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EARLY PREDICTORS OF RACIAL DISPARITIES IN CRIMINAL JUSTICE INVOLVEMENT

Andrew Jordan
Ezra Karger
Derek Neal

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ABSTRACT

We examine ten cohorts of male eighth graders in public schools in Chicago, IL: 1995-2004. We find that composite measures of math achievement, reading achievement, and neighborhood SES during elementary school are strong predictors of future felony arraignment and incarceration, even among students of the same race who attend the same school. Nonetheless, elementary achievement and early SES account for less than half of Black versus non-Black disparities in these outcomes. Value-added measures of eighth grade school quality suggest that schools may reduce criminal justice involvement by better preparing students for the non-cognitive demands of high school.

Andrew Jordan
Department of Economics
Washington University in St Louis
One Brookings Dr.
St Louis, MO 63105
awjordan@wustl.edu

Ezra Karger
Federal Reserve Bank of Chicago
230 South LaSalle Street
Chicago, IL 60604
karger@uchicago.edu

Derek Neal
Department of Economics
University of Chicago
1126 East 59th Street
Chicago, IL 60637
and NBER
n9na@uchicago.edu

Introduction

Existing research documents strong associations between measures of reading and math achievement in elementary or secondary school and future life outcomes.[1] Compared to their lower-achieving peers, students with strong reading and math skills are significantly more likely to graduate from high school, complete post-secondary schooling, and earn high incomes. Further, Chetty et al. (2014*b*) leverage Value-Added Model (VAM) measures of elementary school teacher quality to provide evidence that students can expect higher educational attainment and adult earnings if they are assigned to teachers who excel at fostering math and reading achievement.[2]

However, we know less about the mappings between reading and math skills among youth and their future criminal justice outcomes. Rose et al. (2022) examine relationships between measures of teacher quality and future criminal justice outcomes between ages 16 and 21 among students in North Carolina. However, no other large-scale studies document how expected rates of future convictions and incarcerations vary with individual reading and math achievement among different groups of elementary school students.

We employ data from 10 cohorts of elementary school students in Chicago, IL to map measures of math and reading achievement during elementary school to adult criminal justice outcomes, and we also construct VAM measures of eighth-grade school quality that allow us to look for causal links between school quality during the year prior to the transition to high school and adult criminal justice outcomes. We focus on eighth-grade quality because several studies document a potential causal link between reducing high school dropout rates and reducing criminal justice involvement.[3]

A large literature also explores the relationship between characteristics of childhood environments and adult outcomes, as well as the causal impacts of exposure to better neighborhoods during childhood on future life outcomes.[4] We do not have measures of exogenous variation in neighborhood SES that would allow us to estimate the causal impacts of neighborhood characteristics experienced during elementary school on future criminal justice outcomes, but we do present results that are consistent with the view that neighborhoods matter. We show that measures of neighborhood SES during elementary school are clear predictors of adult criminal justice outcomes, even among students who attend the same school and enjoy similar levels of academic achievement.

Many studies attempt to measure what portions of racial differences in post-secondary education and adult labor market outcomes are predictable based on various measures of childhood environment and childhood skill acquisition. We estimate our models separately by race and perform decomposition exercises that assess what portion of racial differences in adult criminal justice outcomes are predictable given measures of neighborhood SES and elementary achievement in reading and math. Since males have rates of criminal justice involvement that are typically nine times higher than rates for females, our main results describe outcomes for males.[5]

In Chicago, summary measures of reading achievement, math achievement, and neighborhood SES during elementary school are important predictors of criminal justice outcomes for all males, but the associations between these measures and adult criminal justice outcomes are typically stronger among Blacks. As a result, conditional racial disparities in criminal justice outcomes are much smaller among high achieving students from advantaged neighborhoods. In fact, among the highest achieving students from the most advantaged neighborhoods, we find few, if any, significant racial differences in criminal justice outcomes. Nonetheless, the vast majority of Black students have much worse expected criminal justice outcomes than comparable non-Black students.

Our prediction models reveal that, among Black males who attend the same school and live in comparable neighborhoods, reading achievement during elementary school stands out as particularly powerful predictor

[1]See Neal and Johnson (1996),Cunha et al. (2006), Fryer Jr (2011), and Deming (2017) as examples.

[2]Other studies explore the long-term consequences of programs that give students opportunities to attend different schools, either through public choice systems or through access to charter schools. See Deming (2011), Chetty et al. (2011), Dobbie and Fryer Jr (2015), Angrist et al. (2016), and Dobbie and Fryer (2020).

[3]See Lochner and Moretti (2004) and Cook and Kang (2016).

[4]See Kling et al. (2005), Sampson (2012), Chetty et al. (2016), and Chetty and Hendren (2018).

[5]Appendix B provides parallel results for females.

of future differences in criminal justice involvement. Given our data, we cannot discern what portion of this relationship is causal, but the strength of this relationship highlights the need for future research.

Our analyses of the causal impacts of eighth-grade school quality of future criminal justice outcomes focus on three dimensions of school quality, and in concert with several other recent studies, we find evidence that non-cognitive dimensions of school performance impact future criminal justice outcomes. Students who attend schools with teams of eighth-grade teachers who excel in helping students transition to high school and graduate are less likely to face felony charges or incarceration as adults, and these impacts are quite large among Black males. Given our controls, we find limited evidence that students who attend schools that excel at improving academic achievement in eighth grade are less likely to experience criminal justice involvement as adults. These results echo findings in several recent papers that stress the importance of teacher value-added on non-academic skills and the growing labor market returns to non-cognitive skills.[6]

1 Data

Here, we describe the different data sources we employ and the variables we create.

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. 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. Appendix E provides more details.

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.[7] 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. We divide our sample into four subsamples defined by the interaction of gender and race. We code students as male or female and Black or non-Black. During our sample period, CPS codes divide students into five race categories: White, Black, Native American/Alaskan Native, Asian/Pacific Islander, and Hispanic. In most of our work, we collapse these categories to Black and Non-Black. However, we do present some Appendix results for Black versus Hispanic populations and for Black versus Non-Black, Non-Hispanic populations. During our sample

[6]See Deming (2017), Jackson (2018*b*), Jackson et al. (2020), Rose et al. (2022), and Petek and Pope (2023).

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

period, just over half of CPS student were Black, just over one-third were Hispanic, and just over one in ten were white. These three groups made up more than 96 percent of the student population.

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, 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.[8]

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.

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

2 Basic Facts

The two panels of Figure 1 contain three heatmaps that present key patterns in our data. Each map contains 100 cells that correspond to the intersection of the deciles of the distributions of SES and academic achievement in grades 3 through 8. The heatmap in the top panel displays the fraction of male students in each cell who are Black. The second and third maps present, separately by race, the fractions of students, in each cell, who are arraigned on a felony before age 25.

Several patterns stand out. To begin, Black males are over-represented among low SES students and students with low achievement levels. Less than nine percent of the cell defined by the intersection of the top deciles is Black, and less than three percent of the cell defined by the bottom deciles is non-Black. Further, the fraction of Black male students within an SES decile declines as we move to cells associated with higher academic achievement, but this gradient is rather modest. On the other hand, within an academic achievement decile, the fraction of Black students declines dramatically as we move from low to high SES neighborhoods.

The bottom panels show that, within academic achievement deciles, rates of criminal justice involvement decline with neighborhood SES, and within SES deciles, rates of criminal justice involvement decline with academic achievement. However, these gradients tend to be much steeper among Black males. As a result,

[8] We have also examined felony convictions, and we see similar results since conviction rates, conditional on arraignment, are typically over ninety percent. 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.

racial differences in rates of criminal justice involvement are much smaller in cells defined by the intersection of higher SES and achievement deciles, and among the most advantaged students, no significant differences exist. Appendix Table A1 provides the 100 rates presented in each of these figures as well as the corresponding incarceration rates by race for each cell. Among students in the top deciles of both the overall achievement distribution and the distribution of SES, racial differences in both arraignment and incarceration rates among male students are small and not statistically significant. However, among males in the bottom decile of both achievement and SES, the arraignment and incarceration gaps are both 21 percentage points and highly significant. In sum, there is a strong correlation between the fraction of Black males in a given achievement*SES cell and racial differences in rates of criminal justice involvement among males in that cell.

3 Within-School Variation in Predictors of Criminal Justice Involvement

Figure 1 provides clear evidence that measures of early academic achievement and neighborhood SES predict criminal justice involvement as well as racial differences in criminal justice involvement. Given that Chicago schools and neighborhoods are highly segregated by race and SES, some may conjecture that Figure 1 simply reflects the fact that crime is concentrated in disadvantaged communities. However, our achievement and SES metrics are strong predictors of criminal justice involvement even among students of the same race who attend the same elementary school.

Figure 2 presents the results from 24 counterfactual simulations. To create these results, we estimate four logit models.[9] 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 began 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 non-Black males. The third and fourth models take the same form but here the outcome variable in an indicator for incarceration.

Given the results from these four models, we create averages of counterfactual predicted arraignment and incarceration rates for twelve different samples of students. As an example, we select the five percent of Black 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 male students in his school. We then average these predicted arraignment rates. We repeat these calculations for the five percent of Black males in each school who have the best reading achievement. We 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 non-Black males, and for both samples, we create parallel results for incarceration rates.

Figure 2 highlights how variation in achievement and SES within schools impacts expected rates of criminal justice involvment, and several patterns stand out. First, in almost every case, within school differences in achievement and SES are more consequential predictors of criminal justice outcomes among Black males than non-Black males. This result 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 among Non-Black males.[10] Second, within school variation in reading achievement is a particularly strong predictor of criminal justice outcomes among Black males. The difference in reading achievement between the top and bottom ventiles

[9]Linear probability model perform poorly in this context. They produce negative predicted rates of criminal justice involvement for many high-achievement, high-advantage students.

[10]See Neal and Johnson (1996), Lang and Manove (2011), and Fryer Jr (2011)

of reading scores within each school is, on average, associated with a 23 percentage point reduction in the likelihood of a felony arraignment by age 25 and an almost 15 percentage point reduction in the likelihood of adult incarceration by the same age. In each case, the reduction in question is significantly larger than the level of the corresponding arraignment or incarceration rate for non-Black males in the bottom ventiles of their schools' distributions of reading achievement. Further, within school variation in SES is a significantly stronger predictor of criminal justice outcomes among Black males than among non-Black males. 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.[11]

4 Decomposition Results

So far, we have established that Black males in the 1995-2004 cohorts of eighth graders enjoyed lower levels of academic achievement and neighborhood SES during elementary school and that these factors are predictors of adult criminal justice outcomes even within students of the same race who attend the same school. Here, we present decomposition results that help us 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 do not employ school fixed effects in this exercise. Given the level of racial segregation in CPS schools, there are many schools that contain only a handful of non-Black students, and some that contain few Black students. Thus, for many schools, we cannot reliably estimate the impacts of attending these schools on future outcomes for both Black and non-Black students.

We re-estimate the four 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. Thus, we create two separate predicted criminal justice involvement rates for Black students: one using the estimated parameters from the model for Black students and another using the estimated parameters from the model for non-Black students. Similarly, we have two sets of predicted rates for non-Black students. For both Black and non-Black students, we non-parameterically regress the predicted arraignment rate given parameters from the other-race model on each student's own predicted rate and plot the results. We produce parallel results for predicted incarceration rates.

We present all four results in Figure 3, and on each x-axis, we also plot the distribution of the relevant predicted outcome rate from the relevant own-race model. Several noteworthy patterns emerge in these figures. First, among Black males with predicted arraignment rates of a few percentage points or less, we see small differences between these rates and the counterfactual rates we create using coefficients from the non-Black model, and similar results hold for incarceration rates. However, the shaded distributions on the x-axes show that a trivial fraction of Black males face these low predicted rates of criminal justice involvement.

Both racial differences in student characteristics and racial differences in the mappings between characteristics and outcomes contribute significantly to racial gaps in arraignment and incarceration rates. The average predicted arraignment rate is .317 for Black males and .113 for non-Black males. However, the average predicted arraignment rate for Black male students falls to .175 when we create predictions using coefficients from the non-Black model, and the average predicted arraignment rate for non-Black males rises to .223 when we use coefficients from the Black model. In sum, racial differences in student characteristics account for between 29 and 48 percent of the overall racial gap in arraignment rates depending on whether we use coefficients from the non-Black or Black model to produce predicted arraignment rates. For incarceration rates, the corresponding fractions are also 29 percent and 48 percent.[12]

The gaps between the forty-five degree line and the plots of counterfactual average predicted rates in each figure are measures of racial gaps in arraignment or incarceration rates that exist because the mappings

[11] 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.

[12] As an illustration, note that given the coefficients from the Black model, the absolute difference in predicted arraignment rates is .094, and this is 48 percent of the overall gap of .204.

between observed student characteristics and future criminal justice outcomes are race-specific. Among Black males with low expected rates of criminal justice involvement, these gaps are small. However, among most Black males, these gaps are quite substantial. For example, among Black males who face a 30 percent risk of arraignment before age 25, their expected risk given the estimated parameters from the non-Black model is roughly 15 percent.

Appendix C presents parallel results that decompose the differences in criminal justice involvement between Blacks and Hispanics and also between Blacks and students who are neither Black nor Hispanic. The overall patterns are quite similar to those in Figure 3. However, differences in observed students characteristics account for only 24 to 34 percent of the Black-Hispanic gaps in arraignment and incarceration rates, while differences in student characteristics account for roughly one-half to three-fourths on the corresponding gaps between Black males and their counterparts who are neither Black nor Hispanic.

Nonetheless, in both sets of results, predicted arraignment rates and incarceration rates for Black males are significantly higher than the predicted rates for comparable students of other races for the vast majority of Black males. When we consider Black males who have extremely high predicted rates of criminal justice involvement, we do find that predicted arraignment and incarceration rates among comparable non-Black, non-Hispanic students are quite similar. Further, when we consider Black males with extremely low predicted rates of criminal justice involvement, we find that all comparable non-Black students have quite low predicted rates of arraignment and incarceration. However, the typical Black male faces predicted arraignment and incarceration rates that are at least twice the rate that comparable students of other races face, regardless of whether we use Hispanic students or students who are not Black or Hispanic as the comparison group.

5 Eighth-Grade School Quality

The measures of elementary achievement and neighborhood SES at the center of our analyses reflect the outcomes of numerous investments. Families invest directly in their children's human capital through activities in the home, and parents often provide their children with access to the resources available in libraries, parks, schools, and community organizations by choosing both where to live as well as how much to support their children's engagement with these institutions. Yet, we have no data on experiments that manipulate these investments. So, even when we consider the within-race, within-school gradients in Figure 2, we cannot know what portion of these relationships reflect the causal impacts of improved reading skills, improved math skills, or living in higher SES neighborhoods.

Over the past decade or more, a growing literature has explored causal links between the quality of instruction provided by individual teachers during elementary school and future adult outcomes. Our CPS data do not provide identifiers that allow us to link students to individual teachers. However, we can create measures of instructional quality that are specific to the team of teachers that work with students in a given school in a particular grade in a given year.

We create several quality measures that are specific to the team of teachers who work with eighth-grade students in a given year in a given school. We focus on eighth grade because prior work indicates that when students drop out of high school, their criminal justice involvement increases,[13] and eighth grade is an important year of preparation for the transition to high school in ninth grade.

We create three value-added measures of eighth-grade school quality. To construct each measure, we select all eighth grade students and project a specific outcome on an extensive set of controls. The controls include SES during elementary school, grade 3 to 7 reading achievement, grade 3 to 7 math achievement, being off-track in terms of age for grade, patterns of residential moves made during elementary school, and school-cohort averages of these measures. We also include indicators for Black and male, indicators for year, age in months, and the fractions Black and male within a given school*cohort cell. We then collect the residuals from each projection and form the average residual within cells defined by year interacted

[13] See Lochner and Moretti (2004) and Cook and Kang (2016).

with elementary school. Next, we shrink these averages using the method proposed in Chetty et al. (2014*a*). We use three different outcome measures to create measures of eighth-grade school quality, and we run three regressions of our indicator for felony arraignment by age 25 on our control set and one of our school quality measures. We run each regression separately on the sample of Black male students and then on the sample of non-Black males.

The three outcomes we use to derive our VAM metrics of the eighth-grade school quality are: (i) an indicator for completing high school, (ii) each student's 8th grade math score, and (iii) each student's eighth grade reading score. Both achievement scores come from spring exams that are part of school accountability systems. To place each set of results on a comparable and interpretable scale, we report the implied change in either the probability of felony arraignment or adult incarceration implied by moving from either the 25th to 75th or 10th to 90th percentile in a given estimated school quality distribution.

Table 1 presents the results. We find little evidence that better math or reading instruction during eighth grade has significant impacts on future criminal justice outcomes. There is some evidence that better reading instruction reduces future incarceration rates among both Black and non-Black males, but these impacts are only marginally significant.[14] However, there is clear evidence that students who attend schools that excel at supporting students in ways that improve future high school graduation rates have lower rates of criminal justice involvement as adults. Panel A shows that, among Black males, roughly 31 percent of our sample face a felony charge by age 25, and moving a Black male student from the 10th to 90th percentile of the distribution of school effectiveness in promoting future high school graduation reduces the expected arraignment rate by 5 percentage points. The comparable result for non-Black males is 1.7 percentage points, which is more than 15 percent of the sample arraignment rate of 11 percent.

Panel B of Table 1 reports that teams of eighth grade educators whose students are more likely to graduate high school than other comparable students are also reduce incarceration by age 25. Among both Black and non-Black males, our results imply that moving from the 10th to the 90th percentile in the distribution of effectiveness in the promotion of future high school graduation reduces incarceration rates by more than 20 percent of the mean incarceration rate. Appendix D shows that the implied impacts of school effectiveness in promoting high school graduation on both arraignment and incarceration rates are almost identical in regressions that control for all three measures of school quality simultaneously. This result reflects the fact that the reading and math value-added metrics are almost uncorrelated with the high-school graduation metric.[15]

While many researchers are willing to treat the estimated impacts of VAM measures of individual teacher quality on future outcomes as estimates of causal impacts of the effects of improved teacher performance, it is more difficult to make the case that one can assign a causal interpretation to our estimates of the impact of eighth-grade school quality. Most VAM models of teacher quality are exploiting differences in teacher performance within schools. Thus, these models exploit variation in teacher quality among students who all come from families that choose to send them to the same school. In our analyses of school quality, we are exploiting variation among sets of students who attend different schools and who may well go on to attend different high schools. Thus, our results concerning the impacts of teams of eighth-grade teachers who prepare students in ways that promote high school graduation may reflect the sorting of families on unmeasured dimensions to different types of schools or the fact that students who attend certain elementary schools have greater access to high schools that effectively promote graduation.

Table 2 presents results that address some of these concerns. Here, we re-estimate our VAM models, but we add a set of high-school fixed effects that control for the modal high school attended by the students who attend a given elementary school. In most cases, this modal high school will be a neighborhood high school that is geographically linked to a set of elementary schools. So, here our results capture the impacts of differences in eighth grade school experiences among students who attend schools that all feed the same high school. Here, our samples are about seven percent smaller for Blacks and roughly ten percent smaller for non-Blacks because we drop students from elementary schools where the modal student does not attend

[14] A similar result holds for math instruction but only among Black males.

[15] Jackson (2018*a*), Petek and Pope (2023), and Rose et al. (2022) also find weak correlations between cognitive and non-cognitive value-added measures.

any high school in the CPS system. It appears that many students in these elementary schools go on to attend private high schools.[16]

Among Black males, controls for modal high school attended reduce our estimates of the absolute impacts of our measures of high school graduation value-added on arraignment rates and incarceration rates by roughly 36 percent and 44 percent respectively. Nonetheless, the sizes of the impacts that remain are noteworthy. The implied reductions in arraignment and incarceration rates are at least ten percent of the corresponding sample means.

Among non-Black males, controls for the modal high school attended have little impact on our estimates of the impacts of being instructed by a team of eighth-grade teachers whose students are more likely to graduate high school than comparable students. The implied impacts on arraignment rates are slightly larger than the corresponding entries in Table 1, and the implied impacts on incarceration rates are slightly smaller.

We have also estimated these VAM regressions separately for Hispanic males and for males who are neither Hispanic nor Black.[17] The results for Hispanic Males are quite similar to the results for Non-Black males in Tables 1 and 2. The results for non-Black, non-Hispanic males differ in two ways. First, reading value-added is a statistically significant and powerful predictor on future criminal justice outcomes among students who are not Black or Hispanic. Among these students, moving from the 10th to 90th percentile in reading value-added reduces arraignment rates by 1.8 percentage points and incarceration rates by at least one percentage point with or without controls for modal high school attended. These are large effects relative to the mean rates for this population. The incarceration impacts imply reductions in incarceration rates of at least one third. Second, given controls for modal high school attended, high school graduation value-added does not have a statistically significant impact on rates of criminal justice involvement among students who are not Black or Hispanic. For this group, reading value-added and not high-school graduation value-added in eighth grade matters more for future criminal justice outcomes.

The school that students attend in eighth grade is an important predictor of future criminal justice outcomes conditional on their observed characteristics at the beginning of eighth grade, the characteristics of other eighth graders in their school, and the identity of the high school that they are most likely to attend. Further, among Black and Hispanic students, the eighth-grade school they attend matters for criminal justice outcomes because it matters for the likelihood that they will successfully transition to high school and graduate. These results are noteworthy because arraignment and incarceration rates are relatively high for these groups, and previous work establishes causal links between policy induced changes in high school graduation rates and reductions in rates of criminal justice involvement.[18]

5.1 Connections to Recent VAM Literature

Our VAM results echo results from other recent work. Rose et al. (2022) examine the relationship between measures of teacher quality and future criminal justice outcomes in North Carolina elementary schools. They find that, among observationally similar students, those with teachers who excel at promoting math and reading achievement are not less likely to face arrest in the future. However, students of teachers who excel at reducing suspensions and improving attendance are less likely to face arrest.

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 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.[19] Jackson (2018*a*) employs data on ninth graders in North Carolina public schools to

[16] This sample is both relatively advantaged and high achieving.

[17] See Appendix Tables D5 and D6.

[18] See Lochner and Moretti (2004) and Cook and Kang (2016) for more on the links between dropping out of high school and criminal justice involvement.

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

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. For elementary school teachers, they also construct both traditional achievement VAM measures and a non-cognitive VAM measure derived from information on student behaviors for elementary school teachers. They find that improvements in either measure predict better high school outcomes, e.g. lower dropout rates, fewer suspensions, and better high school GPA.

Our results add to the growing literature on the varied dimensions of educator performance. We do find that reading value-added in eighth grade is an important predictor of future criminal justice outcomes for students who are not Black or Hispanic. However, among Black and Hispanic males, our results suggest that eighth grade teachers have important impacts on future criminal justice outcomes by fostering non-cognitive capacities that smooth the transition to high school and reduce high school dropout rates, and these impacts are greatest among Black males, who face the greatest risks of future arraignment and incarceration.

6 Conclusion

Using data from Chicago, we show that detailed measures of early academic achievement and SES predict future criminal justice involvement, and among Black males, variation in elementary school reading achievement is a strikingly powerful predictor of differences in rates of criminal justice involvement, even among students who attend the same school and live in similar neighborhoods. Further, we provide suggestive evidence that Black and Hispanic males who attend elementary schools that succeed in helping their eighth grade students prepare for the transition to high school are also less likely to face felony arraignment and incarceration as young adults. Finally, males who are not Black or Hispanic face lower risks of criminal justice involvement if they attend eighth grade in a school with strong reading value-added.

Reforms that improve school quality and neighborhood environments for Black youth are likely to reduce both overall crime rates and racial disparities in criminal justice involvement. Nonetheless, without additional reforms to policing and other aspects of the criminal justice system, significant racial disparities in criminal justice outcomes would likely remain. We document large conditional racial disparities in criminal justice outcomes over almost the entire joint distribution of SES and academic achievement, and this pattern suggests that investments in families and schools alone cannot eliminate racial disparities in criminal justice involvement.

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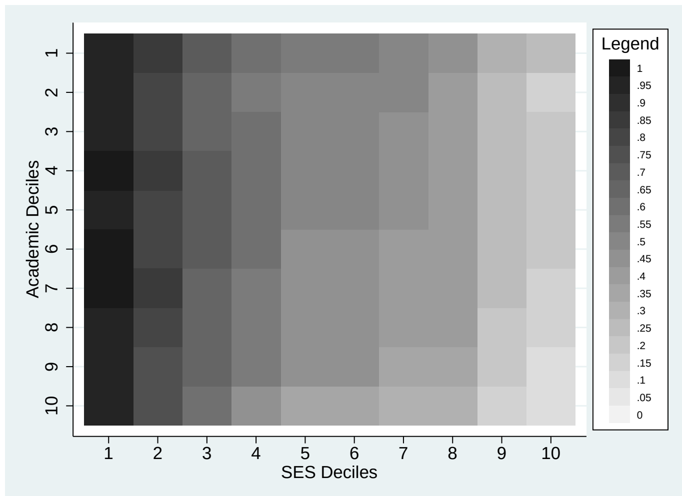
Figures

Figure 1

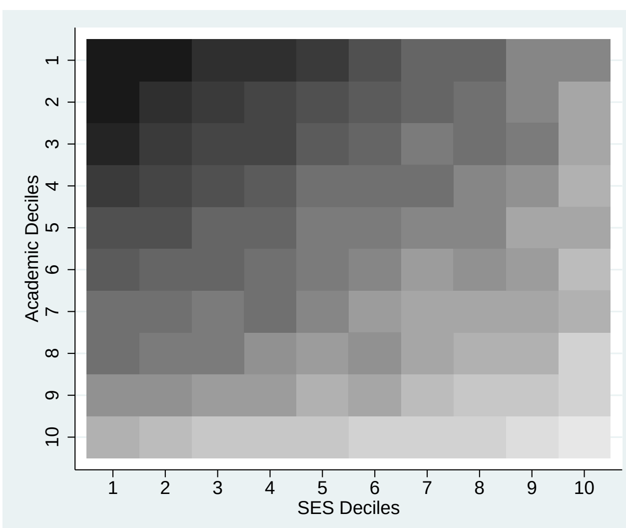
Facts About Male Eighth Graders: Cells Defined By K-8 Achievement*SES

Panel A: Fraction Black

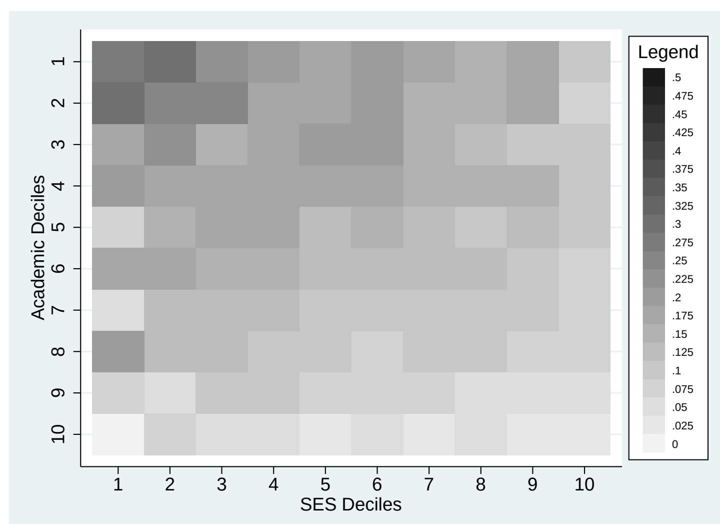


Panel B: % Ever Arraigned on a Felony (Full Wedge) % Ever Incarcerated (Solid Black) By Age 25

Black



Non-Black



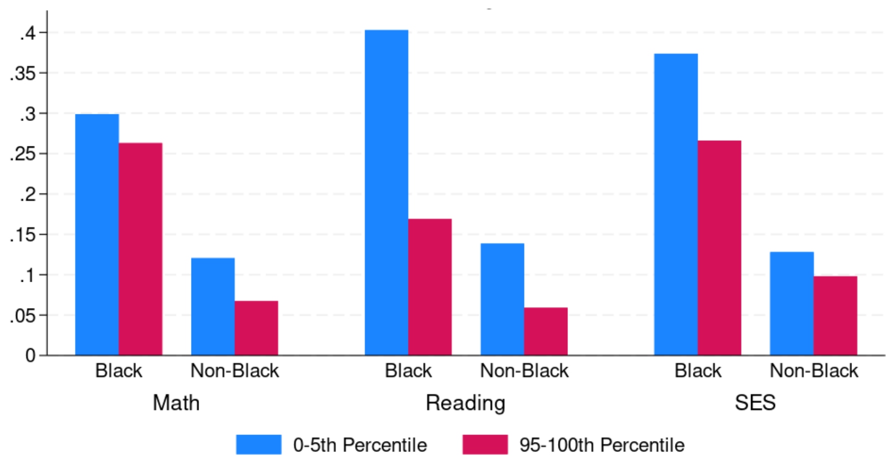
Notes: We define an academic index based on reading and math scores from grades three through eight for all CPS students who began eighth grade during 1995-2004. We define as SES index based on the demographics of the census tracts associated with the addresses reported by each student. See Appendix E for details. We place each male student in one of the 100 cells defined by the intersections of the deciles of these distributions. We then report statistics for each cell. Panel A reports the fraction Black among males in each cell. Panel B reports, separately for Black and non-Blacks, the fractions of males who are arraigned on a felony charge by age 25. The samples sizes are 64,432 for Black males and 62,353 for non-Black males.

Figure 2

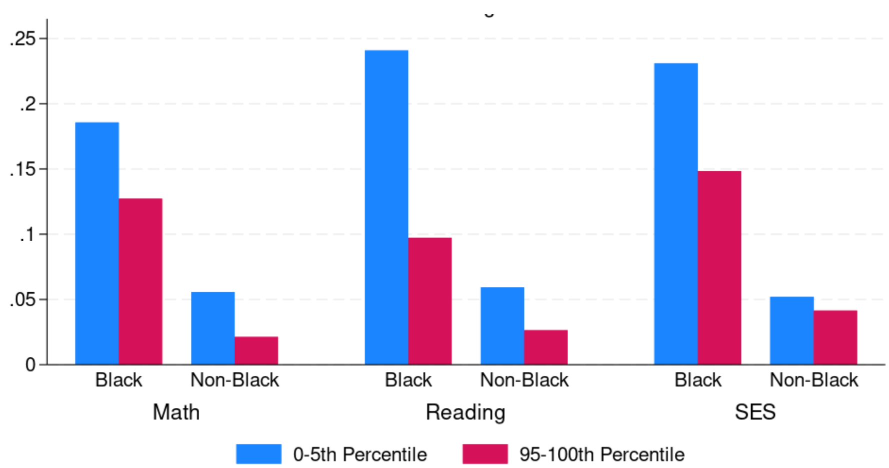
Within-School Gradients for Predicted Criminal Justice Outcomes

Bottom versus Top Ventiles of Reading, Math, and SES: Eighth Grade Males

Panel A: Fraction Ever Arraigned on a Felony by Age 25



Panel B: Fraction Ever Incarcerated by Age 25



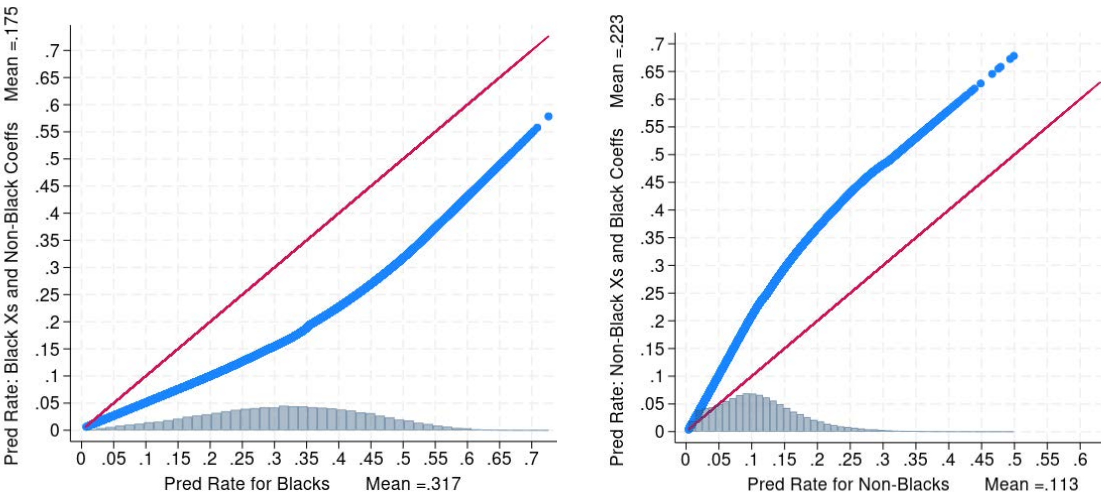
Notes: Each bar displays an average predicted rate of criminal justice involvement for a specific sample of male students of a given race. These predicted values are generated using logit models that take an indicator for either arraignment by age 25 or incarceration by age 25 as the dependent variable. Separately for Black and non-Black males, we estimate these logit models 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

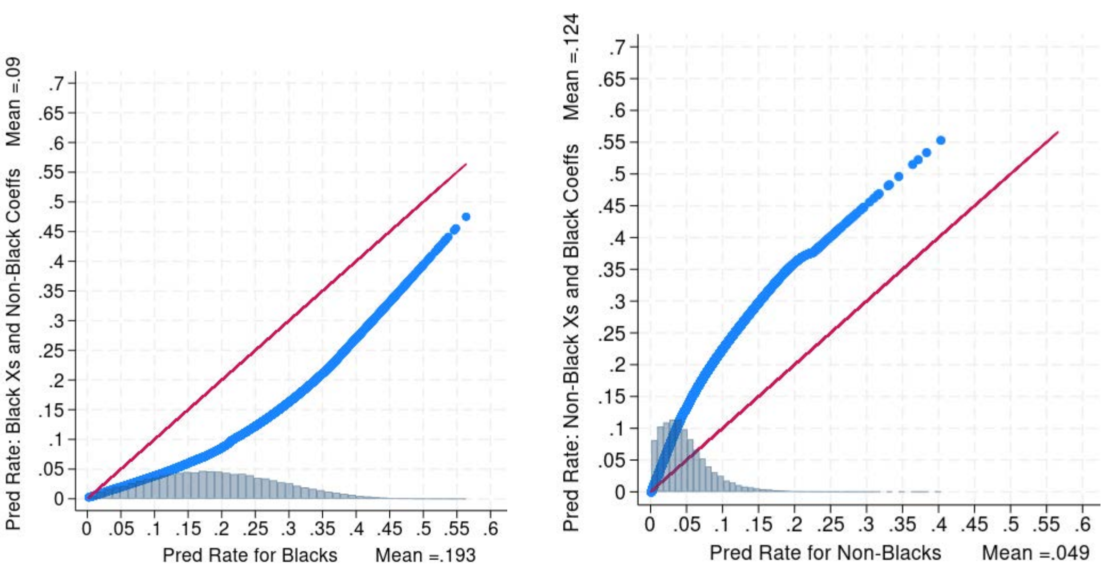
Decomposition of Racial Differences in Criminal Justice Outcomes

Bars on X-axis Give the Fraction of Students with Predicted Values in Each Interval   Red line = 45^0

Panel A: Predicted Felony Arraignment Rates by Age 25



Panel B: Incarceration Rates by Age 25



Notes: Panel A and Panel B presents results from four logit models that parallel the models we employ to produce the results for Figure 2, but these specifications do not include school fixed effects. One goal here is to create hypothetical predicted rates of criminal justice involvement for Black males given the estimated coefficients from the non-Black male models and vice versa. However, Chicago schools are quite segregated, and for many schools, we cannot reliably estimate outcomes for non-Black children. We estimate both our arraignment and incarceration models separately for Black males and non-Black males. After we estimate each model, 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 a predicted probability of felony arraignment that employs coefficients from the model estimated on non-Black males, i.e. an estimate of the likelihood that he would face arraignment if he were not Black. In Panel A, each figure plots the fitted values from a non-parametric regression of these cross-race predictions on each student's own predicted arraignment rate. We order students on the x-axis by their own-sample predicted arraignment rates. Panel B presents parallel results for incarceration. Each graph also plots the empirical distribution of the predicted values on the x-axis.

Tables

Table 1

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Males

Black ($\bar{Y}$: 0.308)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.028	-0.050
8th Grade Reading (p: 0.324)	-0.003	-0.007
8th Grade Math (p: 0.243)	-0.004	-0.009

Non-Black ($\bar{Y}$: 0.11)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.010	-0.017
8th Grade Reading (p: 0.305)	-0.002	-0.005
8th Grade Math (p: 0.752)	-0.001	-0.001

Panel B: Impacts of School Quality on Incarceration by Age 25 For Males

Black ($\bar{Y}$: 0.183)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.024	-0.041
8th Grade Reading (p: 0.122)	-0.004	-0.009
8th Grade Math (p: 0.096)	-0.005	-0.011

Non-Black ($\bar{Y}$: 0.047)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.007	-0.012
8th Grade Reading (p: 0.085)	-0.003	-0.006
8th Grade Math (p: 0.347)	-0.001	-0.002

Notes: Each sub-table presents results from four regressions. In Panel A, these are four regressions of an indicator for a felony arraignment before age 25 on a VAM measure of the quality of the eighth grade educators in the school where the student first attended eighth grade plus controls for 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. We also include a dummy for being off-track in terms of age for grade, measures of the number of residential moves made during elementary school, and measures of the number of residential moves made among low SES neighborhood. We further include the school*cohort averages of each regressor. Finally, we include year effects, age in months, as well as the fractions Black and fraction male within a given school*cohort cell. Panel B presents results from parallel regressions that employ an indicator for incarceration by age 25 as the dependent variable. We construct three measures of quality. The first comes from using all students to regress an indicator for whether the student graduated high school on the controls described above plus an indicator for Black and an indicator for male. We then form mean residuals for each eighth-grade cohort in each school, and shrink these means using the shrinkage estimator proposed by Chetty et al. (2014*a*). We repeat these steps to create standard reading and math VAM scores using the spring math and reading exams given to eighth graders. The two columns describe the predicted impacts of moving between two percentiles in a given school quality distribution. For example, among Black males, attending the 90th percentile instead of the 10th percentile school in the High School Graduation VAM score distribution lowers the probability of receiving a felony charge by age 25 by five percentage points. See Appendix D for more details. We create HAC standard errors clustered at the school level.

Table 2

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Males Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.32)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.018	-0.032
8th Grade Reading (p: 0.61)	-0.002	-0.003
8th Grade Math (p: 0.417)	-0.003	-0.005

Non-Black ($\bar{Y}$: 0.115)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.011	-0.019
8th Grade Reading (p: 0.419)	-0.002	-0.004
8th Grade Math (p: 0.987)	0.000	0.000

Panel B: Impacts of School Quality on Incarceration by Age 25 For Males Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.192)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.013	-0.023
8th Grade Reading (p: 0.474)	-0.002	-0.003
8th Grade Math (p: 0.185)	-0.003	-0.006

Non-Black ($\bar{Y}$: 0.05)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.002)	-0.006	-0.010
8th Grade Reading (p: 0.121)	-0.003	-0.006
8th Grade Math (p: 0.616)	-0.001	-0.001

Notes: See notes for Table 1. These results parallel the results in Table 1, but here the outcome equations include fixed effects for the modal high school attended by the students from each elementary school. See Appendix D for more details.

Appendix A: Decile Tables

Table A1: Frac. of Males with Felonies and Incarcerations by Age 25 within AI*SES Decile by Race

	SES 1	SES 2	SES 3	SES 4	SES 5
AI 1	**Fraction Black:** 0.973 **Fel. Arraign. Rate:** B:0.491 NB:0.277 Δ:0.214** **Incar. Rate:** B:0.331 NB:0.123 Δ:0.208**	**Fraction Black:** 0.834 **Fel. Arraign. Rate:** B:0.491 NB:0.291 Δ:0.2** **Incar. Rate:** B:0.334 NB:0.157 Δ:0.176**	**Fraction Black:** 0.701 **Fel. Arraign. Rate:** B:0.447 NB:0.232 Δ:0.215** **Incar. Rate:** B:0.302 NB:0.109 Δ:0.193**	**Fraction Black:** 0.582 **Fel. Arraign. Rate:** B:0.439 NB:0.199 Δ:0.239** **Incar. Rate:** B:0.312 NB:0.103 Δ:0.208**	**Fraction Black:** 0.527 **Fel. Arraign. Rate:** B:0.416 NB:0.173 Δ:0.243** **Incar. Rate:** B:0.266 NB:0.087 Δ:0.179**
AI 2	**Fraction Black:** 0.972 **Fel. Arraign. Rate:** B:0.495 NB:0.296 Δ:0.199** **Incar. Rate:** B:0.317 NB:0.148 Δ:0.169**	**Fraction Black:** 0.821 **Fel. Arraign. Rate:** B:0.46 NB:0.253 Δ:0.207** **Incar. Rate:** B:0.297 NB:0.145 Δ:0.152**	**Fraction Black:** 0.651 **Fel. Arraign. Rate:** B:0.429 NB:0.25 Δ:0.18** **Incar. Rate:** B:0.284 NB:0.138 Δ:0.147**	**Fraction Black:** 0.565 **Fel. Arraign. Rate:** B:0.39 NB:0.172 Δ:0.218** **Incar. Rate:** B:0.253 NB:0.083 Δ:0.17**	**Fraction Black:** 0.496 **Fel. Arraign. Rate:** B:0.368 NB:0.174 Δ:0.195** **Incar. Rate:** B:0.238 NB:0.088 Δ:0.15**
AI 3	**Fraction Black:** 0.974 **Fel. Arraign. Rate:** B:0.468 NB:0.171 Δ:0.297** **Incar. Rate:** B:0.295 NB:0.146 Δ:0.148**	**Fraction Black:** 0.811 **Fel. Arraign. Rate:** B:0.433 NB:0.218 Δ:0.214** **Incar. Rate:** B:0.286 NB:0.099 Δ:0.187**	**Fraction Black:** 0.656 **Fel. Arraign. Rate:** B:0.4 NB:0.16 Δ:0.24** **Incar. Rate:** B:0.26 NB:0.071 Δ:0.188**	**Fraction Black:** 0.579 **Fel. Arraign. Rate:** B:0.395 NB:0.174 Δ:0.221** **Incar. Rate:** B:0.25 NB:0.085 Δ:0.165**	**Fraction Black:** 0.481 **Fel. Arraign. Rate:** B:0.36 NB:0.191 Δ:0.17** **Incar. Rate:** B:0.212 NB:0.091 Δ:0.121**
AI 4	**Fraction Black:** 0.982 **Fel. Arraign. Rate:** B:0.42 NB:0.2 Δ:0.22** **Incar. Rate:** B:0.271 NB:0.16 Δ:0.111	**Fraction Black:** 0.831 **Fel. Arraign. Rate:** B:0.398 NB:0.169 Δ:0.229** **Incar. Rate:** B:0.252 NB:0.085 Δ:0.167**	**Fraction Black:** 0.675 **Fel. Arraign. Rate:** B:0.365 NB:0.18 Δ:0.185** **Incar. Rate:** B:0.231 NB:0.084 Δ:0.147**	**Fraction Black:** 0.599 **Fel. Arraign. Rate:** B:0.345 NB:0.178 Δ:0.168** **Incar. Rate:** B:0.213 NB:0.08 Δ:0.133**	**Fraction Black:** 0.495 **Fel. Arraign. Rate:** B:0.31 NB:0.166 Δ:0.144** **Incar. Rate:** B:0.18 NB:0.069 Δ:0.111**
AI 5	**Fraction Black:** 0.97 **Fel. Arraign. Rate:** B:0.378 NB:0.086 Δ:0.292** **Incar. Rate:** B:0.227 NB:0.029 Δ:0.198**	**Fraction Black:** 0.815 **Fel. Arraign. Rate:** B:0.371 NB:0.148 Δ:0.223** **Incar. Rate:** B:0.227 NB:0.086 Δ:0.141**	**Fraction Black:** 0.7 **Fel. Arraign. Rate:** B:0.319 NB:0.177 Δ:0.142** **Incar. Rate:** B:0.192 NB:0.073 Δ:0.118**	**Fraction Black:** 0.598 **Fel. Arraign. Rate:** B:0.324 NB:0.185 Δ:0.139** **Incar. Rate:** B:0.201 NB:0.083 Δ:0.118**	**Fraction Black:** 0.48 **Fel. Arraign. Rate:** B:0.28 NB:0.137 Δ:0.143** **Incar. Rate:** B:0.15 NB:0.049 Δ:0.101**
AI 6	**Fraction Black:** 0.975 **Fel. Arraign. Rate:** B:0.355 NB:0.185 Δ:0.169** **Incar. Rate:** B:0.217 NB:0.037 Δ:0.18**	**Fraction Black:** 0.81 **Fel. Arraign. Rate:** B:0.322 NB:0.167 Δ:0.155** **Incar. Rate:** B:0.195 NB:0.067 Δ:0.128**	**Fraction Black:** 0.686 **Fel. Arraign. Rate:** B:0.324 NB:0.154 Δ:0.171** **Incar. Rate:** B:0.187 NB:0.075 Δ:0.112**	**Fraction Black:** 0.576 **Fel. Arraign. Rate:** B:0.308 NB:0.149 Δ:0.159** **Incar. Rate:** B:0.174 NB:0.067 Δ:0.107**	**Fraction Black:** 0.46 **Fel. Arraign. Rate:** B:0.28 NB:0.133 Δ:0.147** **Incar. Rate:** B:0.163 NB:0.064 Δ:0.099**
AI 7	**Fraction Black:** 0.981 **Fel. Arraign. Rate:** B:0.301 NB:0.056 Δ:0.245** **Incar. Rate:** B:0.191 NB:0.056 Δ:0.136**	**Fraction Black:** 0.825 **Fel. Arraign. Rate:** B:0.312 NB:0.13 Δ:0.182** **Incar. Rate:** B:0.185 NB:0.06 Δ:0.126**	**Fraction Black:** 0.643 **Fel. Arraign. Rate:** B:0.265 NB:0.12 Δ:0.145** **Incar. Rate:** B:0.16 NB:0.043 Δ:0.117**	**Fraction Black:** 0.549 **Fel. Arraign. Rate:** B:0.293 NB:0.115 Δ:0.178** **Incar. Rate:** B:0.177 NB:0.053 Δ:0.124**	**Fraction Black:** 0.457 **Fel. Arraign. Rate:** B:0.251 NB:0.11 Δ:0.141** **Incar. Rate:** B:0.119 NB:0.061 Δ:0.058**
AI 8	**Fraction Black:** 0.958 **Fel. Arraign. Rate:** B:0.291 NB:0.188 Δ:0.104 **Incar. Rate:** B:0.158 NB:0.094 Δ:0.064	**Fraction Black:** 0.801 **Fel. Arraign. Rate:** B:0.279 NB:0.125 Δ:0.154** **Incar. Rate:** B:0.151 NB:0.065 Δ:0.086**	**Fraction Black:** 0.659 **Fel. Arraign. Rate:** B:0.273 NB:0.114 Δ:0.159** **Incar. Rate:** B:0.156 NB:0.053 Δ:0.103**	**Fraction Black:** 0.543 **Fel. Arraign. Rate:** B:0.237 NB:0.098 Δ:0.139** **Incar. Rate:** B:0.119 NB:0.041 Δ:0.078**	**Fraction Black:** 0.447 **Fel. Arraign. Rate:** B:0.211 NB:0.1 Δ:0.111** **Incar. Rate:** B:0.105 NB:0.04 Δ:0.065**
AI 9	**Fraction Black:** 0.962 **Fel. Arraign. Rate:** B:0.23 NB:0.087 Δ:0.143** **Incar. Rate:** B:0.13 NB:0.0 Δ:0.13**	**Fraction Black:** 0.763 **Fel. Arraign. Rate:** B:0.214 NB:0.047 Δ:0.166** **Incar. Rate:** B:0.104 NB:0.012 Δ:0.092**	**Fraction Black:** 0.629 **Fel. Arraign. Rate:** B:0.196 NB:0.094 Δ:0.102** **Incar. Rate:** B:0.097 NB:0.035 Δ:0.062**	**Fraction Black:** 0.529 **Fel. Arraign. Rate:** B:0.196 NB:0.096 Δ:0.1** **Incar. Rate:** B:0.104 NB:0.018 Δ:0.086**	**Fraction Black:** 0.445 **Fel. Arraign. Rate:** B:0.162 NB:0.074 Δ:0.088** **Incar. Rate:** B:0.086 NB:0.026 Δ:0.06**
AI 10	**Fraction Black:** 0.95 **Fel. Arraign. Rate:** B:0.156 NB:0.0 Δ:0.156** **Incar. Rate:** B:0.055 NB:0.0 Δ:0.055**	**Fraction Black:** 0.766 **Fel. Arraign. Rate:** B:0.125 NB:0.085 Δ:0.04 **Incar. Rate:** B:0.05 NB:0.017 Δ:0.033**	**Fraction Black:** 0.621 **Fel. Arraign. Rate:** B:0.107 NB:0.04 Δ:0.067** **Incar. Rate:** B:0.052 NB:0.015 Δ:0.037**	**Fraction Black:** 0.461 **Fel. Arraign. Rate:** B:0.111 NB:0.041 Δ:0.07** **Incar. Rate:** B:0.044 NB:0.008 Δ:0.036**	**Fraction Black:** 0.373 **Fel. Arraign. Rate:** B:0.11 NB:0.037 Δ:0.073** **Incar. Rate:** B:0.041 NB:0.018 Δ:0.023*

Notes: The five columns above are the first half of a table that provides more detailed information about the sample used to create Figure 1. The cells are defined by deciles in the SES and Academic Index distributions. * indicates that the Black v. Non-Black difference is statistically significant at the .05 level and ** indicates significance at the .01 level.

Table A1 Continued

	SES 6	SES 7	SES 8	SES 9	SES 10
AI 1	**Fraction Black:** 0.54 **Fel. Arraign. Rate:** B:0.374 NB:0.209 Δ:0.165** **Incar. Rate:** B:0.213 NB:0.108 Δ:0.105**	**Fraction Black:** 0.498 **Fel. Arraign. Rate:** B:0.324 NB:0.178 Δ:0.145** **Incar. Rate:** B:0.18 NB:0.077 Δ:0.103**	**Fraction Black:** 0.439 **Fel. Arraign. Rate:** B:0.337 NB:0.152 Δ:0.185** **Incar. Rate:** B:0.203 NB:0.099 Δ:0.104**	**Fraction Black:** 0.312 **Fel. Arraign. Rate:** B:0.256 NB:0.17 Δ:0.086** **Incar. Rate:** B:0.142 NB:0.077 Δ:0.065**	**Fraction Black:** 0.241 **Fel. Arraign. Rate:** B:0.256 NB:0.102 Δ:0.153** **Incar. Rate:** B:0.122 NB:0.035 Δ:0.087**
AI 2	**Fraction Black:** 0.488 **Fel. Arraign. Rate:** B:0.34 NB:0.189 Δ:0.151** **Incar. Rate:** B:0.219 NB:0.095 Δ:0.124**	**Fraction Black:** 0.477 **Fel. Arraign. Rate:** B:0.334 NB:0.162 Δ:0.172** **Incar. Rate:** B:0.196 NB:0.076 Δ:0.12**	**Fraction Black:** 0.415 **Fel. Arraign. Rate:** B:0.292 NB:0.156 Δ:0.135** **Incar. Rate:** B:0.169 NB:0.082 Δ:0.086**	**Fraction Black:** 0.252 **Fel. Arraign. Rate:** B:0.254 NB:0.171 Δ:0.082** **Incar. Rate:** B:0.148 NB:0.074 Δ:0.074**	**Fraction Black:** 0.155 **Fel. Arraign. Rate:** B:0.179 NB:0.078 Δ:0.102** **Incar. Rate:** B:0.09 NB:0.028 Δ:0.062*
AI 3	**Fraction Black:** 0.512 **Fel. Arraign. Rate:** B:0.333 NB:0.192 Δ:0.141** **Incar. Rate:** B:0.17 NB:0.099 Δ:0.071**	**Fraction Black:** 0.447 **Fel. Arraign. Rate:** B:0.281 NB:0.161 Δ:0.119** **Incar. Rate:** B:0.153 NB:0.064 Δ:0.089**	**Fraction Black:** 0.423 **Fel. Arraign. Rate:** B:0.298 NB:0.135 Δ:0.163** **Incar. Rate:** B:0.178 NB:0.054 Δ:0.124**	**Fraction Black:** 0.246 **Fel. Arraign. Rate:** B:0.282 NB:0.111 Δ:0.171** **Incar. Rate:** B:0.141 NB:0.045 Δ:0.096**	**Fraction Black:** 0.181 **Fel. Arraign. Rate:** B:0.179 NB:0.097 Δ:0.082** **Incar. Rate:** B:0.107 NB:0.045 Δ:0.062**
AI 4	**Fraction Black:** 0.498 **Fel. Arraign. Rate:** B:0.298 NB:0.181 Δ:0.117** **Incar. Rate:** B:0.155 NB:0.073 Δ:0.082**	**Fraction Black:** 0.46 **Fel. Arraign. Rate:** B:0.292 NB:0.143 Δ:0.149** **Incar. Rate:** B:0.169 NB:0.069 Δ:0.1**	**Fraction Black:** 0.405 **Fel. Arraign. Rate:** B:0.262 NB:0.156 Δ:0.106** **Incar. Rate:** B:0.158 NB:0.068 Δ:0.09**	**Fraction Black:** 0.25 **Fel. Arraign. Rate:** B:0.23 NB:0.139 Δ:0.091** **Incar. Rate:** B:0.107 NB:0.061 Δ:0.046**	**Fraction Black:** 0.179 **Fel. Arraign. Rate:** B:0.16 NB:0.095 Δ:0.066* **Incar. Rate:** B:0.069 NB:0.037 Δ:0.032
AI 5	**Fraction Black:** 0.48 **Fel. Arraign. Rate:** B:0.265 NB:0.14 Δ:0.126** **Incar. Rate:** B:0.167 NB:0.058 Δ:0.109**	**Fraction Black:** 0.468 **Fel. Arraign. Rate:** B:0.255 NB:0.133 Δ:0.123** **Incar. Rate:** B:0.151 NB:0.067 Δ:0.084**	**Fraction Black:** 0.401 **Fel. Arraign. Rate:** B:0.249 NB:0.096 Δ:0.153** **Incar. Rate:** B:0.135 NB:0.044 Δ:0.091**	**Fraction Black:** 0.249 **Fel. Arraign. Rate:** B:0.177 NB:0.124 Δ:0.053** **Incar. Rate:** B:0.09 NB:0.044 Δ:0.046**	**Fraction Black:** 0.188 **Fel. Arraign. Rate:** B:0.187 NB:0.101 Δ:0.086** **Incar. Rate:** B:0.102 NB:0.039 Δ:0.063**
AI 6	**Fraction Black:** 0.461 **Fel. Arraign. Rate:** B:0.257 NB:0.136 Δ:0.121** **Incar. Rate:** B:0.132 NB:0.066 Δ:0.066**	**Fraction Black:** 0.425 **Fel. Arraign. Rate:** B:0.204 NB:0.115 Δ:0.089** **Incar. Rate:** B:0.108 NB:0.051 Δ:0.057**	**Fraction Black:** 0.401 **Fel. Arraign. Rate:** B:0.215 NB:0.116 Δ:0.098** **Incar. Rate:** B:0.104 NB:0.04 Δ:0.064**	**Fraction Black:** 0.244 **Fel. Arraign. Rate:** B:0.203 NB:0.093 Δ:0.11** **Incar. Rate:** B:0.097 NB:0.029 Δ:0.068**	**Fraction Black:** 0.179 **Fel. Arraign. Rate:** B:0.137 NB:0.077 Δ:0.06** **Incar. Rate:** B:0.061 NB:0.031 Δ:0.03*
AI 7	**Fraction Black:** 0.445 **Fel. Arraign. Rate:** B:0.2 NB:0.094 Δ:0.106** **Incar. Rate:** B:0.11 NB:0.034 Δ:0.076**	**Fraction Black:** 0.414 **Fel. Arraign. Rate:** B:0.179 NB:0.102 Δ:0.078** **Incar. Rate:** B:0.091 NB:0.037 Δ:0.054**	**Fraction Black:** 0.402 **Fel. Arraign. Rate:** B:0.179 NB:0.097 Δ:0.082** **Incar. Rate:** B:0.076 NB:0.034 Δ:0.043**	**Fraction Black:** 0.248 **Fel. Arraign. Rate:** B:0.172 NB:0.09 Δ:0.082** **Incar. Rate:** B:0.066 NB:0.033 Δ:0.033**	**Fraction Black:** 0.139 **Fel. Arraign. Rate:** B:0.138 NB:0.07 Δ:0.068** **Incar. Rate:** B:0.058 NB:0.024 Δ:0.034*
AI 8	**Fraction Black:** 0.45 **Fel. Arraign. Rate:** B:0.222 NB:0.075 Δ:0.147** **Incar. Rate:** B:0.083 NB:0.038 Δ:0.045**	**Fraction Black:** 0.406 **Fel. Arraign. Rate:** B:0.175 NB:0.09 Δ:0.086** **Incar. Rate:** B:0.081 NB:0.025 Δ:0.056**	**Fraction Black:** 0.405 **Fel. Arraign. Rate:** B:0.14 NB:0.088 Δ:0.052** **Incar. Rate:** B:0.076 NB:0.028 Δ:0.048**	**Fraction Black:** 0.222 **Fel. Arraign. Rate:** B:0.141 NB:0.069 Δ:0.072** **Incar. Rate:** B:0.075 NB:0.025 Δ:0.05**	**Fraction Black:** 0.133 **Fel. Arraign. Rate:** B:0.077 NB:0.068 Δ:0.008 **Incar. Rate:** B:0.041 NB:0.021 Δ:0.019
AI 9	**Fraction Black:** 0.438 **Fel. Arraign. Rate:** B:0.168 NB:0.086 Δ:0.082** **Incar. Rate:** B:0.086 NB:0.024 Δ:0.062**	**Fraction Black:** 0.37 **Fel. Arraign. Rate:** B:0.136 NB:0.073 Δ:0.063** **Incar. Rate:** B:0.065 NB:0.034 Δ:0.031**	**Fraction Black:** 0.355 **Fel. Arraign. Rate:** B:0.098 NB:0.053 Δ:0.045** **Incar. Rate:** B:0.052 NB:0.018 Δ:0.034**	**Fraction Black:** 0.198 **Fel. Arraign. Rate:** B:0.101 NB:0.06 Δ:0.041** **Incar. Rate:** B:0.048 NB:0.024 Δ:0.023*	**Fraction Black:** 0.117 **Fel. Arraign. Rate:** B:0.08 NB:0.042 Δ:0.037** **Incar. Rate:** B:0.048 NB:0.012 Δ:0.036**
AI 10	**Fraction Black:** 0.369 **Fel. Arraign. Rate:** B:0.084 NB:0.045 Δ:0.038** **Incar. Rate:** B:0.02 NB:0.019 Δ:0.002	**Fraction Black:** 0.317 **Fel. Arraign. Rate:** B:0.079 NB:0.03 Δ:0.049** **Incar. Rate:** B:0.032 NB:0.015 Δ:0.017*	**Fraction Black:** 0.321 **Fel. Arraign. Rate:** B:0.08 NB:0.042 Δ:0.038** **Incar. Rate:** B:0.032 NB:0.013 Δ:0.019**	**Fraction Black:** 0.174 **Fel. Arraign. Rate:** B:0.04 NB:0.028 Δ:0.012 **Incar. Rate:** B:0.029 NB:0.006 Δ:0.024**	**Fraction Black:** 0.089 **Fel. Arraign. Rate:** B:0.036 NB:0.025 Δ:0.011 **Incar. Rate:** B:0.016 NB:0.008 Δ:0.008

Notes: The five columns above are the second half of a table that provides more detailed information about the sample used to create Figure 1. The cells are defined by deciles in the SES and Academic Index distributions. * indicates that the Black v. Non-Black difference is statistically significant at the .05 level and ** indicates significance at the .01 level.

Table A2: Frac. of Females with Felonies and Incarcerations by Age 25 within AI*SES Decile by Race

	SES 1	SES 2	SES 3	SES 4	SES 5
AI 1	**Fraction Black:** 0.976 **Fel. Arraign. Rate:** B:0.078 NB:0.023 Δ:0.055** **Incar. Rate:** B:0.014 NB:0.0 Δ:0.014**	**Fraction Black:** 0.809 **Fel. Arraign. Rate:** B:0.085 NB:0.026 Δ:0.059** **Incar. Rate:** B:0.023 NB:0.004 Δ:0.019**	**Fraction Black:** 0.623 **Fel. Arraign. Rate:** B:0.057 NB:0.03 Δ:0.026** **Incar. Rate:** B:0.017 NB:0.009 Δ:0.008	**Fraction Black:** 0.534 **Fel. Arraign. Rate:** B:0.071 NB:0.016 Δ:0.054** **Incar. Rate:** B:0.014 NB:0.004 Δ:0.011**	**Fraction Black:** 0.47 **Fel. Arraign. Rate:** B:0.066 NB:0.016 Δ:0.049** **Incar. Rate:** B:0.014 NB:0.002 Δ:0.013**
AI 2	**Fraction Black:** 0.972 **Fel. Arraign. Rate:** B:0.076 NB:0.0 Δ:0.076** **Incar. Rate:** B:0.02 NB:0.0 Δ:0.02**	**Fraction Black:** 0.827 **Fel. Arraign. Rate:** B:0.069 NB:0.024 Δ:0.046** **Incar. Rate:** B:0.018 NB:0.004 Δ:0.014**	**Fraction Black:** 0.671 **Fel. Arraign. Rate:** B:0.057 NB:0.02 Δ:0.037** **Incar. Rate:** B:0.011 NB:0.011 Δ:-0.0	**Fraction Black:** 0.574 **Fel. Arraign. Rate:** B:0.064 NB:0.012 Δ:0.052** **Incar. Rate:** B:0.014 NB:0.002 Δ:0.013**	**Fraction Black:** 0.478 **Fel. Arraign. Rate:** B:0.068 NB:0.012 Δ:0.056** **Incar. Rate:** B:0.013 NB:0.002 Δ:0.011**
AI 3	**Fraction Black:** 0.976 **Fel. Arraign. Rate:** B:0.074 NB:0.026 Δ:0.049* **Incar. Rate:** B:0.013 NB:0.0 Δ:0.013**	**Fraction Black:** 0.822 **Fel. Arraign. Rate:** B:0.064 NB:0.015 Δ:0.049** **Incar. Rate:** B:0.015 NB:0.0 Δ:0.015**	**Fraction Black:** 0.666 **Fel. Arraign. Rate:** B:0.058 NB:0.016 Δ:0.042** **Incar. Rate:** B:0.019 NB:0.008 Δ:0.011*	**Fraction Black:** 0.581 **Fel. Arraign. Rate:** B:0.069 NB:0.017 Δ:0.052** **Incar. Rate:** B:0.019 NB:0.002 Δ:0.017**	**Fraction Black:** 0.491 **Fel. Arraign. Rate:** B:0.062 NB:0.016 Δ:0.046** **Incar. Rate:** B:0.012 NB:0.003 Δ:0.009*
AI 4	**Fraction Black:** 0.981 **Fel. Arraign. Rate:** B:0.073 NB:0.0 Δ:0.073** **Incar. Rate:** B:0.015 NB:0.0 Δ:0.015**	**Fraction Black:** 0.824 **Fel. Arraign. Rate:** B:0.063 NB:0.023 Δ:0.04** **Incar. Rate:** B:0.013 NB:0.008 Δ:0.005	**Fraction Black:** 0.671 **Fel. Arraign. Rate:** B:0.046 NB:0.024 Δ:0.022** **Incar. Rate:** B:0.006 NB:0.006 Δ:-0.0	**Fraction Black:** 0.579 **Fel. Arraign. Rate:** B:0.051 NB:0.019 Δ:0.032** **Incar. Rate:** B:0.01 NB:0.005 Δ:0.006	**Fraction Black:** 0.486 **Fel. Arraign. Rate:** B:0.041 NB:0.015 Δ:0.025** **Incar. Rate:** B:0.003 NB:0.005 Δ:-0.002
AI 5	**Fraction Black:** 0.976 **Fel. Arraign. Rate:** B:0.061 NB:0.029 Δ:0.033 **Incar. Rate:** B:0.016 NB:0.0 Δ:0.016**	**Fraction Black:** 0.843 **Fel. Arraign. Rate:** B:0.056 NB:0.019 Δ:0.037** **Incar. Rate:** B:0.008 NB:0.005 Δ:0.003	**Fraction Black:** 0.693 **Fel. Arraign. Rate:** B:0.06 NB:0.023 Δ:0.037** **Incar. Rate:** B:0.009 NB:0.002 Δ:0.007**	**Fraction Black:** 0.601 **Fel. Arraign. Rate:** B:0.059 NB:0.022 Δ:0.037** **Incar. Rate:** B:0.009 NB:0.002 Δ:0.007**	**Fraction Black:** 0.509 **Fel. Arraign. Rate:** B:0.05 NB:0.016 Δ:0.034** **Incar. Rate:** B:0.007 NB:0.001 Δ:0.005
AI 6	**Fraction Black:** 0.986 **Fel. Arraign. Rate:** B:0.049 NB:0.0 Δ:0.049** **Incar. Rate:** B:0.007 NB:0.0 Δ:0.007**	**Fraction Black:** 0.835 **Fel. Arraign. Rate:** B:0.038 NB:0.029 Δ:0.009 **Incar. Rate:** B:0.006 NB:0.0 Δ:0.006**	**Fraction Black:** 0.682 **Fel. Arraign. Rate:** B:0.042 NB:0.011 Δ:0.031** **Incar. Rate:** B:0.013 NB:0.004 Δ:0.009*	**Fraction Black:** 0.611 **Fel. Arraign. Rate:** B:0.051 NB:0.009 Δ:0.041** **Incar. Rate:** B:0.009 NB:0.002 Δ:0.008**	**Fraction Black:** 0.496 **Fel. Arraign. Rate:** B:0.054 NB:0.011 Δ:0.043** **Incar. Rate:** B:0.008 NB:0.003 Δ:0.006
AI 7	**Fraction Black:** 0.964 **Fel. Arraign. Rate:** B:0.037 NB:0.0 Δ:0.037** **Incar. Rate:** B:0.006 NB:0.0 Δ:0.006**	**Fraction Black:** 0.857 **Fel. Arraign. Rate:** B:0.023 NB:0.021 Δ:0.003 **Incar. Rate:** B:0.003 NB:0.0 Δ:0.003**	**Fraction Black:** 0.694 **Fel. Arraign. Rate:** B:0.033 NB:0.012 Δ:0.021** **Incar. Rate:** B:0.002 NB:0.0 Δ:0.002	**Fraction Black:** 0.607 **Fel. Arraign. Rate:** B:0.028 NB:0.024 Δ:0.004 **Incar. Rate:** B:0.002 NB:0.002 Δ:0.001	**Fraction Black:** 0.491 **Fel. Arraign. Rate:** B:0.043 NB:0.016 Δ:0.027** **Incar. Rate:** B:0.007 NB:0.004 Δ:0.003
AI 8	**Fraction Black:** 0.983 **Fel. Arraign. Rate:** B:0.027 NB:0.053 Δ:-0.026 **Incar. Rate:** B:0.004 NB:0.0 Δ:0.004**	**Fraction Black:** 0.836 **Fel. Arraign. Rate:** B:0.039 NB:0.025 Δ:0.015 **Incar. Rate:** B:0.006 NB:0.01 Δ:-0.004	**Fraction Black:** 0.695 **Fel. Arraign. Rate:** B:0.035 NB:0.02 Δ:0.015 **Incar. Rate:** B:0.004 NB:0.002 Δ:0.002	**Fraction Black:** 0.622 **Fel. Arraign. Rate:** B:0.035 NB:0.008 Δ:0.027** **Incar. Rate:** B:0.009 NB:0.0 Δ:0.009**	**Fraction Black:** 0.506 **Fel. Arraign. Rate:** B:0.04 NB:0.021 Δ:0.019** **Incar. Rate:** B:0.006 NB:0.005 Δ:0.001
AI 9	**Fraction Black:** 0.972 **Fel. Arraign. Rate:** B:0.036 NB:0.08 Δ:-0.044 **Incar. Rate:** B:0.006 NB:0.04 Δ:-0.034	**Fraction Black:** 0.835 **Fel. Arraign. Rate:** B:0.036 NB:0.0 Δ:0.036** **Incar. Rate:** B:0.003 NB:0.0 Δ:0.003*	**Fraction Black:** 0.698 **Fel. Arraign. Rate:** B:0.019 NB:0.009 Δ:0.01 **Incar. Rate:** B:0.004 NB:0.0 Δ:0.004*	**Fraction Black:** 0.569 **Fel. Arraign. Rate:** B:0.026 NB:0.013 Δ:0.012 **Incar. Rate:** B:0.004 NB:0.002 Δ:0.002	**Fraction Black:** 0.45 **Fel. Arraign. Rate:** B:0.028 NB:0.013 Δ:0.015* **Incar. Rate:** B:0.002 NB:0.003 Δ:-0.001
AI 10	**Fraction Black:** 0.956 **Fel. Arraign. Rate:** B:0.028 NB:0.0 Δ:0.028** **Incar. Rate:** B:0.01 NB:0.0 Δ:0.01**	**Fraction Black:** 0.8 **Fel. Arraign. Rate:** B:0.019 NB:0.031 Δ:-0.012 **Incar. Rate:** B:0.006 NB:0.0 Δ:0.006*	**Fraction Black:** 0.689 **Fel. Arraign. Rate:** B:0.018 NB:0.005 Δ:0.014* **Incar. Rate:** B:0.0 NB:0.0 Δ:0.0	**Fraction Black:** 0.526 **Fel. Arraign. Rate:** B:0.011 NB:0.014 Δ:-0.004 **Incar. Rate:** B:0.0 NB:0.0 Δ:0.0	**Fraction Black:** 0.482 **Fel. Arraign. Rate:** B:0.007 NB:0.011 Δ:-0.004 **Incar. Rate:** B:0.0 NB:0.0 Δ:0.0

Notes: The five columns above are the first half of a table that provides more detailed information about the sample used to create Figure B1 The cells are defined by deciles in the SES and Academic Index distributions. * indicates that the Black v. Non-Black difference is statistically significant at the .05 level and ** indicates significance at the .01 level.

Table A2 Continued

	SES 6	SES 7	SES 8	SES 9	SES 10
AI 1	**Fraction Black:** 0.498 **Fel. Arraign. Rate:** B:0.088 NB:0.016 Δ:0.072** **Incar. Rate:** B:0.018 NB:0.007 Δ:0.011	**Fraction Black:** 0.441 **Fel. Arraign. Rate:** B:0.049 NB:0.016 Δ:0.033** **Incar. Rate:** B:0.012 NB:0.005 Δ:0.007	**Fraction Black:** 0.38 **Fel. Arraign. Rate:** B:0.072 NB:0.015 Δ:0.057** **Incar. Rate:** B:0.02 NB:0.005 Δ:0.015	**Fraction Black:** 0.208 **Fel. Arraign. Rate:** B:0.031 NB:0.019 Δ:0.012 **Incar. Rate:** B:0.0 NB:0.008 Δ:-0.008*	**Fraction Black:** 0.231 **Fel. Arraign. Rate:** B:0.035 NB:0.016 Δ:0.019 **Incar. Rate:** B:0.018 NB:0.011 Δ:0.007
AI 2	**Fraction Black:** 0.493 **Fel. Arraign. Rate:** B:0.063 NB:0.021 Δ:0.043** **Incar. Rate:** B:0.012 NB:0.0 Δ:0.012**	**Fraction Black:** 0.436 **Fel. Arraign. Rate:** B:0.054 NB:0.019 Δ:0.035** **Incar. Rate:** B:0.015 NB:0.004 Δ:0.011*	**Fraction Black:** 0.381 **Fel. Arraign. Rate:** B:0.034 NB:0.019 Δ:0.015 **Incar. Rate:** B:0.006 NB:0.004 Δ:0.002	**Fraction Black:** 0.242 **Fel. Arraign. Rate:** B:0.037 NB:0.022 Δ:0.015 **Incar. Rate:** B:0.012 NB:0.008 Δ:0.004	**Fraction Black:** 0.225 **Fel. Arraign. Rate:** B:0.049 NB:0.007 Δ:0.042* **Incar. Rate:** B:0.0 NB:0.004 Δ:-0.004
AI 3	**Fraction Black:** 0.474 **Fel. Arraign. Rate:** B:0.065 NB:0.013 Δ:0.053** **Incar. Rate:** B:0.016 NB:0.005 Δ:0.011*	**Fraction Black:** 0.444 **Fel. Arraign. Rate:** B:0.031 NB:0.016 Δ:0.014 **Incar. Rate:** B:0.004 NB:0.003 Δ:0.001	**Fraction Black:** 0.391 **Fel. Arraign. Rate:** B:0.034 NB:0.02 Δ:0.014 **Incar. Rate:** B:0.005 NB:0.003 Δ:0.002	**Fraction Black:** 0.22 **Fel. Arraign. Rate:** B:0.033 NB:0.014 Δ:0.019 **Incar. Rate:** B:0.011 NB:0.003 Δ:0.008	**Fraction Black:** 0.16 **Fel. Arraign. Rate:** B:0.026 NB:0.02 Δ:0.006 **Incar. Rate:** B:0.013 NB:0.002 Δ:0.011
AI 4	**Fraction Black:** 0.52 **Fel. Arraign. Rate:** B:0.049 NB:0.018 Δ:0.031** **Incar. Rate:** B:0.007 NB:0.002 Δ:0.006	**Fraction Black:** 0.415 **Fel. Arraign. Rate:** B:0.038 NB:0.015 Δ:0.023** **Incar. Rate:** B:0.002 NB:0.004 Δ:-0.002	**Fraction Black:** 0.434 **Fel. Arraign. Rate:** B:0.028 NB:0.008 Δ:0.02** **Incar. Rate:** B:0.006 NB:0.003 Δ:0.003	**Fraction Black:** 0.262 **Fel. Arraign. Rate:** B:0.012 NB:0.023 Δ:-0.011 **Incar. Rate:** B:0.0 NB:0.001 Δ:-0.001	**Fraction Black:** 0.174 **Fel. Arraign. Rate:** B:0.029 NB:0.018 Δ:0.011 **Incar. Rate:** B:0.0 NB:0.002 Δ:-0.002
AI 5	**Fraction Black:** 0.479 **Fel. Arraign. Rate:** B:0.032 NB:0.013 Δ:0.019** **Incar. Rate:** B:0.004 NB:0.001 Δ:0.003	**Fraction Black:** 0.471 **Fel. Arraign. Rate:** B:0.039 NB:0.015 Δ:0.025** **Incar. Rate:** B:0.005 NB:0.001 Δ:0.003	**Fraction Black:** 0.416 **Fel. Arraign. Rate:** B:0.044 NB:0.023 Δ:0.021** **Incar. Rate:** B:0.006 NB:0.004 Δ:0.002	**Fraction Black:** 0.256 **Fel. Arraign. Rate:** B:0.043 NB:0.013 Δ:0.031** **Incar. Rate:** B:0.01 NB:0.005 Δ:0.005	**Fraction Black:** 0.215 **Fel. Arraign. Rate:** B:0.012 NB:0.016 Δ:-0.004 **Incar. Rate:** B:0.0 NB:0.005 Δ:-0.005*
AI 6	**Fraction Black:** 0.484 **Fel. Arraign. Rate:** B:0.034 NB:0.015 Δ:0.019** **Incar. Rate:** B:0.003 NB:0.004 Δ:-0.001	**Fraction Black:** 0.441 **Fel. Arraign. Rate:** B:0.037 NB:0.011 Δ:0.026** **Incar. Rate:** B:0.006 NB:0.001 Δ:0.005	**Fraction Black:** 0.411 **Fel. Arraign. Rate:** B:0.03 NB:0.023 Δ:0.007 **Incar. Rate:** B:0.007 NB:0.002 Δ:0.005	**Fraction Black:** 0.246 **Fel. Arraign. Rate:** B:0.028 NB:0.011 Δ:0.017* **Incar. Rate:** B:0.0 NB:0.001 Δ:-0.001	**Fraction Black:** 0.191 **Fel. Arraign. Rate:** B:0.027 NB:0.011 Δ:0.015 **Incar. Rate:** B:0.0 NB:0.006 Δ:-0.006**
AI 7	**Fraction Black:** 0.496 **Fel. Arraign. Rate:** B:0.025 NB:0.012 Δ:0.014* **Incar. Rate:** B:0.004 NB:0.001 Δ:0.003	**Fraction Black:** 0.448 **Fel. Arraign. Rate:** B:0.028 NB:0.006 Δ:0.022** **Incar. Rate:** B:0.006 NB:0.0 Δ:0.006**	**Fraction Black:** 0.434 **Fel. Arraign. Rate:** B:0.037 NB:0.014 Δ:0.023** **Incar. Rate:** B:0.009 NB:0.001 Δ:0.008**	**Fraction Black:** 0.249 **Fel. Arraign. Rate:** B:0.038 NB:0.013 Δ:0.026** **Incar. Rate:** B:0.003 NB:0.0 Δ:0.003	**Fraction Black:** 0.182 **Fel. Arraign. Rate:** B:0.013 NB:0.013 Δ:-0.0 **Incar. Rate:** B:0.0 NB:0.003 Δ:-0.003*
AI 8	**Fraction Black:** 0.489 **Fel. Arraign. Rate:** B:0.03 NB:0.02 Δ:0.01 **Incar. Rate:** B:0.007 NB:0.006 Δ:0.0	**Fraction Black:** 0.469 **Fel. Arraign. Rate:** B:0.023 NB:0.005 Δ:0.018** **Incar. Rate:** B:0.004 NB:0.0 Δ:0.004*	**Fraction Black:** 0.439 **Fel. Arraign. Rate:** B:0.028 NB:0.015 Δ:0.013* **Incar. Rate:** B:0.004 NB:0.002 Δ:0.002	**Fraction Black:** 0.246 **Fel. Arraign. Rate:** B:0.022 NB:0.006 Δ:0.015** **Incar. Rate:** B:0.005 NB:0.001 Δ:0.004	**Fraction Black:** 0.154 **Fel. Arraign. Rate:** B:0.008 NB:0.009 Δ:-0.001 **Incar. Rate:** B:0.0 NB:0.002 Δ:-0.002*
AI 9	**Fraction Black:** 0.502 **Fel. Arraign. Rate:** B:0.022 NB:0.008 Δ:0.014** **Incar. Rate:** B:0.001 NB:0.003 Δ:-0.001	**Fraction Black:** 0.43 **Fel. Arraign. Rate:** B:0.012 NB:0.009 Δ:0.003 **Incar. Rate:** B:0.003 NB:0.0 Δ:0.003	**Fraction Black:** 0.429 **Fel. Arraign. Rate:** B:0.017 NB:0.013 Δ:0.004 **Incar. Rate:** B:0.0 NB:0.002 Δ:-0.002	**Fraction Black:** 0.259 **Fel. Arraign. Rate:** B:0.024 NB:0.011 Δ:0.013* **Incar. Rate:** B:0.004 NB:0.001 Δ:0.003	**Fraction Black:** 0.138 **Fel. Arraign. Rate:** B:0.006 NB:0.011 Δ:-0.005 **Incar. Rate:** B:0.0 NB:0.001 Δ:-0.001
AI 10	**Fraction Black:** 0.451 **Fel. Arraign. Rate:** B:0.016 NB:0.003 Δ:0.012** **Incar. Rate:** B:0.002 NB:0.0 Δ:0.002	**Fraction Black:** 0.386 **Fel. Arraign. Rate:** B:0.012 NB:0.007 Δ:0.004 **Incar. Rate:** B:0.002 NB:0.001 Δ:0.001	**Fraction Black:** 0.406 **Fel. Arraign. Rate:** B:0.012 NB:0.004 Δ:0.008* **Incar. Rate:** B:0.002 NB:0.0 Δ:0.002	**Fraction Black:** 0.205 **Fel. Arraign. Rate:** B:0.002 NB:0.003 Δ:-0.001 **Incar. Rate:** B:0.0 NB:0.0 Δ:0.0	**Fraction Black:** 0.104 **Fel. Arraign. Rate:** B:0.002 NB:0.005 Δ:-0.003 **Incar. Rate:** B:0.0 NB:0.001 Δ:-0.001

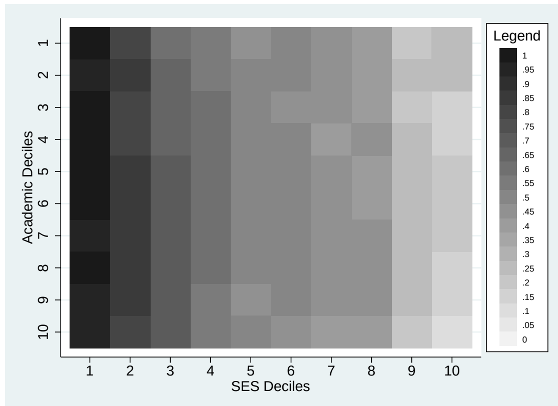
Notes: The five columns above are the second half of a table that provides more detailed information about the sample used to create Figure B1. The cells are defined by deciles in the SES and Academic Index distributions. * indicates that the Black v. Non-Black difference is statistically significant at the .05 level and ** indicates significance at the .01 level.

Appendix B: Main Results for Females

Figure B1

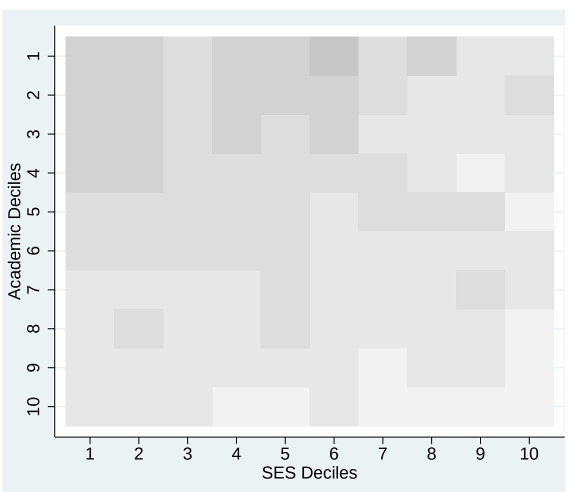
Facts About Female Eighth Graders: Cells Defined By K-8 Achievement*SES

Fraction Black

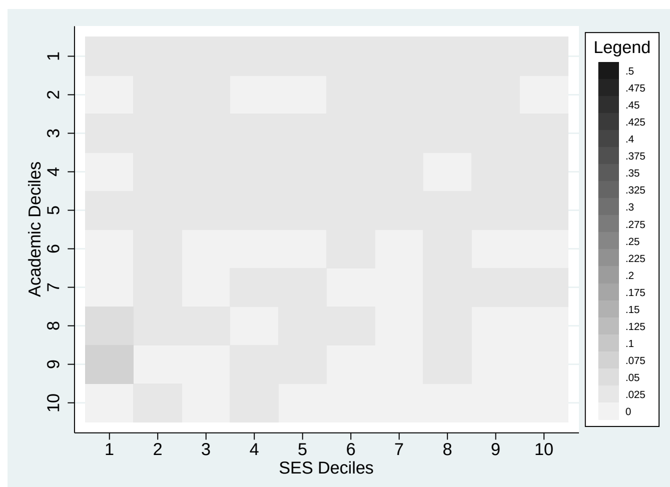


Age 25: % Ever Arraigned on a Felony (Full Wedge) % Ever Incarcerated (Solid Black)

Black



Non-Black



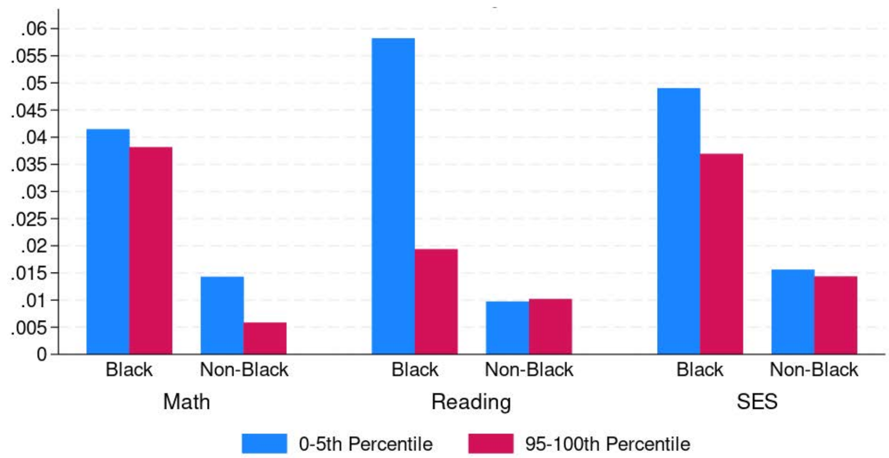
Notes: See note to Figure 1. These are the parallel results for female students. The samples sizes are 68,995 for Black females and 61,139 for non-Black females.

Figure B2: Females

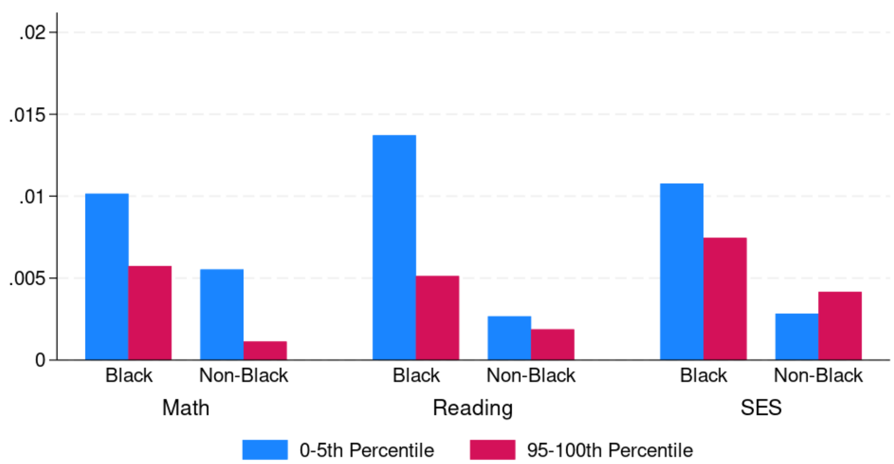
Within-School Gradients for Predicted Criminal Justice Outcomes

Bottom versus Top Ventiles of Reading, Math, and SES: Eighth Grade Females

Panel A: Fraction Ever Arraigned on a Felony by Age 25



Panel B: Fraction Ever Incarcerated by Age 25



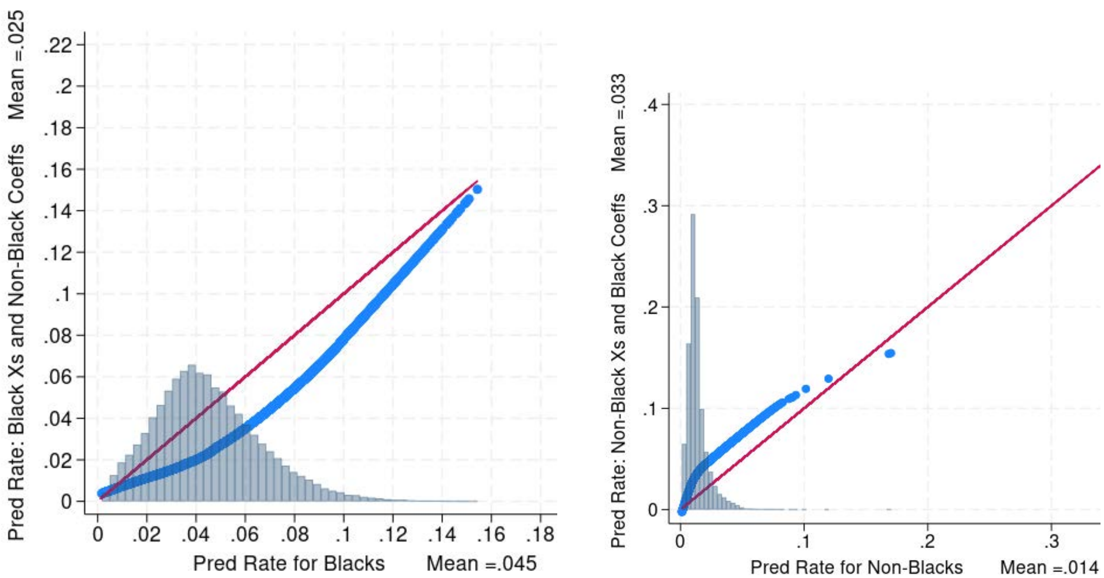
Notes: Each bar displays an average predicted rate of criminal justice involvement for a specific sample of male students of a given race. These predicted values are generated using logit models that take an indicator for either arraignment by age 25 or incarceration by age 25 as the dependent variable. Separately for Black and non-Black females, we estimate these logit models 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 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 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 female eighth graders in each of their schools, the average predicted arraignment rate for this sample is just under six percent. 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 B3:Females

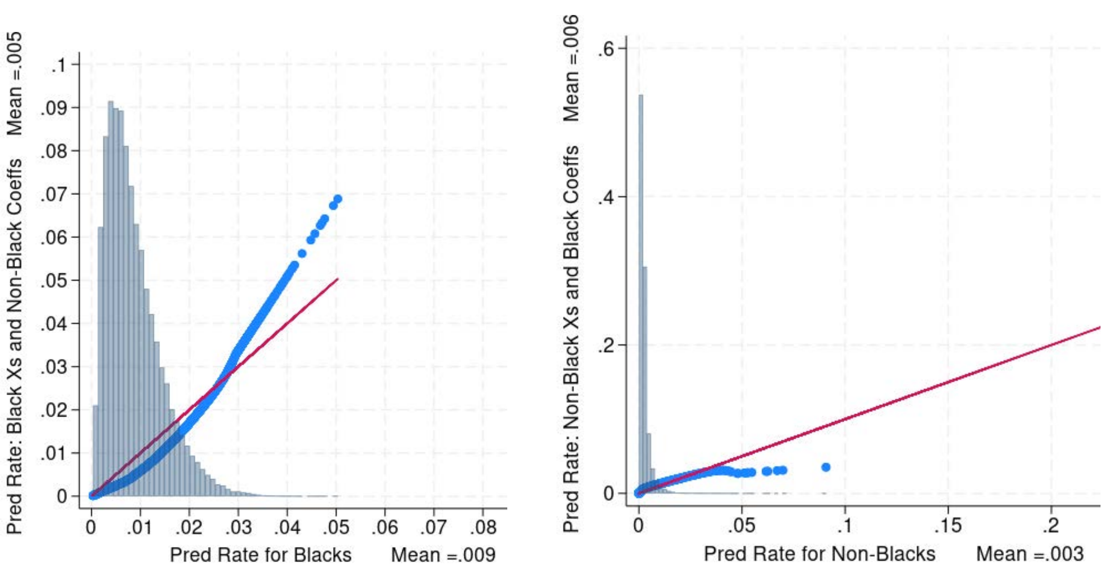
Decomposition of Racial Differences in Criminal Justice Outcomes

Bars on X-axis Give the Fraction of Students with Predicted Values in Each Interval Red line = 45^0

Panel A: Predicted Felony Arraignment Rates by Age 25



Panel B: Incarceration Rates by Age 25



Notes: Panel A and Panel B presents results from four logit models that parallel the models we employ to produce the results for Figure 2, but these specifications include female students and do not include school fixed effects. One goal here is to create hypothetical predicted rates of criminal justice involvement for Black females given the estimated coefficients from the non-Black female models and vice versa. However, Chicago schools are quite segregated, and for many schools, we cannot reliably estimate outcomes for non-Black children. We estimate both our arraignment and incarceration models separately for Black females and non-Black females. After we estimate each model, we generate predicted probabilities for the entire sample based on each model's coefficients. Thus, for each Black female student, we have his predicted probability of felony arraignment and a predicted probability of felony arraignment that employs coefficients from the model estimated on non-Black females, i.e. an estimate of the likelihood that he would face arraignment if she were not Black. In Panel A, each figure plots the fitted values from a non-parametric regression of these cross-race predictions on each student's own predicted arraignment rate. We order students on the x-axis by their own-sample predicted arraignment rates. Panel B presents parallel results for incarceration. Each graph also plots the empirical distribution of the predicted values on the x-axis.

Table B1: Females

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Females

Black ($\bar{Y}$: 0.044)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.007	-0.013
8th Grade Reading (p: 0.768)	0.000	0.001
8th Grade Math (p: 0.61)	0.001	0.001

Non-Black ($\bar{Y}$: 0.013)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.121)	-0.001	-0.002
8th Grade Reading (p: 0.735)	0.000	-0.001
8th Grade Math (p: 0.777)	0.000	0.000

Panel B: Impacts of School Quality on Incarceration by Age 25 For Females

Black ($\bar{Y}$: 0.008)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.002	-0.003
8th Grade Reading (p: 0.425)	0.000	0.001
8th Grade Math (p: 0.945)	0.000	0.000

Non-Black ($\bar{Y}$: 0.002)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.107)	0.000	-0.001
8th Grade Reading (p: 0.015)	-0.001	-0.001
8th Grade Math (p: 0.457)	0.000	0.000

Notes: Each sub-table presents results from four regressions. In Panel A, these are four regressions of an indicator for a felony arraignment before age 25 on a VAM measure of the quality of the eighth grade educators in the school where the student first attended eighth grade plus controls for 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. We also include a dummy for being off-track in terms of age for grade, measures of the number of residential moves made during elementary school, and measures of the number of residential moves made among low SES neighborhood. We further include the school*cohort averages of each regressor. Finally, we include year effects, age in months, as well as the fractions Black and fraction male within a given school*cohort cell. Panel B presents results from parallel regressions that employ an indicator for incarceration by age 25 as the dependent variable. We construct three measures of quality. The first comes from using all students to regress an indicator for whether the student graduated high school on the controls described above plus an indicator for Black and an indicator for male. We then form mean residuals for each eighth-grade cohort in each school, and shrink these means using the shrinkage estimator proposed by Chetty et al. (2014*a*). We repeat these steps to create standard reading and math VAM scores using the spring math and reading exams given to eighth graders. The two columns describe the predicted impacts of moving between two percentiles in a given school quality distribution. See Appendix D for more details. We create HAC standard errors clustered at the school level.

Table B2: Females

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Females
Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.046)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.006	-0.010
8th Grade Reading (p: 0.443)	0.001	0.001
8th Grade Math (p: 0.267)	0.001	0.002

Non-Black ($\bar{Y}$: 0.014)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.071)	-0.002	-0.003
8th Grade Reading (p: 0.706)	0.000	0.001
8th Grade Math (p: 0.405)	0.001	0.001

Panel B: Impacts of School Quality on Incarceration by Age 25 For Females
Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.009)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.016)	-0.002	-0.003
8th Grade Reading (p: 0.261)	0.000	0.001
8th Grade Math (p: 0.656)	0.000	0.000

Non-Black ($\bar{Y}$: 0.002)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.026)	-0.001	-0.001
8th Grade Reading (p: 0.044)	-0.001	-0.001
8th Grade Math (p: 0.729)	0.000	0.000

Notes: See notes to Table B1 above. These results parallel the results in Table B1, but here the outcome equations include fixed effects for the modal high school attended by the students from each elementary school. See Appendix D for more details.

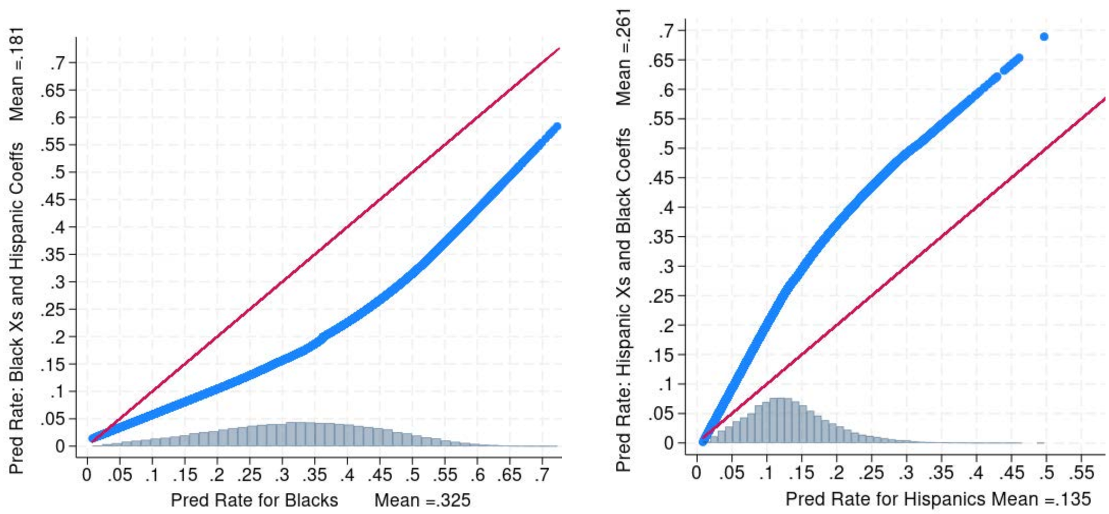
Appendix C: Decompositions Given Other Racial Breakdowns

Figure C1

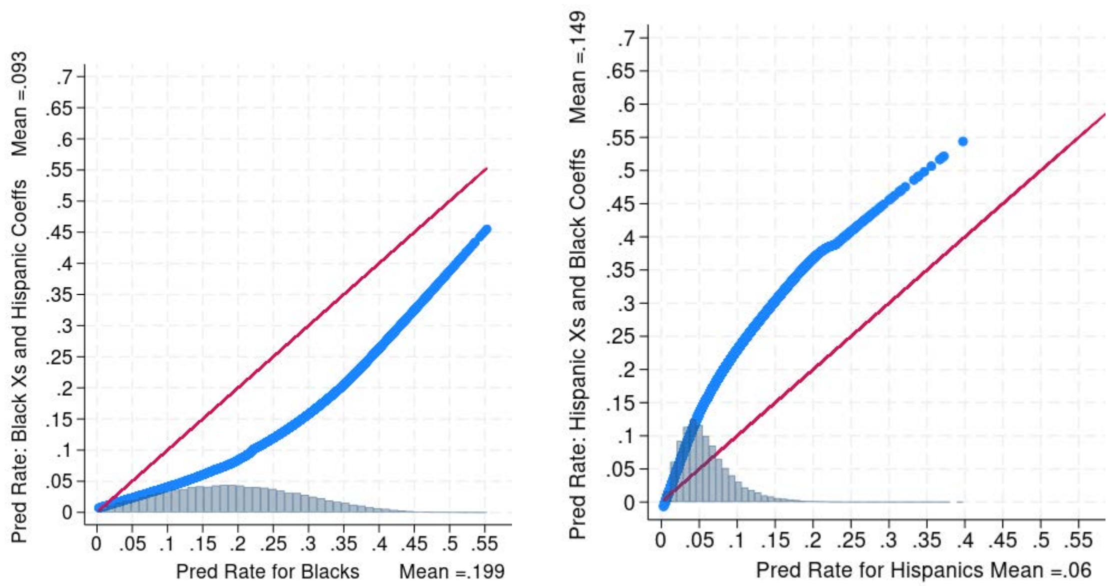
Decomposition of Black vs Hispanic Differences in Criminal Justice Outcomes

Bars on X-axis Give the Fraction of Students with Predicted Values in Each Interval Red line = 45^0

Panel A: Predicted Felony Arraignment Rates by Age 25



Panel B: Incarceration Rates by Age 25



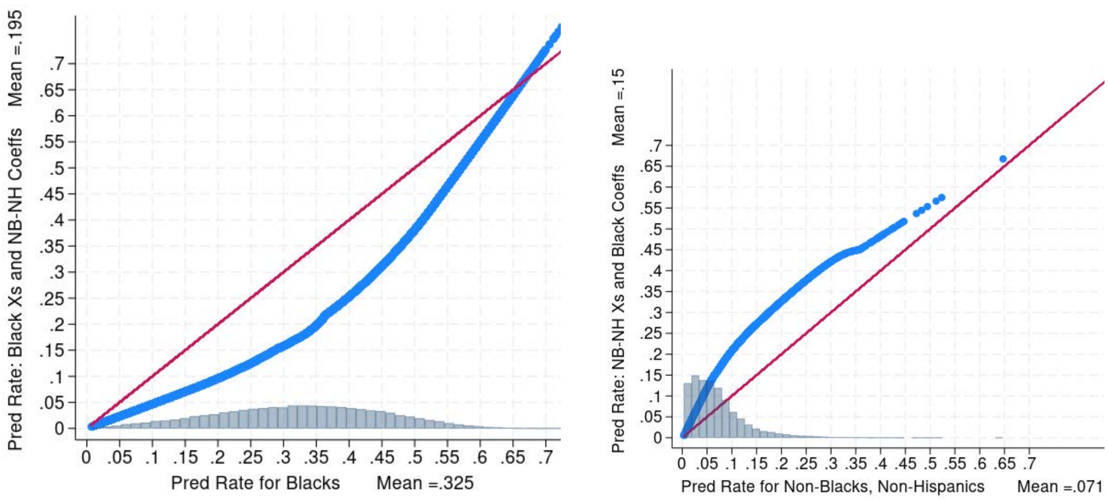
Notes: See notes below Figure 3. These are parallel results, but here the two populations are Black male students and Hispanic male students.

Figure C2

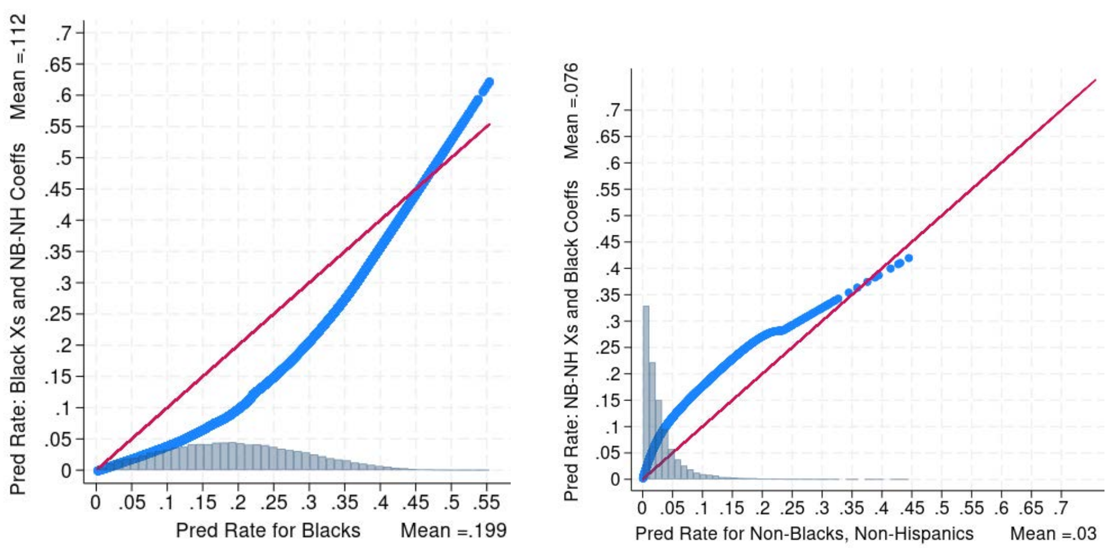
Decomposition of Black vs Non-Black plus Non-Hispanic Differences in Criminal Justice Outcomes

Bars on X-axis Give the Fraction of Students with Predicted Values in Each Interval   Red line = 45^0

Panel A: Predicted Felony Arraignment Rates by Age 25



Panel B: Incarceration Rates by Age 25



Notes: See notes below Figure 3. These are parallel results, but here the two populations are Black male students and male students who are not Hispanic or Black.

Appendix D: VAM Methods and Additional VAM results

We use the methods proposed in Chetty et al. (2014*a*) to create our value-added metrics. The unit of observation is a school year interacted with the set of students enrolled in eighth grade in a given school at the beginning of the 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 all the variables in (i) and (ii). We also include year 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 capture the residuals and form the average residual for each eighth-grade cohort in each school.

Next, we use the projection method developed in Chetty et al. (2014*a*) to create performance metrics that are specific to each combination of school and year. Two features of the method are key. First, the residual for students in school j in year t do not enter the calculation of performance metrics for (j, t). Rather, the performance metric for (j, t) is a weighted average of the average residuals for school j in years other than t. Second, the weights are derived from the variances and covariances of average residuals at the (j, t) level both overall and over t within j so that as these sample moments converge to population moments, each value-added performance metric is the best linear predictor of the true performance metric for (j, t) given the other $(j * t) - 1$ residual means. Finally, we regress either arraignment rates or incarceration rates on one of our value-added metrics and the controls described above. Our regression models take the following form:

$$y_{ij\tau} = \hat{\theta}_{jt}\gamma + x_{ijt}\beta + e_{ij\tau}$$

where $\hat{\theta}_{jt}$ denotes a VAM measure of the quality of eighth grade instruction in school j during year t, x_{ijt} is our control set, i indexes individuals, j indexes the schools where the attend eighth grade, t indexes the year student i starts eighth grade, and τ indexes the date that i reaches age 25.

Our main results in Table 1 report the results of three separate regressions that include each performance metric as a stand-alone measure of quality. Below, we also present parallel results from single regressions that simultaneously include all three performance metrics. Our key results concerning the high school graduation metric change little when we add the math and reading metrics to the regression because the former is weakly correlated with the two latter measures.

We exclude students from any school j such that, in all years t, there are fewer than 30 students with a valid outcome measure who attend school j in a year other than t. Our final sample sizes for the regressions on the high school graduation metric are 62,099 for Black males and 59,996 for non-Black males. The samples sizes for the regressions on math and reading metrics are 62,142 for Black males and 60,031 for non-Black males. The sample sizes for the regressions involving the high school graduation metric are slightly smaller because we had to drop more school*cohort cells from the analyses when forming the baseline residuals. Our high school graduation indicator is missing for students who transfer out of CPS and this reduces the number of students with valid data in school j in years other than t.

Our Table 2 results are created in a parallel manner with two modifications. First, we eliminate students who attend any school j where the modal student in j transfers out of CPS to attend high school. Second, we include a set of indicators for the modal high school attended by students who attended eighth grade in school j. Here, the sample sizes are just over, 57,800 for non-Black males and just under 54,000 for non-Black males.

VAM results w/ Simultaneous Control for All Value-Added Metrics

Table D1

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Males

Black ($\bar{Y}$: 0.308)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.028	-0.049
8th Grade Math (p: 0.351)	-0.003	-0.007
8th Grade Reading (p: 0.849)	-0.001	-0.001

Non-Black ($\bar{Y}$: 0.11)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.010	-0.017
8th Grade Math (p: 0.480)	0.001	0.003
8th Grade Reading (p: 0.439)	-0.002	-0.004

Panel B: Impacts of School Quality on Incarceration by Age 25 For Males

Black ($\bar{Y}$: 0.183)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.023	-0.041
8th Grade Math (p: 0.234)	-0.004	-0.007
8th Grade Reading (p: 0.573)	-0.002	-0.003

Non-Black ($\bar{Y}$: 0.047)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.006	-0.011
8th Grade Math (p: 0.612)	0.001	0.001
8th Grade Reading (p: 0.173)	-0.002	-0.005

Notes: See notes below Table 1. Table 1 reports the results of three regressions that each regress a criminal justice outcome on one VAM metric. Here, we regress each outcome variable on all three VAM measures in a single regression and report the results. See Appendix 2 for more details

Table D2

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Males Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.32)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.018	-0.032
8th Grade Math (p: 0.363)	-0.003	-0.006
8th Grade Reading (p: 0.854)	0.001	0.001

Non-Black ($\bar{Y}$: 0.115)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.011	-0.019
8th Grade Math (p: 0.371)	0.002	0.004
8th Grade Reading (p: 0.363)	-0.003	-0.005

Panel B: Impacts of School Quality on Incarceration by Age 25 For Males Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.192)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.013	-0.023
8th Grade Math (p: 0.167)	-0.004	-0.008
8th Grade Reading (p: 0.752)	0.001	0.002

Non-Black ($\bar{Y}$: 0.05)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.002)	-0.006	-0.010
8th Grade Math (p: 0.428)	0.001	0.002
8th Grade Reading (p: 0.099)	-0.003	-0.006

Notes: See notes to Table 2. Table 1 reports the results of three regressions that each regress a criminal justice outcome on one VAM metric. Here, we regress each outcome variable on all three VAM measures in a single regression and report the results. See Appendix D for more details

Table D3

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Females

Black ($\bar{Y}$: 0.044)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.008	-0.013
8th Grade Math (p: 0.577)	0.001	0.001
8th Grade Reading (p: 0.938)	0.000	0.000

Non-Black ($\bar{Y}$: 0.013)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.119)	-0.001	-0.002
8th Grade Math (p: 0.998)	0.000	0.000
8th Grade Reading (p: 0.895)	0.000	0.000

Panel B: Impacts of School Quality on Incarceration by Age 25 For Females

Black ($\bar{Y}$: 0.008)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: < 0.001)	-0.002	-0.003
8th Grade Math (p: 0.526)	0.000	-0.001
8th Grade Reading (p: 0.238)	0.000	0.001

Non-Black ($\bar{Y}$: 0.002)	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.142)	0.000	-0.001
8th Grade Math (p: 0.560)	0.000	0.000
8th Grade Reading (p: 0.036)	-0.001	-0.001

Notes: See notes to Table B1. Table B1 reports the results of three regressions that each regress a criminal justice outcome on one VAM metric. Here, we regress each outcome variable on all three VAM measures in a single regression and report the results. See Appendix D for more details

Table D4

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Females Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.046)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: $<$ 0.001)	-0.006	-0.010
8th Grade Math (p: 0.522)	0.001	0.001
8th Grade Reading (p: 0.689)	0.000	0.001

Non-Black ($\bar{Y}$: 0.014)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.053)	-0.002	-0.003
8th Grade Math (p: 0.371)	0.001	0.002
8th Grade Reading (p: 0.923)	0.000	0.000

Panel B: Impacts of School Quality on Incarceration by Age 25 For Females Given Modal High School Fixed Effects

Black ($\bar{Y}$: 0.009)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.015)	-0.002	-0.003
8th Grade Math (p: 0.716)	0.000	0.000
8th Grade Reading (p: 0.227)	0.001	0.001

Non-Black ($\bar{Y}$: 0.002)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.026)	-0.001	-0.001
8th Grade Math (p: 0.408)	0.000	0.001
8th Grade Reading (p: 0.055)	-0.001	-0.001

Notes: See notes to Table B2. Table B2 reports the results of three regressions that each regress a criminal justice outcome on one VAM metric. Here, we regress each outcome variable on all three VAM measures in a single regression and report the results. See Appendix D for more details

Main VAM Results Hispanics vs Non-Hispanic, Non-Black

Table D5

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Males

Hispanic ($\bar{Y}$: 0.129)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.008)	-0.008	-0.015
8th Grade Reading (p: 0.805)	0.001	0.002
8th Grade Math (p: 0.502)	0.002	0.003

Non-Hispanic, Non-Black ($\bar{Y}$: 0.066)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.006)	-0.013	-0.022
8th Grade Reading (p: 0.006)	-0.009	-0.018
8th Grade Math (p: 0.091)	-0.005	-0.009

Panel B: Impacts of School Quality on Incarceration by Age 25 For Males

Hispanic ($\bar{Y}$: 0.056)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.003)	-0.007	-0.012
8th Grade Reading (p: 0.44)	-0.002	-0.003
8th Grade Math (p: 0.879)	0.000	0.000

Non-Hispanic, Non-Black ($\bar{Y}$: 0.026)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.004)	-0.007	-0.012
8th Grade Reading (p: 0.011)	-0.005	-0.010
8th Grade Math (p: 0.149)	-0.003	-0.005

Notes: See notes to Table 1. These are parallel results, but here the two populations are Hispanic male students and students who are neither Hispanic nor Black.

Table D6

Panel A: Impacts of School Quality on Felony Arraignment by Age 25 For Males Given Modal High School Fixed Effects

Hispanic ($\bar{Y}$: 0.131)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.003)	-0.009	-0.017
8th Grade Reading (p: 0.717)	0.001	0.002
8th Grade Math (p: 0.328)	0.002	0.005

Non-Hispanic, Non-Black ($\bar{Y}$: 0.072)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.11)	-0.007	-0.012
8th Grade Reading (p: 0.009)	-0.009	-0.018
8th Grade Math (p: 0.229)	-0.003	-0.007

Panel B: Impacts of School Quality on Incarceration by Age 25 For Males Given Modal High School Fixed Effects

Hispanic ($\bar{Y}$: 0.057)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.009)	-0.006	-0.011
8th Grade Reading (p: 0.634)	-0.001	-0.002
8th Grade Math (p: 0.849)	0.000	0.001

Non-Hispanic, Non-Black ($\bar{Y}$: 0.029)		
	Δ School Quality (Percentile)	
VAM Type	25-75	10-90
HS Graduation (p: 0.329)	-0.003	-0.005
8th Grade Reading (p: 0.008)	-0.006	-0.012
8th Grade Math (p: 0.225)	-0.002	-0.005

Notes: See notes to Table 1. These are parallel results, but here the two populations are Hispanic male students and students who are neither Hispanic nor Black.

Appendix E: 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.

Identifying 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% 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.