Names, Expectations and Black Children’s Achievement

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Comments appreciated.

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Names, Expectations and Black Children’s Achievement

Two recent National Bureau of Economic Research working papers come to strikingly different conclusions about the causes of persistent Black-White differences in outcomes. Bertrand and Mullainathan (2003), conducting a field experiment involving job applications in which they randomly assigned distinctively Black and distinctively White names to equivalent resumes, find that potential employers are dramatically less likely to respond to applicants with Black names. Their paper indicates that racial discrimination may contribute to Black-White differences in labor market success. Fryer and Levitt (2003), in an exhaustive study of California administrative data, link children’s birth vital records to their mothers’ birth certificates to gauge whether children with distinctively Black names experience different outcomes as adults. While they find that Black children with racially-identifiable are indeed more likely to face adverse outcomes as adults than are Black children with less identifiable names, they also show that most of these differences can be explained by observable covariates. Indeed, after controlling for covariates, they show that Black women with racially-identifiable names may even tend to have more education than do their counterparts with less identifiable names. They conclude that Black naming patterns are more likely to be a consequence than a cause of poor Black outcomes.

This paper identifies a factor that might be associated with both an increased likelihood of discrimination against individuals with distinctively Black names as well as no difference or even greater levels of human capital accumulation by these same individuals. I hypothesize that perhaps because racially-identifiable names signal an
individual’s socio-economic status and difficult-to-observe variables (Fryer and Levitt, 2003), evaluators may expect less from Blacks with racially-identifiable names than they do from Blacks with more homogenized names. These diminished expectations may be reflected in the evidence of discrimination uncovered by Bertrand and Mullainathan (2003). But, interestingly, they may also be manifested in increased years of schooling as is found by Fryer and Levitt (2003). Figlio and Lucas (forthcoming) show that low grading standards lead to reduced student test scores, while Betts and Grogger (2003) and Lillard and DeCicca (2003) show that low standards lead marginal-achievers to remain longer in school. These two strands of the standards literature suggest that if teachers and school administrators expect less from Black students with racially-identifiable names, these students may attain higher levels of schooling while attaining less human capital than Black students with less identifiable names. One piece of evidence suggests that this might be an explanation: In one large Florida school district, the magnitude of the Black-White test score gap increases by 32 percent between third grade and ninth grade. At the same time, the fraction of the test score gap that can be explained by Black naming patterns increases from 5 percent in third grade to 16 percent in ninth grade, suggesting that names may play a role in explaining why the test score gap rises, rather than falls, with increased school exposure.

I utilize a detailed dataset from a large Florida school district with over ten thousand Black students to directly test the hypothesis that teachers and school administrators expect less on average of Black students with racially-identifiable names, and these diminished expectations in turn lead to reduced student human capital attainment. In
these data I observe student test scores and educational attainment, as well as measures of
teacher and school administrator expectations. Specifically, I observe a student’s grades
and whether the student is labeled as either gifted or learning disabled. While these
labels have specific diagnostic definitions, schools and teachers have the flexibility to
determine which students should be referred for potential placement into these categories,
so expectations could still play an important role in these categorizations.

Most notable about my dataset is that I can compare the outcomes of sibling pairs, as
proxied by children sharing the same home address and phone number. While the trend
in Black naming patterns over time may be due to a desire for increased racial identity
among Black families, this trend is by no means universal. More importantly, racially-
identifiable naming patterns are not even deterministic within the same household. An
analysis of Black sibling pairs born to the same mother in Florida between 1989 and 1994
bears this out: Among Black children with names that are given to Whites between 75
and 100 percent of the time, only 36 percent were followed by siblings with names in this
same group, while 40 percent were followed by siblings with names given to Blacks 75 to
100 percent of the time (including unique names.) And while Black children with
racially-identifiable names were more likely to be followed by siblings with racially-
identifiable names than not, even among the group of Black children with names that are
given to Blacks between 75 and 100 percent of the time (including those with unique
names) only 60 percent were followed by siblings with a name in this group, while nearly
20 percent were immediately followed by a sibling with a name that is only given to
Blacks 0 to 25 percent of the time. Therefore, there exists considerable within-family variation in names and outcomes that I can exploit.

I find that Black children with racially-identifiable names tend to stay in school longer but at the same time perform less well on their standardized tests than do those with names typically given to White children. Moreover, all available measures of grading standards and expectations suggests that, within a family, Black children with racially-identifiable names are treated differently in school than are those with more homogenized names—conditional on observed test performance, they receive higher grades, but at the same time are more likely to be labeled as learning disabled and less likely to be considered gifted than are their siblings. These results are consistent with the notion that teachers and school administrators may subconsciously expect less of Black students with racially-identifiable names, and these expectations may possibly become a self-fulfilling prophecy.

Consistent with this same hypothesis, I find that these relationships vary systematically with the attributes of the school that the Black child attends. I suspect that these expectation differentials would be more pronounced in schools where teachers encounter fewer Black students or where there are fewer Black teachers. I find that this is the case: The test score gap between Black children with racially-identifiable names and their siblings with less identifiable names is larger in these schools. Moreover, the differences in how these siblings are treated by their teachers and schools, in terms of grades and
classifications, vary in the same manner, implying that a causal relationship between names and outcomes is more likely.

**Patterns in Black Children’s Names**

Fryer and Levitt (2003) carefully document trends over time the incidence of racially-identifiable names given to Black children in California. I begin by performing a similar, though less comprehensive, exercise using data provided by the Florida Department of Health for children born in Florida between 1989 and 1994. The first column of Table 1 presents the distribution of names given to Black children during this time period, broken down by the ratio of the number of times that name is observed on a Black child’s birth certificate to the number of times that name is observed on either a Black or White child’s birth certificate.\(^1\) During this time period, 22 percent of Black children were given names where at least three times as many White children as Black children received the name, and 37 percent of Black children received names that were majority-White names. At the same time, 35 percent of Black children received names that were either unique or given 100 percent of the time to Black children, a rate twice that observed in the White population.

The second and third columns of Table 1 break down this distribution by sex. Black males are considerably more likely to be given majority-White names than are Black females (41 percent for males versus 33 percent for females) and are considerably less likely to be given names that are either unique or given 100 percent of the time (26 percent for males versus 44 percent for females.) Therefore, Black families appear to be

\(^1\) This measure is analogous to Fryer and Levitt’s (2003) “Black Name Index.”
more likely to give their daughters racially-identifiable names than they do their sons. However, across the sexes there exist many cases of girls with majority-White names and boys with exclusively Black names.

To get a sense of the generational differences in naming, the next column of Table 1 describes the distribution of names given to the mothers of Black children born in Florida during this time period. One observes that the mothers of Black children are much more likely to have received majority-White names than they gave their children. Nearly half of Black mothers have majority-White names, a 17 percentage point difference relative to their daughters. And only 20 percent of Black mothers have names that are either unique or exclusively-Black, half the rate given to their daughters. Moreover, the difference between mothers and daughters is more pronounced for mothers born before 1965 (54 percent have majority-White names and 15 percent have exclusively-Black names) than for mothers born in 1965 or afterward (47 percent have majority-White names, 22 percent have exclusively-Black names.) Therefore, the naming patterns in Florida parallel those reported by Fryer and Levitt (2003) in California.

This paper exploits within-family differences in the character of the names given to Black children. Therefore, it is necessary that there exist considerable variation in the attributes of names within a family. Table 2 compares the names of children with their next siblings born during the period over which I have data from the state of Florida. One observes that Black children who are given overwhelmingly White names (at least three times as many White children as Black children receive the name) have next siblings who
receive majority-White names 51 percent of the time. But still 40 percent of their succeeding siblings receive names that are at least 75 percent Black, and 24 percent of siblings receive names that are either unique or given exclusively to Black children. At the other extreme of the naming distribution, Black children with unique names or names given 100 percent of the time to Black children are followed 45 percent of the time by siblings who have similarly-identifiable (or unique) names. But 28 percent of these families have next children who have majority-White names. Because Table 1 shows that Black girls are more likely to receive unique names than are Black boys and Black boys are more likely to receive majority-White names than are Black girls, I repeat the same exercise for pairs of brothers or pairs of sisters, and find similar patterns. For instance, constraining siblings to have the same sex, children with names that are exclusively Black are followed by same-sex siblings with similar names 48 percent of the time, and are followed by same-sex siblings with majority-White names 27 percent of the time. This analysis therefore makes clear that there exists considerable within-family heterogeneity in names, and that this heterogeneity is not due either to sex differences among children nor to birth order. Nonetheless, in all regression analyses below, I control for birth order and sex.

**Measuring Expectations and Student Outcomes**

My data used to compare siblings’ outcomes come from a large unidentified Florida district. For confidentiality purposes, I cannot provide precise information on demographic information or sample sizes. However, this school district is one of nine Florida districts with more than 15,000 Black students and over 400 Black full-time
teachers, and I observe over 5,000 pairs of siblings. I have test score data for four school
years, from 1996-97 through 1999-2000, and attendance information for the 2000-01
school year.

My primary measure of student outcomes is the student’s national percentile ranking on a
nationally-norm-referenced mathematics examination such as the Stanford-8 or Iowa Test
of Basic Skills (the precise test cannot be identified because it could identify the district)
in grades three through nine. In the 2000-01 school year, the state of Florida institutes a
statewide norm-referenced examination, so to avoid the potential effects of switching to a
different examination I use test score data from the four previous years. The benefit of
the national percentile ranking is that it is directly comparable across grade levels, a
crucial point since my identification comes from pairs of siblings. My basic estimating
equation is

\[(\text{Math test score NPR})_{ift} = \alpha_f + \beta(\text{Black name ratio})_i + \delta(\text{Unique name})_i + \gamma(\text{Birth order})_i \]

\[+ \eta(\text{Sex})_i + \varepsilon_{ift},\]

for student i in family f at time t. The coefficients \(\alpha\) represent family fixed effects. Since
the variable of interest, the Black name propensity, does not vary for student i even
though I typically observe more than one test score for each child, I adjust the standard
errors to account for clustering at the student level. It is impossible to know for certain
whether a name that appears only once in the dataset is legitimately a unique name, or is
rather a typographical error, so I choose to agnostically control for a name’s uniqueness
without interpreting its coefficient estimate.
My other outcome variable of interest is the highest grade completed in school. Here, because I only have school attendance data through the 2000-01 school year, I must utilize a smaller sample to minimize the chances of right-censoring of the dependent variable. Therefore, I measure years of school completion as the highest grade completed through 2000-01, but restrict the analysis to children who were in at least the eighth grade in 1996-97. These are students who, if they did not drop out or repeat a grade, would have completed grade twelve by the end of the 2000-01 school year. Fortunately, I observe a sufficiently large number of high-school-aged sibling pairs in 1996-97 that I can still estimate the following equation:

\[(\text{Highest grade completed by 2000-01})_{it} = \alpha_t + \beta (\text{Black name ratio})_{it} + \delta (\text{Unique name})_{it} + \gamma (\text{Birth order})_{it} + \eta (\text{Sex})_{it} + \varepsilon_{it} \mid (\text{In grade 8 or above in 1996-97})_{i},\]

where all notation is the same as above, except that I now only have one observation per child i.

It is impossible to measure expectations with certainty, so I take several tacks. One approach is to measure grading standards. In the grading standards literature (such as Betts and Grogger, 2003; and Figlio and Lucas, forthcoming) standards are measured by comparing the letter grades assigned to students conditional on their test scores. For all students in grades six through nine, I observe the student’s grade-point average in each year t, where grade-point average is measured along the standard four points for A, three points for B, etc. system in which I count each semester course attempted in English/reading/Language Arts, mathematics, science, social studies, or foreign
languages equally. I therefore attempt to gauge whether teachers treat Black students with racially-identifiable names differently by estimating:

\[
(Academic \ grade-point \ average)_{it} = \alpha_t + \theta(Math \ test \ score \ NPR)_{it} + \beta(Black \ name \ ratio)_{i} + \delta(Unique \ name)_{i} + \gamma(Birth \ order)_{i} + \eta(Sex)_{i} + \epsilon_{it}.
\]

Conditional on observed test scores, a higher grade-point average signifies lower academic standards. Therefore, if teachers have lower expectations of Black students with racially-identifiable names, one would expect the coefficient on $\beta$ to be positive.

I measure teacher expectations in two other ways as well. The procedures for identifying a student as learning disabled or gifted begin at the teacher level, where the teacher submits a subjective checklist of attributes of a gifted or learning disabled child. If teachers expect less of Black children with racially-identifiable names, they may be less likely to refer them for further screening into the gifted program, and may be more likely to single them out as potentially learning disabled, all else equal. I therefore estimate variants of the preceding equation, using gifted or learning disabled placement as the dependent variable in place of grade-point average. If teachers have lower expectations of Black students with racially-identifiable names, one would expect the coefficient on $\beta$ to be negative with respect to gifted placement and positive with respect to learning disability placement.

**Results**

The first row of Table 3 presents estimates of the coefficients on $\beta$ from the regression equations described above. One observes that, conditional on family fixed effects, birth
order, sex and a unique name indicator, Black children with racially-identifiable names tend to score worse on their mathematics examinations than do their siblings with names more frequently given to White children. To put this coefficient estimate in perspective, the results suggest that a Black child named Jermaine or Latoya will have test scores that are 1.7 percentile rankings lower than their siblings named David or Ashley, names that are equally prevalent in the Black community. This is a modest estimated effect, but it is about eight percent of the magnitude of the overall Black-White test score gap, so it is economically meaningful as well as statistically significant.

While test scores are negatively related to the degree of racial identifiability among Black children’s names, educational attainment measured by highest grade completed as of 2000-01 for students in eighth grade or higher in 1996-97 is positively related to racial identifiability. The same Jermaine-David or Latoya-Ashley comparison within family is associated with greater educational attainment of one-quarter of a grade. While this result is only marginally statistically significant, this is a large estimated effect, given that statewide the mean grade completed among Black children is 10.6 years. In the absence of a causal explanation it is surprising to see this dispersion of results, with the estimated effect of Black naming on test scores being negative while the estimated effect on educational attainment is positive, as the correlation between these two variables is nearly 0.4. That the effects move in opposite direction suggests that some third factor associated with Black naming patterns is at play.
The remainder of the results from the top row of Table 3 indicate that this factor may be expectations. One observes that, conditional on test scores, the more racially-identifiable a Black child’s name is, the more likely that he or she will have higher grades, but at the same time be less likely to be referred to the gifted program and more likely to be classified as learning disabled, than his or her sibling with a name given more frequently to White children. The program placement results are statistically significant and large in magnitude, with a Jermaine-David effect of –0.007 on the probability of being labeled as gifted (as compared to a statewide mean for Black students of 0.02) and a Latoya-Ashley effect of 0.007 on the probability of being labeled as learning disabled (as compared to a statewide mean for Black students of 0.09). All of these findings are consistent with the story that teachers and school administrators expect less of Black students with racially-identifiable names, and while these students in turn tend to stay in school longer, they apparently learn less.

*Within-family heterogeneity by student type*

The second panel of Table 3 breaks down these findings by sex. One observes that the male-female differences in the estimated effects of name on outcomes is statistically significant at conventional levels for four of the five outcomes, and in the case of the test score outcome is statistically significant at the twelve percent level. In all cases, the estimated effect of name on outcomes is strongly statistically significant for male students, and weaker for female students. In the three “expectations” equations, the male-female differences work in the same way, with more racially-identifiable names leading to more positive grade-point average effects for males than for females, more
negative gifted effects for males, and more positive learning disabled classification effects. The main outcomes of interest, test scores and years of schooling, move in the patterns that follow from the expectations story: Given that the implied effects of names on expectations is stronger for Black males than for Black females, it is unsurprising that the estimated effect of names on test scores is more negative for males than for females, and the estimated effect of names on highest grade attained is more positive for males than for females.

Table 3 also breaks down these effects by birth order, comparing the oldest observed sibling with his or her younger sibling(s). Never is the birth order interaction close to statistically significant, suggesting that birth order does not play a role in these findings. This is reassuring, though not surprising given the findings in Table 2 that there is little apparent relationship between birth order and Black naming practices.

**Do School Attributes Make a Difference?**

The results presented in Table 3 are mean effects. But are the results uniform across school settings? Specifically, are teachers with more exposure to Black students (or Black peers) less likely to make assumptions about students’ abilities and respond less to naming differences? Table 4 presents results of model specifications that address this question. In the top panel of Table 4 I separate schools into “majority Black” and “majority non-Black” schools. There exists some evidence that Black students are treated differently by name depending on school setting, stratified in this manner. My three measures of expectations differences, while only on the cusp of statistical
significance in two cases, tell the same basic story: Conditional on test scores, Black children with racially-identifiable names are relatively more likely to have higher grades (p-value of difference between majority-Black and majority-White schools is 0.21), less likely to be classified as gifted (p=0.03), and more likely to be classified as disabled (p=0.16) in majority-non-Black schools than in majority-Black schools. The estimated effect of names on mathematics test scores follows the same pattern, with Black students with racially-identifiable names scoring particularly worse relative to their siblings in majority-non-Black schools (p=0.10). There is, however, no evidence of a difference across school settings in maximum grade level attained.

The second panel of Table 4 presents the results of a similar specification, with schools stratified according to the race of their full-time teachers. The correlation between share of the student body that is Black and the share of the faculty that is Black is remarkably low for Black students in the school district—this correlation is only 0.05. I divide schools into those with above-median shares of Black teachers on the faculty to those with below-median shares of Black teachers on the faculty, and find very similar results to those presented with respect to the racial status of the school’s student body. Black students in schools with more Black teachers are less likely to face differential expectations based on their names than are Black students in schools with few Black teachers, and the differences between schools are statistically significant at conventional levels. And students with racially-identifiable names perform relatively better on mathematics tests in schools with more Black teachers than they do in schools with few Black teachers (p=0.08). As with the student body distinction, there is no apparent
difference between the schools in the relationship between name and highest grade completed.

Conclusions

The persistence of the Black-White test score gap, and its widening over the course of the school cycle, is an issue of significant public policy concern. This paper presents evidence that a portion of these patterns could be due to the names given to Black children. Black children (particularly boys) with more racially-identifiable names fare worse on standardized tests than do their siblings with less identifiable names. At the same time, however, Black children with more racially-identifiable names tend to stay in school for longer than their siblings with names more frequently given to White children.

I suggest that the mechanism through which these seemingly conflicting patterns come about involves the expectations of teachers and school administrators regarding Black students. Black students with racially-identifiable names receive higher grades than would be expected given their test scores, but they are also less likely to be called gifted and more likely to be called learning disabled. Given the literature on the effects of grading standards, this differential treatment of Black children with racially-identifiable names could result in these students staying longer in school than their siblings with less-identifiable names, but learning less.

The hypothesis that teacher expectations are responsible for these results is bolstered by the evidence that my results are stronger in cases in which teachers have less exposure to
Black students than in cases where exposure is greater. The negative effects of racially-identifiable naming on mathematics test scores, as well as evidence of differential teacher expectations, are smaller in majority-Black schools than in majority-non-Black schools, and are also smaller in schools with more Black teachers rather than fewer Black teachers. It follows that in schools with larger numbers of Black students and teachers, teachers perhaps form fewer preconceived notions about children purely on the basis of their names, and do not adjust their expectations based on names as much as they may in schools where contact with Black students and peers is more limited.

Bertrand and Mullainathan (2003) report evidence of racial discrimination even in firms that claim to take active non-discriminatory steps. I suspect that a similar phenomenon occurs in education, as my findings indicate that teachers treat students within a race, and even within a family, differently. This finding suggests a role for professional development and teacher training; if teachers are more sensitive to the apparent tendency to treat Black students differently based on their names, they may respond accordingly.
Table 1: The Prevalence of Distinctively Black Names
Black Children Born in Florida, 1989-1994

<table>
<thead>
<tr>
<th>Racial composition of name</th>
<th>All Black children</th>
<th>Black males</th>
<th>Black females</th>
<th>Mothers of Black children</th>
<th>Mothers born after 1965</th>
<th>Mothers born 1965 or before</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-24.9% Black</td>
<td>22.1%</td>
<td>25.8%</td>
<td>18.3%</td>
<td>24.7%</td>
<td>23.8%</td>
<td>26.6%</td>
</tr>
<tr>
<td>25-49.9% Black</td>
<td>15.0</td>
<td>15.1</td>
<td>14.8</td>
<td>24.4</td>
<td>23.2</td>
<td>27.0</td>
</tr>
<tr>
<td>50-74.9% Black</td>
<td>9.4</td>
<td>10.7</td>
<td>3.9</td>
<td>15.8</td>
<td>14.5</td>
<td>16.3</td>
</tr>
<tr>
<td>75-94.9% Black</td>
<td>11.7</td>
<td>14.5</td>
<td>10.1</td>
<td>12.0</td>
<td>11.3</td>
<td>13.5</td>
</tr>
<tr>
<td>95-99.9% Black</td>
<td>7.0</td>
<td>7.1</td>
<td>4.7</td>
<td>3.2</td>
<td>4.1</td>
<td>1.4</td>
</tr>
<tr>
<td>100% Black or unique name</td>
<td>34.8</td>
<td>25.7</td>
<td>44.2</td>
<td>19.9</td>
<td>22.1</td>
<td>15.2</td>
</tr>
</tbody>
</table>

Source: Author’s computations from Florida Department of Health data
Table 2: Transitions in Within-Family Naming Patterns
Racial Identifiability of Next Child’s Name (Row Percentages)

<table>
<thead>
<tr>
<th>First child name</th>
<th>0-24.9% Black</th>
<th>25-49.9% Black</th>
<th>50-74.9% Black</th>
<th>75-94.9% Black</th>
<th>95-99.9% Black</th>
<th>100% Black or unique name</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-24.9%</td>
<td>36.1%</td>
<td>14.6%</td>
<td>9.0%</td>
<td>9.9%</td>
<td>6.4%</td>
<td>24.1%</td>
</tr>
<tr>
<td>25-49.9%</td>
<td>26.9</td>
<td>18.7</td>
<td>9.1</td>
<td>9.8</td>
<td>7.2</td>
<td>28.3</td>
</tr>
<tr>
<td>50-74.9%</td>
<td>23.4</td>
<td>13.3</td>
<td>12.3</td>
<td>10.8</td>
<td>7.8</td>
<td>32.5</td>
</tr>
<tr>
<td>75-94.9%</td>
<td>21.9</td>
<td>12.6</td>
<td>9.6</td>
<td>15.3</td>
<td>8.1</td>
<td>32.3</td>
</tr>
<tr>
<td>95-99.9%</td>
<td>18.3</td>
<td>11.4</td>
<td>9.0</td>
<td>10.6</td>
<td>15.1</td>
<td>35.6</td>
</tr>
<tr>
<td>100% Black or unique name</td>
<td>17.3</td>
<td>11.3</td>
<td>9.1</td>
<td>9.9</td>
<td>7.7</td>
<td>44.7</td>
</tr>
</tbody>
</table>

Source: Author’s computations from Florida Department of Health data
Table 3: Family Fixed Effect Regressions: Effects ofNaming on Black Children’s Outcomes

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Math test score</th>
<th>Maximum grade attained</th>
<th>Grade-point average</th>
<th>Gifted classification</th>
<th>Learning disabled classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean effect of fraction receiving name who are Black</td>
<td>-2.016 (0.783)</td>
<td>0.329 (0.257)</td>
<td>0.034 (0.022)</td>
<td>-0.009 (0.002)</td>
<td>0.008 (0.004)</td>
</tr>
<tr>
<td>Males</td>
<td>-2.956 (1.046)</td>
<td>0.537 (0.184)</td>
<td>0.074 (0.030)</td>
<td>-0.015 (0.003)</td>
<td>0.022 (0.006)</td>
</tr>
<tr>
<td>Females</td>
<td>-0.854 (1.136)</td>
<td>0.071 (0.203)</td>
<td>-0.013 (0.033)</td>
<td>0.003 (0.003)</td>
<td>-0.008 (0.007)</td>
</tr>
<tr>
<td>p-value of difference</td>
<td>0.12 0.08</td>
<td>0.04 0.00</td>
<td>0.04 0.00</td>
<td>0.00 0.00</td>
<td></td>
</tr>
<tr>
<td>Oldest sibling</td>
<td>-1.683 (1.105)</td>
<td>0.278 (0.179)</td>
<td>0.013 (0.032)</td>
<td>-0.011 (0.003)</td>
<td>0.013 (0.007)</td>
</tr>
<tr>
<td>Younger sibling</td>
<td>-2.217 (1.022)</td>
<td>0.404 (0.201)</td>
<td>0.053 (0.029)</td>
<td>-0.007 (0.003)</td>
<td>0.004 (0.006)</td>
</tr>
<tr>
<td>p-value of difference</td>
<td>0.71 0.62</td>
<td>0.34 0.41</td>
<td>0.41 0.37</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard errors adjusted for student-level clustering (in cases of multiple observations per student) are in parentheses. Regressions control for unique name, sex and birth order. Grade-point average, gifted and learning disabled regressions also control for mathematics test scores.
Table 4: Family Fixed Effect Regressions:  
Heterogeneity in Effects of Naming on Black Children’s Outcomes

<table>
<thead>
<tr>
<th></th>
<th>Math test score</th>
<th>Maximum grade attained</th>
<th>Dependent variable</th>
<th>Learning disabled classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority non-Black school</td>
<td>-2.810</td>
<td>0.305</td>
<td>0.048</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.913)</td>
<td>(0.178)</td>
<td>(0.026)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Majority Black school</td>
<td>-1.220</td>
<td>0.409</td>
<td>0.012</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.942)</td>
<td>(0.218)</td>
<td>(0.031)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>p-value of difference</td>
<td>0.10</td>
<td>0.70</td>
<td>0.21</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Below median share of Black teachers in school</td>
<td>-2.874</td>
<td>0.208</td>
<td>0.057</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>(0.909)</td>
<td>(0.202)</td>
<td>(0.027)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Above median share of Black teachers in school</td>
<td>-1.306</td>
<td>0.384</td>
<td>0.008</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.898)</td>
<td>(0.187)</td>
<td>(0.028)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>p-value of difference</td>
<td>0.08</td>
<td>0.51</td>
<td>0.10</td>
<td>0.02</td>
</tr>
</tbody>
</table>

p-value of difference

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