**Appendix for “School Segregation and Racial Gaps in Special Education”**

*A. Selection on Unobservable Determinants of Special Education Identification*

Our findings in the main text suggest that minority students in heavily-minority schools are underrepresented in special education while minority students in heavily-white schools are slightly overrepresented. Without knowledge of students’ true underlying disability incidence, our inferences are based on comparisons of actual and predicted disability rates. Although we have access to an unusually rich set of health characteristics, along with measures of both economic resources and achievement, it is possible that our estimates of predicted disability rates are missing the roles of important unobserved determinants of disability identification.

As a way to gauge the importance of these unobserved factors, we ask what patterns of selection on unobservable dimensions would be necessary to eliminate the negative gradient between disability gaps and school minority shares. In other words, if we suppose that the observed negative association between school minority shares and disability rates captured true disability incidence, what patterns of sorting (across schools) on unobservables would be consistent with this phenomenon? To address this question, we adopt the approach of AET, who use selection on observable determinants of outcomes to gauge the extent of selection on unobservable determinants of outcomes.

For simplicity, assume that a student’s latent disability status ($SpEd$)is a linear function of school minority shares ($MS$) and the same observable and unobservable factors included in expression (1) in the main text:

(A1) $SpEd=αMS+XΦ+ε$.

Expression (A1) is equivalent to expression (1) apart from the inclusion of the term involving $MS$. For simplicity, we assume that (A1) is linear in $MS$, and we also suppress subscripts. We are interested in gauging what patterns of sorting across schools are consistent with $α$ = 0, i.e., what patterns of sorting are consistent with the observed correlations between $SpEd$ and$ MS$ being driven entirely by variation across schools in observable ($X$) and unobservable ($ε$) determinants of disability. We work with the following condition:

(A2) $\frac{cov\left(ε,MS\right)}{var(ε)}=λ\frac{cov\left(XΦ,MS\right)}{var(XΦ)}$.

Expression (A2) states that the relationship between $MS$ and the index of unobservables that determine disability identification is $λ$ times as strong as the relationship between $MS$ and the observable index $XΦ$, after adjusting for the variances of $ε $and $XΦ$**.** The “equality of selection on observables and unobservables” case corresponds to $λ$ = 1. Under the null that $α$ = 0, we can use our estimates of expression (1) based on white students only (reported in Tables 3 and 4) to estimate $Φ$. Similarly, we estimate $var(ε)$, $cov\left(XΦ,MS\right)$, and $var(XΦ)$ using the sample of white students. Given a value of $λ$, expression (A2) then implies a value of $cov\left(ε,MS\right)$; our goal is to estimate the value of $λ$ such that the negative value of $cov\left(SpEd,MS\right)$ is entirely attributable to $cov\left(ε,MS\right)$, i.e., to the true underlying (and unobservable) determinants of disability.

 We present our estimates for black students in Appendix Table A2; estimates for Hispanic students, which generate similar conclusions, are available upon request. The first column presents results for “any disability”, with the top row reporting the estimated gradient of predicted disability rates among black students with respect to school minority shares. This corresponds to a linearized version of the “predicted value” series in the top-left panel of Figure 3. The second row presents the implied gradient if $λ$ = 1, which answers the question, “given that black students in heavily-minority schools are disadvantaged along observable dimensions in comparison to black students in heavily-white schools, what would we expect identification patterns to look like if they were similarly disadvantaged along unobservable dimensions as well?” Note that the point estimate, 0.147, is much larger than the estimate in the top row. This arises because the estimated value of $var(ε)$ is much larger than the estimate of $var(XΦ)$ – the *r*2 from an OLS regression of model (1) is only 0.038 for “any disability”. As a result, a relatively modest difference in the observable index $XΦ$ between black students in high- and low-minority schools is consistent with a large difference in average values of $ε $under condition (A2). The estimate in the third row, -0.098, represents the actual gradient in disability identification for black students. This is large and negative (as implied by the upper-left panel of Figure 3), while we would expect it to be large and positive under equality of selection on observables and unobservables.

The final row of the table shows the implied value of $λ$ that would reproduce the actual gradient, given selection on observables. The negative estimated value, ‑0.665, reflects that the gradients in actual and predicted disability rates in the top-left panel of Figure 3 have opposite signs. In sum, the gradient in the disability gap for black students would only disappear if the relationship between unobservables and minority shares were of opposite sign as the analogous relationship between observables and minority shares. Put another way, if we had access to all individual-level determinants of disability identification – both observed and unobserved – the resulting “predicted value” line in Figure 3 would be strongly downward-sloping to match the gradient in actual identification rates only if sorting on unobservables across schools were both strong and opposite in sign as the sorting on observables.

 Finally, we have also pursued an analysis into sorting on unobservables based on eventual Advanced Placement (AP) course-taking rates. Our primary concern with the AET analysis above is that, even though students in schools with low minority shares appear to have characteristics that are negatively associated with underlying disabilities (in comparison to students in schools with high minority shares), it may be the case that these students’ parents are more likely to actively pursue disability identifications. In order words, parents in low-minority schools may be more active in advocating for disability identifications than are parents in heavily-minority schools.

Although we are unable to directly assess whether minority shares are correlated with parental advocacy, one indirect measure of parents’ willingness to advocate for their children is eventual AP course enrollment. Specifically, relatively involved parents may push for more AP classes in schools – and urge their children to take those classes – in comparison to less-involved parents. Our linked Florida data includes AP course-taking information at the student level among those students who reach high school by the end of the data collection period (recall that we have information on all students born in Florida between 1992 and 2002). As a result, we can construct the average numbers of AP courses taken by students from each elementary school in our data, by race.

We consider two different groups “at risk” for taking AP courses. The first includes children who graduated from high school with no grade repetition from fifth grade onward, and the second (which we denote as the “top25” sample) further restricts kids to be in the top quartile statewide in both reading and math in the tenth grade FCAT examinations. The logic underlying these risk groups is that all students within them could reasonably be expected to take at least one AP course. We limited the samples to cases in which there were at least 10 on-time high school graduates in the data from the given racial/ethnic group (black, Hispanic, or white).

Regardless of which risk group we study, we find essentially no relationship between school-level AP course taking and school-level disability identifications. For example, when we estimate a linear regression of the school-level black-white disability gap as a function of the black-white gap in AP credits using the “top25” sample via OLS, we estimate that a one-credit increase in the black-white AP gap is associated with a 0.09 percentage-point decrease in the black-white disability gap (with a standard error of (0.16). In other words, in elementary schools in which black students eventually take more AP exams, relative to their white peers, black students are slightly (and insignificantly) less likely to be diagnosed with disabilities by fourth grade. We find very similar results for Hispanics and regardless of which risk group we consider: more AP taking is associated with slightly less disability identification. These patterns are inconsistent with a story in which black and Hispanic parents in low-minority schools are systematically strong advocates for their children – relative to black and Hispanic parents in heavily-minority schools – which would increase both AP course taking and disability identification, conditional on underlying health.

## B. Transitions into Disability Status as a Function of Achievement

 In our central specifications in the text, we predicted disability status based only on information available at the time of a child’s birth, as this information is obviously determined prior to special education identification. However, schools use a host of additional factors – such as student achievement – to determine disability status. Our linked birth-education records include individual students’ scores from the Florida Comprehensive Assessment Test (FCAT), which was first administered to third and fourth grade students in the 1997-98 school year. We excluded achievement from our central specifications above because it is potentially endogenous to disability status, i.e., receipt of special education services likely influences learning for those children who would otherwise struggle in the absence of special education. Nonetheless, achievement may play an important role in producing the racial composition gradients shown in the text.

To investigate the role of achievement while avoiding bias due to endogeneity, we estimate identification gaps in fourth grade using models that condition on third grade FCAT scores (in addition to the health and economic measures) and are restricted to students who are not identified in third grade. Figure A16 presents results from these models for any disability. Because none of the students are identified as disabled in third grade, the fourth grade identification rates in this subsample are far lower than in the full sample, as are the gaps. Nonetheless, we see similar patterns to those shown in Figure 3. For black students and, to a lesser extent, Hispanic students, there is a negative relationship between minority shares and identification gaps. At the same time, there is a slight positive gradient for white students. These findings suggest that excluding achievement from the decomposition does not substantially affect our inferences about the minority share gradients.

Similarly, achievement is often used to identify gifted status, so Figure A17 shows analogous results for gifted students. As the leftmost panels show, black students transition into gifted status in fourth grade at higher than predicted rates in schools with high minority shares, and the gradient in the raw-predicted gap is positive. Note that raw gifted rates among black students are lower than among Hispanic and white students for all minority share categories (again, conditional on not being identified as gifted in third grade). The gradients in the gaps are also positive for Hispanic and white students. Once again, these results are inconsistent with resource constraints playing a dominant role in the identification of minority students: if heavily-minority schools did not have sufficient resources to serve exceptional students (including both gifted students and students with disabilities), one would expect that gifted identification gaps would decline with respect to school minority shares.



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| **Appendix Table A2: The Amount of Selection of Unobservables Relative to Selection on Observables Required to Attribute the Entire Minority Share Gradient to Unobservables among Black Students** |
|  |  |  |  |  |  |  |  |
|  | Any Disability | SLI | SLD | ASD / Dev Delay | Intellectual | Physical | Other |
|  |  |  |  |  |  |  |  |
| Gradient in The Predicted Value with respect to Minority Shares | 0.006 | -0.001 | 0.004 | 0.000 | 0.000 | 0.000 | 0.001 |
|  | (0.005) | (0.001) | (0.005) | (0.000) | (0.001) | (0.000) | (0.001) |
|  |  |  |  |  |  |  |  |
| Implied Gradient under Equality of Selection (λ = 1) | 0.147 | -0.112 | 0.154 | 0.091 | 0.020 | -0.020 | 0.179 |
|  | (0.130) | (0.199) | (0.183) | (0.089) | (0.058) | (0.012) | (0.104) |
|  |  |  |  |  |  |  |  |
| Actual Gradient Among Black Students | -0.098 | -0.019 | -0.051 | -0.001 | -0.007 | -0.001 | -0.011 |
|  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
| Value of λ that Matches Actual and Implied Gradient | -0.665 | 0.169 | -0.332 | -0.011 | -0.347 | 0.051 | -0.062 |
|  |  |  |  |  |  |  |  |
| Notes: Standard errors derived from 100 bootstrap replications resampled at the school district-cohort level. |

Figure A1



Each point reflects the difference between raw average identification rates for children who have or do not have English as their native language and predicted values from a regression restricted to white students with the same language status of identification rates on the variables included in equation (1) in the paper text. Estimates are calculated separately by racial composition conditional on not being disabled in listed grade. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A2



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text along with zip code of birth fixed effects. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A3



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

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Figure A4



Each point reflects the difference between raw average identification rates from a regression restricted to the listed baseline students of identification rates on the variables included in equation (1) in the paper text. Estimates are calculated separately by racial composition. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A5



Each point reflects the difference between raw average identification rates from a regression restricted to the listed baseline students of identification rates on the variables included in equation (1) in the paper text. We calculate estimates separately by racial composition. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A6



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A7



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A8



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A9



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A10



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A11



Each point reflects the difference between raw average identification rates and predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. Estimates are calculated separately by racial composition conditional on not being disabled in listed grade. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A12



Each point reflects the difference between raw average identification rates and predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text. Estimates are calculated separately by racial composition conditional on being disabled in listed grade. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A13

Each line reflects the difference between raw average identification rates and predicted values from a regression restricted to white students of identification rates on the variables listed in the figure legend calculated in 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort.

Figure A14



Each line reflects the difference between raw average identification rates and predicted values from a regression restricted to white students of identification rates on the variables listed in the figure legend calculated in 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. Negative values reflect underrepresentation.

Figure A15



Figures show correlations between raw values of the given maternal or birth characteristic with White share in students’ Kindergarten cohorts. The lines provide linear fits.

Figure A16



The solid line in the top panel shows the raw average identification rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of identification rates on the variables included in equation (1) in the paper text and prior year (3rd grade) achievement. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.

Figure A17



The solid line in the top panel shows the raw average gifted rates by student race and 10 percentage point bins of black/Hispanic share in the student’s Kindergarten cohort. The dotted line provides the predicted values from a regression restricted to white students of gifted rates on the variables included in equation (1) in the paper text and prior year (3rd grade) achievement. The bottom panels shows the results of the Blinder-Oaxaca decomposition by plotting the difference between the solid and dotted line in the top panels. Confidence intervals are derived using the 2.5th and 97.5th percentiles of the distribution of estimated gaps from 100 bootstrap replications (resampled at district-cohort level) of the Blinder-Oaxaca decomposition.