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ABSTRACT

We examine ten cohorts of male eighth graders in public schools in Chicago, IL: 1995-2004. We find large racial disparities in academic achievement, socioeconomic status (SES), and adult criminal justice involvement. Although our measures of SES and academic achievement are strong predictors of future felony arraignment and incarceration, even among students of the same race who attend the same school, these measures predict only small portions of the overall Black-Hispanic disparities in adult criminal justice involvement. These same measures predict between roughly half or more of Black-White criminal justice disparities and over eighty percent of Hispanic-white disparities. The relationships between various value- added measures of eighth-grade school quality and future criminal justice outcomes vary by race. Schools that excel at promoting on-time matriculation from eighth grade to high school significantly reduce rates of criminal justice involvement among Black males.

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Introduction

An enormous body of research explores the extent to which characteristics of neighborhoods, home environments, and schools predict final educational attainment, labor market success, and other adult outcomes, and a related literature examines the relationships between early learning outcomes and various measures of success in adulthood. Given the persistence of large racial gaps in adult economic outcomes in the US, several papers also seek to understand what portion of the inter-group inequality we observe among adults in the US can be traced back to group differences in environments, experiences and outcomes measured during childhood. We contribute to this literature by providing new information about the contribution of racial differences in academic outcomes and neighborhood quality during childhood to racial differences in adult criminal justice outcomes.

We follow ten cohorts of students who began 8th grade in the Chicago, IL public school system between 1995 and 2004. We construct detailed measures of their academic achievement during elementary school and an index of the average SES of the neighborhoods where they lived during grades K-8. We also construct student-specific measures that characterize patterns of residential mobility and grade progression during the same period. We then merge these records with data from the Clerk of Court of Cook County and the Illinois Department of Corrections. We identify students who are arraigned on felony charges as adults and identify those who are convicted and sent to prison. For all cohorts, we measure these criminal justice outcomes through age 25.

In our main analyses, we restrict our attention to male students.[1] We analyze Black, Hispanic, and white males separately. We first establish that rates of criminal justice involvement in Chicago vary greatly by race. We also show that, among eighth-grade CPS students, distributions of SES and academic achievement during elementary school also vary greatly by race. We then show that, even among eighth grade students of the same race who attend the same school, variation in reading achievement, math achievement, and SES predict adult criminal justice outcomes. Further, the strength of these statistical relationships varies by race.

We conduct a series of statistical decomposition exercises that assess what portions of various racial differences in criminal justice outcomes are predictable based on student characteristics that we observe by eighth grade. We discover that Hispanic-white gaps in prison admission rates are almost completely predictable based on measures of academic achievement and SES that we observe by eighth grade, and

[1] Incarceration rates for males are more than ten times higher than rates for women. See Carson (2019). Further, in our sample, rates of arraignment and incarceration are exceedingly low among girls over a wide range of the achievement and SES distributions

more than half of Black-white gaps in adult criminal justice outcomes are predictable based on these same early measurements. However, these metrics predict only a small portion of the large Black-Hispanic gaps in felony arraignment and incarceration rates we observe in Chicago.

In the penultimate section of the paper, we examine how the quality of schooling provided in eighth grade, the grade right before students transition to high school, impacts adult criminal justice involvement. We use value-added models (VAM) to create three VAM measures of the quality of education provided by the team of teachers who work with eighth-grade students in a given school in a given year. The first two are standard metrics that capture variation among schools in reading and math achievement growth during eighth grade. The third captures variation among schools in the likelihood that students complete eighth grade successfully on their first attempt. We highlight this metric because previous research shows that CPS students who succeed in eighth grade are more likely to make a smooth transition to high school and less likely to drop out of high school. Further, several existing papers find that dropping out of high school increases the likelihood of criminal justice involvement.[2]

Among all male students, those who attend eighth grade in a school where teachers excel at helping students complete eighth grade on schedule are significantly more likely to complete high school, and among Black males, these same students are also less likely to face felony arraignment or incarceration as adults. Moving a Black, male, eighth-grade student from a 10th to a 90th percentile school in the distribution of school effectiveness at promoting on-time matriculation from eighth to ninth grade reduces future felony arraignment rates by more than five percentage points and reduces future prison admission rates by more than four percentage points. Further, these results remain when we add our VAM measures of school performance in reading and math performance as additional controls and when we add fixed effects for the default high schools that are linked to certain elementary schools. White males who attend eighth grade in schools with higher reading value-added scores are more likely to graduate high school and less likely to face felony arraignment or imprisonment as an adult. Yet, in contrast to our results for Black and white males, none of our VAM metrics predict rates of criminal justice involvement among Hispanic students.

[2]See Allensworth (2005), Allensworth and Easton (2007) for work on CPS students' transitions from eighth to ninth grade. See Lochner and Moretti (2004*a*) and Cook and Kang (2016) for evidence on the links between dropping out of high school and criminal justice involvement. Further, Chicago schools, community groups, and families often host elaborate eighth-grade graduation celebrations. In Chicago, eighth grade graduation is an important social event, and as a result, students who repeat eighth grade may suffer social stigma. See https://www.nytimes.com/2008/06/22/fashion/22grad.html and https://www.chicagotribune.com/2006/06/11/its-just-8th-grade/.

1 Literature Review

In recent years, numerous scholars have explored the relationship between racial gaps in family and neighborhood environments during childhood and racial gaps in adult labor market outcomes. Chetty et al. (2020) examine US children born between 1978–1983. They examine the mappings between the parental incomes of these children during the period 1994-2000 and their own adult incomes during 2014–2015, and they focus on racial differences in these statistical relationships. In terms of individual incomes, Black men fare worse as adults than whites or Hispanics who grew up in homes with comparable household income. However, among women, differences in the relationships between parental incomes and own adult incomes are relatively small. Nonetheless, adult household income among Black women remains lower than adult household income among women of other races raised in homes with comparable financial resources. Holding parental income constant, Black women marry less often and marry lower-earning spouses.[3]

Chetty et al. (2020) produce their results by merging tax records and census records, and they also use the 2010 American Community Survey to examine relationships between parental income and the future incarceration of children in 2010 for a subsample of the children in their data. They find large racial differences in the relationship between growing up in a low-income family and being incarcerated in 2010.[4] Yet, it is difficult to determine what the Chetty et al. (2020) results imply about conditional racial gaps in standard measures of adult arrest rates, conviction rates, or imprisonment rates. Many persons who faced numerous charges and even prison admissions during the 2000s were not in prison in 2010. The Chetty et al. (2020) sample ranged in age from 27 to 32 in 2010, but rates of offending among the non-incarcerated fall steadily as men age through their 20s, and many prison spells last less than two years.[5]

Chetty et al. (2020) also examines how racial differences in parents' success in using their own resources to improve the adult incomes of their children vary with characteristics of the neighborhoods where children grow up. On average, young black males can expect worse outcomes than their white peers who live in the same census tract and grow up in families with the same financial resources. However, these gaps are smaller in some types of communities. Black male youth tend to fare better as adults, relative to their white peers, if they grow up in communities where relatively high fractions of Black fathers reside with

[3] Mazumder (2014) employs different data sets and slightly different methods, but he reaches conclusions that echo those in Chetty et al. (2020). Mazumder (2014) merges data from the U.S. Census Bureau's Survey of Income and Program Participation (SIPP) and data from the administrative earnings records of the Social Security Administration (SSA). He also uses data from the National Longitudinal Survey of Youth 1979 (NLSY79) that provide measures of parental income for adolescents in the late 1970s and early 1980s and future measures of adult income for these respondents when they were in their late 30s and 40s. In both data sets, he finds that when Black children reach adulthood, they enjoy lower incomes than white children who grew up in homes with similar parental income.

[4] Twenty-one percent of Black males raised in low income families were incarcerated in 2010, but the corresponding rate for white males is only 6 percent.

[5] See Kaeble (2021). The median time-served in state prisons among those admitted is less than 16 months.

their children or where white residents harbor less racial bias.

While a large literature examines the relationships between the characteristics of neighborhoods during childhood and a variety of future adult outcomes, Chetty et al. (2020) is one of few studies that examines the relationship between racial differences in neighborhood characteristics during childhood and future racial disparities in education attainment, adult incomes, and adult criminal justice involvement.[6] Gase et al. (2016) is a partial exception to this rule. They examine participants in the National Longitudinal Study of Adolescent to Adult Health (NLSAAH), which follows over 12,000 persons from their mid-teen years through their late twenties and early thirties. The early waves of this panel survey provide measures of school characteristics, home environment, neighborhood crime rates and SES, as well as delinquent behaviors during junior high and high school. They find no racial differences in adult arrest rates when they condition on all of their full set of early measures of environment and delinquent behavior.[7]

An earlier literature examines the extent to which racial differences in measures of early learning outcomes or measures of school quality serve as predictors of racial disparities in adult labor market outcomes. Neal and Johnson (1996), Johnson and Neal (1998), Murnane et al. (2001), Neal (2006), Fryer Jr (2011), and Thompson (2024) all document significant relationships between measures of student skills in childhood or adolescence and adult measures of employment, wages, or earnings. Further, these papers all estimate statistical models that seek to measure what fraction of the racial gaps in various adult labor market outcomes are predictable given the racial skill gaps that exist among children and adolescents. Yet, we have found no studies that conduct comparable exercises to assess what portion of racial gaps in criminal justice outcomes are predictable based on racial achievement gaps that exist prior to adulthood.[8]

In the late 20th century, economists debated how much of the dramatic Black-white convergence in adult

[6] Chetty and Hendren (2018*a*) and Chetty and Hendren (2018*b*) examine how the characteristics of commuting zones and counties during childhood impact adult outcomes, but they do not assess the extent to which equalizing these factors among children of different races would impact adult inequality by race. Oreopoulos (2003) examined the consequences of random assignment to different public housing units in Toronto and concluded that childhood neighborhood characteristics had few impacts on adult outcomes. Several papers assess the impacts of the Moving to Opportunity (MTO) Experiments, e.g. Ludwig et al. (2013). However, these experiments induced modest shifts in the neighborhood characteristics among treated families and therefore provide little direct evidence concerning the overall contribution of racial differences in neighborhood characteristics to racial gaps in adult outcomes.

[7] We find it difficult to interpret these results because the authors present no results that control for environment variables without also controlling for the presence of delinquent behaviors. The authors are asking whether police arrest people of different races who share comparable backgrounds at the same rates, but the authors are holding constant a set of behaviors that may justify arrest. The authors are not exploring how family and community resources shape opportunities and therefore shape choices that may lead to arrests.

[8] In one set of analyses, Fryer Jr (2011) employs data from the National Longitudinal Survey of Youth 1979 (NLSY79) to examine relationships between racial disparities in early achievement and disparities in adult incarceration in the NLSY79, but comparisons with other data sources indicate that NLSY79 undercounts incarceration events. Bellair and McNulty (2005) employ data from the first two waves of the National Longitudinal Study of Adolescent to Adult Health (NLSAAH). They demonstrate that racial differences in academic achievement explain only a modest portion of Black-white differences in rates of violent behavior among teens. However, their outcome variable is an index of violent behavior derived from self-reports of violent actions during adolescence. It is not a measure derived from arrests, charges, convictions, or incarcerations during adulthood.

economic outcomes that began around 1940 reflected convergence in the quantity and quality of schooling that Black versus white youth receive, and related debates have continued since.[9] Here as well though, researchers did not explore whether the evolution of racial differences in school quality bore any relationship to the evolution of racial differences in adult criminal justice outcomes.

More recent papers on the long-term impacts of school quality explore how variation in class-sizes, school spending per-student, and teacher quality impacts future adult outcomes. However, these papers do not focus on how various proposals to equalize specific dimensions of school quality among children of different races would impact group differences in adult outcomes. Further, these papers did not examine criminal justice outcomes.[10]

The literature on the impacts of granting families more school choice, not only within the public sector but also through the expansion of charter and voucher schools, is not specifically focused on understanding overall racial gaps in adult outcomes. However, many of these papers do assess the long-run impacts of granting disadvantaged youth, who are often Black or Hispanic, access to different types of schools.[11] For the most part, these papers focus on adult attainment and earnings outcomes. However, Deming (2011) is an exception. He studies middle and high school students in Charlotte, NC who won lotteries that allowed them to attend the school they listed as their first choice in a public school assignment mechanism. Relative to similar students who did not get their first choice, these students faced lower future arrest rates and spent fewer days in county jails and state prisons during their adolescent and young adult years. Further, Dobbie and Fryer Jr (2015) show that male students who won lotteries that allowed them to attend the Promise Academy middle school in New York City were less likely to be incarcerated in juvenile detention facilities when surveyed roughly six years later. Neither of these papers focus explicitly on whether expansions of school choice or high-quality charter schools could eliminate racial gaps in adult criminal justice involvement, but Deming (2011) finds the strongest relationships between attending a first-choice school and reduced criminal justice involvement among Black males, and the vast majority of the students in the application lottery for Promise Academy were Black.

In recent decades, numerous researchers have developed value-added models (VAM) that produce measures of school or teacher quality. They then examine relationships between specific dimensions of the quality of educators who work with specific students and future outcomes for these students. Most of the literature focuses on future achievement or attainment outcomes, but Chetty et al. (2014*b*) find that students

[9]See Smith and Welch (1989), Donohue and Heckman (1991), Card and Krueger (1992), Neal (2006), and Bayer and Charles (2018).

[10]See Chetty et al. (2011), Jackson et al. (2016), and Rothstein and Schanzenbach (2022). Krueger and Whitmore (2001) do explore how across the board changes in class-size would impact Black-white test score gaps.

[11]See Angrist et al. (2016) and Dobbie and Fryer (2020) as examples.

assigned to elementary-school teachers who are more effective at fostering achievement growth in language skills and math enjoy higher earnings in their late 20s, and two recent VAM studies examine the impacts of better school quality on criminal justice outcomes. Jackson et al. (2020) show that students who attend high schools that have higher VAM scores for the socioemotional development of students are less likely to face arrest at school. Rose et al. (2022) show that students assigned to elementary school teachers who excel at reducing student behavior problems, e.g. absences and suspensions, face arrest less often in adolescence and early adulthood.

The Jackson et al. (2020) and Rose et al. (2022) results indicate that educator performance on dimensions other than effectiveness in promoting math and reading achievement likely impacts the future criminal justice outcomes of their students, and we present some results that are consistent with this conclusion. However, our results also differ on one key dimension. Jackson et al. (2020) do not estimate separate models by race, and Rose et al. (2022) find little evidence that the mappings between their VAM metrics and adult criminal justice outcomes are race-specific. However, we find that these mappings vary greatly by race and many of these racial differences we document are statistically significant.

In the next section, we describe out data. We then present several descriptive analyses that flesh out the extent of racial disparities in SES, academic achievement, and adult criminal justice outcomes among males who attend public schools in Chicago, and we show that our measure of SES and achievement are powerful predictors of future criminal justice outcomes for male students of all races. Next, we perform several decomposition exercises that flesh out what portions of various racial disparities in criminal justice outcomes are predictable given racial disparities in early measures of SES and academic achievement. In the penultimate section, we develop VAM models of several different dimensions of eighth-grade school quality, and we demonstrate how school quality in the final year of primary school impacts future criminal justice outcomes and high graduation rates. We close by discussing how our results inform future work on the sources of racial disparities in criminal justice outcomes.

2 Data

We employ administrative data from schools and local courts. We also employ data from the Census Bureau. In this section, we describe the variables we create, and how we combine data sets. Appendix D provides more details.

School Data

We begin by constructing academic achievement measures for elementary school students in Chicago Public Schools (CPS). Our primary analyses involve students who first attended eighth grade in CPS between the 1995-96 and 2004-05 school years. In many of our empirical models, we employ summary measures of academic achievement during primary school. We use reading and math test scores from third through eighth grades.[12] We employ only scores that we are able to place on Iowa Test of Basic Skills (ITBS) scales that are specific to a given subject and grade and invariant over time. This allows us to create measures of math and reading achievement during elementary school that have the same meaning for all cohorts of students.

Some students are not tested in all years. We use regression-based imputations to fill in missing test scores based on test results for other students who have comparable records in years where scores are available. Given these collections of actual and imputed scores, we create various summary measures of primary reading, math, and overall achievement by taking the first principal component of different collections of scores recorded during grades 3-8.

Neighborhoods

We also create a measure of neighborhood SES for each student. We begin by identifying the census tract for each residence that each student reports to CPS during elementary school. We then combine census tracts into a collection of supertracts that have fixed boundaries over time. For each combination of year and supertract, we gather demographic information. We use census data from 1990 and 2000, as well as the five American Community Survey (ACS) samples for 2008 to 2012 that surround 2010. For each tract and each year, 1990, 2000, and 2010, we collect the high school dropout rate, college completion rate, poverty rate, public assistance use rate, and median family income.[13] We calculate supertract-level SES as the first principal component of these variables. For each non-census year, we use linear interpolation to create supertract SES by year. For each student, we then construct the average SES of the neighborhoods of residence that the student reports to CPS during elementary school.

During our sample period, CPS divides students into five race categories: white, Black, Native American/Alaskan Native, Asian/Pacific Islander, and Hispanic. The Native American/Alaskan Native,

[12] We are technically using math scores and English Language Arts (ELA) scores. We use the labels math and reading to facilitate exposition.

[13] When a supertract includes multiple census tracts, we create population-weighted averages of each of these variables at the tract level.

Asian/Pacific Islander samples represent less than four percent of the total student population, and more than 90 percent of these students are Asian. We include these students in our white category. During our sample period, just over half of CPS student were Black, just over one-third were Hispanic, and we code less than 15 percent as white.

Criminal Justice Data

We rely on data from the Clerk of Court for Cook County Il and the Illinois Department of Corrections (IDOC) to create criminal justice outcomes. Our court data cover cases filed from 1984 to 2019. Our IDOC data contain prison admission records for 1990 through 2014.

Using court records, we create an indicator for the presence of a felony arraignment. In Cook County, when charges involve felonies, the State's Attorney (SA) reviews the charges before allowing the case to proceed to a preliminary hearing. If the SA proceeds with the case and establishes probable cause at the preliminary hearing, the court schedules a felony arraignment. In the several weeks between preliminary hearing and felony arraignment, the SA decides to reduce some charges to misdemeanors and drops many cases entirely. Our felony arraignment indicator equals one only if a person is arrested and charged with a felony, the charges pass felony review in the SA office, the SA establishes probable cause at the preliminary hearing, and the SA proceeds with a felony arraignment.[14]

We also create an indicator for presence of an incarceration. This indicator does not mark time in jail between arrest and the resolution of cases as incarceration. Our incarceration indicator equals one only for persons who are sentenced to incarceration after receiving a guilty verdict in a case against them. In almost all cases, these terms of incarceration involve admission to a state prison operated by IDOC.[15]

We track criminal justice outcomes through age 25. Given the birth dates in our main analysis sample, the majority of the students in our sample turn 25 well before the end of 2014. When the court sentences a current or former CPS student to prison before the end of 2014, we use IDOC admission records to better identify cases where defendants receive a prison sentence but also receive so much credit for time-served in jail awaiting a verdict that they never serve time in prison. For sentences after 2014, we rely on

[14]Many weak cases that begin as felony cases are reduced to misdemeanor cases and many others are dropped or dismissed. However, conditional on felony arraignment, conviction rates are typically over ninety percent. We have also examined felony conviction as our outcome of interest, and we see similar results. We highlight the arraignment results because we can measure felony arraignments directly. Coding felony convictions is complex since plea agreements may involve pleas of nolo contendere or provisions that reduce felony charges to misdemeanors.

[15]A small fraction of persons sentenced to prison served their sentence in a special program run by the Cook County Department of Corrections (CCDOC). This Bootcamp program involved four months of incarceration and special programs plus eight months of additional programming and supervision.

information available in the disposition history of each case to identify cases that likely involved prison sentences but no time in prison.

3 Key Patterns

We focus on results for male CPS students. In our data, rates of felony arraignment are roughly six to ten times greater among males than females depending on student race. Further, the prevalence of criminal justice involvement is close to zero among the highest-achieving females from more advantaged neighborhoods regardless of student race. Thus, attempts to statistically decompose racial differences in female arraignment rates are not that informative.[16] However, Appendix B provides results from all of our key models for the sample of female CPS students who entered eighth grade between 1995 and 2004.

Racial Disparities

Figure 1 describes the prevalence of felony arraignments among different types of male students. It contains three panels: one for white, Hispanic, and Black males respectively. Each panel contains 16 cells defined by intersections of the quartiles of two indices: SES is our index of neighborhood characteristics and AI is our index of overall academic achievement. As we note in the previous section, the SES index is the first principal component of the characteristics of the neighborhoods where students reside during elementary school. The AI metric is the first principal component of the math and reading scores for each student from grades three through eight.

The headings for each panel report that felony arraignment rates vary greatly by race. Almost 32 percent of Black male eighth graders in our sample face felony arraignment by age 25. Yet, among their Hispanic peers the rate is 13 percent, and among their white peers, the rate is just under seven percent. As we note above, just over half of these eighth graders are Black, slightly more than one third are Hispanic, and less than one sixth are white.

In total, Figure 1 presents results for 48 samples of students: 16 cells defined by the intersection of AI and SES quartiles within the samples of Black, Hispanic, and white males. To better understand these results, let us consider the results for one of these 48 samples. The bar chart in the top left corner of the charts for Black males presents results for Black males who score in the lowest quartile of the achievement distribution, AI=1, and reside in neighborhoods in the lowest quartile of the SES distribution, SES=1. The

[16] Prison admission rates for these females are even closer to zero.

blue bar reports that 87 percent of males with AI=1 and SES=1 are Black. The red bar tells us that among these Black males, 48 percent face felony arraignment by age 25. In the corresponding chart for white males, the blue bar is barely visible because less than one percent of male students in this cell are white. However, among the small sample of white males with AI=1 and SES=1, 28 percent face a felony arraignment by age 25.[17]

The blue bars illustrate how students of different races are distributed among the 16 (AIxSES) cells. The red bars illustrate how felony arraignment rates vary among these cells within race and how these rates vary by race within a cell. For all three races, rates of criminal justice involvement fall with academic achievement holding SES quartile constant and fall with SES holding academic achievement constant. However, it is also true that the fraction Black decreases as SES increases within each achievement quartile and also decreases with achievement within each SES quartile, while the opposite patterns hold among whites.

Taken together, these three figures show that Black males are over-represented in cells associated with lower achievement, lower SES, and higher overall rates of criminal justice involvement, while white males are greatly over-represented in cells associated with high achievement, high SES, and low rates rates of criminal justice involvement. For example, whites males make up less than 15 percent of the total sample but more than 57 percent of the subsample defined by the highest quartiles of achievement and SES, and in this cell, the overall rate of felony arraignment is less than five percentage points.[18] Black males are just over half of the total sample of male students, but as we note above, Blacks males are 87 percent of the male students in the cell defined by the lowest quartiles of SES and AI, where arraignment rates are more than .25 for white, Hispanic, and Black students. Hispanic males are much more evenly distributed among these cells, and overall, arraignment rates among Hispanic males are higher than the rates among white males but lower than the rates among Black males.

Appendix Figure A.1 presents parallel results, but here the red bars report the fraction of males in each cell that enter prison at least once by age 25. Differences in incarceration rates follow the same patterns that we see in Figure 1, but these rates are somewhat lower. The overall prison admission rates are .191 for Black males, .058 for Hispanic males, and .028 for white males.

We see large overall differences in arraignment and incarceration rates by race in our sample. However, we also see strong sorting by race among the AIxSES cells. Black males are concentrated in the cells where

[17]In the cell defined by the bottom decile of both distributions, more than 97 percent of male are Black, and less than four in 1,000 male students are white. The felony arraignment rates for these groups and .5 and .3 respectively

[18]White students account for 77 percent of the male students in both top decile of SES and AI, and the overall fraction of students facing felony arraignment in this group is around .03

rates of criminal justice involvement are greatest for all races. These sorting patterns motivate the following question: to what extent do racial differences in our measures of achievement and SES during elementary school *predict* racial differences in adult criminal justice involvement? While racial differences in arraignment rates exist within the 16 cells we define, the overall patterns here suggest that, if we divide the joint distribution of AI and SES into more granular cells, average within-cell variation in arraignment and incarceration rates by race may be negligible. We show below that this is not the case, but first we demonstrate that our measures of early achievement and early environment are strong predictors of adult criminal justice outcomes.

Patterns Within Schools by Race

Figure 2 illustrates the marginal predictive power of our measures of math achievement, reading achievement, and neighborhood SES for future criminal justice outcomes within samples of students of the same race who attend the same school and match on numerous other characteristics. The figure presents the results from 36 counterfactual simulations. To create these results, we estimate six logit models. The first model involves data for Black males. We model an indicator for the presence of a felony arraignment by age 25 as a function of indicators for the year each student begins eighth grade, indicators for the school where each student begins eighth grade, an indicator for being off-track in terms expected age at the beginning of eighth grade, student age in months at the beginning of eighth grade, controls for each student's patterns of residential mobility during elementary school, and three spline functions: one in our SES index, one in a composite index of reading achievement during grades 3 through 8, and one in a composite index of math achievement in grades 3 through 8. The second model takes the same form but employs data on Hispanic students. The third model uses data on white students. We then re-estimate these models using an indicator for incarceration by age 25 as the outcome variable.[19]

Given the results from these six models, we examine the extent to which variation in our metrics – within schools among students of the same race – predicts differences in future criminal justice outcomes. We do this by focusing on students who are either in the top or bottom five percent of their peers with respect to math achievement, reading achievement, or SES. For example, we select the five percent of Black, eighth-grade males within each school who have the lowest reading achievement. Then, for each student, we create a predicted arraignment rate based on the student's own reading score and the median values of other characteristics among Black, eighth-grade males who attend his school. We average these predicted

[19] We place everyone who attends a school that did not enroll at least 100 male eighth graders of his race between 1995 and 2004 in a composite school when estimate the logit models. However, we do not include these students in the simulation results that generate Figure 2.

arraignment rates and then repeat these same calculations for the five percent of Black, eighth-grade males in each school who have the best reading achievement. We then form similar averages for students who are at the top or bottom of the math and SES distributions for Black males in their schools. We repeat these calculation for Hispanic males and white males. Finally, we repeat each set of calculations using incarceration as the criminal justice outcome. In total, we create average predicted arraignment and incarceration rates for 18 samples of students: (Black, Hispanic, white) * (Reading, Math, SES) * (top five percent, bottom five percent).

Figure 2 presents the results. within-school variation in all three metrics predicts differences in rates of criminal justice involvement for males for all races. However, the strength of these relationships often varies by metric within race and by race for a given metric.

Among the three samples, within-school differences in math achievement are associated with modest but roughly comparable changes in criminal justice outcomes. However, within-school differences in reading achievement are typically stronger predictors of criminal justice outcomes, and these differences are particularly consequential predictors of criminal justice outcomes among Black males.[20] Among Black males, moving from the bottom to top ventile of reading scores within a given school is, on average, associated with a 23 percentage point reduction in the likelihood of a future felony arraignment and an almost 15 percentage point reduction in the likelihood of adult incarceration. In each case, the reduction in question is significantly larger than the overall arraignment or incarceration rates for either Hispanic or white males.[21]

Within-school variation in SES among Black males is also a noteworthy predictor of criminal justice outcomes. Among Black males who attend the same school in eighth grade, moving from the bottom to top ventile of neighborhood SES reduces expected incarceration rates by roughly eight percentage points.[22] within-school variation in SES is less important as a predictor of criminal justice involvement among white and Hispanic males, and this is particularly true among Hispanics.

These results demonstrate that the measures of early achievement and neighborhood SES that we construct are important predictors of criminal justice outcomes, even among students who are similar on

[20] These patterns may not be surprising given that many previous studies have found that measures of academic achievement and educational attainment are stronger predictors of adult employment, wages, and earnings among Black males than males of other races. See Neal and Johnson (1996), Lang and Manove (2011), and Fryer Jr (2011)

[21] We find no evidence that this outcome simply reflects greater within-school dispersion of reading scores among Black males. The average reading score among Black males in the bottom five percent of their school is quite close to the comparable average score in the Hispanic male sample. However, Hispanic males who earn reading scores in the top five percent of their school have an average reading score that is roughly .3 standard deviations greater than the average for the corresponding sample of Black males. The spread between average scores in the top and bottom five percent of each school is greatest among white males, but here both the top and bottom averages are significantly greater than the corresponding averages for Blacks or Hispanics.

[22] When we compare results for Black males to those of non-Black males, within-school changes in math achievement levels have smaller impacts on arraignment rates and larger impacts on incarceration rates.

other dimensions and attend the same school. Further, the mappings between these characteristics and both of our criminal justice outcomes vary by race. These results motivate how we conduct the decomposition exercises we present in the next section.

Before turning to the details of these decompositions, we note that the models we employ for our decomposition exercises do not contain school fixed effects. These decompositions require that we predict criminal justice outcomes for each student based on his own characteristics and three race-specific mappings between those characteristics and adult criminal justice outcomes. We do not include a set of school fixed effects in our control set because, in many cases, we cannot predict what criminal justice outcomes would be if a particular white student were assigned to particular school. During our sample period, many schools enrolled either no white students or only a handful. Further, there are also schools that enroll very few Hispanic students. For many schools, we do not have data that would allow us to estimate race-specific school effects for Black, Hispanic, and white students.[23]

4 Decomposing Racial Differences in Criminal Justice Outcomes

Here, we seek to better understand how much of observed racial differences in adult criminal justice outcomes we are able to predict with our measures of elementary school math achievement, reading achievement, neighborhood SES, student age, and residential mobility during elementary school.

We re-estimate the six logit models we describe in the previous section without school fixed-effects. Given the estimated parameters from each model, we create predicted rates of criminal justice involvement for each male student in our sample. For example, we create three separate predicted felony arraignment rates for each Black male student: one using the estimated parameters from the model for Black students, another using those from the model for Hispanic students, and yet another using those from the model for white students. We create three predicted prison admission rates for each Black male in the same manner. We then repeat these calculations for Hispanic and white males.

Given our predicted felony arraignment rates, we non-parameterically regress the predicted arraignment rate given the characteristics of a given student and the parameters from a model estimated on students of

[23]Further, racial patterns of sorting among schools does not appear to be an important driver of racial differences in adult criminal justice outcomes holding constant the student achievement outcomes. Appendix Table A.5 presents results from several regressions of adult criminal justice outcomes on student characteristics. All regressions include indicators for the year a student began eighth grade plus indicators for the students race. Some regressions add controls for measures of student achievement, measures of on-time grade progression, and measures of student SES. Others contain these controls plus a set of indicators for the school the student attended at the beginning of eighth grade. When we add controls for student achievement and background characteristics, the raw racial gaps in arraignment and incarceration rates fall substantially, but when we take the additional step of adding indicators for eighth-grade school attended, the conditional racial gaps are quite similar to the gaps we estimate when we condition only on our set of achievement measures and background characteristics.

a different race on each student's own predicted rate, i.e. the predicted rate given his characteristics and the estimated coefficients from the model for his own race. Since there are two sets of "other-race" coefficients for students of each race, we run six of these non-parametric regressions. We plot the results in two sub-figures each for Black, Hispanic, and white students. Figure 3 presents these six plots for felony arraignment rates. Figure 4 presents similar plots for predicted incarceration rates.

Before we discuss our findings, let us walk through how these plots present our results. Consider the population of males students of a given race, e.g. Black. The blue plot in the top left corner of Figure 3 plots average expected arraignment rates for these students, given model parameters estimated using data on the sample of Hispanic students, against their own predicted arraignment rates. The red line is the 45 degree. If the estimated coefficients from the model estimated on Hispanic males were identical to those from the model estimated on Black males, both models would produce the same predicted arraignment rates for all Black students, and the blue non-parametric plot would fall on top of the red 45 degree line. However, the two models do not produce similar results. The average predicted arraignment rates for Black students are always lower when we create the predictions using the Hispanic-model parameters, and therefore, the blue plot is always below the 45 degree line. At each point, the absolute distance between the blue plot and the 45 degree line is a measure of a racial gap in arraignment rates that a particular Black student experiences, relative to similar Hispanic students. The plot in the top right of Figure 3 reports the results from a parallel exercise that again compares predicted criminal justice outcomes from both the Black and Hispanic model, but here we use the sample of Hispanic males as the reference population.

Along each x-axis in Figure 3, we also plot the distribution of predicted rates arraignment rates for each reference population. We plot our non-parametric regression results over the 5th to 95th percentile values of each reference distribution. We trim these plots to focus attention on comparisons that do not require us to extrapolate beyond the support of the samples used to estimate race-specific model parameters. For example, there are almost no white males who possess the observed characteristics of the Black students who are most likely to face felony arraignment or imprisonment. Thus, if we create predicted values for these Black students based on the coefficients from models estimated on the sample of white males to generate their expected rates of criminal justice involvement, "if they were white," we are extrapolating well beyond the support of the data used to estimate the model for white students.

Figure 3 demonstrates that our measures of early achievement and SES account for only a small portion of observed Black-Hispanic differences in expected arraignment rates. Black-Hispanic differences in these rates are smallest among students with the lowest expected rates of criminal justice involvement, and the exact sizes of these gaps vary slightly when we use Black students as opposed to Hispanic students as the reference group. In both plots, the initial gap is a little less than five percentage points. Yet, from this starting point, the Black-Hispanic gap grows rapidly as we consider students who are more likely to face arraignment. In the two plots in the top row of Figure 3, the implied Black-Hispanic gap in arraignment rates is often more than fifteen percentage points.

Overall, Black-Hispanic differences in student characteristics account for a small portion of the total Black-Hispanic gap in arraignment rates, and two sets of calculations illustrate this point. First, fix the parameters from the model estimated on the Black sample and use these parameters to calculate the average predicted arraignment rate for both Black and Hispanic students. Then, take the difference between these two rates. Next, conduct the same exercise using the parameters from the model estimated on the Hispanic sample. Both calculations yield Black-Hispanic differences in average predicted arraignment rates that are small in absolute value relative to the overall Black-Hispanic gap in arraignment rates. The former is $.316 - .254 = .062$. The latter is $.172 - .131 = .041$, but the overall gap is $.316 - .131 = .185$. These results imply that we can attribute only 22 to 34 percent of the Black-Hispanic arraignment gap to Black-Hispanic differences in student characteristics.

The middle panel of Figure 3 decomposes Black-white differences in arraignment rates. Here, implied racial differences in arraignment rates do not increase as sharply when we move from students with low likelihoods of criminal justice involvement to those with higher ones. As a result, Black-white differences in student characteristics account for a larger share of overall Black-white differences in arraignment rates. Black-white differences in students characteristic account for between 49 and 69 percent of the overall arraignment rate gap of .247.

The bottom panel shows that our decomposition results for the Hispanic-White arraignment rate gap are quite different. Here, racial differences in student characteristics account for the vast majority of the overall gap. A quick glance at these figures reveals that regardless of the weighting choice we use to form comparisons, Hispanic students face arraignment rates that are close to those of similar white students. Whether white or Hispanic students serve as the reference group, Hispanic-white differences in student characteristics account for 82 percent of the overall Hispanic-White arraignment gap.

Figure 4 presents parallel results for prison admission rates. Here, Hispanic-White differences in student characteristics account for roughly the entire Hispanic-White gap in incarceration rates. Black-white differences in students characteristics explain slightly more of the Black-white incarceration gap, but the overall results are quite similar to the arraignment-rate results. Further, decomposition results for Black-Hispanic differences prison admission rates also echo the results for felony arraignment rates. Racial differences in student characteristics account for 23 to 35 percent of the Black-Hispanic gap in prison admission rates

The results in Figures 3 and 4 show that Black identity matters for future rates of criminal justice involvement, even among students are observationally similar on numerous dimensions of achievement, SES, and family environments. At the same time, racial differences in student characteristics contribute more to overall racial gaps in predicted rates of criminal justice involvement when we use parameters from the model estimated on the sample of Black students to create predicted arraignment or incarceration rates. Recall that the contribution of racial disparities in measured characteristics to the Black-Hispanic arraignment gap is 22 percent if we use parameters from the Hispanic model but 34 percent if we use the Black-model parameters. The corresponding figure for the decomposition of the Black-white arraignment gap are 49 percent given the white-model parameters but 69 given the Black-model parameters.[24] These patterns indicate that our early measures of student achievement and SES are more important predictors of adult criminal justice outcomes among Black students than among Hispanic or white students. Likewise, Figure 2 shows that within-school variation in achievement and SES matters most for within-school differences in criminal justice outcomes among Black students.

These patterns point in several directions. The fact that rates of criminal justice involvement among Black males are so much higher that one would predict using parameters from either the Hispanic or white models suggests that Black males may confront discrimination in labor markets that shape their relative incentives to engage in crime or that, conditional on their levels of criminal activity, they face discriminatory treatment in the criminal justice system. However, the relative strength of achievement and SES as predictors of criminal justice involvement among Black males suggests that policies that improve early environments and early skill development may significantly reduce rates of criminal justice involvement among Black males.

Both of these claims are speculations concerning potential avenues for future research. The results in Figures 2 through 4 are not causal estimates derived using experimental variation in SES, academic achievement, or other student characteristics, and to this point, we have offered no estimate of the casual impact of racial differences in any specific early factor on racial differences in adult criminal justice outcomes. However, in the next section, we take a step in this direction. We examine relationships between criminal justice outcomes and value-added measures of school quality. These results provide information that speaks more directly to the potential causal impacts of specific types of educational interventions during primary school on racial differences in adult criminal justice outcomes.

[24] Similar patterns hold in the prison admission rate decompositions

5 VAM

We note in section 1 that a significant literature examines how improvements in school quality may improve future adult outcomes. Here, we examine what dimensions of eighth-grade school quality impact future criminal justice involvement. Our focus on eighth grade allows us to condition on an extensive set of controls that characterize each student's record of achievement and SES prior to eighth grade, and we are particularly interested in eighth grade because prior research argues that the transition from eighth grade to ninth grade is an important step for CPS students. These prior studies show that achievement and attendance during eighth grade impact student performance in the first year of high school and that strong performance in the freshman year of high school is a key predictor of finishing high school successfully. Further, holding achievement levels constant, policy shifts that induce elementary schools to require marginal students to repeat eighth grade lower the likelihood that these marginal students will actually graduate from high school.[25]

The fact that several dimensions of eighth-grade school quality may impact dropout decisions in high school is important because both Lochner and Moretti (2004*a*) and Cook and Kang (2016) report that dropping out of high school increases rates of criminal justice involvement among males. Here, we examine how the performance of teams of eighth grade teachers both in terms of how well they foster student achievement in math and reading and how well they promote on-time matriculation from 8th to 9th grade impacts future criminal justice outcomes.

Creating VAM Metrics

We create three VAM measures of eighth-grade school quality. The three outcomes we use to derive these metrics are: (i) each student's 8th grade math score, (ii) each student's eighth grade reading score, and (iii) an indicator for completing 8th grade in one academic year.[26] In our VAM analyses, we restrict our sample to schools that enrolled at least 20 eighth graders in each school year from 1995 to 2004.[27]

To construct each measure, we select all eighth-grade students and project one of our three eighth-grade outcomes on an extensive set of controls. The controls include splines that capture variation in average SES during elementary school, average grade 3 to 7 reading achievement, and average grade 3 to 7 math

[25]See Allensworth (2005), Allensworth and Easton (2007), and Roderick et al. (2014).

[26]We code a student as completing 8th grade in one year if CPS records the student as enrolled in ninth grade in fall of the next academic year or if CPS records that the student transferred to another school system. Given the large number of private high schools in Chicago, we assume that transfer students are starting high school outside CPS.

[27]This restriction allow us to avoid small programs for children with special needs as well as new schools that went through a start-up phase or incumbent schools that went through the process of closing during our sample period.

achievement, plus indicators for being off-track in terms of age for grade, and measures of residential mobility during elementary school. We also include age in months at the start of eighth grade, school fixed effects, indicators for Black and male, and indicators for year. We further include mean SES and the fractions Black, male, and off-track within a given school*cohort cell. We add the regression residual for each student to our estimate of the fixed effect for the school each student attended. This sum is an estimate of the residual outcome variation for each student who attends a given school in a given year. It is influenced by unmeasured factors specific to the student, to his school, and to his classmates. We form the average of these residuals within cells defined by interactions of two sets of indicator variables: one for academic year and one for school attended.[28]

Next, we shrink these averages using a variant of the method proposed in Chetty et al. (2014*a*), but in contrast to Chetty et al. (2014*a*), we do not impose stationarity. For each academic year, we regress (school*cohort) average residuals for that year $t = 1995, 1996, ..., 2004$ on all available (school*cohort) average residuals for 8th-grade cohorts from the same school who entered 8th grade within two years of t, and we weight these regressions by the class size in each school in year t. The fitted values from these regressions are best linear predictors of the value-added of a given team of educators who worked with a given cohort of 8th-grade students in year t. We do not impose stationarity because CPS experienced several waves of reform during our sample period that likely influenced educator performance on the dimensions of school quality that we seek to measure. Some of these policy reforms involved the introduction of accountability systems linked to test scores. Others involved changes in the recommended requirements for promotion from eighth to ninth grade.[29]

Impacts of School Quality on Criminal Justice Outcomes

Here, we discuss our econometric model and the assumptions we make. We begin with the following data generating process:

$$Y_{ijt} = \theta_{jt}^{k}\alpha_k + X_{ijt}\beta + e_{ijt}$$

Here, Y_{ijt} is a future criminal justice outcome for student i who attended eighth grade in school j in year t. θ_{jt}^{k} is the eighth-grade school quality in school j during year t on value-added dimension k, where

[28] To be more pedantic, the residual for student i who attends school j in year t is the sum of the estimated school fixed effect for school j plus the projection residual for student i, who entered eighth grade in school j in year t. See Chetty et al. (2014*a*).

[29] All of our models include indicators for academic year, but the impacts of these reforms likely involved more than year-specific shifts in performance common to all teams of educators. See Neal and Schanzenbach (2010) for more on the timing of these reforms. See Allensworth (2005) for a detailed treatment of grade repetition policies.

$k \in \{\text{math, reading, promotion}\}$. X_{ijt} is our set of controls for the characteristics of student i, plus several controls that describe the demographic characteristics of student i's classmates in school j, plus fixed effects for each academic year, and e_{ijt} captures the influence of unobserved factors that shape outcomes for i given his experience in school j and time t.

For each sample of male eighth graders, i.e. Black, Hispanic, and white, we estimate the following regression model:

$$Y_{ijt} = \hat{\theta}^k_{jt}\alpha_k + X_{ijt}\beta + u_{ijt}$$

We use $\hat{\theta}^k_{jt}$ to denote the shrunken estimate of eighth-grade school quality in school j during year t on value-added dimension k. We assume that our VAM estimators are forecast unbiased, i.e. $\theta^k_{jt} = \hat{\theta}^k_{jt} + \eta_{jt}$, and η_j satisfies $E(\eta_{jt}|\hat{\theta}^k_{jt}) = 0 \ \forall j, k, t$. Thus, the population regression of θ^k_{jt} on $\hat{\theta}^k_{jt}$ has a slope of one.[30]

Here, $u_{ijt} = e_{ijt} + \eta_{jt}\alpha_k$, and we further assume that $E(u_{ijt}|X_{ijt}, \hat{\theta}_{jt}) = 0$. This assumption requires that, given our control set X_{ijt}, the unobserved characteristics of students that influence future criminal justice outcomes are not correlated with their schools' value-added scores, i.e. residual variation in measured school effectiveness on dimension k is not correlated with unmeasured student traits that impact criminal justice involvement.[31] Given these assumptions, our regression estimators, $\hat{\alpha}_k$, are consistent estimators of the per-unit impacts of changing the kth-dimension of value-added performance for the team of educators who teach a given student by randomly changing his school assignment.

We run two regressions for each k. In the first set of regressions, Y_{ijt} is an indicator for felony arraignment by age 25. In the second set, Y_{ijt} is an indicator for prison admission by age 25. In both cases, we place the three $\hat{\alpha}_k$ results on a comparable and interpretable scale. We report, for each school quality dimension k, the implied change in the probability that $Y_{ijt} = 1$ associated with moving a student from the 10th to 90th percentile in the estimated quality distribution. Appendix Table A.1 provides results implied by 25th to 75th percentile changes in school quality. Appendix Table A.2 presents parallel set regression results that use an indicator high school graduation at the outcome variable. All valued-added measures that improve criminal justice outcomes within a given sample also improve high school graduation outcomes. We note this pattern because both Lochner and Moretti (2004*a*) and Cook and Kang (2016) provide evidence that policy changes that reduce high school dropout rates also reduce future rates of criminal justice

[30] See Chetty et al. (2014*a*) for more on the forecast unbiased property

[31] Here, it is worth noting that $\hat{\theta}_{jt}$ is a weighted average of mean outcome residuals in school j from years other than year t. Shocks that are specific to students who attend school j in year t do not impact $\hat{\theta}_{jt}$

involvement.[32]

The top panel of Table 1 presents our main results. Eighth-grade teachers in CPS do not impact future criminal justice involvement through their efficacy in math instruction. The estimated impacts of math value-added on both criminal justice outcomes are small and statistically insignificant for Black, Hispanic, and White students. However, both Black and White students are less likely to face arraignment or incarceration in the future if they attend an 8th grade school that excels at promoting reading achievement. Moving a white student from a 10th to 90th percentile school in the distribution of reading value-added reduces the probability of felony arraignment by more than three percentage points and the probability of prison admission by roughly two percentage points. The comparable impacts for Black students are just under and just over two percentage points. The magnitudes of the implied impacts of reading value-added on future criminal justice outcomes among white males are quite striking. Recall that, overall, less than seven percent of the white sample faces felony arraignment and less than three percent enter prison.[33]

Black students who attend eighth grade in schools that are effective at promoting on-time matriculation from 8th to 9th grade are significantly less likely to face future criminal justice involvement. Here, moving from a 10th percentile school to a 90th percentile school generates a reduction in felony arraignment rates of just over 5.3 percentage points and a reduction in prison admission rates of just under 4.7 percentage points. Recall that the baseline rates of arraignment and incarceration for Black males are .316 and .191 respectively. These results imply that schools that help Black males successfully complete 8th grade lower future arraignment rates by almost one sixth and lower future incarceration rates by almost one fourth.[34]

We see considerable variation by race in the mappings between our VAM metrics and future outcomes. The 8th-grade promotion metric is an important dimension of school quality for Black students but not for Hispanic and white students. Further, none of our three VAM measures is a noteworthy predictor of future criminal justice outcomes among Hispanic students. Among Hispanic males, all estimates of value-added impacts are small, and none are close to statistically significant.[35]

The second panel of Table 1 present results from multivariate regressions that include all three VAM

[32]Here, we use only a subset of the original data for these regressions because CPS does not record graduation outcomes for students who transfer to private schools or other public school systems during high school. We do not count GED certificates or alternative diplomas as evidence of high school graduation. We drop all students who transferred out of the system after starting eighth grade.

[33]The sample for our VAM regressions does not contain students who attended schools that did not enroll at least 20 eighth graders in every sample year, 1995-20004, but the rates of criminal justice involvement among white males are almost identical to the rates in Figures 3 and 4.

[34]Further, the estimated slope parameters on promotion value-added in the Black regressions are statistically different from the estimated slopes in the Hispanic and white models with $p < .01$

[35]The estimated slope parameter on reading value-added among Hispanics in the felony arraignment regression is statistically different than the corresponding slope in the white regression, $p < .05$. The estimated slope parameters from the corresponding prison admission regressions are not statistically different.

metrics at once. Among white males, controls for the other two VAM metrics do little to diminish the estimated impacts of reading value-added on future criminal justice outcomes. Among Black males, reading value-added matters much less for future criminal justice outcomes when we condition on school effectiveness in promoting matriculation from eighth to ninth grade, although the implied impact on prison admission rates remains statistically significant. However, among Black males, the impacts of promotion value-added on future criminal justice outcomes in our multivariate regressions are comparable to the impacts we see in our univariate regressions.

Our three school performance metrics measure value-added during eighth grade. So, our results provide estimates of the impacts of eighth-grade school quality on long term outcomes for students. Nonetheless, some readers may worry that the quality of schooling an eighth grader receives is correlated with the quality of the high school that is linked to his eighth-grade school through attendance zones.

We discount this concern for two reasons. First, CPS gives students the opportunity to apply to attend high schools throughout the district, and as a result, few students attend an elementary school where a significant fraction of their classmates go on to attend one particular high school.[36] Second, Tables A.3 and A.4 present three additional versions of our univariate regression results that employ either reading value-added or promotion value-added as a measure of school quality. The first set of alternative regressions contains all of our standard controls plus indicators for the default high school attended by students from a given elementary school. Here, we define the default high school for a given elementary school as follows: high school Y is the default high school for elementary school X if Y is the modal high school attended by students from X and at least 25 percent of eighth graders in X go on to attend Y.[37] We also report results from similar regressions that use 20 percent and then 15 percent as the attendance-share rule that defines a default high school. Given any of the rules that define a default high school, adding controls for default high schools has no noteworthy impacts on our results. The impacts of promotion value-added on criminal justice outcomes among Black males and the impacts of reading value-added on criminal justice outcomes among white males are quite similar with or without controls for default high schools.[38]

Comparisons with Existing VAM Results

Rose et al. (2022) is only other paper that estimates relationships between VAM metrics of educator

[36]See https://toandthrough.uchicago.edu.

[37]Given the degree of High school choice available to CPS students, only about one fourth of CPS students in our sample attend a school where at least 25 percent of their schoolmates attend the same high school.

[38]We examine the impacts of controls for default high schools because access to these default schools is de facto a property right linked to attendance in specific elementary schools. We do not employ controls for actual high school attended because, given the numerous competitive admission schools in Chicago, the final high school assignment for many students is, in part, an outcome of the quality of instruction they received in eighth grade.

quality and adult criminal justice outcomes. Rose et al. (2022) examine the relationship between VAM measures of teacher quality and future criminal justice outcomes using data from North Carolina elementary schools. They have measures of arrests, convictions, and admissions to either jails or prisons, but they highlight their results for arrests on criminal charges between the ages of 16 and 21.

They find that students assigned to teachers who excel at promoting academic achievement are not less likely to face arrest. Their measures of reading value-added and math value-added have no impact on future criminal arrests. However, Rose et al. (2022) construct a third VAM metric that they call behavioral value-added. They form an index of problematic behaviors using data on suspensions, days absent, and grade repetition, and they find that students assigned to teachers who improve student behavior are less likely to face criminal arrest between age 16-21.[39]

We also find that math value-added has no effect on future criminal justice outcomes. Further, we find that our one behavioral performance measure, promotion value-added, matters for future criminal justice involvement among Black males. However, we find that white students who attend schools with strong reading value-added have lower future levels of criminal justice involvement, and Rose et al. (2022) find no relationship between reading value-added and criminal justice involvement.[40] In addition, we find that the impacts of specific value-added measures vary with student race, while Rose et al. (2022) report little evidence of racial differences in the future impacts of educator quality.

The fact that our results differ from the Rose et al. (2022) results on some dimensions is not shocking. Racial disparities in many of the drivers of criminal justice involvement are likely quite different in NC than they are in Chicago. Figure 4 reports that the prison admission rate among Black males in our Chicago sample is almost seven times greater than the rate for white males, but over the past decade, the incarceration rate for Black males in NC has been just less than three times the rate for white males.[41]

On the other hand, our results concerning the impact of promotion value-added on future criminal justice outcomes among Black males may reinforce results in Rose et al. (2022) and Jackson et al. (2020) concerning the long-term impacts of dimensions of educator performance that do not involve math or reading achievement growth. Rose et al. (2022) conclude that students assigned to teachers with high behavioral value-added are less likely to face criminal arrest between ages 16 and 21, and grade repetition is one of the components of their behavior index. Jackson et al. (2020) employ data on high school students from Chicago, IL. They construct school-level value-added measures for ninth grade students that capture

[39] In appendix results, Rose et al. (2022) do not find statistically significant impacts of a grade repetition VAM alone.

[40] Rose et al. (2022) do find that reading and math value-added matter for high school graduation outcomes, just as we do

[41] These data come from the North Carolina State Center for Health Statistics. https://schs.dph.ncdhhs.gov/units/ldas/docs/4-Incarceration-SHIP2023-101723.pdf

socioemotional development (SED) during ninth grade. They conclude that, conditional on school effectiveness at promoting achievement, schools that enhance SED also reduce future arrests at school and increase high school graduation rates and college attendance rates.[42]

Like Rose et al. (2022) and Jackson et al. (2020), our paper adds to the growing literature on the impacts of educator quality on non-cognitive development among students. Jackson (2018) employs data on ninth graders in North Carolina public schools to estimate teacher level value added measures for both achievement gains and non-cognitive skills development. He uses an index of student behaviors such as grade repetition, absences, and suspensions as a proxy for non-cognitive skill, and he finds that non-cognitive value-added is a more powerful predictor of high school graduation than achievement value-added. Petek and Pope (2023) employ data from the Los Angeles Unified School District elementary classrooms. They construct both traditional achievement VAM measures and a non-cognitive VAM measure derived from information on student behaviors. They find that both measures of teacher quality improve high school outcomes, e.g. lower dropout rates, reduce suspensions, and improve grades.

6 Conclusions

Our first conclusion is clear. Early measures of neighborhood SES and academic achievement are important predictors of adult criminal justice outcomes among male students in Chicago Public schools. Although we cannot determine what portions, if any, of the within-school/within-race relationships between measures of early SES or early achievement and future criminal justice outcomes are causal, several patterns in these results point to avenues for future research. To begin, conditional on other student characteristics, variation in student math achievement is not a strong predictor of adult criminal justice involvement for students of any race. However, we see much more evidence that reading skills matter for adult criminal justice outcomes. These patterns deserve more attention because several existing papers argue that math skills are important predictors of labor market success.[43]

Second, the contrast between the Hispanic-white decomposition results and the Black-Hispanic decomposition results is quite striking. The overall Hispanic-white differences in rates of criminal justice involvement are significant, but Hispanic-white differences in student characteristics observed during elementary school predict the vast majority of these criminal justice outcomes. However, the same

[42]The Chicago Public Schools did not collect the SED measures that Jackson et al. (2020) employ until after our sample period.

[43]See Rose and Betts (2004) and James (2013). VAM results indicate that reading value-added in eighth grade has an impact on future criminal justice outcomes among Black and white males, but math value-added has no impact on future criminal justice outcomes for Black, Hispanic, or white males.

characteristics explain little of the observed Black-Hispanic gaps in criminal justice involvement. The criminal justice system in Chicago may treat Black males differently than males of other races who engage in the same criminal behaviors. Black students may be more prone to engage in crime than observationally similar students of other races, or both may true. Whatever the correct answers are to this puzzle, our results document large unexplained Black-Hispanic gaps in criminal justice involvement that deserve further exploration.[44]

Third, our measures of early achievement and SES are stronger predictors of criminal justice involvement among Black males than among other males. Figure 2 demonstrates that reading achievement and SES are particularly strong predictors of future rates of criminal justice involvement among Black males who attend the same eighth grade school. Further, the results in Figures 3 and 4 show that racial differences in measured student characteristics always account for a larger portion of racial differences in rates of criminal justice involvement when we weight these characteristics using parameters from a model estimated on the sample of Black males. More research is required to determine whether these patterns are evidence that early interventions that improve achievement and early environments could reduce racial disparities in rates of criminal justice involvement.

Fourth, our VAM results show that some dimensions of school quality in eighth grade matter for future criminal justice outcomes, even given extensive controls for achievement and environment during the rest of elementary school. Reading value-added matters among white males and also matters among Black males. However, among Blacks males, attending a school with high reading value-added appears to reduce future criminal justice involvement because schools with high reading value-added in eighth grade tend to have high eighth-grade promotion value-added. The between-school correlation between these two measures is .38. On the other hand, math value-added has almost no impact on future criminal justice outcomes and the between-school correlation between math-value added and promotion value-added is only .1.[45]

Finally, more research is required to understand the mechanisms that drive our VAM results. For example, we find that Black males who attend schools that excel at helping eighth grade students finish eighth grade in one year are significantly less likely to face future criminal justice involvement than observationally similar Black males who attend other schools. Allensworth (2005) examines data from CPS and finds that

[44]Given our extensive set of controls, Black-Hispanic residual gaps in criminal justice involvement are likely larger than some readers expect given the literature on racial gaps in labor market outcomes. Fryer Jr (2011) reports that, among men in the National Longitudinal Survey of 1979 (NLSY79), racial differences in a single composite measure of reading and math achievement, recorded prior to adult labor market entry, predict roughly forty percent of the Black-Hispanic wage gap. Fryer Jr (2011) also reports logistic regression results for an incarceration outcome variable derived from self-reports and interviewer notes about locations of interviews. Given how these results are reported, it is not possible to make the decomposition calculations that we make in section 4. Further, the overall incarceration rates in the NLSY79 are much lower than the rates reported in other sources.

[45]The correlation between math and reading-value added is .46

both how much students learn in eighth grade as well as whether they matriculate on time from eighth to ninth grade matter for how well students do in high school and for whether they drop out of high school, and our Appendix Table A.2 results show that, among both Black and Hispanic males, eventual graduation rates are significantly higher among students who attend eighth grade in schools with higher promotion valued-added.[46]

Since results in Lochner and Moretti (2004*b*) and Cook and Kang (2016) indicate that educational interventions that reduce high school dropout rates also reduce future rates of criminal justice involvement, it is possible that promotion value-added in eighth grade reduces criminal justice involvement among Black males by creating smoother transitions to high school that reduce high school drop out rates. Drop out rates are much lower in CPS than they were among the cohorts who began high school in 1995, in part, because CPS made an effort to support students who struggle during ninth-grade as they transition to high school.[47] Have these programs or related programs in other cities that target eighth or ninth grade students not only reduced drop out rates but also reduced future rates of criminal justice involvement? Researchers and policy makers should devote attention to this question.

[46] Reading value-added improves graduation rates among white males.

[47] See Allensworth (2005), Allensworth and Easton (2007), and Roderick et al. (2014).

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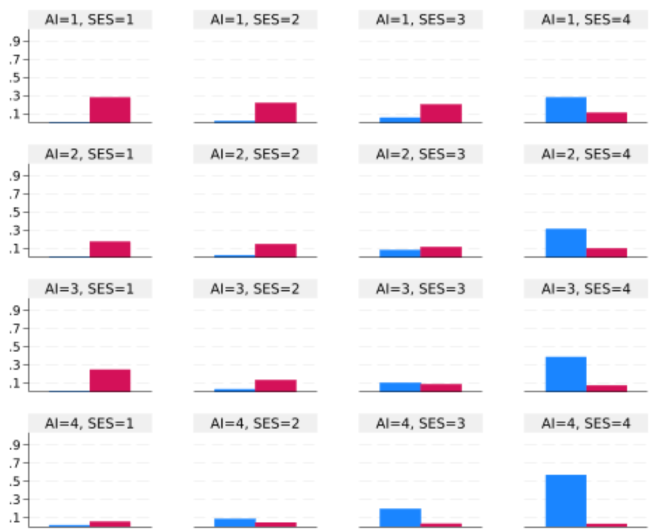
7 Figures

Figure 1

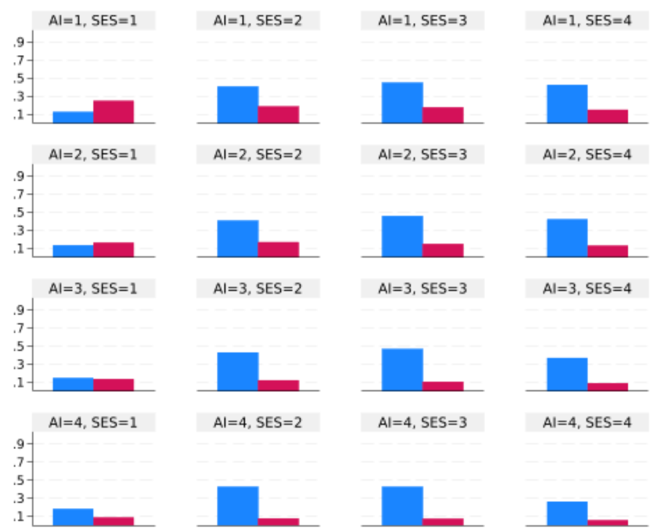
Criminal Justice Involvement by Race, Achievement, and SES

Blue = Fraction Own Race in Cell   Red = Felony Arraignment Rate

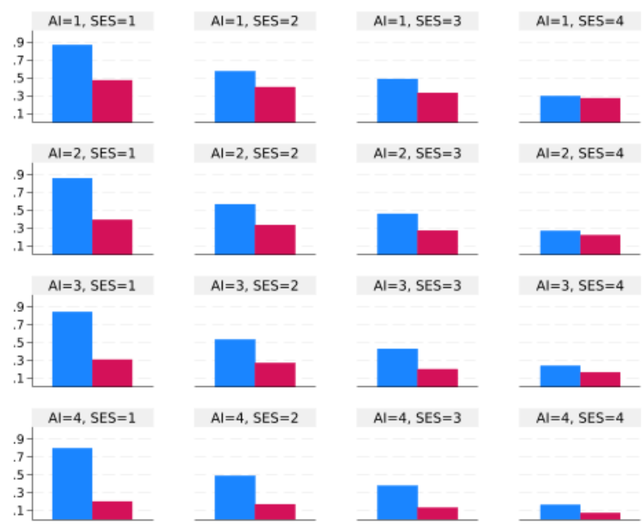
White Males
Felony Rate = .069



Hispanic Males
Felony Rate = .131



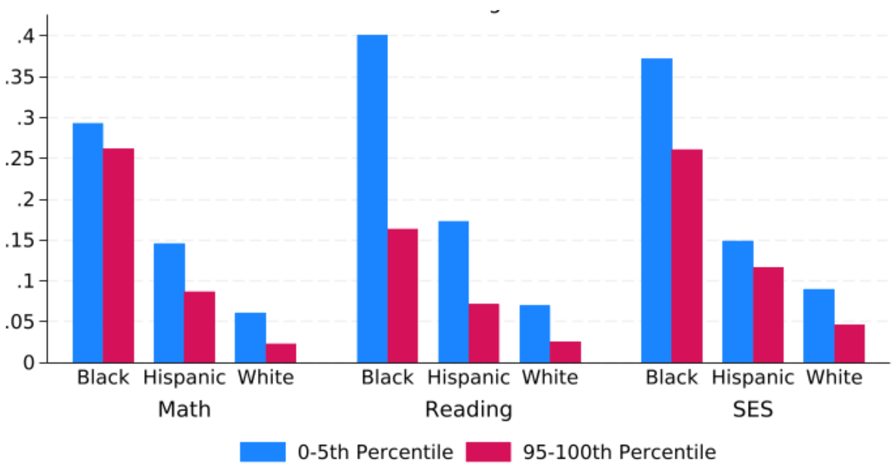
Black Males
Felony Rate = .316



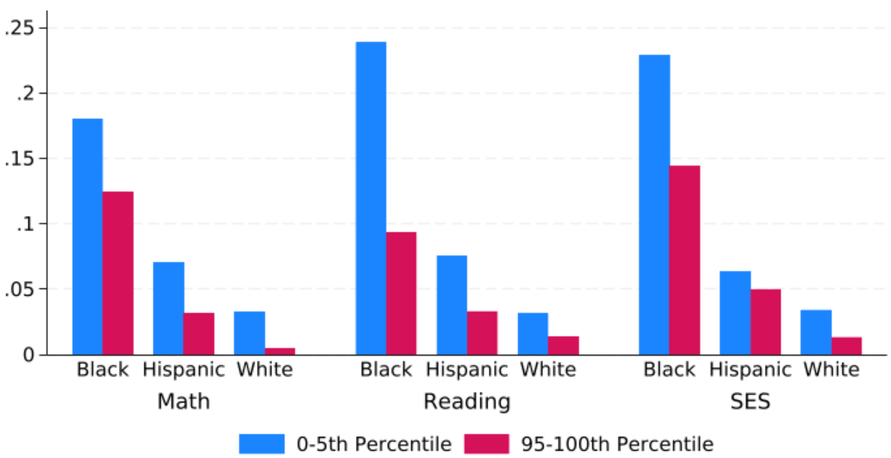
Notes: We define an academic index based on reading and math scores from grades three through eight for all CPS students who began eighth grade during 1995-2004. We define as SES index based on the demographics of the census tracts associated with the addresses reported by each student. We place each male student in one of the 16 cells defined by the intersections of the quartiles of these distributions. We order quartiles such that quartile 4 contains the highest values. The blue bars report the fractions of males in each cell who are Black, Hispanic, and white. The red bars report the felony arraignment rates by age 25 for each sample. See Appendix D for details.

Figure 2
Intra-School Differences in Expected Criminal Justice Involvement: Predicted by Intra-School Variation in Math, Reading, and SES

Felony Arraignment by Age 25



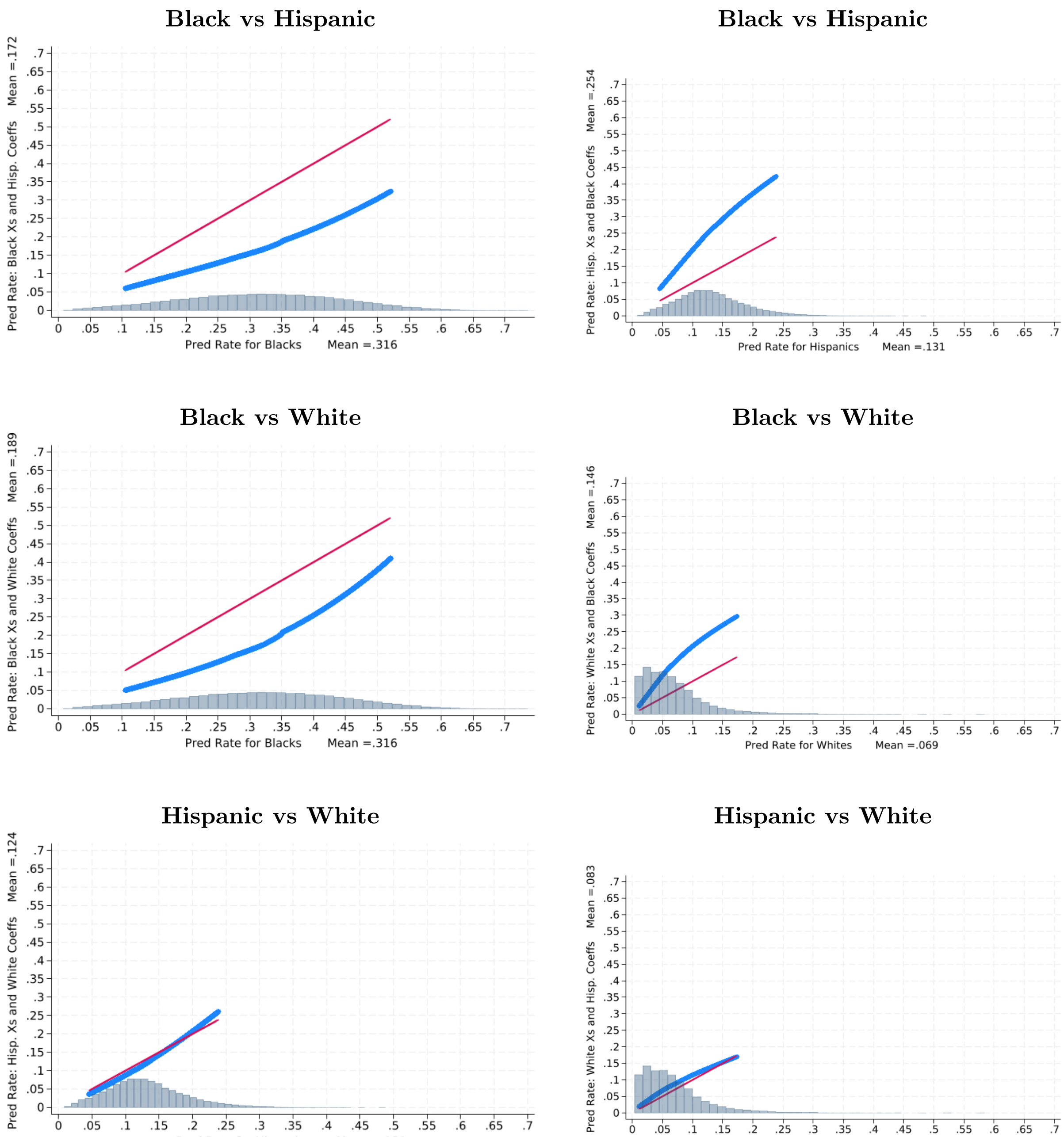
Prison Admission by Age 25



Notes: Each bar displays an average predicted rate of criminal justice involvement for a specific sample of male students of a given race. These predicted values are generated using logit models that take an indicator for either felony arraignment by age 25 or incarceration by age 25 as the dependent variable. We estimate these logit models separately by race given indicator controls for year and eighth-grade school attended, plus a control for age at the start of eighth grade. We also include two-segment splines in grades 3 to 8 reading achievement, grades 3 to 8 math achievement, and SES. We control for measures of the number of residential moves during elementary school and the number of moves among low-SES neighborhoods. Finally, we include an indicator for being off-track in terms of age for grade school. In the top panel, each bar gives an average predicted felony arraignment rate. For example, the 0-5 percentile bar for Reading among Black male students indicates that if we (i) take the sample of all Black male eighth graders in each elementary school, (ii) select the students who are in the bottom five-percent of reading achievement within each school-specific sample, and (iii) create predicted rates of felony arraignment for these students while imputing to them the median math achievement, SES, and other characteristics of Black male eighth graders in each of their schools, the average predicted arraignment rate for this sample is .40. The corresponding 95-100th percentile bar reports that, if we repeat the same exercise with the students who are in the top five percent in reading among the Black male students in each school, the corresponding rate is .17. We define the within-school distributions for reading achievement, math achievement, or SES using all eighth grade males of a given race group who attend a particular school during our 1995-2004 sample period. We place males who attend a school that did not, over this period, enroll at least 100 eighth graders of their race and gender into a composite school.

Figure 3

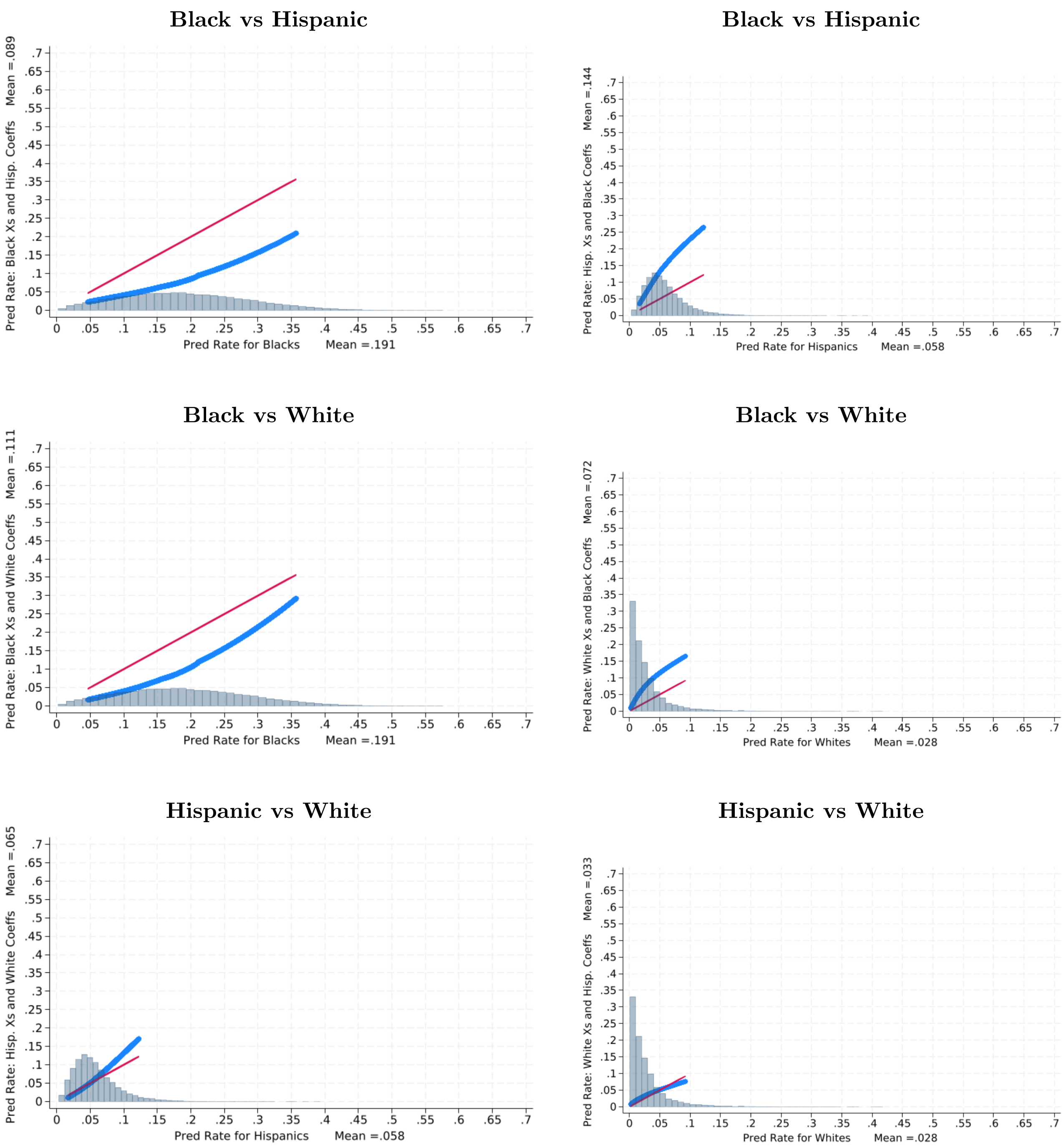
Decomposition of Racial Differences in Felony Arraignment Rates



Notes: Each row presents results from logit models that parallel the models we employ to produce the felony arraignment results in Figure 2, but these specifications do not include school fixed effects. We estimate both our felony arraignment model separately for Black, Hispanic, and white males, and we generate predicted probabilities for the entire sample based on each model's coefficients. Thus, for each Black male student, we have his predicted probability of felony arraignment and two counterfactual probabilities of felony arraignment: one that employs coefficients from the Hispanic model and one that employs coefficients from the white model. The first row of graphs decomposes differences in arraignment rates between Black and Hispanic males. The second row presents the parallel decomposition for Black-white differences. The third row presents the results for Hispanic-white differences. The gross difference in arraignment rates is the difference in the predicted rates on the two x-axes. Holding constant the coefficients from one model, the change in predicted arraignment rates associated with changing the distribution of X's is a measure of how much racial differences in elementary student characteristics contribute to future racial differences in arraignment rates. For example, the overall difference between the Black and Hispanic arraignment rates is $.316 - .131 = .185$. Holding constant the coefficients from the Hispanic model, the difference in predicted arraignment rates is $.172 - .131 = .041$. So, using the Hispanic weights, differences in student characteristics account for $(.041/.185) = 22$ percent of the Black-Hispanic gap in arraignment rates.

Figure 4

Decomposition of Racial Differences in Prison Admission Rates



Notes: See notes for Figure 3 above. These six figures present parallel results. However, the outcome variable in these logit models is a indicator admission to prison by age 25.

8 Tables

Table 1

8th-grade VAM Impacts on Adult Criminal Justice Outcomes: Δ = 10th - 90th Percentile of VAM School Quality

Regressions of CJ Indicators on Individual VAM Metrics

	Felony Arraignment			Prison Admission		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	-0.0104	-0.0184	-0.0535	-0.0132	-0.0223	-0.0466
N=49,962	[p=0.266]	[p=0.046]	[p<0.001]	[p=0.102]	[p=0.005]	[p<0.001]
Hispanic	-0.0005	-0.0047	-0.0094	-0.0037	-0.0065	-0.0036
N=35,896	[p=0.932]	[p=0.573]	[p=0.259]	[p=0.356]	[p=0.261]	[p=0.548]
White	-0.0102	-0.0327	-0.0081	-0.0065	-0.0194	-0.0091
N=16,540	[p=0.104]	[p<0.001]	[p=0.517]	[p=0.132]	[p=0.001]	[p=0.228]

Results from 18 regressions: 3 (race groups) x 3 (VAM metrics) x 2 (outcomes).

Regressions of CJ Indicators on Three VAM Metrics Jointly

	Felony Arraignment			Prison Admission		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	0.0037	-0.0068	-0.0523	0.0016	-0.0118	-0.0429
N=49,962	[p=0.521]	[p=0.288]	[p<0.001]	[p=0.742]	[p=0.028]	[p<0.001]
Hispanic	0.0023	-0.0039	-0.0091	-0.0016	-0.0051	-0.0020
N=35,896	[p=0.666]	[p=0.577]	[p=0.149]	[p=0.678]	[p=0.291]	[p=0.638]
White	-0.0010	-0.0319	-0.0022	-0.0011	-0.0181	-0.0057
N=16,540	[p=0.858]	[p<0.001]	[p=0.795]	[p=0.761]	[p<0.001]	[p=0.292]

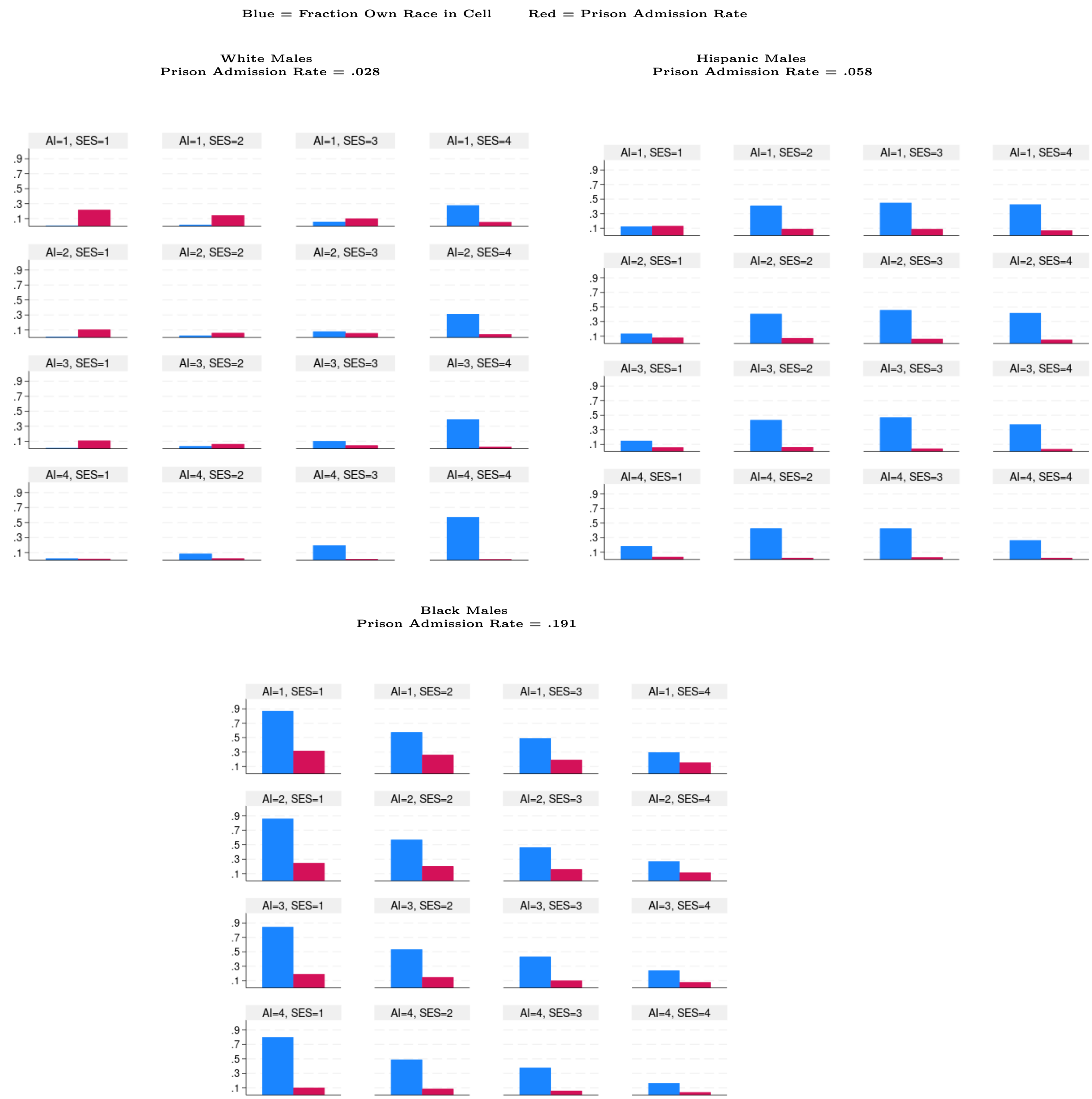
Results from 6 regressions: 3 (race groups) x 2 (outcomes).

Notes: These tables present results from regressions that we run separately on the sample of Black, Hispanic, and white males who entered 8th grade in Chicago Public Schools for the first time during the years 1995-2004. Each entry reports the estimated change in a given outcome associated with moving a student from the 10th to 90th percentile of the distribution of school performance for a given metric. The first panel reports results from six regressions on each sample. The two outcome variables are an indicator for felony arraignment by age 25 and an indicator for entry into prison by age 25. For each outcome, we run three regressions: one on each VAM metric. All regressions also contain controls for each student's prior achievement, history of residential mobility, neighborhood SES during elementary school, as well as fraction over the standard age for eighth grade, fraction Black, fraction male, and average SES at the school*cohort level. The VAM metrics measure the performance of the team of 8th grade teachers in a given student's school during the year the student entered 8th grade. Appendix C describes the construction of Math-VAM, Read-VAM, and Promotion-VAM and provides more details concerning the regression specifications. Math-VAM and Read-VAM are standard VAM measures. The final measure captures variation in educator effectiveness in promoting student graduation from 8th to 9th grade in one year. The second panel contains results from two regressions on each sample that include all three VAM metrics simultaneously. These samples contain only students who attend schools that enrolled at least twenty eighth graders in every year from 1995 to 2004. Rates of criminal justice involvement for Black males are roughly one percentage point lower in this sample than the rates reported in Figures 3 and 4. Rates for Hispanic and white males are less than one percentage point lower.

A Appendix: Additional Results:

Figure A.1

Criminal Justice Involvement by Race, Achievement, and SES



Notes: We define an academic index based on reading and math scores from grades three through eight for all CPS students who began eighth grade during 1995-2004. We define as SES index based on the demographics of the census tracts associated with the addresses reported by each student. We place each male student in one of the 16 cells defined by the intersections of the quartiles of these distributions. We order quartiles such that quartile 4 contains the highest values. The blue bars report the fractions of males in each cell who are Black, Hispanic, and white. The red bars report the prison admission rates by age 25 for each sample. See Appendix D for details.

Table A.1

8th-grade VAM Impacts on Adult Criminal Justice Outcomes: Δ = 25th - 75th Percentile of VAM School Quality

Regressions of CJ Indicators on Individual VAM Metrics

	Felony Arraignment			Prison Admission		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	-0.0056	-0.0094	-0.0285	-0.0072	-0.0113	-0.0248
N=49,962	[p=0.266]	[p=0.046]	[p<0.001]	[p=0.102]	[p=0.005]	[p<0.001]
Hispanic	-0.0003	-0.0024	-0.0050	-0.0020	-0.0033	-0.0019
N=35,896	[p=0.932]	[p=0.573]	[p=0.259]	[p=0.356]	[p=0.261]	[p=0.548]
White	-0.0055	-0.0166	-0.0043	-0.0035	-0.0099	-0.0048
N=16,540	[p=0.104]	[p<0.001]	[p=0.517]	[p=0.132]	[p=0.001]	[p=0.228]

Results from 18 regressions: 3 (race groups) x 3 (VAM metrics) x 2 (outcomes).

Regressions of CJ Indicators on Three VAM Metrics Jointly

	Felony Arraignment			Prison Admission		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	0.0020	-0.0034	-0.0278	0.0009	-0.0060	-0.0229
N=49,962	[p=0.521]	[p=0.288]	[p<0.001]	[p=0.742]	[p=0.028]	[p<0.001]
Hispanic	0.0013	-0.0020	-0.0048	-0.0008	-0.0026	-0.0011
N=35,896	[p=0.666]	[p=0.577]	[p=0.149]	[p=0.678]	[p=0.291]	[p=0.638]
White	-0.0005	-0.0162	-0.0012	-0.0006	-0.0092	-0.0030
N=16,540	[p=0.858]	[p<0.001]	[p=0.795]	[p=0.761]	[p<0.001]	[p=0.292]

Results from 6 regressions: 3 (race groups) x 2 (outcomes).

Notes: These tables present result from regressions that we run separately on the sample of Black, Hispanic, and white males who entered 8th grade in Chicago Public Schools for the first time during the years 1995-2004. Each entry reports the estimated change in a given outcome associated with moving a student from the 25th to 7th percentile of the distribution of school performance for a given metric. The first panel reports results from six regressions on each sample. The two outcome variables are an indicator for felony arraignment by age 25 and an indicator for entry into prison by age 25. For each outcome, we run three regressions: one on each VAM metric. All regressions also contain controls for each student's prior achievement, history of residential mobility, neighborhood SES during elementary school, as well as fraction over the standard age for eighth grade, fraction Black, fraction male, and average SES at the school*cohort level. The VAM metrics measure the performance of the team of 8th grade teachers in a given student's school during the year the student entered 8th grade. Appendix C describes the construction of Math-VAM, Read-VAM, and Promotion-VAM and provides more details concerning the regression specifications. Math-VAM and Read-VAM are standard VAM measures. The final measure captures variation in educator effectiveness in promoting student graduation from 8th to 9th grade in one year. The second panel contains results from two regressions on each sample that include all three VAM metrics simultaneously. These samples contain only students who attend schools that enrolled at least twenty eighth graders in every year from 1995 to 2004. Rates of criminal justice involvement for Black males are roughly one percentage point lower in this sample than the rates reported in Figures 3 and 4. Rates for Hispanic and white males are less than one percentage point lower.

Table A.2

8th-grade VAM Impacts on Student Outcomes
Δ = 10th - 90th Percentile of School Quality

Regressions of Indicator for High School Graduation on VAM Metrics

	Univariate Regressions			Multivariate Regressions		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	0.0110	0.0197	0.0550	-0.0042	0.0076	0.0536
N=40,673	[p=0.349]	[p=0.074]	[p<0.001]	[p=0.531]	[p=0.296]	[p<0.001]
Hispanic	0.0026	0.0236	0.0782	-0.0151	0.0136	0.0790
N=27,298	[p=0.832]	[p=0.110]	[p<0.001]	[p=0.088]	[p=0.232]	[p<0.001]
White	0.0298	0.0801	0.0491	0.0079	0.0715	0.0337
N=10,712	[p=0.039]	[p<0.001]	[p=0.105]	[p=0.506]	[p<0.001]	[p=0.058]

Notes: The table presents result from regressions that we run separately on the sample of Black, Hispanic, and white males who entered 8th grade in Chicago Public Schools for the first time during the years 1995-2004. The outcome variable in each regression is an indicator for graduating high school. The sample graduation rates are .46, .58, and .69 for Black, Hispanic, and white males respectively. Sample sizes are smaller than those in Table 1 because we cannot use records for students that transfer when CPS does not record their final graduation status. Each entry reports the estimated change in a given outcome associated with moving a student from the 10th to 90th percentile of the distribution of school performance for a given metric. The first panel reports results from six regressions on each sample. For each outcome, we run three regressions: one on each VAM metric. All regressions also contain controls for each student's prior achievement, history of residential mobility, neighborhood SES during elementary school, as well as fraction over the standard age for eighth grade, fraction Black, fraction male, and average SES at the school*cohort level. The VAM metrics measure the performance of the team of 8th grade teachers in a given student's school during the year the student entered 8th grade. Appendix C describes the construction of Math-VAM, Read-VAM, and Promotion-VAM and provides more details concerning the regression specifications. Math-VAM and Read-VAM are standard VAM measures. The final measure captures variation in educator effectiveness in promoting student graduation from 8th to 9th grade in one year. The second panel contains results from two regressions on each sample that include all three VAM metrics simultaneously. These samples contain only students who attend schools that enrolled at least twenty eighth graders in every year from 1995 to 2004. Rates of criminal justice involvement for Black males are roughly one percentage point lower in this sample than the rates reported in Figures 3 and 4. Rates for Hispanic and white males are less than one percentage point lower.

Table A.3

Impacts of 8th-Grade Promotion Value-Added on Adult Outcomes: Given Controls for Default High School Δ = 10th - 90th Percentile of School Quality

Panel A: Felony Arraignment

VAM-metric	No HS Controls	Default HS (25%)	Default HS (20%)	Default HS (15%)
Sample				
Black N=49,962	-0.0535 [p<0.001]	-0.0547 [p<0.001]	-0.0544 [p<0.001]	-0.0518 [p<0.001]
Hispanic N=35,896	-0.0094 [p=0.259]	-0.0071 [p=0.372]	-0.0072 [p=0.363]	-0.0062 [p=0.437]
White N=16,540	-0.0081 [p=0.517]	-0.0115 [p=0.340]	-0.0101 [p=0.401]	-0.0092 [p=0.445]

Panel B: Prison Admission

VAM-metric	No HS Controls	Default HS (25%)	Default HS (20%)	Default HS (15%)
Sample				
Black N=49,962	-0.0466 [p<0.001]	-0.0470 [p<0.001]	-0.0471 [p<0.001]	-0.0444 [p<0.001]
Hispanic N=35,896	-0.0036 [p=0.548]	-0.0041 [p=0.487]	-0.0040 [p=0.494]	-0.0033 [p=0.575]
White N=16,540	-0.0091 [p=0.228]	-0.0122 [p=0.116]	-0.0112 [p=0.149]	-0.0116 [p=0.141]

Notes: The results provide robustness checks for the VAM results in Table 1 concerning the univariate regression impacts of promotion value-added on criminal justice outcomes. The "No HS Controls" reproduces the relevant results from the top panel of Table 1. Each "Default HS" column present results from an alternative specification that includes dummies for any high school that is a default high school for one or more elementary schools. We use 25, 20, 15 percent shares of students matriculating from a given elementary school to a single high school as cutoffs for defining a default high school. Most CPS students attend an elementary school that is not associated with even one high school that enrolls at least 15 percent of its students. See note below Table 1 for more details.

Table A.4

Impacts of 8th-Grade Reading Value-Added on Adult Outcomes: Given Controls for Default High School Δ = 10th - 90th Percentile of School Quality

Panel A: Felony Arraignment

VAM-metric	Default	A	B	C
Sample				
Black	-0.0184	-0.0151	-0.0143	-0.0164
N=49,962	[p=0.046]	[p=0.115]	[p=0.141]	[p=0.078]
Hispanic	-0.0047	-0.0015	-0.0018	-0.0019
N=35,896	[p=0.573]	[p=0.848]	[p=0.826]	[p=0.810]
White	-0.0327	-0.0302	-0.0299	-0.0299
N=16,540	[p<0.001]	[p=0.001]	[p=0.001]	[p=0.001]

Panel B: Prison Admission

VAM-metric	Default	A	B	C
Sample				
Black	-0.0223	-0.0205	-0.0203	-0.0213
N=49,962	[p=0.005]	[p=0.015]	[p=0.020]	[p=0.011]
Hispanic	-0.0065	-0.0058	-0.0056	-0.0053
N=35,896	[p=0.261]	[p=0.299]	[p=0.318]	[p=0.344]
White	-0.0194	-0.0195	-0.0190	-0.0190
N=16,540	[p=0.001]	[p=0.001]	[p=0.001]	[p=0.001]

Notes: The results provide robustness checks for the VAM results in Table 1 concerning the univariate regression impacts of reading value-added on criminal justice outcomes. The "No HS Controls" reproduces the relevant results from the top panel of Table 1. Each "Default HS" column present results from an alternative specification that includes dummies for any high school that is a default high school for one or more elementary schools. We use 25, 20, 15 percent shares of students matriculating from a given elementary school to a single high school as cutoffs for defining a default high school. Most CPS students attend an elementary school that is not associated with even one high school that enrolls at least 15 percent of its students. See note below Table 1 for more details.

Table A.5

Racial Gaps in Felony Arraignment Rates: Males

	A	B	C
Hispanic	-.182	-.131	-.109
Black	-.247	-.116	-.102
Controls			
Year Fixed Effects	x		
Student Characteristics	x	x	
School Fixed Effects	x	x	x

Notes: This table presents results from three regressions of an indicator for felony arraignment by age 25 on two indicators for race and three different sets of control variables. Specification A contains indicators for the year each student began eighth grade. Specification B adds controls for splines in SES, an index of math achievement during grades 3 through 8, and an index of reading achievement during grades 3 through 8 plus additional controls for age in months, an indicator for being above the normal age for eighth grade, and controls for patterns of residential mobility during elementary school. Specification C adds a set of school fixed effects. We place students who attend a school that enrolled less than 50 students in eighth grade between 1995 and 2004 in a composite school. The sample includes only male students. The omitted race category is white. The sample size for each regression is 132,242. The adjusted R-squared values are .067, .113, and .128 respectively for specifications A, B, and C.

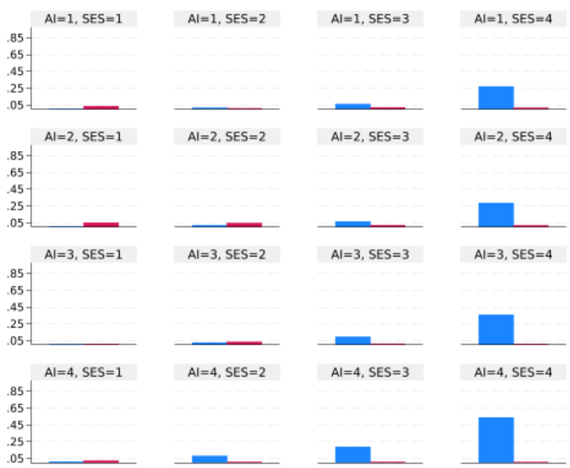
B Appendix: Figures for Female Results

Figure B.1

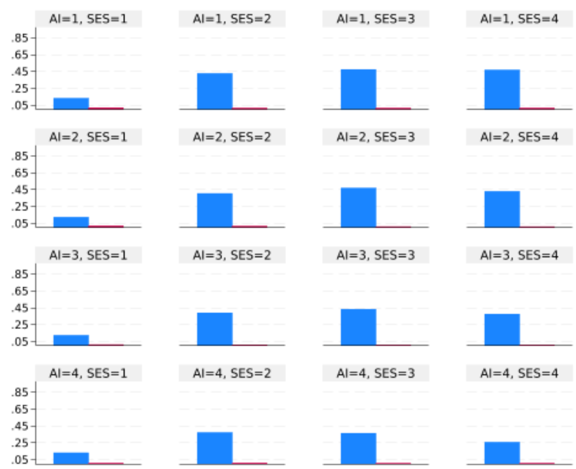
Distributions of Race and Criminal Justice Involvement
Within Quartiles of Achievement and SES
Females

AI = K-8 Academic Achievement **SES = Neighborhood SES**
Blue = Fraction Own Race in Cell **Red = Felony Arraignment Rate**

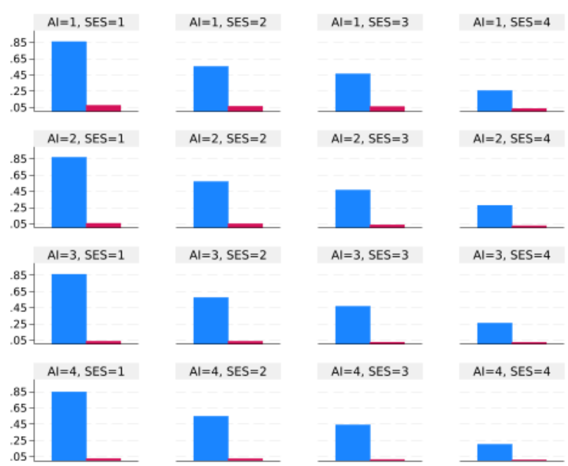
White Females



Hispanic Females



Black Females

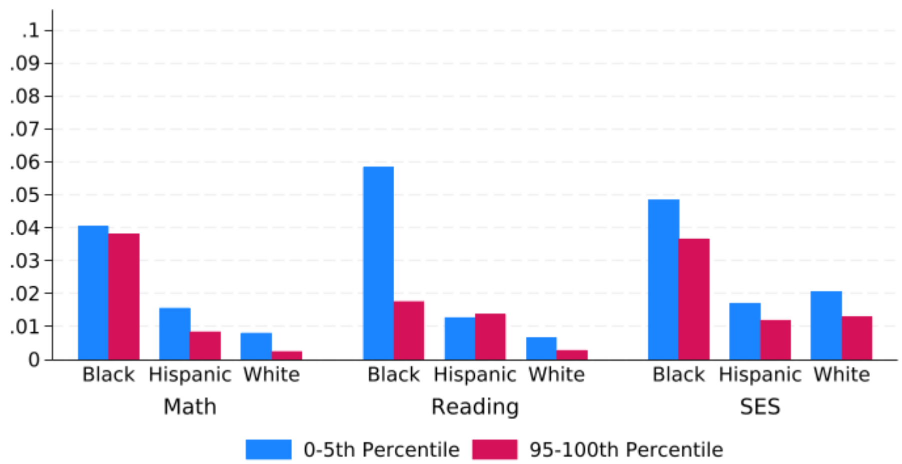


Notes: We define an academic index based on reading and math scores from grades three through eight for all CPS students who began eighth grade during 1995-2004. We define as SES index based on the demographics of the census tracts associated with the addresses reported by each student. We place each female student in one of the 16 cells defined by the intersections of the quartiles of these distributions. We order quartiles such that quartile 4 contains the highest values. The blue bars report the fractions of females in each cell who are Black, Hispanic, and white. The red bars report the felony arraignment rates by age 25 for each sample. See Appendix D for details.

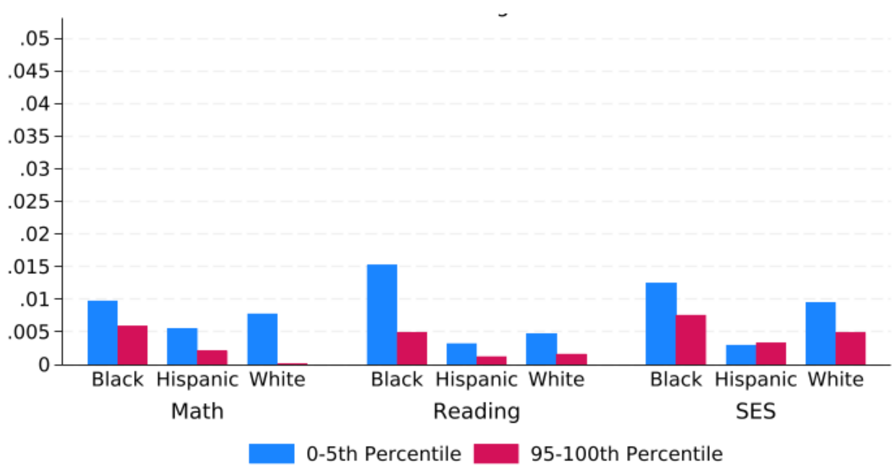
Figure B.2

Intra-School Differences in Expected Criminal Justice Involvement: Predicted by Intra-School Variation in Math, Reading, and SES Females

Felony Arraignment by Age 25



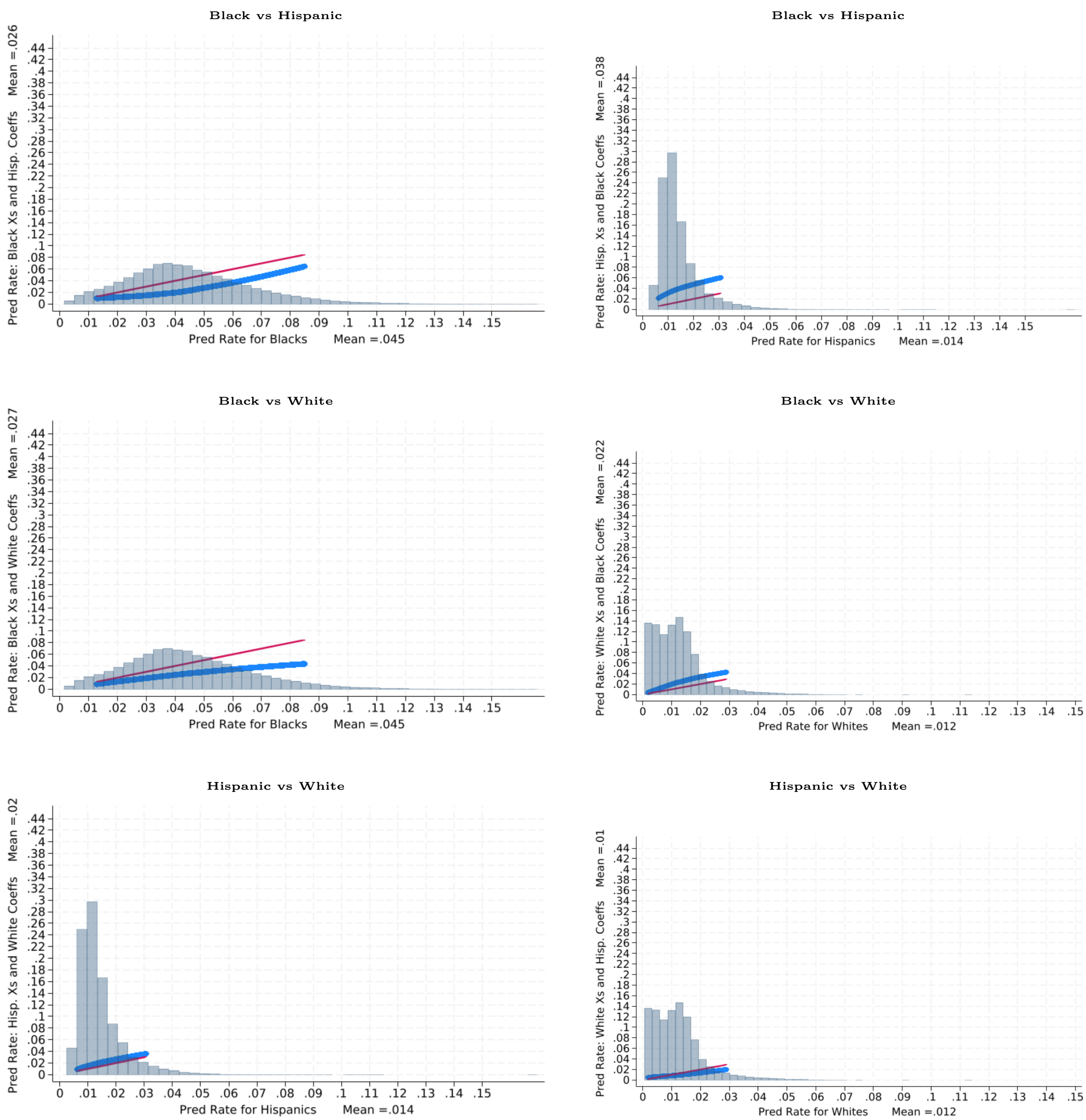
Prison Admission by Age 25



Notes: Each bar displays an average predicted rate of criminal justice involvement for a specific sample of female students of a given race. These predicted values are generated using logit models that take an indicator for either felony arraignment by age 25 or incarceration by age 25 as the dependent variable. We estimate these logit models separately by race given indicator controls for year and eighth-grade school attended, plus a control for age at the start of eighth grade. We also include two-segment splines in grades 3 to 8 reading achievement, grades 3 to 8 math achievement, and SES. We control for measures of the number of residential moves during elementary school and the number of moves among low-SES neighborhoods. Finally, we include an indicator for being off-track in terms of age for grade school. In the top panel, each bar gives an average predicted felony arraignment rate. For example, the 0-5 percentile bar for math among Black female students indicates that if we (i) take the sample of all Black female eighth graders in each elementary school, (ii) select the students who are in the bottom five-percent of math achievement within each school-specific sample, and (iii) create predicted rates of felony arraignment for these students while imputing to them the median reading achievement, SES, and other characteristics of Black female eighth graders in each of their schools, the average predicted arraignment rate for this sample is .04. We define the within-school distributions for reading achievement, math achievement, or SES using all eighth grade females of a given race group who attend a particular school during our 1995-2004 sample period. We place females who attend a school that did not, over this period, enroll at least 100 eighth graders of their race and gender into a composite school.

Figure B.3

Decomposition of Racial Differences in Felony Arraignment Rates
Females



Notes: Each row presents results from logit models that parallel the models we employ to produce the felony arraignment results in Figure 2, but these specifications do not include school fixed effects. We estimate both our arraignment model separately for Black, Hispanic, and white females, and we generate predicted probabilities for the entire sample based on each model's coefficients. Thus, for each Black female student, we have her predicted probability of felony arraignment and two counterfactual probabilities of felony arraignment: one that employs coefficients from the Hispanic model and one that employs coefficients from the white model. The first row of graphs decomposes differences in arraignment rates between Black and Hispanic females. The second row presents the parallel decomposition for Black-white differences. The third row presents the results for Hispanic-white differences. The gross difference in arraignment rates is the difference in the predicted rates on the two x-axes. Holding constant the coefficients from one model, the change in predicted arraignment rates associated with changing the distribution of X's is a measure of how much racial differences in elementary student characteristics contribute to future racial differences in arraignment rates.

Table B.1

8th-grade VAM Impacts on Adult Criminal Justice Outcomes: Δ = 10th - 90th Percentile of VAM School Quality

Regressions of CJ Indicators on Individual VAM Metrics

	Felony Arraignment			Prison Admission		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	0.0008	-0.0021	-0.0086	0.0001	-0.0011	-0.0027
N=53,495	[p=0.771]	[p=0.527]	[p=0.010]	[p=0.947]	[p=0.284]	[p=0.038]
Hispanic	0.0005	0.0002	0.0008	0.0007	-0.0019	-0.0003
N=35,644	[p=0.840]	[p=0.926]	[p=0.733]	[p=0.300]	[p=0.012]	[p=0.771]
White	-0.0021	-0.0073	-0.0048	-0.0009	-0.0014	-0.0020
N=16,083	[p=0.512]	[p=0.043]	[p=0.345]	[p=0.271]	[p=0.363]	[p=0.307]

Results from 18 regressions: 3 (race groups) x 3 (VAM metrics) x 2 (outcomes).

Regressions of CJ Indicators on Three VAM Metrics Jointly

	Felony Arraignment			Prison Admission		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	0.0035	-0.0019	-0.0091	0.0011	-0.0011	-0.0027
N=53,495	[p=0.158]	[p=0.491]	[p=0.001]	[p=0.311]	[p=0.399]	[p=0.027]
Hispanic	0.0004	-0.0002	0.0008	0.0017	-0.0029	-0.0001
N=35,644	[p=0.835]	[p=0.934]	[p=0.725]	[p=0.036]	[p=0.007]	[p=0.912]
White	-0.0001	-0.0068	-0.0033	-0.0006	-0.0008	-0.0018
N=16,083	[p=0.972]	[p=0.043]	[p=0.388]	[p=0.572]	[p=0.588]	[p=0.305]

Results from 6 regressions: 3 (race groups) x 2 (outcomes).

Notes: These tables present result from regressions that we run separately on the sample of Black, Hispanic, and white females who entered 8th grade in Chicago Public Schools for the first time during the years 1995-2004. Each entry reports the estimated change in a given outcome associated with moving a student from the 10th to 90th percentile of the distribution of school performance for a given metric. The first panel reports results from six regressions on each sample. The two outcome variables are an indicator for felony arraignment by age 25 and an indicator for entry into prison by age 25. For each outcome, we run three regressions: one on each VAM metric. All regressions also contain controls for each student's prior achievement, history of residential mobility, neighborhood SES during elementary school, as well as fraction over the standard age for eighth grade, fraction Black, fraction male, and average SES at the school*cohort level. The VAM metrics measure the performance of the team of 8th grade teachers in a given student's school during the year the student entered 8th grade. Appendix C describes the construction of Math-VAM, Read-VAM, and Promotion-VAM and provides more details concerning the regression specifications. Math-VAM and Read-VAM are standard VAM measures. The final measure captures variation in educator effectiveness in promoting student graduation from 8th to 9th grade in one year. The second panel contains results from two regressions on each sample that include all three VAM metrics simultaneously. These samples contain only students who attend schools that enrolled at least twenty eighth graders in every year from 1995 to 2004.

Table B.2

8th-grade VAM Impacts on Student Outcomes
Δ = 10th - 90th Percentile of School Quality

Regressions of Indicator for High School Graduation on VAM Metrics

	Univariate Regression			Multivariate Regression		
VAM-metric	Math-VAM	Read-VAM	Promotion-VAM	Math-VAM	Read-VAM	Promotion-VAM
Sample						
Black	0.0135	0.0224	0.0436	-0.0006	0.0123	0.0396
N=45,032	[p=0.073]	[p=0.009]	[p<0.001]	[p=0.921]	[p=0.071]	[p<0.001]
Hispanic	0.0281	0.0281	0.0765	0.0160	0.0019	0.0722
N=27,803	[p=0.008]	[p=0.044]	[p<0.001]	[p=0.046]	[p=0.853]	[p<0.001]
White	0.0342	0.0731	0.0672	0.0153	0.0575	0.0518
N=10,642	[p=0.062]	[p<0.001]	[p=0.018]	[p=0.148]	[p<0.001]	[p=0.001]

These regression models parallel the models described in the notes to Table B.1. However, here the outcome variables is an indicator variable for graduating from high school. The sample graduation rates are .64, .71, and .79 for Black, Hispanic, and white females respectively. The sample sizes are smaller because we do not use records for students who transferred out of CPS after eighth grade if the CPS has not information concerning whether they finished high school or not.

C Value-Added Measures

We use a variant of the method proposed in Chetty et al. (2014*a*) to create our value-added metrics. The unit of observation is a cohort of students who begin eighth grade in a given school in the fall of the same school year. The procedure involves the following steps: First, we use student-level data to project high school graduation, spring of eighth grade reading scores, and spring of eighth grade math scores on the following set of controls: (i) three two-segment splines in SES, an index of grade 3 to 7 reading achievement, and an index of grade 3 to 7 math achievement plus (ii) an indicator for being off-track in terms of age for grade, measures of the number of residential moves made during elementary school, measures of the number of residential moves made among low SES neighborhoods and (iii) school-cohort averages of SES and the off-track indicator. We also include year effects, a set of school fixed effects, an indicator for Black, an indicator for male, age in months, and the fractions Black and male within a given school*cohort cell. For each outcome variable, we do the following calculations: for each student i who attends school j in year t, we capture the residual for student i from the regression and add the estimated school effect for school j to form v_{ijt}. Within each eighth-grade cohort in each school, we take the average of these residuals and call this average $\bar{\theta}^k_{jt}$.

We then run ten regressions, one for each t, that involve projecting $\bar{\theta}^k_{jt}$ on all values $\bar{\theta}^k_{jt'}$ such that $|t - t'| \leq 2$. For years $t = 1995$ or $t = 2004$, we are projecting on mean residuals from two other years. For years $t = 1996$ or $t = 2003$, we are projecting on mean residuals from three other years. In all other cases, we are projecting on mean residuals from four other years. We are not able to use data from years before 1995 or after 2004 because we cannot place test scores from these earlier and later years on the scale we use for 1995 through 2004 scores. We weight these regressions by the number of students in our sample who attend school j in year t, and we then capture the fitted values for each of these ten regressions. We repeat these steps for each dimension of school performance k. These fitted values, $\hat{\theta}^k_{jt}$, are our shrunken estimates of the value-added of school j in year t on student outcome k, where $k \in \{\text{reading, math, promotion}\}$.

Our method does not impose the stationarity assumptions that Chetty et al. (2014*a*) do, and we do not use data from all years 1995-2004 when performing shrinkage on each $\bar{\theta}^k_{jt}$. CPS went through at least three different changes in accountability systems during the period 1995-2004, and the reforms dealt with standards for promotion from one grade to another as well as the sanctions that schools face when students earn low math or reading scores. See Neal and Schanzenbach (2010) and Allensworth (2005). For these reasons, we chose to shrink each $\bar{\theta}^k_{jt}$ using projections specific to t.

D Data Appendix

School and Neighborhood Data

We begin by cleaning and standardizing the Chicago Public School "masterfiles." These files are snapshots of the CPS administrative database. CPS creates the masterfile snapshots once in the Fall and once in the Spring of each school year. We do not know the exact creation dates of each file, though the Fall file is typically created around October 1st, and the Spring file is created around May 31st pre-2008, and around June 14th in years 2008 and later. **Unique Students**

The CPS uses Student ID numbers (SIDs) to identify student records. In theory, CPS does not change the SID associated with a given student as he progresses through school. In practice, administrative errors within CPS can result in a given student being associated with multiple SIDs over time. CPS most often associates multiple SIDs with a student when it treats a returning student as a new student. Here, rather than correctly assigning the returning student to their existing SID, CPS creates a new SID. We use the following rules to convert SIDs to a unique identifier (which we call a CHMSID):

- Singletons: We convert the singular SID to the singular CHMSID for all time. We process 97.65 percent of CHMSIDs in this way.
- Multiples without overlap: We combine the multiple SIDs into a single history, which is then assigned the singular CHMSID. When a SID is active, we include it in the combined history. For half-years when no SID is active, we use the last active SID. We process 1.51% of CHMSIDs in the final data this way.
- Multiples with overlap: We arbitrarily select the numerically lowest SID and convert this SID to the singular CHMSID for all time. We process 0.84% of CHMSIDs in the final data this way.
- We place all remaining SIDs in a "sequestered" file. We do not use these records in our work.

School enrollment

We first record whether a student was actively enrolled on the date when CPS constructed a given masterfile. Note that each masterfile is a snapshot of CPS administrative data, so if a student was not enrolled on the day the snapshot was taken, but was enrolled at some other time in the semester, she will be listed as not active. If a student was active, we record the grade in which the student was enrolled. Pre-2008, we also create an indicator variable for whether a student was enrolled in a self-contained or ungraded special education classroom.

We also rely on two variables which together uniquely describe the school each student attended. Pre-2008, CPS uses 'unit' as a school ID number. In 2008 and later, CPS uses 'schlid' as a school ID number. In our analyses, we are using unit numbers to identify elementary schools. We use both unit and schlid numbers in our efforts to identify modal high schools for each elementary school. Overall, one third of the eighth graders in our analysis sample start high school in the CPS high school that is modal for their elementary school. If we restrict the sample to students who remain in CPS for high school, this fraction increases to 38 percent.

Demographics

The masterfiles contain a record for every half-year that a student is active in CPS. There are cases where one CHMSID is associated with i) multiple birthdays, ii) multiple races, and/or iii) multiple sexes over time. We conjecture that correct values for these variables are more common than incorrect values, even within the cases where discrepancies appear. Therefore, we assign the modal birthday, race, and sex within the collection of records associated with each CHMSID to that CHMSID for all time. We consider only non-missing values when calculating the mode. This data-cleaning procedure affects 4.56% of CHMSIDs in our data.

During our sample period, CPS coded race using five categories. (White, African American, Native American/Alaskan Native, Asian/Pacific Islander, Latino). Most of our results use two categories. Black corresponds to African American. Non-Black maps to the other four categories. In some Appendix results, we present results for Hispanic students (Latino) and for Non-Black, Non-Hispanic students (White, Native American/Alaskan Native, Asian/Pacific Islander).

School Exit

We construct a variable from the masterfile that takes 7 values that describe a student's exit from CPS. This variable indicates the status of students who left CPS and distinguishes between students who graduated, dropped out, transferred out, left CPS for an unknown reason, left CPS to go to jail or be institutionalized, graduated from an alternative program, or died. A student is an alternative graduate if he was either a special education student who completed his Individual Education Plan (IEP) without the credits to graduate or if he received a non-CPS diploma (eg. a state diploma with lower standards). This variable reflects CPS's best understanding during each semester of each student's reason for not being in CPS during that semester. So it is possible for a student's exit code to change in a later semester if, for example, the student re-enters CPS or CPS gets new information about why a student left CPS. If CPS claims that a student has graduated for 3 consecutive semesters, we carry that exit code forward. We apply the same logic to students who are deceased for 3 consecutive semesters according to CPS. This imputation only affects 242 CHMSIDs. Of the exit code categories, we consider the following 3 exit categories to be "terminal": graduation, death, and graduation from an alternative program.

The high school graduation indicator that we use as an outcome in our VAM regressions equals one if a student graduates from a CPS high school with a regular diploma. It is coded as missing if the student transfers out of CPS, since we have no way to know whether the student went on to graduate from another school. In all other cases, we set this indicator equal to zero.

Neighborhood SES

We use Census tracts as the starting point for our calculation of neighborhood SES. The Census made only small changes to tract definitions in Chicago between 1990 and 2000. We ignore these changes. However, the Census did make substantial changes to tracts in the Chicago area in 2010. We accommodate these changes by creating "supertracts". We construct supertracts such that if two (populated) tract areas overlap, both tracts belong to the same supertract. To illustrate this idea, consider consider the following scenarios with hypothetical tracts:

- Tract 100 splits into tracts 101 and 102. Supertract 1 includes the entire area of tract 100.
- The border between tracts 201 and 202 changes such that some of tract 201's area is transferred to tract 202. Supertract 2 includes the entire area of both tract 201 and tract 202.
- Tract 300 does not change. Supertract 3 includes the entire area of tract 300.

In practice, most of the 2010 changes involved splitting or combining existing tracts rather than making small adjustments to tract borders, so the set of supertracts is not significantly smaller than the set of tracts. There are 867 Chicago tracts before 2010, 795 Chicago tracts after 2010, and 721 supertracts.

SES Construction

We calculate SES for 1990 and 2000 using Census tract-level data from the 1990 and 2000 decennial censuses. We calculate SES for each year in 2010 using the 5 years of ACS data centered around 2010. For each tract and data sample, we collect high school dropout rate, college completion rate, poverty rate, public assistance use rate, and median family income. When a supertract includes multiple tracts, we use the population-weighted average of the variables in the underlying tracts. We calculate supertract-level SES as the first principal component of these variables. We extended the decennial predicted values to inter-census years with linear interpolation.

Criminal Justice Data

We employ criminal justice data that we created for Jordan et al. (2023). Here, we comment on key aspects of the data cleaning and variable creation. The data appendix in Jordan et al. (2023) provides even more information about court records in Cook County and prison records in Illinois.

Our raw data come from the Clerk of Court for Cook County, IL, and the Illinois Department of Corrections (IDOC). The Clerk of Court of Cook County provides three types of data:

- the *root* data contain basic demographic information about the defendant and the case initiation date.
- the *charge* data describe each charge initiated by prosecutors.
- the *dispositions* file describes the 54 million dispositions filed during these felony cases.

Each record in the charge file represents a case where the defendant is arraigned on a felony charge. These events are our arraignment events.

We use the dispositions to create our incarceration measure. We code a person who is arraigned as incarcerated if we see that the case ends in a sentence to prison, and the sentencing information, which includes credits for jail time, clearly indicates that the defendant is required to serve time in prison. We also code a person as incarcerated if the admission files for the Illinois Department of Corrections (IDOC) record that they entered a prison. We have admission files for IDOC prisons from 1990 through 2014. We also code persons as incarcerated when the court sentences them to Bootcamp program run by the Sheriff. This program involves four months of incarceration and eight months of follow-up programming.

Linking Criminal Justice and CPS Records

This paper relies on a mapping of CPS students to Cook County criminal justice records. We match these datasets in several steps.

The key matching variables for the court data come from the root dataset, which provides: first name, last name, sex, date of birth, and an ID number (called an IR number). Some court records do not have IR numbers. We assign these records unique synthetic IR numbers in the hopes of still matching that record to the CPS data. We extract these potential matching variables and make a dataset of all unique combinations. A given person can appear in this dataset multiple times if they have an IR number, but reported different names (aliases) or birth dates at different points in time.

The key matching variables for the CPS data come from the raw administrative data, which provides: first name, last name, sex, date of birth, and a CPS student ID (SID). We make a unique dataset of all available students in CPS data, with one observation for each combination of first name, last name, sex, date of birth, and SID.

To match records from CPS to Cook County, we begin by identifying all potential matches along any of these sets of variables:

- First name soundex, last name soundex, birth day, birth month, sex
- First name soundex, last name soundex, birth day, birth year, sex
- First name soundex, last name soundex, birth year, birth month, sex

If a CPS SID (A) matches to a Court IR number (B), and if A does not match to any other IR numbers in the Court data, and B does not match to any other SIDs in the CPS data, we are very confident of the match. But, in many cases, a SID will match to multiple IR numbers or an IR number will match to multiple SIDs. In these cases, as a first pass, we will prioritize matches that match exactly on as many demographic characteristics as possible.

There are six variables which could be equal for each proposed match: first name, last name, birth day, birth month, birth year, and sex. A perfect match will have all six variables identical in the CPS and Court data.

We now have a list of IR number to SID pairs, and for each pair we have a score ranging from 3 to 6, indicating the number of components that match for that pair. 3 is a lower bound, because we require that two of the three birth date components and sex match from CPS to a court record. We want to ensure that each SID only matches to one IR number, and that each IR number only matches to one SID. To do this, think of each IR number and SID as nodes of a network, with an edge between two nodes if the link is in our crosswalk.

As an example, consider this crosswalk of SIDs (A-C) to IR numbers (1-3), with the score in parentheses after the link

- A $\leftrightarrow$ 1 (score: 6)
- A $\leftrightarrow$ 2 (score: 5)
- B $\leftrightarrow$ 1 (score: 4)
- C $\leftrightarrow$ 3 (score: 4)

We mark each connected component in this network. In this example crosswalk, there are two connected components: C$\leftrightarrow$3 is the first, and the other three matches are all in a second connected component. We then delete the weakest link in each connected component with more than one element. So our first step is to delete the weakest match (B $\leftrightarrow$ 1). We still have two connected components: C$\leftrightarrow$3 and A$\leftrightarrow$1,A$\leftrightarrow$2. We then delete (A$\leftrightarrow$2), leaving us with our final two matches: A$\leftrightarrow$1 and C$\leftrightarrow$3. We proceed with this process until it terminates, which it must do because we begin with a finite set of links.

At this point, we have a SID $\leftrightarrow$ IR number crosswalk. For each potential match, we have a measure of quality: the number of components that matched between the court record and the CPS record.

We hand-check 50 random matches with 3 mismatched components, 50 random matches with 2 mismatched components, and 50 matches with 1 mismatched component. There is a clear divide in quality between the matches with 3 and 2 mismatched components (eg. first name and birth year or last name and birth month) and the matches with only 1 mismatched component. So, in our main analysis sample, we rely on matches with zero or one mismatched component.