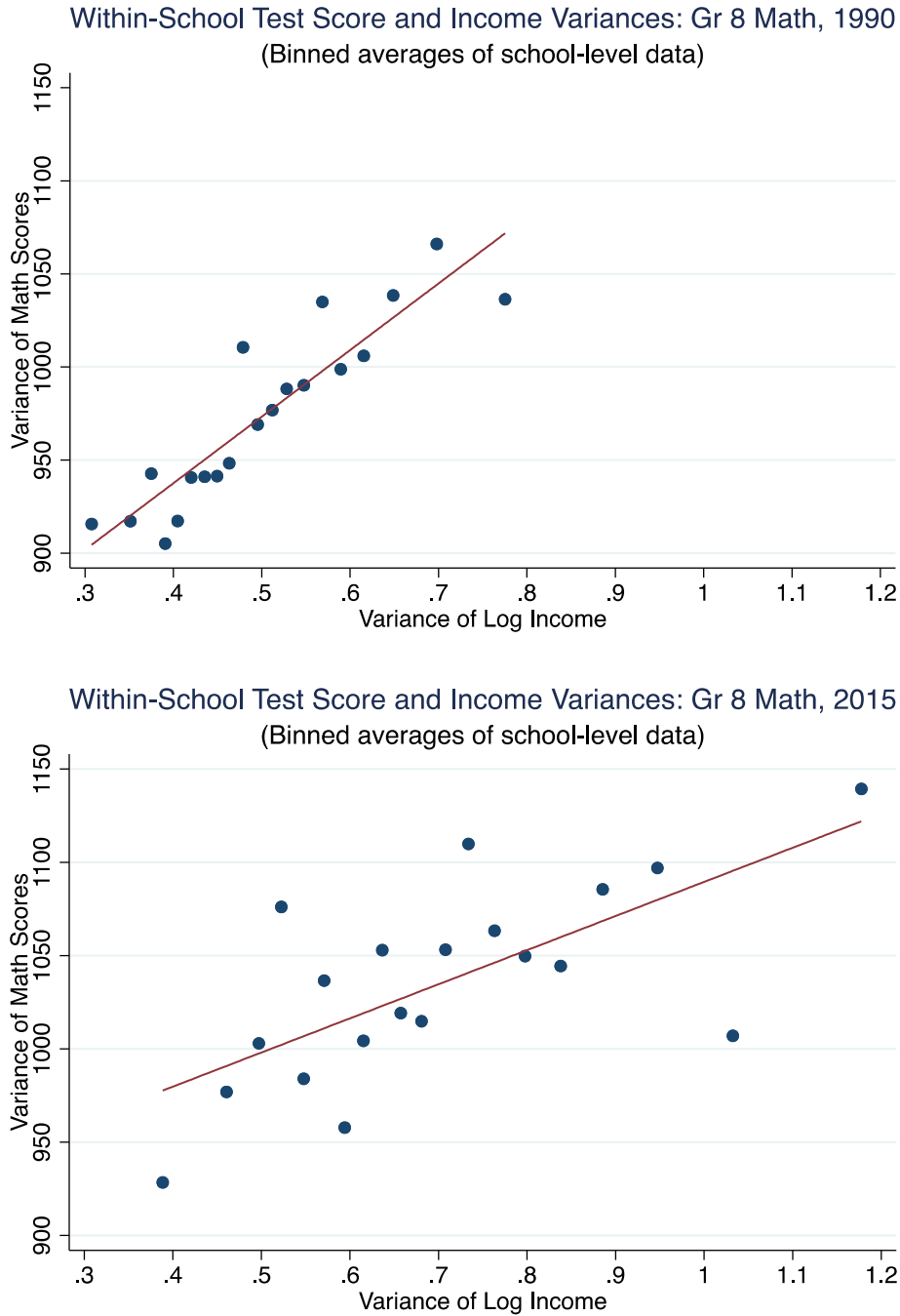
Figure 5: Within-School Variance in Achievement by Variance in Log Income By Year (Binned Averages, 4th Grade Reading, 1992 and 2015)



Note: Each point is a binned average of school-level data. Bin averages were weighted by the number of student scores in each school. Schools with estimated income variance in the top 5% of the distribution are excluded. Sample is limited to consistent state sample (see Data section for details).

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. The variance in ln income in each school was estimated using data from the U.S. Bureau of the Census.

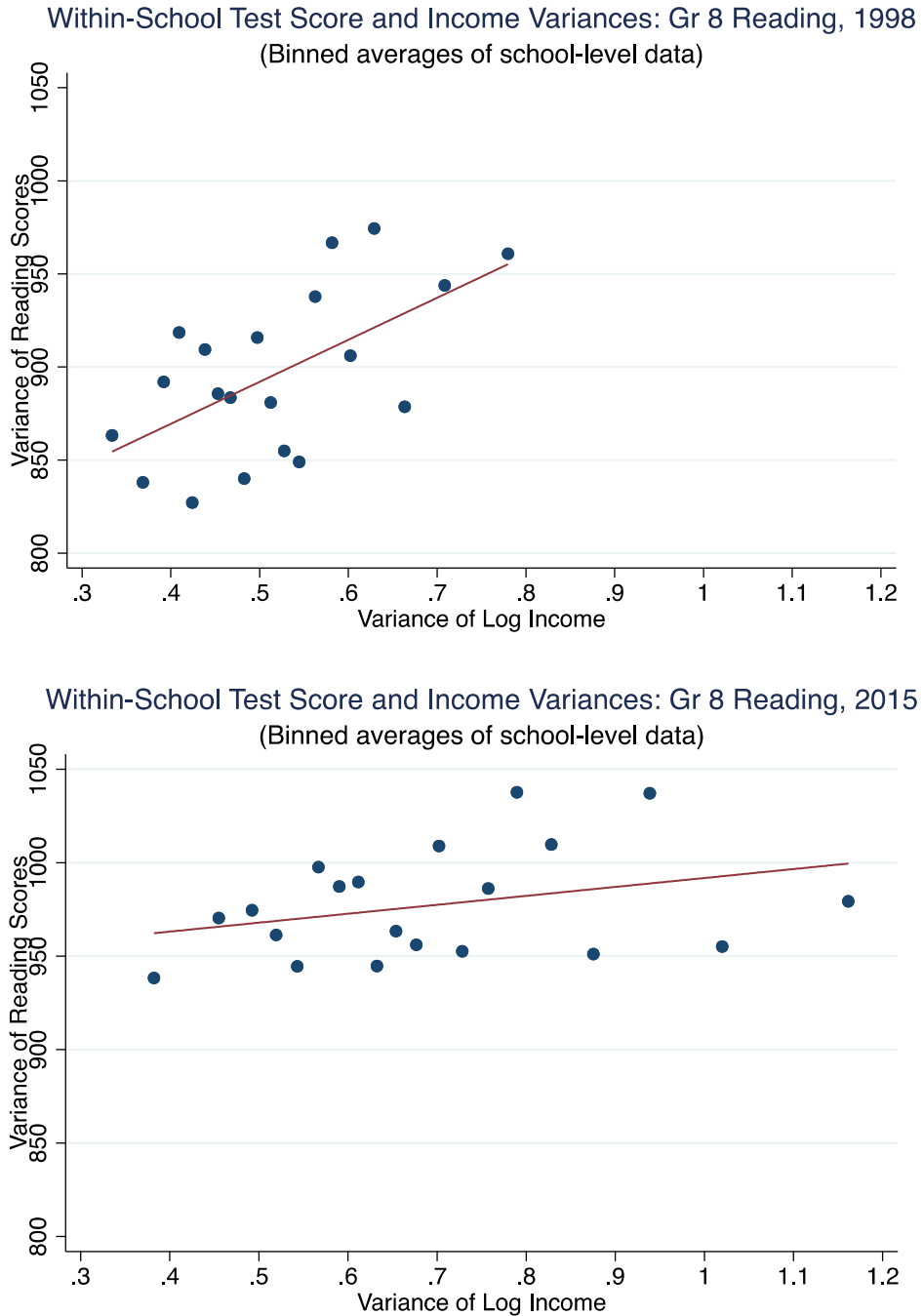
Figure 6: Within-School Variance in Achievement by Variance in Log Income By Year (Binned Averages, 8th Grade Math, 1990 and 2015)



Note: Each point is a binned average of school-level data. Bin averages were weighted by the number of student scores in each school. Schools with estimated income variance in the top 5% of the distribution are excluded. Sample is limited to consistent state sample (see Data section for details).

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. The variance in ln income in each school was estimated using data from the U.S. Bureau of the Census.

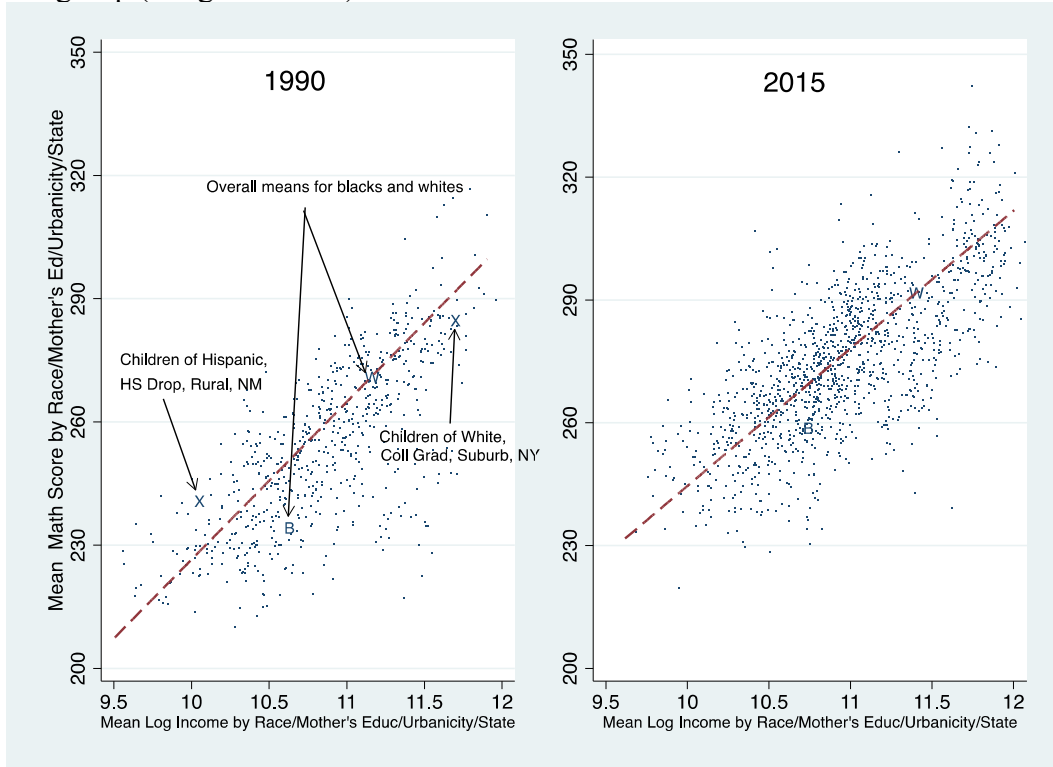
Figure 7: Within-School Variance in Achievement by Variance in Log Income By Year (Binned Averages, 8th Grade Reading, 1998 and 2015)



Note: Each point is a binned average of school-level data. Bin averages were weighted by the number of student scores in each school. Schools with estimated income variance in the top 5% of the distribution are excluded. Sample is limited to consistent state sample (see Data section for details).

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Mathematics and Reading Assessments. The variance in ln income in each school was estimated using data from the U.S. Bureau of the Census.

Figure 8: Mean Test Scores and Ln Incomes by Race, Mother's Education, Urbanicity and State Subgroup (8th grade Math)

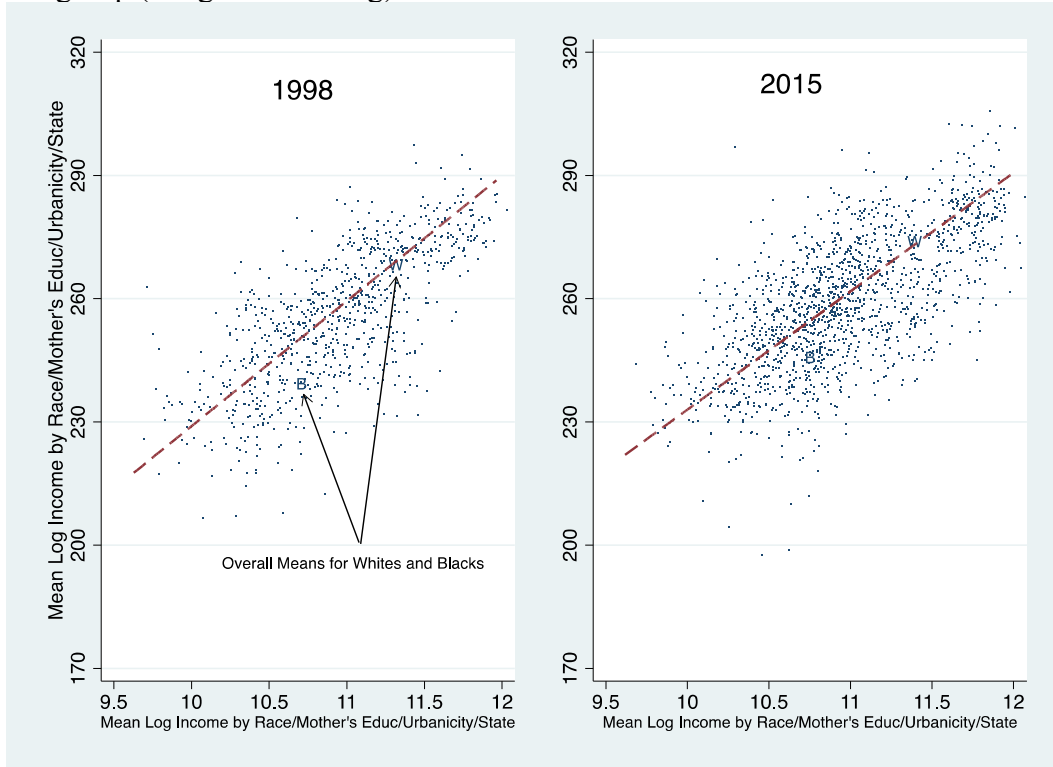


Note: Each point represents the mean NAEP score and mean ln income for a subgroup defined by race, mother's education, urbanicity and state, weighted by the inverse of students' probability of being selected, adjusted for non-response.

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Mathematics Assessments. Imputed income based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).



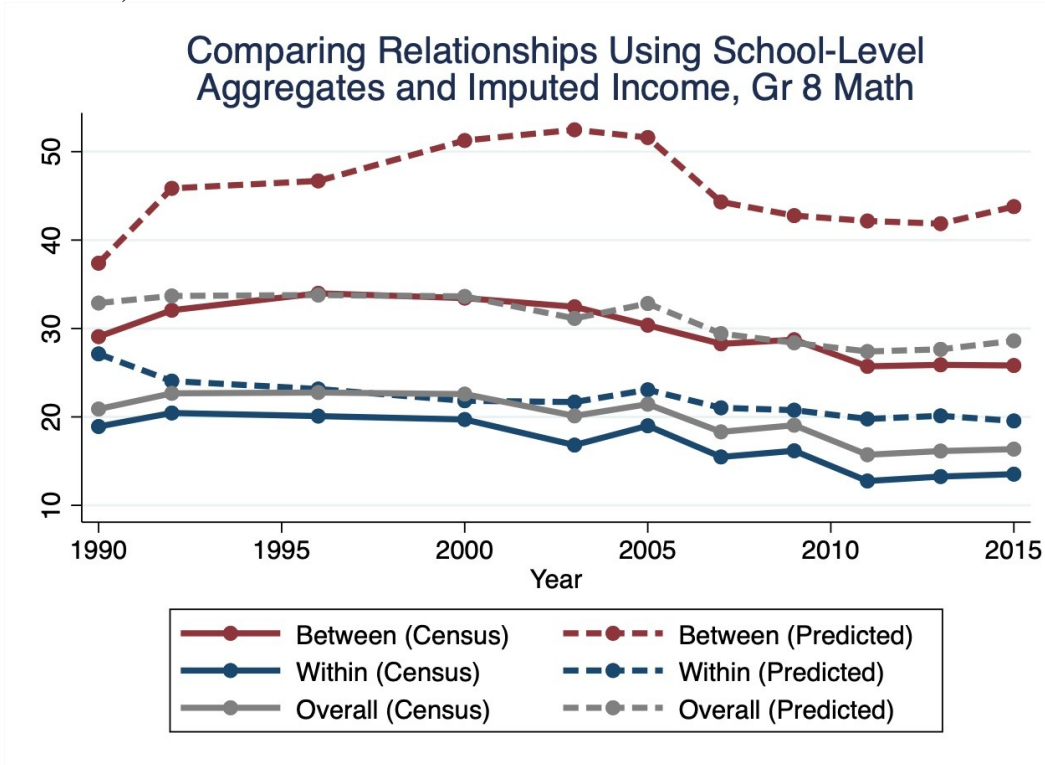
Figure 9: Mean Test Scores and Ln Incomes by Race, Mother's Education, Urbanicity and State Subgroup (8th grade Reading)



Note: Each point represents the mean NAEP score and mean ln income for a subgroup defined by race, mother's education, urbanicity and state, weighted by the inverse of students' probability of being selected, adjusted for non-response.

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Mathematics Assessments. Imputed income based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).

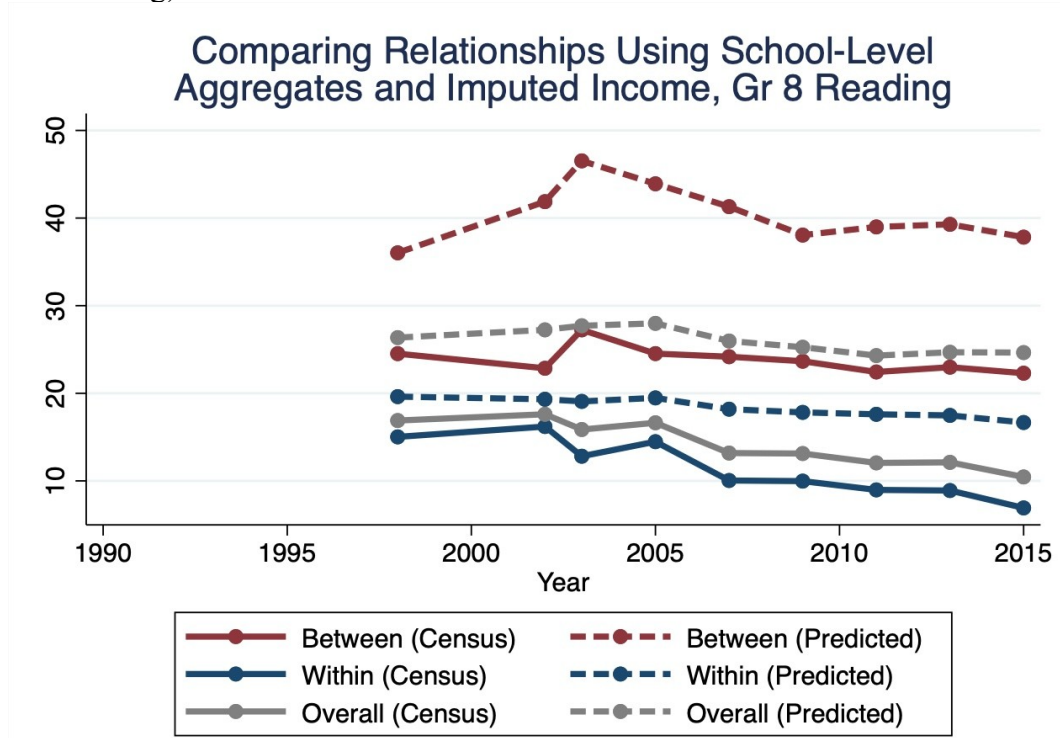
Figure 10: Comparing Relationships using Using School-Level Aggregates and Imputed Income (8th Grade Math)



Note: Points are estimated beta coefficients using the relationship described in the Methods section. Each point is estimated separately for each year for each method (census or predicted).

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Mathematics Assessments. Mean household income data are constructed using data from the U.S. Bureau of the Census or imputed based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).

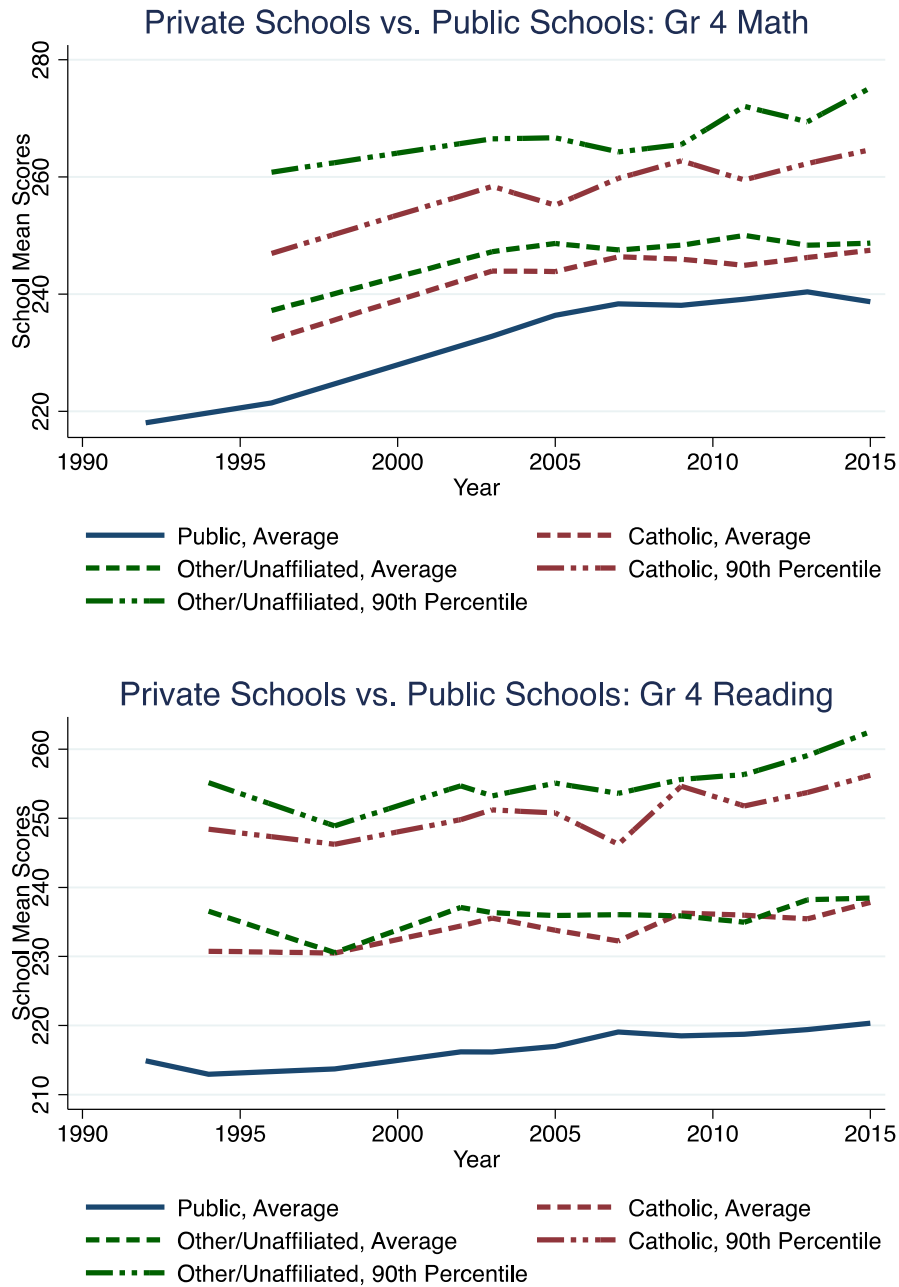
Figure 11: Comparing Relationships using Using School-Level Aggregates and Imputed Income (8th Grade Reading)



Note: Points are estimated beta coefficients using the relationship described in the Methods section. Each point is estimated separately for each year for each method (census or predicted).

Source: Student test score data are from U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on 8th Grade Mathematics Assessments. Mean household income data are constructed using data from the U.S. Bureau of the Census or imputed based on data from IPUMS-CPS, University of Minnesota, [www.ipums.org](http://www.ipums.org).

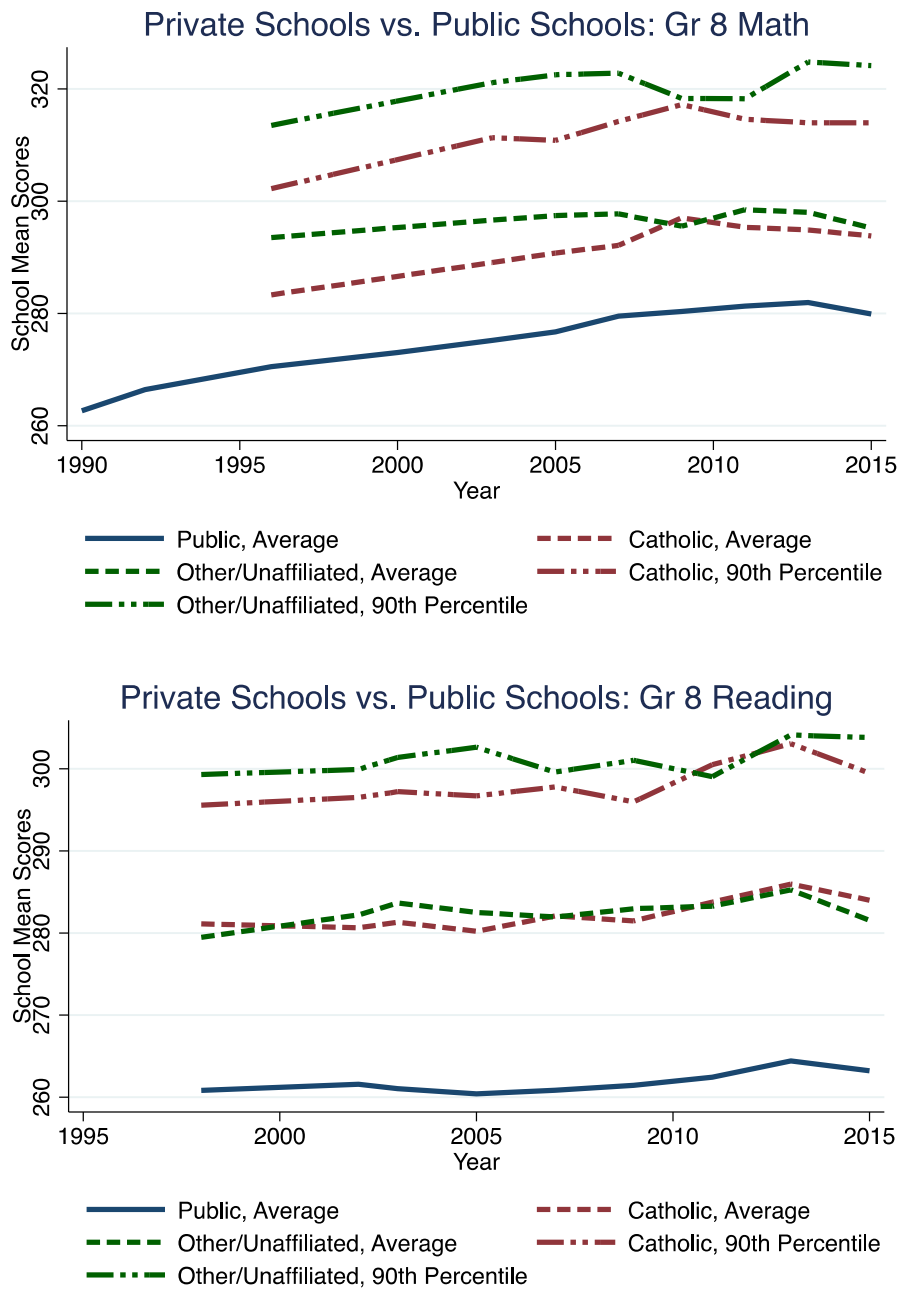
Figure 12: Trend in Achievement in Private Schools (Grade 4)



Note: For each school type, school-level weighted averages are calculated using NAEP’s student-level weights. The average and 90<sup>th</sup> percentile of these school-level estimates are plotted for each year where school type is available.

Source: U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Reading and Mathematics Assessments.

Figure 13: Trend in Achievement in Private Schools (Grade 8)



Note: For each school type, school-level weighted averages are calculated using NAEP’s student-level weights. The average and 90<sup>th</sup> percentile of these school-level estimates are plotted for each year where school type is available.

Source: U.S. Department of Education, National Center for Education Statistics, Main State National Assessment of Educational Progress (NAEP) various years 1990 on Reading and Mathematics Assessments.