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Unmeasured Confounding and Racial or Ethnic Disparities in Disability Identification

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Students who are Black or Hispanic are now reported to be less likely to be identified as having disabilities than similarly situated students who are White. Although repeatedly replicated, this finding is often characterized as in error. I use a new statistical technique, the E-value, to quantify the likelihood that unmeasured confounding explains observed associations between race or ethnicity and disability identification. Results based on calculations across three population-based studies using extensive statistical controls suggest that unmeasured confounding is an unlikely explanation for the observed associations. Unmeasured confounding that would result in levels of overidentification consistent with federal law and regulation is especially unlikely.

Keywords: *at-risk students, disparities, educational policy, special education, effect size, observational research, regression analyses, secondary data analysis, statistics*

Students who are Black or Hispanic have been reported to be more likely to be identified as having disabilities while attending U.S. schools including for specific conditions (e.g., Grindal et al., 2019; U.S. Department of Education, 2016a). Reports of overidentification have resulted in suggestions that the U.S. special education system may be racially biased (Blanchett, 2006; Codrington & Fairchild, 2012; Grindal et al., 2019). Federal law and regulation require monitoring for significant disproportionality in disability identification based on race or ethnicity (the Individuals with Disabilities Education Act [IDEA], 2004, §300.646) based on "clear evidence that overrepresentation on the basis of race and ethnicity continues to exist at both the national and local levels" (U.S. Department of Education Equity in IDEA Rule, 2016, p. 10977).

Yet other empirical work is now reporting that students who are Black or Hispanic are less likely to be identified as having disabilities than similarly situated students who are White (e.g., Morgan et al., 2015), suggestive of differential treatment on the basis of race and ethnicity (U.S. Department of Education, 2016a). Although repeatedly replicated, findings of under-identification have been dismissed as "in error" (Skiba et al., 2016, p. 221; for a reply, see Morgan & Farkas, 2016) and resulting from "simplistic investigations that overreach both their data set and their own analyses" (Skiba et al., 2016, p. 224). Dismissals of findings of under-identification have been justified based on methodologically flawed data collection procedures, sampling, and statistical analysis (Grindal et al., 2019; Skiba et al., 2016; Whitford & Carrero, 2019).

Replication studies continue to find evidence of under-identification including in analyses of other nationally representative samples (Morgan et al., 2017) as well as both student- and district-level data sets that indicate overidentification in unadjusted analyses, helping to address criticisms about data collection and sampling (Farkas et al., 2020; Morgan et al., 2017). The replication work has also statistically controlled for a wide range of student-, family-, and school-level confounds including family socioeconomic status (SES) and student achievement (Morgan et al., 2017). Student achievement is considered an especially strong confound of disability identification disparities (Donovan & Cross, 2002).

The Importance of Assessing for Unmeasured Confounding in Studies Reporting Disability Under-Identification

To date, studies reporting under-identification have mostly used regression-based adjustment of measured covariates (e.g., differential exposure to poverty) to account for alternative explanations of overrepresentation observed in unadjusted analyses. Yet other factors have not been included as measured covariates and so may constitute potential confounds. Examples include exposure to lead or air pollution, violence in the home or neighborhood, and maternal depression, which are associated with both disability identification (e.g., Ang, 2020; McGuinn et al., 2020; Rogers et al., 2020; Sioen et al., 2013) and race or ethnicity (e.g., Chan et al., 2020; Sheats et al., 2018; Tessum et al., 2019). Methodologically, omitted variable bias due to unmeasured confounding is possible. Use of random assignment is not possible because eligible students with disabilities are legally entitled to receive special education services. (Use of random assignment would, on expectation, control for both measured and unmeasured confounds.) If sufficiently strong, unmeasured confounding may be obscuring findings of overidentification. Yet to what extent unmeasured confounding may explain under-identification observed in adjusted analyses is currently unknown.

Quantifying whether unmeasured confounding may explain the disability under-identification of students attending U.S. schools who are Black or Hispanic has important policy implications. Federal law requires U.S. schools to monitor for racial and ethnic disparities in disability identification. New federal regulations require U.S. states to use specific risk ratio (RR) thresholds to monitor for significant disproportionality in disability identification (U.S. Department of Education Equity in IDEA Rule, 2016). (An RR is the probability of an event occurring for one group divided by the probability of the event occurring for another group.) For example, school districts in Colorado, Maryland, Mississippi, or Washington reporting RRs of about 2.0 or greater may be identified as having significant disproportionality in disability identification. School districts reporting significant disproportionality will have to reallocate up to 15% of their federal special education funding for coordinated early intervening services (U.S. Department of Education, Office of Special Education and Rehabilitative Services, 2017). Corrective action is required regardless of the underlying cause of the racial or ethnic disparities including between-group differences in disability prevalence rates.

How might unmeasured confounding as an alternative explanation for disability under-identification be assessed? A new statistical technique, the *E*-value, quantifies on the RR scale the strength that an unmeasured confounder would need to have to fully explain an observed association between two variables, conditional on measured covariates (Haneuse et al., 2019). The *E*-value is a sensitivity analysis. If the strength of the unmeasured confounder is weaker than the estimated *E*-value, then the observed association would not be fully explained by the unmeasured confounder (Haneuse et al., 2019). By quantifying the robustness of an association to unmeasured confounding, *E*-values provide a measure related to potential evidence of causality (Ding & VanderWeele, 2016; Haneuse et al., 2019). *E*-values can be used in conjunction with confidence intervals (CIs) to assess the strength an unmeasured confounder would have to have to shift a lower bound (LB) 95% CI to include a null association or, alternatively, to reverse the directionality of the association.

Study's Purpose

I calculated *E*-values to estimate the strength necessary for an unmeasured confounder to fully explain the recently reported disability under-identification of students who are Black or Hispanic. These calculations provide an example of how *E*-values might be used to quantify whether unmeasured confounding explains observed associations in education research. For robustness, I calculated *E*-values across three recently published peer-reviewed studies analyzing population-based samples and reporting associations by both race and ethnicity. Across Studies 1, 2, and 3, I calculated *E*-values necessary to shift the reported associations to RRs of (a) 1.0, indicating null associations and (b) 2.0, indicating that students who are Black or Hispanic are relatively overidentified as having disabilities. RRs of 1.5-2.0 are consistent with levels of significant disproportionality possibility requiring corrective action (U.S. Department of Education, 2016b) including for disabilities generally and for specific conditions (e.g., learning disabilities, speech language impairments, other health impairments). (Somewhat higher levels are suggested for lower prevalence conditions including RRs of 3.0 and 2.5 for emotional disturbance and intellectual disabilities, respectively.) These *E*-value calculations answer the following question: What would the size an unmeasured confounder need to be to (a) fully explain recently reported disability underidentification of Black and Hispanic students and (b) instead result in evidence of overidentification at levels consistent with federal law and regulation?

Method

E-*Values*

The *E*-value formula for an observed RR greater than 1 is $E = RR + \sqrt{RR \times (RR - 1)}$ (for the *E*-value's statistical proof, see VanderWeele & Ding, 2017; for additional technical discussion, see VanderWeele, Ding, & Mathur, 2019). The formula is designed to provide the magnitude of the confounding on the RR scale that would produce bias equal to the observed association (VanderWeele & Ding, 2017). *E*-value calculations make no assumptions including about the confounder's structure (e.g., binary, continuous, or categorical), distribution, or number (Ding & VanderWeele, 2016; VanderWeele & Ding, 2017). *E*-values of 1.5 to 2.0 suggest that small-to-moderate confounding may otherwise explain an observed association (Trinquart et al., 2019). I calculated *E*-values using publicly available software (https://www.evalue-calculator.com). *E*-values can be calculated based on RRs, odds ratios (ORs), linear regression coefficients, or other measures of effect size. (Odds are the probability of an event occurring divided by the probability of the event not occurring. An OR is the ratio of the odds for one group relative to another group.) RRs of 1.5 to 2.0 approximate the size of associations of measured confounders (e.g., economic disadvantage) as well as of unadjusted RRs for race or ethnicity reported in recent work (Morgan et al., 2017; U.S. Department of Education, Office of Special Education and Rehabilitative Services, Office of Special Education Programs, 2020).

Data Sets

Study 1 (i.e., Morgan et al., 2017) reported ORs for disability identification generally as well as specific conditions based on analyses of student-level data from large surveys of fourth, eighth, and 12th graders (*N*s of 183,570, 165,540, and 48,560 students, respectively) participating in the National Assessment of Educational Progress. Measured confounds included reading achievement, biological sex, free or reduced-price lunch eligibility, and English Language Learner status as well as school fixed effects. Study 2 (i.e., Farkas et al., 2020) reported adjusted RRs for disability identification generally based on analyses of district-level data (*N* = 1,952 and 2,571 U.S. school districts) from the U.S. Department of Education's Civil Rights Data Collection merged with the Stanford Education Data Archive. Measured confounds included the district's Black- or Hispanic-White achievement gaps, enrollment size, percentage of students receiving free or reduced-price lunch, and the percentage of Black or Hispanic students as well as state fixed effects. Study 3 (i.e., Odegard et al., 2020) reported ORs for learning disabilities in reading based on analyses of student-level data from 7,947 second graders from a U.S. state. Measured confounds included student-level reading achievement, biological sex, and eligibility for free or reduced-price lunch as well as school-level factors including racial, ethnic, or economic composition.

Analyses

For Studies 1 and 3, I calculated *E*-values based on the reported Black- and Hispanic-White ORs and CIs. For relatively uncommon events (e.g., those occurring less than 15% in a population), ORs closely approximate RRs and so are used interchangeably in the standard *E*-value formula (VanderWeele & Ding, 2017). I used the standard *E*-value formula because the disability prevalence rate in the United States is less than 15% for children aged 6 to 21 (U.S. Department of Education, Office of Special Education and

Rehabilitative Services, Office of Special Education Programs, 2020). (For ORs of events occurring more than 15%, the *E*-value is calculated using the square root of the OR; see VanderWeele, 2017; VanderWeele & Ding, 2017.) For Study 1, I calculated *E*-values for (a) disabilities generally using the 4th, 8th, and 12th grade surveys and (b) six specific conditions using the very large fourth grade survey. The U.S. Department of Education Equity in IDEA Rule (2016) regulations require monitoring of significant disproportionality in disability identification for disabilities generally and for these six specific conditions. For Study 2, I calculated *E*-values for disability identification generally based on the reported Black- and Hispanic-White RRs and CIs. For Study 3, I calculated *E*-values for learning disability identification. Consistent with best practice (Trinquart et al., 2019; VanderWeele & Mathur, 2020), I report LB 95% CIs for the *E*-values. Table 1 displays the originally reported ORs or RRs from Studies 1, 2, and 3, the LB CIs, and resulting *E*-values based on RRs of 1.0 and 2.0. Figures 1 and 2 display the obtained *E*-values from Studies 1 and 2 as the joint minimum strength of association on the RR scale that an unmeasured confounder must have to fully explain the observed associations for racial or ethnic and disability status and disability identification generally, conditional on measured covariates, to instead be 2.0 on the RR scale.

Results

General Disability Identification

For Study 1, the strength of unmeasured confounding necessary to shift the reported Black-White ORs to null associations were 3.97 (LB CI = 3.59), 3.50 (LB CI = 3.18), and 4.19 (LB CI = 3.18) for 4th, 8th, and 12th grade, respectively. The strength of an unmeasured confounder necessary to shift Study 1's reported Hispanic-White ORs to null associations ranged from 3.33 (LB CI = 2.90) to 4.57 (LB CI = 3.68). The values are larger than those of measured confounds (e.g., RRs of about 1.5–2.0 for economic disadvantage) reported in recent work (Morgan et al., 2017). Unmeasured confounding necessary to shift the reported Black- and Hispanic-White ORs to levels of overidentification suggested by the U.S. Department of Education (2016a) as possibly requiring corrective action was especially unlikely. The Black-White and Hispanic-White *E*-values ranged from 7.63 (LB CI = 7.01) to 8.99 (LB CI = 7.01) and from 7.31 (LB CI = 6.48) to 9.73 (LB CI = 7.98), respectively.

For Study 2, the strength of an unmeasured confounder necessary to shift the reported associations to Black- and Hispanic-White RR to null associations was 4.44 (LB CI = 2.90) and 8.99 (LB CI = 5.51), respectively. Unmeasured confounding necessary to directionally reverse the estimates to Black- and Hispanic-White RRs to instead indicate overidentification was again especially unlikely. These *E*-values were 9.47 (LB CI = 6.48) and 18.53 (LB CI = 11.60) for the Black- and Hispanic-White RRs, respectively.

Specific Disability Identification

For Study 1, the strength of an unmeasured confounder necessary to shift the reported identification associations for Black-White students and the specific disability conditions to null associations were as follows: learning disabilities, 3.59 (LB CI = 3.11); speech or language impairments, 2.78 (LB CI = 2.35); other health impairments, 2.72 (LB CI = 2.21); autism, 5.91 (LB CI = 4.08); emotional disturbances, 2.55 (LB CI = 1.67); and intellectual disabilities, 2.12 (LB CI = 1.0). The LB 95% CIs suggested that small-to-moderate unmeasured confounding, conditional on Study 1's controls, might result in null associations for emotional disturbance and intellectual disabilities but less so for other specific conditions. However, unmeasured confounding necessary to shift the associations to instead indicate overidentification was consistently unlikely. These *E*-values were as follows: learning disabilities, 7.80 (LB CI = 6.87); speech or language impairments, 6.24 (LB CI = 5.42); other health impairments, 6.12 (LB CI = 5.16); autism, 12.38 (LB CI = 8.77); emotional disturbances, 5.8 (LB 4.19); and intellectual disabilities, 5.0 (LB CI = 3.22).

The strength of an unmeasured confounder necessary to shift Study 1's reported associations for Hispanic-White students and the specific disability conditions to null associations were as follows: learning disabilities, 2.97 (LB CI = 2.61);

TABLE 1

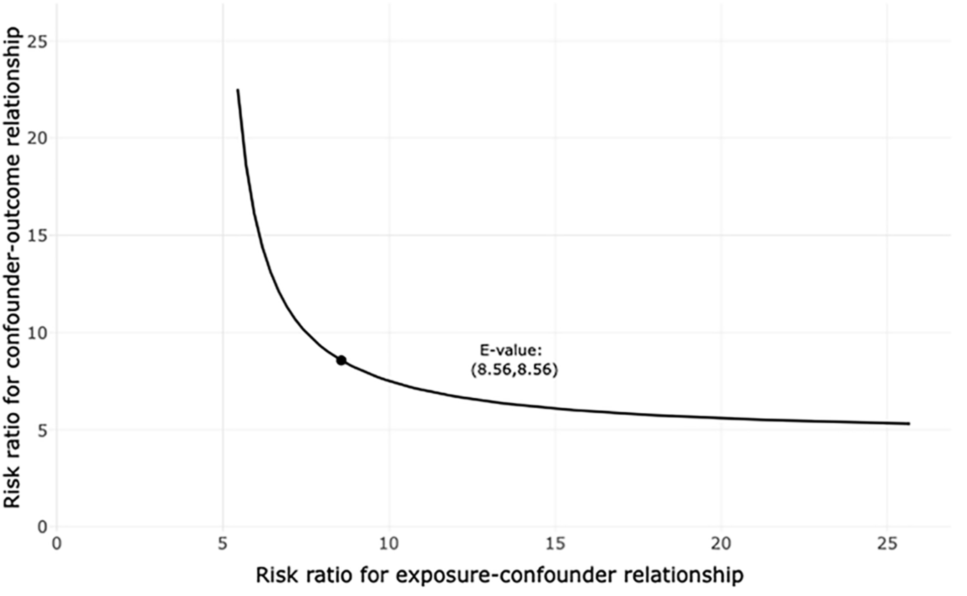
Study 1, Study 2, and Study 3 Odds Ratios or Risk Ratios, Lower Bound Confidence Internals, and Calculated E-*Values for Disabilities Generally and for Specific Disability Conditions*

Study estimates	OR or RR[a] (Lower and higher bound CI)	*E*-value (LB CI) for 1.0 RR	*E*-value (LB CI) for 2.0 RR
All disabilities			
Study 1			
Black-White			
4th grade	0.44 [0.40, 0.48]	3.97 (3.59)	8.56 (7.8)
8th grade	0.49 [0.44, 0.53]	3.50 (3.18)	7.63 (7.01)
12th grade	0.42 [0.34, 0.53]	4.19 (3.18)	8.99 (7.01)
Hispanic-White			
4th grade	0.51 [0.47, 0.55]	3.33 (3.04)	7.31 (6.73)
8th grade	0.51 [0.47, 0.57]	3.33 (2.90)	7.31 (6.48)
12th grade	0.39 [0.32, 0.47]	4.57 (3.68)	9.73 (7.98)
Study 2			
Black-White	0.40[a] [0.23, 0.57]	4.44 (2.90)	9.47 (6.48)
Hispanic-White	0.21[a] [0.08, 0.33]	8.99 (5.51)	18.53 (11.6)
Specific conditions			
Study 1			
Learning disabilities			
Black-White	0.48 [0.42, 0.54]	3.59 (3.11)	7.80 (6.87)
Hispanic-White	0.56 [0.50, 0.62]	2.97 (2.61)	6.6 (5.91)
Speech/language impairments			
Black-White	0.59 [0.51, 0.67]	2.78 (2.35)	6.24 (5.42)
Hispanic-White	0.64 [0.57, 0.72]	2.5 (2.12)	5.7 (5.0)
Other health impairments			
Black-White	0.60 [0.51, 0.70]	2.72 (2.21)	6.12 (5.16)
Hispanic-White	0.53 [0.46, 0.61]	3.18 (2.66)	7.01 (6.01)
Autism			
Black-White	0.31 [0.22, 0.43]	5.91 (4.08)	12.38 (8.77)
Hispanic-White	0.48 [0.35, 0.66]	3.59 (2.40)	7.8 (5.51)
Emotional disturbance			
Black-White	0.63 [0.48, 0.84]	2.55 (1.67)	5.8 (4.19)
Hispanic-White	0.57 [0.43, 0.76]	2.90 (1.96)	6.48 (4.7)
Intellectual disabilities			
Black-White	0.72 [0.50, 1.05]	2.12 (1.0)	5.0 (3.22)
Hispanic-White	0.69 [0.48, 0.97]	2.26 (1.21)	5.25 (3.54)
Study 3			
Learning disabilities			
Black-White	0.52 [0.36, 0.76]	3.26 (1.96)	7.15 (4.70)
Hispanic-White	0.68 [0.50, 0.93]	2.30 (1.36)	5.33 (3.72)

Note. CI = 95% confidence interval; LB = lower bound; OR = odds ratio.
[a]RR = risk ratio.

speech or language impairments, 2.5 (LB CI = 2.12); other health impairments, 3.18 (LB CI = 2.66); autism, 3.59 (LB CI = 2.40); emotional disturbances, 2.90 (LB CI = 1.96); and intellectual disabilities, 2.26 (LB CI = 1.21). The LB 95% CIs again suggested that small-to-moderate

Black-White E-value



Hispanic-White E-value

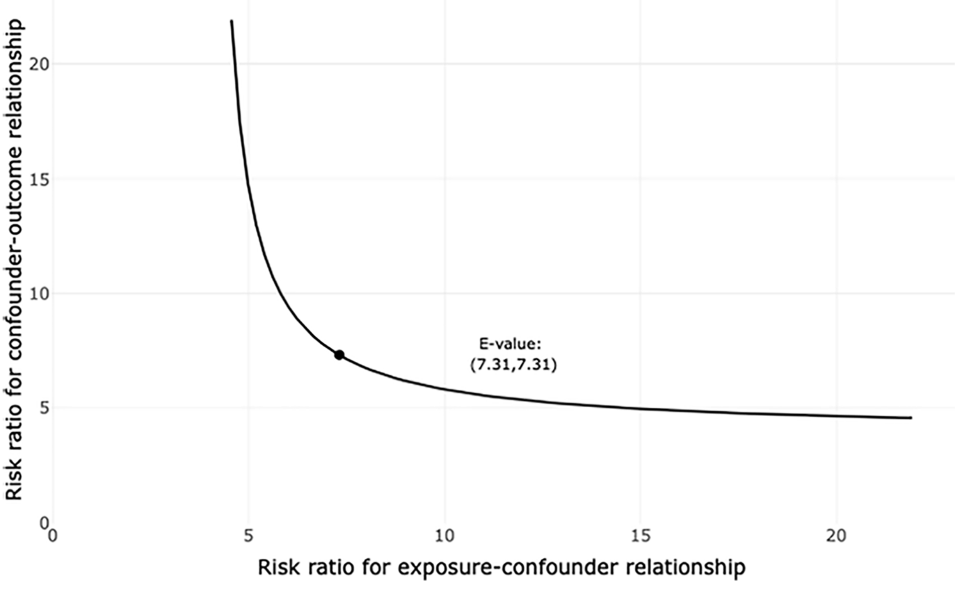


FIGURE 1. *Plot of* E-*value necessary to explain Black- and Hispanic-White OR reported in Study 1 to RR of 2.0, 4th grade.*
Note. OR = odds ratio; RR = risk ratio.

unmeasured confounding resulting in null associations was relatively more possible for emotional disturbances and intellectual disabilities but less so for other specific conditions. However, unmeasured confounding necessary to shift the Hispanic-White and disability identification associations to instead indicate overidentification was consistently unlikely. These *E*-values were as follows: learning disabilities, 6.6 (LB CI = 5.91); speech or language impairments, 5.7

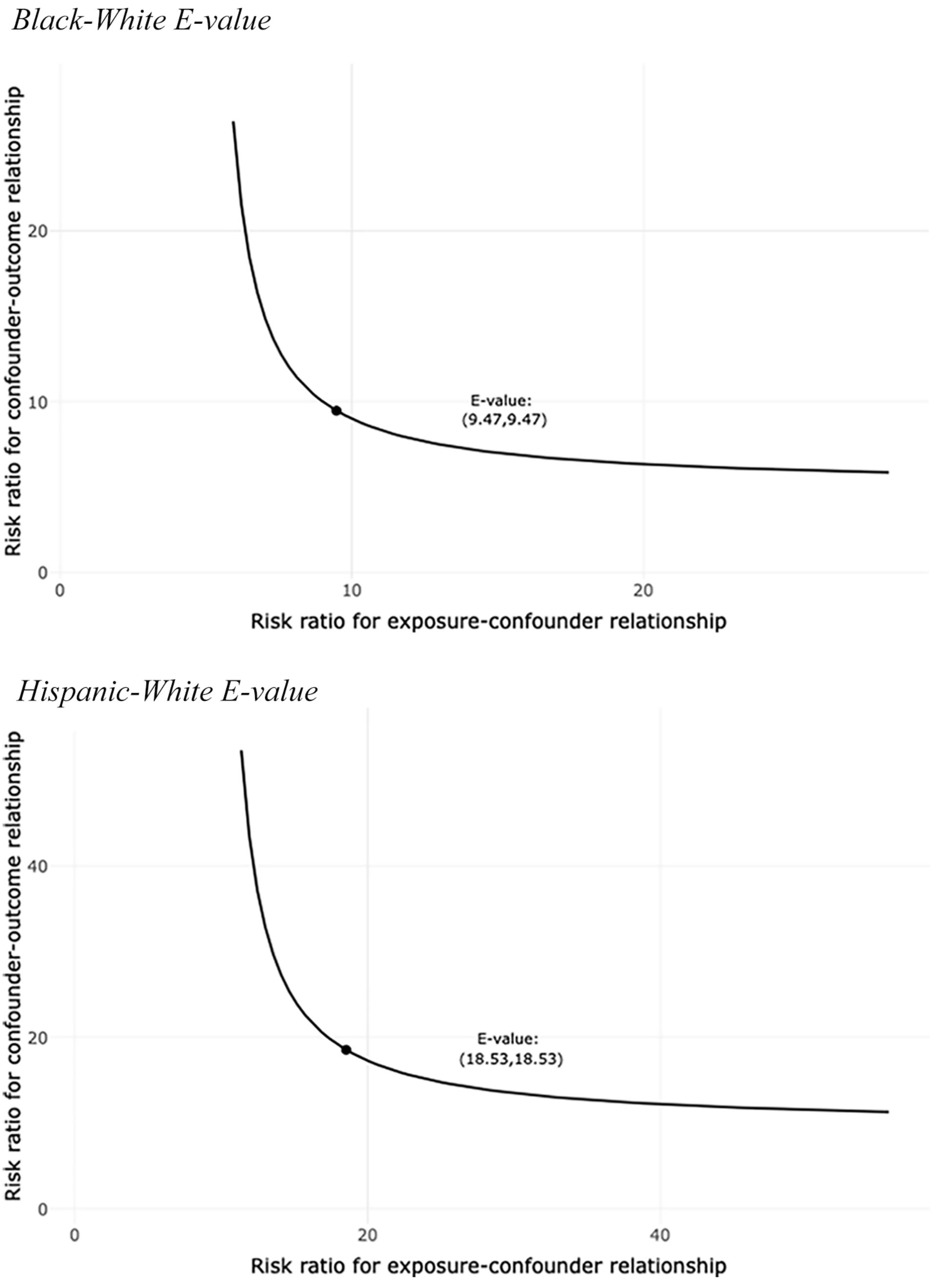


FIGURE 2. *Plot of* E-*value necessary to explain Black- and Hispanic-White RR reported in Study 2 to 2.0.*
Note. OR = odds ratio; RR = risk ratio.

(LB CI = 5.0); other health impairments, 7.01 (LB CI = 6.01); autism, 7.8 (LB CI = 5.51); emotional disturbances, 6.48 (LB CI = 4.70); and intellectual disabilities. 5.25 (LB CI = 3.54).

For Study 3, unmeasured confounding necessary to shift the reported associations for learning disability identification to null associations were 3.26 (LB CI = 1.96) and 2.30 (LB CI = 1.36) for the Black- and Hispanic-White RRs, respectively. The LB 95% CIs suggested that null associations might result from small-to-moderate unmeasured confounding, conditional on Study 3's measured covariates. Unmeasured confounding necessary to shift these associations to instead indicate overidentification for Black or Hispanic students was 7.15 (LB CI = 4.70) and 5.33 (LB CI = 3.72), and so especially unlikely.

Discussion

Study 1, 2, and 3's *E*-value calculations suggest that unmeasured confounding is an unlikely explanation of the repeatedly observed disability under-identification of Black or Hispanic relative to similarly situated students who are White. Unmeasured confounding necessary to result in racial or ethnic overidentification consistent with federal law and regulation is especially unlikely. This is the case both for disability identification generally and for specific conditions. Unmeasured confounding necessary to result in levels of overidentification suggested in unadjusted analyses of recent federal data (U.S. Department of Education, 2016b) for disabilities generally (e.g., an RR of 1.7) including for specific disabilities conditions (e.g., RRs of 3.0 or 2.5 for emotional disturbance or intellectual disabilities, respectively) are either unlikely or especially unlikely. The strength necessary for an unmeasured confounder to result in overidentification is also much larger than the risk observed for other factors including biological sex or economic disadvantage (e.g., adjusted ORs 1.64–1.99, or approximately RRs of 1.5–1.73; Morgan et al., 2017).

Limitations

This brief has several limitations. The *E*-values do not provide direct evidence of under-identification. Instead, the *E*-values help quantify the extent to which recently reported evidence of disability under-identification is robust to unmeasured confounding including in studies using extensive but regression-based statistical control that may still be susceptible to omitted variable bias. I calculated *E*-values for general disability identification and for six specific conditions. *E*-values for additional specific conditions might be calculated in future work. I examined for one source of bias (i.e., confounding) using one type of method. There are other types of sensitivity analyses for quantifying bias (Lash et al., 2009), although the *E*-value is considered particularly straightforward (VanderWeele & Mathur, 2020). Measurement error, misclassification, and selection are other sources of potential bias (Lash et al., 2009). Because measurement error and misclassification would, on expectation, bias toward null findings, the examined studies of population-based samples may be less susceptible to unmeasured confounding than indicated by these *E*-values (Trinquart et al., 2019). An *E*-value provides a conservative estimate of the confounder's potential bias of an observed relation (VanderWeele, Ding, & Mathur, 2019). *E*-value uses and interpretations are currently being debated (Fox et al., 2020; Groenwold, 2020; Ioannidis et al., 2019; VanderWeele, Mathur, & Ding, 2019) and best-practice reporting guidelines as well as extensions are still emerging (Blum et al., 2020; Cusson & Infante-Rivard, 2020; VanderWeele & Mathur, 2020). Because studies reporting under-identification have adjusted for measured confounders (e.g., economic disadvantage) likely related to unmeasured confounders (e.g., lead exposure), the residual confounding may be relatively small (Morgan et al., 2015, 2017). More broadly, students who are Black or Hispanic continue to be disproportionately overrepresented in the U.S. special education system due to underlying societal inequities resulting from historical and ongoing structures and policies (e.g., economic disadvantage, lower access to health care, housing and school segregation). These societal inequities are also important to understand and address.

Contributions and Implications

Although findings of under-identification are characterized as in error and resulting from flawed analyses (Skiba et al., 2016), under-identification has been repeatedly replicated including in analyses of other nationally representative samples and data collection methods (e.g., Farkas et al., 2020; Morgan et al., 2017). Yet education researchers continue to dismiss evidence of under-identification (Artiles, 2019; Grindal et al., 2019; Whitford & Carrero, 2019). To what extent unmeasured confounding might explain findings of under-identification has been unclear.

These *E*-value calculations provide an example of how the likelihood of unmeasured confounding might be quantified to strengthen observational research including in education (Groenwold, 2020). Sensitivity analysis for unmeasured confounding in observational studies is frequently recommended but infrequently conducted (Hemkens et al., 2018; Pouwels et al., 2016). *E*-values provide a straightforward method for doing so in observational research (VanderWeele & Mathur, 2020). *E*-value packages are now available for both Stata and R (Linden et al., 2020; Mathur et al., 2018). *E*-value extensions have recently been developed for both mediation analyses (Smith & VanderWeele, 2019) and meta-analysis (Mathur & VanderWeele, 2020).

These *E*-value calculations also provide new robustness evidence of reported disability under-identification of students attending U.S. schools who are Black or Hispanic. Because these *E*-values assess for unmeasured confounding conditional on measured covariates, large unmeasured confounding resulting from factors other than those already included in recent studies would generally be necessary to explain recently reported disability under-identification of students who are Black or Hispanic. Weaker confounding than indicated by these *E*-values would not fully explain the recently reported disability under-identification of students who are Black or Hispanic (Farkas et al., 2020; Morgan et al., 2015, 2017). Although small-to-moderate unmeasured confounding might possibly result in null associations for some specific conditions, as mostly indicated by smaller LB 95% CIs that themselves are based on conservative *E*-value point estimates and conditional on each study's measured covariates, large-to-very large unmeasured confounding would be necessary to result in levels of overidentification consistent with federal regulation. This is the case for both disabilities generally and for specific conditions.

Because findings of disability under-identification have been repeatedly replicated (e.g., Farkas et al., 2020; Morgan et al., 2015, 2017; Odegard et al., 2020) and, as indicated here, are largely robust to the possibility of unmeasured confounding, federal law and regulation may need to be redirected to instead monitor for systemic bias resulting in disability under-identification for students who are Black or Hispanic (Morgan et al., 2015, 2017). A recently proposed way to do so would for U.S. school districts to adjust the reported RRs for achievement gaps (Farkas et al., 2020; Morgan et al., 2017). Doing so would more accurately identify U.S. school districts where overidentification may be occurring as well as help ensure that students with disabilities who are Black or Hispanic are not being denied access to services based on their race or ethnicity.

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