Running Head: MODIFIED SCREENING

The Application of Differential Normative Criteria to the Gifted Education Screening Phase:
Implications for Demographic Representation

Scott J. Peters, Ph.D.
University of Wisconsin - Whitewater

Matthew T. McBee, Ph.D.
East Tennessee State University

Paper presented at the American Education Research Association annual meeting, April 2019

Toronto, Canada

OSF Page: <https://osf.io/v5sdg/>
Word Count: 4980

Abstract

Scholars and practitioners within gifted and talented education have devoted substantial effort to understanding and mitigating the disproportional representation of students from certain racial / ethnic, income, language, and disability groups. In mitigating this underrepresentation, most research has focused on the actual identification or evaluation criteria, with comparatively little research considering how the screening phase might be manipulated in order to facilitate the proportional identification of underrepresented groups. This paper uses numerical methods to evaluate if, and under what conditions, modified screening criteria can be used as a way to increase the representation of traditionally underrepresented groups in gifted education programs. The results show that this intervention has only a modest effect on reducing disproportionality. It can only have an impact when the identification process is poorly-designed at baseline.

Keywords: Gifted, equity, disproportionality, identification

The disproportional representation of students from various ethnic, racial, language, disability, and income groups within K-12 gifted and talented educational services has been documented since at least the 1970s (Peters, Gentry, Whiting, & McBee, in press). As of the 2015 - 2016 school year, nationally, public school students from African American, Latinx, and Native American families were underrepresented, with representation index¹ (RI) values of .57, .70, and .87 respectively compared to their representation in the overall K-12 population. Similarly, students from Asian American and European American families have been overrepresented at rates of 2.01 and 1.18 respectively. Students served by limited English proficiency (LEP) and special education (IDEA) programs were also underrepresented at rates of .27 and .21. Because of these pervasive disproportionalities, students from African American, Latinx, and Native American families as well as those who are served as LEP or under IDEA are commonly referred to a disproportionately underrepresented populations within K-12 gifted education. Students from low-income families are also two-and-a-half times less likely to be identified as similarly-achieving peers (Hamilton et al., 2017). This disproportionate representation of various student demographic groups has served as a persistent stain on the field.

Successfully combating disproportional representation depends on the source of the problem. Scholars in gifted and talented education have suggested a number of causes: bias and deficit thinking on the part of teachers (Ford, 2014), the “wrong” or biased assessments being used to identification (Naglieri & Ford, 2003), a lack of access to gifted services in the schools where large percentages of students from traditionally underrepresented populations are enrolled (Kettler, Russell, & Puryear, 2015), exclusionary “multi hurdle” identification systems (Lakin,

¹ The representation index compares a group’s representation in the gifted program with its proportion of the overall student population. For example, if a group comprises 20% of the gifted students but 40% of the school population, its RI value is $(.2 / .4) = 0.5$.

2018; McBee, Peters, & Waterman, 2014), poorly-designed two-stage identification systems (McBee, Peters, & Miller, 2016) or societal inequality of opportunity in general (Peters & Engerrand, 2016; Worrell & Dixon, 2018). These various causes fall into two categories: societal factors (e.g, teacher bias, societal inequality) and identification factors (e.g., multi-hurdle identification or invalid methods being used for identification). Societal factors are much harder, more expensive, and more time consuming to mitigate than are identification factors. After all, improving an identification system is a simpler task than changing an entire culture or eliminating inequality of educational opportunity.

Literature Review

Plucker and Peters (2016), McBee et al. (2016), and Hamilton et al. (2018) argued for universally considering all students for gifted and talented program eligibility as opposed to only formally considering those who are nominated or pass some other screening phase. Not only would this better identify all students for gifted services (increased sensitivity), but it would also help combat underrepresentation since students from traditionally underrepresented groups are the most likely to be left behind by a two-phase identification system (Grissom & Redding, 2016). Two-stage identification systems are common in gifted identification with students only being formally considered for gifted services following a nomination by a teacher or a parent (NAGC, 2015). Such systems will always miss more students (false negatives) than will systems under which all students are formally evaluated for program eligibility, simply due to the fact that the two phases are never going to be perfectly correlated. No matter how close the content is that is measured by each phase, simply due to measurement error, a two-phase system will miss more students than a single-phase system, with students from traditionally underrepresented

groups being disproportionately harmed by decreased system performance. And often the two phases are far from perfectly correlated, causing system sensitivity to be even worse.

Modified Identification Pathways

Universal consideration identification systems are expensive and time consuming because 100% of students in a given grade level need to be formally evaluated. McBee et al. (2016) presented methods that can be used to determine the ideal phase-one cutoff that will balance false negatives with issues of cost. This balancing point depends on several factors: 1) the reliability of all assessments, 2) the correlation between the phases, and 3) the cutoffs on both phases. Modifying any of these components, to the extent possible, can help increase sensitivity and result in fewer students being overlooked. Lowering cutoffs on the formal confirmation phase will also cause fewer students to be overlooked. Going a step farther, the state of Florida allows for differential cutoffs on the actual confirmation phase whereby students from certain underrepresented groups can be identified for services by meeting lower cutoffs than their peers from well-represented demographic groups. In Florida's case, students who are served as English language learners (ELL) or who are from low-income families need only score one standard deviation above average compared to other students who must score two standard deviations above. A study by McBee, Shaunessy, and Matthews (2012) found that districts that implemented these alternative cutoff policies mitigated their rate of disproportional underrepresentation.

Alternative Identification Criteria

Local and Group-Specific Norms. Changing the identification criteria for specific groups can take on a number of forms. In addition to simply setting a different cutoff for some groups (e.g., Florida), Lohman (2005) was one of the first to outline local building or group-

specific norms as a method to mitigate underrepresentation. In building norms, students are compared to other same-grade students within the same school building instead of national norms where students are compared to all same-grade or same-age peers from across the country. Group-specific norms go a step further and only compare students within their income, language, or racial group. Studies by Carman, Walther, and Bartsch (2018) and Peters, Rambo-Hernandez, Makel, Matthews, and Plucker (in press) found that building norms do result in a large increase in the diversity of the identified population at the aggregate level. Carman et al. evaluated group-specific norms and found that while they did work to increase the diversity of the identified population, identifying students based on an income-group specific norm was about as effective as building norms.

Modified Screening Phases. When local or group specific norms are utilized, it's most often to the confirmation or eligibility phase of student identification – to the criterion that actually determines service eligibility. The screening phase determines who is formally evaluated via the confirmation phase, whereas the confirmation phase determines who is served in gifted programming. As noted above, past research has found that high screening phase criteria are harmful to overall system sensitivity and that they are disproportionately harmful to students from traditionally underrepresented groups. Similarly, past research has found that modifying the cutoff or criteria on the confirmation phase can help combat underrepresentation. However, little attention has been paid to how screening phase criterion might be modified, within the context of fixed confirmation phase criteria, in order to identify larger numbers of students from traditionally underrepresented programs for gifted services. This has logistical appeal since the actual program eligibility criteria would be maintained with the only difference being who is

evaluated or considered with those formal evaluation criteria. Here is an example of what this might look like in practice:

Case A: Two-phase system with consistent criteria

Screening phase: Any student who scores at the 90th percentile (national norm) on a universally-administered achievement test passes the screening phase.

Confirmation phase: Those who pass the screening phase are then given an individually-administered intelligence test. Those who score two standard deviations above the mean are identified for gifted services.

Case B: Two-phase system with differential criteria

Screening phase: Any student who scores at the 90th percentile on a universally-administered achievement test passes the screening phase. In addition, students from low-income families who score at the 90th percentile compared to other students from low-income families also pass the screening phase.

Confirmation phase: Those who pass the screening phase are then given an individually-administered intelligence test. Those who score two standard deviations above the mean are identified for gifted services.

The only difference between these two cases is *who* is formally evaluated for program eligibility via the confirmation phase: is it just the students who score at the 90th percentile compared to the rest of the nation on academic achievement (Case A)? Or does it also include those low-income students who scored at the 90th percentile only when compared to other low-income students (Case B)? Under universal consideration this question is moot since all students are formally evaluated - there is only one phase. However, in schools, this is likely impractical and is also highly inefficient. This study sought to explore whether or not manipulating the screening phase / phase one criteria, in the context of a consistent confirmation phase criteria, might help combat disproportional underrepresentation.

Methods

We utilized mathematical calculations to examine the impact of adjusting the nomination phase cutoff for one group of students while retaining a constant 90th percentile cutoff (using national norms) for the confirmatory testing phase. We operationalized the modified screening phase by setting a group-specific cutoff of the 90th percentile. In short, we tested the effect of implementing Case B from above. These analyses relied on equations derived and presented in McBee et al. (2016) as well as in McBee, Peters, and Godkin (in preparation²), which are conveniently implemented in the second author's *giftedCalcs* R package³.

The analyses presented in this paper presume that the underrepresented group has a lower population mean ability or achievement level as a consequence of differential opportunities to learn (OTL: Peters & Engerrand, 2016). These unequal learning opportunities then manifest as differences in test scores and in the pervasive achievement and excellence gaps. We are not aware of any convincing evidence that underrepresentation is caused by test bias, when the term “bias” is properly defined as different outputs generated from identical inputs (Camilli, 2006). For example, Grissom and Redding (2016) showed that African American students were less likely to be identified as gifted when they had a different-race teacher, signaling a potential bias. However, this same bias was not found for Latinx students. The possibility of bias in the nomination process remains a question that has not yet been adequately investigated by our field, particularly when informal nomination processes are employed. In this paper, we adopt a pessimistic position on this issue, assuming that the baseline identification process is unbiased, and that underrepresentation is wholly caused by OTL discrepancies. This position is necessary in order to motivate the treatment intervention of lowering the nomination threshold to the lower-performing group's 90th percentile.

² An incomplete draft of this paper may be found here: <https://osf.io/v657a/>

³ <https://github.com/mcbeem/giftedCalcs>

Results

Table 1 displays group-specific nomination cutoff versus the underrepresented group's population mean ability or achievement level. The baseline nomination cutoff considered here was at the 90th percentile for the demographic group that is well represented, that is, the group whose mean ability or achievement z -score defines the mean of $z = 0$. The second column shows the adjustment to the nomination cutoff that is required to ensure that 10% of students from the underrepresented group are nominated, thus guaranteeing equal representation. The third column displays the percentile of that adjusted cutoff relative to the typical group. For example, for an underrepresented group with a mean score of one standard deviation below the mean ($z = -1.0$), the adjusted nomination cutoff at that group's 90th percentile is at the typical group's 61st percentile. This is the level of compensatory bias that would need to be inserted into the system in order to assure proportionality of the underrepresented group.

Table 1 here

Relative Identification Rates by Group Mean

Under the differential OTL assumption, where groups mean differences are caused by real lower levels of readiness, and ignoring the detrimental impact of the nomination process and test measurement error, there are simply fewer students from the underrepresented group whose ability or achievement true scores meet the identification criteria on the confirmation phase. This is one possible explanation for underrepresentation. Figure 1 displays how the size of this reservoir of qualifying students changes with the group's population mean score, holding the shape and standard deviation of the distributions constant across groups. A small mean score

differential of 0.25 standard deviations means that 6.3% (compared with the nominal 10%) of students from the target group can qualify. In such a case even small true score differences result in large disproportionalities of identification rate. Differences of a full standard deviation mean that only 1.1% qualify (compared to 10% in the population). These relative percentages are *relative identification rates* (RIR), which are ratios of the representation index (RI) values for two groups -- and where the underrepresented group's RI defines the numerator. Thus, an RIR value of 0.5 means that students from the underrepresented group are identified at only half the rate of students from the typically-represented group.

Table 2 displays these RIR values for different levels of the group mean discrepancy between the typically-represented and underrepresented groups. Clearly, relatively small mean score discrepancies can result in low RIR values for students from any underrepresented group.

Figure 1 and Table 2 here

Compensatory Bias

Other than by equalizing OTL by significantly mitigating inequality of learning opportunities, the differential representation presented in the previous section can be only be reduced by the application of compensatory bias to the identification process. In this study, our goal was to understand the effect of applying this bias to the nomination process only, leaving the confirmatory test cutoff equal across groups. As previously stated, psychometricians define bias as unequal output for identical input - cases where two students who should have received the same observed scores, due to identical true scores, did not. An intuitive way of visualizing bias, which is commonly used in item response theory (IRT), is to plot the probability of some

outcome against the individual's true score with a separate line for each group. Overlapping lines indicate no bias as this represents an equal chance of experiencing the outcome for a given true score, regardless of group membership. Non-overlapping lines indicate bias, as individuals with the same ability have different outcomes as a function of group membership.

McBee et al. (2016) analyzed the mathematics of two-stage identification processes and found that a high nomination cutoff, coupled with low nomination validity, results in identification systems with extremely poor sensitivity. Such systems may successfully identify only 30-40% of qualifying students. Unfortunately, these conditions are quite common in gifted identification. When two-stage nomination processes are used, the nomination cutoff tends to be as high as the confirmatory test cutoff or even higher, which can be surmised from the proportion of students that are nominated. Thus, the typical gifted identification process, if there is such a thing, has low sensitivity. This baseline low sensitivity is required in order for compensatory bias affecting the nomination process to have any effect.

Figure 2 displays plots of a student's true ability (or achievement) score versus the probability of identification under different baseline nomination cutoffs. In all cases, the nomination validity coefficient is 0.5. That is, the correlation between the nomination phase and the formal confirmation phase is .5. When nomination validity is this low, the nomination cutoff must be also be quite low in order to achieve reasonable sensitivity. The ideal shape of these curves is a step function situated at the test cutoff, such that 0% of students below the confirmatory test cutoff are identified (i.e., no false positives) while 100% of students above the test cutoff are identified (i.e., no false negatives). A step function identification curve would therefore imply perfect sensitivity and also perfect specificity. In reality, these curves are s-shaped sigmoid functions in high-performing identification systems, where the steepness of the

rise is proportional to the sensitivity of the process. In other words, steeper is better. These curves diverge from idea step functions for two reasons. The first reason is the inherent and unavoidable measurement error in the confirmatory assessment. The second reason is the additional harm to sensitivity imposed by the nomination process, which can be negligible or devastating depending on the nomination validity and cutoff.

Figure 2 here

Each panel of Figure 2 displays two curves. The population of students represented in the figure is an underrepresented group with mean score of $z = -0.5$. The population mean does not impact the identification prospects of a particular student with a given true ability or achievement score, but it does mean that a given percentile nomination cutoff corresponds to different values depending on whether national or group-specific comparisons are made (see Table 1).

For example, in panel A of Figure 2, the baseline nomination cutoff is set to the 90th percentile. Based on national norms, this implies that students must have a “nomination score” of $z = 1.28$ or higher to be nominated and therefore be eligible for confirmatory assessment. But based on group-specific norms, a nomination score of at least $z = 0.78$ is required for nomination (90th percentile for the underrepresented group). The red and blue curves, respectively, display the probability of identification versus the student’s true ability under these two identification systems. The probability of identification for qualified students (those whose true scores exceed the test cutoff, and are located to the right of the vertical reference line), is substantially higher when the nomination cutoff is $z = 0.78$ rather than $z = 1.28$. This is because the sensitivity of the identification process is increased when the nomination cutoff is lowered; fewer qualified

students are held back by the nomination phase. Neither of these curves is remotely similar to the idealized step function, or even the achievable sigmoid function. Both systems are “bad” or have low sensitivity, but one is much worse than the other. Furthermore, the curves do not overlap, indicating the presence of substantial compensatory bias in favor of students from the underrepresented group. This bias is intentional and designed to offset the underrepresentation caused by group mean differences. As we will discuss later on, it is this form of compensatory bias that is needed to achieve greater proportionality if the source of the disproportionality in societal inequality (differential OTL) manifesting as group mean differences in developed ability or achievement.

The remaining panels of Figure 2 lower the baseline nomination cutoff to the 70th percentile, 50th percentile, and finally to zero (e.g., universal consideration) in panels B, C, and D. The identification curves progressively adopt a healthier appearance, characterized by increasingly steep sigmoid shapes, as the nomination threshold is reduced and finally eliminated. The sensitivity of the identification process improves dramatically from panel A to D. But with it, the ability of alterations to the nomination process to create compensatory bias is reduced. In panel D (universal consideration), there is no longer any nomination process to manipulate. This is an important finding in its own right. Under universal consideration, where every student is put through the formal evaluation process, there is no way to make the system better via the nomination stage because there is no nomination stage. Taken one step farther, this also means that the better a system’s overall sensitivity, the harder it is to insert a compensatory bias to the nomination phase in order to improve sensitivity for one group but not another.

Figure 3 is identical to Figure 2, except the group’s population mean score has been lowered from $z = -0.5$ to $z = -1$. This has no effect on the identification curves that are based on a

national norm comparison (red). But the group-specific target nomination cutoffs (for the 90th, 70th, or 50th percentiles) are now lower, because they are based on a hypothetical group with average scores that are a full standard deviation below that of their higher-performing peer group. As a result, the degree of countervailing bias that results from adopting group-specific nomination standards is stronger. Compared to the blue lines in Figure 2, the blue lines in Figure 3 are higher, especially in the 90th percentile cutoff condition (panel A).

Figure 3 here

Effect on Relative Identification Rates

The system is now faced with a clash of opposing forces. As the underrepresented group's population mean becomes more depressed compared to their peer group, the reservoir of available qualifying students (those who would meet the 90th percentile confirmation cutoff) to be identified gets smaller (Figure 1). This tends to reduce that group's relative identification rate (RIR) away from proportionality (Table 2). However, the sensitivity-boosting impact of adopting a group-specific nomination standard tends to increase the proportion of students who will be identified, thus increasing the RIR toward proportionality. Figure 4 displays the composite effect of these influences on the RIR.

Figure 4 here

As the figure indicates, adopting group-specific nomination standards does make a contribution toward equalizing the RIR in some conditions, but it is never able to move the RIR

to 1.0 or perfect proportionality. The reservoir problem dominates because modifying the nomination phase does nothing to increase the actual number of students who will meet the confirmation phase cutoff. The impact of this policy change on RIR is illustrated by the vertical gap between the red and blue curves; where this gap is largest, the impact on RIR is greatest. This impact appears to be the greatest when the underrepresented group's population mean was half a standard deviation lower than the typical group's mean. However, the impact of this policy is much more strongly affected by the baseline sensitivity of the nomination process. In panel A, the nomination cutoff is at the 90th percentile. This is far higher than can be tolerated given the weak (though typical) nomination validity of 0.5. Simply put, this is a terrible identification process. Making it less terrible for the underrepresented group increases the chances that a qualifying student from this group is identified, as they would follow the blue curves instead of the red curve in Panel A of Figures 2 or 3. The maximum impact of this policy change is to change the underrepresented group's RIR from 0.34 to 0.60, an improvement of 1.76x, but still far short of equal representation.

The remaining panels of Figure 4 display the RIR impact of the group-specific nomination cutoff in systems with lower baseline nomination cutoffs: 70th percentile for Panel B, 50th percentile for Panel C, and universal consideration (the limiting case) for panel D. The baseline sensitivity of the identification process improves sequentially across panels as the harm imposed by the nomination process is weakened and then eliminated. This sensitivity improvement is echoed by the change in shape of the identification curves across panels in Figures 2 and 3. However, improving the sensitivity of the process has the side effect of weakening the impact of switching to group-specific norms for the nomination process. When the nomination threshold is low enough (i.e. universal consideration), it ceases to be a factor. It

hardly matters whether the absolute nomination cutoff is at $z = 0$ or $z = -.5$, all or nearly all of the students who could pass the confirmatory test get to take it. Actual differences in manifest achievement or ability alter pass rates and create a RIR discrepancy for students from the disadvantaged group.

Figure 5 is similar to Figure 4, except the nomination validity coefficient has been increased from 0.5 to 0.9. This greatly increases the sensitivity of the identification process and allows higher nomination cutoffs to be tolerated without harm. The sensitivity increase benefits students from all groups. Because there are many fewer false negative errors affecting students from the typically-represented group, it is much more difficult to insert a compensatory bias in favor of students from the underrepresented group. There is simply less headroom for a differential increase in performance.

Figure 5 here

The plots in Figure 5 illustrate that the only condition in which the adoption of group-specific nomination standards for the underrepresented group can meaningfully affect representation is when the baseline nomination cutoff is too high, which is represented in Panel A (90th percentile). This cutoff is still too high even when the nomination validity coefficient is an exceptional 0.90. The nomination phase is still harming sensitivity overall, and this harm can be differentially reduced for students from the underrepresented group, thus improving that group's representation. In this condition, the maximal effect of this intervention is for a group with a population mean half a standard deviation below that of the typical group, raising the RIR from about 0.35 to 0.50 (1.43x improvement). In the remaining panels, the high nomination

validity coupled with the lower nomination cutoff means that the nomination process is no longer materially affecting the identification system performance. Thus, the intervention of compensatory bias on the nomination phase can have no effect.

Discussion

In this paper, we have presented results from a mathematical policy analysis of the impact of adopting group-specific nomination standards while maintaining equal confirmatory test standards. This intervention has some potential appeal because, as far as we know, it has not been legally prohibited and maintains the appearance of fairness because ultimately, all students must meet the same admission standards (the confirmation phase). It may therefore be perceived as more politically palatable than altering confirmatory test cutoff, such as Florida's "Plan B" identification process. It also has the appeal of not adding seats to the programming since the confirmation criteria remain the same. All that would change under this intervention is who is formally evaluated for program eligibility; not who actually gets into the program.

The constellation of causes of underrepresentation are well-understood. They include differences in developed ability or achievement, bias in nomination, and bias in testing. But what is not understood is their relative contribution to the problem. Our analysis was premised on the notion that the cause is 100% real differences, 0% nomination bias, and 0% test bias. In this case, the *only* way to reduce disproportionality in identification⁴ is by the introduction of a countervailing bias into the process favoring students from underrepresented groups. Whether this is desirable or not is a question of values and politics. Of course, it is possible that the cause is actually 0% real differences and 100% nomination bias. In this case, lowering the nomination threshold differentially is not creating an compensatory bias but rather removing a bias that is

⁴ Short of a societal revolution where students from all subgroups have the same opportunities to develop academic potential

already present. Given that adopting universal consideration procedures seems to somewhat reduce but not eliminate disproportionalities in identification (Card & Giuliano, 2016), we deem a 0% real difference, 100% nomination bias distribution of blame to be discredited by evidence. But some mixture of causes certainly seems likely when nomination processes are used, especially when the nominations are informal, subjective, or parent-based. Whether the blame is 50-50, 70-30, or 90-10 is something that will need to be addressed by future research. It likely varies tremendously across contexts.

The second values conflict that is raised by contemplating a policy of inserting a compensatory bias with the goal of greater proportionality is that its effectiveness is directly related to the initial terribleness of the existing identification procedure. Baseline low sensitivity is a requirement for this intervention to have any effect, and low sensitivity means that many qualifying students will fail to be identified. Simply improving the identification process for *everyone*, not just students from an underrepresented category, by some combination of raising nomination validity and lowering the nomination cutoff, will increase sensitivity for all students. It would increase both the absolute numbers and the proportion of students identified from all backgrounds. However, it will only improve underrepresented group RIs to the extent that nomination bias causes disproportionalities.

Consider two scenarios. In both, there are two groups of students, one whose true population mean is half a standard deviation lower than the other.

Scenario 1: poor sensitivity. The identification process is two-stage. Students must be at the 90th percentile to be formally identified on a test that has excellent reliability of 0.95. Only 10% of students are nominated (e.g., 90th percentile cutoff), and the nomination is only loosely

related to the test (validity = 0.5). Result: 3.2% of students from the “typical” group and 1.2% of students from the underrepresented group are nominated. The resulting RIR is 0.37.

Scenario 2: good sensitivity. The identification process is two-stage. Students must be at the 90th to be formally identified on a test that has excellent reliability of 0.95. Now 30% of students are nominated (e.g., 70th percentile cutoff), and the nomination is closely related to the test (validity = 0.85). Result: 9.4% of students from the “typical” group and 3.6% of students from the underrepresented group are nominated. The resulting RIR is still 0.37, but 3.3 times as many students from the underrepresented category are identified. The RIs for each group are also the same. Proportionality has not changed, but far more students from underrepresented groups are being served.

The results of contemplating these scenarios reveals the serious limitations of the RI (and the RIR) as single-number summaries of underrepresentation. A high-performing student from an underrepresented group would be far better off under scenario two versus scenario one even though they have identical RIs and RIRs, in spite of the fact that the more sensitive identification process also results in numerically more additional student identifications from the “typical” group. In this case, the rising tide has lifted all the boats.

In conclusion, the policy considered in this study is one that we cannot generally endorse. It cannot fix underrepresentation (unless the cause is predominantly nomination bias), though it can somewhat reduce it under certain conditions. The extent to which it can be effective is precisely the extent to which the existing system needs to be overhauled for all students. The intervention amounts to selectively repairing a bad system preferentially for some students (i.e. the compensatory bias). We are certainly willing to entertain affirmative-action style bias to alleviate historical disproportionalities, but we believe that these should be layered on top of an

identification system that is effective at baseline. In short: fix the system for everyone first. This alone will make a substantial positive impact on students from underrepresented groups.

References

- Camilli, G. (2006). Test fairness. In R. L. Brennan (Ed.), *Educational Measurement 4th ed.* (pp. 221-256). Washington, DC: American Council on Education.
- Card, D., & Giuliano, L. (2016). Universal screening increases the representation of low-income and minority students in gifted education. *Proceedings of the National Academy of Sciences*, *113*, 13678-13683. doi:10.1073/pnas.1605043113
- Carman, C. A., Walther, C. A. P., & Bartsch, R. A. (2018). Using the Cognitive Abilities Test (CogAT) 7 Nonverbal Battery to identify the gifted/talented: An investigation of demographic effects and norming plans. *Gifted Child Quarterly*, *62*, 193-209. doi:10.1177/0016986217752097
- Hamilton, R., McCoach, D. B., Tutwiler, M. S., Siegle, D., Gubbins, E. J., Callahan, C. M., Broderson, A. V., & Mun, R. U. (2017). Disentangling the roles on institutional and individual poverty in the identification of gifted students. *Gifted Child Quarterly*, *62*, 6-24. doi:10.1177/0016986217738053
- Kettler, T., Russell, J., & Puryear, J. S. (2015). Inequitable access to gifted education: Variance in funding and staffing based on locale and contextual school variables. *Journal for the Education of the Gifted*, *38*, 99-117. doi:10.1177/0162353215578277
- Ford, D. Y. (2014). Segregation and the underrepresentation of Blacks and Hispanics in gifted education: Social inequality and deficit paradigms. *Roeper Review*, *36*, 143-154.
- Grissom, J. A., & Redding, C. (2016). Discretion and disproportionality: Explaining underrepresentation of high-achieving students of color in gifted programs. *AERA Open*, *2*(1), 1-25. doi:10.1177/2332858415622175

- Lakin, J. (2018). Making the cut in gifted selection: Score combination rules and their impact on program diversity. *Gifted Child Quarterly*, 62, 210-219. doi:10.1177/0016986217752099
- McBee, M. T., & Peters, S. J., & Miller, E. M. (2016). The impact of the nomination stage on gifted program identification: A comprehensive psychometric analysis. *Gifted Child Quarterly*, 60, 258-278. doi:10.1177/0016986216656256
- McBee, M. T., Peters, S. J., & Waterman, C. (2014). Combining scores in multiple-criteria assessment systems: The impact of combination rules. *Gifted Child Quarterly*, 58, 69-89. doi:10.1177/0016986213513794
- McBee, M. T., Shaunessy, E., & Matthews, M. S. (2012). Policy matters: An analysis of district-level efforts to increase the identification of underrepresented learners. *Journal of Advanced Academics*, 23, 326-344. doi:10.1177/1932202X12463511.
- Naglieri, J. A., & Ford, D. Y. (2003). Addressing underrepresentation of gifted minority children using the Naglieri Nonverbal Ability Test (NNAT). *Gifted Child Quarterly*, 47, 155-160. doi:10.1177/001698620304700206
- National Association for Gifted Children. (2015). *State of the states in gifted education: 2014–2015*. Washington, D.C.: Author
- Peters, S. J., & Engerrand, K. G. (2016). Equity and excellence: Proactive efforts in the identification of underrepresented students for gifted and talented services. *Gifted Child Quarterly*, 60, 159-171. doi:10.1177/0016986216643165.
- Plucker, J. A., & Peters, S. J. (2016). *Excellence gaps in education: Expanding opportunities for talented students*. Cambridge, MA: Harvard Education Press.
- Worrell, F. C., & Dixon, D. D. (2018). Recruiting and retaining underrepresented gifted students.

In S. I. Pfeiffer (ed.), *Handbook of giftedness in children* (pp. 209-226). Cham, Switzerland: Springer International Publishing.

*Table 1**Adjusted group-specific nomination cutoffs by group mean ability or achievement*

Population mean (z)	Cutoff (z)	Cutoff relative percentile
0.0	1.282	0.900
-0.1	1.182	0.881
-0.2	1.082	0.860
-0.3	0.982	0.837
-0.4	0.882	0.811
-0.5	0.782	0.783
-0.6	0.682	0.752
-0.7	0.582	0.720
-0.8	0.482	0.685
-0.9	0.382	0.649
-1.0	0.282	0.611

Note: The first column displays the population mean ability or achievement for the underrepresented group. The second column displays the adjusted nomination cutoff for that group, which is at the 90th percentile relative to that group's distribution. The third column displays the nomination percentile for the underrepresented group relative to the typically represented group, which has a population mean ability of $z=0$.

Table 2

Relative identification rate (RIR) as a consequence of group mean in an idealized universal consideration identification process

Population mean (compared to reference group)	Relative identification rate
0.0	1.000
-0.1	0.836
-0.2	0.692
-0.3	0.569
-0.4	0.463
-0.5	0.374
-0.6	0.299
-0.7	0.238
-0.8	0.187
-0.9	0.146
-1.0	0.113

Note: Assumes an unbiased single-stage identification process with zero measurement error.

Figure 1. Proportion of qualifying students by population mean

Note: In all panels, the confirmatory test cutoff is assumed to be at the 90th percentile ($z=1.28$), which is denoted by the dashed vertical line. The 'typical' group (red) always has a group mean of $z = 0$, and 10% exceeding the 90th percentile cutoff. The underrepresented group's true mean score is $z = -0.25$ (Panel A), $z = -0.5$ (Panel B), $z = -0.75$ (Panel C), or $z = -1.0$ (Panel D). The resulting proportions of those groups with true scores above the cutoff are indicated in the panels.

Figure 2. Probability of identification versus individual true score for national versus group-specific nomination cutoffs at four baseline nomination thresholds for students from a group with a population mean of $z = -0.5$.

Note: Bias is displayed by non-overlapping curves. The lines plot the probability of identification versus the individual's true ability or achievement score when the nomination cutoff is based on national norms (red line) versus group-specific norms (blue line): *Panel A:* 90th percentile nomination cutoff. *Panel B:* 70th percentile nomination cutoff. *Panel C:* 50th percentile nomination cutoff. *Panel D:* universal consideration. The nomination validity coefficient is 0.50 in all conditions. The dashed vertical line represents the confirmatory test cutoff, which is set to the 90th percentile with respect to national norms.

Figure 3. Probability of identification versus individual true score for national versus group-specific nomination cutoffs at four baseline nomination thresholds for students from a group with a population mean score of $z = -1$.

Note: This figure is similar to Figure 2, except the target group has a population mean of $z = -1$ (instead of $z = -0.5$). This implies that switching to a group-specific norm for the nomination cutoff results in a larger absolute reduction in the nomination cutscore. *Panel A:* 90th percentile nomination cutoff. *Panel B:* 70th percentile nomination cutoff. *Panel C:* 50th percentile nomination cutoff. *Panel D:* universal consideration.

Figure 4. Relative identification rate versus the population mean score differential for nomination cutoffs based on national and group-specific norms by nomination cutoff based on nomination validity of 0.5

Note: Panels display nominal nomination cutoffs, which are referenced against either national norms (red) or group-specific (blue) norms. The confirmatory test cutoff is fixed to the 90th national percentile, and the nomination reliability is 0.50. *Panel A:* 90th percentile nomination cutoff. *Panel B:* 70th percentile nomination cutoff. *Panel C:* 50th percentile nomination cutoff. *Panel D:* Universal consideration.

Figure 5. Relative identification rate versus the population mean score differential for nomination cutoffs based on national and group-specific norms by nomination cutoff based on nomination validity of 0.9.

Note: This figure is similar to Figure 4, except the nomination validity has been increased from 0.5 to 0.9. *Panel A:* 90th percentile nomination cutoff. *Panel B:* 70th percentile nomination cutoff. *Panel C:* 50th percentile nomination cutoff. *Panel D:* Universal consideration.