PULLING BACK THE CURTAIN: INTRA-DISTRICT SCHOOL SPENDING INEQUALITY AND ITS CORRELATES*

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Abstract

Despite concerns about funding inequities between schools within districts, data constraints have limited large-scale analyses of intra-district inequality in the United States. We use new school-level finance data to calculate measures of vertical inequality for nearly all U.S. districts. Using independent high-quality data sources, we validate the school-level data and the resulting inequality measures. With a valid analytic sample at hand, we find that poor and minority students on average receive 1 to 2 percent more resources than non-poor and white students in the same district, but also that a large share of districts under-allocate resources to disadvantaged students. We also examine correlates of inequality. Districts that under-allocate resources to poor students relative to non-poor students tend to be poorer and have less income segregation. Districts that under-allocate resources to minority students relative to white students tend to have smaller racial income gaps, less racial segregation, and (when it comes to under-allocation to black students) larger white student populations.

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1 Introduction

There are longstanding concerns about how public education funds are distributed across schools within districts in the United States. Such *intra*-district inequality provided the backdrop of *Brown v. Board of Education* (1954) and subsequent Supreme Court rulings that found quality differences among segregated schools unconstitutional. Knowledge of such inequality also influenced federal legislation during the Civil Rights era. Most notably, Title I of the Elementary and Secondary Education Act (1964) not only established a federal commitment to providing additional support to high-need students, but also held that districts that receive federal aid—the vast majority of districts today—must distribute local resources equitably. However, because of low standards for complying with these requirements and few efforts to collect systematic finance data at the school-level, relatively little is known about intra-district funding inequality across a large number of U.S. districts.

In this paper, we describe within-district spending inequality for nearly all districts in the United States for years 2011-12 to 2013-14, drawing on new data collected as part of the Department of Education's Civil Rights Data Collection (CRDC).[1] These data include expenditure information on the universe of schools located in districts that receive federal support. We focus on personnel expenditures, which have been shown elsewhere to track true salary differences between schools as opposed to merely tracking teacher counts (Atchison, Baker, Doyle, Levin, & Manship, 2017).

We organize our analysis into three parts. In the first part of the paper, we subject the school-level data to a series of data quality checks and, with a valid analytic sample in hand, construct three measures of spending inequality. Our final analytic sample includes 11,287 school districts between years 2011-12 and 2013-14, respectively. Of districts with more than one school, our data retains 91.4 percent of the K-12 public school population. Our key measures capture the degree

[1]The data are also available for 2008-09 and 2009-10. As we describe below, we find that the 2008-09 data align poorly with data from independent state sources. In addition, 2009-10 includes a sample rather than the universe of districts. We therefore do not focus on these two years.

of vertical inequality in each of these districts.[2] Specifically, we measure per pupil expenditure differences between poor and non-poor students (given their eligibility for free and reduced-price lunch), black and white students, and Hispanic and white students. As we describe in greater detail below, we structure these measures as logged ratios, where values above (below) 0 indicate greater (less) spending on disadvantaged students than on advantaged students.

In the second part of the paper, we carry out a descriptive analysis of each of these inequality measures. Our key descriptive result is that, on average, across nearly all districts in the United States, intra-district spending inequality is limited. Average spending on poor or minority students is 1 to 2 percent higher than on non-poor or white students. There is variation among districts, however. We estimate that in the districts in which poor or minority students fare worst (the 10th percentiles on each inequality measure), the spending gap between these students and their non-poor or white counterparts is \$300 to \$500 per pupil. We also benchmark these measures against equivalent measures calculated across districts within states. While intra-district inequality between the poor and non-poor is nearly identical to the level of inter-district inequality within states, intra-district inequality exceeds inter-district inequality for black and Hispanic students relative to white students. In other words, the share of resources allocated to black or Hispanic students at the state level is greater than that allocated to black or Hispanic students at the district level.

In the third part of the paper, we examine correlates of inequality. Three features of the analysis stand out. First, the poor and Hispanic shares of school resources are greater in districts with higher family incomes; conversely, the black share of school resources is lower in districts with higher family incomes. Second, districts with more socioeconomic and racial segregation among schools allocate a greater share of school resources to poor and minority students. Third, while income inequality does not predict poor to non-poor spending inequality, racial income inequality does

[2] Berne & Stiefel (1984) provide a typology of intra-district inequality measures, distinguishing between "horizontal" and "vertical" inequality. Although we also calculated horizontal measures (e.g., the Gini coefficient), these measures are less informative for our purposes to the extent that they do not reflect spending differences between groups of students. We also considered an alternative measure, a weighted Gini coefficient, in which the per pupil weights are multiplied by a factor to account for free lunch or special-needs status. These adjustments reduce the per pupil expenditures in high-need districts, and can therefore be used to describe how vertically equitable a state's funding system is. The limitation to this approach is that the weights are arbitrary.

predict racial differences in spending: minorities receive a lower share of district resources in districts with a smaller income gap between white and minority parents.

This paper paves the way for future research on intra-district inequality. First, we have constructed a dataset with inequality measures for almost all U.S. districts. By validating the quality of the measures, researchers can draw on this dataset in future analyses. Second, we have uncovered patterns of inequality that present some puzzles. Why do poor and Hispanic students receive fewer resources relative to non-poor and white students in poorer districts? Why does a smaller income gap between white and minority residents undermine resource distribution to minority students? While our descriptive analysis does not identify the causal mechanisms that underlie these correlations, future research may be able to uncover such mechanisms. This way, the paper attempts to advance research that seeks to understand variation in educational opportunity in the United States.

2 Prior Literature

Using case studies of large urban districts like New York City, Chicago, and Baltimore, the education finance literature has gained valuable insights into the nature of within-district inequality. This literature highlights the important role that teacher choice plays in driving distribution of resources within districts. More senior and better educated teachers usually have better salaries *and* are more likely to choose schools located in wealthier neighborhoods.[3] Consistent with this expectation, teachers in high-poverty schools in large urban districts are more likely to have failed a certification exam, teach a subject outside their expertise, and be paid lower salaries (Iatarola & Stiefel, 2003; Lankford, Loeb, & Wyckoff, 2002; Roza, Hill, Sclafani, & Speakman, 2004; Rubenstein, 1998; Stiefel, Rubenstein, & Berne, 1998).

This literature has found somewhat more mixed evidence about the degree of intra-district *spending* inequality. At least in Chicago, high-poverty elementary schools have more teacher positions than low-poverty schools (Rubenstein, 1998). Thus, despite lower average teacher salaries, Rubenstein (1998) finds that total per pupil spending is higher in high-poverty schools than in

[3] Collective bargaining agreements negotiated between teachers unions and school districts often facilitate such decisions by giving more senior teachers a priority in choosing where to teach (Moe, 2011).

low-poverty schools in Chicago. Whether or not researchers have found a negative relationship between spending and poverty at the school-level also appears to depend on the type of spending measure used for analysis. For example, results differ depending on whether researchers use "general fund" or "total fund" expenditures and depending on whether federal funds are included in the analysis. See Houck (2011) for a review of the intra-district funding literature and further discussion of these issues.

To our knowledge, Heuer & Stullich (2011) provide the only large-scale study of intra-district inequality. They improve upon previous studies in two ways. First, they use school-level finance data from nearly all U.S. districts in 2008-09. Their study was facilitated by requirements put on school districts as part the American Recovery Reinvestment Act (ARRA), which mandated that all districts receiving Title 1 funds report school-level expenditures information. We draw on the same data collection effort (subsequently lead by CRDC) for data from 2011-12 and 2013-14. Second, they attempt to use a uniform measure of spending across districts, which facilitates measures of inequality that are comparable across a single expenditure dimension. In later work, Atchison et al. (2017) confirm that districts are able to accurately report spending on one such dimension, namely personnel expenditures.

Our analysis differs from that in Heuer & Stullich (2011) in several ways. While Heuer & Stullich (2011) focus on expenditure differences between Title I and non-Title schools within the same district, our measures of inequality do not discretize poverty. Rather, we rely on a continuous measure of poverty based on the share of students eligible for free or reduced-price lunch in a school. Following this logic, we are also able to construct inequality measures that capture spending differences between minority and white students. Furthermore, unlike Heuer & Stullich (2011), we validate the quality of our inequality measures using data collected from independent state sources. Our efforts to validate the inequality measures lead to the conclusion that data from 2008-09 are not reliable, and that data from 2011-12 and 2013-14 are better suited for descriptive analysis. Finally, we extend the analysis by examining district level correlates of intra-district spending inequality.

3 Data

We gather data from four sources. Our primary data for school-level expenditures are taken from the Civil Rights Data Collection (CRDC) for years 2008-09, 2011-12, and 2013-14. Beginning in 2008-09, the American Recovery and Reinvestment Act of 2009 (ARRA) required each school district receiving Title I, Part A, ARRA funds to report school-level expenditures coming from state and local revenues. The CRDC took over data collection in 2009-10; this first year was a trial year, and only a sample of schools were included in the survey. We therefore do not focus on data from 2009-10 below. The remaining years include the universe of U.S. schools. Data were ordered from the CRDC using the flat-file data request tool.

We combine these school-level spending data with district-level finance data from the National Center for Education Statistics (NCES) School District Finance Survey (the F-33). The F-33 data are audit data and provide a useful benchmark. To investigate the correlates of within district spending inequality, we combine spending data with additional sources, including: (i) demographic, segregation, revenue and expenditure information from the U.S. Department of Educations Common Core of Data (CCD); (ii) teacher experience and school discipline data from the CRDC; and (iii) economic, employment and housing information from the U.S. Census and American Community Survey (ACS). With these data, we construct district-specific measures of economic and demographic inequality, including between-school racial and income segregation, novice teacher segregation (the concentration of novice teachers in schools within districts), socioeconomic inequality, and other measures of dispersion.

3.1 Data Quality

Data quality is a known concern in school-level finance data.[4] Atchison et al. (2017) evaluate the alignment between the CRDC data we use here and school-level finance data from five states and four school districts with high-quality independent data collection systems. They find a high degree of consistency between CRDC and independent data sources for salary expenditures. Furthermore,

[4]See Denison, Hartman, Stiefel, & Deegan (2011) for a review of general challenges.

their results indicate that reported salary expenditure differences across schools within a district usually reflect true differences rather than formula-based allocations.[5] However, school districts are less successful at reporting non-personnel expenditures. For this reason, we focus our data quality tests and analyses on the personnel expenditure data from CRDC.

Our goals for ensuring data quality are somewhat different from those of Atchison et al. (2017), as we aim to construct a sample of districts that provide a plausible description of within-district inequality that preserves a large share of the U.S. student population. In other words, we aim to efficiently prune the sample to preserve as many observations as possible while discarding observations that lack validity. With this goal in mind, we take three steps: (1) we remove school-level outliers; (2) we remove districts whose aggregate district-level per pupil personnel expenditures greatly departed from the NCES F-33 district per pupil personnel expenditures; (3) we ensure that intra-district inequality measures from the CRDC correspond to intra-district inequality measures from other data sources and that any differences between the sources are not systematic.[6]

3.1.1 School Outliers

We remove school-level expenditures that are less than half the 5th percentile and greater than 1.5 times the 95th percentile of the within state (across year) per pupil personnel expenditures. This procedure is comparable to what is often done to exclude district-level expenditure outliers (e.g, Murray, Evans, & Schwab, 1998; Berry, 2007) and is preferred to the extent that inequality statistics are sensitive to extreme values. We show that intra-district inequality measures are better correlated across CRDC and Texas data using this outlier restriction. Removing school-level outliers eliminates only 0.5, 1.4 and 2.8 percent of the K-12 school population for years 2009, 2012 and 2014, respectively.

[5]Most importantly, at least in the nine sites included in Atchison et al. (2017), school-level salary expenditures were not obtained through ”salary averaging,” whereby average district salaries are multiplied by head counts (e.g., Roza, Miller, & Hill, 2005).

[6]In about 6,000 cases, the school IDs from the CRDC did not match to school IDs from the Common Core of Data (CCD) school-universe file. We were informed by CRDC staff that this was primarily due to charter schools in California not being assigned NCES school ID numbers in the CRDC. To improve data coverage, we augment the merge by using the school name (stripped of spaces and miscellaneous text) and the state two-digit FIPS code. We recover over 3,000 schools from the CRDC that did not successfully merge to the CCD school universe file.

3.1.2 Aggregate Personnel Expenditures

We then aggregate school-level personnel expenditures to the district level for each year, constructing a measure of per pupil personnel expenditures from CRDC data for each district. We then compare this variable with an equivalent per pupil personnel expenditures variable constructed from the NCES F-33 file, using the variable for total salaries.[7] The trade-off we face is between the correspondence of the two data sets and the share of students to be kept. Data visualization suggested we could identify outliers easily. To this end, we construct a district measure that is the ratio of per pupil spending from CRDC to per pupil spending from F33. We compare the share of students preserved and the enrollment weighted correlation between the CRDC and F33 per pupil expenditure measures. Ideally, we would find a frontier along which both student share and correspondence are optimized. Figure 1 summarizes results.

Insert Figure 1

Figure 1 plots enrollment weighted ρ and the share of the student population that is retained for a variety of CRDC to F33 comparisons. Marker shapes indicate within sample outlier adjustments: circles represent the entire population of districts; diamonds represent within state district-level population outlier adjustments (less than one-half the 5th percentile or greater than 1.5 times the 95th percentile of district per pupil personnel expenditures are removed from either sample); triangles represent population outlier adjustments (same adjustment but percentiles are taken from entire population). Marker colors indicate between sample outlier adjustments, which is defined as the ratio of CRDC to F33 per pupil personnel expenditures for each district. Black represents the entire population; navy represents districts dropped because the CRDC to F33 ratio is in the 1st to 99th percentile; maroon represents districts dropped because the CRDC to F33 ratio is in the 5th to 95th percentile.

Black markers all show that the correlation between CRDC and F33 is low if we do not exclude between sample outliers. We improve correlation (and keep 85 to 95 percent of student sample) by excluding districts in the 1st to 99th percentile of the CRDC/F33 ratio. For 2014, this restriction

[7] In the F-33 database, this variable is coded "Z32".

gives a correlation maximum at 0.78. The 5th to 95th percentile outlier removal lifts correlation above 0.85 for all years; this is the adjustment we prefer.[8]

3.1.3 Inequality Measures

Having placed two sample restrictions on the data—eliminating school-level expenditure outliers as well as districts for which CRDC and F33 data do not align—we generate three vertical inequality measures: poor to non-poor spending ratio, black to white spending ratio, and Hispanic to white spending ratio.

To see how these measures are generated, consider a district d with M schools and N_j students in group $j \in \{1, 2\}$, where $j = 1$ for poor, black, or Hispanic students and $j = 2$ for non-poor or white students.[9] Each school s within the district has a proportion ϕ_j of students from group j and total personnel expenditures equal to Exp.[10] The inequality measure is then calculated as follows:

$$Ineq_d = \ln\left(\frac{\dfrac{1}{N_{1d}}\displaystyle\sum_{s=1}^{M_d}(\phi_{1sd} \cdot Exp_{sd})}{\dfrac{1}{N_{2d}}\displaystyle\sum_{s=1}^{M_d}(\phi_{2sd} \cdot Exp_{sd})}\right) \tag{1}$$

where $Ineq_d$ is the inequality statistic between groups 1 (e.g., poor students) and 2 (e.g., non-poor students).[11] The numerator is equivalent to the district's poor, black or Hispanic share of per pupil personnel expenditures; the denominator is equivalent to the non-poor or white share. The ratio of the two shares characterizes the level of vertical equality in the district. Taking the natural logarithm centers this ratio on 0 and linearizes it for values of the ratio below 1. Values above 0 on the logged ratio indicate pro-poor (or pro-black/Hispanic) spending, while values below 0

[8]Additional within sample outlier adjustments impose additional trade-offs. For 2012, using the entire population that falls within the 5th to 95th percentile of the CRDC/F33 ratio is optimal (highest student share and correlation). For 2009, we can improve correlation slightly by eliminating within state outliers, but we lose many students (from 90 percent of student share to 78 percent). For 2014, we can improve correlation slightly by eliminating within state outliers, but we lose a few students. Our preference is to not remove any additional districts, preserving as many students as possible (within the 5th to 95th percentile rule) in exchange for a slight reduction in correspondence between the two data sets. The summary statistics and descriptive analyses we present in subsequent sections are not sensitive to these additional exclusion criteria.

[9]For example, for the poor to non-poor spending ratio, $j = 1$ for poor students and $j = 2$ for non-poor students.

[10]Counts and shares of student groups are taken from the Common Core of Data (CCD) school-universe survey.

[11]We construct measures for each year, but drop the subscript on year for convenience.

indicate pro-non-poor (or pro-white) spending. Th variable $Ineq_d$ gives the relative shares of per pupil spending per group (e.g., poor relative to non-poor). Throughout the essay, the variable will be referred as describing intra-district spending inequality, or poor, black or Hispanic shares of school resources. These descriptors are interchangeable.

Note that the measure will equal 0, indicating perfect spending equality, if two district characteristics are present. First, perfect equality will arise if there is no segregation between the two groups—that is, if the group shares are uniformly distributed across schools. Second, perfect equality also arises from equal spending on each school within the district (regardless of the across-school distribution of the two groups). Thus, both segregation and spending variation are necessary for the measure to deviate from 0.

3.1.4 Correspondence between CRDC and Texas Inequality Measures

As an additional quality check, we compare the inequality measures generated from CRDC data with equivalent measures generated from Texas school-level finance data. The Texas Education Agency has collected such data for several decades. We would have additional confidence in the CRDC measures if they align well with this robust data source. We collect the Texas data from Texas Public Education Information Management System (PEIMS).[12] From this dataset we use a variable for payroll expenditures, which corresponds to personnel expenditures.

In a first set of data quality tests, we calculate enrollment-weighted correlations between the CRDC and Texas inequality measures. For years 2012 and 2014, this correlation is greater than 0.8 for each of the three inequality measures. Data alignment is much worse for 2009, leading us to exclude data from this year from the substantive analysis below.[13] Scatter plots for years 2009 to 2014 are shown in Figure 2.

[12]A flat file request for PEIMS Individual Campus Financial Actual Reports was placed for overlapping CRDC years. School-level files are also available for download at `http://tea.texas.gov/financialstandardreports/`.

[13]For the poor to non-poor ratio, ρ equals 0.85 in both 2012 and 2014. For the black to white ratio, ρ equals 0.81 in both years. For the Hispanic to white ratio, ρ equals 0.85 and 0.82 in 2012 and 2014, respectively. On the other hand, for 2009, the poor to non-poor enrollment weighted ρ equals 0.25, the black-white ρ equals 0.48, and the Hispanic-white ρ equals 0.17.

Insert Figure 2

In a second set of tests, we analyze whether the (relatively minor) measurement error we observe in the comparison between CRDC and Texas inequality measures for 2012 and 2014 can be attributed to district-level characteristics. If measurement error is not correlated with observable district characteristics, then we can be more confident that the error is stochastic noise that would not bias regression estimates. To do so, for each of our inequality measures, we estimate a series of bivariate regression models of the form:

$$\Delta Ineq_d = \alpha + \beta X_d + \varepsilon_d \tag{2}$$

where $\Delta Ineq_d$ equals the CRDC inequality statistic in district d minus the Texas inequality statistic for the same district. The district covariates substituted for X in separate regressions include: enrollment; number of teachers; number of schools; number of Title 1 schools; the proportion of Title 1 students; proportion black, Hispanic and white students; proportion students eligible for free or reduced-price lunch; and per pupil finance variables (including instructional and total spending as well as revenues from local, state, and federal sources). Given 17 variables, three inequality measures, and two years, we estimate a total of 102 regressions. To make the results comparable across models, we standardize the inequality measures (before differencing them) as well as the covariates by dividing each variable by their (within-year) standard deviation. We adjust the standard errors to account for heteroskedasticity.

The parameter of interest in Equation 2 is β, which indicates how the measurement error changes given a one standard deviation increase in X.[14] If $\widehat{\beta}$ is small and statistically indistinguishable from 0 across a range of models, then we have evidence that the error is stochastic.

The results from these regressions are shown in Figures 3, 4, and 5, which plot $\widehat{\beta}$ from each regression. Somewhat remarkably, for years 2012 and 2014, we find almost no statistically significant or meaningful association between district characteristics and differences between CRDC and Texas intra-district inequality. The only variables that emerge are for the black-to-white and

[14] The parameter α gives the baseline difference between the CRDC and Texas measures, which has already been examined using the correlation analysis above.

Hispanic-to-white spending ratios in year 2014. For these outcomes and year, district enrollment, number of teachers, and number of schools are negatively correlated with CRDC/Texas differences, suggesting that CRDC under-reports spending shares on Hispanic and black students in larger districts. The predictors for the poor to non-poor ratio are never significant or systematically signed for years 2012 and 2014; the predictors for the black-to-white and Hispanic-to-white ratios are not significant in any other case.

Insert Figure 3

Insert Figure 4

Insert Figure 5

Recall that the CRDC school-revenues data are intended to *exclude* revenues from federal sources. It is not known how successful districts are at disentangling revenue sources when reporting personnel expenditures. These results suggest that they were not successful. Approximately 40 percent of federal revenues are allocated based on entitlements for Title 1 and student disabilities.[15] If districts reporting to the CRDC are successful at excluding federal aid, we would expect the CRDC poor to non-poor inequality measure to be downward biased in districts with more Title 1 schools, Title 1 students, and students qualifying for free/reduced price lunch. Moreover, since districts reporting to Texas were under no such obligation to ignore federal aid, we would expect the CRDC measure to be predictably downward biased (relative to the equivalent Texas measure) in districts with more poor students. We find no such relationship; in fact, the CRDC poor to non-poor ratio is slightly (but not remotely significantly) higher than the equivalent Texas measure in districts with more poor students.

All of these results suggest that the CRDC is not systematically under-counting personnel expenditures for poor students (even when districts are asked to do so), and that the inequality statistics generated using CRDC data closely align with alternative data sources.[16]

[15] In 2011-12, Title 1 comprised 22.2 percent of total federal revenues and IDEA comprised 17.3 percent. Data from National Center for Education Statistics Fiscal/Nonfiscal (F-33) available for download at `https://nces.ed.gov/ccd/f33agency.asp`.

[16] While it would be preferable to match the CRDC data with independent data sources from additional states, these data sources are not easily obtained.

3.1.5 Summary of Final Finance Inequality Sample

Our final analytic sample discards (1) school-level outliers, (2) district per pupil personnel expenditure outliers, and (3) data for years 2008-09 (as well as for 2009-10, the CRDC trial year). We preserve 91.2 and 91 percent of the K-12 population for years 2011-12 and 2013-14, respectively. This sample of district correlates with the F-33 with a weighted ρ of 0.87 and 0.86. The sub-sample of districts in Texas correlate at 0.86 and are not associated with the district-level characteristics we were able to evaluate.

3.2 Additional Covariates

We combine spending data with additional sources, including: (i) demographic, segregation, revenue and expenditure information from the U.S. Department of Educations Common Core of Data (CCD); (ii) teacher experience and school discipline data from the CRDC; and (iii) economic, employment and housing information from the U.S. Census and American Community Survey (ACS). With these data, we construct district-specific measures of economic and demographic inequality, including between-school racial and income segregation, novice teacher segregation (the concentration of novice teachers in schools within districts), socioeconomic inequality, and other measures of dispersion.

Predictor variables are separated into four categories: background characteristics (averages and inequalities) and school or district characteristics (averages and inequalities). For average background characteristics, we include median family income, median house price, parent education levels, geographic stability (living in the same house for more than one year), single parent households, SNAP qualification, and unemployment. These variables are taken from the American Community Survey, 2006-2010 wave, using the parent tabulation of children enrolled in public school.[17] Data are downloaded using the School District Demographic System (SDDS) Education Demographic and Geographic Estimates (EDGE).

Background inequality variables include the Gini index for parent income, the log ratio of black

[17] We use the 2006-2010 wave because this is the only ACS wave for which parent tabulations are available.

or Hispanic to white median income, and the mean to median ratio of parent income. Income inequality statistics are taken from the parent income categories from the ACS.

Average school quality characteristics are taken from the CCD or F-33 and include instructional expenditures, charter school enrollment, enrollment by ethnicity, class size, and proportion of schools within the district that are elementary or secondary.

School inequality characteristics include three measures of between school segregation (white black, white Hispanic and poor to non-poor), variation in school spending within the district (the enrollment weighted standard deviation in per pupil spending), novice teacher between school segregation, and inequalities in class sizes (by poor/non-poor, black/white and Hispanic/white) for novice and full time equivalent teachers. Between school segregation is measured as the information (entropy) index, using data from the CCD school-universe survey of enrollment counts by ethnicity and free and reduced lunch status. School spending variation is generated based on school-level personnel expenditures from the CRDC. Between school novice segregation is a measure of segregation that describes the concentration of novice teachers, in which novice teachers are defined as having two or fewer years of experience. These variables are taken from the CRDC school-level teachers file. Finally, inequality statistics in class size are analogous to spending inequality statistics, in which shares of full time equivalent teachers are allocated to student groups g. Teacher data are taken from the CRDC and ethnic enrollment counts are taken from the CCD school-universe file. Summary statistics are shown in Table 4.[18]

Table 4

[18] Specifically, the inequality statistic in class size is equal to

$$Ineq_d = \ln\left(\frac{N_{1sd} \cdot (\sum_{s=1}^{M_d}(\phi_{1sd} \cdot Teachers_{sd}))^{-1}}{N_{2sd} \cdot (\sum_{s=1}^{M_d}(\phi_{2sd} \cdot Teachers_{sd}))^{-1}}\right)$$

where the terms are the same as in Equation 1. Values greater than 0 indicate that the average student to teacher ratio for poor, black or Hispanic students is larger than that for non-poor or white students.

4 Results

We present results in three stages. First, we provide summary statistics and interpretation for the three measures of intra-district spending inequality. Our main finding is that there is no evidence that districts *on average* under-allocate personnel expenditures to disadvantaged students. The enrollment weighted means for the three inequality measures are between 0.01 and 0.02 for all years. However, variation among districts (primarily within states) is substantial, as average per pupil spending on the poor, blacks or Hispanics is \$300 to \$500 less than the non-poor or whites in the least equitable districts.

Second, we estimate bivariate regression models to determine whether and to what extent district characteristics predict intra-district spending inequality. In general, in districts with greater socioeconomic status, per pupil instructional expenditures and socioeconomic and racial segregation students who are poor, black or Hispanic tend to receive a *greater* share of school resources than non-poor or white students. While the poor to non-poor spending ratio is not predicted by parent income inequality, the black and Hispanic to white spending ratio is negatively predicted by black/Hispanic income inequality, meaning that black and Hispanic shares of school resources tend to be lower in districts where relative black and Hispanic parent income is greater.

Finally, in order to explore heterogeneity in the data, we estimate multivariate regression and models with interactions. After controlling for all predictors, the poor, black and Hispanic school resource shares are greater in districts with more segregation and income inequality. Interaction models indicate that racial segregation is an important predictor of greater black and Hispanic resource shares: across all income and racial income inequality quintiles, relative spending for black and Hispanic students is greatest in the most segregated districts.

We now turn to the summary of these results.

4.1 Summary Statistics

We begin our analysis of vertical inequality in U.S. school districts by providing descriptive statistics for our three inequality measures: the (logged) poor to non-poor spending ratio, black to white spending ratio, and Hispanic to white spending ratio. Means, standard deviations, quantiles, and between and within state standard deviations for each year in the data are provided in Table 1.[19]

Table 1

We find no evidence that districts *on average* under-allocate personnel expenditures to disadvantaged students. The enrollment weighted means for the three inequality measures are between 0.01 and 0.02 for all years. There is meaningful variation across districts, however, and this variation primarily from within states.

Table 2 translates this variation into dollar terms. For each decile of the inequality measures, we estimate spending on each group comprising the measure (e.g., poor versus non-poor students). The table shows that the least equal (decile 1) districts spend about \$400 to \$500 less per pupil on poor, black and Hispanic students. In the most vertically equal (decile 10) districts, poor and minority students receive \$300 to \$500 more. Lafortune, Schanzenbach, & Rothstein (2016) estimate that \$400 per pupil and per year purchases about 0.01 standard deviations of achievement per year, which can translate into meaningful boosts to learning over several years of elementary and secondary schooling.

Table 2

To benchmark these descriptive statistics, we calculate $Ineq_f$ in state f for years 2012 and 2014, with summary statistics in Table 3. The unweighted and weighted *inter*-district poor to non-poor ratio is nearly identical to the *intra*-district poor to non-poor ratio in both years, ranging between 0 to 0.01. Likewise, variation across states is very similar to variation across districts (σ between 0.05 to 0.06 for the intra-district measure and 0.03 to 0.04 for the inter-district measure).

The black-white spending ratio, on the other hand, is greater between districts than within.

[19] In the Appendix, we also show maps of the inequality measures for each district for which we have data (dropping the 25 largest and smallest values for visualization purposes). See Figures B.1–B.3.

The mean black-white ratio is between 0.04 to 0.06 for inter-district spending, or about 5 percent higher; the mean black-white ratio is between 0 and 0.02 for intra-district spending, or only about 1 to 2 percent higher. Hispanic shares are lower for intra-district spending as well (between -0.01 to 0.01 for intra-district spending and between 0.02 to 0.03 for inter-district spending).

4.2 Bivariate Regressions

To find out what district characteristics predict greater or less intra-district spending inequality, we first estimate bivariate regressions of the form:

$$Ineq_{dt} = \beta X_{dt} + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt} \tag{3}$$

where d indexes district, f state, and t year. $Ineq_{dt}$ is one of the three inequality measures for district d in year t. This measure is regressed on each variable in Table 4 in separate regressions that also account for state and year fixed effects (λ_f and γ_t). The fixed effects effectively restrict the analysis to cross-sectional within-state comparisons.[20] We adjust the standard errors for heteroskedasticity.

In all models we standardize the independent variables to have mean 0 and standard deviation 1 to facilitate comparisons across different coefficient estimates.

Our main results are described in Figure 6, which plots point estimates and the 95% confidence interval from separate bivariate regression models with standardized variables. Point estimates greater than zero indicate a positive association between the predictor and greater allocations of personnel expenditures to poor, black, or Hispanic students relative to non-poor or white students. Panel (1) plots results for the poor to non-poor ratio, Panel (2) plots results for the black to white ratio, and Panel (3) plots results for the Hispanic to white ratio.

For poor to non-poor inequality, depending on one's priors, many of the bivariate correlations

[20] In models not show, excluding state fixed effects has very little impact on estimated coefficients. The limited impact of state fixed effects is not that surprising, given that Table 1 shows that nearly all of the variation in $Ineq_{dt}$ is within states.

appear counter-intuitive. There is a consistent positive association between district socioeconomic status and increased expenditures on poor students. In other words, richer districts (and those districts with greater per pupil expenditures) tend to spend more of their resources on poor and minority students. Conversely, we see that in districts with lower socio-economic status—as indicated by the proportion of parents with a high school diploma or less—poor students receive less.

Looking at district and school resource inequality predictors, we see little evidence that intra-district income inequality is correlated with intra-district spending inequality. Conversely, socioeconomic segregation positively correlates with the poor to non-poor spending gap, meaning that in districts with greater concentration of poor students in schools, those poor students receive a greater district share of resources. Class size variables are less informative but do provide a type of sanity check on the estimates. In districts where there are more poor students per teacher than non-poor students per teacher, personnel expenditures are smaller for poor students.[21]

For spending inequality among racial groups, most of the associations between the predictors and black/Hispanic to white spending ratios are similar to those of poor to non-poor spending ratios. On average, the Hispanic to white spending ratio is greater in districts with more income and educated adults. In districts with greater per pupil spending, spending on black and Hispanic students is greater. In districts with greater socioeconomic and racial segregation, spending on black and Hispanic students relative to whites is also higher (more so for blacks).

Three divergent patterns are worth highlighting. The first is that, while there is a clear pattern between district socioeconomic status and Hispanic to white spending inequality (a pattern that aligns with the relationship for poor to non-poor spending inequality), there is an ambiguous relationship between black to white spending inequality and socioeconomic status. In districts with greater proportions of educated adults and larger house prices, the black share of expenditures is greater; however, in districts with more single parent households, SNAP recipients and unemployed adults (in other words, in places that are more disadvantaged), the black share is also

[21] This relationship is almost necessarily true, given the spending measure is for personnel and the majority of personnel expenditures is used for teachers.

greater. The correlation between median family income and black to white spending inequality is negative. These conflicting relations suggest that the bivariate correlations are picking up different samples of districts.

The second is the logged median income difference between blacks/Hispanics and whites. Unlike the poor to non-poor measure, which found no relationship between income inequality and spending inequality, here we see that in districts with greater black or Hispanic to white income inequality the black or Hispanic share of district resources is lower. In other words, as black/Hispanic shares of parent income increase, black/Hispanic shares of district resources decrease. The relationship between intra-district income inequality and intra-district spending inequality better tracks racial differences than socioeconomic differences alone.

Third, in districts with larger white shares of students, the black share of resources is smaller; analogously, in districts with larger black shares of students, the black share of resources is smaller. This demographic association is not observed for the other intra-district inequality variables.

Figure 6

To provide some context for these bivariate relationships, we also present predicted per pupil dollar amounts for the different groups G (poor, non-poor, black, Hispanic and white) using a selection of covariates from the bivariate regression models that were statistically significant at p-value$\leq$.05. Predicted per pupil expenditures (PPE) for group G are derived from $\widehat{Ineq_{dt}}$ in equation $Ineq_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Per pupil expenditures for non-poor or white students are derived from from $\widehat{Y_{dt}}$ in equation $Y_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where Y_{dt} is non-poor or white per pupil expenditures (the denominator of $Ineq_{dt}$) and values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Mean poor, black or Hispanic per pupil expenditures are then equal to $e^{\widehat{Ineq_{dt}|X_{10,90}}} \times \widehat{Y_{dt}|X_{10,90}}$, i.e. the exponentiated $Ineq_{dt}$ times the predicted mean per pupil expenditures for non-poor, black or Hispanic students. Confidence intervals are calculated using the delta method and 95% confidence intervals are shown in parentheses.[22]

[22]Predicted values estimated using Stata margins command.

One of the key take-aways from these tables is that, while the correlations identified in Figure 6 are statistically significant, the magnitudes of the correlations are modest. This means that across most of the range of X, values of $Ineq_{dt}$ vary slightly. This can be seen in Table 5. One of the largest predictors of poor to non-poor spending differences was average per pupil instructional expenditures (PPE). At the 10th percentile of PPE, where we would expect $Ineq_{dt}$ to be smallest, average non-poor spending is about \$30 less than poor spending. At the 90th percentile, where we would expect the poor share to be greatest, average non-poor spending is about \$147 dollars less than poor spending. Thus, across nearly the entire range of X, the difference in spending is slightly over \$100. That range is typical for most of the variables included for the poor to non-poor ratio. Note that these values are taken from bivariate regressions, and we would obtain a wider range of predicted values with additional covariates.

Table 5

In Table 6, we present predicted spending for black to white inequality. As expected, relative black spending is lower in low income (10th percentile median family income) and predominantly white (90th percentile proportion white) districts, although in both cases predicted black spending still exceeds predicted white spending. It is worth emphasizing the relative importance of racial segregation as a positive predictor of black to white spending differences. In districts with high levels of segregation (90th percentile), predicted black spending is \$195 higher than predicted white spending; in districts with low levels of segregation, predicted black spending is only \$4 higher.

Table 6

Table 7 shows predicted spending for Hispanic to white inequality. Segregation is again the largest predictor of spending differences. In the most segregated districts, Hispanic spending is \$83 larger than white spending, and in the least segregated districts, Hispanic spending is only \$8 larger.

Table 7

These descriptive patterns present some puzzles. In general, many of the relationships between

predictor variables and intra-district spending inequality are similar for poor to non-poor, black to white and Hispanic to white spending. However, there is a positive association between district income and poor to non-poor and Hispanic-white spending inequality and a negative association between district income and black-white spending inequality. What accounts for this reversal?

Second, as background, black- and Hispanic-white income inequality are positively correlated with district family income, whereas black- and Hispanic-white segregation are negatively correlated with district family income.[23] However, while Hispanic-white spending inequality is positively predicted by district income, it is negatively predicted by Hispanic-white income inequality and positively predicted by Hispanic-white segregation (these relationships should be reversed). Conversely, black-white spending inequality is negatively associated with district income, but the relationship for black to white income inequality and segregation mimics that of Hispanic to white spending inequality. It therefore remains unclear what dimensions of district resources, segregation and income inequality are most influencing spending inequality.

4.3 Multivariate Regressions

We attempt to disambiguate these relationships in two ways. First, we estimate multivariate regression models that include an entire vector of district characteristics as well as interactions—that is, replacing βX_{dt} above with $\boldsymbol{X}_d^{'}\beta$ where $\boldsymbol{X}$ and β now are column vectors of district characteristics and coefficients, respectively. Second, we test for interactions between (1) segregation and parent income, (2) segregation and income inequality and (3) parent income and income inequality.

We divide socioeconomic and racial segregation, median family income and socioeconomic and racial income inequality (measured by the Gini index and log black to white median income ratio, respectively) into quintiles. We then estimate three models: in the first, we regress the variable $Ineq_{dt}$ against the income-segregation interactions (of which there are 25), controlling for income inequality. In the second, we regress $Ineq_{dt}$ against the income inequality-segregation

[23]The enrollment weighted correlations for black- and Hispanic-income inequality and district income are 0.055 0.001, respectively. The corresponding correlations between segregation and family income are -0.105 and -0.98, respectively. Segregation also negatively associated with black and Hispanic income inequality, at -0.059 and -0.099, respectively.

interactions (of which there are 25), controlling for median family income. In the third, we regress $Ineq_{dt}$ against the income-income inequality interactions (of which there are 25), controlling for segregation. Each model additionally controls for year and state fixed effects. We can then generate contour plots that map variation in spending inequality among socio-demographic regions. We show the estimated 25 coefficients for the poor to non-poor and black/Hispanic to white spending inequality variables separately.

Results for multi-variate regressions are shown in Figure 7. Even after controlling for all of the predictors from Table 4, the primary relations persist, albeit with additional imprecision. For both black- and Hispanic-white spending inequality, the signs and approximate magnitudes for logged income differences and between school segregation are equivalent. For black to white spending inequality, demographic composition loses importance, whereas for Hispanic to white spending inequality, these demographic variables (especially proportions white and black) gain in significance. Finally, the relationship between district income and spending inequality is now negative for both black- and Hispanic-spending shares. In sum, multivariate regressions confirm the relative consistency of some of these findings: income inequality negatively predicts black and Hispanic resource share, whereas district segregation positively predicts black and Hispanic resource share. We now turn to interactions.

Figure 7

Figures 8, 9 and 10 allow us to compare relative black- and Hispanic resource shares along two dimensions. Panel A shows estimated interactions across income inequality-by-segregation quintiles, net of income levels. Panel B shows estimated interactions across income-by-segregation quintiles, net of income inequality. Panel C shows estimated interactions across income-by-income inequality quintiles, net of segregation.

Figure 8 Panel A shows interactions between income inequality and socioeconomic segregation, net of income levels. Income segregation is a consistent positive predictor of poor resource share. However, the relationship is not monotonic. At the low end of socioeconomic segregation, relative poor spending is higher than in the middle of the distribution. There is little variation ver-

tically in Panel A, indicating that income inequality is not predictive. Panel B plots segregation by income level interactions, net of income inequality. Again, segregation dominates the plot, but the middle of the distribution has lower poor spending than the lower part of the distribution. In general, higher income districts have greater poor to non-poor spending.

Panel C shows that in the districts with the most income and income inequality (top right quadrant), relative poor spending is greatest. The poor share is generally smallest in the lowest income districts, irrespective of income inequality.

Figure 8

Figure 9 Panel A shows interactions between black to white income inequality and segregation, net of income levels. Segregation consistently positively predicts black resource share. In general, there is little variation among racial income inequality quintiles, conditional on segregation quintile. Panel B shows interactions between family income levels and racial segregation, net of black to white income inequality. Once again, segregation consistently positively predicts black resource share. As seen in bivariate regressions, there is lower black to white spending in areas with greater family income; however, this relationship is not monotonic. Black to white spending is lower in regions with low segregation; in regions with moderate segregation (segregation quintiles 2 and 3), black to white spending inequality is similar across income levels.

Panel C provides a partial explanation for the negative relationship between black to white parent income and black to white spending differences. In the bottom right quadrant, black to white income is highest but overall income is lowest. In these districts, black to white spending is relatively high. However,in other cases, when black to white spending is lowest (quintile 1 of income inequality), black to white spending is also high, and becomes higher as district income increases. Conversely, in the upper right quadrant with the largest income and greatest black to white income ratio, the black to white spending ratio is lowest.

Figure 10

Figure 10 plots the same estimated interactions for Hispanic to white spending inequality. The consistent pattern to emerge in Figure 10 corresponds to what was observed for black to white

spending inequality: in districts with greater racial segregation, the Hispanic to white spending ratio is greater, irrespective of racial income inequality and family income. Panel A shows that racial segregation is heavily influential; segregation quintiles 4 and 5 have the largest Hispanic share of school spending. Variation among income inequality quintiles is limited, although there is a concentration of greater Hispanic spending ratios when relative white income is highest (income quintiles 1 to 4).

In contrast to black to white spending inequality, Panel B shows Hispanic to white spending is greatest in districts with more segregation and greater family income (segregation and income quintiles 5). Moreover, there is meaningful patterning across income quintiles: in the highest income districts, the Hispanic to white spending ratio is consistently higher. In general, relative Hispanic spending tends be to be higher in more segregated or richer districts, and in the most segregated and richest districts the share is greatest.

Panel C shows that Hispanic to white spending is highest in the richest districts where relative Hispanic income is lowest (income quintile 5 and income inequality quintiles 1 to 3).

Figure 9

5 Discussion

In this paper we have presented results from new data about the magnitude, distribution and correlates of intra-district spending inequality for nearly all districts in the United States. We have shown that a reliable sample of data can be obtained with only minor pruning, preserving observations that cover over 91 percent of the K-12 student population.

Our primary result is that average intra-district inequality is nearly zero for years 2012 and 2014. Variation among districts is non-trivial; in districts with the most intra-district inequality, the poor receive up to $500 less per pupil than the non-poor. The intra-district poor to non-poor share is nearly identical to the inter-district poor to non-poor share. However, we find evidence that intra-district relative black and Hispanic shares of school spending are lower than what would be expected based *inter*-district allocations.

District socioeconomic status positively correlates with poor to non-poor and Hispanic to white spending inequality, meaning that higher income districts spend a greater share of their resources on poor and Hispanic students, relative to non-poor and white students. Conversely, district socioeconomic status negatively correlates with black to white spending inequality. Three measures of between school segregation–socioeconomic, white black and white Hispanic–all positively correlate with each measure of spending inequality, meaning that poor, black and Hispanic shares of school resources are greater in more segregated districts. District income inequality is not correlated with poor to non-poor spending inequality. However, district racial income inequality, measured as the logged difference in black/Hispanic and white median income, is negatively correlated with spending inequality, meaning that in districts with greater income disparity between ethnic groups, the black and Hispanic school resource share is smaller.

These patterns are largely robust when we include multiple variables, although the positive relationship between district income and relative poor and Hispanic school resource shares attenuates to zero, likely due to the inclusion of multiple highly correlated variables. Parent education, especially in districts with larger proportions of adults with a high school degree or lower, is consistently negatively associated with spending inequality, suggesting that districts with more uneducated adults, the poor, black or Hispanic resource share is lower. Finally, looking within income or income inequality quintiles, there is a consistent pattern showing positive relationships between segregation and relative poor, black and Hispanic resource share. While it is mechanically necessary for there to be a correlation between between school segregation and our measure of spending inequality, the direction of that correlation was not preordained. Why districts with greater segregation tend to be those that spend a greater share of resources on disadvantaged students is an important question for further research.

Finally, we emphasize that the purpose of the paper is not normative; we make no claim about what the appropriate allocation of resources should be. Instead, the paper serves as an accounting tool, allowing researchers and policy makers to determine whether allocations to students are meeting normative and policy objectives.

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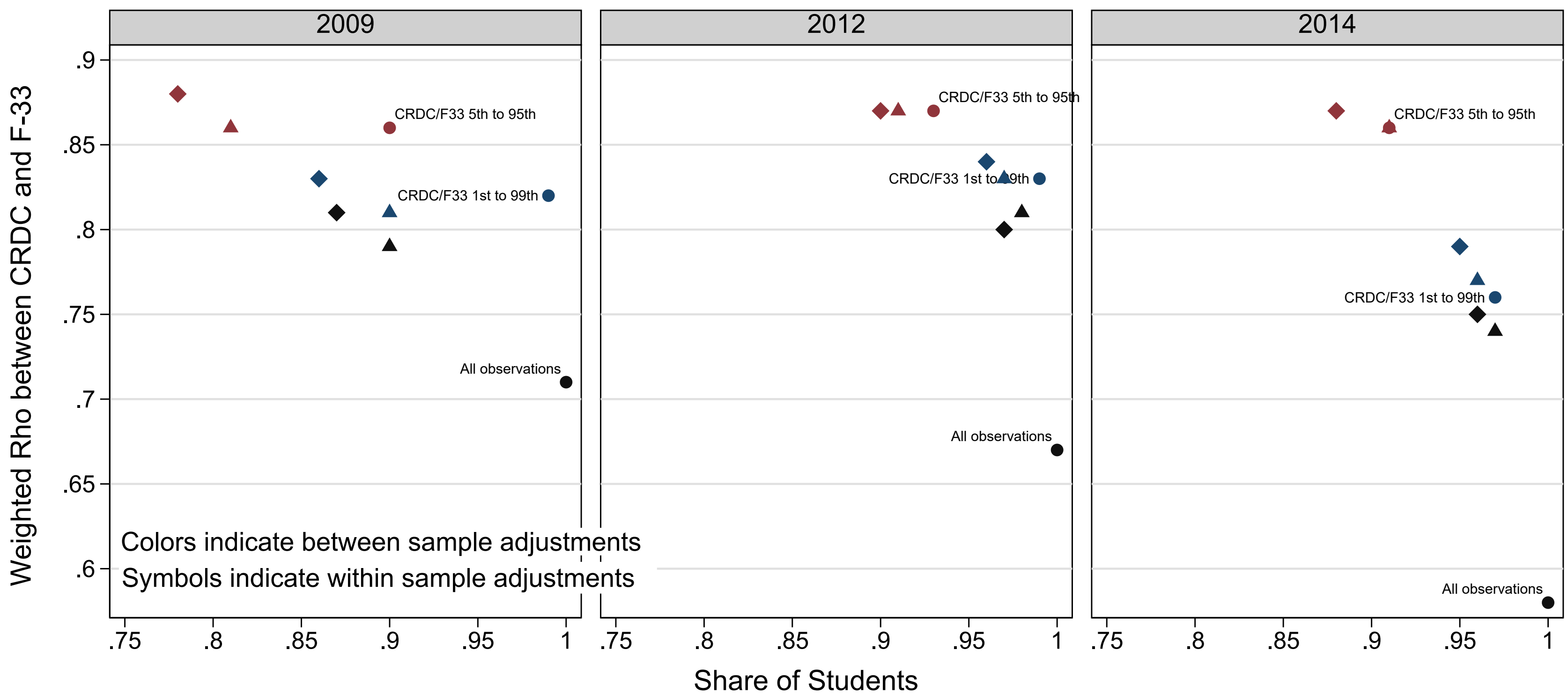
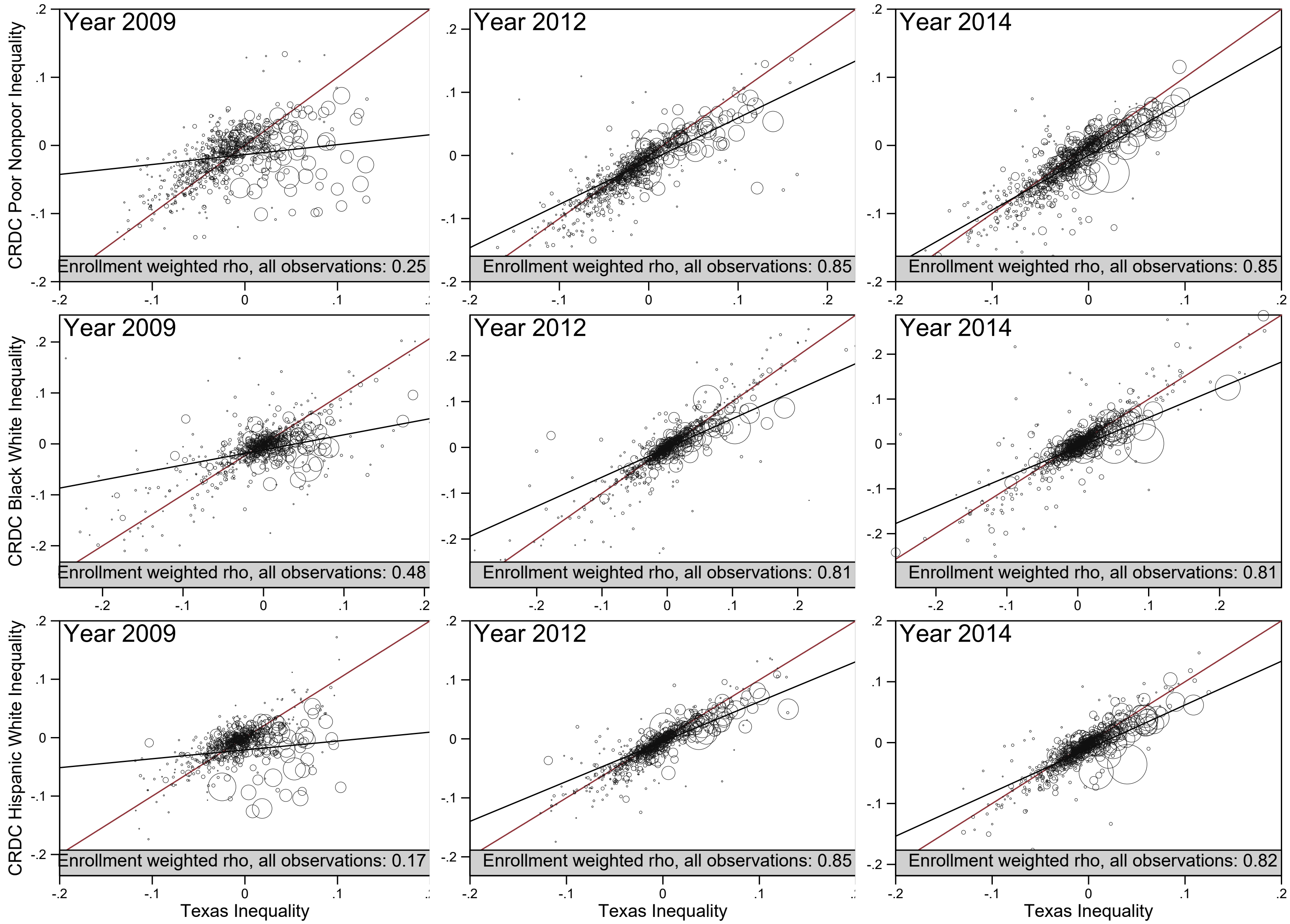
Figures

Figure 1: CRDC & F33 Data Alignment, by Year



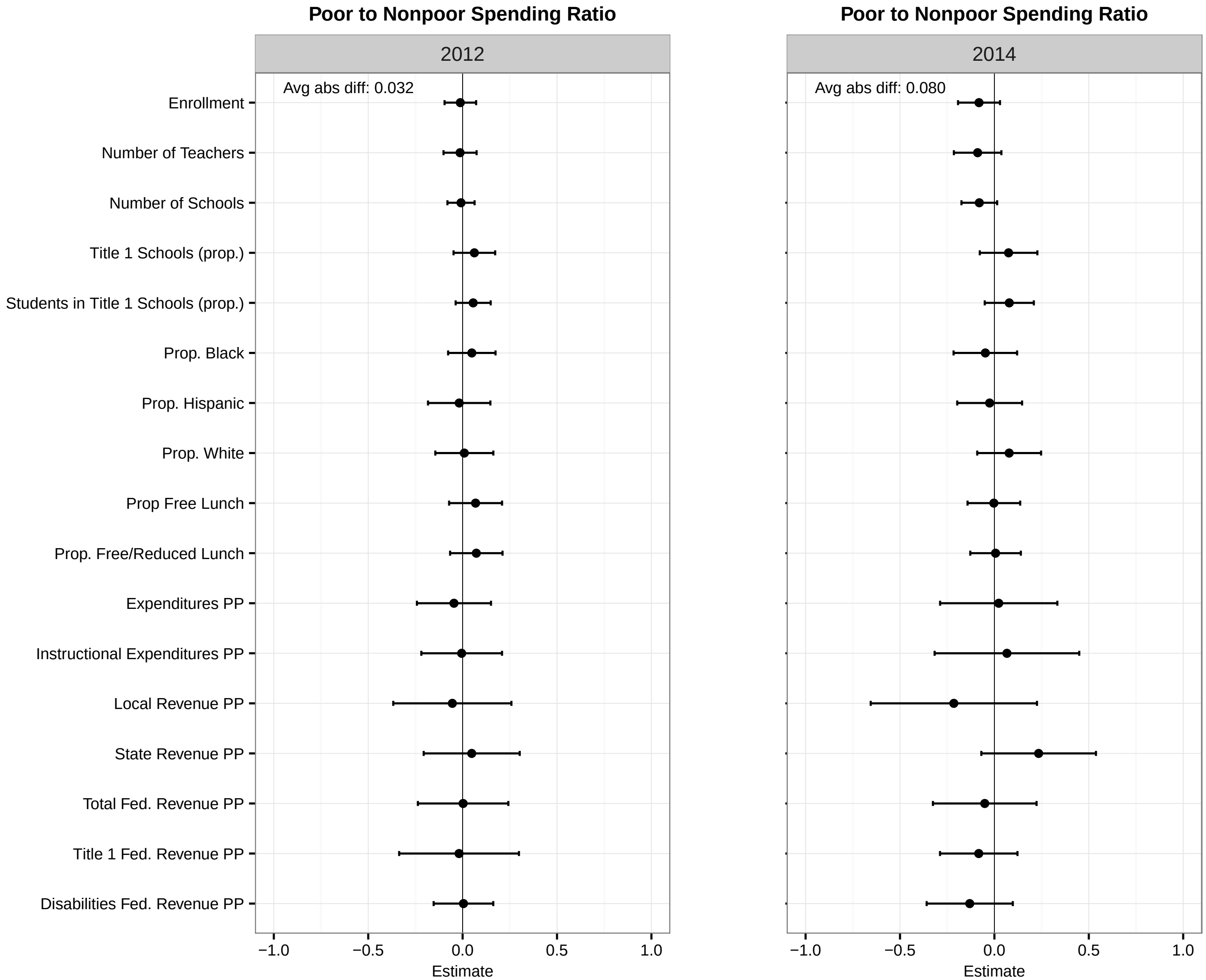
Within data outliers: Circle all obs; Diamond within state district outliers dropped; Triangle population outliers dropped.
Between data outliers: Black all obs; Navy CRDC/F33 1st to 99th percentile; Maroon CRDC/F33 5th to 95th percentile

Figure 2: CRDC & Texas Inequality Alignment, by Year & Inequality Statistic



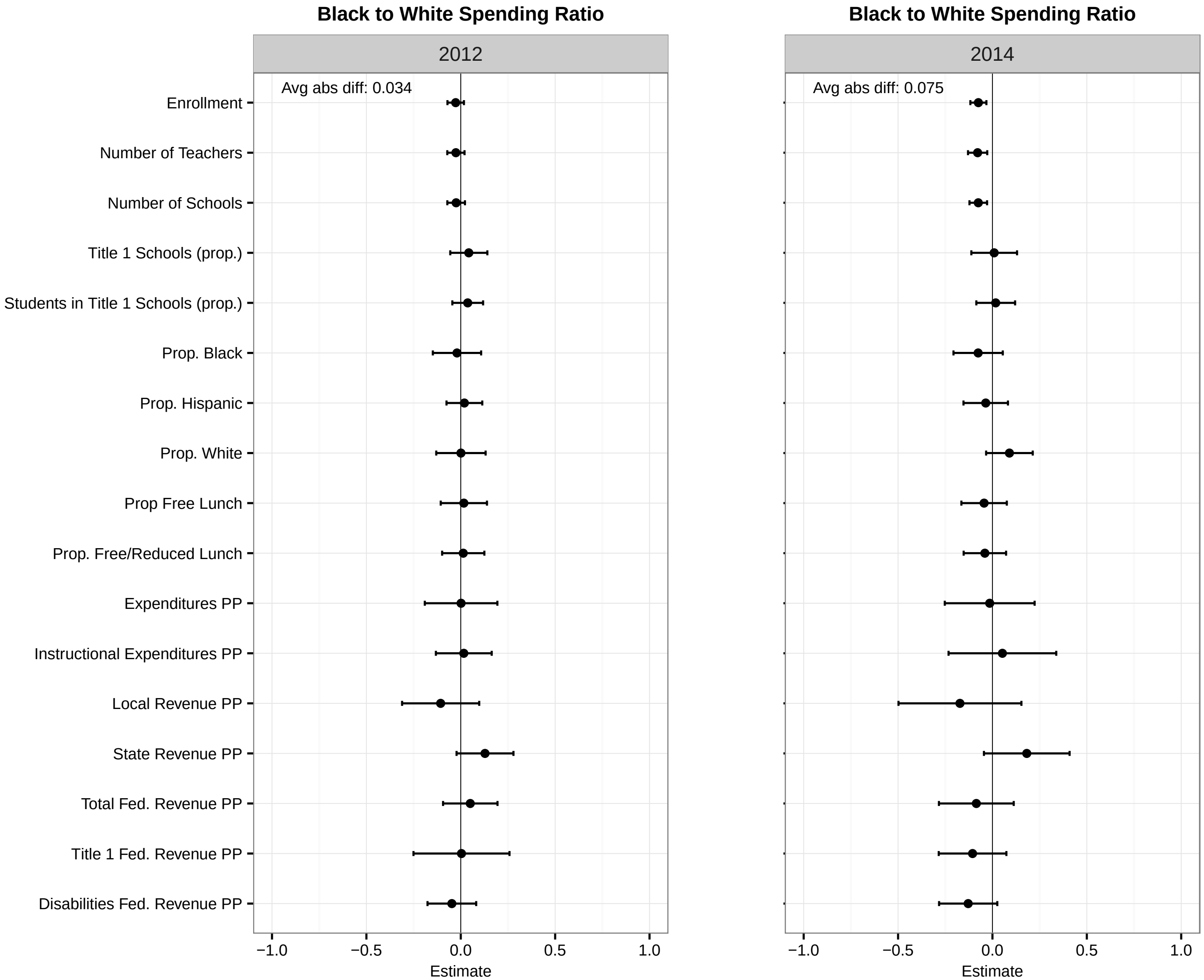
Plotted data exclude outliers beyond 1st to 99th percentile for CRDC and Texas data. This adjustment was done purely for data visualization. Reported enrollment weighted correlation coefficients exclude only specified restrictions: school-level per pupil expenditures outside the within state one-half 5th percentile and 1.5 times 95th percentile, and the CRDC/F33 outlier values. 45-degree line shown in maroon; enrollment weighted fitted regression line in black.

Figure 3: Predictors of CRDC & Texas Data Alignment: Poor to Non-poor



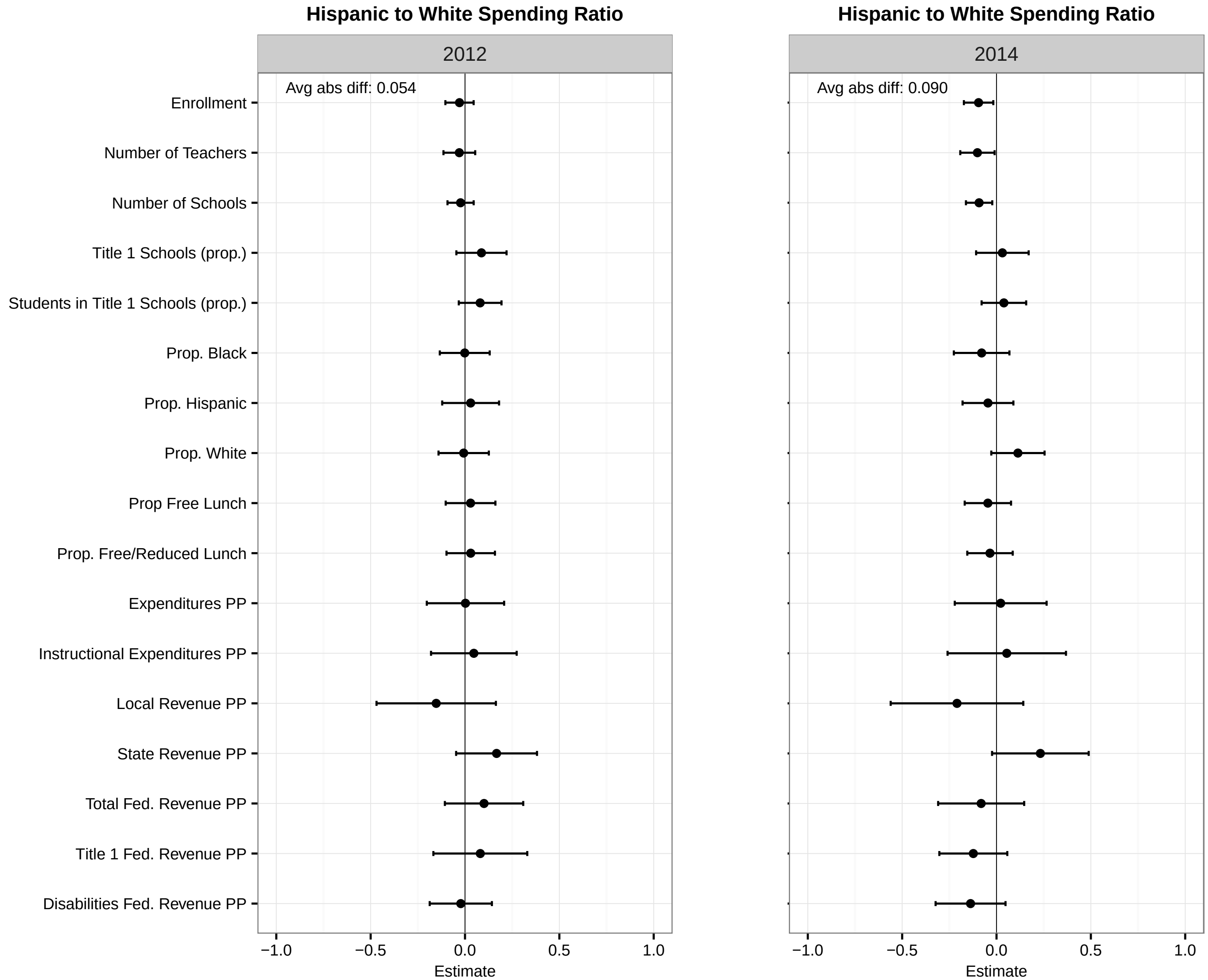
Notes: The dependent variable is $\Delta Ineq_{dt}$, where $Ineq$ is the poor to non-poor spending ratio and the Δ is CRDC minus Texas. Covariates and dependent variable have been standardized. Average absolute deviation (ADD) is the mean of the absolute value of the coefficients; weighted ADD is the same statistic weighted by the inverse of the variance of the coefficients. Coefficients are estimated from a series of enrollment weighted bivariate regressions.

Figure 4: Predictors of CRDC & Texas Data Alignment: Black to White



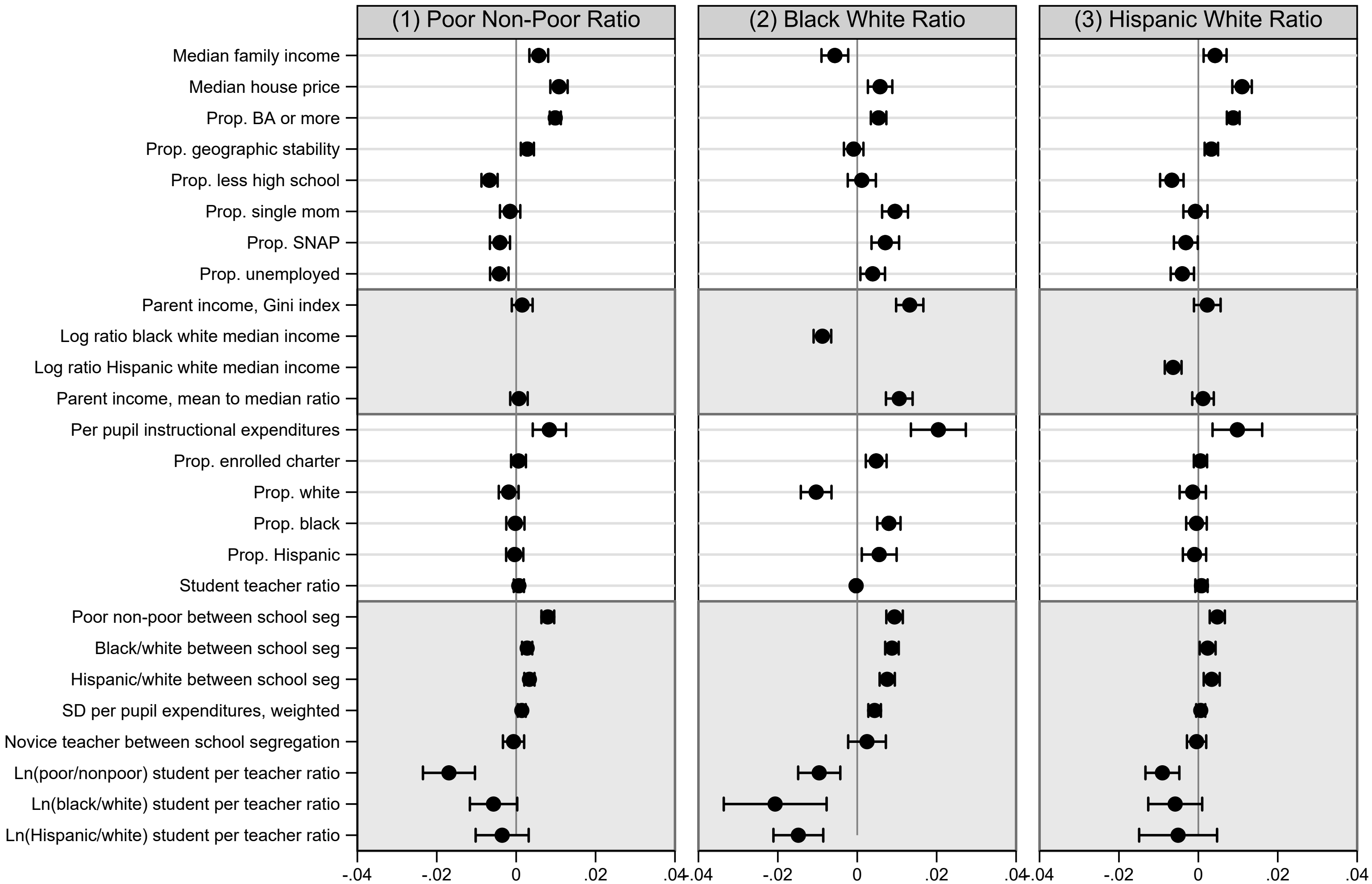
Notes: The dependent variable is $\Delta Ineq_{dt}$, where $Ineq$ is the black to white spending ratio and the Δ is CRDC minus Texas. Covariates and dependent variable have been standardized. Average absolute deviation (ADD) is the mean of the absolute value of the coefficients; weighted ADD is the same statistic weighted by the inverse of the variance of the coefficients. Coefficients are estimated from a series of enrollment weighted bivariate regressions.

Figure 5: Predictors of CRDC & Texas Data Alignment: Hispanic to White



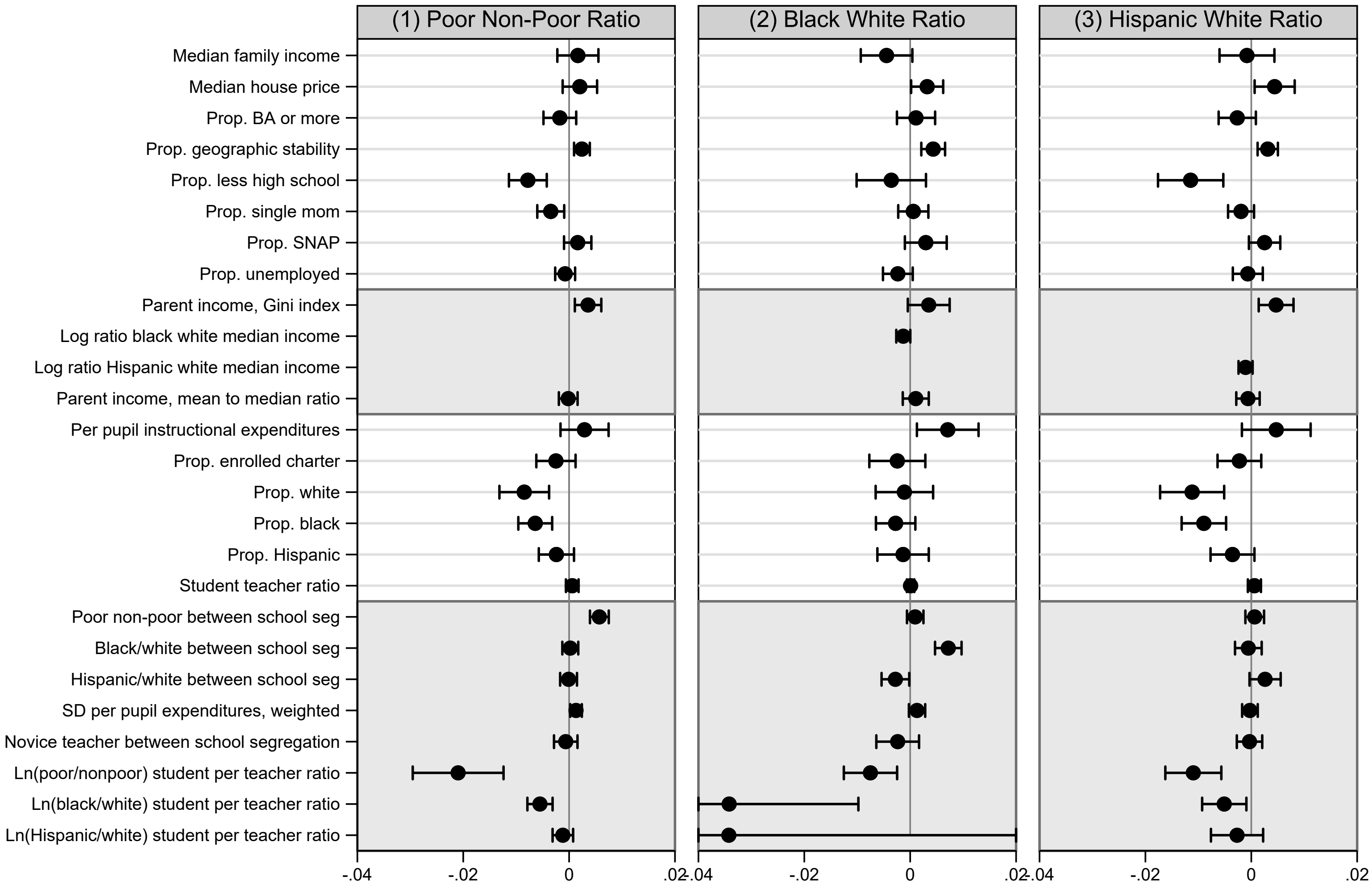
Notes: The dependent variable is $\Delta Ineq_{dt}$, where $Ineq$ is the Hispanic to white spending ratio and the Δ is CRDC minus Texas. Covariates and dependent variable have been standardized. Average absolute deviation (ADD) is the mean of the absolute value of the coefficients; weighted ADD is the same statistic weighted by the inverse of the variance of the coefficients. Coefficients are estimated from a series of enrollment weighted bivariate regressions.

Figure 6: Bivariate Regressions of Intra-District Spending Inequality, 2011-12 to 2013-14



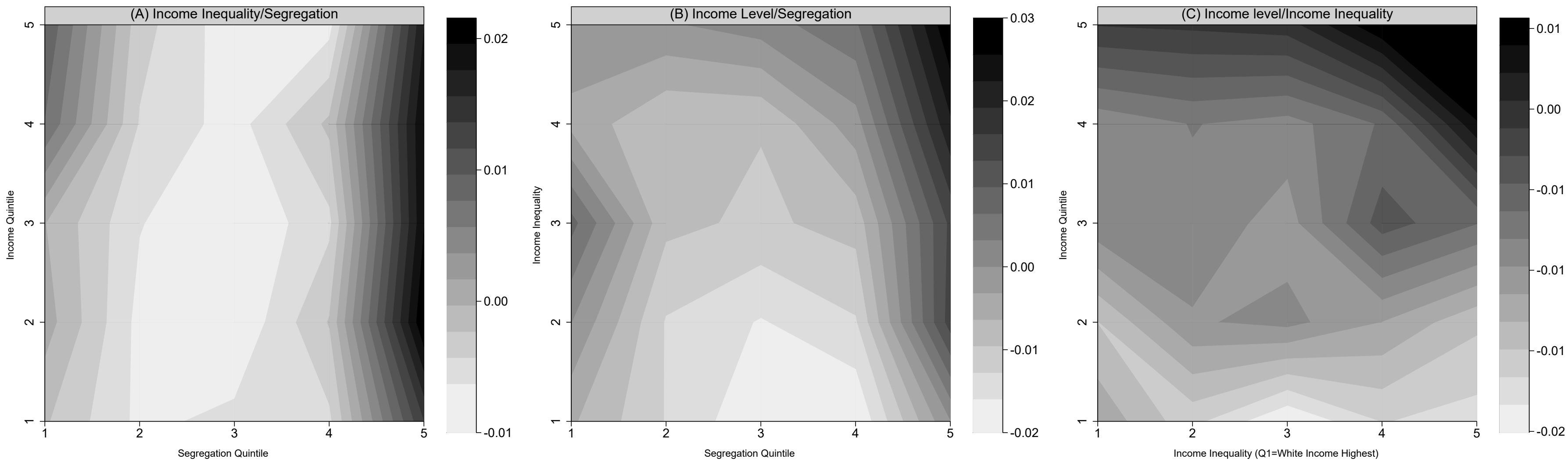
Notes: Model includes state and year fixed effects; robust standard errors. Beta coefficients and 95% confidence interval shown for bivariate regression models on standardized **X**. Shaded regions indicate predictor categories from Table 4. Analytic sample for poor to non-poor ratio is 16,347 districts, for black to white ratio is 9,693, for Hispanic to white ratio is 12,993. Additional sample restrictions limit districts to those with: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

Figure 7: Multivariate Regressions of Intra-District Spending Inequality, 2011-12 to 2013-14



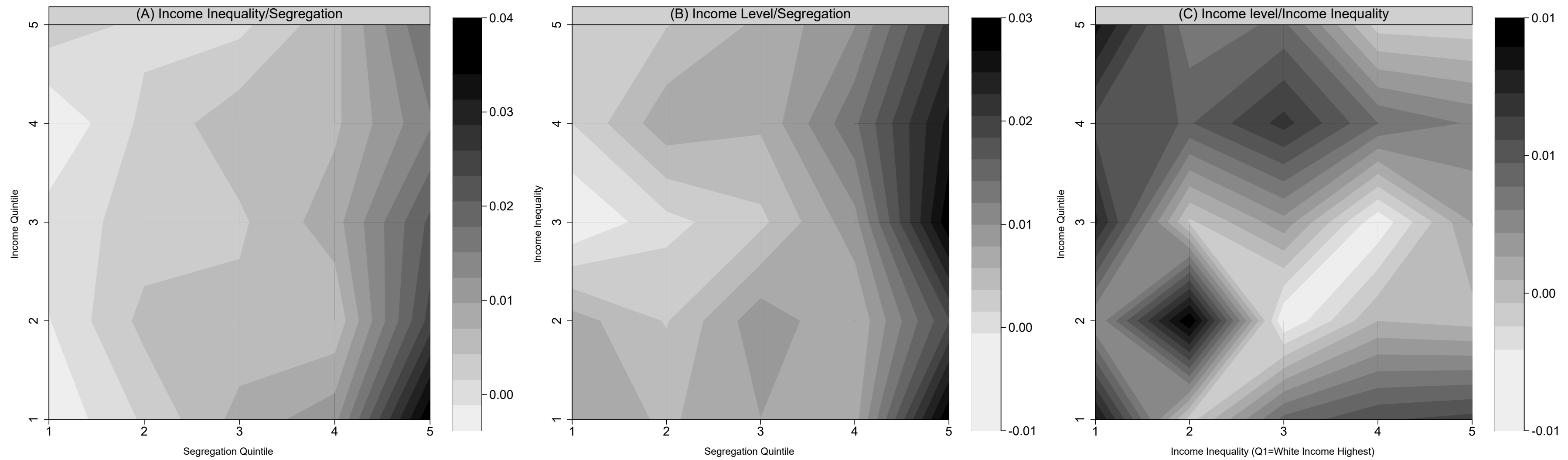
Notes: Model includes all variables from Table 4., as well as state and year fixed effects; robust standard errors. Beta coefficients and 95% confidence interval shown for multivariate regression models on standardized **X**. Shaded regions indicate predictor categories from Table 4. Analytic sample for poor to non-poor ratio is 16,347 districts, for black to white ratio is 9,693, for Hispanic to white ratio is 12,993. Additional sample restrictions limit districts to those with: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles. For visualization purposes, we trim the lower bound confidence interval on the variables black and Hipsanic white student teacher ratios for the black to white inequality measure.

Figure 8: Poor to Non-poor Intra-District Spending, Income and Segregation Interactions, 2011-12 to 2013-14



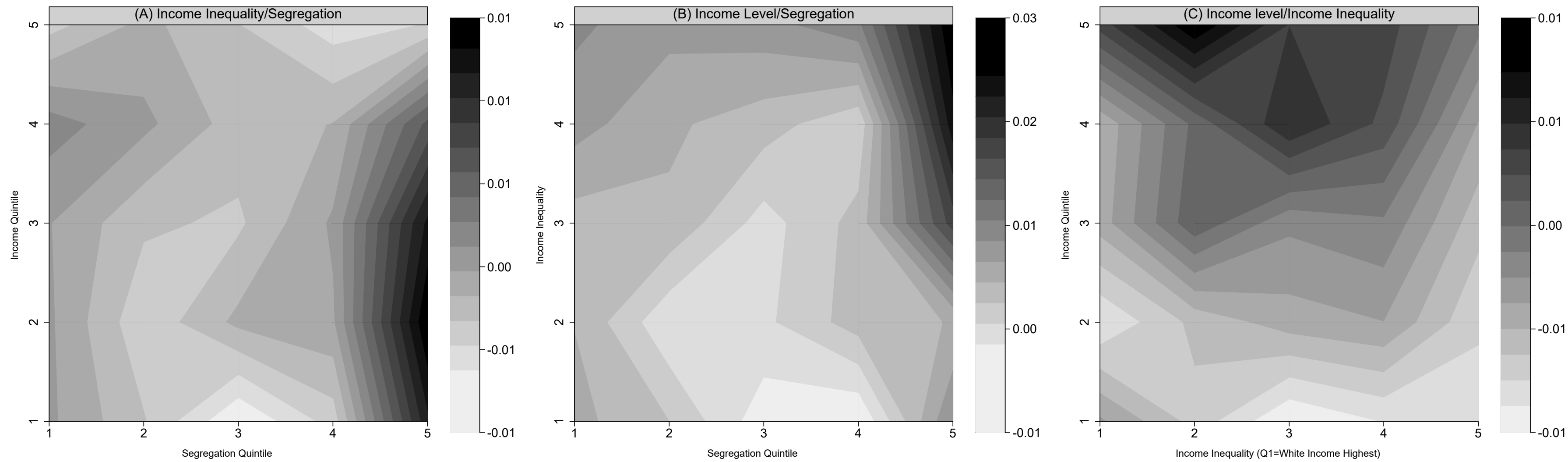
Notes: Model includes state and year fixed effects; robust standard errors. Beta coefficients correspond to interactions of white Hispanic between school segregation quintiles (Q1 = least segregated) and, in panel 1, parent income inequality (Q1 = lowest inequality) and, in panel 2, median family income. Analytic sample is 16,347 district-years. Additional sample restrictions limit districts to those with: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

Figure 9: Black to White Intra-District Spending, Income and Segregation Interactions, 2011-12 to 2013-14



Notes: Model includes state and year fixed effects; robust standard errors. Beta coefficients correspond to interactions of white black between school segregation quintiles (Q1 = least segregated) and, in panel 1, black to white income inequality (Q1 = highest white income) and, in panel 2, median family income. Analytic sample is 9,693 district-years. Additional sample restrictions limit districts to those with: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

Figure 10: Hispanic to White Intra-District Spending, Income and Segregation Interactions, 2011-12 to 2013-14



Notes: Model includes state and year fixed effects; robust standard errors. Beta coefficients correspond to interactions of white Hispanic between school segregation quintiles (Q1 = least segregated) and, in panel 1, Hispanic to white income inequality (Q1 = highest white income) and, in panel 2, median family income. Analytic sample is 12,993 district-years. Additional sample restrictions limit districts to those with: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

Tables

Table 1: **Intra-district Inequality, Summary Statistics**

	Unweighted						Enrollment Weighted						
Variable	Mean	SD	Q_{10}	Q_{90}	σ_{btw}	σ_{within}	Mean	SD	Q_{10}	Q_{90}	σ_{btw}	σ_{within}	N
<u>Panel A</u>: 2011-2012													
poor to non-poor ratio	0	0.06	-0.05	0.04	0.01	0.05	0.02	0.05	-0.03	0.07	0.00	0.04	9,931
black to white ratio	0.00	0.09	-0.06	0.07	0.01	0.09	0.02	0.05	-0.02	0.07	0.00	0.05	9,336
Hispanic to white ratio	-0.01	0.07	-0.06	0.04	0.01	0.05	0.01	0.04	-0.03	0.06	0.00	0.04	9,830
<u>Panel B</u>: 2013-2014													
poor to non-poor ratio	0.00	0.06	-0.05	0.04	0.01	0.06	0.01	0.04	-0.03	0.06	0.00	0.04	9,857
black to white ratio	0.00	0.09	-0.06	0.07	0.01	0.09	0.01	0.05	-0.03	0.06	0.00	0.05	9,301
Hispanic to white ratio	-0.01	0.07	-0.05	0.04	0.01	0.07	0.01	0.04	-0.03	0.05	0.00	0.04	9,815

Notes: Authors' calculations taken from Civil Rights Data Collection and the Common Core of Data School Universe Survey. Weighted values are generated using average district enrollment in years 2011-2012 and 2013-2014. Sample limited to those districts: (i) school per pupil expenditures fall within state distribution of one-half the 5th percentile and 1.5 times the 95th percentile, (ii) with more than one school, (iii) with more than one non-missing school expenditures value, and (iv) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

Table 2: **Average Per Pupil Personnel Expenditures, by Year & Intra-District Inequality Decile**

Decile	1	2	3	4	5	6	7	8	9	10
Year 2011-2012										
Panel A: poor to non-poor										
Poor	4067	4051	4163	4370	4647	4699	4697	4380	4249	4360
Non-poor	4446	4201	4255	4424	4673	4702	4678	4327	4138	4063
Panel B: black to white										
Black	3737	4167	4092	4100	4457	4428	4457	4129	4276	5376
White	4318	4332	4163	4131	4461	4406	4400	4029	4084	4821
Panel B: Hispanic White										
Hispanic	4069	4261	4291	4308	4264	4355	4401	4175	4158	4784
White	4529	4428	4385	4360	4285	4354	4376	4119	4045	4436
Year 2013-2014										
Panel A: poor to non-poor										
Poor	4075	4138	4310	4700	4424	4760	4603	4429	4239	4300
Non-poor	4458	4295	4404	4760	4448	4762	4583	4376	4127	4019
Panel B: black to white										
Black	3924	4143	4108	4540	4412	4489	4481	4264	4495	4824
White	4457	4306	4180	4574	4416	4468	4424	4158	4293	4282
Panel B: Hispanic White										
Hispanic	4189	4202	4432	4230	4549	4640	4374	4272	4234	4479
White	4653	4372	4526	4283	4572	4639	4351	4215	4114	4158

Notes: Authors' calculations taken from Civil Rights Data Collection and the Common Core of Data School Universe Survey. Values correspond to mean per pupil personnel expenditures for group g in decile q of $Ineq_{gd}$. Group personnel expenditures are the per pupil share of expenditures in district d based on CRDC school-level data. Sample limited to those districts: (i) school per pupil expenditures fall within state distribution of one-half the 5th percentile and 1.5 times the 95th percentile, (ii) with more than one school, (iii) with more than one non-missing school expenditures value, and (iv) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

Table 3: **Inter-district Inequality, Summary Statistics**

	Unweighted				**Enrollment Weighted**				
Variable	Mean	SD	Q_{10}	Q_{90}	Mean	SD	Q_{10}	Q_{90}	N
Panel A: 2011-2012									
poor to non-poor ratio	.01	.04	-.03	.05	0	.04	-.05	.04	49
black to white ratio	.04	.07	-.03	.14	.05	.07	-.01	.14	49
Hispanic to white ratio	.02	.04	-.03	.08	.03	.04	-.01	.09	49
Panel B: 2013-2014									
poor to non-poor ratio	.01	.03	-.04	.05	.01	.03	-.04	.04	49
black to white ratio	.04	.06	-.02	.14	.04	.06	-.01	.14	49
Hispanic to white ratio	.02	.04	-.03	.08	.03	.04	-.01	.08	49

Notes: Authors' calculations taken from National Center for Education Statistics Local Education Agency (School District) Finance Survey (F-33) Data. Weighted values are generated using district enrollment for years 2011-2012 and 2013-2014. Sample limited to those districts: (i) district per pupil expenditures fall within state distribution of one-half the 5th percentile and 1.5 times the 95th percentile, (ii) with more than one non-missing school expenditures value from CRDC, and (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles. Variable is the F-33 total salaries.

Table 4: **Summary Statistics, Independent Variables**

Variable	**Unweighted** Mean	SD	**Weighted** Mean	SD
Panel A: Background Characteristics, Averages				
Median family income	6.30	2.63	6.30	2.57
Median house price	1.97	1.59	2.46	1.64
Prop. BA or more	0.25	0.15	0.30	0.14
Prop. geographic stability	0.87	0.07	0.86	0.05
Prop. less high school	0.12	0.08	0.13	0.08
Prop. single mom	0.23	0.10	0.26	0.10
Prop. SNAP	0.15	0.11	0.16	0.10
Prop. unemployed	0.05	0.02	0.05	0.02
Panel B: Background Characteristics, Inequality				
Parent income, Gini index	0.36	0.06	0.38	0.05
Parent income, mean to median ratio	1.16	0.15	1.19	0.14
Log ratio black to white median income	-0.53	0.68	-0.57	0.49
Log ratio Hispanic to white median income	-0.46	0.64	-0.55	0.45
Panel C: School Characteristics, Averages				
Per pupil instructional expenditures	6.60	2.33	6.29	2.26
Prop. enrolled charter	0.01	0.06	0.03	0.07
Prop. white	0.71	0.27	0.51	0.29
Prop. black	0.09	0.16	0.15	0.18
Prop. Hispanic	0.14	0.20	0.25	0.25
Student teacher ratio	16.86	95.25	18.90	88.97
Panel D: School Characteristics, Inequality				
Poor to non-poor between school seg	0.04	0.06	0.11	0.10
Black/white seg	0.03	0.06	0.12	0.14
Hispanic/white seg	0.03	0.05	0.10	0.11
SD per pupil expenditures, weighted	1.00	1.45	1.16	1.64
Novice teacher between school segregation	0.09	0.09	0.10	0.09
Ln(poor/non-poor) student per novice teacher ratio	-0.02	0.27	-0.10	0.25
Ln(poor/non-poor) student per teacher ratio	0.00	0.08	-0.03	0.08
Ln(black/white) student per teacher ratio	0.00	0.11	-0.02	0.08
Ln(Hispanic/white) student per teacher ratio	0.00	0.07	-0.02	0.06
Total Districts	16,374			

Notes: Authors' calculations taken from the American Community Survey, 2006-2010 Child and Parent Tabulations of children enrolled in public schools, the 2011-2012 and 2013-2014 Civil Rights Data Collection and the 2011-2012 and 2013-2014 Common Core of Data School Universe Survey. Weighted values are generated using district enrollment in years 2012 and 2014. Data from the ACS do not vary across time. Data from the CRDC and CCD vary by year. Summary statistics for these variables are the average over the two years. The sample for the independent variables described here is restricted to non-missing data among these variables. Because the variables $Ineq_{gd}$ have different samples depending on group g, there will be additional missing data when describing $Ineq_{gd}$. In addition, sample limited to those districts: (i) school per pupil expenditures fall within state distribution of one-half the 5th percentile and 1.5 times the 95th percentile, (ii) with more than one school, (iii) with more than one non-missing school expenditures value, and (iv) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

* Sample sizes for black and Hispanic economic variables are smaller. The overlapping sample includes 9,698 for black to white income differences and 13,004 for Hispanic to white income differences.

Table 5: **Predicted Per Pupil Expenditures, Poor & Non-Poor, by Selected Covariates**

Predictor Variable	Quantile	Predicted $Ineq_d$	PPE Non-poor	PPE Poor
Median family income	10th	0.01	4118.75	4158.95
		(0.01-0.01)	(4040.94-4196.56)	(4144.28-4173.66)
	90th	0.02	4544.69	4649.3
		(0.02-0.03)	(4489.73-4599.66)	(4636.50-4662.14)
Prop. BA or more	10th	0	4091.9	4109.42
		(0.00-0.01)	(4044.21-4139.58)	(4101.09-4117.78)
	90th	0.03	4559.73	4693.46
		(0.03-0.03)	(4500.25-4619.22)	(4680.37-4706.59)
Per pupil instructional expenditures	10th	0.01	3442.04	3474.11
		(0.01-0.01)	(3316.83-3567.25)	(3464.76-3483.49)
	90th	0.03	5722.72	5869.25
		(0.02-0.03)	(5375.10-6070.34)	(5834.66-5904.05)
Poor non-poor between school seg	10th	0	4355.09	4367.93
		(0.00-0.00)	(4321.94-4388.23)	(4359.95-4375.92)
	90th	0.03	4226.37	4366.4
		(0.03-0.04)	(4127.49-4325.25)	(4345.90-4387.00)

Notes: Authors' calculations taken from Civil Rights Data Collection, the American Community Survey (parents of children in public education tabulation, 2006-2010) and the Common Core of Data School Universe Survey. Predicted per pupil expenditures (PPE) for group G are derived from $\widehat{Ineq_{dt}}$ in equation $Ineq_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Per pupil expenditures for non-poor are derived from $\widehat{Y_{dt}}$ in equation $Y_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where Y_{dt} is non-poor per pupil expenditures (the denominator of $Ineq_{dt}$) and values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Mean poor per pupil expenditures are then equal to $e^{\widehat{Ineq_{dt}|X_{10,90}}} \times \widehat{Y_{dt}|X_{10,90}}$, i.e. the exponentiated log $Ineq_{dt}$ times the predicted mean per pupil expenditures for non-poor students. All variables shown here were statistically significant (p$\leq$.05) from bivariate regression models shown in Figure 6. Confidence intervals in parentheses based on delta method. Estimated using Stata margins command. Previous sample restrictions in place.

Table 6: **Predicted Per Pupil Expenditures, Black & White, by Selected Covariates**

Predictor Variable	Quantile	Predicted $Ineq_d$	PPE White	PPE Black
Median family income	10th	0.02	4078.97	4168.67
		(0.02-0.03)	(3995.38-4162.57)	(4147.18-4190.27)
	90th	0.01	4530.29	4572.88
		(0.01-0.01)	(4470.37-4590.21)	(4556.75-4589.08)
Prop. white	10th	0.03	4304.8	4441.46
		(0.02-0.04)	(4162.86-4446.74)	(4407.95-4475.22)
	90th	0	4234.75	4242.98
		(-0.00-0.01)	(4162.14-4307.37)	(4226.30-4259.72)
Log ratio black white median income	10th	0.02	4298.07	4398.59
		(0.02-0.03)	(4237.54-4358.59)	(4381.46-4415.79)
	90th	0.01	4237.88	4276.9
		(0.01-0.01)	(4196.26-4279.49)	(4266.78-4287.05)
Black/white between school seg	10th	0	4330.04	4334.3
		(-0.00-0.00)	(4274.19-4385.90)	(4326.05-4342.56)
	90th	0.05	4155.8	4350.36
		(0.04-0.05)	(3969.57-4342.04)	(4318.51-4382.45)

Notes: Authors' calculations taken from Civil Rights Data Collection, the American Community Survey (parents of children in public education tabulation, 2006-2010) and the Common Core of Data School Universe Survey. Predicted per pupil expenditures (PPE) for group G are derived from $\widehat{Ineq_{dt}}$ in equation $Ineq_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Per pupil expenditures for white are derived from from $\widehat{Y_{dt}}$ in equation $Y_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where Y_{dt} is white per pupil expenditures (the denominator of $Ineq_{dt}$) and values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Mean black per pupil expenditures are then equal to $e^{\widehat{Ineq_{dt}|X_{10,90}}} \times \widehat{Y_{dt}|X_{10,90}}$, i.e. the exponentiated log $Ineq_{dt}$ times the predicted mean per pupil expenditures for white students. All variables shown here were statistically significant (p≤.05) from bivariate regression models shown in Figure 6. Confidence intervals in parentheses based on delta method. Estimated using Stata margins command. Previous sample restrictions in place.

Table 7: **Predicted Per Pupil Expenditures, Hispanic & White, by Selected Covariates**

Predictor Variable	Quantile	Predicted $Ineq_d$	PPE White	PPE Hispanic
Median family income	10th	0 (-0.00-0.01)	4088.49 (4003.34-4173.63)	4106.01 (4087.86-4124.24)
	90th	0.01 (0.01-0.02)	4557.28 (4498.88-4615.67)	4620.11 (4606.75-4633.52)
Prop. BA or more	10th	0 (-0.00-0.00)	4072.08 (4018.78-4125.37)	4067.12 (4056.37-4077.90)
	90th	0.02 (0.02-0.02)	4549.29 (4488.71-4609.87)	4640.26 (4626.32-4654.24)
Log ratio Hispanic white median income	10th	0.01 (0.01-0.02)	4304.56 (4229.82-4379.31)	4360.44 (4346.51-4374.42)
	90th	0 (0.00-0.01)	4270.11 (4238.68-4301.54)	4284.87 (4277.64-4292.11)
Hispanic/white between school seg	10th	0 (-0.00-0.00)	4359.3 (4305.97-4412.63)	4367.57 (4357.08-4378.08)
	90th	0.02 (0.01-0.03)	4160 (3986.39-4333.62)	4242.63 (4206.65-4278.92)

Notes: Authors' calculations taken from Civil Rights Data Collection, the American Community Survey (parents of children in public education tabulation, 2006-2010) and the Common Core of Data School Universe Survey. Predicted per pupil expenditures (PPE) for group G are derived from $\widehat{Ineq_{dt}}$ in equation $Ineq_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Per pupil expenditures for white are derived from from $\widehat{Y_{dt}}$ in equation $Y_{dt} = \beta(X_{dt}|X_{10,90}) + \lambda_{f[d]} + \gamma_t + \varepsilon_{dt}$, where Y_{dt} is white per pupil expenditures (the denominator of $Ineq_{dt}$) and values of $X_{10,90}$ are the 10th and 90th percentiles of X_{dt}. Mean Hispanic per pupil expenditures are then equal to $e^{\widehat{Ineq_{dt}|X_{10,90}}} \times \widehat{Y_{dt}|X_{10,90}}$, i.e. the exponentiated log $Ineq_{dt}$ times the predicted mean per pupil expenditures for white students. All variables shown here were statistically significant (p≤.05) from bivariate regression models shown in Figure 6. Confidence intervals in parentheses based on delta method. Estimated using Stata margins command. Previous sample restrictions in place.

Appendices

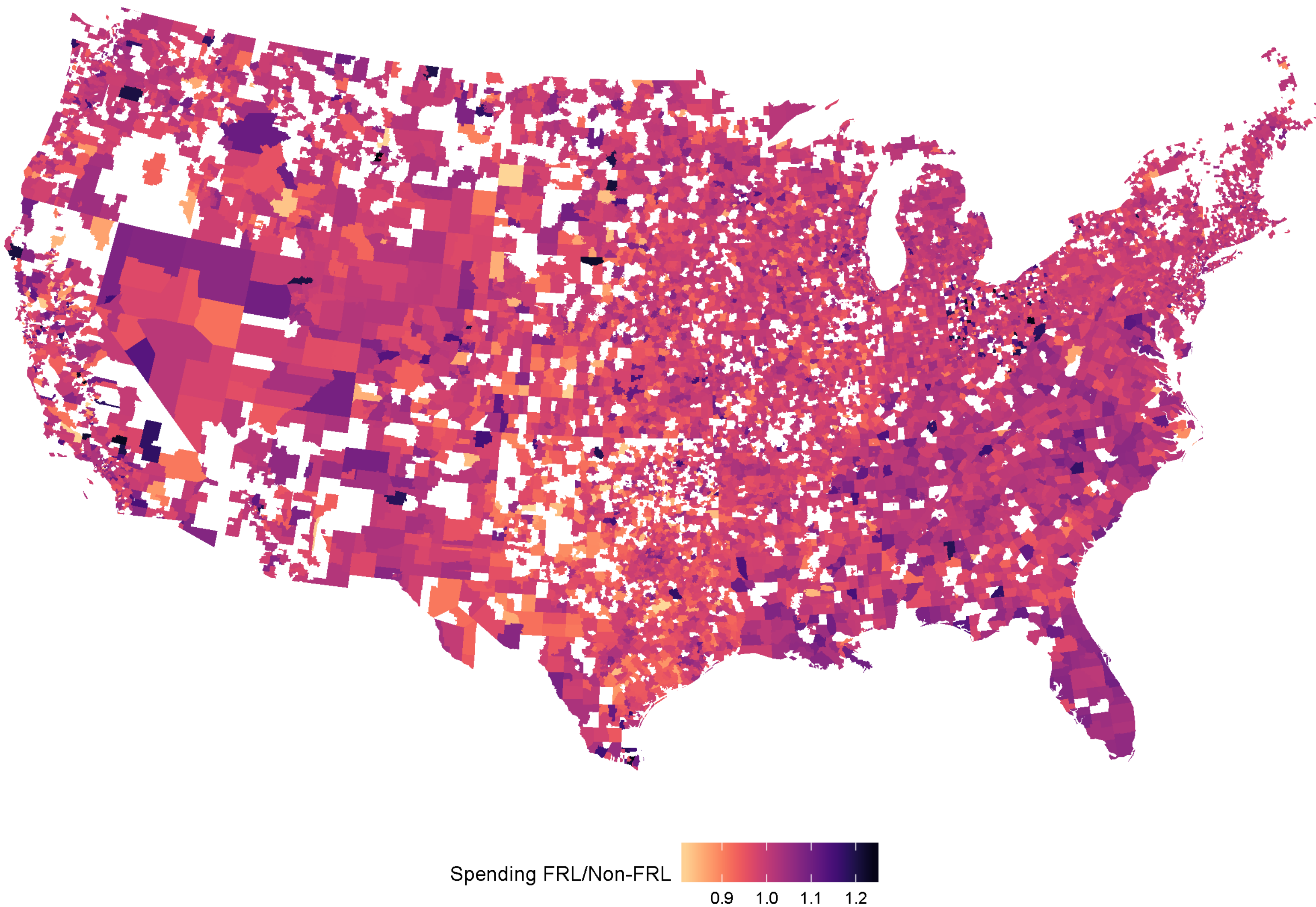
A Data Appendix

A.1 Data Sources

B Additional Results

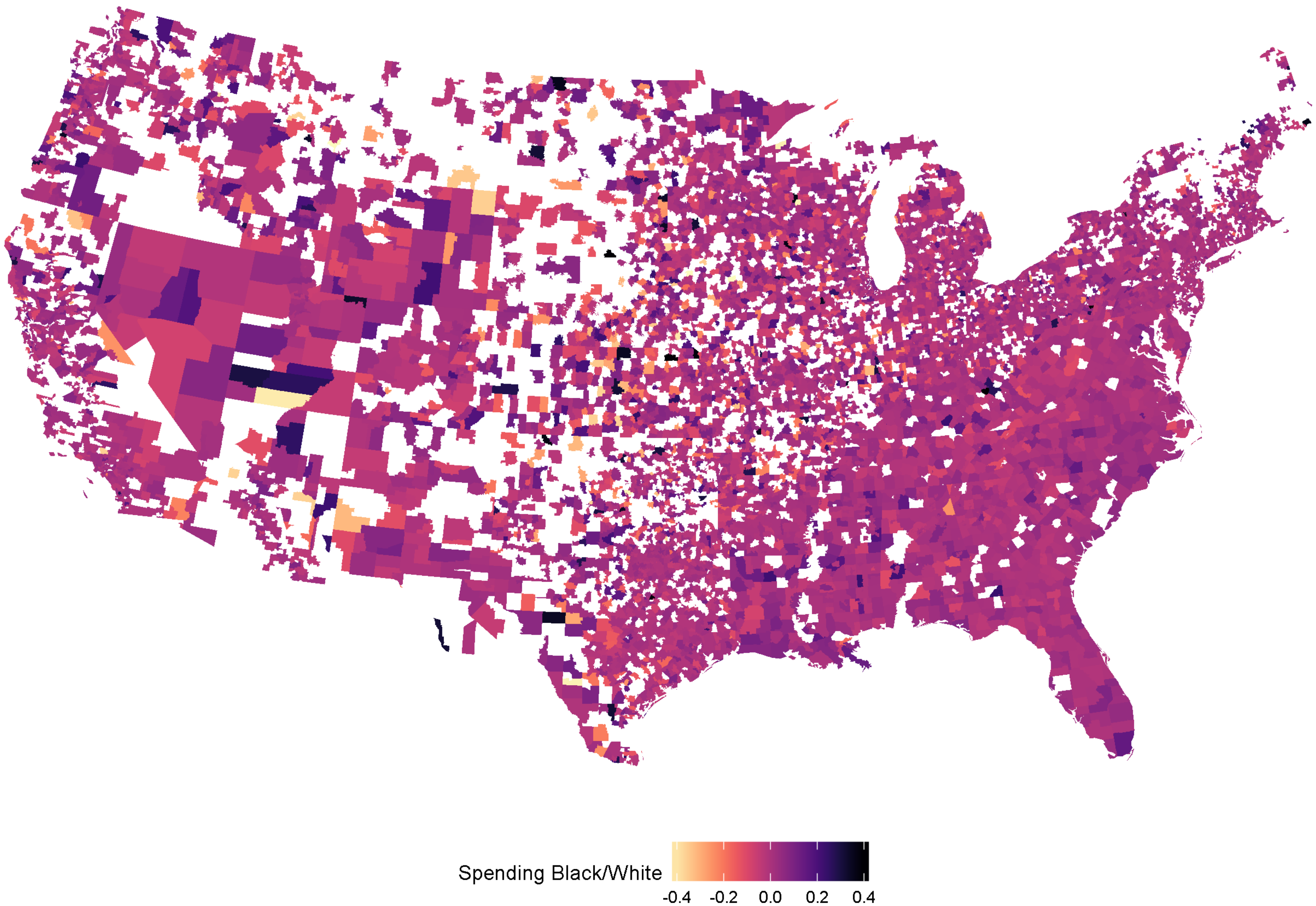
B.1 Maps

Figure B.1: poor to non-poor Spending Ratio, 2013-14



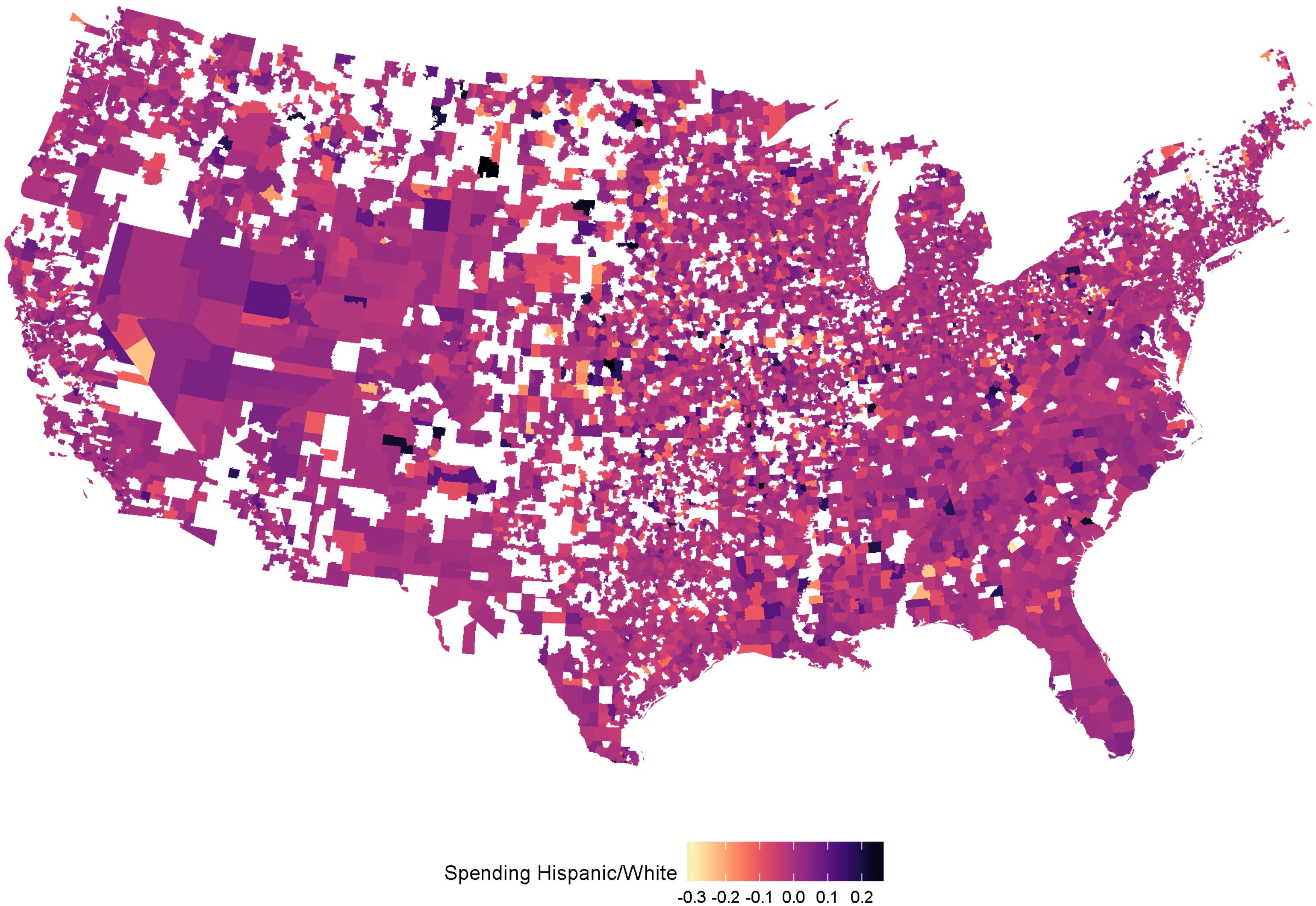
Notes: Based on authors' calculations using data from the Civil Rights Data Collection and the Common Core of Data School-Universe Survey, year 2013-2014. Sample limited to those districts: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles. For visualization purposes, we remove the 25 largest and smallest values.

Figure B.2: black to white Spending Ratio, 2013-14



Notes: Based on authors' calculations using data from the Civil Rights Data Collection and the Common Core of Data School-Universe Survey, year 2013-2014. Sample limited to those districts: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles. For visualization purposes, we remove the 25 largest and smallest values.

Figure B.3: Hispanic White Spending Ratio, 2013-14



Notes: Based on authors' calculations using data from the Civil Rights Data Collection and the Common Core of Data School-Universe Survey, year 2013-2014. Sample limited to those districts: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles. For visualization purposes, we remove the 25 largest and smallest values.

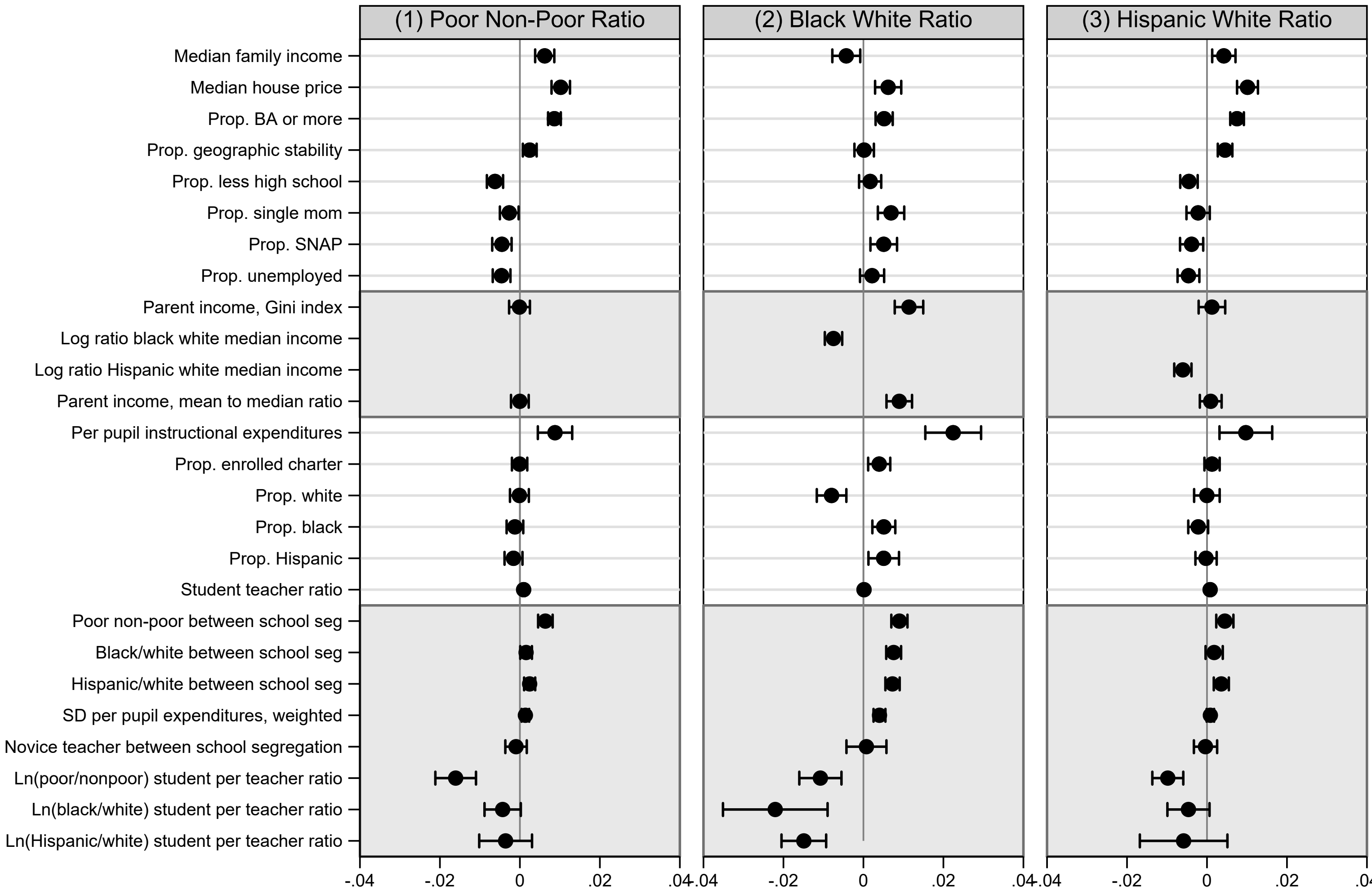
B.2 Elementary Schools Only

Table B.1: **Intra-district Inequality, Summary Statistics, Elementary Schools Only**

	Unweighted						Enrollment Weighted						
Variable	Mean	SD	Q_{10}	Q_{90}	σ_{btw}	σ_{within}	Mean	SD	Q_{10}	Q_{90}	σ_{btw}	σ_{within}	N
Panel A: 2011-2012													
poor to non-poor ratio	0.01	0.05	-0.03	0.04	0.01	0.05	0.02	0.05	-0.02	0.07	0.00	0.04	8,195
black to white ratio	0	0.07	-0.05	0.06	0.01	0.07	0.02	0.05	-0.03	0.08	0.00	0.05	7,837
Hispanic to white ratio	0	0.05	-0.04	0.04	0.01	0.05	0.01	0.04	-0.03	0.06	0.00	0.04	8,174
Panel B: 2013-2014													
poor to non-poor ratio	0	0.05	-0.03	0.04	0.01	0.05	0.01	0.04	-0.02	0.06	0.00	0.04	8,204
black to white ratio	0	0.07	-0.05	0.06	0.01	0.07	0.01	0.05	-0.03	0.06	0.00	0.05	7,848
Hispanic to white ratio	0	0.06	-0.04	0.04	0.00	0.06	0.01	0.04	-0.03	0.05	0.00	0.04	8,216

Notes: Authors' calculations taken from Civil Rights Data Collection and the Common Core of Data School Universe Survey. Weighted values are generated using average district enrollment in years 2011-2012 and 2013-2014. Sample limited to those districts: (i) school per pupil expenditures fall within state distribution of one-half the 5th percentile and 1.5 times the 95th percentile, (ii) with more than one school, (iii) with more than one non-missing school expenditures value, and (iv) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.

Figure B.4: Bivariate Regressions of Intra-District Spending Inequality, 2011-12 to 2013-14, Elementary Schools Only



Notes: Model includes state and year fixed effects; robust standard errors. Beta coefficients and 95% confidence interval shown for bivariate regression models on standardized **X** Analytic sample for poor to non-poor ratio is 16,347 districts, for black to white ratio is 9,693, for Hispanic to white ratio is 12,993. Additional sample restrictions limit districts to those with: (i) with more than one school, (ii) with more than one non-missing school expenditures value, (iii) for which the ratio of CRDC to F33 per pupil personnel expenditures fall within the 5th to 95th percentiles.