THE RELATIONSHIP BETWEEN READING ACHIEVEMENT AND SLD RISK RATIOS IN STATES IMPLEMENTING RTI

by

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For Jocelyn, Phineas, and Oxford. I love you.

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ABSTRACT

Students who display persistent reading deficits are sometimes diagnosed with a specific learning disability (SLD). Historically, eligibility for an SLD diagnosis has been made either through a discrepancy model, which utilizes IQ and reading achievement testing, or a response to intervention (RtI) model, which utilizes progress monitoring data through multiple tiers of support. Between 2014 and 2015 two neighboring states mandated that all districts begin implementing RtI models and use data from RtI to evaluate students for SLD rather than relying on IQ discrepancy models. The current study leveraged multiple public-use district-level datasets to analyze the relationship between SLD identification and reading achievement in these states both before and after RtI implementation. The study answers two key questions: 1) To what extent do district-level achievement gaps by gender and race/ethnicity explain the overrepresentation of male and minority students—as measured by district-level risk ratios—in states that adopted RtI requirements for SLD identification? 2) Does the relationship between district-level achievement gaps and district-level risk ratios observed in RQ1 differ between pre-RtI adoption (2011-2012) and post-RtI adoption (2017-2018) group?

In this retrospective observational study, regression analyses showed that the relationship between male overrepresentation and male achievement gaps was not statistically significant pre-RtI adoption, while the same relationship for BHN students was statistically significant. Post-RtI adoption, male overrepresentation decreased, while BHN student overrepresentation increased. The relationship between overrepresentation and achievement gaps for male students remained statistically non-significant post-RtI, whereas the relationship between overrepresentation and achievement gaps for BHN

students remained statistically significant and became stronger. The amount of variance in BHN student overrepresentation that was explained by achievement gaps in the post-RtI was more than double the amount of variance explained pre-RtI adoption.

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LIST OF ABBREVIATIONS

BHN: Black, Hispanic, and Native Americans

CRDC: Civil Rights Data Collection

ED: Economically Disadvantaged

IDEA: Individuals with Disabilities Education Act

LEA: Local education agency

MTSS: Multi-Tier System of Support

NCDPI: North Carolina Department of Public Instruction

NCES: National Center for Education Statistics

RtI: Response to Intervention (a general model)

RTI^2: Response to Instruction and Intervention (Tennessee's RtI model)

SEA: State education agency

SLD: Specific Learning Disability

SWD: Students with Disabilities

TDOE: Tennessee Department of Education

USDOE: United States Department of Education

CHAPTER I: INTRODUCTION

Response to Intervention (RtI) models, also sometimes referred to as a Multi-tier System of Support (MTSS) models, are instructional frameworks designed to ensure all students have access to appropriate, high-quality instruction, and educators have the data necessary to determine if struggling readers are making adequate progress (Gersten et al., 2008). Statewide RtI models have been implemented in states such as Iowa, Pennsylvania, and Ohio since the late 1980s and early 1990s. In addition to serving as a special education referral process, all of these statewide RtI models were implemented to improve general education outcomes for all students, including improved reading and math performance, reduced grade retentions, improved adaptive behaviors, increasing time on task, and improved performance on high stakes tests (Burns & Ysseldyke, 2005). Currently, all 50 states have policies that provide guidance on RtI practices and procedures used in public schools.

The components of a RtI model include 1) strong, evidence-based general, or tier 1, instruction for all students, 2) universal screening that targets specific skills of all students, 3) intensive small-group scientifically-based intervention for at-risk (tier 2) students, typically defined as below the 25th percentile on national norms, 4) frequent progress monitoring, 5) increasingly intensive intervention for students who do not demonstrate the necessary rate of improvement (i.e., tier 3, below the 10th percentile on national norms), and 6) possible referral or placement in special education for students who do not respond in tier 3 (Gersten et al., 2008; Hughes & Dexter, 2011; Preston et al., 2016). These features are often applied as a framework for reading intervention, but the same principles apply to other content areas, such as math (Fuchs & Fuchs, 2001). Some states or LEAs may refer to their RtI model as a multitiered system of support (MTSS). The term MTSS can sometimes refer to instructional models that include more generalized supports than are typical of RtI, such as behavioral support, but in many contexts the terms RtI and MTSS are used interchangeably (Oslund, et al., 2021; Schiller et al., 2020). For the purposes of this study, the term RtI will refer generally to multitiered models, including MTSS.

In 2000, the population of school-aged children receiving special education services for a specific learning disability (SLD) reached an all-time high of around 2.9 million. At that time, students with SLD made up approximately half of all students with disabilities (SWD) and more than 6% of all school-aged children (Zirkel, 2013). The President's Commission on Excellence in Special Education was convened to investigate the phenomenon and address the concern that rising numbers may be attributable to misidentifications of low-achieving but non-disabled children (2002). The Commission found that including response to intervention (RtI) in the SLD diagnostic criteria should be a viable option to reduce the risk of misidentification and that IQ testing is not necessary for SLD diagnosis (Etscheidt, 2013, National Joint Committee on Learning Disabilities, 2011). As a result, the 2004 reauthorization of the Individuals with Disabilities Education Act (IDEA) mandated that LEAs cannot require the use of the IQ-discrepancy model for SLD diagnosis, and they must allow the use of RtI as part of a comprehensive diagnosis (Etscheidt, 2013; IDEA, 2004; NJCLD, 2011).

In 2007, three years after the reauthorization of IDEA, two states—Delaware and Georgia—had implemented statewide policies requiring RtI as the only method for SLD identification (Berkeley et al., 2009). By 2011, the number of states requiring RtI as the exclusive method of SLD identification had grown to eleven. At that time, 45 states provided official guidance documents to support implementation of RtI as a model of instruction, and 28 of those documents explicitly addressed SLD identification (Hauerwas et al., 2013). Eight states explicitly prohibited the use of the discrepancy model for SLD identification. Additionally, seventeen of those states provided guidance for RTI as an instructional model only, without any emphasis on using RTI for SLD identification (Hauerwas et al., 2013).

Tennessee

The Tennessee Department of Education (TDOE) began promoting RtI as an instructional framework to serve the educational needs of all students in 2012. Beginning with the 2014-15 school year, the state officially replaced the discrepancy model with an RtI model called Response to Instruction and Intervention (RTI^2) as the required method for SLD identification in elementary grades (K-5). RTI^2 was then phased in for middle school and high school grades in 2016 and 2017, respectively (TDOE, 2015).

Prior to statewide RTI^2 implementation in 2015, school districts were allowed to identify elementary students with an SLD using either an RtI method or an IQ discrepancy method. Under both methods, SLD evaluations required multiple components: evidence of the students' strengths and weaknesses, underachievement in a specific area that is not explained by other factors, evidence of appropriate instruction delivered by qualified staff, weekly assessment of progress, and parent notification. The discrepancy method required school psychologists to document a severe discrepancy between a student's performance on a criterion-referenced assessment of achievement and an assessment of cognitive ability, as well as two observations of student performance in the general education classroom. Both methods lacked a universal screening of all students as part of the pre-referral process; in fact, Tennessee’s Special Education Manual at the time lacked any explicit guidelines regarding the initiation of a referral (TDOE, 2008).

The RTI^2 model in Tennessee was implemented primarily as a framework of instruction for all students. The official guidance document stated, “The Special Education Guidelines and Standards require all districts and schools to use RTI^2 to determine the eligibility of students to receive special education services for SLDs; however, identification is not the sole purpose of RTI^2” (TDOE, 2015, p. 4). Although the document emphasizes instructional aspects of the framework, it does include explicit guidance regarding how the framework interacts with the SLD evaluation process. The document recommends that the decision to initiate a referral should come from a data team consisting of a school psychologist, administrator, and an interventionist. The referral should include evidence that the child has not responded Tier III intervention, such as screening and progress monitoring data, and eight documented fidelity checks (TDOE, 2015).

As part of the instructional framework of RTI^2, the state recommended universal screening of all students three times per year with a grade-level skills-based assessment. For the screener, national norms are recommended, but local norms are allowable for schools with large numbers of at-risk students. All students receive differentiated high-quality Tier I instruction, but students who score below the 25$^{\text{th}}$ percentile on the screener should be considered for intensive small-group (1:5 ratio for grades K-5) Tier II intervention. The intervention should be provided at least 30 minutes per day and have strong evidence of effectiveness at addressing the student's specific skill deficit.

To monitor their response to intervention, students in Tier II should be assessed on their specific area of skill deficit at least every other week. Data teams consisting of administrators, teachers, interventionists, and school psychologists review the progress monitoring data every four and a half weeks to consider changing the time, frequency, grouping, or even the intervention itself. Once the student has at least eight data points, the team may also consider placing the student in a different tier. If the student's rate of improvement is inadequate, the team may decide to place the student in a more intensive Tier III intervention for at least 40 minutes per day with a teacher student ratio of 1:3 (TDOE, 2015).

The Tennessee Department of Education released a report summarizing findings from the first four years of RTI^2 implementation in elementary grades (TDOE, 2018b). According to the report, SLD identifications in elementary grades have reduced substantially from a high of around 18 per thousand (1.8%) elementary students in 2013 down to a low of around 5 per thousand (0.5%) in 2015—the first year of implementation—then increasing to around 9 per thousand (0.9%) and remaining steady the next two years. Given Tennessee's reported elementary population of around 457,000 students (TDOE, 2017) this decrease should represent close to 3,000 fewer students being identified per year with an SLD under the statewide RTI^2 model in 2016 and 2017. This overall decrease in SLD diagnosis should not be entirely unexpected, as the 2004 IDEA reauthorization—which universally allowed the use of RtI and eliminated discrepancy model mandates—was specifically in reaction to the rising SLD population across the country and was presented as a way to reduce potential over-identification (President's Commission on Excellence in Special Education, 2002; NJCLD, 2011). However, a reduction in SLD identifications is not necessarily indicative of high-quality RtI implementation. In fact, multiple national case law reviews have found that a majority of legal cases involving SLD diagnosis, or lack thereof, involved the timeliness of identification or the fidelity of general education supports (Etscheidt, 2013).

The TDOE report also noted that Black, Hispanic, and Native American (BHN) students and male students were being identified as SLD at higher rates than their counterparts in the four years prior to RTI^2 implementation. Prior to RTI^2 implementation discrepant rates of SLD identification existed between BHN students (18 per thousand or 1.8%) and non-BHN students (14 per thousand or 1.4%), as well as between males (19 per thousand or 1.9%) and females (12 per thousand or 1.2%). After RTI^2 implementation the discrepant rates disappeared between BHN and non-BHN students, with both settling around 9 per thousand (0.9%), and substantially reduced between males (10 per thousand or 1.0%) and females (8 per thousand or 0.8%) (TDOE, 2018b). The TDOE also reports that other categories of students with disabilities (SWD) have not experienced any change in rate of identification, and that students are still predominately identified with an SLD in the second or third grade. The report concludes that these findings are consistent with an effective tiered intervention framework (TDOE, 2018b). The report does not include any analysis of academic outcomes for students.

North Carolina

The North Carolina Department of Public Instruction (NCDPI) phased in a statewide RtI model generally on the same timeline as that of Tennessee. North Carolina began with the hiring of state and regional staff to support RtI and the creation of a Specific Learning Disability Task Force in 2013 and 2014 (NCDPI, 2015). Based on recommendations from the SLD Task Force, the state adopted a policy during the 2015-2016 school year that prohibited both IQ discrepancy models and patterns of strengths and weaknesses models as a means of SLD identification statewide. The policy also required that RtI be used as part of a child's comprehensive evaluation for SLD. Rather than phasing in by grade levels like Tennessee, North Carolina implemented the policy statewide in 2016, but did not require full compliance until 2020 (North Carolina Department of Public Instruction, 2021a).

As of 2015, North Carolina estimated that out of almost 2,500 public schools, only 135 were using RtI to identify SLD as permitted under the 2004 reauthorization of IDEA (NCDPI, 2015). Prior to statewide RtI implementation schools in North Carolina were using IQ discrepancy and/or patterns of strengths and weaknesses as the primary means of identifying SLD. As early as 2016 guidance from NCDPI described the state's RtI model as a flexible framework to address the unique learning needs of both general and special education students. When evaluating students for a potential specific learning disability, schools were encouraged to collect evidence that the student received quality high-quality core instruction, failed to make progress toward grade-level standards, demonstrated low academic performance relative to peers, and that the student's lack of progress could not be attributed to factors other than a potential disability (North Carolina Department of Public Instruction, 2020).

As part of North Carolina's RtI model, schools are required to assess all students at least twice per year with a valid and reliable universal screener in the areas of literacy, math, and behavior. In regard to literacy specifically, the universal screener should measure discrete literacy skills in kindergarten through first grade. In second and third grade the universal screener should measure phonics, accuracy, and fluency, and then continue with accuracy and fluency through grade twelve. Students who progress to more intensive tiers of support based on the universal screener are further assessed with a battery of formal and informal diagnostic measures, followed by regularly administered curriculum-based measures for progress monitoring (North Carolina Department of Public Instruction, 2016).

According to guidance documents from NCDPI, a referral for special education evaluation can be initiated at any point during the RtI process, and RtI processes cannot delay or deny a student's evaluation for a suspected disability (NCDPI, 2021b). Although psychological testing may be included as part of a comprehensive evaluation for SLD, the evaluation must include documentation of evidence-based interventions and multiple sources of assessment data that must include progress monitoring data (NCDPI, 2021c).

North Carolina's guidance was less prescriptive than Tennessee's in the details of its RtI model, but the structure was generally the same. When analyzing universal screener data, North Carolina recommended that schools use anywhere from the 10^{th} to 25^{th} percentile (or two grade levels behind) as the decision point for moving students into a second, more intensive tier of support. While the student is receiving the small group intervention appropriate for the student tier of support, the state recommended that school-based RtI teams set an appropriate criterion or norm-referenced goal for the student or a target rate of improvement of 1.5 to 2 times that of typical peers. The state also had guidance for monitoring progress toward the student's target goal or rate of improvement which varied depending on the type of measure used. The guidance regarding frequency of progress monitoring ranged from one collection per month to up to two collections per week. The guidance on duration of progress monitoring was more explicit, with a minimum of 10 weeks and a recommendation of at least 7-10 total data points collected (NCDPI, 2016). Unlike Tennessee, North Carolina has not published an evaluation of their statewide RtI model.

Criticisms of Disproportionate Representation Research

There is considerable controversy within the field of education regarding the disproportionate representation in special education. Descriptive analyses have routinely pointed to a long-standing overrepresentation of racial minority students in special education (TDOE, 2018b; USDOE, 2018a), and these apparent disproportionalities have guided various public policies in the direction of reducing the observed overrepresentation of minority students in special education (Sullivan & Osher, 2019). However, many recent studies have challenged the premise of overrepresentation by using logistic regression models that control for student demographics, reading achievement, and (in some cases) school-level effects (Morgan et al., 2017a; Morgan et al., 2017b; Morgan et al., 2020; Farkas et al., 2020; Odegard et al., 2020). The methods in these studies consistently demonstrate how datasets that descriptively appear to show overrepresentation can mask what is actually an underrepresentation of students who fit a reading profile that puts them at greater risk of needing special education services. In other words, minority students may be less likely to be recognized as needing special reading services compared to white peers with similar reading abilities.

The disproportionality controversy is far from settled, however. Cavendish et al. (2014) acknowledges the limitations of descriptive risk ratio calculations of disproportionality but still argue that overrepresentation of minority students in special education is an inevitable consequence of the power structures that have existed in schools for decades and school systems which in many cases are, at least in practice, largely segregated by race. Likewise, Collins et al. (2016) raise concerns about unmeasured confound factors that may contribute to special education diagnosis, as well as concerns about the use of a generic special education classification as the outcome variable in many studies finding underrepresentation. They note that disability categories such as autism, health impairments, and emotional disturbance have different diagnostic criteria and are much less understood in terms of their relationship to overrepresentation compared to other categories such as specific learning disability or intellectual disability. They also point out that Morgan et al. (2015) does not acknowledge gender as a potential confounding factor.

Whitford and Carrero (2019) raise concerns about the subjective nature of survey data used by Morgan et al. (2017a), Morgan et al. (2017b), Morgan et al. (2020), and Farkas et al. (2020), specifically in regard to controlling for socioeconomic factors. For example, the reliance on free/reduced lunch is a dubious indicator of economic hardship due to its self-reported status. Skiba et al. (2016) questioned the use of self-reported socioeconomic status as a covariate in many studies finding underrepresentation and suggested this may be the reason the conclusions drawn by Morgan et al. differed from the larger body of research. Skiba et al. (2016) goes even further to challenge the use of survey data for this purpose by demonstrating how the teacher-reported data conflicts with official child counts reported elsewhere. They note, for example, that teachers in the Morgan et al. (2015) sample reported students with speech or language impairments at almost three times the national proportion according U.S. Department of Education data from the same year. This finding by Skiba et al. (2016) casts doubt on the use of teacher-reported data when analyzing over- or under-representation in special education, as teachers' perceptions of a student's disability status may not align with their actual diagnosis (or lack thereof).

Statement of Purpose

While the challenges to methods that typically find underrepresentation are well reasoned, this study is particularly well positioned to address many of these challenges, specifically, the sampling issues raised by Skiba et al. (2016), the issue of self-reporting of economic status raised by Whitford and Carrero (2019), as well as the issue of teacher-reporting of disability status raised by Skiba aet al. (2016). Rather than relying on self-reported or teacher-reported survey data, this study will utilize publicly available data from the U.S. Department of Education, the North Carolina Department of Education, and the Tennessee Department of Education to describe the district level representation of male and minority students in the Specific Learning Disability (SLD) category of special education. The purpose of this study is to describe the relationship between academic achievement and representation in SLD. By focusing on these two states, the study is also positioned to determine if that relationship changes after statewide RtI implementation.

Research Questions

1. To what extent do district-level achievement gaps by gender and race/ethnicity explain overrepresentation of male and minority students for SLD identification?
2. Does the relationship between district-level achievement gaps and district-level risk ratios observed in RQ1 differ between pre-RtI adoption (2011-2012) and post-RtI adoption (2017-2018) groups?

CHAPTER II: LITERATURE REVIEW

Several analyses have found that large scale RtI implementation tends to be associated with decreases in the overall SLD populations. Zirkel (2013) analyzed annual special education enrollment reports from the U.S. Department of Education from 1996 to 2012 and found that since the 2004 reauthorization of IDEA, the percentage of U.S. students receiving services for SLD had declined from 5.91% in 2004 (just 0.22% below its all-time high in 2000) to 4.75% in 2012. This decline represented around 500,000 fewer students receiving special education services for SLD nationwide. Pullen et al. (2020) also noted a statistically significant nation-wide decrease in SLD identification from 2001 to 2011 which was greater than any decrease in the prior twelve-year span.

Other large-scale but short-term studies found much smaller differences in the percentage of students with SLD associated with RtI implementation. Balu et al. (2015) found that 5.4% of students in schools implementing RTI were receiving special education services for SLD compared to the average of 5.6% in all schools in the same states. Likewise, O'Connor et al. (2014) found that 5.19% of their RtI implementation group had an SLD, compared to 5.25% in a historical comparison group from two years prior. No large-scale study has found an increase in SLD diagnoses as a result of RtI implementation.

RtI's Impact on Misidentification of SLD

By the early 2000s it was widely theorized that the rapid rise in the number of students identified with SLD was likely due to increasing misidentifications rather than an increase in prevalence of the actual disability. The decision to no longer require a discrepancy model method and universally allow RtI methods in the 2004 reauthorization of IDEA was part of widespread effort to reduce misidentification of SLD (President's Commission on Excellence in Special Education, 2002). Scruggs and Mastropieri (2002) suggested that anywhere from one-third to one-half of students identified with SLD are identified without meeting state criteria. MacMillan and Siperstein (2001) proposed that apparent over-identification of SLD may be due to a variety of school-level factors including the reliance on assessment data from a single time point, inadequate exclusion of other potential causes of students' under-achievement, and subjectivity in a teacher's decision to refer a student for IQ testing. Other research suggests that these same school-level factors are likely responsible for disproportionate representation of minority students in special education (Voulgarides et al., 2017).

Studies of RtI models tend to suggest that RtI implementation will result in fewer students being identified with SLD. A meta-analysis of 24 large-scale studies found that less than 2% of students were referred for special education under RtI. Compared to the national SLD rate around 6% during the same time period, this would suggest a substantial decrease (Burns et al., 2005). Other longitudinal studies have found that small reductions in SLD identifications occur within the first two years of implementation of a large-scale RtI model (Wanzek & Vaughn, 2011).

There are multiple theoretical and empirically based rationales for why RtI implementation should identify fewer students with SLD relative to an IQ-discrepancy model. A longitudinal, large-scale study of RtI implementation in 318 elementary schools found that SLD identification rates decreased across grade K-3. In grade 3 specifically there was a decrease from 10.4% of 3rd graders in year one of the study to 6.0% in year three (Torgesen, 2009). One rationale is that RtI provides a framework for excluding causal factors (i.e., lack of instruction, behavioral factors) other than the presence of an SLD—a framework that is lacking in an IQ-discrepancy model that relies on arbitrary cut scores (Fletcher et al., 2002). Another rationale is that RtI provides an opportunity to respond to scientifically based instruction prior to a special education diagnosis, as opposed to requiring an IQ-discrepancy as prerequisite to receiving such instruction (Fletcher et al., 2004).

Multiple studies have shown that inclusion of specific RtI components leads to fewer, but more precise SLD diagnoses. Peterson and Shinn (2002) demonstrated that using relative achievement, as with local norms, contributed to 85-95% accuracy of SLD classification, compared to 60% with a traditional IQ-discrepancy method. Screening students at multiple time-points has been shown to reduce false positives in identification of reading disability (Compton et al., 2010), but the inclusion of IQ data does not reduce false positives (Fuchs et al., 2008). Another study found that including data-team referral decisions in an RtI model reduced the number of initial special education referrals and greatly increased the proportion of initial referrals who actually qualified for special education, from 52% qualifying prior to RtI to 88% under RtI with data team decisions (Van Der Heyden et al., 2007). Likewise, Speece and Case (2001) collected both IQ-discrepancy assessment data (reading achievement and IQ) and repeated curriculum-based measures (similar to RtI progress monitoring) from a sample of first grade students who were severely at risk for having a reading disability. Using CBM data allowed more severely at-risk students to be referred to special education. Likewise, among school psychologists randomly assigned to review deidentified student data and make SLD diagnostic decisions using either using either an IQ-discrepancy, PSW, or RtI method, the

RtI school psychologist group was statistically significantly more accurate to the students' actual diagnoses (Maki & Adams, 2020).

Disproportionalities in SLD

Disproportionality in special education generally refers to a frequently documented phenomena in which certain groups of students are over- or underrepresented in special education relative to their representation in the general student population. Much of the attention on disproportionality in special education has focused on the persistent overrepresentation of BHN students in special education (Artiles et al., 2018). The U.S. Department of Education utilizes risk ratios to quantify each racial group's risk of identification relative to all other students not in that racial group; a risk ratio of 1.0 would represent no disproportionality (i.e., equal risk rates). Risk ratios less than 1.0 would indicate that the target group is disproportionately underrepresented to some degree relative to all other students, while risk ratios greater than 1.0 would indicate that the target group is disproportionately overrepresented to some degree relative to all other students. The U.S. Department of Education (2018) reports that Black, Hispanic, and Native American students are disproportionately represented among students receiving services for SLD, with risk ratios of 1.5, 1.4, and 1.9, respectively. Racial disproportionality in special education has been at the center of multiple legal challenges, including a landmark case—*Larry P. v. Riles*—which led to bans on the use of IQ tests to place minority students into special education programs that isolate them from general education peers (Prasse & Reschly, 1986).

In response to pervasive racial disproportionality in special education, the U.S. Government Accountability Office (2013) issued a mandate that LEAs with significant racial disproportionality must spend 15% of federal funding for special education toward the provision of pre-referral services in general education settings. A potential response to this mandate would be for LEAs to use these funds for assessments and interventions to support RtI implementation (Sullivan & Osher, 2019).

RtI has been promoted as a means of reducing disproportionality by both race and gender in special education (National Education Association, 2007). Although not under the same level of regulatory scrutiny, much research has also been dedicated to gender disproportionality. Research in this field tends to focus on the apparent overrepresentation of male students in special education. Some of the studies that have found greater precision from SLD diagnosis made through RtI compared to the discrepancy model also found that children identified through RtI are more likely to be demographically representative of the populations from which they are drawn. Van Der Heyden et al. (2007) found that school based RtI data teams substantially reduced the disproportionate SLD identification of males, from 1.52 males per female, down to 1.35. Likewise, a meta-analysis of sixteen studies concluded that males were 1.83 times more likely to be recognized as having reading difficulties compared to female peers. Among studies that utilized an IQ-discrepancy method, the pooled odds ratio for males compared to females was 2.01, which was a higher pooled odds ratio among studies that utilized a school-based multi-tiered method (1.69), although the difference in odds ratios between the two methods was not statistically significant (Quinn, 2018). Similarly, in another study the racial distribution of students referred for special education through the use of CBM data closely resembled the racial distribution of the at-risk population, while the IQ-discrepancy data did not. In fact, no Black or Hispanic students were referred for special education in the IQ-discrepancy condition despite these students making up 37% of the at-risk population. Unlike the IQ-discrepancy condition, Black and Hispanic students made up 36% of the referred students under the CBM condition, which roughly matches the population base rate (Speece & Case, 2001).

RtI and Reading Achievement

Although much public reporting on disproportionality in special education has focused descriptively on minority group representation in special education school programs relative to their representation in the total school population (Artiles et al., 2010; Cooc & Kiru, 2018; Zirkel, 2013; U.S. Government Accountability Office, 2013; TDOE, 2018b), there is a growing body of research that deploys a variety of analytic methods to focus on minority group representation relative their representation in the population of students at greatest risk of having reading difficulties.   For example, a state or school district is likely to be evenly split between male and female students, but young male students are much more likely to score below the 25th percentile on a variety of reading measures (Limbrick et al., 2012). Therefore, male students may be identified with SLD disproportionate to the total student population, but not disproportionate to the population of students who are most likely at-risk of reading disabilities, as found by Speece and Case (2001).

Likewise, interpretation of racial disproportionality can shift depending on the inclusion of student-level covariates, such as socio-economic status and academic achievement. Morgan et al. (2017b) found that BHN students actually had statistically significantly lower odds of having an IEP for SLD compared to white students after controlling for these student-level factors. A recent best-evidence synthesis found only

11 studies of racial disproportionality in special education that controlled for student-level academic achievement among nationally representative samples, only one of which found that Black children were actually disproportionately represented at rates higher than expected. The remaining studies found that on average Black children were under-represented in special education (Morgan et al., 2017a). Morgan et al. (2020), also found under-identification of Black and Hispanic students across multiple states, including Tennessee, after controlling for math achievement as recent as 2015.

In addition to student level factors, district and school-level controls can improve estimates of minority group under-identification in special education. Farkas et al. (2020) demonstrated how controlling for district size, minority enrollment, economic status, state fixed effects, and math achievement gap can explain 35% to 40% of the variance in the observed over-representation of Black and Hispanic students in special education as represented by their district-level risk ratios. Adding school fixed effects to student-level controls also improved model accuracy across racial groups and disability category in Morgan et al. (2017b).

Likewise, Odegard et al. (2020) used extensive assessment data to create dyslexia profiles for a large sample of 2nd grade students and compare their profiles to their school-assigned dyslexia designation. They found that in addition to the student's assessment profile, race, economic status, and gender, the percentage of minority enrollment at the school-level was a statistically significant factor in reducing a student's odds of being recognized by the school as being at risk for dyslexia (OR = 0.24). In other words, students in schools with greater minority student enrollment were less likely to be recognized as having dyslexia regardless of their actual dyslexia profile. Schools with large enrollments of students fitting a dyslexic profile also greatly increased the odds of a student failing to be recognized as such by the school (OR = 41.95).

Summary of Literature

The scientific literature on large-scale RtI models suggests that a reduction in SLD identifications is a predictable outcome from the elimination of a discrepancy model and imposition of an RtI model for SLD evaluation. The evidence further suggests that such observed reductions occur due to the universal screening process, which eliminates the subjective decision to refer a student for IQ testing, and the provision of scientifically based interventions in the general education. When all students are equally likely to be screened for possible reading deficits and all struggling readers are equally likely to receive appropriate interventions, the result is that SLD identifications should be roughly equally distributed across different student populations. However, the literature also points to the need to account for reading ability when investigating equity issues in special education, as the SLD population should be representative of the population most at risk of reading failure and not necessarily representative of the general population.

When used for special education evaluation purposes, statewide RtI models are almost exclusively applied to student evaluations for SLD; therefore, much of the scientific literature on the effects of large-scale RtI models focus on outcomes for these students (Zirkel, 2011). However, RtI models may also have unintended impacts on evaluations for other special education categories.

Findings from this study will have implications both in research and in policy. The study will advance the conversation in the research field regarding the apparent contradiction between descriptive over-representation relative to the general population versus modeled under-identification relative to the at-risk population. It will also inform the type of guidance policymakers should offer in setting outcome metrics for RtI program evaluations and offer a more nuanced interpretation of the descriptive risk ratios mandated by the IDEA disproportionality provision.

CHAPTER III: METHODOLOGY

This study utilized a retrospective observational research design. This research design was necessary because neither Tennessee nor North Carolina utilized randomization in the rollout of their statewide RtI models. Students were not randomly assigned to be evaluated for SLD via IQ discrepancy or RtI, nor were a subset of districts randomly selected to begin using RtI prior to statewide implementation. Rather, Tennessee's RtI model was implemented universally for all K-5 students at a single point in time (with other grades implementing the following year); likewise, North Carolina mandated that all districts in the state begin the transition from IQ discrepancy to RtI at the same time. Therefore, this research design is not capable of demonstrating causation, but it is well suited to comparing the observed district-level relationship between SLD risk ratios and reading achievement gaps before and after the implementation of a statewide RtI model.

This design traditionally has some threats to validity, including selection bias and population validity. Selection bias effects the study's ability to attribute the observed outcomes to the intervention (Grimes & Shulz, 2002). This study minimized, but did not eliminate, the threats to validity posed by selection bias by applying the same inclusion criteria for districts in the pre-intervention group and for the post-intervention group. That is, districts must have ample data available for both the 2011-12 and 2017-18 school years to be included in the analysis. Although these district groups may not be equivalent on potentially confounding factors such as demographic shifts, the proposed study will utilize free/reduced lunch and economically disadvantaged status as a covariate to minimize potential confounds. Threats to population validity, which effects the ability to generalize findings to the general population, will be somewhat reduced due to the diversity of districts between the two states in terms of size, urbanicity, and demographics, which generally mirror the rest of the country. However, while the findings of this study have relatively strong ability to generalize to the states involved, the findings may have less generalizability to other states.

SLD Data

Downloadable public-use data files were obtained from the U.S. Department of Education's Civil Rights Data Collection (CRDC) (USDOE, 2012a; USDOE, 2018b). The collection includes school-level supplemental data that includes student counts by federal disability category (including SLD) by race/ethnicity and gender. These supplemental data submitted by State Education Agencies (SEAs) to the federal government as part of the ED*Facts* data initiative. These counts are published for public use along with the biennial survey data that the CRDC collects directly from public schools. The collections from the 2011-12 and 2017-18 school years were selected for use in this study because they approximately center around the dates when both Tennessee and North Carolina transitioned from IQ discrepancy to RtI models of SLD evaluation (2014 and 2015 respectively). The supplemental file collection contained separate excel files for each federal disability category that include school-level counts disaggregated by seven different race/ethnicity categories and gender (e.g., Hispanic males, Hispanic females). These files were used to obtain SLD counts for each race/ethnicity by summing the male/female counts for each race/ethnicity group. The supplemental file collection also contained an excel file with school-level counts disaggregated by gender, disability category, and eight different educational environment categories (e.g., Females with SLD in the general education classroom 80% or more of the day, Females with SLD in the general education classroom 40% to 79% of the day). Both files (gender by race/ethnicity and gender by environment) involved a suppression of values less than or equal to two (see Data Cleaning section below for a description of how suppressed values were resolved). A comparison of the total gender counts obtained from each file revealed less data loss due to suppression in the gender by environment file; therefore, it was selected as the source of SLD counts by gender for this study. Both file types included unique state and district identifiers, allowing the school-level to be aggregated by district for each state.

Reading Achievement Data

As part of the ED*Facts* data initiative, the U.S. Department of Education also collects state, district, and school level assessment data from SEAs (USDOE 2012b; USDOE 2018c). The assessment data submitted by SEAs includes the federally required standardized reading/language arts (RLA) assessment that SEAs administer to all public school students in grades 3 through high school. Public-use versions of these assessment data collections are made available for download in comma delimited (.csv) formats on the Ed*Facts* website for each school year in which they were collected. For this study, the district level RLA assessment files were obtained for the 2011-12 and 2017-18 school years. These files contain counts of students who tested and who achieved proficiency on their state's grade level RLA assessment, as well as percentages of tested students who achieve proficiency. Counts and percentages across all grades (3 through high school) are disaggregated by gender and race/ethnicity for each district in the file. These counts and percentages are stored as text and had to be converted to numeric values prior to analysis (see Data Cleaning below). Unlike disability counts provided by ED*Facts*, both the 2011-12 and 2017-18 assessment files followed the same data suppressions rules which included total suppression for cell sizes less than six and leveled blurring (percent ranges) for cell sizes of six to 300 in a given district. These files contained unique state and district identifiers to allow merging with other district-level datasets.

Enrollment and Demographic Data

Total district enrollment by gender and race/ethnicity was obtained from the National Center for Education Statistics' ElSi Table Generator tool (NCES, n.d.). From the tool, district level data variables were selected for each school year in the study, including counts by gender and race/ethnicity for students enrolled in public schools within each district. District identifiers were also included, and a filter was applied so that only data Tennessee and North Carolina would be included in the excel export. The resulting ElSi tables included some districts in which all or some values were missing. In these cases, the missing values were supplemented with counts obtained from each state website.

District level data on free/reduced price lunch and/or economically disadvantaged status was obtained from Tennessee and North Carolina's respective department of education websites. Tennessee published these data in Profile Data files available as downloadable excel spreadsheets by school year on their Data Downloads page. For 2011-12 Tennessee reported the count and percentage of students receiving free or reduced-price lunch by district. By 2017-18 the state had begun reporting the count and percentage of students directly certified as being economically disadvantaged based on their participation in various public assistance programs (TDOE, n.d.). North Carolina published these data in Economically Disadvantaged Student Data files, which are available as downloadable Excel spreadsheets by school year on the School Nutrition Data & Reports page (NCDPI, n.d.). North Carolina reported the count and percentage of students receiving free or reduced-price lunch by school and district for both the 2011-12 and 2017-18 school years.

Data Cleaning

Stata Statistics/Data Analysis software version 14.2 was used to import, clean, merge, and analyze all the various data files for this study. The CRDC files from which SLD data were obtained were large files containing counts of all 13 federal disability categories from schools across multiple U.S. states/territories. The first step in cleaning these files was to exclude all disabilities other than SLD and all states/territories other than Tennessee and North Carolina. The 2011-12 file used for race/ethnicity also contained 267 schools (6.2%) with only non-numerical values indicating missing data. These schools were not included the 2011-12 gender file and were therefore excluded from analysis. This initial cleaning of the SLD data resulted in a total population of 4,070 schools across multiple districts in 2011-12 and 4,091 schools in 2017-18.

Next, non-numeric values ("<=2") indicating suppressed data values less than or equal to two in the 2011-12 SLD files were treated as zero. This was done using Stata's *destring* and *force, replace* functions. Although the 2017-18 SLD files were not suppressed in this way, the suppression was then artificially applied to the data using Stata's *foreach* looping function to find values less than or equal to two and replace with zero. The purpose of this artificial suppression of 2017-18 data was to preserve comparability of findings from the 2011-12 analysis. From the resulting numeric values in each gender, race/ethnicity, and educational environment category, the total number of students with SLD in each gender and race/ethnicity category was calculated using Stata's *egen* and *rowtotal* functions. A BHN group total was calculated by summing the values for Black, Hispanic, or Native American students. For the calculation of risk ratios for BHN students a comparison group of non-BHN students is needed, so a non-BHN total was also calculated consisting of the totals for Asian, Multiracial, Pacific Islander, and White students in each school. Final district-level totals for each group were calculated using Stata's *collapse* function with unique district identifiers to aggregate each group by district and school year.

One large urban county in Tennessee was divided into two school districts in 2011-12 (Shelby County Schools and Memphis City Schools), but by 2017-18 the same county was represented by seven separate districts (Shelby County Schools plus six smaller municipal districts) with new district identifiers. To prevent the loss of data from this county—which represents a large number of students in Tennessee—all the schools inside Shelby County were assigned a new unique district identifier prior to district aggregation. The same process was repeated for achievement, enrollment, and demographic files to allow merging between school years and data sources.

The district-level SLD counts were merged using the unique district identifiers resulting in 370 unique districts across both states and school years (see Figure 1). Of all districts, 252 successfully merged, meaning the same district existed in both 2011-12 and 2017-18. A majority of the districts that merged successfully were traditional county or municipal districts in each state. A majority of districts that did not merge were individual charter schools that North Carolina reported as districts in 2011-12 but did not

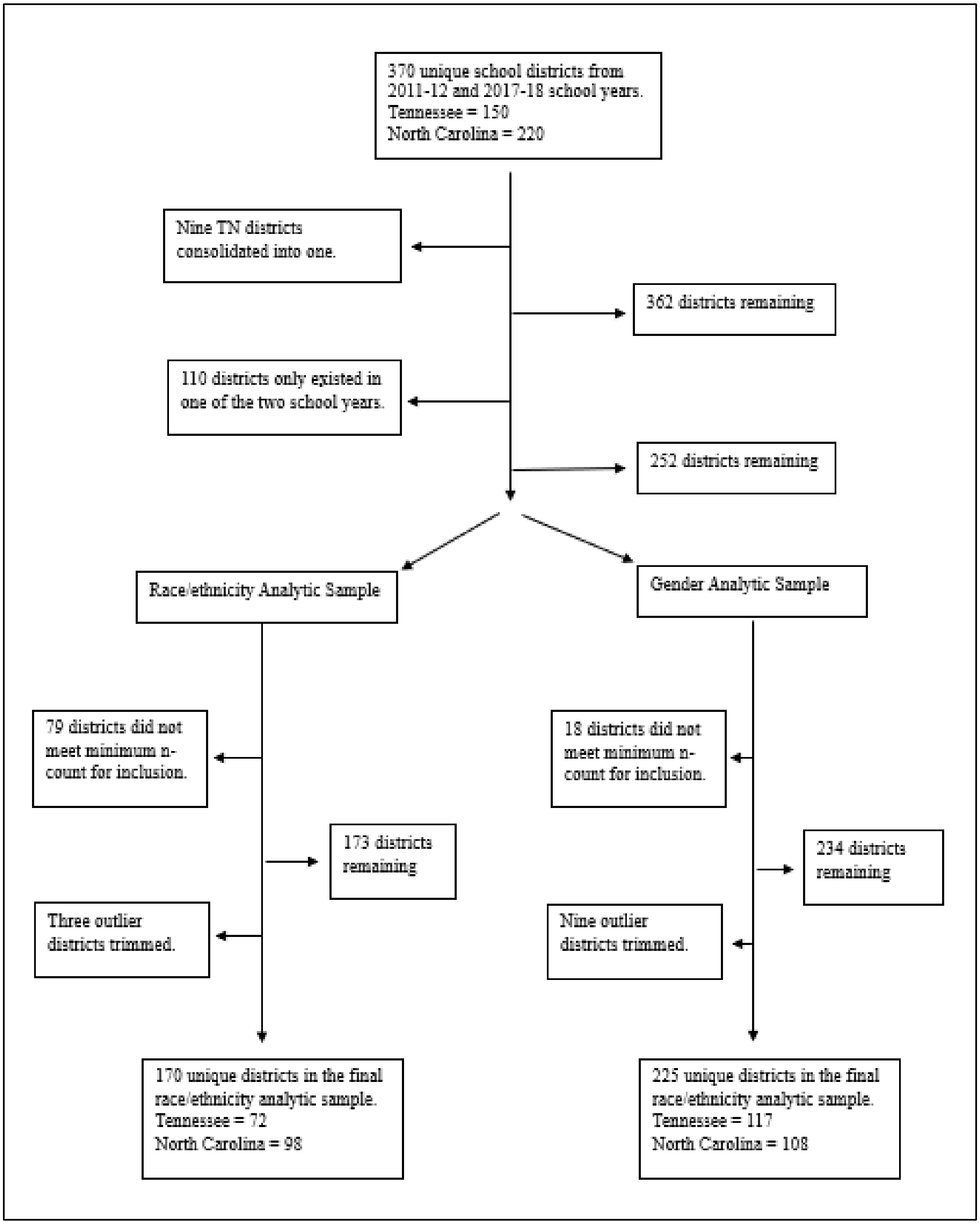

Figure 1. Analytic Sample Flow Chart.

report in 2017-18. Districts that did not exist in one of the school years were excluded from all subsequent analyses. Districts that did not have at least 5 BHN students with SLD and at least 5 non-BHN students with SLD were excluded from analysis of risk ratios by race/ethnicity, resulting in 79 districts excluded from that analysis. Districts that did not have at least 5 female students with SLD and at least 5 male students with SLD were excluded from analysis of risk ratios by gender, resulting in 18 districts excluded. Ultimately, 173 districts met the eligibility criteria for inclusion in the race/ethnicity analytic sample, and 234 districts met the criteria for inclusion in the gender analytic sample. Additional outlier analysis (see Results below) resulted in the trimming of three districts from the race/ethnicity analytic sample and nine districts from the gender analytic sample, resulting in a final race/ethnicity analytic sample of 170 districts and a final race/ethnicity analytic sample of 225 districts.

Cleaning of reading achievement data consisted of replacing percent ranges with their median value. Percent proficient was reported as a percent range (i.e., 40-44%) for any group with 300 of fewer students in that group tested in grade 3 through high school in any given district. To assign numeric values to these cases the range was replaced by the median value (i.e., the percent range of 40-44% was assigned the median value of 42%) and converted from text to a numeric using Stata's *destring* and *force, replace* functions. Reading achievement data was then merged with the SLD analytic samples using the unique district identifiers.

The only cleaning necessary for enrollment data from NCES was to calculate the total of BHN and non-BHN students in each district using Stata's *egen* and *rowtotal* functions on the counts by race/ethnicity. The NCES enrollment files used the same unique district identifiers as those in the SLD and assessment files, which allowed the total counts of enrolled female, male, BHN, and non-BHN to be merged with the analytic samples.

The free/reduced price lunch and economically disadvantaged files obtained from state websites did not use the same unique district identifiers; therefore, cleaning of these files consisted of manually entering unique district identifiers and merging them with the analytic samples.

Analytic Variables

SLD risk ratios for male students and Black students were calculated using the formula specified in IDEA (2017). First, SLD rates were calculated for females, males, BHN students, and non-BHN students by dividing the number of students in each group with SLD in a given district by the total number of students in that group in the same district. For example, females with SLD were divided by the total number of female students. Then the rate of each target group (male students and BHN students) was divided by the comparison group (female students and non-BHN students). The resulting risk ratio describes the risk of SLD identification of the target group relative to the risk of SLD identification of the comparison group. A risk ratio less than one indicates that the target group is less likely to be identified with SLD, while a risk ratio greater than one indicates the target group is more likely to be identified with SLD.

Reading achievement gaps were calculated by subtracting the percentage of students in the target group who were proficient on their state's standardized reading/English language arts assessment from the percentage of students in the comparison group who were proficient on the same assessment in the same district. For example, the achievement gap for Black students would be equal to percent proficient for non-Black students minus the percent proficient for Black students in the same district.

The percentage of students who are economically disadvantaged is calculated and reported by each state. It represents the number of students meeting the state's criteria as economically disadvantaged divided by the total number of students in a given district. Percentages were then converted to z-scores by subtracting the mean for each state and year from the percentage and dividing by the standard deviation of that state and year.

Analysis

This study utilized a descriptive and inferential analysis modeled after Farkas et al. (2020). First, SLD risk ratios and reading achievement gaps were analyzed descriptively using histograms, means, standard deviations, and paired t-tests of means at the district levels. The goal of this analysis was to describe the overall directional shift in SLD identification and achievement from 2011-12 to 2017-18. Next, correlations and scatterplots were analyzed to determine the strength of the observed directional shift. Regression analysis was then used to determine the statistical significance of the relationship and the amount of variance in SLD risk ratios explained by reading achievement gaps while controlling for economically disadvantaged (ED) status:

$$\textit{SLD Risk Ratio} = b0 + b1(\textit{Reading Achievement Gap}) + b2(\textit{Percent ED})$$

This regression model was run four times, once for each target group (male students and BHN students) and each school year in the study. Finally, R-squared coefficients were compared to determine the model explained more variance before or after RtI implementation.

The purpose of these analyses is to establish the relationship between district-level SLD risk ratios and achievement gaps and to determine if that relationship changed between the 2011-2012 and the 2017-2018 school years. The descriptive analysis of SLD risk ratios and achievement gaps will indicate if each target group is in fact more likely to be identified with SLD and more likely to have lower reading achievement relative to their comparison groups. The correlation analysis will describe the strength of the relationship between SLD risk ratios and reading achievement gaps and allow a descriptive comparison between school years. Paired t-tests will determine if the average SLD risk ratio for each target group in 2011-2012 is statistically significantly different from the average SLD risk ratio in 2017-2018. The R-squared coefficient of each regression model will describe the proportion of variance in SLD risk ratios that is explained by the model (i.e., 1.0 would be 100% of the variance explained by the regression model). Therefore, comparing these R-squared coefficients between schools will show if reading achievement gaps were a stronger predicter of SLD risk ratios before or after RtI implementation.

CHAPTER IV: RESULTS

Outlier analysis of risk ratios for each analytic sample was conducted. Analysis of histograms, skewness, kurtosis, and z-scores revealed nine outlier districts that were subsequently trimmed from the gender analytic sample and three outlier districts that were trimmed from the race/ethnicity analytic sample. The districts that were trimmed tended to have relatively small total enrollment with few students identified with SLD, resulting in extreme risk ratios that were more than three standard deviations from the mean. The removal of these outliers resulted in final analytic samples of 225 (62%) districts for gender analysis and 170 (47%) districts for race/ethnicity analysis. Although the loss of data due to the inclusion criteria and trimming of outliers is noteworthy, it is far less than that of similar analyses. For comparison, the final analytic samples in Farkas et al. (2020) represented 11-15% of their total population.

Gender Analysis

Total student enrollment across all 225 districts included in the gender analysis was 2,409,402 students in 2011-2012 and 2,383,404 students in 2017-2018. For the 2011-2012 school year 51.44% of students were male, compared to 51.38% in 2017-2018. Prior to RTI adoption 4.20% of all students were identified with a specific learning disability, whereas 4.21% were identified after RTI adoption in 2017-2018. Table 1 shows how the sample was distributed between the two states.

Table 1. *Enrollment by gender and state*

	2011-2012	2017-2018
Tennessee Districts (*n* = 117)		
Total Enrollment	972,881	946,442
Percent Male	51.47%	51.27%
Percent SLD	4.23%	3.79%
North Carolina Districts (*n* = 108)		
Total Enrollment	1,436,521	1,436,962
Percent Male	51.41%	51.45%
Percent SLD	4.18%	4.50%

Note. SLD = Specific Learning Disability

The mean SLD risk ratio for male students was 1.96 across all districts in the final analytic sample (N = 225) in the 2011-2012 school year. In 2017-2018 the mean risk ratio was 1.69 for the same districts. These risk ratios indicate that on average male students were 1.96 times more likely than female students to have a specific learning disability in 2011-2012, but by 2017-2018 male students were only 1.69 times more likely than female students to have a specific learning disability on average. A paired *t*-test indicated that the mean difference of 0.28 was statistically significant, $t(224) = 9.14$, $p < .001$, Hedges $g = 0.61$. The mean district-level ELA achievement gap between male and female students (female percent proficient minus male percent proficient) was 7.73% in 2011-2012 and 7.99% in 2017-18. A paired *t*-test indicated that the mean difference of 0.26% was not statistically significant, $t(224) = -1.02$, $p < .311$, Hedges $g = -0.07$.

The mean percentage of students who were economically disadvantaged was 62.11% in 2011-2012 and 51.68% in 2017-2018. A paired t-test indicated that the mean difference of 10.43% was statistically significant, $t(224) = 9.38$, $p < .001$, Hedges $g = 0.62$. A state-level comparison of mean percentage of students who were economically disadvantaged suggested that much of the decrease in 2017-18 occurred in Tennessee, which changed methodology for identifying economically disadvantaged students between 2012 and 2017. Therefore, the z-transformed version of this variable—standardized by state and year—was used for subsequent regression analysis.

Table 2. *Descriptive statistics for gender analysis by year*

	2011-2012		2017-2018	
Variable	M	SD	M	SD
Male risk ratio	1.96	0.47	1.68	0.39
ELA Achievement Gap	7.73%	3.32%	7.99%	2.90%
Percent ED/FRPL	62.11%	12.71%	51.68%	21.30%

Note. ELA = English Language Arts; ED/FRPL = Economically Disadvantaged/ Free or Reduced Price Lunch.

Correlation analysis indicated that the relationship between standardized percentage of students who were economically disadvantaged (zED/FRPL Percent) and SLD risk ratios was statistically significant across both school years. Likewise, the relationship between standardized percentage of students who were economically disadvantaged and ELA achievement gaps was statistically significant across both school years. Notably, the relationship between percentage of students who were economically disadvantaged and ELA achievement gaps was positive in 2011-2012, $r(224) = .170$, $p = .010$, but negative in 2017-2018, $r(224) = -.169$, $p = .011$. Conversely, the relationship between SLD risk ratios and ELA achievement gaps was negative in 2011-2012, $r(224) = -0.040$, $p = .548$, and positive in 2017-2018, $r(224) = 0.008$, $p = .909$, but both were not statistically significant. The lack of a statistically significant relationship between SLD risk ratios and ELA achievement gaps for male students suggests that districts in which male students are more overrepresented in SLD do not necessarily have fewer male students performing proficiently on their statewide ELA assessment and vice versa.

Table 3. *Correlations between variables for gender*

	2011-2012		2017-2018	
	1	2	1	2
1. SLD Risk Ratio	1.000		1.000	
2. ELA Achievement Gap	-0.040	1.000	0.008	1.000
3. zED/FRPL Percent	0.274**	0.170*	0.334**	-0.169*

Note. SLD = Specific Learning Disability; ELA = English Language Arts; ED/FRPL = Economically Disadvantaged/Free or Reduced Price Lunch.

**Correlation is statistically significant at the .01 level (2-tailed).

*Correlation is statistically significant at the .05 level (2-tailed).

Table 4 displays the results of regression models by school year with district-level male SLD risk ratios as the dependent variable and ELA achievement gaps as the independent variable, controlling for the standardized percentage of students who are economically disadvantaged. ELA achievement gaps were not significant predictors of male SLD risk ratios in either year. The unadjusted correlation coefficients the relationship shifted from negative in 2011-2012 to positive in 2017-2018; however, this shift is not meaningful given the lack of statistical significance. The model explained 7.5% of variance in male SLD risk ratios in 2011-2012 and 10.8% of variance in 2017-2018.

Table 4. *Male SLD risk ratio regression analysis*

Variable	2011-2012	2017-2018
Intercept	2.061*	1.615*
ELA Achievement Gap	-1.258	0.882
zED/FRPL Percent	0.137*	0.140*
R^2	0.083*	0.116*
Adj R^2	0.075*	0.108*

Note. SLD = Specific Learning Disability; ELA = English Language Arts; ED/FRPL = Economically Disadvantaged/Free or Reduced Price Lunch.

*Coefficient is statistically significant at the .01 level (2-tailed)

Race/Ethnicity Analysis

Total student enrollment across all 170 districts included in the analysis by race/ethnicity was 2,194,198 students in 2011-2012 and 2,187,011 students in 2017-2018. Across both states 39.80% of students were Black, Hispanic, or Native American, compared to 43.04% in 2017-2018. Prior to RTI adoption 3.97% of all students were identified with a specific learning disability, whereas 4.41% were identified after RTI adoption in 2018-2018.

Table 5. *Enrollment by race/ethnicity status and state*

	2011-2012	2017-2018
Tennessee Districts (*n* = 72)		
Total Enrollment	791,566	783,660
Percent BHN	36.51%	39.82%
Percent SLD	4.03%	3.81%
North Carolina Districts (*n* = 98)		
Total Enrollment	1,402,632	1,403,351
Percent BHN	41.66%	44.84%
Percent SLD	3.94%	4.75%

Note. BHN = Black, Hispanic, or Native American; SLD = Specific Learning Disability

The mean SLD risk ratio for BHN students was 1.18 across all districts in the final analytic sample (N = 170) in the 2011-2012 school year. In 2017-2018 the mean risk ratio was 1.37 for the same districts. A paired *t*-test indicated that the mean difference of 0.19 was statistically significant, $t(169) = -5.40$, $p < .001$, Hedges $g = -0.44$. The mean district-level ELA achievement gap between BHN and non-BHN students (non-BHN percent proficient – BHN percent proficient) was 21.14% in 2011-2012 and 21.46% in 2017-18. A paired *t*-test indicated that the mean difference of 0.32% was not statistically significant, $t(169) = -0.71$, $p < .476$, Hedges $g = -0.05$. The mean percentage of students who were economically disadvantaged was 61.27% in 2011-2012 and 54.66% in 2017-2018. A paired *t*-test indicated that the mean difference of 6.61% was statistically significant, $t(169) = 5.38$, $p < .001$, Hedges $g = 0.41$. As with analysis by gender, the z-transformed version of this variable—standardized by state and year—was used for subsequent regression analysis.

Table 6. *Descriptive statistics for race/ethnicity analysis by year*

	2011-2012		2017-2018	
Variable	M	SD	M	SD
BHN risk ratio	1.18	0.57	1.37	0.46
ELA Achievement Gap (%)	21.14%	6.67%	21.46%	6.93%
Percent ED/FRPL	61.27%	13.01%	54.66%	22.62%

Note. BHN = Black, Hispanic, or Native American; ELA = English Language Arts; ED/FRPL = Economically Disadvantaged/Free or Reduced Price Lunch.

Unlike the analysis by gender, unadjusted correlations coefficients indicated a relatively strong and statistically significant relationship between BHN risk ratios and ELA achievement gaps for 2011-2012, $r(169) = .439$, $p < .001$, and for 2017-2018, $r(169) = .565$, $p < .001$. Also unlike with gender, the relationship between standardized percentage of students who were economically disadvantaged (zED/FRPL Percent) and all other variables was only statistically significant in 2017-18 and was negative in all cases. The statistically significant relationships suggest that districts with greater overrepresentation of BHN students with SLD did tend to have larger ELA achievement gaps for BHN students in both school years. However, districts with greater BHN overrepresentation and achievement gaps tended to have more students who were economically disadvantaged only during the 2017-2018 school year.

Table 7. *Correlations between variables for race/ethnicity*

	2011-2012		2017-2018	
	1	2	1	2
1. SLD Risk Ratio	1.000		1.000	
2. ELA Achievement Gap	0.439**	1.000	0.565**	1.000
3. zED/FRPL Percent	-0.077	-0.031	-0.353**	-0.172*

Note. SLD = Specific Learning Disability; ELA = English Language Arts; ED/FRPL = Economically Disadvantaged/Free or Reduced Price Lunch.

**Correlation is statistically significant at the .01 level (2-tailed)

*Correlation is statistically significant at the .05 level (2-tailed)

Table 8 displays the results of regression models by school year with district-level BHN SLD risk ratios as the dependent variable and ELA achievement gaps as the independent variable, controlling for the standardized percentage of students who are economically disadvantaged. These models indicate that ELA achievement gaps were statistically significant predictors of BHN risk ratios in both 2011-2012 and 2017-2018, after controlling for the percentage of students who were economically disadvantaged. The adjust R-squared coefficients indicate that the entire model explained a statistically significant 18.7% of variance in BHN risk ratios in 2011-2012, and twice as much variance (37.9%) in 2017-2018.

Table 8. *BHN SLD risk ratio regression analysis*

Variable	2011-2012	2017-2018
Intercept	0.387*	0.623*
ELA Achievement Gap	3.729*	3.441*
zED/FRPL Percent	-0.037*	-0.121*
R^2	0.197*	0.387*
Adj R^2	0.187*	0.379*

Note. BHN = Black, Hispanic, or Native American; SLD = Specific Learning Disability; ELA = English Language Arts; ED/FRPL = Economically Disadvantaged/Free or Reduced Price Lunch.

*Coefficient is statistically significant at the .01 level (2-tailed)

DISCUSSION

Since the reauthorization of IDEA in 2004, RtI models have become increasingly prevalent as a means of identifying students with SLD. As states develop and implement RtI processes for their schools and LEAs, they do so with the goal identifying those students in their states who are most at risk of having a specific learning disability. One tool that education researchers have developed to help stakeholders know if they are in fact identifying their most at-risk students, is to control for academic achievement. This study looked at the district-level reading achievement gaps of two target groups who have been historically considered to be overrepresented in SLD: male students and students who are Black, Hispanic, or Native American. The reading achievement gaps were analyzed in relation to each group's district-level representation in SLD as represented by a risk ratio. By focusing the analysis on two states that implemented statewide RtI models during the same time period and analyzing data from before and after RtI implementation, this study was able to describe the relationship between reading achievement and SLD representation for each group, as well as the way in which that relationship changed after RtI implementation.

Descriptively, both male and BHN students in Tennessee and North Carolina were overrepresented in SLD relative to their comparison peers during the 2011-2012 school year; however, male students were overrepresented to greater degree than BHN students. Male students had an average risk ratio of 1.96 in 2011-2012, while the risk ratio for BHN was only 1.18 in the same year. Similarly, both target groups had fewer students scoring proficiently on the statewide ELA assessment relative to their comparison peers in the same districts. In this case, male students had a smaller average achievement gap (7.73%) compared to the average district-level achievement gap of BHN students (21.14%).

The unique relationship between male overrepresentation and male achievement gaps was negative and non-significant in 2011-2012. Meaning, districts that had more male students in SLD relative to female peers did not necessarily have fewer male students performing proficiently on the statewide ELA assessment compared to female students and vice versa. The entire regression model, including the standardized percentage of students qualifying as economically disadvantaged, did explain a statistically significant amount of variance in male overrepresentation with an adjusted R-squared of 0.075 or 7.5%. Although the model as a whole was statistically significant, the standardized percentage of students qualifying as economically disadvantaged carried the load in the model's predictive capability. This means that in 2011-12 districts that over-identified males with SLD did not necessarily have more male students with low reading achievement, but rather more students who were economically disadvantaged. Therefore, ED status was more influential to a districts risk ratio than ELA achievement gaps.

Conversely, the relationship between BHN overrepresentation in SLD and BHN student reading achievement gaps was positive and statistically significant. Meaning, districts that had more BHN students in SLD relative to other race/ethnicities did tend to have fewer BHN students performing proficiently on the statewide ELA assessment compared to other race/ethnicities. Likewise, the 2011-2012 regression model for BHN students was statistically significant, explaining 18.7% of the variance in BHN overrepresentation in SLD. Unlike the model for male overrepresentation, both achievement gaps and economically disadvantaged status contributed to the explanatory power of the BHN regression model. Additionally, ELA achievement gaps contributed more to the model than economically disadvantaged status, meaning that in 2011-12 districts that over-identified BHN students with SLD did tend to have more BHN students with low reading achievement and that these districts also—to a lesser extent—tended to have more students who were economically disadvantaged.

Male students and BHN students also shifted in ways that differed from each other following RtI implementation in 2017-2018. While the average achievement gap size did not change in any meaningful or statistically significant way for either group from 2011-2012 to 2017-2018, the average risk ratio for each group was statistically significantly different. For male students the average risk ratio decreased from 1.96 to 1.68, meaning male students after RtI implementation were still more likely to have an SLD in 2017-2018 relative to female students, but to a lesser extent. The unique relationship between male overrepresentation and male reading achievement gap switched from negative to positive but remained statistically non-significant. The regression model for male students in 2017-2018 remained statistically significant, but only explained slightly more variance compared to the equivalent model in 2011-2012, increasing from 7.5% to 10.8% of variance explained. This means that following RtI implementation districts were less likely to over-identify male students with SLD, but over-identification, when it did occur, was still unrelated to the reading achievement gap between male and female students. The fact that reading achievement gaps did not contribute significantly to the model indicates that when male overrepresentation did occur after RtI implementation, it continued to occur more often in districts with larger numbers of economically disadvantaged students rather than in districts with larger numbers of males with low reading achievement.

Conversely, BHN students experienced a statistically significant increase in average SLD risk ratio from 1.18 in 2011-2012 to 1.37 in 2017-2018. BHN students were more likely to have SLD relative to other race/ethnicities in 2017-2018. The unique relationship between BHN overrepresentation and BHN reading achievement gaps was positive and statistically significant as it was in 2011-2012. The regression model for BHN in 2017-2018 remained statistically significant and explained substantially more variance than in 2011-2012, more than doubling from 18.7% explained to 37.9%. Therefore, both before and after RtI implementation, districts with larger BHN reading achievement gaps were more likely to over-identify BHN students with SLD compared to districts with smaller BHN achievement gaps. However, after RtI implementation this relationship strengthened resulting more BHN students being identified with SLD from districts with low reading achievement and high rates of economically disadvantaged status. This finding suggests that districts are doing a better job of identifying students with SLD after RtI implementation.

Findings from the BHN analysis are generally consistent with the Farkas et al. (2020) district level analysis, with district level achievement gaps explaining a substantial and statistically significant amount of variance in descriptively observed overrepresentation in special education. If the same conclusion can be drawn from these findings, then it could be seen as encouraging news to stakeholders seeking to implement RtI models that successfully identify more of the most at risk students with SLD compared to IQ discrepancy and other models of identification. If the observed overrepresentation of BHN students in 2011-2012 was actually underrepresentation of a larger at-risk population of BHN students as the findings suggest, then the increased risk ratio after RtI implementation would be a favorable outcome for practitioners and stakeholders. The fact that district level reading achievement gaps became better predictors of SLD risk ratios after RtI implementation in these districts suggests that this may be the case in these particular states.

It's not entirely clear why the same pattern was not observed for male students. One possible explanation could be that the observed overrepresentation of male students with SLD is more attributable to under identification of female students than it is misidentifying male students. In theory, if this was true and RtI implementation had the same effect potentially observed in the BHN analysis (i.e., more of the most at-risk female students were being identified with SLD under RtI), then it would explain the observed effect of a decreased risk ratio for male students despite the lack of a strong relationship between male risk ratios and male achievement gaps. Unfortunately, district level data is not suited to testing this particular hypothesis, as few—if any—districts have ELA achievement gaps in which female students are less likely to be proficient than male students. Student level data would be needed with female student identification of SLD as the outcome of interest.

As previously stated, the answer to question the first research question (i.e., how much gender and race explain overrepresentation) differs depending on the target group in question. In regard to male students, achievement gaps do not explain male overrepresentation in SLD. Male overrepresentation is better explained by the overall economic status of the district than it is by the proportion of male performing proficiently on the ELA assessment in each of the two states. On the other hand, the achievement gap for BHN students does explain BHN overrepresentation in SLD to a substantial degree. Between the two school years analyzed, BHN student achievement gaps explained anywhere from roughly one-fifth to one-third of the variation in BHN overrepresentation in SLD at the district level.

The answer to the second research question (i.e., differences in relationships pre- and post-RtI implementation) is different for male and BHN students. For male students, there was no change in the relationship between male achievement gaps and male overrepresentation in SLD. Other than a non-substantial directional shift (from slightly negative to slightly positive), achievement gaps were not predictors of male overrepresentation after RtI implementation just as they were not predictors before RtI implementation in these two states. Conversely, the relationship between BHN achievement gaps and BHN overrepresentation in SLD became substantially stronger after RtI implementation. After these two states eliminated the use IQ-discrepancy as a means to determine eligibility for SLD and implemented statewide RtI models, districts where BHN students were more likely be non-proficient on their state's ELA assessment were also more likely to recognize BHN students who have a specific learning disability.

Implications

These findings have implications at the federal, state, and local levels. Currently, federal law requires states to monitor districts for having a significant disproportionality based on race or ethnicity in respect to the identification of students with disabilities in specific disability categories, including SLD. If a district is found to have a significant disproportionality for any specific race or ethnicity, then the district must dedicate up to

15 percent of IDEA funds toward a comprehensive early intervention system targeted to the student group experiencing the significant disproportionality (IDEA, 2004).

In many cases, RtI models would be part of a district's comprehensive early intervention system that would receive these targeted funds. Although the findings in this study suggest that these states generally do not have significant disproportionalities in SLD, it is noteworthy that after implementing RtI (a federally recommended practice) the risk ratio went up for BHN students, not down. Therefore, if a district does in fact have a large proportion of students who are at risk for SLD in certain race ethnic category, this policy could create a continuous cycle in which the district has a finding of significant disproportionality, improves RtI processes by directing additional resources to it (as mandated), and then becomes more likely to have additional findings as they correctly identify students in need of services.

Given these findings, in addition to other research that has found observed overrepresentation to actually be an underrepresentation of the most at-risk students, the federal government should consider offering guidance and resources for states to account for academic achievement—specifically reading achievement in regard to SLD—when calculating significant discrepancies in their districts. Without controlling for achievement in some way, districts with an apparent discrepancy may essentially be incentivized to identify fewer students from a given racial or ethnic group when in fact they should be identifying more.

These findings also contribute to the larger body of evidence that RtI is a more accurate method for identifying students with dyslexia, or SLD, as compared to the IQ discrepancy method. States that do not currently implement RtI or that allow the use of

IQ discrepancy as a sole means to determine eligibility for students should consider changing those policies statewide. Both North Carolina and Tennessee pivoted from allowing the use of IQ discrepancy to statewide RtI models and they experienced positive outcomes for students in just six years. In regard to male students, their overrepresentation—which was unrelated to academic achievement—was reduced. For Black, Hispanic, and Native American students, their “overrepresentation” was likely a masked underrepresentation, given its strong relationship to academic achievement. Therefore, their increased representation in SLD may also be a positive outcome as more students who are in need of services begin to receive them.

Regarding future research, these findings should be replicated using data at the student level. Especially if states are collecting assessment data in addition to their annual statewide standardized assessment (i.e., universal screener, progress monitoring), researchers could combine and analyze these data to create student profiles that quantify their individual level of risk for SLD or dyslexia similar to Odegard et al. (2020). Tracking these students longitudinally to see they are eventually found eligible for services would allow the state to know if their RtI model is in fact identifying their most at-risk students. As previously mentioned, having individual student outcomes would allow researchers to determine RtI actually helps female students who struggle with reading become identified with SLD, rather than by reducing male misidentification. Additionally, this would essentially side-step the whole question of over- vs. underrepresentation based on demographic characteristics and allow practitioners to focus on more important question that lies underneath: are we getting special education services to the students who actually need them?

Limitations

This research is limited in a number of ways. First, this study alone is not causal. Although both states did implement a statewide RtI model during the same six-year period, this study cannot account for other changes that may have occurred in those states at the same time that may have influenced outcomes (i.e., literacy initiatives, curriculum changes, major demographic shifts). Additionally, this study cannot account for variability of implementation across districts and schools within these states. These states each released statewide guidance for districts to implement the statewide RtI model, but it is impossible to know the extent to which state guidance was followed with fidelity in each district.

Another potential limitation of this study is limitation that is intrinsic of any extant dataset involving counts. That is, there are different ways to count. The public-facing datasets used in this study reflect each state's federally mandated child count of students with disabilities as of December 1, 2011 and December 1, 2017, respectively. Although this consistent one-day census count allows for comparability across time and between states, by definition, it does not actually reflect all the students served by the state over course of a school year. Students can be found eligible or non-eligible for a disability at any point during the school year. Students can also move in or out of a state at any point. These variations throughout the year are not captured by a one-day census; therefore, the particularities of the dataset used in this study could potentially lead to conclusions may differ from those from another dataset with different business rules for counting students with disabilities. Variations in business rules and/or data definitions across public-facing datasets explain why research that seems be measuring the same outcome may have different results (i.e., Zirkel (2013) and Pullen et al. (2020).

Finally, these states were chosen for analysis because they both adopted statewide RtI models during the same six-year time period. They were not chosen to be representative of the entire United States of America. Given that these are neighboring states in the southeastern region of the country, it is unlikely that they are representative the entire U.S. demographically, socio-economically, educationally, or in terms of urbanicity. States that differ dramatically from North Carolina and Tennessee in any of those aspects, or that implement RtI models that differ dramatically from those two states, may or may not have findings that conflict with those in this study. This threat to external validity means that these findings may not generalize beyond the two states involved.

Future Directions

In summary, these findings are consistent with other research that highlights the need to control for academic achievement in the study of representation in special education (Morgan et al., 2017a; Morgan et al., 2017b; Morgan et al., 2020; Farkas et al., 2020; Odegard et al., 2020). Federal policy-makers should consider these findings when mandating requirements for LEA actions in response to a perceived significant discrepancy in special education. Continued research in this area is needed to determine how SEAs and LEAs can best identify both over- and under-representation of specific student groups, monitor progress toward addressing discrepancies in representation, and optimize RtI models to support the needs of their student populations. Additionally, more states should apply rigorous analytic methods to examine student outcomes attributable to their RtI models and publish their findings. By sharing these internal evaluation, states can learn from each other and innovate as they each work identify students with specific learning disabilities and provide them with the services they need.

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