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An Examination of Underrepresentation in Florida, Indiana, and Washington

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AN EXAMINATION OF UNDERREPRESENTATION IN FLORIDA, INDIANA, AND WASHINGTON

by

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This work is dedicated to my wife and family. I know my father would have been proud.

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ABSTRACT

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Black, Latinx, and Native American students are underrepresented in gifted education programs across the United States. This underrepresentation is one way in which the excellence gap manifests in gifted education. In turn, the underlying causes for underrepresentation are debated by scholars. This dissertation examines the issue of underrepresentation through three case studies. In all case studies, a generalized linear mixed model is used as the framework to analyze publicly available data acquired from the associated state departments of education.

The first case study examines underrepresentation in the state of Florida. In this study, the influence of socioeconomic status on rates of representation between the 2011-2016 academic years are examined. The results from this case study suggest that the representation of Black students from low SES homes for gifted services was 68% higher than the non-SES adjusted likelihood of identification. In contrast, the representation for Latinx and Native American students decreased by 44% and 49% respectively.

The second case study examines underrepresentation in the state of Indiana. In this study, the influence of multiple criteria on rates of representation between the 2006-2016 academic years are examined. The results from this case study suggest that multiple criteria increased rates of representation in gifted programs by 10% to 20% in comparison to using only intelligence tests.

Finally, the third case study examines underrepresentation in the state of Washington. In this study, the influence of early identification on rates of representation between the 2002-2012

academic years are examined. The results from this case study suggest that identification in early elementary years increased proportional representation by 10%.

These three case studies contribute to the overall body of literature on underrepresentation. The overall message is that the issues of underrepresentation are nuanced. In particular, how socioeconomic status, multiple criteria, and early identification relate to Black, Latinx, and Native American students is not the same across all three groups. Regardless, the dissertation provides a clearer picture to the issue of underrepresentation in gifted education.

CHAPTER 1. INTRODUCTION

1.1 Introduction

The purpose of this chapter is to concisely introduce the three studies that comprise this dissertation. I describe the purpose for using a three-study approach and why it is appropriate for this dissertation. Further, I introduce the theoretical rationale for conducting research on this topic.

1.2 Underrepresentation of Black, Latinx, and Native American Students in Gifted Education

Underrepresentation in gifted education and programming has been the focus of extensive research by scholars in the field (Daniels, 1998; Donovan & Cross, 2002; Erwin & Worrel, 2012; Ford, 2014; Konstantopoulos, Modi & Hedges, 2001; Naglieri & Ford, 2003; Stambaugh & Ford, 2015; Yoon & Gentry, 2009). The idea that a school district's identified gifted population should reflect the composition of its general population is a simple notion, yet in most states, Black, Hispanic and Native American children go underrepresented in gifted programs compared to their Asian and White peers (Yoon & Gentry, 2009).

The reasons for unequitable representation in gifted programming among Black, Hispanic and Native American students compared to Asian and White students is an on-going area of research in gifted education (Daniels, 1998; Erwin & Worrel, 2012; Ford, 2014; Naglieri & Ford, 2003; Stambaugh & Ford, 2015; Yoon & Gentry, 2009). Scholars in the field debate causes that range from identification practices (Erwin & Worrel, 2012) to continuing microaggressions and lack of multicultural policies (Stambaugh & Ford, 2015). Understanding why the proportional gap in representation exists is paramount to developing methods and policies to narrow that gap.

In this dissertation, I examined three states (Florida, Indiana, and Washington) in an analysis of underrepresentation in the United States.

1.3 Rationale for Using Three Studies

The purpose in analyzing states using a case study format is to explore what policies, enacted at the state level, affect identification of underrepresented populations for gifted services. There is no unified approach to identification of underrepresented populations across the United States. States like Florida provide specific legislative mandates for the identification of underrepresented populations while others like Indiana leave the identification of students to the individual school districts. Other states, like Washington, mandate services and identification but not how or when those services are delivered. The purpose of this dissertation is to, then, provide some means of generalizations so that inferences can be drawn from the diverse educational landscape of gifted education policy. In these studies, I used the framework of a generalized linear mixed effect model to control for nuisance variance to more accurately estimate how different policies affect rates of identification for underrepresented populations in the United States.

I used a case study approach to isolate characteristics involved in underrepresentation of Black, Hispanic and Native American students in gifted education and to examine what factors surround those characteristics. By isolating the characteristics, a researcher can assess the effectiveness of policies, identification procedures, and definitions of giftedness. By examining each of the states separately, a researcher can examine potential causes for underrepresentation based on what the state mandates for schools to report or the policies they enact. For example, Florida mandates that districts provide alternative means of identification for underrepresented students. They also define underrepresented students in gifted programs in terms of socioeconomic status and ethnicity (Florida Department of Education, 2013). Schools are then required to report identification of gifted students by ethnicity and socioeconomic status rather than ethnicity or socioeconomic status. This allows a researcher to examine just how the mandated policy has manifested within the state.

1.3.1 Florida

In the first case study I examined underrepresentation in the state of Florida. Detaching the effect of race from poverty has been pursued by few researchers in the field of gifted education. McBee (2010) investigated the identification of elementary students in Georgia by examining rates of identification for students of different ethnicities while controlling for socioeconomic status. He found that socioeconomic status and ethnicity both contributed to the likelihood of identification. Warne, Anderson, and Johnson (2013) examined identification rates in Utah for students of different ethnicities while controlling for student achievement. The authors found that when achievement on state standardized tests was controlled, underrepresented groups were more likely to be identified. To the usefulness of the Naglieri Nonverbal Ability Test ([NNAT], Naglieri & Ford, 2003) for identification of underserved ethnic groups, Carman and Taylor (2010) controlled for low socioeconomic status. The authors discovered that even in tests meant for identification of underrepresented populations, this group of students still performed statistically lower than Asian and White peers. The lack of research examining the effect of ethnicity on identification while controlling for confounding variables such as SES remains a critical gap in the field of gifted education. Further, these studies represent cross sectional samples of students and do not consider long-term trends in identification rates. The first study extends the literature by controlling for socioeconomic status while examining rates of underrepresentation in the state of Florida.

1.3.2 Indiana

In the second case study I examined underrepresentation in Indiana. Indiana identifies students for gifted services in one of four categories: general, mathematical, language arts, and other (Indiana Education Code 20.36.1.2). Further, Indiana public schools are experiencing rapid demographic change. From the last census period of 2000 to 2010, the Hispanic population in Indiana nearly doubled (U.S. Census, 2010). Much of this rapid growth has stemmed not from immigrants to the United States from Central America but from births (Pew Research Center, 2016). I examine whether these multiple avenues of identification have resulted in proportional representation for underrepresented populations (especially Hispanic students) in high ability programs throughout the state.

1.3.3 Washington

In the final case study, I examined underrepresentation by ethnic groups in Washington state. Scholars have demonstrated that school readiness is correlated to underrepresented group identification for gifted services and success in early elementary grades (Gormley, Phillips, & Gayer, 2008; Henfield, Owens, & Moore, 2008; Winsler, Karkhanis, Kim, & Levitt, 2013). These scholars agree that if educators hope to have a high ability program reflect the diversity of their school's general population then the school must provide services and support early. The reality of contemporary public K-12 education is that resources are finite. In this final case study, I examined the effects of early identification on rates of proportional representation in a school district.

1.4 Significance

Each of the three studies examined one aspect of underrepresentation in addition to rurality: socioeconomic status, multiple criteria, and early identification. The overall approach of the three case studies is to use a common methodological framework replicated across three states. This replication forms the core of the analysis process while also making provisions in the methodological framework for the unique characteristics of gifted education in each state. Those unique characteristics are addressed with specific research question pertaining to that state while contributing to the overall research question that addresses underrepresentation of Black, Hispanic and Native American students.

This research provides state legislators and school district administrators with a benchmark on how the current policies enacted at the district level effect representation of underrepresented student groups in gifted services. Further, this research can influence future policy decision by providing clarity on how identification practices influence Black, Hispanic, and, Native American representation in gifted programming.

Finally, this research contributes to the overall body of research concerning underrepresentation of Black, Hispanic, and Native American students in gifted programming. Early identification with appropriate services is a NAGC standard. This research provides longitudinal evidence to the validity of early identification procedures when implemented in practice across a diverse state educational field.

1.5 Research Questions

RQ1: To what extent are Black, Hispanic, and Native American students underrepresented in gifted programs in public schools in Florida, Indiana, and Washington?

RQ2: To what extent does socioeconomic status relate to Black, Hispanic, and Native American student representation in gifted programs in public schools in Florida?

RQ3: To what extent does providing multiple criteria for identification relate to Black, Hispanic, and Native American student representation in gifted programs in public schools in Indiana?

RQ4: To what extent does the time of identification relate to Black, Hispanic, and Native American student representation in gifted programs in public schools in Washington?

RQ5: To what extent does the rurality relate to Black, Hispanic, and Native American student representation in gifted programs in public schools in Florida, Indiana, and Washington?

CHAPTER 2. FLORIDA INTRODUCTION

2.1 Abstract

The state of Florida's efforts to achieve proportional representation in gifted programming were examined to assess underrepresentation. A generalized linear mixed effect model was used to analyze data from the Florida Department of Education containing information from the 2011-2016 academic years. Achieving proportional representation of all students in gifted programming is a persistent goal within gifted education research. Black, Latinx, and Native American students are consistently underrepresented in gifted programming. The state of Florida's efforts to achieve proportional representation in gifted programming were examined to assess underrepresentation. A multi-level model was used to analyze data from the Florida Department of Education containing information from the 2011-2016 academic years. The likelihood of identification of Black students from low SES homes for gifted services was 59% higher than their peers from non-Low SES homes. However, the likelihood of identification for Latinx and Native American students decreased by 47% and 38% respectively.

2.2 Introduction

Proportional representation of culturally, linguistically, and economically diverse students in gifted programs continues to be a critical issue in the field of gifted education. The idea of proportional representation is a simple one. A school district's identified gifted population should be demographically similar to its general population. However, Black, Latinx, and Native Americans are historically underrepresented in gifted programs (Yoon & Gentry, 2009).

The reasons for unequitable representation in gifted programming among Black, Latinx, and Native American students compared to Asian and White students is a longstanding and on-going area of research in gifted education (Daniels, 1998; Erwin & Worrell, 2012; Ford, 2014; Naglieri & Ford, 2003; Stambaugh & Ford, 2015; Yoon & Gentry, 2009). Scholars debate causes that range from identification practices (Erwin & Worrell, 2012) to microaggressions and lack of multicultural policies and practices (Stambaugh & Ford, 2015). Understanding why the proportional gap in representation exists is paramount to developing methods and policies to narrow that gap.

A few studies in gifted education have separated race from other confounding variables such as income status. McBee (2006) examined the identification of elementary students in Georgia by investigating rates of identification for students of different ethnicities while controlling for socioeconomic (SES) status. Warne, Anderson, and Johnson (2013) examined identification rates in Utah for students of different ethnicities while controlling for student achievement. Carman and Taylor (2010) controlled for low SES status with regard to identification rates for gifted services for students identified using the Naglieri Nonverbal Ability Test (NNAT, Naglieri & Ford, 2003). The lack of studies examining race while controlling for confounding variables remains a critical gap in the field of gifted education. Further, these studies represent cross sectional samples of students and do not examine long-term trends in identification rates.

Florida is an ideal state to examine how the ethnic and SES status of a student influences the likelihood of gifted identification. With the majority of its student population (57.8%) coming from traditionally underidentified ethnic populations for gifted services (Black, Latinx, Native American), underrepresentation has been an issue in Florida. Not only this, the state of

Florida's education code contains mandated provisions explicitly for the purpose of identifying students from traditionally underrepresented groups for gifted services. As such, examining the rates of identification in a state with a highly diverse student population coupled with legislative mandates pertaining to identification can provide insight into how SES status and race interact to influence a child's likelihood of identification.

2.3 Purpose

This study addresses a gap in literature by examining gifted identification rates among underserved groups in the state of Florida. Longitudinal analysis of identification rates for gifted services in Florida public school districts was performed while controlling for race, SES status, and rurality. To examine the possible influences of why Black, Latinx, and Native American students are underrepresented in gifted programs, SES status, and race must be separately analyzed to understand how these variables influence the gap in proportional representation.

2.4 Research Questions

1. To what extent are Black, Latinx, and Native American students underrepresented in gifted programs in the state of Florida in comparison to their Asian and White peers from the 2011-2012 through the 2015-2016 academic years?
2. To what extent are gifted identification rates influenced by race when conditioning for SES status in the state of Florida from the 2011-2012 through the 2015-2016 academic years?
3. To what extent does rurality moderate how ethnicity interacts with SES status in terms of identification rates for gifted services from the 2011-2012 through the 2015-2016 academic years?

CHAPTER 3. FLORIDA LITERATURE REVIEW

3.1 Underrepresentation

Equitable representation of Black, Latinx, and Native American children in gifted programs and services is a critical issue within the field of gifted education (Daniels, 1998; Donovan & Cross, 2002; Erwin & Worrell, 2012; Ford, 2014; Konstantopoulos, Modi, & Hedges, 2001; Naglieri & Ford, 2003; Stambaugh & Ford, 2015; Yoon & Gentry, 2009). Scholars have stated that the causes for identification are due to inherent biases in testing (Naglieri & Ford, 2003), cultural bias towards underrepresented groups (Gentry, Fugate, Wu, & Castellano, 2014; Stambaugh & Ford, 2015), or due to issues stemming from academic achievement rather than race (Erwin & Worrell, 2012).

Gifted education researchers have noted progress toward proportional identification of underrepresented population for gifted services. Donovon and Cross (2002) noted that rates of proportional identification have increased for Black, Latinx, and Native American students through the latter quarter of the 20th century following legislative initiatives by the United States Department of Education and the Office of Civil Rights. Despite this, these students still are largely underrepresented in gifted education programs (Yoon & Gentry, 2009). Using the National Education Longitudinal Study of 1988, Konstantopoulos et al. (2001) examined the rates of identification for Black, Latinx, and Native American students for gifted services in public schools across the United States. To quantify rates of identification, the authors used the odds ratio. An odds ratio is the proportion of students identified for gifted services in comparison to the proportion from another group. The authors discovered that, compared to their Asian and White peers, Black

(*OR* = 0.37), Latinx (*OR* = 0.45), and Native American students (*OR*= 0.17) were all identified at lower rates.

Yoon and Gentry (2009) used the Elementary and Secondary School Survey data and Civil Rights Data Collection of the Office for Civil Rights (OCR) to examine identification rates by race of students for gifted services across the United States. Yoon and Gentry disaggregated the data by states to assess proportional identification by state. The authors found that Asian students were overrepresented in 41 of 50 states; whereas, White students were overrepresented in 26 states. In contrast, Native Americans were underrepresented in 27 states, Latinx students in 43 and Black students in 42 states.

Gentry et al. (2014) called for research in their examinations of three Native American nations. The authors worked with Diné, Ojibwe, and Lakota tribe members to assess cultural barriers to inclusion for Native youth in gifted programs. Gentry et al. (2014) identified issues of communication style, talent development, learning preferences, and cultural differences as barriers to identification and services among these youths. The authors noted that these factors were in addition to those of race, poverty, and rurality.

Like Native American students, Latinx are historically underrepresented in gifted programming (Esquierdo & Arrequin-Anderson, 2012; Yoon & Gentry, 2009). In addition, Latinx represents one of the fastest growing student populations in the nation (Brown & Lopez, 2013). Esquierdo and Arrequin-Anderson (2012), in their examination of gifted identification in the state of Texas, found that Latinx children were underidentified compared to White students. The authors argued that despite the inclusive definition of giftedness used by the state of Texas, lack of awareness of differences in the manifestation of talent among Latinx students by their teachers was one of the primary causes for the underidentification of Latinx students for gifted programs.

Black students have been historically underrepresented in gifted programs (Yoon & Gentry, 2009). Although identification of Latinx students has increased within the last decade (Esquierdo & Arrequin-Anderson, 2012), identification rates of Black students continues to be an issue for concern (Stambaugh & Ford, 2015). Researchers have developed alternative means of identification for gifted services to address the lack of proportional identification of Black students (Lohman, 2011; Naglieri & Ford, 2003; Raven, 2000). For example, Naglieri and Ford (2003) developed the *Naglieri Nonverbal Achievement Test* (NNAT) to address the authors' concerns that the traditional IQ tests did not accurately identify underrepresented populations due to the verbal nature of traditional IQ tests. Despite the development of novel identification procedures, these methods have not increased identification rates of Black students (Hodges, Tay, & Maeda, 2016).

In contrast, other scholars have posited that race is an uninfluential factor in identification rates when other factors are controlled (Erwin & Worrell, 2012; Warne, Anderson, & Johnson, 2013). Erwin and Worrell (2012) examined race by controlling for achievement. They found that when achievement was taken into account, race was no longer an influencing factor in identification. These results coincided with Warne, Anderson, and Johnson (2013) who examined the rates of identification of underrepresented students in the state of Utah. They found that when achievement on state standardized tests was controlled for, race also did not have a significant effect on identification rates. Both authors cite that the lack of identification is a larger symptom of the achievement gap noted by Plucker, Burroughs, and Song (2010).

3.2 Rural Gifted Education

The U.S. Census does not define rurality as much as it defines urbanized areas. There are varying levels of urbanization with the lowest level being classified as rural (U.S. Census, 2010). In contrast, the Office of Management and Budget defines rurality in terms of population density.

They define a metropolitan area as one with an urban core of 50,000 and a micropolitan core as one with 10,000. An area with less than those thresholds is then defined as rural (Office of management and Budget, 2016).

The definition of rurality that has largely been adopted in education literature is the definition presented by the National Center for Education Statistics (NCES) (Johnson, Showalter, Klein, & Lester, 2014). In 2006, the NCES revised its definitions of rurality to be “urban-centric”. School rurality is defined in three categories: rural fringe, rural distant, and rural remote. The three categories are differentiated by their proximity to urban clusters and how the census defines them. For example, a school in a rural remote locale is one that is in a census defined rural area that is more than 25 miles away from an urban area.

Rural schools can vary in terms of wealth, remoteness, and ethnic composition (Fishman, 2015). These factors directly influence the gifted programs in those schools. Scholars have noted that rural environments can suffer due to lack of funding (Azano, Callahan, Missett, & Brunner, 2014). When schools are funded from property taxes, economically depressed areas have fewer resources or tax revenues from which a school can draw. The remote locations and lower pay can also deter qualified staff trained in meeting the needs of gifted children (Cross & Burney, 2005).

Despite economic shortcomings, scholars have highlighted the strengths of rural areas (Azano et al., 2014; Colangelo, Assouline, & New, 1999; Paul & Seward, 2016). Azano et al. (2014) found that despite rural teachers having access to fewer resources than their non-rural peers, rural teachers’ students did not perform statistically lower than their non-rural peers in tests of achievement. Colangelo et al. (1999, 2001, 2006) provided insight into the strengths of gifted education in three reports on rural gifted education through the Belin-Blank center. This series highlighted the unique strengths and opportunities that rural communities afford their gifted students. The authors noted that community engagement and involvement were effective means of implementing gifted programming in rural communities.

3.2.1 Underrepresentation in Rural Schools

Rural schools have had difficulty identifying Black, Latinx, and Native American students for gifted services (Hébert, 2001; Kettler, Puryear, & Mullet, 2016; Montgomery, 2001; Pendarvis & Wood, 2009). Montgomery (2001) described the efforts of a university to work with Native American high school students who were identified as high ability by the university. The population had been underrepresented in gifted programs in their local school districts. Montgomery determined that the causes for underrepresentation stemmed from lack of authenticity and cultural relevance of the curriculum. In a case study examining one high ability Black student from rural poverty, Hébert (2001) found that causes from non-identification stem from misconceptions about poverty and race. Further, in rural contexts, where people are more connected and aware of other's familial ties, local community knowledge work to the detriment of gifted children from families who are viewed negatively by the community. Pendarvis and Wood (2009) approached the issue of underrepresentation in rural communities from the perspective of professional development. The authors postulated that the primary cause for underrepresentation of Black, Latinx, and Native American students in gifted education in rural schools was due to lack staff development. After providing training in alternative identification to a rural school district, that district saw a 29% increase in identification rates of traditionally underrepresented populations or gifted services. Kettler, Puryear, & Mullet (2016) examined the effect of rurality on ethnicity in terms of funding. The authors found that rural districts with high proportions of Black, Latinx, or Native American students do not fund their gifted programs differently from other rural school districts. The authors assert that this provides evidence that the racial demographics of a rural school do not have a meaningful effect on administrative decisions in terms of funding and resources.

3.2.2 Florida Rurality

Florida contains some of the densest population centers in the United States (U.S. Census, 2010). For example, Miami-Dade County has a population of 2,662,874. In contrast, Liberty County, in the Florida Panhandle, has a population of 8,365. Of Florida's 67 counties, 27 of them are classified as rural (U.S. Census, 2010). These counties are in two areas in the state. One rural center is within the Florida Panhandle, which is in the northwest portion of the state. The other rural center is located around the Everglades in the central and southern central portion of the state.

3.3 Gifted Education in Florida

Florida has 74 school districts. This number is comprised of one school district per each of the 67 counties in the state, the four research universities (Florida A&M University, Florida Atlantic University, Florida State University, and the University of Florida) each maintain a school district; a school district for children who are blind and/or deaf, a virtual school campus and a youth detention center (Florida Department of Education, 2016). In total, 2,626,008 students are enrolled in the Florida public school systems. Of these students, educators have identified 165,495 students as gifted and talented representing 6.3% of the state's public school population (Department of Education, 2016).

The state legislators have defined gifted as a child who "has superior intellectual development and is capable of high performance" (Florida Department of Education, 2016). Florida has a dual system for identification. First is an IQ based identification system in which a child must demonstrate intellectual ability two standard deviations above the mean (IQ = 130). Second is “Plan B” with specific provisions for underrepresented groups within a district. The “Plan B” identification system is determined by the district. Each district must assess identification measures or processes to use to identify underrepresented students for gifted services (Florida Department of Education, 2016). Issues of underrepresentation in Florida public school systems for gifted services were first formally acknowledged in 1983 when the Office of Civil Rights issued an inquiry into the identification practices (Florida Department of Education, 2016). Following the inquiry, the Florida Department of Education developed a new policy for identifying underrepresented populations that they entitled “Plan B” in 1991 (Florida Department of Education, 2016). Under this plan, school districts must have a second identification procedure in place for student groups labeled as underrepresented by the state. The groups initially labeled as underrepresented were Black, Latinx, and Native American. This was revised in 2002 to include students learning English as second language and students from low SES families (Florida Department of Education, 2016).

CHAPTER 4. FLORIDA METHODS

4.1 Sample

The dataset used in this study was acquired from the Accountability and Reporting department of the Florida Department of Education (Florida Department of Education [FDOE] Education Statistics, 2017). Florida annually requires that all 74 school districts report the student demographics and testing results to the Accountability and Reporting department. The FDOE publishes annual aggregate reports for the public and state legislature. This dataset was specifically obtained via public access through the PK-20 Education Information Portal (FDOE Education Statistics, 2017). The PK-20 Education Information Portal includes reports on general enrollment by school district, fine arts enrollment by school district, and graduation rates by school district. In the case of this analysis, the report on general enrollment by school district was used with the unit of analysis being the school district.

The general enrollment by school district report data set included information on total enrollment by student SES status, student race, English language learner status, gifted identification status, grade, gender, and disability status. Further, Florida mandates reporting of gifted students by race and SES status rather than by race or SES status as is the case in some other states. These data are aggregated at the district level rather than school level.

The data set used in this analysis encompassed five academic school years (2011-2012 to 2015-2016) and used the variables SES status, race, gifted education identification, and school district. An additional variable designating rurality as denoted by the National Center for Education Statistics was added to the dataset.

The dataset included all school districts in Florida from the academic school years 2011-2012 through 2015-2016 (n = 74). Three school districts were eliminated from analysis using listwise deletion because they reported no identified gifted students. Since the dependent variable in this study is a ratio, division by zero will yield an undefined result making the observation unsuitable for analysis. The final dataset contained 71 school districts over five years with 355 observations for all variables.

4.2 Variables

Given that rates of identification are being examined, an odds ratio is an appropriate statistic to test in the analysis (Bland & Atman, 2000). An odds ratio can be defined as the ratio of the proportion of a group identified as having and not having trait *x* with the proportion of another group identified as having and not having trait *x* (Bland & Atman, 2000). Since the purpose of the study is to examine rates of identification when race and SES status are controlled, an odds ratio was calculated while conditioning for non-low SES status:

$$OR_{T,N} = \left(\frac{p(\text{gifted}|\text{B/L/N HSES})_{T,N}}{1 - p(\text{gifted}|\text{B/L/N HSES})_{T,N}}\right)\left(\frac{1 - p(\text{gifted}|\text{A/W HSES})_{T,N}}{p(\text{gifted}|\text{A/W HSES})_{T,N}}\right)$$

Where *T* indexes time points and *N* represents districts. The notation B/L/N HSES refers to Black, Latinx, and Native American Students who are not from Low SES households and W/A HSES to Asian and White students who are not from Low SES household.

Finally, a second odds ratio was calculated for students who are designated as being from low SES households:

$$OR_{T,N} = \left(\frac{p(\text{gifted}|\text{B/L/N LSES})_{T,N}}{1 - p(\text{gifted}|\text{B/L/N LSES})_{T,N}}\right)\left(\frac{1 - p(\text{gifted}|\text{A/W LSES})_{T,N}}{p(\text{gifted}|\text{A/W LSES})_{T,N}}\right)$$

Where *T* indexes time points and *N* represents districts. The notation B/L/N LSES refers to Black, Latinx, and Native American Students who are from Low SES households and W/A LSES to Asian and White students who are from Low SES household.

Finally, this odds ratio strategy was repeated for Black, Latinx, and Native American students separately. In total, there were 8 odds ratios calculated for each school district for a given year. Two for the aggregated odds ratio for underrepresented students, two for Black students, two for Latinx students, and two for Native American students.

4.2.1 Weighting Procedure

To accurately model the phenomena using regression, a weighting procedure was used. Analytic weights were used as suggested by Dupraz (2013). When using analytical weights, each school district is weighted by the total number of students in that district in a given year. For example, in 2011, Dade County School District had 314,183 students enrolled. In contrast, Glade County School District had 1,490 students enrolled. The weight associated with the odds ratio for Dade County School District in 2011 would be 314,183 and for Kittitas School District it would be 1,490.

For ethnicity specific dependent variables, an analytic weight was calculated based on the total number of students in that district of a given ethnicity in a given year. For example, in 2011, Dade County School District had 53,433 Hispanic students enrolled, 12,040 Black students and 96 Native Americans. Its corresponding analytic weight would be 53,433 for Hispanic students, 12,040 for Black students and 96 for Native Americans.

4.2.2 Predictors

One set of predictors and the time variable were examined for their effect on the dependent variable in the model. The first predictor was socioeconomic status. The second predictor was rurality.

4.2.2.1 Socioeconomic Status

A binary variable was constructed to describe the SES status associated with the population in each odds ratio. This variable was coded as 1 or 0 where 1 indicated that the odds ratio was associated with Low SES status and 0 indicated that it was not. The low SES indicator was associated with odds ratios that only included students who were designated as being from low SES households. Using this strategy, odds ratios calculated from students from non-low SES households would be the reference group in the regression. In this way, in the regression, the beta coefficient derived from the binary indicator variables is the log mean difference between the odds ratio calculated using the formula for the odds ratio describing students from low SES households and the associated odds ratio for non-low SES.

4.2.2.2 Rurality

A binary variable was created to designate a given odds ratio as being associated with a school from a rural district. The rural designation was derived from the codes assigned to the district from the National Center for Education Statistics (NCES). The NCES locale designations describe rurality in terms of distance from an urban population center and census designation (2016).

4.2.2.3 Wave

A time variable was created to describe the academic school years. Time was reverse coded such that the academic school year 2011-2012 was coded as -4, 2012-2013 as -3, 2013-2014 as -2, 2014-2015 as -1, and 2015-2016 as 0.

4.2.3 Dependence

The model contained two sources of dependence. The first was that a school district was sampled multiple times. The second is that a set of odds ratios were calculated from a single school district in a single year.

4.2.3.1 District

Repeated measures of odds ratios over time were nested under school districts. This variable accounts for that source of dependence. This variable was coded as the unique identification number associated with a school district.

4.2.3.2 Annual District

Repeated measures of odds ratios were calculated from a single district in a single year. For example, two odds ratios are calculated in each school district in any given year. This variable was coded by using the identification number associated with the district cross referenced with the given year. For example, a given district might be coded as district1. For the year 2011, its code would be district12011. In this case, twoodds ratios would be assigned this code (one for the low SES odds ratio and the non-low SES odds ratio).

4.1 Analysis

Due to the fact that the set of odds ratio used in analysis was extracted from a school district, these odds ratios were not independent from each other. In this case, generalized linear mixed effect model is an appropriate analysis (Faraway, 2014). The data set included repeated measures over time (the odds ratio), which lead to biased estimates if those estimates were not adjusted for lack of independence between observations.

4.3.1 Model Testing

Because the model contains repeated measures of odds ratios over time a multi-level model (MLM) is appropriate. The following model was used in this analysis:

$$Y_{ti} = \alpha + \beta_1(low\ SES\ \ status_i) + \beta_2(rural_i) + \beta_3(wave_t) + \beta_4(low\ SES\ \ status_i)(wave_t) + \beta_5(rural_i)(wave_t) + \beta_6(low\ SES\ \ status_i)(rural_i) + [u_{00i} + u_{000i} + u_{1i}(\ wave_{ti})] + e_{tij}$$

Where Y_{ti} is a log odds ratio of identification for school district *i* in year *t* and α indicates the intercept. $\beta_1(low\ SES\ \ status_i)$ is a binary variable indicating an odds ratios for school district *i* that was calculated from children from low SES households. The variable $\beta_2(rural_i)$ is a binary variable indicating if school district *i* is in a rural designated county. $\beta_3(wave_t)$ is the time variable. u_{00i} represents the random intercept school district *i* and u_{000i} represents the random slope for repeated measures of odds ratios within school district *i* in year *t*. Further, $u_{1i}(\ wave_{ti})$ represents the random effect of the time variable on slope. Finally, due to a reduced number of degrees of freedom for sub analyses for Black, Latinx, and Native American students, the random intercept for school district and random slope for *wave* were uncorrelated.

A Wald *t* was used as the test statistic in the analysis as suggested by Faraway (2014). Since the regression model incorporates fixed and random effects, a more parametric test statistic is inappropriate (Faraway, 2014). To calculate the degrees of freedom in the error for the Wald *t*, Farway (2014) suggested the use of a Satterthwaite approximation. Finally, Xu (2003) noted that using traditional effect size calculations for multi-level models can lead to over optimistic effect sizes. The authors suggested the use of a modified coefficient of determination called Ω^2 (2003). This coefficient of determination was used in all effect size calculations reported in the analysis.

4.3.2 Assumptions

Linear regression assumes a linear relationship between the predictors and outcome, equal variance of errors, independence of residuals, and that the residuals are normally distributed (Seber & Lee, 2012). The use of an odds ratio as a response variable will lead to a violation of normality. In this case, Faraway (2014) suggested the use a log transformation of the response variable serves to address issues of normality.

Further, since the model incorporates repeated measures (multiple years), independence of residuals was violated. As such, a multi-level model (MLM) must be used (Faraway, 2014). Finally, the assumption of constant variance of fixed and random effects was addressed by analyzing residual plots.

CHAPTER 5. FLORIDA RESULTS

5.1 Demographics

During the time frame of this study, total enrollment increased from 2,443,674 to 2,533,505. Asian student enrollment increased from 59,443 to 63,488. Black student enrollment increased from 598,457 to 612,813. Latinx enrollment increased from 724,312 to 834,189. Native American enrollment decreased from 9336 to 8521. Finally, White student enrollment decreased from 1,052,126 to 1,0114494. See Figure 1.

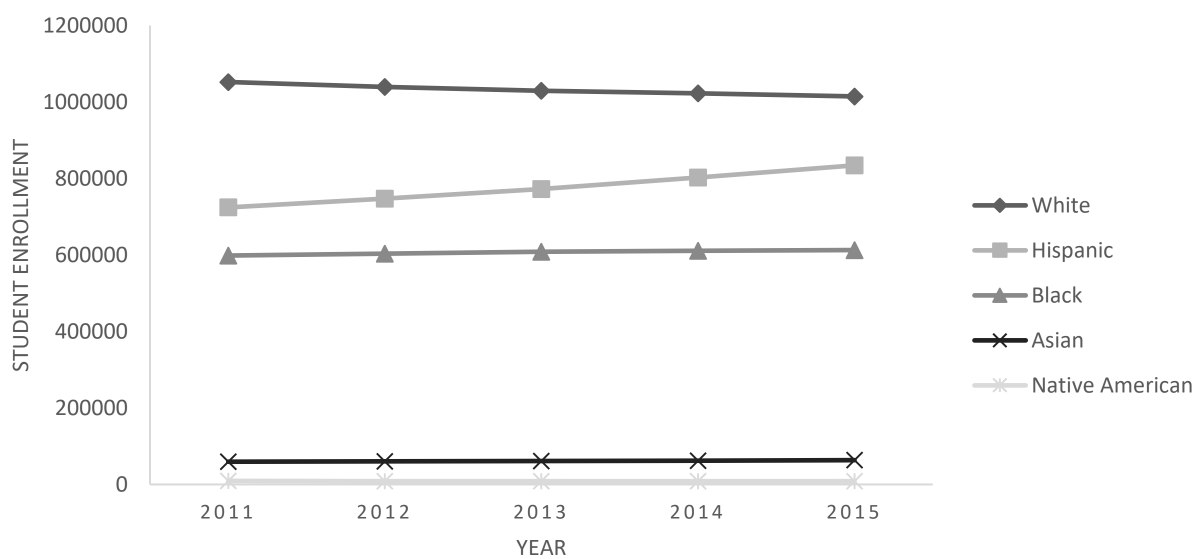

Figure 1. Enrollment by race in Florida public schools from the 2011-2012 to 2015-2016 academic school years.

During the timeframe of the study, the percentage of students identified for gifted services averaged 5.71% or 150,365 students. Students from lower socioeconomic households were identified at lower rates than students from non-lower socioeconomic households. Students from all socioeconomic backgrounds and ethnicities were identified at higher rates during the timeframe apart from Native American students from low socioeconomic households. See Figures 2 and 3.

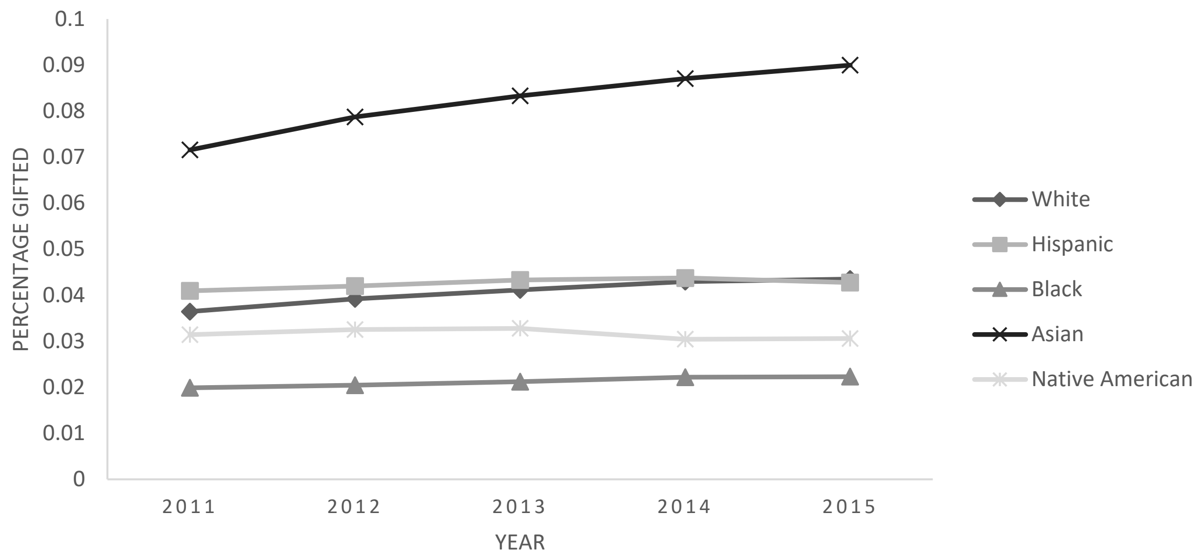

Figure 2. Identification rates by race for gifted services for students from low SES households in Florida public schools from the 2011-2012 to 2015-2016 academic school years.

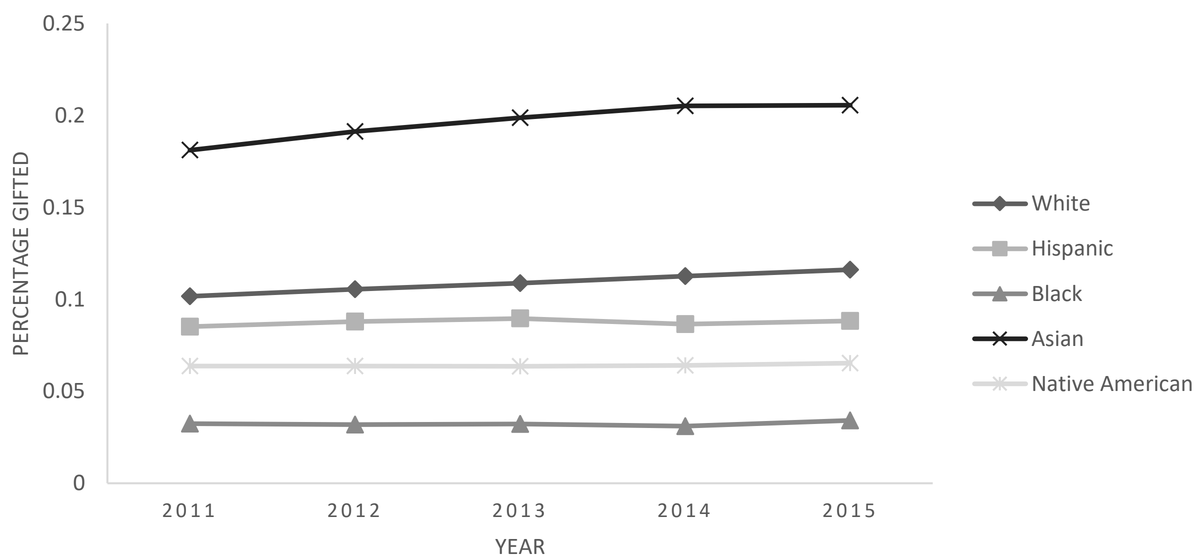

Figure 3. Identification rates by race for gifted services for students from non-low SES households in Florida public schools from the 2011-2012 to 2015-2016 academic school years.

The overall likelihood for identification for gifted services for Black, Latinx, and Native American students was less than half that for Asian and White students (OR = 0.484). The likelihood of identification decreased from the 2011-2012 school year (OR = 0.497) to the 2015-2016 school year (OR = 0.472). A small note to readers on the interpretation of odds ratios: an odds ratio of 1 equates to equal representation. An odds ratio of 2 equates to the group of interest being twice as represented as the reference group. An odds ratio of .5 equates to the group of interest being only half as represented as the reference group. In this case, an OR of .484 means that Black, Latinx, and Native American students are represented at 48.4% of the rate that Asian and White students are. For example, if Asian and White students are represented at a rate of 10 for everyone 100 students, that means that Black, Latinx, and Native American students are represented at a rate of 5.37 for everyone 100 students. Since the odds of identification for Asian and White students is 10 to 90, then 48.4% of that is 5.37 to 94.63.

In contrast to the overall identification rate for underrepresented students, Black students in the state of Florida are only identified at about a quarter the rate of Asian and White students (OR = 0.277). The odds ratio identification rates for Black students decreased from 0.284 to 0.276 between 2011 and 2016. The odds ratio identification rates for Latinx students decreased during this time frame, falling from 0.672 to 0.617. The Latinx students (OR = 0.645) were identified at nearly two thirds the rate compared to Asian and White students. Finally, Native American students were being identified at a rate of 0.529. This is only over half the rate of identification for their Asian and White peers. Identification rates for Native American students also declined from 0.564 to 0.498. It should be noted that between the 2011-2012 school year and 2015-2016 school year the overall Black and Latinx student populations increased, while the Native American student populations declined. For full descriptive statistics, see Table 1.

Table 1
Descriptive statistics about Florida's student population from 2011 - 2016

Student Group	School Year	*n*	*OR*
Underrepresented	2011-2012	1,384,522	0.497
	2012-2013	1,414,866	0.487
	2013-2014	1449,786	0.485
	2014-2015	1,482,022	0.478
	2015-2016	1,517,604	0.472
Black	2011-2012	611,929	0.284
	2012-2013	617,467	0.276
	2013-2014	625,567	0.274
	2014-2015	625,769	0.275
	2015-2016	628,066	0.276
Latinx	2011-2012	762,840	0.672
	2012-2013	788,084	0.656
	2013-2014	815,239	0.650
	2014-2015	847,423	0.633
	2015-2016	880,634	0.617
Native American	2011-2012	9,753	0.564
	2012-2013	9,315	0.548
	2013-2014	8,980	0.532
	2014-2015	8,830	0.506
	2015-2016	8,904	0.498

5.2 Model Diagnostics and Fit

An examination of the intraclass correlation (ICC) provided evidence that observations were clustered under *district* (*ICC* = .581) and *annual district* (*ICC* = .554). Again, *district* denotes the repeated measures over time and *annual district* denotes the repeated measures within a single year. Residual plots provided evidence that constant variance was maintained for fixed and random effects. An examination of the QQ-plot provided evidence that a linking function was necessary. After transformation of the dependent variable, normality was achieved.

In modeling best fit, I discovered that the best fitting model was one with a linear relationship with time (Bayesian Information Criterion [*BIC*] = 1258.72) and not with a non-linear relationship (*BIC* = 1269.30).

5.3 Regression Results

The reported beta coefficients have been exponentiated to provide clear interpretations of effects. In a model that analyzes odds ratios, a one-unit increase in a coefficient correlates to an increase in the log odds ratios (Faraway, 2014). For this reason, the coefficients reported have all been transformed and will be written as exp(β) to remind readers of the transformation. The transformation was done for ease of interpretation by the reader. This transforms the scale from log odds ratios to odds ratios.

5.3.1 Underrepresentation

The likelihood of being identified as gifted for underrepresented students from low SES households is not significantly different from their peers in non-low SES households (exp(β) = 0.955, p = .457). Further, traditionally underrepresented students from rural school districts were less likely to be proportionately identified than their non-rural peers (exp(β) = 0.848, p = .017). Proportion of variance explained by the model was 65.55%. Full results can be seen in Table 2.

Table 2
Regression results for all students

Fixed Effects	Exp(β)	*SE*	*T*	*p*
Intercept	0.493	0.086	8.191	< .001*
Low SES	0.955	0.061	0.743	.457
Year	0.996	0.020	-0.210	.833
Rural	0.848	0.069	2.378	.017*
Low SES * Year	0.967	0.019	1.740	.082
Year * Rural	0.986	0.021	0.644	.520
Low SES * Rural	0.865	0.079	0.629	.530

Random Effects	Variance	*SD*	*Corr*
District	0.330	0.574	
Year	0.004	0.062	-.530
Residual	0.003	0.058	

Note. * *p* < .05

5.3.2 Black Students

For Black students rates of proportional identification for Black students from low SES households increased was 59% (exp(β) = 1.594, p < .001) greater compared to their Black peers from non-low SES households. This means that the odds ratio for identification of Black students is 59% greater than the odds ratio of 0.286 for Black students from non-low SES households. Though it should be noted that this translates into an odds ratio of 0.456. Black students from non-low SES households in rural areas were not identified differently than their non-rural peers overall (exp(β) = 1.139, p = .701). This was not the case for Black students from low SES households in rural areas (exp(β) = 0.549, p < .001). Proportion of variance explained by the model was 28.99%. Full results can be seen in Table 3.

Table 3

Regression results for Black students only

Fixed Effects	Exp(β)	*SE*	*T*	*p*
Intercept	0.286	0.086	14.550	< .001*
Low SES	1.593	0.086	5.414	< .001*
Year	1.000	0.023	0.015	.988
Rural	1.139	0.126	1.031	.302
Low SES * Year	1.022	0.032	0.688	.491
Year * Rural	1.014	0.033	0.423	.672
Low SES * Rural	0.549	0.091	6.610	< .001*

Random Effects	Variance	*SD*	*Corr*
District	0.085	0.292	
Year	< 0.001	0.001	
Residual	0.008	0.091	

*Note. * p < .05*

5.3.3 Latinx Students

In contrast to Black students, the rates of proportional identification for Latinx students from low SES households decreased by 47% (exp(β) = 0.532, p < .001) when compared to their peers from non-low SES households. Similar to Black students, there was no statistically significant change in identification rates for Latinx students from non-low SES households in rural school districts when compared to their non-rural peers (exp(β) = 1.122, p = .300). Conversely, a time interaction was a significant predictor. The rates of proportional identification for Latinx students from low SES households increased by 10% each year during the period of the analysis (exp(β) = 1.100, p < .001). Proportion of variance explained by the model was 43.12%. Full results can be seen in Table 4.

Table 4
Regression results for Latinx students only

Fixed Effects	Exp(β)	*SE*	*T*	*p*
Intercept	0.655	0.076	5.547	< .001*
Low SES	0.532	0.077	8.252	< .001*
Year	0.956	0.023	1.957	.050
Rural	1.122	0.111	1.037	.300
Low SES * Year	1.100	0.028	3.384	< .001*
Year * Rural	1.003	0.029	0.092	.927
Low SES * Rural	0.817	0.082	2.475	.013

Random Effects	Variance	*SD*	*Corr*	
District	0.067	0.260		
Year	< 0.001	0.001		
Residual	0.007	0.081		

Note. * $p < .05$

5.3.4 Native American Students

The rates of proportional identification for Native American students from low SES households decreased by 38% (exp(β) = 0.624, p < .001) when compared to their peers from non-low SES households. Similar to the other demographic groups, there was no statistically significant change in identification rates for Native American students from non-low SES households in rural school districts when compared to their non-rural peers (exp(β) = 1.212, p = .504). There was no statistical difference between Native American students for low SES households in rural school districts and their non-rural peers (exp(β) = 1.151, p = .821). Proportion of variance explained by the model was 21.01%. Full results can be seen in Table 5.

Table 5
Regression results for Native American students only

Fixed Effects	Exp(β)	*SE*	*T*	*p*
Intercept	0.778	0.110	2.290	.022*
Low SES	0.624	0.130	3.616	< .001*
Year	0.978	0.037	0.610	.542
Rural	1.212	0.288	0.668	.504
Low SES * Year	1.065	0.053	1.186	.236
Year * Rural	1.204	0.094	1.969	.049*
Low SES * Rural	1.151	0.622	0.226	.821

Random Effects	Variance	*SD*	*Corr*
District	0.084	0.290	
Year	0.001	0.025	
Residual	0.012	0.112	

Note. * *p* < .05

CHAPTER 6. FLORIDA DISCUSSION

6.1 Research Question One

With regard to research question one: *To what extent are Black, Latinx, and Native American students underrepresented in gifted programs in the state of Florida in comparison to their Asian and White peers between the years 2011 and 2016?* The overall rate of identification for the combined underrepresented populations is only half of that compared to their Asian and White peers. This coincides with the results of numerous researchers who have noted similar trends across the United States (Esquierdo & Arrequin-Anderson, 2012; Konstantopoulos et al. 2001; Stambaugh & Ford, 2015; Yoon & Gentry, 2009).

As reported by Yoon and Gentry (2009), Florida is no exception to the national norm of underrepresentation of Black, Latinx, and Native American students for gifted services in K-12 public schools. The authors noted that Black and Latinx children were identified at a lower rate than their Asian and White peers; whereas, Native Americans were proportionately identified in the state of Florida. Yoon and Gentry used a representation index (proportion of students of a given race in the gifted program over the proportion of students in the general population) to quantify representation in gifted programs. The authors noted that Black students were identified at one-third the rate of White students and only a quarter of the rate of Asian students. This likelihood of identification from Yoon and Gentry (2009) closely aligns with the findings of this study.

However, the findings for the rate of identification for Native American students in this study did not align with the findings of Yoon and Gentry (2009). In Florida, Native American students were identified at a lower rate than what the Office of Civil Rights data indicated under the Yoon and Gentry study. Yoon and Gentry (2009) indicated a representation index for Native American students of nearly 1. This would suggest an odds ratio of over 0.8. This index is higher than the one reported in this study (0.529). The results from this paper provide evidence that they were only identified at half the rate of Asian and White students. Native Americans are the smallest of the three populations analyzed (Black, Latinx, and Native American students). A possible cause for differences between estimation of representation reported by Yoon and Gentry (2009) when using the Office of Civil Rights data and this study that used data from the Florida Department of Education is the estimation procedures on a small population. When a population is small, a misspecification can lead to a biased result (Faraway, 2014). Further another explanation is that the data used in this study is a direct temporal extension of Yoon and Gentry (2009). The dataset used by the authors was from 2006 at the latest. Given this, it is likely that some of the difference between the results is due to the time in which data from Florida was analyzed.

In comparison to the national averages presented by Konstantopoulos et al. (2001), Florida has improved rates of identification for Latinx students and improved rates of identification for Native American children from non-low SES households. Similar to the findings by Yoon and Gentry (2009), Florida has a lower rate of identification for the Black student population. Konstantopoulos et al. found a national odds ratio average for Black students to be 0.37. With an odds ratio of identification of only 0.277, Florida educators continue to struggle to identify Black students despite the legislative mandates and provisions issued by the state.

Another finding was that time was a significant predictor in only one model. This provides strong evidence that identification rates for underrepresented population were stable during the time frame of this study. With the exception of Latinx students from low SES households, there was no year to year change in proportional identification. In other words, the adoption of "Plan B" by the state of Florida has not led to the closing of the excellence gap observed by Plucker et al. (2010). Further, the effect from the policy adoption has plateaued. This demonstrates that closing gaps in excellence cannot be addressed solely through legislative mandates aimed at identification.

6.2 Research Question Two

With regard to research question two: *To what extent are gifted identification rates influenced by race when conditioning for SES status in the state of Florida from the 2011-2012 through the 2015-2016 academic years?* The results from this study provide evidence that the interaction between race and socioeconomic status is not uniform across Black, Latinx, and Native American students. Further, the results of this study extend those of Erwin and Worrell (2012) and Warne, Anderson, and Johnson (2013). In both studies, the authors controlled for one factor while examining the effect of ethnicity on identification and found that ethnicity was not significant a determinant in identification for gifted services. Both groups of researchers found that ethnicity was not a significant predictor when achievement was controlled for. However, the data from Florida revealed that when conditioning on SES status the representation gap between Black, Latinx, and Native American children and their Asian and White peers was not eliminated. In other words, based on Erwin and Worrell (2012) and Warne, Anderson, and Johnson (2013) studies, if a Black, Latinx, or Native American child and an Asian or White child achieve on similar levels, they are equally likely to be identified for gifted services. However, this study provides evidence that if a Black, Latinx, or Native American is from a low SES household, the odds for identification for gifted services is lower when compared to an Asian or White child from a similar economic background.

Stambaugh and Ford (2015) and Esquierdo and Arrequin-Anderson (2012) noted that race was still consequential in determining whether a child would be identified for gifted services. Stambaugh and Ford (2105) speculated that microaggressions and inherent biases led to underidentification of Black students. It should be noted, that even when SES status was conditioned on, and despite seeing some increase in identification rates, Black students were still more underrepresented compared to all other ethnic groups within the state of Florida. When conditioning on SES status, Black students from low SES households are only identified at 45% of the rate of their Asian and White peers from low SES households. Also, Black students who are not from low SES households are identified at only 29% of the rate of their Asian and White peers from similar SES households. This means that affluent school districts within the state are having similar issues identifying Black students compared to school districts with large populations of students from low SES families. Although this does not directly confirm Stambaugh and Ford's assertions (2015), the results provide evidence that underrepresentation of Black children stems from causing beyond socioeconomic factors.

Of all student populations, Latinx students from non-low SES households are most favorably identified (0.66) when compared with their similar economic status Asian and White peers. However, Latinx students from low SES homes are identified at a much lower rate than their peers from non-low SES homes (0.35). This finding corroborates Esquierdo and Arrequin-Anderson (2012) who advised caution to states with large Latinx student populations and issues of under identification. Despite a rate of identification equal to nearly 0.62 during the five-year time frame in comparison to that of Asian and White students, when conditioning on socioeconomic status, the rate of identification for Latinx students from low SES homes falls to nearly 0.35. It should be noted, though, that during the time frame analyzed in the study, the likelihood of proportional identification increased by 10% per year for Latinx students from low SES households. Though a 10% increase on an odds ratio of .35 equates to a nearly 20 year time frame to achieve proportional rates of identification.

In the case of Native American students, the effect of race when conditioning on SES status, the result is disconcerting. Although the identification rates were still greater than what Konstantopoulos et al. (2001) reported, it is alarming to note that conditioning for SES only shows the disparity in likelihood of identification for Native youth and Latinx students from low SES-homes. In other words, when you condition on socioeconomic status for these students, their likelihood of identification is lower. This finding aligns with the observations of Gentry et al. (2014) with regard to Native American students. The authors in that study found the factors of race and culture influenced how these students interacted with gifted programs, even when poverty and rurality were considered.

6.3 Research Question Three

With regard to research question three*: To what extent does rurality moderate how race interacts with socioeconomic status in terms of identification rates for gifted services between the academic years 2011-2012 and 2015-2016?* The addition of the SES status provided more clarity to the relationship between rurality and race. The results of this study indicate that the relationship between the rurality and race are nuanced. In terms of the aggregated odds ratio for underrepresentation, there is a general decrease in the rates of identification when SES status is conditioned on. Black, Latinx, and Native American students from non-low SES homes, when compared to their Asian and White peers from similar homes, are identified at 16% lower rates when examined in aggregate.

Further, in the case of Black students, the effect of rurality and SES status is more complicated. For Black students living in rural areas, SES status did not have a uniform effect. Black students from non-low SES homes identification rates did not differ between rural and non-rural students; whereas, Black students from low SES homes were identified at lower rates in rural settings. In other words, if you are a Black student from a low socioeconomic home in a rural school district then you are less likely to be identified as gifted than a Black student from a low socioeconomic home not from a rural school district. Hébert (2001) described the stigma and ostracizing that gifted Black student faced in rural Alabama. In his case study, teachers and the principal characterized a boy from a low SES household with stereotypes associated with rural Black poverty rather than the child's individual abilities.

Where Hébert noted the child's creativity and intellect, his teachers saw only a penchant for causing trouble. The perception of Hébert's (2001) work is a case study of a single child, but it provided a powerful lens into the life of gifted Black children living in rural poverty. The results from this study provide quantitative evidence corroborating themes from Hébert's qualitative study. In Florida, Black students are the least likely to be identified as gifted. A Black student going to school in a rural county, from a low SES household, that likelihood is further decreased.

Like Black students, Latinx students from a non-low SES household has an increased likelihood of being identified for gifted services in rural schools. Since Latinx students were identified at higher rates than Black students, even though their likelihood of identified increased by the same amount, being from a non-low SES household has a bigger effect on Latinx students than for Black students. In other words, a 27% increase from an odds ratio of 0.67 for Latinx students is a greater increase for an odds ratio of 0.22 for Black students.

For Native American students, there was no effect of rurality in conjunction with SES status on likelihood of identification for gifted services. This provides evidence that the, for Native American students, the overall causes of underrepresentation are independent from rurality. Montgomery (2001) observed that the causes for underrepresentation were due to cultural misunderstanding and lack of awareness. The results from this study did not provide evidence to support the Montgomery's (2001) observation, but they can at least extend the findings by providing evidence that rurality is not related to underrepresentation of Native American students in gifted education programs.

Though the main effect results of rurality extend the findings of Kettler et al. (2016), when SES status is controlled for, race becomes a significant factor in how rural gifted programs are structured. This interaction between locale, race, and SES status represents a new finding in the field of gifted education. Further, the intersection between locale, race, and SES status does not have a uniform effect across all three ethnic groups. Though all three ethnic groups are underrepresented in rural communities, the effect of socioeconomic status for Native American students is different from Black and Latinx.

Each area has largely been examined separately by scholars, with the exception of Hébert (2001). The results from this study provide an extension of the literature into an area that has remained unexplored in terms of quantitative analysis. Further, the results demonstrate that the interaction of rurality, socioeconomic status, and race (all considered factors contributing to the excellence gap by Plucker et al. (2010)), is nuanced.

6.4 Limitations

This study is limited to data from Florida. This makes drawing inference for other states inappropriate; but what it does is it provides a model and method that others can use to examine similar data. In both Yoon and Gentry (2009) and Konstantopoulos et al. (2001), the identification rates of underrepresented populations presented in those studies differed from the findings in this study. This is likely due to the distinct makeup of the population of Florida and the laws and policies associated with gifted programming in the state as well as the different time frames examined.

A further limitation is that the district level identification policies were unknown. Florida mandates a two-plan structure for identification but districts have some level of autonomy in enacting this mandate. This is especially true for “Plan B” identification procedures. There is a distinct possibility that a portion of the error variance can be explained by the differences in identification procedures used for "Plan B" across districts.

A statistical limitation should be noted. Although this study reported the odds ratio and controlled for covariance between school and years, there is likely covariance that still exists within the data, which is impossible to control for given the nature of the dataset. The dataset lacked student level data and was only aggregated at the school district level. Thus, true independence of observations is impossible to obtain. As such, inference must be limited or at least approached with caution. It is likely, though, that the results of this study would not greatly change if student level data were incorporated into the formulation of the odds ratios. In part, the use of a multi-level model accounted for this lack of independence.

Finally, there is another issue stemming from data not being aggregated at the student level. There is the possibility that the lack of student level data could create unaccountable noise in the results. For example, a Black child identified as gifted moves from a rural district to a large district (e.g. Miami-Dade). Given the likely fewer black students in the rural district, and the nature of the odds ratio, that student's exit from the district can have a large effect on the odds ratio calculation for the rural district. Conversely, the entrance of the student to the large district would have little effect on the odds ratio. This limitation is partially addressed through the use of weighting.

6.5 Future Research

Two areas immediately lend themselves to future research: replication in other states and extension of the time line examined. The methodological structure utilized in this research can be used to replicate the analysis across other states. This replication will allow researchers to determine if the results that were observed in Florida hold across other states. Further, an extension of the time line analyzed will allow a research to draw stronger conclusions about trends over time.

The results from this study illustrated a need in research in gifted education: the interaction between race and poverty are not uniform across underrepresented student populations. The findings from this research provide evidence that the interaction between race and poverty is nuanced. This suggests that grouping underrepresented populations together might be inappropriate. As such, further studies on the differences between underrepresented populations is appropriate.

CHAPTER 7. FLORIDA CONCLUSION

The results from this study demonstrate that race still matters. Further, results demonstrate that the effects of race are in some cases (Native Americans) magnified when SES status is controlled for. This demonstrates that the construct of race does not behave uniformly with regard to SES status.

Even though Black, Latinx, and Native American students are often clustered together under the label of underrepresented populations, each group is culturally different from the other. It should then come as no surprise that SES status does not have a uniform effect across all three underrepresented student populations.

The public education system in Florida has made provisions during the last 30 years to include a more diverse group of students in its gifted services. The state has revised its gifted education identification policy and adopted a more inclusive definition of giftedness. Despite these efforts, the gap in representation still exists and when examined through the lens of SES status, the gap is actually greater than it first appears. However, the findings of this paper should not dissuade legislators and educators from continuing the work on closing the representation gap. With continued work, the gap in representation can be reduced.

CHAPTER 8. INDIANA INTRODUCTION

8.1 Abstract

Proportional representation exists when a school district's identified population of high ability students is representative of the larger general student population. In other words, the number of Black, Latinx, and Native American students identified for gifted services should be proportional to their representation in the general population. Historically, this has not been the case. This study examines whether Indiana's use of multiple criteria for identification for gifted services has influenced the representation of students from traditionally underserved groups. Aggregated data by school corporation were acquired from the Indiana Department of Education. These data contained information about students identified as "high ability" including their race and how they were identified for gifted services from the academic school years 2006-2007 through 2015-2016. A generalized linear mixed effect model was used as a framework for analysis. Results provided evidence that multiple criteria increased rates of proportional identification in gifted programs by 10% to 20% in comparison to using only intelligence tests across school corporations in the state of Indiana.

8.2 Introduction

Across the United States, Black, Latinx, and Native American students are underrepresented in gifted education programs in public schools (Yoon & Gentry, 2009). The idea that a school district's identified gifted population should be demographically similar to the school district's general population is a simple idea, yet one that has been difficult to achieve within U.S. public schools. This historical lack of identification and the resulting underrepresentation of Black, Latinx, and Native American students in gifted education programs has led to a gap in excellence (Plucker, Hardesty, & Burroughs, 2013). Scholars within the field of gifted education have argued about the underlying mechanisms that cause disproportionality in representation as gifted. In particular, traditional testing measures in including the use of IQ tests and other standardized achievement measures may result in underrepresentation in gifted programming (Lohman, 2011; Naglieri & Ford, 2003; Raven, 2000). However, scholars do not agree about the underlying cause for underrepresentation when using traditional IQ tests.

One remedy that has seen increasing use across the United States to address underrepresentation is the use of multiple criteria for identification as gifted. An option for school districts is to use a battery of measures to assess a student's potential ability to be successful in a gifted education program rather than just a single testing measure for program entrance (e.g. an IQ test) (McBee, Peters, & Waterman, 2014). In other words, the school district could use multiple criteria to assess a student.

The National Association for Gifted Children (2010, [NAGC]) provides an outline of best practices in gifted education. In this set of guidelines, the NAGC states that the use of multiple identification criteria is a best practice in gifted education (NAGC, 2010), which can lead to an identified gifted population that is more representative of the overall general population of a school district. In response to this call to action, states across the U.S. have adopted multiple criteria to identify diverse groups of students for gifted education (Davidson Institute, 2017).

Though scholars and the NAGC have called for school districts to adopt multiple criteria for identification in place of a single measure (Lohman & Renzulli, 2007), research examining the effect of multiple criteria on underrepresentation is limited. McBee (2006) used a multilevel path analysis to examine how different factors (including identification criteria) influenced identification rates based on socioeconomic status and race and found that race significantly influences identification rates when identification method and socioeconomic status are controlled. In a later study, McBee, Peters, and Waterman (2014) examined the issue of multiple criteria using mathematical simulations to show that multiple criteria will identify more students for gifted services. The only state thoroughly examined has been Georgia by McBee (2006). This leaves a tremendous gap in the field since policy and practice vary by state.

The study described here provides evidence concerning how the inclusion of multiple criteria is related to representation of Black, Latinx, and Native American students as gifted in the state of Indiana. Indiana is a suitable state for the purpose of this study for three reasons: Indiana mandates that districts identify students using multiple criteria (Indiana Education Code 20.36.2.2), Indiana has experienced increased levels of diversity throughout the state (U.S. Census Bureau, 2010), and finally Indiana reporting procedure requires school districts to report under which criteria a student was identified as gifted (Administrative Code, Rule 511).

8.3 Purpose

The purpose of the study was to examine the effect of multiple criteria on proportional identification of Black, Latinx, and Native American students for gifted services in the state of Indiana. The NAGC (2010) called for the use of multiple criteria to identify a broader spectrum of students for gifted services. The research presented in this paper examines how the addition of three different pathways (state achievement on mathematics, language arts, and performance-based assessment) influence equitable representation for Black, Latinx, and Native American students in Indiana in rural and non-rural areas.

8.4 Research Questions

1. To what extent did Indiana public schools proportionally identify Black, Latinx, and Native American students for gifted education services during the timeframe from 2006-2007 through 2015-2016?
2. To what extent do multiple identification categories relate to proportional identification of Black, Latinx, and Native American students for gifted education services in Indiana, and how do these proportions compare with Asian and White students?
3. To what extent does rurality moderate proportional identification of Black, Latinx, and Native American students for gifted education services in Indiana?

CHAPTER 9. INDIANA LITERATURE REVIEW

9.1 Testing in Gifted Education

Traditionally, intelligence tests have been used to identify students for gifted services (Pfeiffer & Blei, 2008). School districts assigned a specific cut-off score, and students who achieved above the cut-off are identified as gifted (Lakin & Lohman, 2011; Peters & Gentry, 2012). Pfeiffer (2012) cautioned that the use traditional intelligence tests could result in underrepresentation in gifted programs. Further, intelligence tests inherently lack the context of the test taker's experiences (Peters & Engerrand, 2016). School districts that use national norms as cut-offs are likely to identify few, if any, students in economically depressed locations (Peters & Engerrand, 2016; Peters & Gentry, 2012). Additionally, Erwin and Worrell (2012) pointed out that regardless of perceived biases by researchers, IQ tests measured the constructs that they were intended to measure: verbal and quantitative ability.

In contrast with Erwin and Worrell (2012), Naglieri and Ford (2003) claimed that the reason for underrepresentation was due to the format of the tests. The scholars argued that IQ tests were biased against Black, Latinx, and Native American students since traditional IQ tests incorporate a strong verbal component within testing items. Naglieri and Ford (2003) remarked that the verbal component was culturally biased and assumed a prior verbal ability that could cloud the ability of the item to accurately measure the student's true ability. In response to these concerns, Naglieri and Ford (2003) developed a non-verbal test, the Naglieri Nonverbal Achievement Test (NNAT). The authors claimed that non-verbal tests were free of cultural bias. Lohman, Korb, and Lakin (2008) examined the effects of non-verbal tests and found that the rates of variability were similar to verbal tests. In short, the authors questioned the benefit of adopting non-verbal tests to identify underrepresented student in comparison to traditional IQ tests. Further, Carman and Taylor (2010) examined the performance of the NNAT in a large urban Texas city. The authors found that kindergarteners from low socioeconomic homes scored 11.4 points lower on the NNAT than children from non-low socioeconomic homes. As well, kindergarteners from traditionally underrepresented groups (e.g., Black, Latinx, and Native American) scored 8.1 points lower on the NNAT than their Asian and White peers. Kindergarteners who were from low socioeconomic homes and were from a traditionally underrepresented group scored 19.5 points lower on the NNAT when compared to Asian and White students from non-low socioeconomic homes. Carman and Taylor (2010) concluded that though Naglieri and Ford (2002) claimed that the NNAT was an effective identification measure for underrepresented student groups, the test did not proportionately identify students from underrepresented groups or children from low socioeconomic families.

Peters and Gentry (2012) discussed the issues arising from using state standardized achievement tests to identify students for gifted services. The authors noted that using state wide norms rather than local group norms can lead to underrepresentation of Black, Latinx, and Native American students in public schools. The authors argued that using local norms (creating cut-off scores in relation to local performance rather than state performance) would identify a more representative student group for gifted services in school districts. Conversely, Warne, Anderson, and Johnson (2013) found that when achievement on state standardized tests were controlled for, underrepresented students were more likely to be identified as gifted.

Peters and Engerrand (2016) conducted a comprehensive analysis on the identification of underrepresented populations in gifted education. The authors argued that no testing measure can be truly bias-free. Instead, the authors extended the work of Peters and Gentry (2012) and proposed the use of multiple group norms, rather than multiple tests, for whatever measure a school adopts. Peters and Engerrand (2016) pointed out that the effect of the environment on a student's testing outcome cannot be adequately mitigated by a testing measure. Instead, the authors recommended teachers consider the environment when assessing a student for gifted services. Rather than identifying students who score in the top percentiles throughout the state as gifted, the authors argued that students would be better served if districts identified the top scoring students compared with similar others. Peters and Engerrand (2016) argued that those students would have similar opportunities to learn and gifted programming could be developed accordingly.

Not all testing comes in the form of quantitative assessments completed by students. The *HOPE Teacher Rating Scale* (Gentry, Peters, Pereira, McIntosh, & Fugate, 2015) was developed to identify students for gifted education based on observed behaviors and characteristics. The instrument works as a checklist for classroom behaviors that a teacher can use to help identify students based on behavioral characteristics indicative of giftedness (Gentry, Pereira, Peters, McIntosh, & Fugate, 2015). This form of identification relies on the assessment behavioral traits observed by an educator rather than an intelligence or achievement test taken by a student.

9.2 Underrepresentation

Stambaugh and Ford (2015) argued that, outside of urban areas, underrepresented students attend schools where most identified students are not students from underrepresented groups. This makes solutions, like local norms as suggested by Peters and Gentry (2012), more challenging to implement in schools outside of urban areas. Overt aggressions and obstructions standards or micro-aggressions serve to impede novel solutions (Stambaugh & Ford, 2015). Further, Esquierdo and Arreguín-Anderson (2012) argued that increasing rates of immigration from Mexico has led to higher proportions of Latinx students in schools in the U.S. The authors critique align with the points made by Stambaugh and Ford (2015) that a primarily white teaching staff is unable to identify or meet the needs gifted immigrant students. Even accounting for issues in identifying students as gifted who are also not native speakers of English, the political climate surrounding issues of Mexican immigrants has created structural biases against this group of students. Gentry, Fugate, Wu, and Castellano (2014) pointed out that structural problems do not always stem from covert aggressions but can instead be a product of unfamiliarity with the student population. The authors worked with Native American tribes to understand the barriers facing Native American students. They found that Native American parents considered cultural differences to be the primary barrier facing Native American students rather than structural racism.

9.3 Multiple Criteria

The use of multiple criteria to identify diverse populations (both in terms of race and gender) for gifted programs is not a recent idea in the field of gifted education. Borland and Wright (1994) recognized the need for multiple criteria to identify underrepresented populations for gifted services. They worked with an urban school district to design and implement a comprehensive identification procedure that used multiple criteria (e.g., classroom observations, creativity tests, and student product portfolios) to identify students for gifted services in the school district. The authors found that implementing a comprehensive process to successfully identify underrepresented students was achievable but required allocation of sufficient resources in terms of personnel, time, and money.

McBee (2006) examined the nomination process for children in the state of Georgia. He found that nominations stemming from teachers rather than state standardized tests or intelligence tests led to higher levels of inequity for Black students. In a meta-analysis looking at referral practices, Peterson (2013) found that when using state achievement tests or intelligence tests, boys were 1.19 times more likely to be identified than girls. However, the author did not find any significant differences in the identification rate of boys and girls when using a teacher referral method.

In a mathematical simulation study, McBee et al. (2014) examined the effects of different multiple criteria score formulations. The authors used simulations to assess how having multiple criteria and pathways to identification led to either false negatives (children not identified who should have been) or false positive (children identified who should not have been). The first way in which scores from multiple criteria can be combined the authors examined was the “and” rule. In this rule, students needed to have a minimum score on multiple measures to be identified as gifted (e.g. a minimum IQ score and minimum state standardized test score). The next was the “or” model where students needed to have a minimum score on one measure out of a number of measures to be identified as gifted. The final form of multiple criteria examined was the “mean” rule where a student needed to have a certain minimum average on multiple tests to be identified as gifted. The authors conclude that none of the three forms of multiple criteria is universally superior to the other two. The authors state that if, for example, a school district has rigorous program with a potentially high fail rate, it would want to use an “and” rule as their multiple criteria to ensure students admitted can be successful in their program. Conversely, if the school had a gifted program where risk of failure was low (e.g. an enrichment program), then the “or” rule would be more appropriate to be as inclusive as possible. Finally, the authors suggest the use of the “mean” rule if the school district is primarily concerned with reliably identifying students for gifted services. The results from the simulations run by the authors provide evidence that the "mean" rule has the greatest efficiency in identifying students (2014).

9.4 Gifted Education in Indiana

9.4.1 Definition of Gifted Education in Indiana

The state of Indiana defines a student with high ability as one who "performs at, or shows the potential for performing at, an outstanding level of accomplishment in at least one domain when compared to other students of the same age, experience, or environment; and is characterized by exceptional gifts, talents, motivation, or interests" (Indiana Education Code 20.36.1.3). The domains identified by the state are: general intellectual; general creative; specific academic; technical and practical arts; visual and performing arts; and interpersonal (Indiana Education Code 20.36.1.2). This definition aligns with the NAGC (2010) definition for gifted children through an acknowledgement of domain specific ability. NAGC makes provisions for comparing children to their local peers, but the Indiana definition does not.

9.4.2 Gifted Education Policy in Indiana

The state of Indiana mandates schools to identify and provide services to high-ability students in kindergarten through grade 12. The state does not specify how a school corporation should identify a student as high ability only that the assessment be "multifaceted…to ensure that students not identified by traditional assessments because of economic disadvantage, cultural background, underachievement, or disabilities are included" (Indiana Education Code 20.36.2.2). The state specifies that a plan must be developed and updated with regularity (though no specification on what regularity entails) to provide services for gifted children that includes professional development for staff, a district level planning committee, identification procedures, implementation of local services, and an evaluation of the gifted program. The state allows school corporations the leeway to interpret what the district considers to be appropriate services, and how corporation will evaluate their own programs (Indiana Education Code 20.36.2.2). The identification procedures in Indiana align with the NAGC (2008) call for the use of multiple criteria and the “or” rule for identification (McBee et al., 2014). What this entails is that Indiana offers different identification criteria for services and a child only needs to be identified in one area to be considered gifted. The reporting procedures required by the state, has influenced how students are identified.

Indiana requires reporting of identified gifted students in one of four categories: general ability, mathematics ability, language arts ability, or a performance-based category. The first three are identified under what the state refers to as “potential based” identification measures and the latter is referred to as “performance based” identification measures (Administrative Code, Rule 511.1.i). Potential based identifications refer to achievement and intelligence tests. Performance based identification refer to the performance of students and is measured through: portfolios, rating scales, observations, and interviews. If a child is identified as having high general ability, it means they have achieved a minimum score on an intelligence test used by the district to identify high ability students. A child identified in this manner is deemed to also be identified in having high mathematics ability and high language arts ability. Alternatively, a child can be identified as having high mathematics ability or language arts ability through performance on state standardized achievement tests or within a quantitative domain of an intelligence test. Finally, the performance-based domain allows a district to identify a child for gifted services based on observations, recommendations, rating scales, and work portfolios (Administrative Code, Rule 511).

9.5 Rurality

9.5.1 Rural Gifted Education

Scholars in the field of gifted education have observed that schools located in rural areas have had difficulty identifying and serving diverse gifted student populations (Burton & Johnson, 2010; Howley, Rhodes, & Beall, 2009; Plucker et al., 2013). Qualified teachers with the training to identify students from diverse backgrounds (e.g. students from underrepresented populations in Indiana) can be deemed an economic luxury by administrators of rural schools during times of budgetary shortfalls (Howley et al., 2009). Plucker et al. (2013) stated that poverty in conjunction with scarcity of financial resources and the ability to attract qualified teachers to rural areas have been consistent problems for schools in rural areas. This scarcity of resources was exacerbated during the 2008 recession during which time state legislators cut education budgets throughout the United States (Leachman & Mai, 2014). In addition, Burton and Johnson (2010) noted, since the inception of No Child Left Behind (2002), accountability has been a concern for rural schools. The combination of increased accountability and limited financial resources has created an educational landscape in which gifted education is an afterthought (Howley et al., 2009).

Rural communities do have unique characteristics that can enhance gifted education programs. In 1999, the Belin-Blank Center at the University of Iowa began a three-part series of national reports to assess gifted education in rural school districts in the United States (Colangelo, Assouline, & New, 1999, 2001, 2006). These three reports were meant to provide a national overview of gifted education in rural communities, provide case studies of gifted students and teachers of gifted children in rural schools, and finally, assess the cultural diversity in rural schools. In their first report, *Gifted Education in Rural Schools: A National Assessment* (1999), the authors provided an overview of gifted education in the rural United States. They described how economic instability and declining and aging populations adversely influenced gifted education. The authors were also concerned that the diversity present in rural general populations did not exist in the schools' gifted programs. Last, the authors asked educators for their opinion regarding the largest obstacle for rural gifted education. These educators reported misunderstanding about the needs of gifted children was the largest obstacle towards implementing successful gifted education programs in rural schools.

Colangelo, Assouline, and New (2001) provided vignettes of rural gifted educators in *Gifted Voices from Rural America.* The first of their vignettes provided a view into the class of a rural gifted educator in Iowa. The authors described how due to the small size of the school (n>1500), the high school gifted educators developed a curriculum to challenge the gifted students in the school, keep them motivated, and prepare them for college. In another vignette Colangelo et al. (2001) described in detail one of the Virginia governor's schools serving a rural Appalachian county. The schools used available (though scarce) resources and adapted bus routes to meet the transportation needs of students from low socioeconomic households. In turn, these students could participate in gifted programs at the Virginia governor's schools.

Gifted in Rural America: Faces of Diversity provided a look into ethnic and cultural diversity in rural gifted education programs in four states: Alabama, Iowa, Washington and Hawaii (Colangelo et al., 2006). Colangelo et al. (2006) also provided vignettes, but this time dealing specifically with issues of diversity. In Iowa, the authors described how recent immigration from Mexico changed the demographic make-up of a rural school district and how the school district worked to modify its gifted education program. The vignette explained how the district's elementary gifted program adopted new identification measures to bring equitable representation to its gifted program. Although the educators admitted that disparity still existed, they worked to close the representation gap through adopting more inclusive definitions of giftedness.

9.5.2 Indiana Rurality

According to the U.S. Census, 40.8% of the population of Indiana reside in rural or small town areas (U.S. Census, 2010). Indiana rural areas are concentrated along the eastern and western borders with northern and central Indiana more urbanized than other areas of the state.

Rural designation for school corporations in Indiana is defined using the National Center for Education Statistics (NCES) locale codes (2016). Under the NCES definition, rurality is defined in terms of population density and distance from urban centers. In Indiana, 103 of the 236 school corporations are defined as rural by the NCES. Student enrollment in rural school corporations declined from 215,277 (23.11%) in 2006 to 197,570 (22.25%) in 2015. In terms of proportions, the overall percentage of students enrolled in rural school corporations decreased from 23.11% of total enrollment in 2006 to 22.25% of total enrollment in 2015 (Indiana Department of Education, 2016).

CHAPTER 10. INDIANA METHODS

10.1 Sample

The dataset was acquired from the Indiana Department of Education (IDOE). Indiana mandates that all schools within the state report student enrollment figures as part of its public education accountability program. In these reports, aggregated statistics are reported annually. These aggregated statistics include statewide enrollment by gender, race, free and reduced lunch status and the proportion of students identified for special services, such as gifted education, English language learners, and special education.

Indiana does not make disaggregated datasets by school corporation available publicly. Given this, the dataset that was used in this analysis was acquired via public request through the Office of Legal Affairs in the Indiana Department of Education. This dataset contains information for each school corporation on the identification of students for gifted services by race. In addition, the dataset provides information about how many students were identified as gifted in a given category (i.e. general intelligence, mathematics, languages arts, or performance-based). Note, all data is at the school corporation level.

The dataset contains student enrollment data for the 374 school corporations in Indiana between the academic school years of 2006-2007 to 2015-2016. The total number of observations within the dataset is 3,740 (representing 10 years of repeated measures from 374 school corporations). Nine school corporations had no Native American population (seven were rural), four school corporations had no Black students (all four were rural), and one non-rural school corporation had no Latinx population. In should be noted that in the regression analysis, not all observations are included.

Representation indices (RI) and odds ratios were derived from the dataset. The representation indices, as described in Yoon and Gentry (2009) were used in the demographic analysis and the odds ratios were used in the regression analysis as dependent variables. Since this study uses odds ratios as the dependent variable, it is not possible to calculate an odds ratio for schools without a population of Black, Latinx, or Native American students. As a result, in the regression, the total number of observations used in the analysis was 2776.

10.2 Variables

10.2.1 Dependent Variable

School corporation personnel in the state of Indiana identify students as gifted through more than one procedure. Students can be identified as having high general intellect, mathematic ability, language arts ability, or in a performance-based category at the discretion of the school corporation. With this considered, a set of four odds ratios was calculated for school corporations, which described the likelihood of Black, Latinx, or Native American students being identified for gifted services. One odds ratio was calculated for each identification category.

Since the comparison of rates of identification between focal (i.e., underrepresented group) and reference (i.e., represented group) groups are the dependent, an odds ratio is an appropriate statistic to examine in this analysis (Bland & Atman, 2000). An odds ratio was calculated for each identification category in a school corporation per year. This odds ratio compares the identification of underrepresented groups (Black, Latinx, or Native American students) to non-underrepresented groups (Asian and White American students) using the following formula:

$$OR_{T,N} = \left(\frac{p(\text{gifted}|\text{B/L/N})_{T,N,I}}{1 - p(\text{gifted}|\text{B/L/N})_{T,N,I}}\right)\left(\frac{1 - p(\text{gifted}|\text{A/W})_{T,N,I}}{p(\text{gifted}|\text{A/W})_{T,N,I}}\right)$$

Where T indexes time points, N represents corporations, and I indicates the identification category. The notation B/L/N refers to Black, Latinx, and Native American Students and W/A to Asian and White students. The categories that were calculated are as follows: general ability, general ability and language arts, general ability and mathematics, and overall (where overall is students identified in the three prior categories with the addition of the performance-based criteria category).

As such, for each school corporation n in year t, there were a total of 16 odds ratios calculated. Four were calculated for each underrepresented group. One odds ratio was calculated for students identified using the general intellect category. A second odds ratio was calculated for students identified using the general intellect category or mathematics category. A third odds ratio was calculated for students identified using the general intellect category or language arts category. A final odds ratio was calculated for students identified in high general ability, high math ability, high language arts ability, or the performance-based category.

Analytical weights were used as the weighting strategy in this analysis (Dupraz, 2013). In an analytical weighting strategy, a school corporation is weighted by the total number of students in that corporation in a given year. For example, if a school corporation has 100 students in 2010 and 105 students in 2011 then its corresponding analytic weight is 100 for 2010 and 105 for 2011. A reader should note that the analytical weights were normalized within a given year to 1 such that the sum of weights in a given year equaled one. The purpose of using this weighting strategy is to control for difference in enrollment between corporations. One school corporation could have an enrollment of 50 and another 500 but within the regression, the associated weight on the estimate would be the same between the schools. Using a weighting strategy weights a school corporation's influence on estimates based on that school corporation's enrollment.

As well, in the analyses for specific ethnicities, an analytic weight was calculated based on the total number of students in that corporation of a given ethnicity in a given year. This is identical to the overall weighting strategy with the exception that instead of all students, only the group of interest is used to determine the weights. For example, a school corporation has 10 Black students, 15 Latinx students, and 5 Native American students so its corresponding weights are 10 for Black students, 15 for Latinx students, and 5 for Native American students. Again, a reader should note that the analytical weights were normalized within a given year to 1 such that the sum of weights in a given year equaled one.

10.2.2 Predictors

Four independent variables were included in the model as predictors. The independent variables in the model were a set of dummy variables indicating the method of identification and a dummy variable indicating rurality.

10.2.2.1 Identification Category

This variable describes category for identification for a given odds ratio with one for high general ability (*general*) and high mathematics (*mathematics*) ability, high general ability and high language arts (*language arts) ability*, and high general ability, high mathematic ability, high language arts ability, and the performance-based criteria (*overall)*. The variables are defined as follows:

General. Students identified under this category are identified as gifted using an intelligence test. Odds ratios calculated using this metric serve as baseline during the analysis.

Mathematics. Students identified under this category are identified as gifted using a state standardized achievement test in mathematics. Students identified as having high general ability (*general*) are included in this category.

Language arts. Students identified under this category are identified as gifted using a state standardized achievement test in language arts. Students identified as having high general ability (*general*) are included in this category.

Overall. The final odds ratio calculated encompasses all forms of identification used by Indiana (general, mathematics, language arts, and performance-based). The final group of identified students includes those who were identified by the school corporation using the performance-based criteria by the school. A student who has been identified as having high math ability, high language arts ability, or high general ability is included in this category.

All four variables are coded as binary variables (where 1 represents the identification category and zero equals any other identification category). It should be noted that in the analysis, the odds ratios associated only with general ability was used as baseline. In this manner, the identification category variable will describe how the addition of a category of identification influences the overall level of representation. For example, the log difference in rates of identification between the baseline general ability identification and *general and mathematics* ability will describe what effect the addition of an alternate pathway to identification had in comparison to only traditional methods.

10.2.2.2 Rurality

This variable is a binary variable denoting whether a school corporation is designated as rural by the state of Indiana or not. Rurality of a school corporation is denoted by the National Center for Education Statistics locale codes of 41, 42, and 43 (NCES, 2016).

10.2.3 Dependence

Two sources of dependence were in the model and needed to be addressed. The first is the serial correlation due to repeated measures over time. The second is the correlation between odds ratio calculated from the same time and school corporation. To address these sources of dependence, three variables were coded: *year*, *corporation,* and *annual corporation.*

Year. A time variable was coded to control for the serial correlation due to time across all school corporations. This time variable was reverse coded in the following format: the academic school year 2006-2007 is coded as -9, 2007-2008 as -8, 2009-20010 as -7, and so on with the 2015-2016 academic school year coded as 0. Coding time in this manner changes the reference year in the regression from the 2006-2007 academic school year to the 2015-2016 year. In so doing, the focus is shifted to where districts were at the end of the time series rather than where they were in the 2006-2007 academic school year.

The *corporation* variable was a created to account for repeated measures of school corporations within the studies. This categorical variable was coded as the school corporation's state designated ID. The *annual corporation* variable was created to account for multiple odds ratios being extracted from the same school corporation in the same year. This categorical variable was coded with an ID indicating school corporation and year.

10.3 Analysis

Since dependent variables are in the form of a log transformed odds ratio, a generalized mixed effect regression was used. A linear mixed effect model (LMM) is appropriate because it contains repeated measures of odds ratios over time (Faraway, 2014). The following model was used in this analysis:

$$Y_{ijt} = \alpha + \beta_1(identification\ category_i) + \beta_2(rural_i) + \beta_3(year_t)$$
$$+ \beta_4(identification\ category_i)(year_t) + \beta_5(rural_i)(year_t)$$
$$+ [\gamma_{000ij} + u_{00i} + \gamma_{1ij}(year_t) +] + e_{ijt}$$

Where Y_{ijt} is the *i*th odds ratio for the *j*th school corporation in year *t* and where α indicates the intercept. Finally, a Wald *t* was used as the test statistic for statistical significance with degrees of freedom estimated via a Satterthwaite approximation procedure (Faraway, 2014).

Model assumptions. The assumption of normality of the dependent variable was addressed by the log transformation of the dependent variable. The QQ-plot was analyzed for normality for both random and fixed effects. The assumption of constant variance of random effects was addressed by analyzing residual plots. The assumption of independent observations is addressed through the GLMM. Observations are not independent as the data are longitudinal with repeated measures taken from each school corporations. Further, multiple odds ratios calculated from a single year are nested under the associated school corporation. This violation of independence is addressed through the use of random and fixed effects in model fitting (via allowing intercepts and slopes to vary).

10.3.1 Assumptions

The assumption of normality of the dependent variable was addressed by the log transformation of the dependent variable. The QQ-plot was analyzed for normality for both random and fixed effects. The assumption of constant variance of random effects was addressed by analyzing residual plots. The assumption of independent observations is addressed through the GLMM. Observations are not independent as the data are longitudinal with repeated measures taken from each school corporations. Further, multiple odds ratios calculated from a single year are nested under the associated school corporation. This violation of independence is addressed through the use of random and fixed effects in model fitting (via allowing intercepts and slopes to vary).

CHAPTER 11. INDIANA RESULTS

11.1 Demographics

Between the 2006-2007 academic year and 2015-2016 academic year, the percentage of Asian students attending public schools in Indiana nearly doubled increasing from 1.29% to 2.28% of the general school population. Further, representation of Asian students in gifted services increased in that same timeframe from 2.74% to 4.21%. In contrast, the percentage o f White students decreased in the state from 79.36% in 2006-2008 to 74.23%. In the same period, the percentage of White students identified for gifted services decreased from 88.28% to 84.46% of the total gifted students identified for gifted services.

The percentage of Black students attending public schools decreased from 12.78% to 11.70% while the percentage of Black students identified for gifted services also decreased from 5.54% to 4.79% during the time frame of the study. The percentage of Latinx students attending public schools increased from 6.28% to 11.54%. At the same time, the percentage of Latinx students identified for gifted services increased from 3.30% to 6.41%. The percentage of Native American in the public schools decreased from 0.29% to 0.25%. The percentage of students identified for gifted services who were Native American decreased from 0.14% to 0.13%. Full descriptive results of representation by race schools and as gifted can be seen in Table 1.

Table 1

General enrollment and gifted enrollment proportions in Indiana public schools by race

Academic Year	Total Public K-12 Enrollment (Total gifted students)	% of Asian (% of gifted Asian)	% of Black (% of gifted Black)	% of Latinx (% of gifted Latinx)	% of Native American (% of gifted Native American	% of White (% of gifted White)
2006-2007	931646 (96950)	1.29 (2.74)	12.78 (5.54)	6.28 (3.30)	0.29 (0.14)	79.36 (88.28)
2007-2008	927868 (108712)	1.40 (2.81)	12.97 (5.93)	6.86 (3.87)	0.30 (0.14)	78.47 (87.25)
2008-2009	915420 (127801)	1.51 (3.12)	13.10 (5.82)	7.38 (4.12)	0.30 (0.15)	77.71 (86.8)
2009-2010	913191 (129421)	1.63 (3.24)	12.91 (5.71)	7.80 (3.92)	0.30 (0.17)	77.35 (86.96)
2010-2011	925958 139867)	1.75 (3.32)	12.64 (5.71)	7.91 (4.78)	0.30 (0.17)	77.40 (86.01)
2011-2012	928031 (139921)	1.80 (3.45)	12.48 (5.39)	9.01 (4.97)	0.35 (0.15)	76.37 (86.04)
2012-2013	921107 (138714)	1.91 (3.53)	12.59 (5.09)	9.51 (5.42)	0.32 (0.15)	75.66 (85.80)
2013-2014	906880 (131627)	2.02 (3.85)	12.65 (4.26)	10.18 (5.42)	0.30 (0.15)	74.85 (86.32)
2014-2015	908031 (135016)	2.13 (3.89)	12.26 (4.53)	10.89 (5.96)	0.27 (0.13)	74.45 (85.49)
2015-2016	887724 131920	2.28 (4.21)	11.70 (4.79)	11.54 (6.41)	0.25 (0.13)	74.23 (84.46)

Note. The top number or percentage in a row is associated with the general population (the percentage of the general population of a given race). The number in parentheses is associated with the identified gifted population (the percentage of the gifted population of a given race).

During the time frame of the study, the percentage of students identified for gifted services through the criteria of high general ability who were Asian increased from 3.11% to 4.79%. The percentage of students identified for gifted services through the criteria of high general ability who were Black decreased from 6.29% to 4.61%. The percentage of students identified for gifted services through the criteria of high general ability who were Latinx increased from 3.64% to 5.62%. The percentage of students identified for gifted services through the criteria of high general ability who were Native American remained the same at 0.13%. Finally, the percentage of students identified for gifted services through the criteria of high general ability who were White decreased from 86.63% to 84.46%.

Table 2

Enrollment in gifted programs by identification as high general ability and by multiple criteria (overall) in Indiana public schools by race

Academic Year	Total high general ability students (Total overall identified students)	% of Asian (% of gifted Asian)	% of Black (% of gifted Black)	% of Latinx (% of gifted Latinx)	% of Native American (% of gifted Native American	% of White (% of gifted White)
2006-2007	59386 (96950)	3.11 (2.74)	6.29 (5.54)	3.64 (3.30)	0.13 (0.14)	86.83 (88.28)
2007-2008	65809 (108712)	3.34 (2.81)	6.72 (5.93)	4.08 (3.87)	0.12 (0.14)	85.73 (87.25)
2008-2009	76858 (127801)	3.34 (3.12)	6.71 (5.82)	4.47 (4.12)	0.13 (0.15)	85.34 (86.8)
2009-2010	80165 (129421)	3.54 (3.24)	6.71 (5.71)	3.96 (3.92)	0.15 (0.17)	85.65 (86.96)
2010-2011	80854 (139867)	3.76 (3.32)	6.64 (5.71)	4.70 (4.78)	0.15 (0.17)	84.75 (86.01)
2011-2012	78268 (139921)	3.88 (3.45)	6.26 (5.39)	5.00 (4.97)	0.14 (0.15)	84.72 (86.04)
2012-2013	77860 (138714)	3.74 (3.53)	5.37 (5.09)	5.31 (5.42)	0.15 (0.15)	85.43 (85.8)
2013-2014	74208 (131627)	4.36 (3.85)	4.55 (4.26)	4.95 (5.42)	0.15 (0.15)	85.99 (86.32)
2014-2015	74400 (135016)	4.36 (3.89)	4.44 (4.53)	5.42 (5.96)	0.13 (0.13)	85.65 (85.49)
2015-2016	70949 (131920)	4.79 (4.21)	4.61 (4.79)	5.62 (6.41)	0.13 (0.13)	84.85 (84.46)

Note. The top number or percentage in a row is associated with the population of students identified as having high general ability using an intelligence test. The bottom number or percentage in a row is associated with total gifted population identified with multiple criteria (*overall*).

In terms of representation during the time frame of the study, the overall aggregated odds ratio for identification of Black, Latinx, and Native American students for gifted services ranged from 0.32 to 0.41 (see Figure 1). Individually odds ratios for the individual races ranged as follow for Black (0.25 to 0.37), Latinx (0.40 to 0.46), and Native American students (0.33 to 0.45) as shown in Figure 1. It should be noted that during the time frame of the study, 18.76% (*n* = 1749) of all school observations and 32.79% (*n* = 438) of all rural school corporation observations did not contain a Black, Latinx, or Native American student identified as gifted despite having a population of those students enrolled.

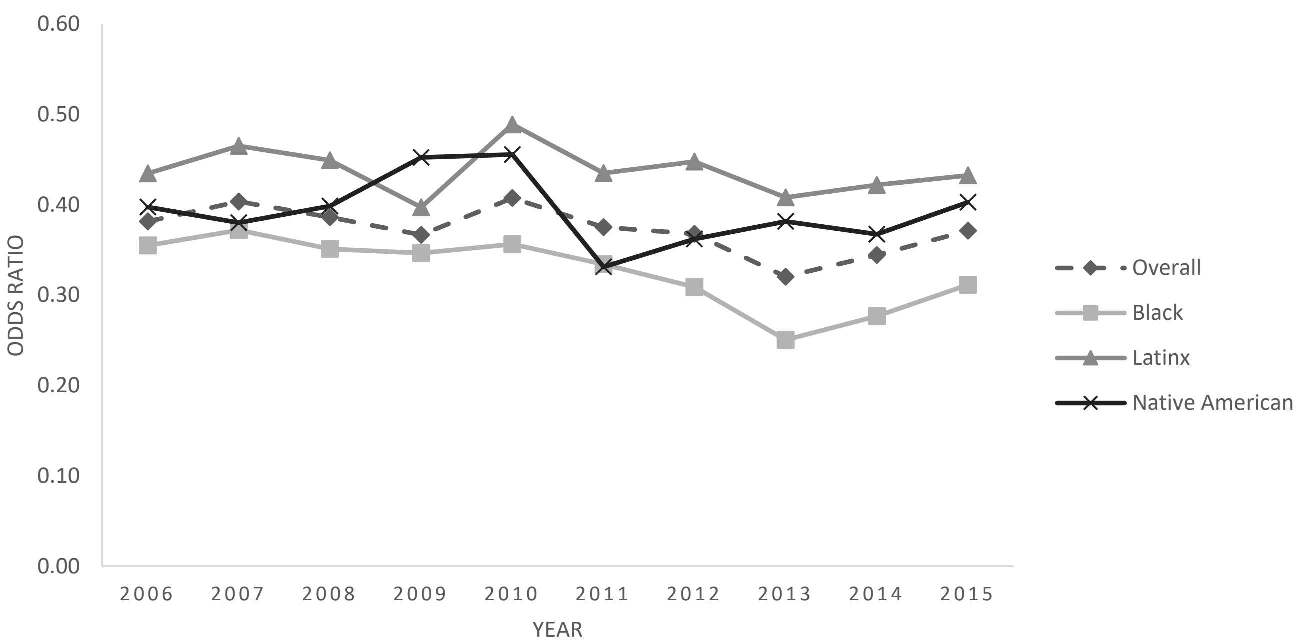

Figure 1. The odds ratio of identification for gifted services in Indiana of Black, Latinx and Native American students in comparison to Asian and White students from the 2006-2007 through the 2015-2016 academic school years.

The percentage of Black students attending public schools decreased from 12.78% to 11.70% while the percentage of Black students identified for gifted services also decreased from 5.54% to 4.79% during the time frame of the study. The percentage of Latinx students attending public schools increased from 6.28% to 11.54%. At the same time, the percentage of Latinx students identified for gifted services increased from 3.30% to 6.41%. The percentage of Native American in the public schools decreased from 0.29% to 0.25%. The percentage of students identified for gifted services who were Native American decreased from 0.14% to 0.13%. Full descriptive results of representation by race schools and as gifted can be seen in Table 1.

During the time frame of the study, the percentage of students identified for gifted services through the criteria of high general ability who were Asian increased from 3.11% to 4.79%. The percentage of students identified for gifted services through the criteria of high general ability who were Black decreased from 6.29% to 4.61%. The percentage of students identified for gifted services through the criteria of high general ability who were Latinx increased from 3.64% to 5.62%. The percentage of students identified for gifted services through the criteria of high general ability who were Native American remained the same at 0.13%. Finally, the percentage of students identified for gifted services through the criteria of high general ability who were White decreased from 86.63% to 84.

In terms of representation during the time frame of the study, the overall aggregated odds ratio for identification of Black, Latinx, and Native American students for gifted services ranged from 0.32 to 0.41 (see Figure 1). Individually odds ratios for the individual races ranged as follow for Black (0.25 to 0.37), Latinx (0.40 to 0.46), and Native American students (0.33 to 0.45) as shown in Figure 1. It should be noted that during the time frame of the study, 18.76% (n = 1749) of all school observations and 32.79% (n = 438) of all rural school corporation observations did not contain a Black, Latinx, or Native American student identified as gifted despite having a population of those students enrolled.

11.1.1 Descriptive Analysis of Multiple Criteria by Race

Asian student enrollment increased from 1.29% of total student enrollment in the 2006-2007 academic year to 2.27% of total student enrollment in the 2015-2016 academic year. In that same time, the proportion of Asian students identified as having high general ability increased from 3.11% to 4.79% of the total students identified as having high general ability. However, the proportion of Asian students identified as gifted with all criteria (overall) increased from 2.74% to 4.21%, representing a lower proportion of total gifted students than those identified with general high ability alone (see Figure 2).

Asian student enrollment increased from 1.29% of total student enrollment in the 2006-2007 academic year to 2.27% of total student enrollment in the 2015-2016 academic year. In that same time, the proportion of Asian students identified as having high general ability increased from 3.11% to 4.79% of the total students identified as having high general ability. However, the proportion of Asian students identified as gifted with all criteria (overall) increased from 2.74% to 4.21%, representing a lower proportion of total gifted students than those identified with general high ability alone (see Figure 2).

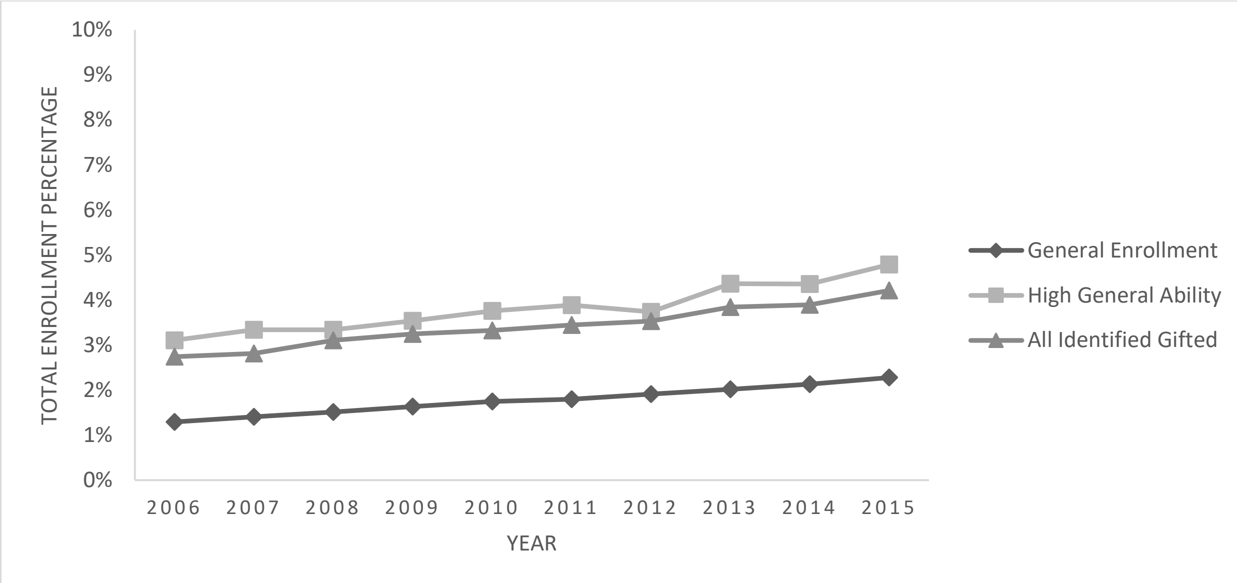

Figure 2. The percentages of Asian students enrolled in K-12 public school corporations in Indiana; identified as having high general ability; and identified using multiple criteria. The percentages correspond to the percentage of the total associated population.

In rural school corporations, Asian student enrollment increased from 0.57 % of total student enrollment in the 2006-2007 academic year to 0.76% of total student enrollment in the 2015-2016 academic year. Asian students identified as having high general ability increased from 1.00% to 1.12% of the total students identified as having high general ability; whereas, the total percentage of students identified as gifted who are Asian increased from 1.66% to 2.05% (see Figure 3).

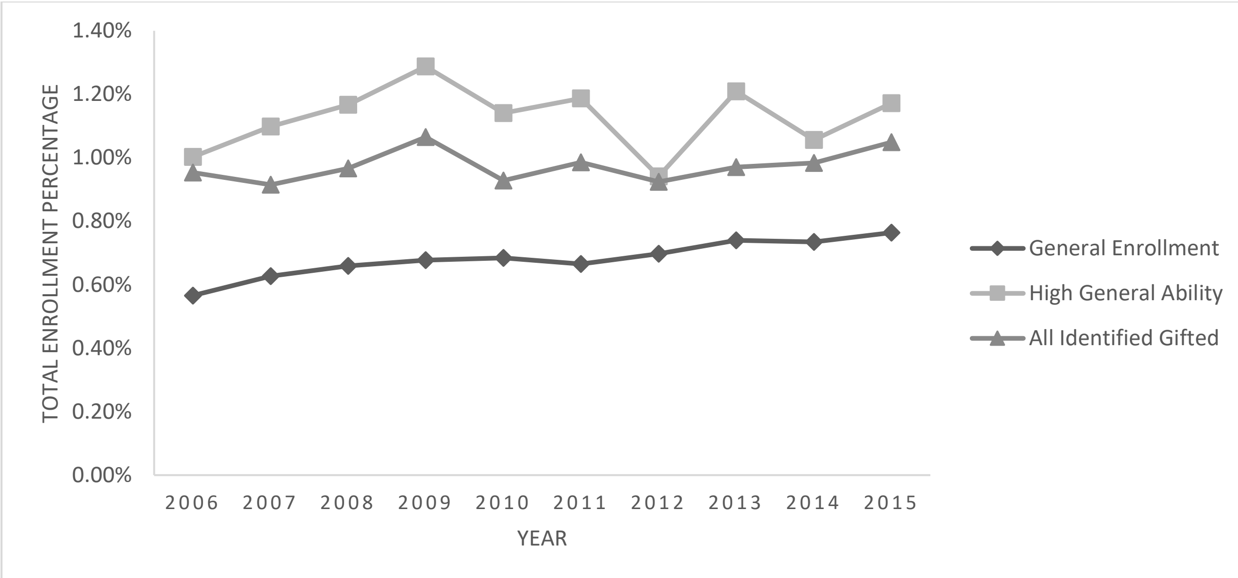

Figure 3. The percentage students enrolled in K-12 rural public school corporations in Indiana who are Asian. The percentage of students identified as either having high general ability who are Asian and the percentage of students identified as gifted using multiple criteria who are Asian in rural school corporations. The percentages correspond to the percentage of the total associated population.

Black student enrollment decreased from 12.78% of total students in the 2006-2007 academic year to 11.70% of total students in the 2015-2016 academic year. In that same time, Black students identified as having high general ability decreased from 6.29% to 4.61% of the total students identified as having high general ability. The total percentage of Black students identified as gifted using all criteria decreased from 5.54% to 4.79% (see Figure 4).

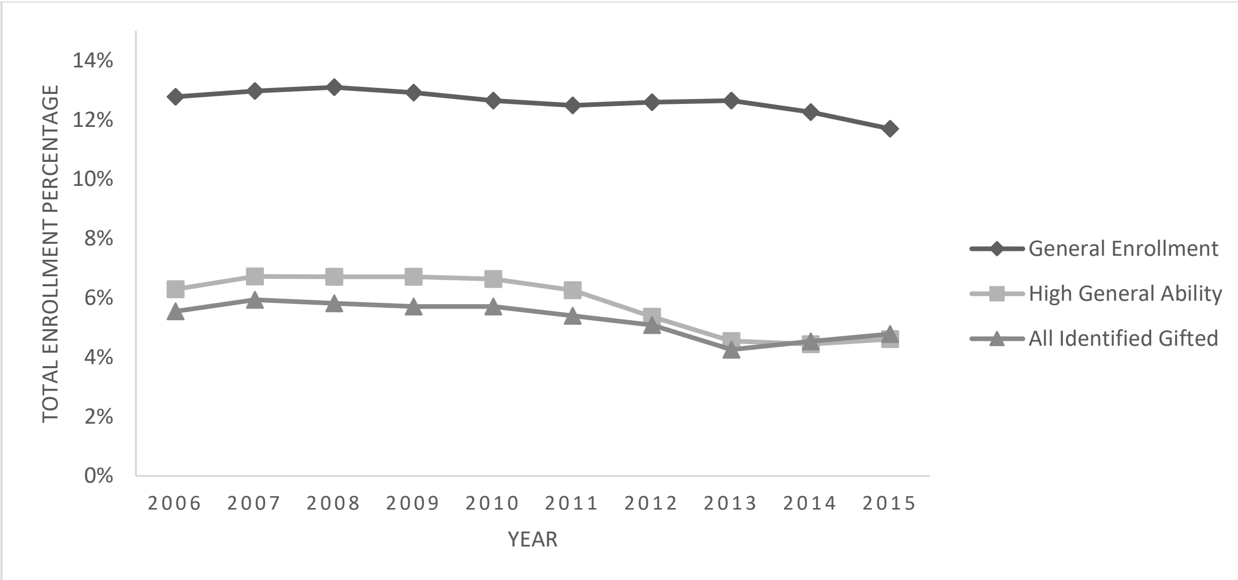

Figure 4. The percentage students enrolled in K-12 public school corporations in Indiana who are Black. The percentage of Black students identified as having high general ability and the percentage of Black students identified using multiple criteria.

In rural school corporations, Black student enrollment increased from 0.72 % of total student enrollment in the 2006-2007 academic year to 0.98% of total student enrollment in the 2015-2016 academic year. During this time, Black students identified as having high general ability decreased from 0.32% to 0.31% of the total students identified as having high general ability. However, the total percentage of Black students identified as gifted with any criteria increased from 0.36% to 0.38% (see Figure 5).

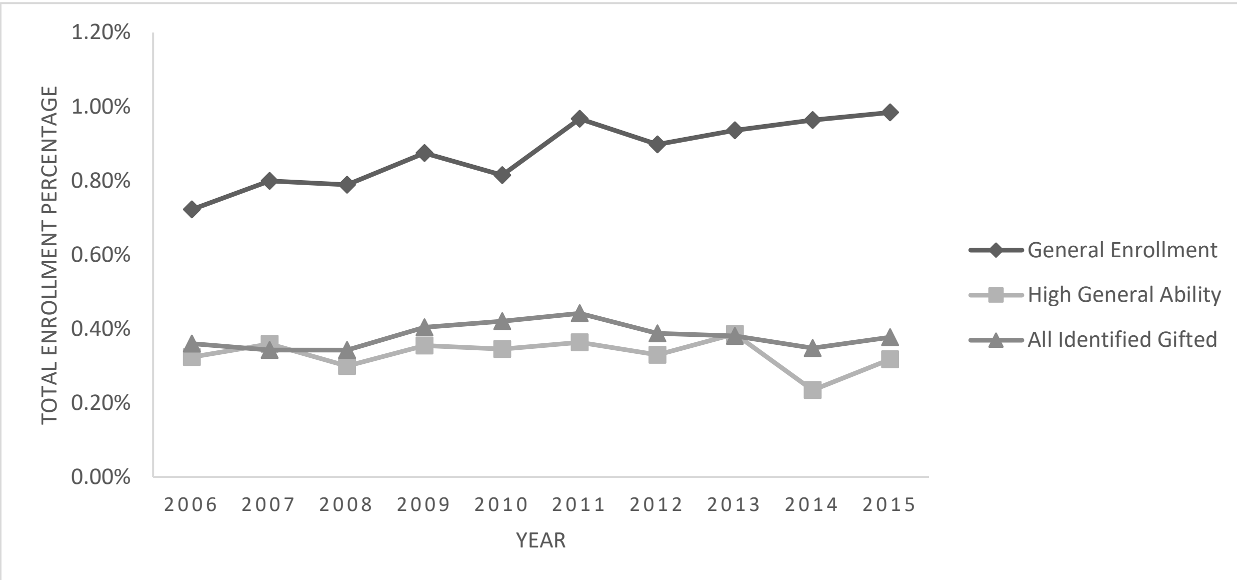

Figure 5. The percentage students enrolled in K-12 rural public school corporations in Indiana who are Black; the percentage of Black students identified as having high general ability who are and the percentage of Black students identified as gifted using multiple criteria in rural school corporations.

Latinx student enrollment nearly doubled from 6.28% of total student enrollment in the 2006-2007 academic year to 11.56% of total student enrollment in the 2015-2016 academic year. Latinx students identified as having high general ability increased from 3.64% to 5.62% of the total students identified as having high general ability. The total percentage of Latinx students identified as gifted increased from 3.30% to 6.41% (see Figure 6).

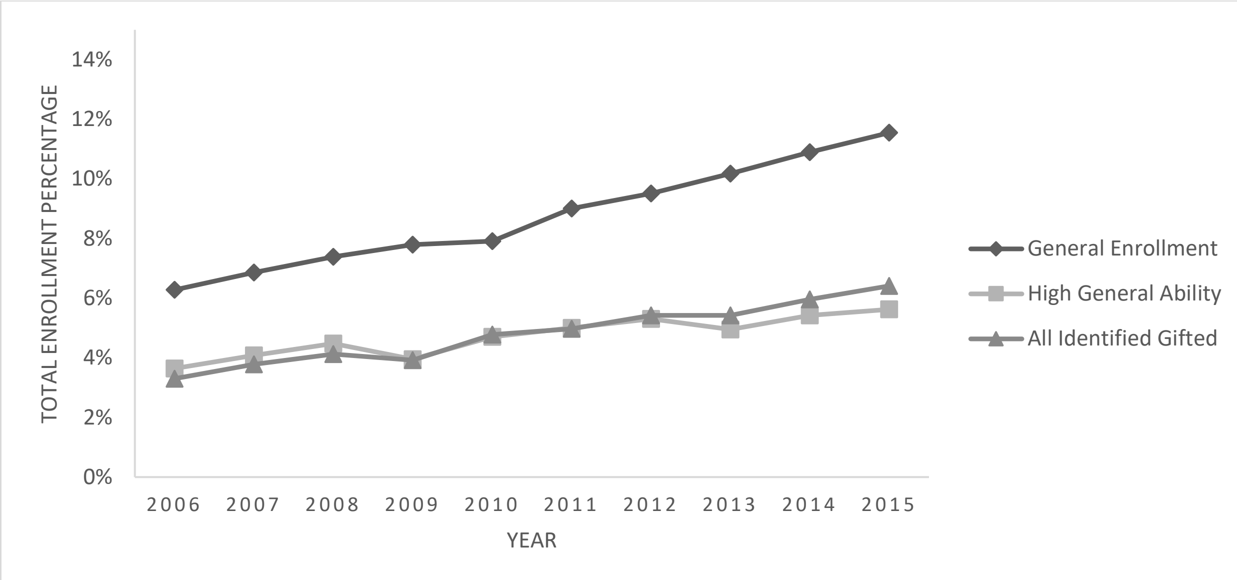

Figure 6. The percentage Latinx students enrolled in K-12 public school corporations in Indiana. The percentage of Latinx students identified as having high general ability and the percentage of Latinx students identified as gifted using multiple criteria.

In rural school corporations, Latinx student enrollment increased from 2.67% of total student enrollment in the 2006-2007 academic year to 5.20% of total student enrollment in the 2015-2016 academic year. Latinx students identified as having high general ability increased from 1.49% to 2.81% of the total students identified as having high general ability. The total percentage of Latinx students identified as gifted more than doubled from 1.51% to 3.15% (see Figure 7).

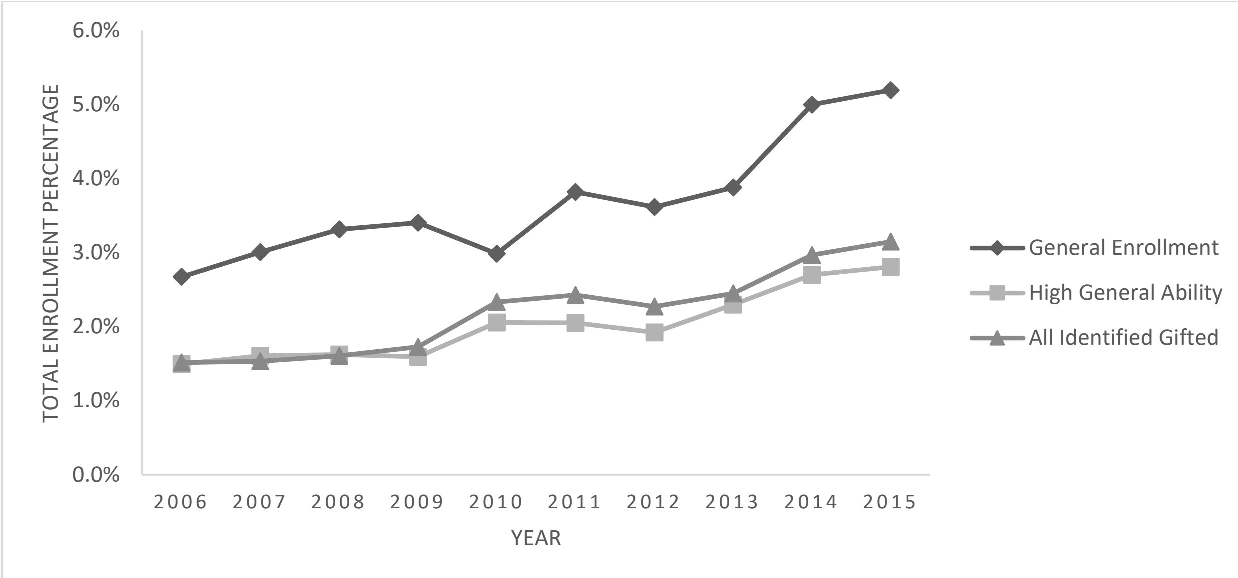

Figure 7. The percentage of Latinx students enrolled in K-12 rural public school corporations in Indiana. The percentage of Latinx students identified as having high general ability and the percentage of Latinx students identified as gifted using multiple criteria in rural school corporations.

Native American student enrollment decreased from 0.29% of total student enrollment in the 2006-2007 academic year to 0.25% of total student enrollment in the 2015-2016 academic year. Native American students identified as having high general ability remained relatively stable at 0.13% of the total students identified as having high general ability. The total percentage of Native American students identified as gifted decreased from 0.14% to 0.13% (see Figure 8).

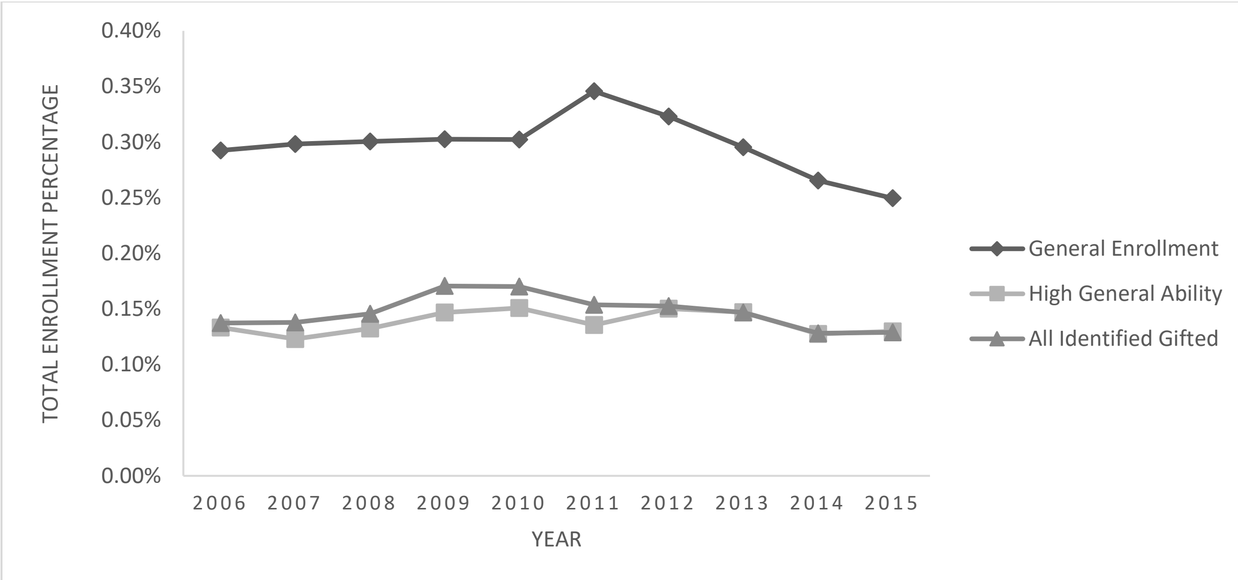

Figure 8. The percentage Native American students enrolled in K-12 public school corporations in Indiana. The percentage of Native American students identified as having high general ability and the percentage of Native American students identified as gifted using multiple criteria.

In rural school corporations, Native American student enrollment decreased from 0.35% of total student enrollment in the 2006-2007 academic year to 0.29% of total student enrollment in the 2015-2016 academic year. Native American students identified as having high general ability decreased from 0.10% to less than 0.08% of the total students identified as having high general ability. The total percentage of Native American students identified as gifted under any criteria decreased from 0.11% to 0.07% (see Figure 9).

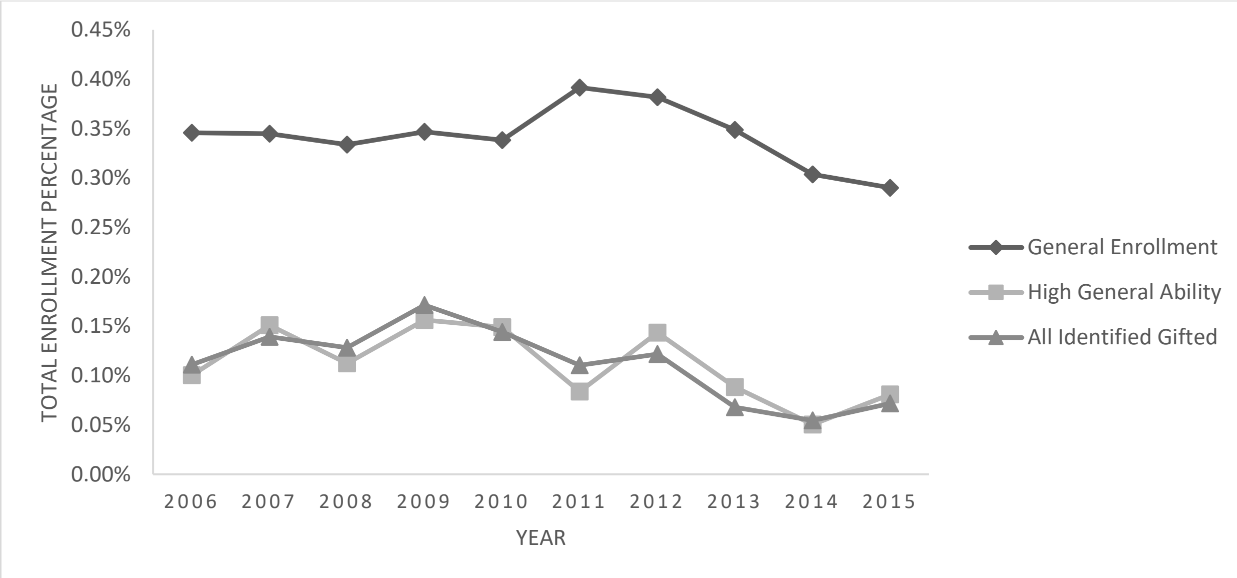

Figure 9. The percentage Native American students enrolled in K-12 rural public school corporations in Indiana. The percentage of Native American students identified as having high general ability and the percentage of Native American students identified as gifted using multiple criteria in rural school corporations.

White student enrollment decreased from 79.36% of total student enrollment in the 2006-2007 academic year to 74.23% of total student enrollment in the 2015-2016 academic year. White students identified as having high general ability decreased from 86.83% to 84.85% of the total students identified as having high general ability. The total percentage of White students identified as gifted under any criteria from 88.28% to 84.46% (see Figure 10).

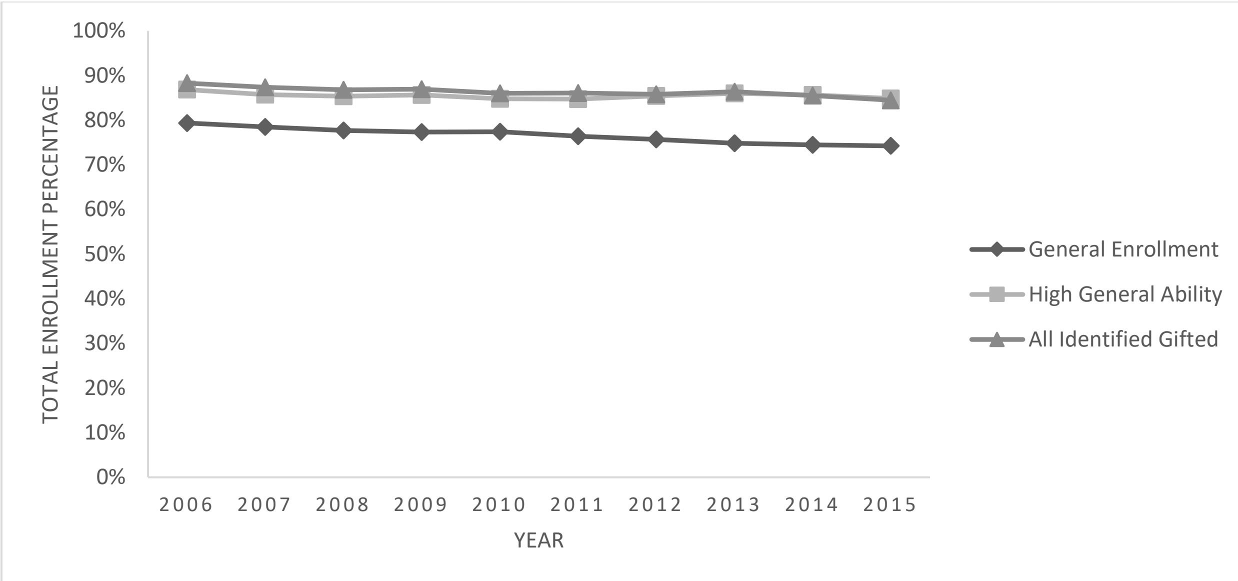

Figure 10. The percentage White students enrolled in K-12 public school corporations in Indiana. The percentage of White students identified as having high general ability and the percentage of students identified as gifted using multiple criteria.

In rural school corporations, White student enrollment decreased from 95.69% of total student enrollment in the 2006-2007 academic year to 92.77% of total student enrollment in the 2015-2016 academic year. White students identified as having high general ability decreased from 97.08% to 95.62% of the total students identified as having high general ability. The total percentage students identified as gifted who are White decreased from 97.06% to 95.36% (see Figure 11).

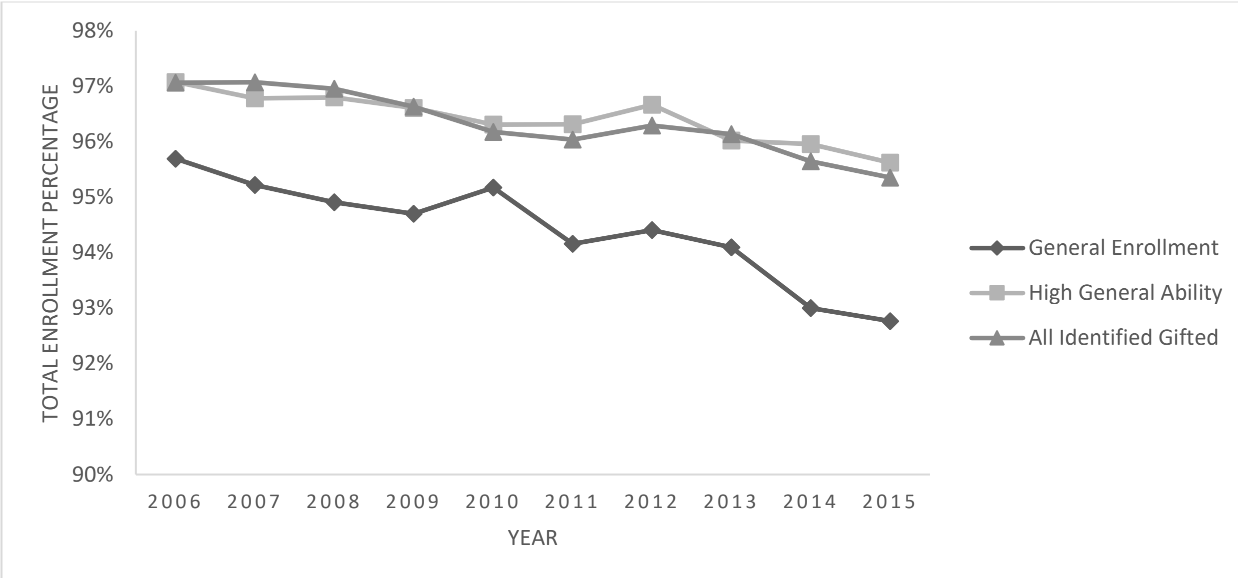

Figure 11. The percentage of White students enrolled in K-12 rural public school corporations in Indiana, percentage of White students identified as having high general ability and the percentage of White students identified as gifted using multiple criteria in rural school corporations.

Aggregated figures of Figures 1 through 11 were created by locale. Two figures were created for each graph (one truncated and one not truncated). The aggregated results for Indiana can be seen in Figures 12a, 12b, 13a, and 13b. The aggregated results for rural Indiana can be seen in Figures 14a, 14b, 15a, and 15b. Finally, the aggregated results for non-rural Indiana can be seen in Figures 16a, 16b, 17a, and 17b.

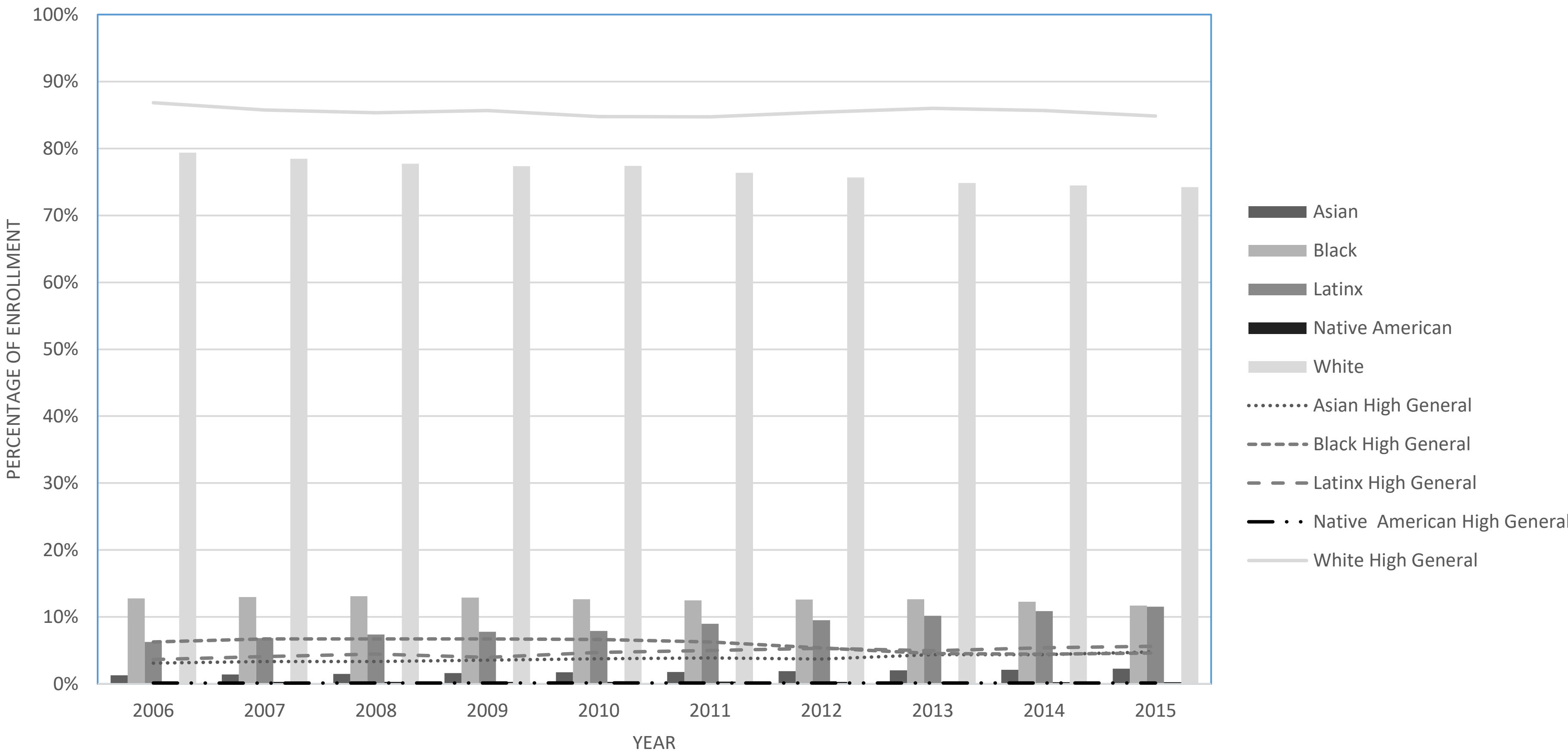

Figure 12a. The enrollment by percentage of Asian, Black, Latinx, Native American, and White students in Indiana schools. The bars represent percentage total student enrollment. The lines represent the percentage student enrollment in the gifted program through identification as high general ability.

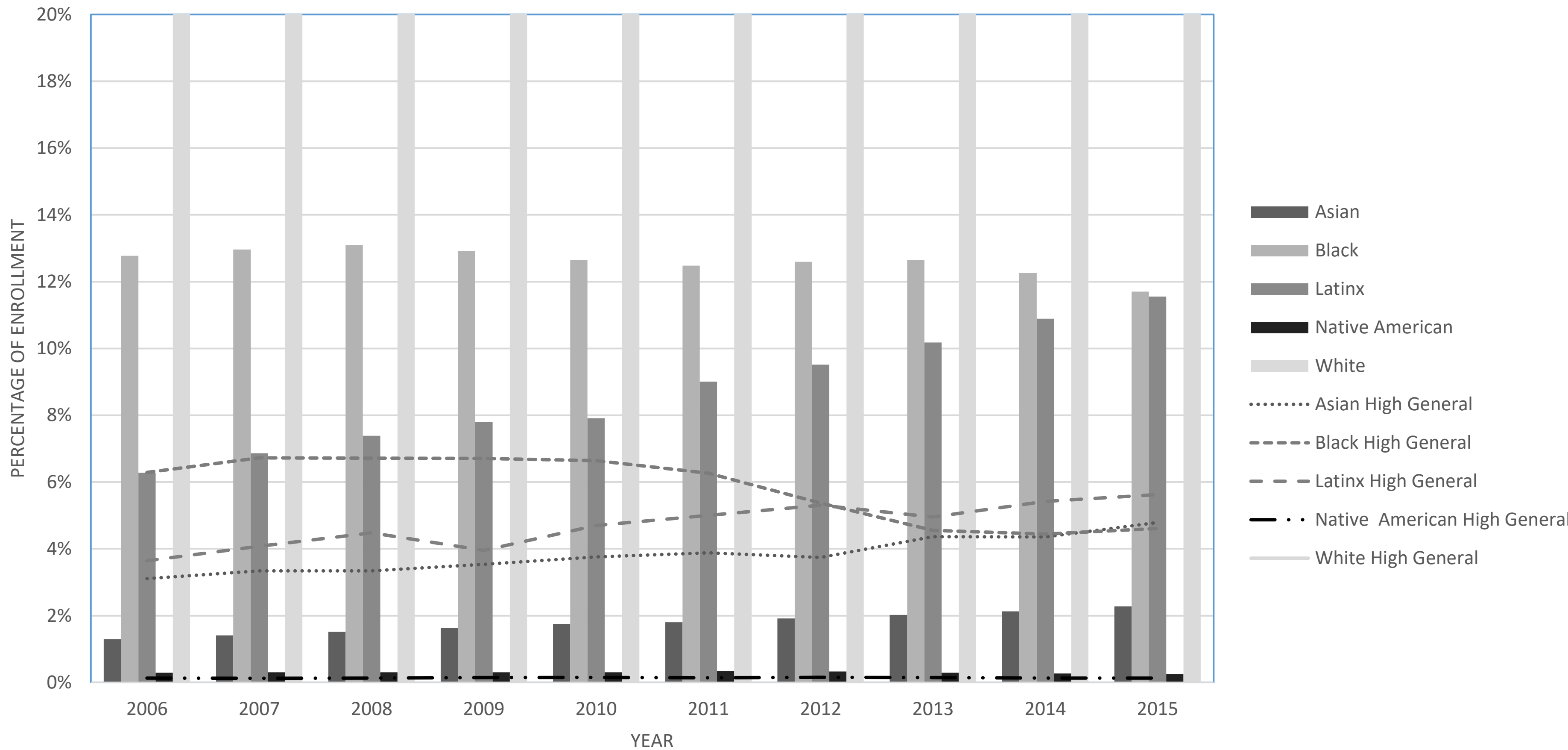

Figure 12b. A truncated version of Figure 12a. The y axis is truncated at 20% in order to highlight Asian, Black, Latinx, and Native American enrollment.

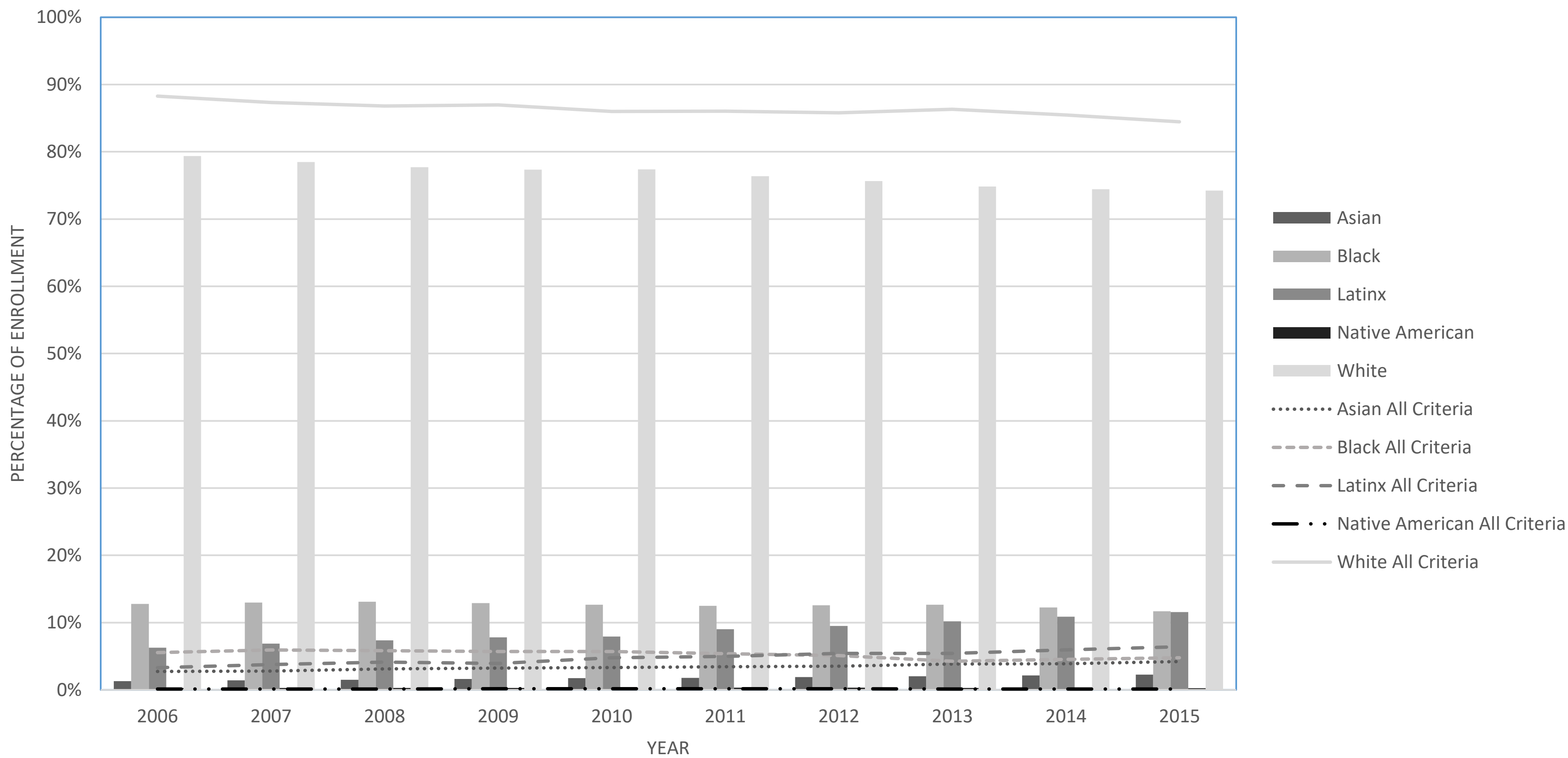

Figure 13a. The enrollment by percentage of Asian, Black, Latinx, Native American, and White students in Indiana schools. The bars represent percentage total student enrollment. The lines represent the percentage student enrollment in the gifted program through identification using multiple criteria (*overall*).

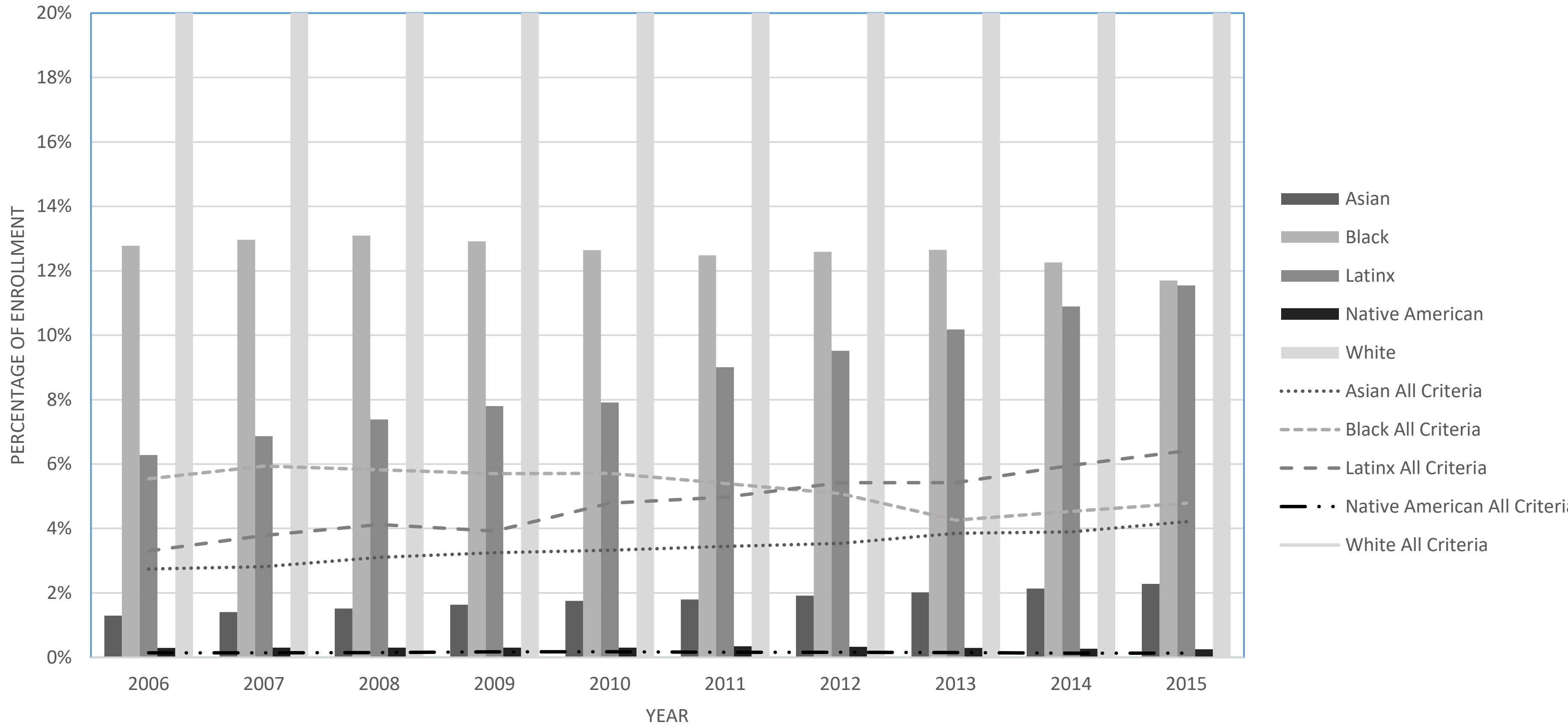

Figure 13b. A truncated version of Figure 13a. The y axis is truncated at 20% in order to highlight Asian, Black, Latinx, and Native American enrollment.

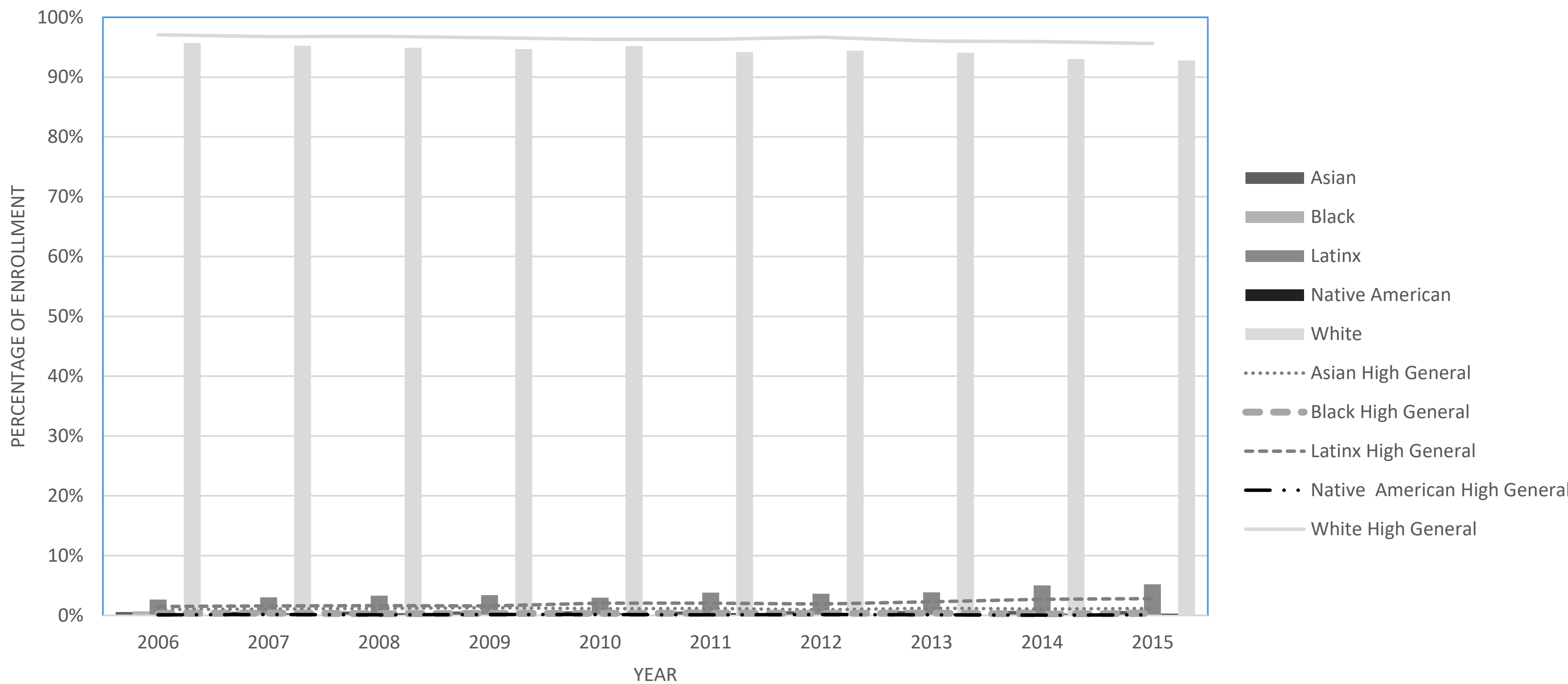

Figure 14a. The enrollment by percentage of Asian, Black, Latinx, Native American, and White students in Indiana rural schools. The bars represent percentage total student enrollment. The lines represent the percentage student enrollment in the gifted program through identification as high general ability.

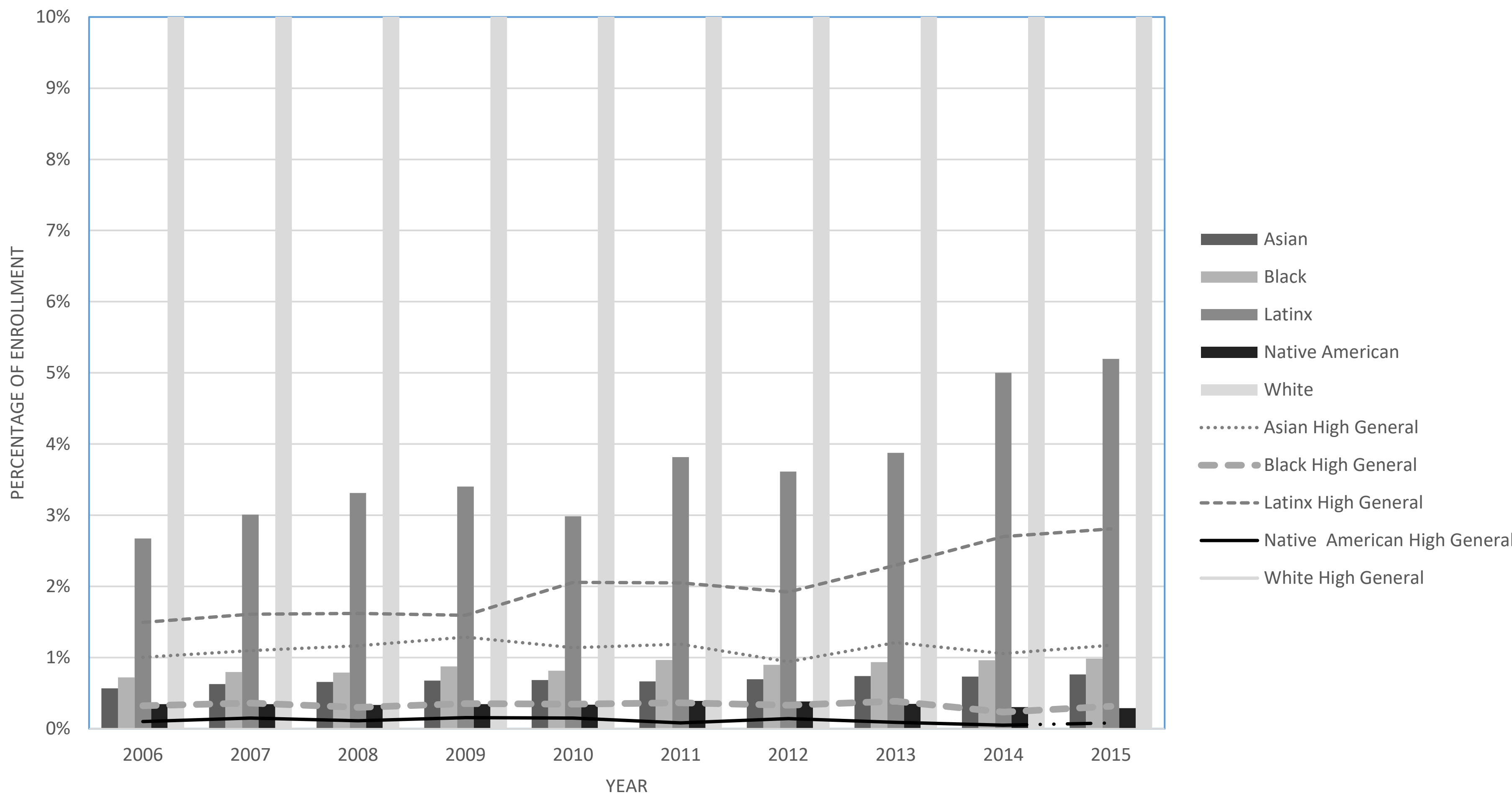

Figure 14b. A truncated version of Figure 14a. The y axis is truncated at 10% in order to highlight Asian, Black, Latinx, and Native American enrollment.

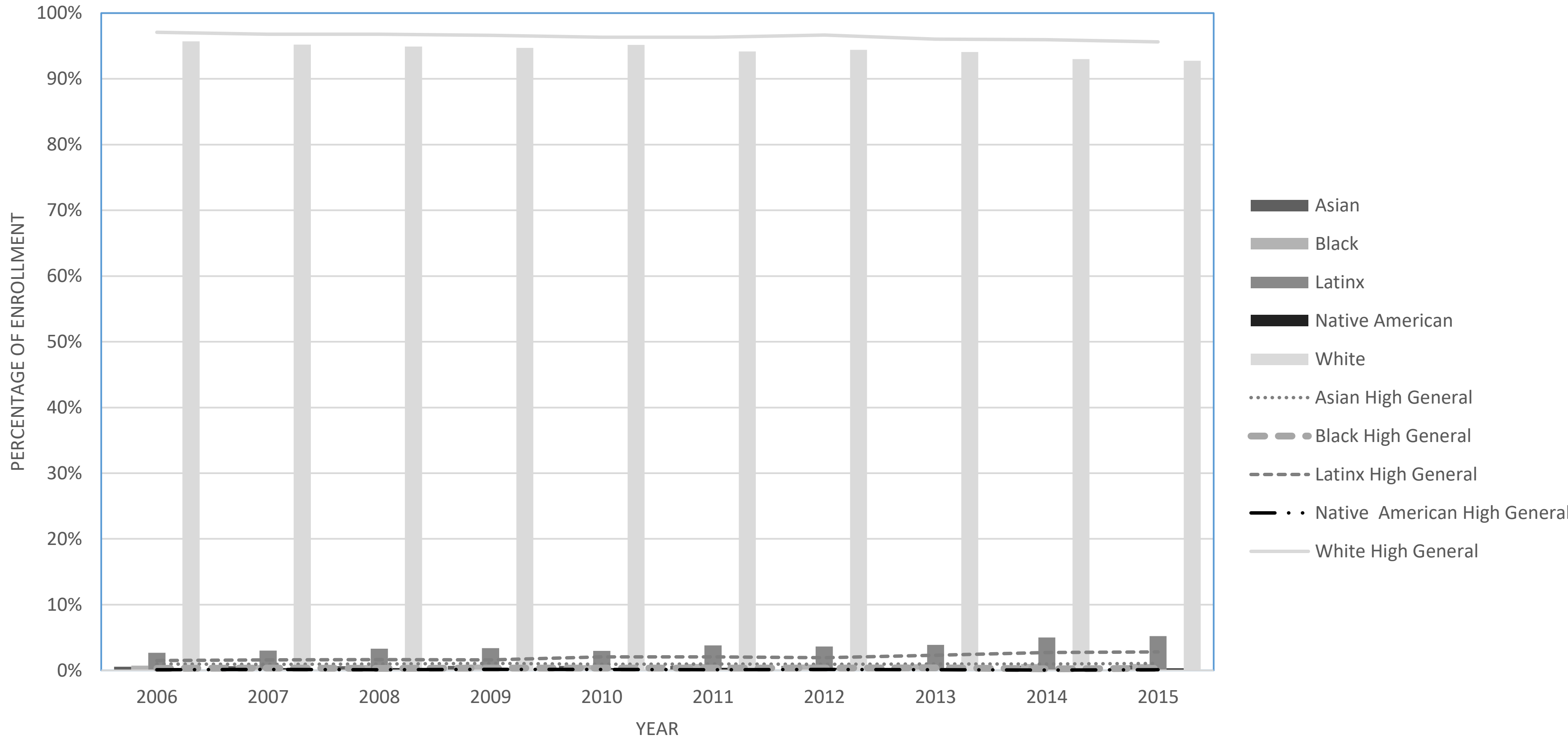

Figure 15a. The enrollment by percentage of Asian, Black, Latinx, Native American, and White students in Indiana rural schools. The bars represent percentage total student enrollment. The lines represent the percentage student enrollment in the gifted program through identification using multiple criteria (*overall*).

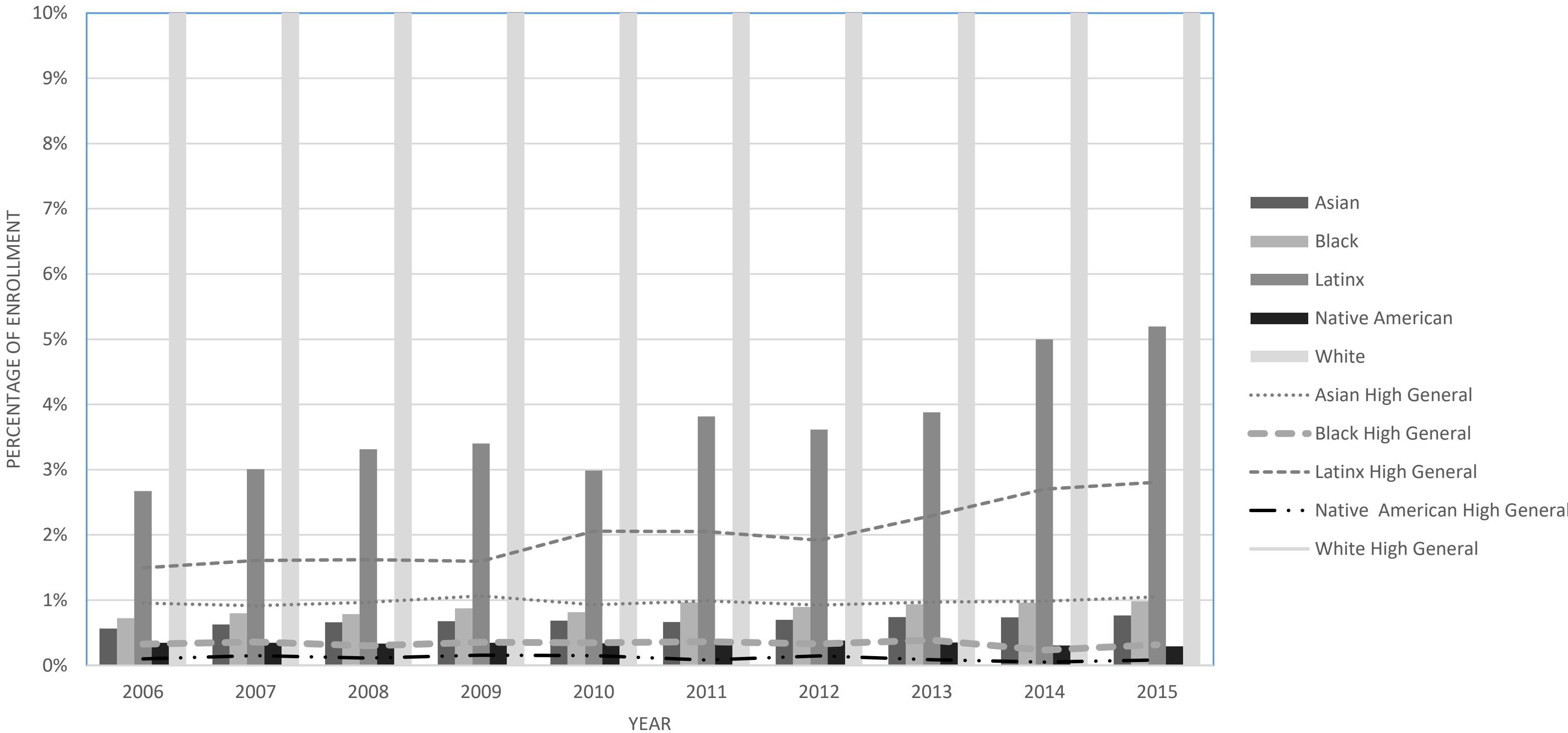

Figure 15b. A truncated version of Figure 15a. The y axis is truncated at 10% in order to highlight Asian, Black, Latinx, and Native American enrollment.

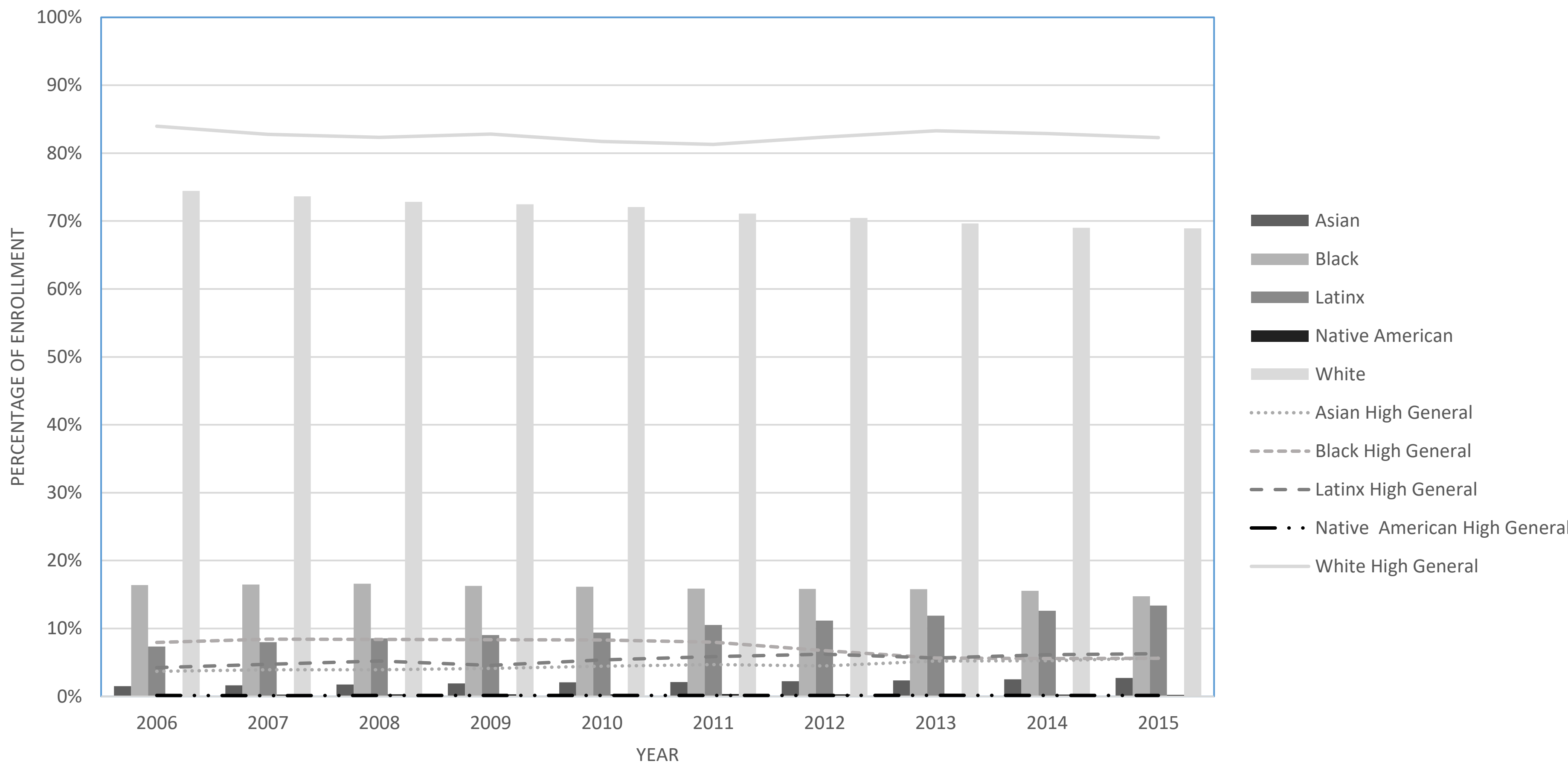

Figure 16a. The enrollment by percentage of Asian, Black, Latinx, Native American, and White students in Indiana non-rural schools. The bars represent percentage total student enrollment. The lines represent the percentage student enrollment in the gifted program through identification as high general ability.

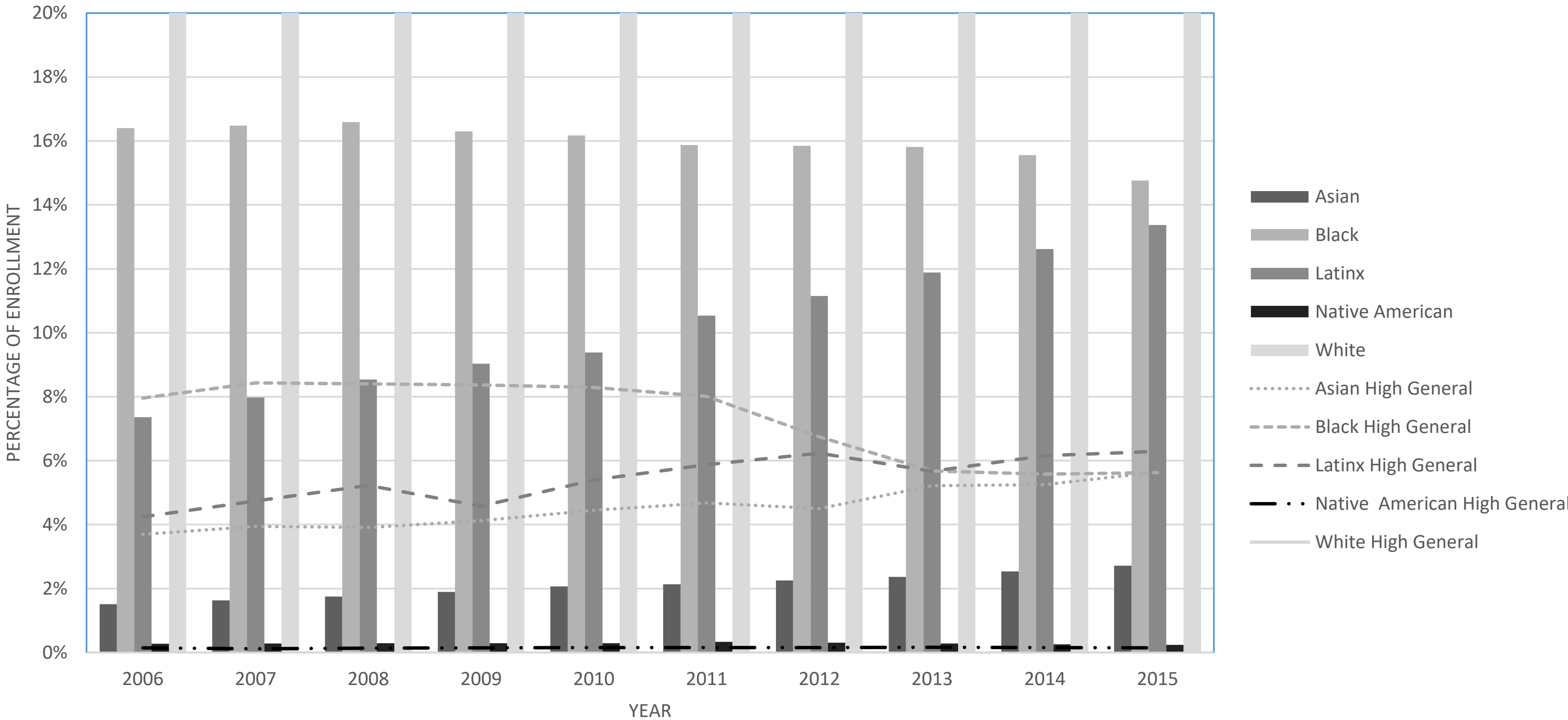

Figure 16b. A truncated version of Figure 16a. The y axis is truncated at 20% in order to highlight Asian, Black, Latinx, and Native American enrollment.

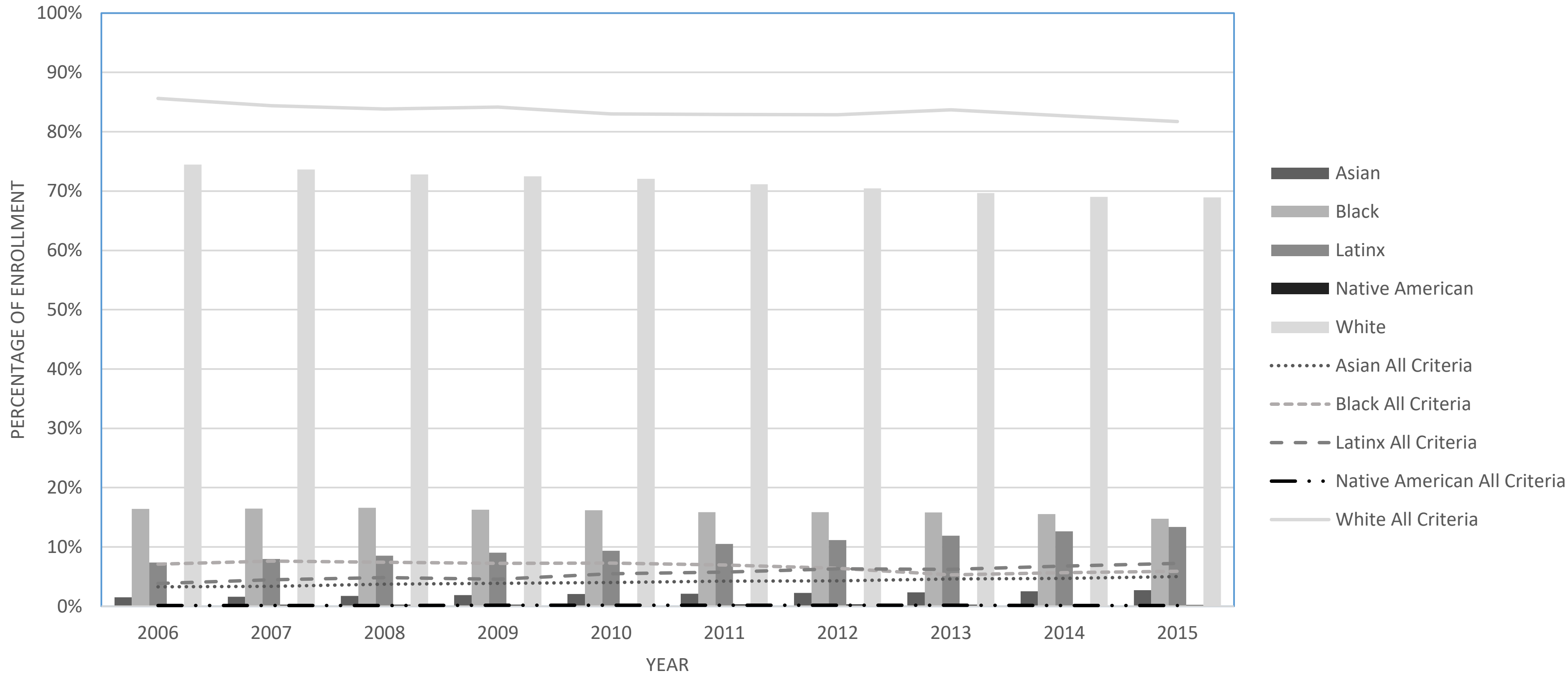

Figure 17a. The enrollment by percentage of Asian, Black, Latinx, Native American, and White students in Indiana non-rural schools. The bars represent percentage total student enrollment. The lines represent the percentage student enrollment in the gifted program through identification using multiple criteria (*overall*).

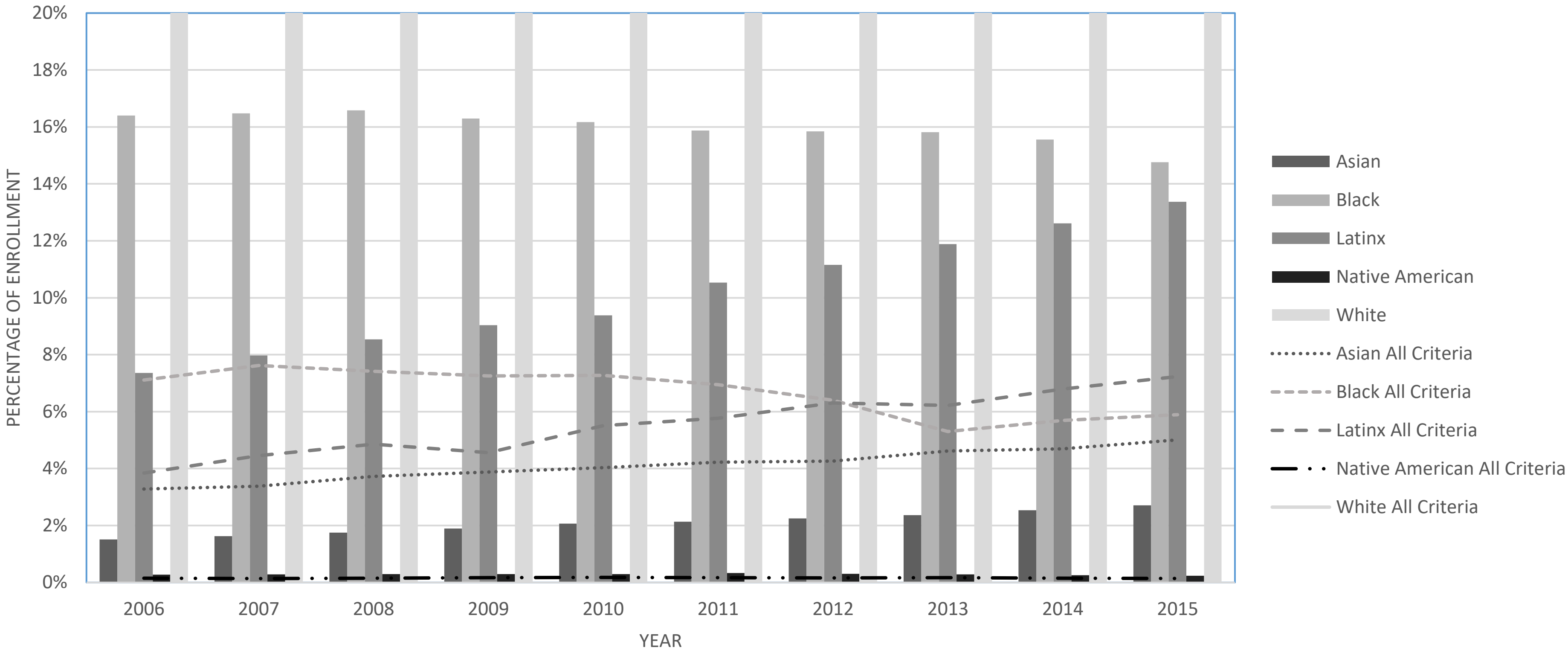

Figure 17b. A truncated version of Figure 17a. The y axis is truncated at 20% in order to highlight Asian, Black, Latinx, and Native American enrollment.

In rural school corporations, Asian student enrollment increased from 0.57 % of total student enrollment in the 2006-2007 academic year to 0.76% of total student enrollment in the 2015-2016 academic year. Asian students identified as having high general ability increased from 1.00% to 1.12% of the total students identified as having high general ability; whereas, the total percentage of students identified as gifted who are Asian increased from 1.66% to 2.05% (see Figure 3).

Black student enrollment decreased from 12.78% of total students in the 2006-2007 academic year to 11.70% of total students in the 2015-2016 academic year. In that same time, Black students identified as having high general ability decreased from 6.29% to 4.61% of the total students identified as having high general ability. The total percentage of Black students identified as gifted using all criteria decreased from 5.54% to 4.79% (see Figure 4).

In rural school corporations, Black student enrollment increased from 0.72 % of total student enrollment in the 2006-2007 academic year to 0.98% of total student enrollment in the 2015-2016 academic year. During this time, Black students identified as having high general ability decreased from 0.32% to 0.31% of the total students identified as having high general ability. However, the total percentage of Black students identified as gifted with any criteria increased from 0.36% to 0.38% (see Figure 5).

Latinx student enrollment nearly doubled from 6.28% of total student enrollment in the 2006-2007 academic year to 11.56% of total student enrollment in the 2015-2016 academic year. Latinx students identified as having high general ability increased from 3.64% to 5.62% of the total students identified as having high general ability. The total percentage of Latinx students identified as gifted increased from 3.30% to 6.41% (see Figure 6).

In rural school corporations, Latinx student enrollment increased from 2.67% of total student enrollment in the 2006-2007 academic year to 5.20% of total student enrollment in the 2015-2016 academic year. Latinx students identified as having high general ability increased from 1.49% to 2.81% of the total students identified as having high general ability. The total percentage of Latinx students identified as gifted more than doubled from 1.51% to 3.15% (see Figure 7).

Native American student enrollment decreased from 0.29% of total student enrollment in the 2006-2007 academic year to 0.25% of total student enrollment in the 2015-2016 academic year. Native American students identified as having high general ability remained relatively stable at 0.13% of the total students identified as having high general ability. The total percentage of Native American students identified as gifted decreased from 0.14% to 0.13% (see Figure 8).

In rural school corporations, Native American student enrollment decreased from 0.35% of total student enrollment in the 2006-2007 academic year to 0.29% of total student enrollment in the 2015-2016 academic year. Native American students identified as having high general ability decreased from 0.10% to less than 0.08% of the total students identified as having high general ability. The total percentage of Native American students identified as gifted under any criteria decreased from 0.11% to 0.07% (see Figure 9).

White student enrollment decreased from 79.36% of total student enrollment in the 2006-2007 academic year to 74.23% of total student enrollment in the 2015-2016 academic year. White students identified as having high general ability decreased from 86.83% to 84.85% of the total students identified as having high general ability. The total percentage of White students identified as gifted under any criteria from 88.28% to 84.46% (see Figure 10).

In rural school corporations, White student enrollment decreased from 95.69% of total student enrollment in the 2006-2007 academic year to 92.77% of total student enrollment in the 2015-2016 academic year. White students identified as having high general ability decreased from 97.08% to 95.62% of the total students identified as having high general ability. The total percentage students identified as gifted who are White decreased from 97.06% to 95.36% (see Figure 11).

Aggregated figures of Figures 1 through 11 were created by locale. Two figures were created for each graph (one truncated and one not truncated). The aggregated results for Indiana can be seen in Figures 12a, 12b, 13a, and 13b. The aggregated results for rural Indiana can be seen in Figures 14a, 14b, 15a, and 15b. Finally, the aggregated results for non-rural Indiana can be seen in Figures 16a, 16b, 17a, and 17b.

11.1.2 Representation Index

Yoon and Gentry (2009) used a representation index to examine proportional representation of Asian, Black, Latinx, Native American, and White students in the United States. A representation index is the proportion of students identified as gifted in a racial group by the proportion of all students present in that racial group, in this case within schools. A representation index was calculated for each race of students identified as gifted using the criteria of high general ability. A second representation index was calculated for students identified as gifted using all criteria for identification. The average representation index between 2006-2007 and 2015-2016 for Asian was 2.17 with identification using high general ability only and 1.94 with multiple criteria. The average representation index for Black students was 0.46 with identification using only high general ability and 0.42 with multiple criteria. The representation index for Latinx students was 0.55 with identification using high general ability and with multiple criteria. The average representation index for Native American students was 0.47 with identification using high general ability only and 0.50 with multiple criteria. Finally, the average representation index for White students was 1.12 with identification using only high general ability and 1.13 with multiple criteria. See Figure 18 and Figure 19 for the overall trend in proportional representation in Indiana school corporations.

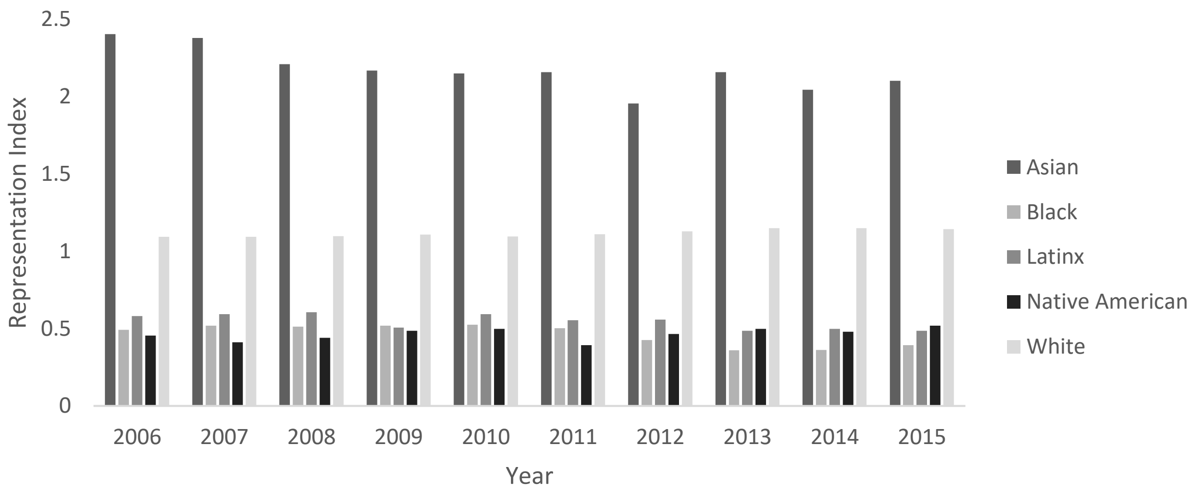

Figure 18. The representation index for Asian, Black, Latinx, Native American and White students identified as gifted using the criteria for high general ability in Indiana school corporations.

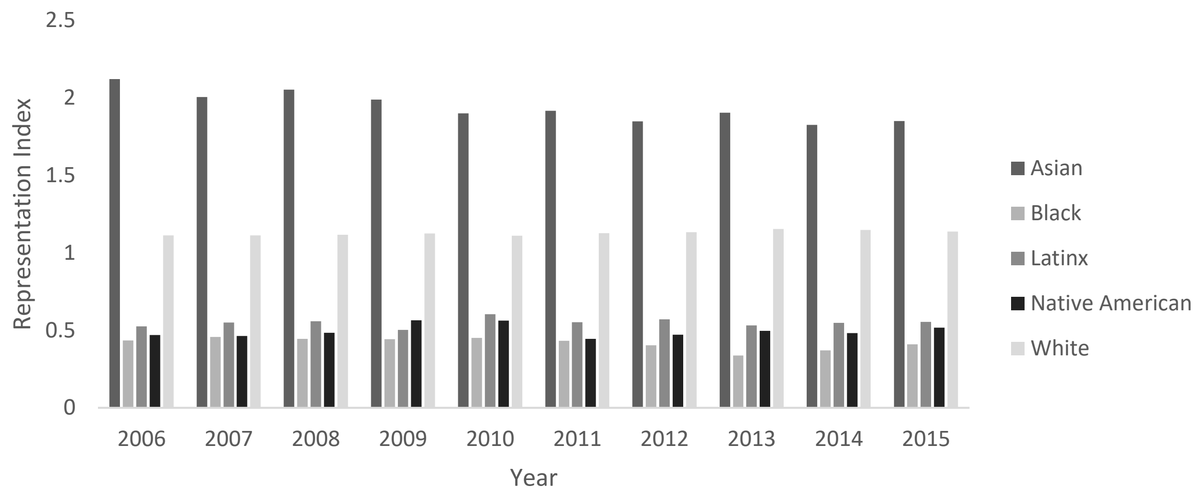

Figure 19. The representation index for Asian, Black, Latinx, Native American and White students identified as gifted using all criteria for identification in Indiana school corporations.

A representation index for Asian, Black, Latinx, Native American and White students identified as gifted using the criteria of high general ability in rural Indiana school corporations was calculated. A representation index was also calculated for students identified as gifted using all criteria for identification in rural Indiana school corporations. The average representation index between 2006-2007 and 2015-2016 for declined for Asian students from 1.66 using only high general ability to 1.43 with the inclusion of multiple criteria. The representation index for White students was 1.02 for identification using high general ability and multiple criteria. And the representation index (RI) increased for Black (.38 to .44), Latinx (.54 to .55), and Native American (.51 to .55) students increased with the inclusion of multiple criteria from only using high general ability for identification. See Figure 20 and Figure 21 for the overall trend in proportional representation in rural Indiana school corporations.

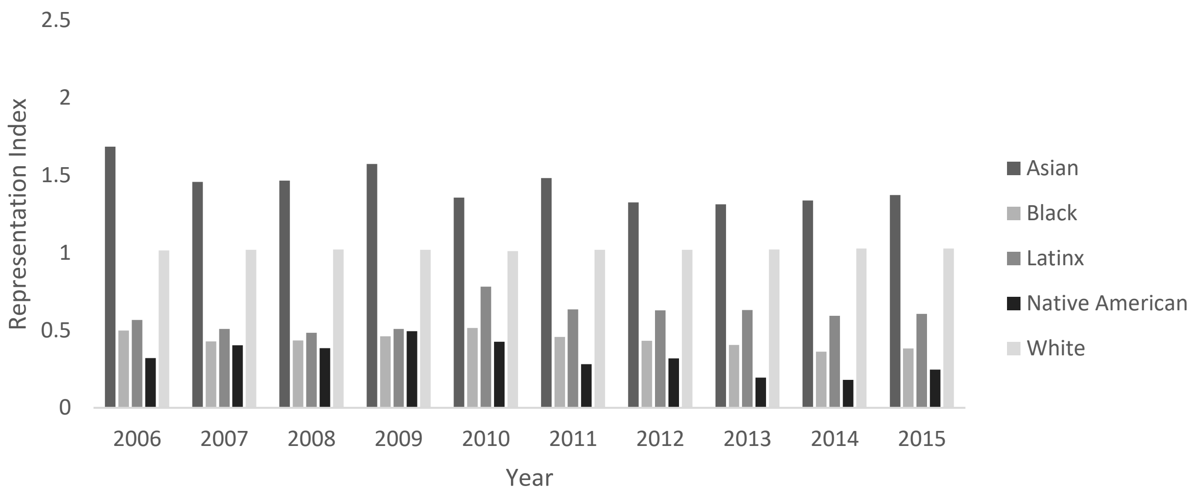

Figure 20. The representation index for Asian, Black, Latinx, Native American and White students identified as gifted using the criteria for high general ability in rural Indiana school corporations.

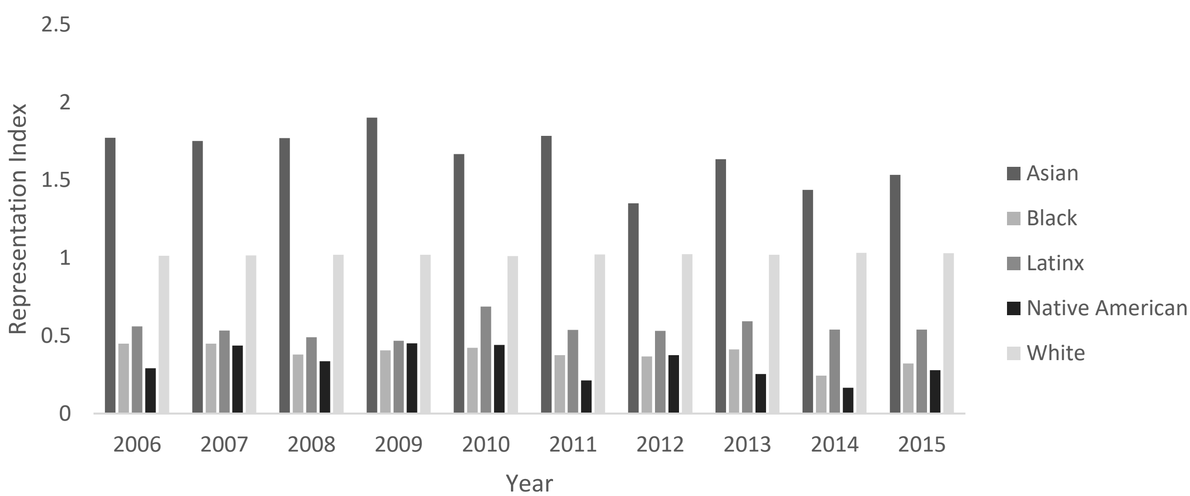

Figure 21. The representation index for Asian, Black, Latinx, Native American and White students identified as gifted using all criteria for identification in rural Indiana school corporations.

A representation index for Asian, Black, Latinx, Native American and White students identified as gifted using the criteria of high general ability in non-rural Indiana school corporations was calculated. A representation index was also calculated for students identified as gifted using all criteria for identification in non-rural Indiana school corporations. The average representation index declined between 2006-2007 and 2015-2016 for Asian (2.20 to 1.99) and

Black students (.46 to .42) with the inclusion of multiple criteria. During that same time the RI increased for Latinx (.54 to .55), Native American (.51 to .55), and White students (1.16 to 1.17). See Figure 22 and Figure 23 for the overall trend in proportional representation in non-rural Indiana school corporations.

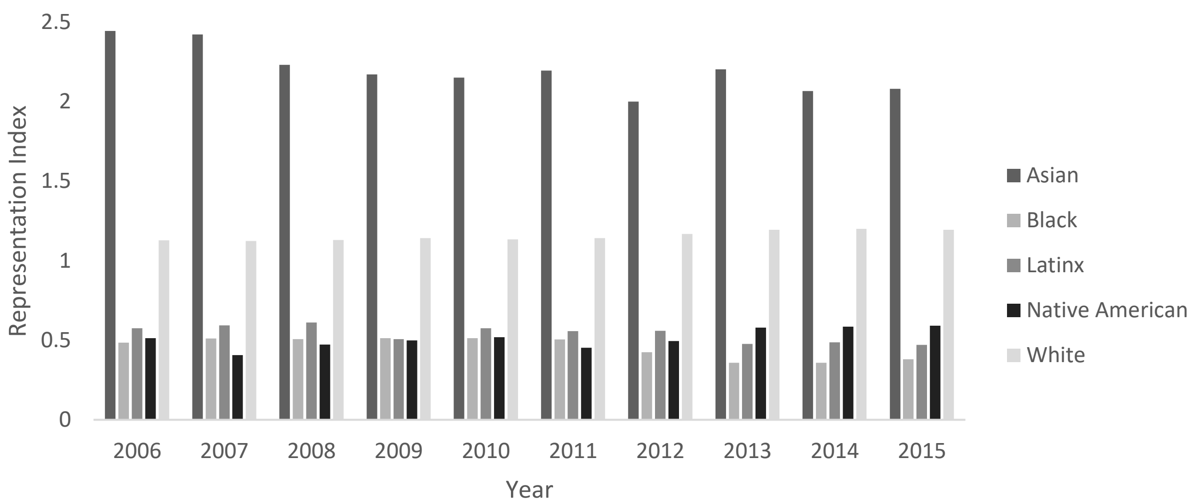

Figure 22. The representation index for Asian, Black, Latinx, Native American and White students identified as gifted using the criteria for high general ability in non-rural Indiana school corporations.

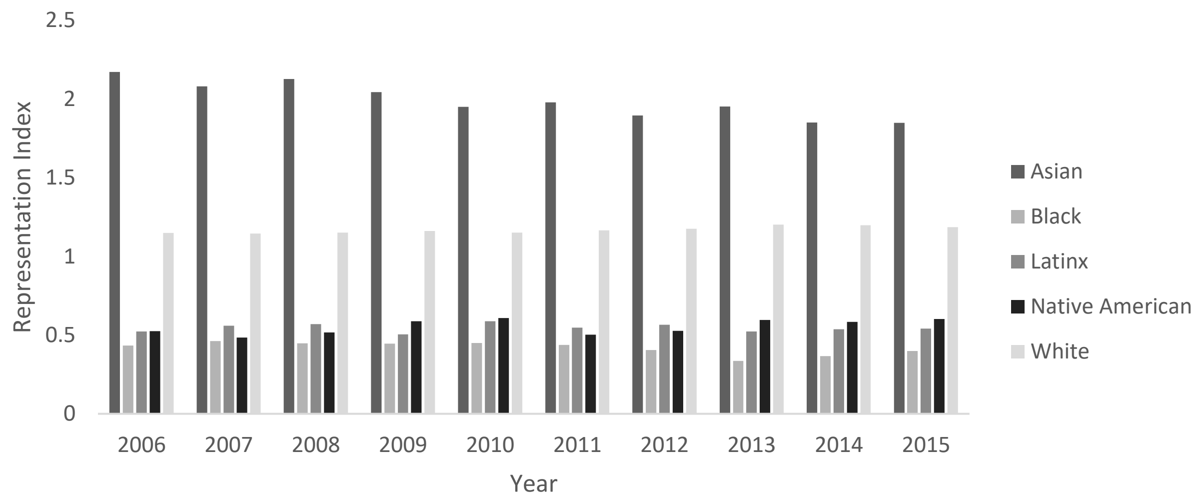

Figure 23. The representation index for Asian, Black, Latinx, Native American and White students identified as gifted using all criteria for identification in non-rural Indiana school corporations.

11.2 Regression Results

11.2.1 Model Diagnostics and Fit

The QQ plot for fixed effects demonstrated heavy tails. Given the large sample size in the data set (n > 1000), the heavy tails in the fixed effect error terms is unlikely to bias estimates (Faraway, 2014). Further, the QQ plot for random effects also demonstrated that the normality assumption was maintained (See Figure 24). An examination of the residual plot provided evidence that constant variance was maintained through the majority of observations though there was some moderate dispersion towards the upper end of the proportional identification spectrum. Given the rather unique characteristics surrounding a school district that has an odds ratio of identification of ~3 (suggesting under represented students are 3 times as likely to be identified as their Asian and White peers), it is not surprising that variance would not remain constant for these schools. Again, given the large sample size, the bias caused by these observations are unlikely to influence estimates (Faraway, 2014).

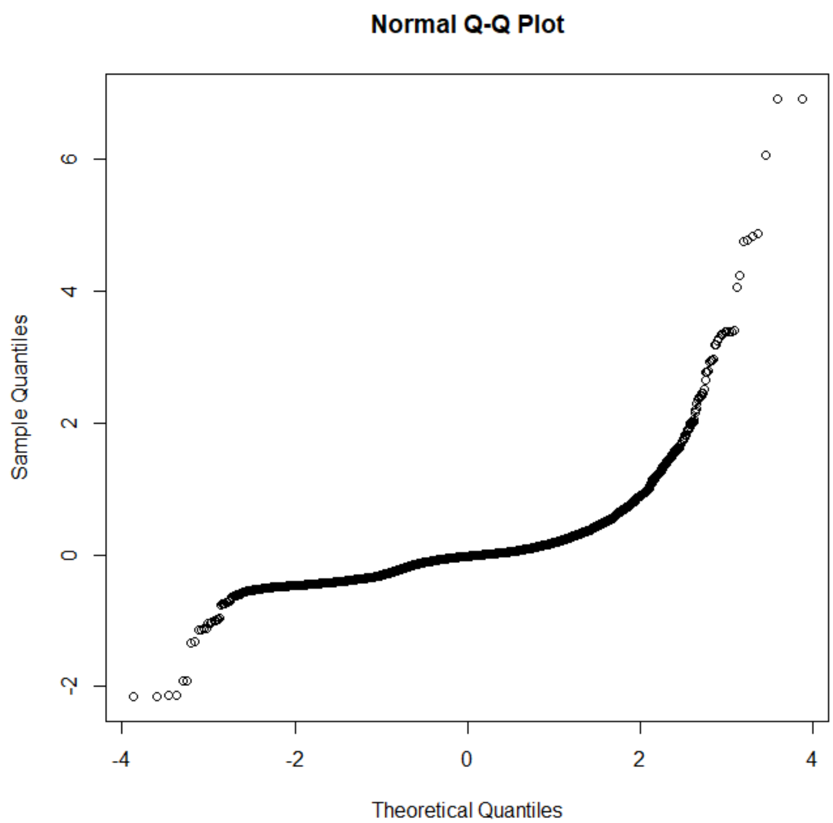

Figure 24. Quantile-Quantile of fixed effect residuals.

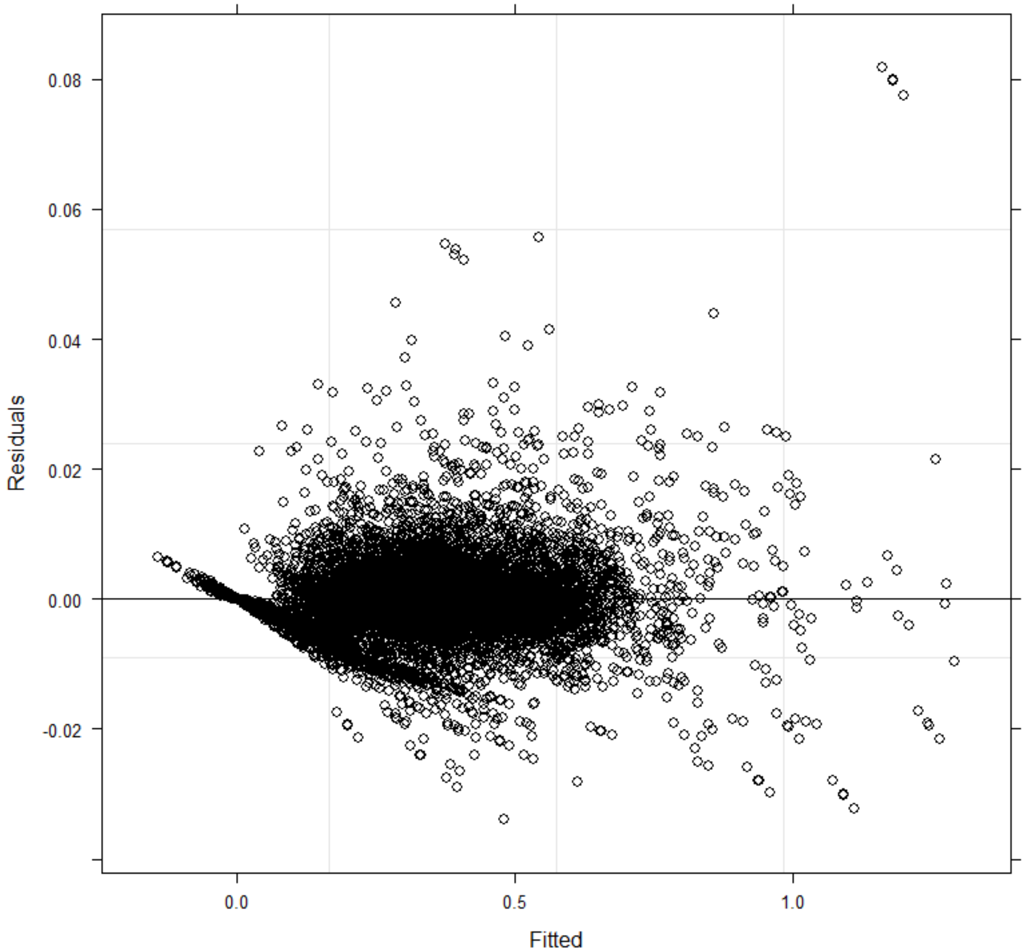

Figure 25. Residual vs. fitted plot showing some dispersion.

The intraclass correlation (ICC) associated with *corporation* was .48. The intraclass correlation associated with *annual corporation* was .85. This result provides strong evidence for the use of a mixed effects model (Faraway, 2014). Further, upon the inclusion of predictors to the null model (model only including fixed and random time variables), the model Bayesian information criteria (*BIC*) improved from 10949.97to 10449.67.

11.2.2 Overall

The odds ratio of identification during the time frame was 0.37. This means that Black, Latinx, and Native American students are only represented at 37% of the rate of Asian and White students. In other words, if a school has 1000 Asian and White students and 100 are identified as gifted, then in that same school, then the odds of identification is 1 to 9 (100 are identified, 900 were not). In turn, if there are 1000 Black, Latinx, and Native American students and 40 are identified as gifted, then the odds of identification is 1 to 24. Taking the ratio of these two odds yields roughly ~.37. The overall rates of representation did not statistically change during the time frame of the study (exp(β) = 0.99, $p = .79$). In terms of different identification paths, *math* (exp(β) = 1.10, $p < .01$) and *language arts* (exp(β) = 1.11, $p < .01$) led to statistically significant increases in rates of representation. For *math*, the increase accounted for a 10% increase and for *language arts*, it accounted for an 11% increase. Finally, the increase for all identification pathways (*overall*) was statistically significant (exp(β) = 1.21, $p < .01$). It should be noted that the percentage increase is multiplicative rather than additive. For example, a 10% increase in an odds ratio of 0.30 does not increase the odds ratio to 0.40 but to 0.33.

Rural led to a statistically significant decrease in the rates of identification (exp(β) = 0.90, $p < .01$). This means that rural school corporations in Indiana identify students at a reduced rate of 10%. However, alternate pathways for identification did increase rates of identification in rural school corporations. *Math* (exp(β) = 1.01, $p = .09$), language arts (exp(β) = 1.01, $p = .17$) were not significant predictors but overall (exp(β) = 1.02, $p = .01$) was statistically significant. Finally, the change overtime in identification rates in rural school corporations increased in the time frame of the study (exp(β) = 1.01, $p < .01$). This result suggests that rural school corporations averaged an increase in proportional identification rates of 1% yearly during the period of the study.

For random effects, *annual corporation* had a variance component of 0.01 (*SD* = 0.12) in comparison to *corporation*'s variance component of 0.05 (*SD* = 0.22). Considering the differences in representation between Black, Latinx, and Native American students across the state, this within school variance is not surprising. The random effect of year only accounted for > .01 variance (*SD* = 0.02) (full model results can be seen in Table 3). The small standard deviation provides further evidence that there was little annual change across districts though it is worth noting that given the -.60 correlation with the corporation intercept, this does suggest that there were corporations that had decreases in the proportional representation across the time frame. Model effect size was .81.

Table 3
Regression results for all students

Fixed Effects	Exp(β)	*SE*	*T*	*p*
Year	1.00	0.01	0.33	.743
Math	1.02	0.01	14.04	< .001
Language Arts	1.02	0.01	7.69	< .001
Overall	1.04	0.01	21.47	< .001
Rural	0.90	0.03	4.12	< .001
Year x Rural	1.01	0.01	3.15	.002
Math x Rural	1.01	0.01	1.71	.088
Language Arts x Rural	1.01	0.01	1.38	.167
Overall x Rural	1.02	0.01	2.74	.006

Random Effects	Variance	*SD*	*Corr*
Annual Corporation	0.01	0.12	
Corporation	0.05	0.22	
Year	> 0.01	0.02	-.60
Residual	> 0.01	> 0.01	

11.2.3 Black

The odds ratio of identification during the study period was 0.32. *Year* was not a statistically significant predictor in the model describing proportional identification odds for

Black students ($\exp(\beta) = 1.02$, $p = .274$). Identification through *math* led to increased odds of proportional identification by 6% ($\exp(\beta) = 1.06$, $p < .001$). *Language arts* identification increased proportional identification of Black students by 9% ($\exp(\beta) = 1.09$, $p < .001$). When all pathways to identification were considered, the proportional identification rates of Black students increased by 14% ($\exp(\beta) = 1.14$, $p < .001$).

Rural corporations had 20% of the rates of proportional identification of non-rural corporations ($\exp(\beta) = 0.18$, $p < .001$). Though *rural* reduced odds of identification for Black students, *math* ($\exp(\beta) = 1.20$, $p < .001$), language *arts* ($\exp(\beta) = 1.24$, $p < .001$), and *overall* ($\exp(\beta) = 1.45$, $p < .001$) all increased rates of identification significantly in rural school corporations. This means that in rural school corporations, the inclusion of mathematics ability along with general ability increased proportional identification rates of Black students by 20%. Further, the inclusion of all pathways for identification increased the rates of proportional identification by 45%.

The random intercept for corporation accounted for 2.42 (*SD* = 1.56) of explained random variance compared to .68 (*SD* = 0.83) from *annual corporation*. The random slope for year explained .02 (*SD* = 0.14) of residual variance and had a correlation with the intercept of -.55 (full model results can be seen in Table 4). Model effect size was .89.

Table 4
Regression results for Black students

Fixed Effects	Exp(β)	*SE*	*T*	*p*
Year	1.02	0.02	1.10	.274
Math	1.06	0.01	9.55	< .001
Language Arts	1.09	0.01	14.45	< .001
Overall	1.14	0.01	22.62	< .001
Rural	0.18	0.20	8.67	< .001
Year x Rural	0.99	0.03	0.38	.705
Math x Rural	1.20	0.05	3.98	< .001
Language Arts x Rural	1.24	0.05	4.75	< .001
Overall x Rural	1.45	0.05	8.09	< .001
Random Effects	Variance	*SD*	*Corr*	
Annual Corporation	0.68	0.83		
Corporation	2.42	1.56		
Year	0.02	0.14	-.55	
Residual	> 0.01	> 0.01		

11.2.4 Latinx

The odds ratio of identification for Latinx students in the time frame of the study was 0.45. During the time frame of the study, *year* had a negative effect on likelihood of identification (exp(β) = 1.03, p = .041). This means that there was an annual 3% increase in the rate of proportional identification for Latinx students. Further, the main effects for *math* (exp(β) = 1.12, $p < .001$), *language arts* (exp(β) = 1.04, $p < .001$), and *overall* (exp(β) = 1.14, $p < .001$) were significant predictors in the model. This means that *math* increased the rates of proportional identification by 12%, *language arts* by 4%, and the inclusion of all pathways increased the likelihood of identification by 14%.

Rural school corporations had 22% of the rates of proportional identification of non-rural school corporations (exp(β) = 0.26 $p < .001$). This means that Latinx students in rural schools are represented proportionally at only 26% of the rate as Latinx students in non-rural schools. *Math* increased odds of identification by 13% in rural school corporations (exp(β) = 1.13, $p < .001$). *Language arts* increased odds of identification by 13% (exp(β) = 1.13, $p < .001$). *Overall* increased the odds of identification by 23% (exp(β) = 1.23, $p < .001$). Finally, the likelihood of identification increased by 10% annually in rural communities (exp(β) = 1.10, $p < .001$).

In terms of random effects, *corporation* had a variance component of 3.02 (*SD* = 1.73). *Annual corporation* accounted for a smaller share of variance with a variance component of 0.57 (*SD* = 0.76). *Year* had a -.42 correlation with the slope and had a variance component of 0.02 (*SD* = 0.16) (full model results can be seen in Table 5). This provides evidence that the increase in proportional representation was not uniform across the states. The correlation suggests that corporations that had lower odds of proportional identification had greater increases across the time frame of the study. Model effect size was .89.

Table 5
Regression results for Latinx students

Fixed Effects	Exp(β)	*SE*	*T*	*p*
Year	1.03	0.02	2.05	.041
Math	1.12	0.01	14.39	< .001
Language Arts	1.04	0.01	4.83	< .001
Overall	1.14	0.01	17.63	< .001
Rural	0.26	0.28	8.63	< .001
Year x Rural	1.10	0.02	4.06	< .001
Math x Rural	1.13	0.02	4.88	< .001
Language Arts x Rural	1.13	0.02	4.93	< .001
Overall x Rural	1.23	0.02	8.31	< .001

Random Effects	Variance	*SD*	*Corr*
Annual Corporation	0.57	0.76	
Corporation	3.02	1.73	
Year	0.02	0.16	-.42
Residual	< 0.01	0.04	

11.2.5 Native American

In the time frame of the study, the odds ratio of identification for Native American students was 0.39. There was a statistically significant decline in the rate of identification for Native American students during the time frame of the study ($\exp(\beta) = 0.98$, $p = .019$). This means that there was a 2% annual decline in the odds of identification. *Math* increased the odds of identification by 33% ($\exp(\beta) = 1.33$, $p < .001$). *Language arts* also increased the odds of identification by 22% ($\exp(\beta) = 1.22$, $p < .001$). Finally, the inclusion of all pathways of identification increased odds of identification by 62% ($\exp(\beta) = 1.62$, $p < .001$).

Rural corporations had 48% of the rates of proportional identification of non-rural corporations ($\exp(\beta) = 0.48$ $p < .001$). There was no significant change in the rate of proportional identification over time in rural locales ($\exp(\beta) = 1.00$, $p = .974$). *Math* ($\exp(\beta) = 0.87$, $p < .001$) and *overall* ($\exp(\beta) = 0.86$, $p < .001$) statistically decreased odds of identification. This means that the additions of mathematics ability as an identification path along with general ability decreased odds of identification by 13%. Using all pathways for identification lowered the likelihood of identification by 14%. *Language arts* was not statistically related to identification odds ($\exp(\beta) = 0.98$, $p = .623$).

The random intercept for *corporation* had a variance component of 2.09 ($SD = 1.45$). In comparison, the variance component for *annual corporation* was 1.26 ($SD = 1.12$). The addition of a random slope for *year* accounted for a variance component of .03 ($SD = 0.16$) and had a correlation with the intercept of -50 (full model results can be seen in Table 6). Model effect size was .92.

Table 6
Regression results for Native American students

Fixed Effects	Exp(β)	*SE*	*T*	*P*
Year	0.98	0.02	0.83	.410
Math	1.33	0.02	11.78	< .001
Language Arts	1.22	0.02	8.24	< .001
Overall	1.62	0.02	19.70	< .001
Rural	0.48	0.21	3.51	< .001
Year x Rural	1.00	0.03	0.03	.974
Math x Rural	0.87	0.05	2.89	.003
Language Arts x Rural	0.98	0.05	0.49	.623
Overall x Rural	0.86	0.05	3.21	< .001

Random Effects	Variance	*SD*	*Corr*
Annual Corporation	1.26	1.12	
Corporation	2.09	1.45	
Year	0.03	0.16	-.50
Residual	> 0.01	0.01	

CHAPTER 12. INDIANA DISCUSSION

12.1 Research Question One

With regard to question one: *To what extent did Indiana public schools proportionally identify Black, Latinx, and Native American Students for gifted education services during the timeframe of 2006-2007 to 2015-2016?* Black, Latinx, and Native American students are underrepresented in the state of Indiana. The likelihood of representation (odds ratio) ranged from 0.32 to 0.44 for Black, Latinx, and Native American students combined. These findings corroborate and extend Yoon and Gentry's (2009) results by extending the time frame of their study, which had a final time point of 2006. The results of this study provided evidence that despite progressive definitions and policies used by the state of Indiana, a decade did not erase the underrepresentation issues observed by Yoon and Gentry (2009).

Black students had the lowest overall odds ratio of identification ranging from 0.39 in 2006-2007 to 0.36 in 2015-2016. Yoon and Gentry (2009) observed that Black students were only proportionally represented at ~45% of the rate of white students in Indiana. This means that the current levels of proportional identification of Black students has declined in the decade since the Yoon and Gentry (2009) study.

The Latinx population in Indiana has nearly doubled in the last ten years (see Table 1). Thus, it is likely that Indiana is experiencing the same difficulties as the Southwest in identifying immigrant students (Esquierdo & Arreguín-Anderson, 2012). The overall percentage of Latinx students identified as gifted rose to 6.41% by the 2015-2016 academic school year from 3.30% in 2006-2007. The odds ratio of identification for gifted services for Latinx students was 0.47 in

2006-2007 and 0.49 in 2015-2016. Though still underrepresented in Indiana, the representation of Latinx students slightly rose throughout the time frame of the study.

The overall number of Native American students in Indiana declined between 2006-2007 and 2015-2016. Despite the population decline, the odds ratio of identification for gifted services of Native American students identified as gifted rose from 0.42 in 2006-2007 to 0.45 in 2015-2016. Gentry et al. (2014) discussed that in conjunction with issues of rurality, race, and poverty, educators' cultural unfamiliarity acted as a barrier to identification for gifted services for Native American students.

12.2 Research Question Two

With regard to question two: *To what extent do multiple identification categories increase proportional identification of Black, Latinx, and Native American students for gifted education services in Indiana and how do these proportions compare with Asian and White students?* In all populations, the addition of other pathways to identification increased identification of underrepresented populations for gifted services. In other words, the gap in representation in gifted narrowed between traditional underrepresented populations (Black, Latinx, and Native American students) and overrepresented populations (Asian and White students). This finding provides quantitative evidence to the theoretical arguments made by McBee et al. (2014). The authors argument was that there are three possible "rules" for gifted education identification: "and", "or", or "mean". Indiana uses what the authors referred to as the "or" rule. To be identified as gifted, a child needed to be identified in one of four pathways. In other words, a child could be identified as gifted through performance on an intelligence test or performance in mathematics on a state achievement test or performance in language arts on a state achievement test or by a measure determined by the school corporation that assesses student characteristics and classroom performance. As McBee et al. (2014) noted, the implementation of the “or” rule led to a categorical rise in the number of students identified as gifted in a school corporation. The findings from this study demonstrated how the use of the “or” rule benefited Indiana’s Black, Latinx, and Native American students; students who are traditionally underrepresented in gifted programs.

In terms of overall increase in rates of identification, the inclusion of a performance-based identification measure led to the largest increase in the likelihood of identification for Black, Latinx, and Native American students. Gentry et al. (2015) noted that performance-based assessments (e.g. those based on behavioral characteristics) can lead to additional Black, Latinx, and Native American students being identified as gifted than traditional intelligence tests or state achievement tests. The results from this research provide evidence to support this claim. Of all additional criteria for identification, the inclusion of performance-based assessments along with the other three assessment categories provided the highest increase to the overall rates of proportional identification. This 20% increase in the likelihood of identification does not close the gap in representation, but at the very least it is a promising start. Further, it provides evidence that these methods do produce the results that the authors claim.

In terms of the effect of multiple criteria on the three ethnic groups, language arts assessments led to the same increase in proportional representation as math assessments. Further, the inclusion of performance-based assessments along with mathematics and language arts assessment tests increased representation by 4%. This further provides evidence supporting the claims made by Gentry et al. (2015). The authors stated that alternative forms of assessment, such as teacher rating scales, can lead to a more proportionately representative identified gifted population.

In contrast, the difference in representation likelihood between mathematics and languages arts contradicts the claims of Naglieri and Ford (2003), who stated that verbal components on assessments were an underlying cause of underrepresentation. In contrast to this, the assessment that is firmly grounded in verbal ability (language arts assessment) produced greater likelihood of identification for Black students in comparison than the more quantitative mathematics assessment. The effectiveness of non-verbal tests to identify Black students for gifted services has been met with skepticism from scholars. Lohman et al. (2008) found that using non-verbal intelligence tests produced similar disparities in representation as observed with verbal intelligence tests. Further, Carman and Taylor (2010) found that Black, Latinx, and Native American students were underrepresented in an urban school corporation that used the NNAT to identify children. Black students were proportionately identified better using the language arts test in Indiana between 2006 and 2015. If Naglieri and Ford (2002) were correct, then the language arts assessment would produce greater disparity. The reason that Lohman et al. (2008) and Carman and Taylor (2010) had poor results when using the NNAT is likely due to a flaw in the fundamental assumption that non-verbal tests best identify Black, Latinx, and Native American children.

12.3 Research Question Three

With regard to question three: *To what extent does rurality moderate proportional identification of Black, Latinx, and Native American students for gifted education services in Indiana?* In all cases, the likelihood of identification in rural school corporations was less than non-rural locales. When Black, Latinx, and Native American students were examined together, the likelihood of identification was 10% less than in non-rural school corporations. Colangelo et al. (2006) described how rural schools were meeting the needs of diverse learners. The authors convey a promising message that, though disparity in identification exists in rural areas, work is being done to close the representation gap. The results from this study convey a less positive status in rural Indiana for the identification of Black, Latinx, and Native American students.

The difference in rates of identification in rural and non-rural school corporations is staggering. A 10% reduction in likelihood of identification for these already underserved youth is a finding that urgently necessitates change. What this means is that Black, Latinx, and Native American students are identified at less than one quarter of the rate at which they are identified in non-rural schools. Considering the fact that 32.79% of rural school observations were zeros (meaning that there were Black, Latinx, and Native American students in the corporation but none were identified as gifted) this finding is, unfortunately, not surprising. When the overall non-identification rate (a population exists but none are identified) of the Black, Latinx, and Native American students for gifted services in the state is 18.76% and rural school corporations have nearly double the rate, a problem exists. Colangelo et al. (1999) stated that the diversity that might be in a rural school's general population is not always reflected in its gifted program. The evidence presented by this study strongly supports this notion. Despite a 17-year gap, the observations made by Colangelo et al. (1999) in their national report on rural gifted education at the Belin-Blank Center still exist within rural Indiana schools today. Further, for Latinx and Native American students, the trend in proportional identification is worsening in rural areas.

Of the three underrepresented populations, the results suggested that rural school corporations had the most success in identifying Native American students (0.53 versus 0.22 and 0.20 for Latinx and Black students respectively). It should be considered, though, that success in these terms still entails a 47% decrease in proportional identification rates in comparison to Asian and White students. It is likely that the cultural influences cited by Gentry et al. (2014) are exacerbated by lack of qualified teachers noted by Plucker et al. (2013). In other words, rural teachers lack the cultural competencies to meet the needs of gifted Native American students. It is difficult, though, to make the claim that the race of majority of Indiana's teaching staff, being white, is the cause for underrepresentation as described by Stambaugh and Ford (2015). What is a more likely reason for the disparity in likelihood of identification is a combination of lack of training and lack of resources to provide the necessary training. As such, what is needed to address this disparity is for cultural competence training of the teaching staff and the resources (in time and money) to see it implemented.

Despite rural school corporations having difficulty in identifying Black, Latinx, and Native American students as gifted, multiple criteria of identification did increase the likelihood of identification. These results provide strong evidence that even though rural communities face unique challenges (Howley et al., 2009), the success of using multiple criteria in conjunction with the "or" rule (McBee et al., 2014) increases the likelihood of identification even if this likelihood is small to begin with and disparate when compared with non-rural schools.

12.4 Limitations

A limitation is that the dataset only extends to the past decade. Further time points would allow for a model that better estimated the effect of time during the model. In line with this limitation is that only one state is included in the analysis. Each state has its own gifted identification procedures. Further, each state is demographically unique. The demographic make-up of the K-12 student population in Indiana is unique. As a result, the results from this study do not generalize to other states with multiple criteria for identification.

Another limitation is due to the properties of an odds ratio. The denominator of the odds ratio is defined by multiplying two groups of students together. If either of those groups are not present in a school district, then the odds ratio becomes undefined. Since the analysis is longitudinal rather than cross-sectional, there is the possibility that a school district will have undefined odds ratio. This creates the possibility for biased estimates since those undefined values are then imputed by the longitudinal model.

A final limitation is the sensitivity of the odds ratio to smaller sample sizes. When a school district has a small population of students of a give student group ($n < 20$), there is a possibility for an inaccuracy from lack of sensitivity. For example, if a school district has ten Native American students, an ideal identification rate of 5% would imply that .5 students would be identified. Averaging over ten years, this would mean that the identified population would fluctuate between 0% and 10%. While the mean is still 5%, the standard error of this estimate is far more volatile than from a larger sample size. Further, when a school district only has a single student of an ethnic group, an odds ratio cannot be calculated for that student if that student is also identified as gifted.

12.5 Future Research

One area that could benefit from further research would be the efficacy of different performance-based measures. All Indiana school corporations use IQ testing in conjunction with scores on the state standardized tests. Where they differ is in their implementation of the performance-based measure. A meaningful extension would be to replicate this study with the inclusion of a variable that controls for different performance-based measures.

Further, Indiana is not the only state that uses multiple criteria for gifted services identification. A natural extension of this study is to replicate it in other states that use multiple criteria. Indiana is demographically different than other areas of the United States. It would be useful to examine if the results presented in this study can be generalized to other states.

CHAPTER 13. INDIANA CONCLUSION

Having multiple pathways for identification increases proportional representation of Black, Latinx, and Native American students in gifted programs. Further, having a performance-based criterion for identification as gifted in addition to state achievement tests and general ability tests results in the highest likelihood for proportional representation in gifted classrooms. The message for state policy makers and administrators is clear. If they wish to have a more representative population of gifted students in schools, then multiple criteria for identification must be used.

Researchers and practitioners should be aware that the gaps in proportional identification were lessened but not closed by using multiple criteria. Underrepresentation in Indiana exists and must be addressed, especially in rural areas where the problem is huge. Local norms (Peters & Gentry, 2012) used with multiple criteria is one solution that can be used to address the persistent gap in representation between underrepresented and over represented groups in gifted education. Grounding identification procedures in environmental factors along with having a multi-faceted testing battery ensures that a more representative population will be identified. Peters and Gentry (2012) showed that using achievement tests with local norms can produce a more representative population of identified students. Further, McBee et al. (2014) demonstrated that multiple criteria identify a wider range of students. Combining both authors' work leads to the conclusion that local norms with multiple criteria can potentially close the gap in representation.

CHAPTER 14. WASHINGTON INTRODUCTION

14.1 Abstract

Underrepresentation of Black, Latinx, and Native American children in gifted programming is an ongoing focus of research in the field of gifted education. This study examines the state of Washington's gifted education practices and how school district policies surrounding a gifted program relate to the proportional rates of underrepresented groups identified for gifted services over time in that district. A general linear mixed effects model was used to model longitudinal data obtained on district identification rates for the highly capable program in the state of Washington. Results provide evidence that identification proportional representation increases with the grade level start of identification in Washington school districts. That said, the increase was small (2% increase per later grade level) suggesting that the grade level in which identification begins does not have a large effect on proportional identification of underrepresented students for gifted education.

14.2 Introduction

The excellence gap in education is pervasive and manifests itself through all facets of public schooling (Plucker, Hardesty, & Burroughs, 2013). Rates of graduation, discipline referrals, standardized test scores, and college entrance rates vary along racial lines. In gifted education programming, this excellence gap exists through the underidentification and underrepresentation of Black, Latinx, and Native American students compared to their Asian and White peers (Yoon & Gentry, 2009). Although scholars in the field are aware of the gap in representation, the underlying mechanics that cause underrepresentation are debated (Callahan, 2005; Erwin & Worrell, 2012; Lakin & Lohman, 2011; McBee, 2006; Milner & Ford, 2007; Plucker & Callahan, 2012; Subotnik, Olszewski-Kubilius, & Worrell, 2011).

One cause for underrepresentation involves differing levels of academic exposure prior to entering school, with some students entering school academically behind their peers (Campbell, Ramey, Pungello, Sparling, & Miller-Johnson, 2002). Thus, when testing is administered to identify for gifted services at a young age, these disparities in verbal skills can lead to inaccurate identifications for gifted services (Kaufman, 1994; Pfeiffer & Petscher, 2008). Further, when a child is identified for gifted services without requisite school readiness needed to succeed in the gifted program, that child would not have an equal chance at retention in gifted programs as their peers with greater levels of school readiness (Gormley, Phillips, & Gayer, 2008). In contrast, the National Association for Gifted Children (NAGC) calls for the early identification of students in conjunction with appropriate services (2012).

The National Association for Gifted Children (NAGC) advocates the use of early identification in their programming standards (NAGC, 2012, NAGC Programming Standard 2.2), and early identification needs to be accompanied by appropriate services (Gentry, 2009). In an ideal academic environment, students from underrepresented populations would be identified using multiple criteria designed with the philosophy of comparing children to their similar-background peers, using non-biased measures, and recognizing diversity (NAGC Programming Standard 2.3.1, 2012).

Scholars have demonstrated that school readiness is correlated to underrepresented group identification for gifted services and success in early elementary grades (Gormley, Phillips, & Gayer, 2008; Henfield, Owens, & Moore, 2008; Winsler, Karkhanis, Kim, & Levitt, 2013). These scholars and the NAGC agree that the educators hoping to have a high ability program reflective of the diversity of the general population of a school district must provide services and support early.

The Washington state public school system offers an opportunity to examine the effects of identifying students for gifted services on the identification proportions and retention rates of Black, Latinx, and Native American students in gifted programs. The Washington state legislature mandated that identification and services be provided for gifted students but only provided suggestions regarding how this mandate should be enacted (Washington Administrative Code, 2015). The state provides funding to hire teachers, but the district must locate other funding sources to meet the legislative mandates for identification and programming. Thus, school districts are provided near autonomy in meeting the needs of their gifted populations (Washington Administrative Code 392-170-078), unified only by legislative mandates. Districts throughout the state participate in honors programs in middle school followed by advanced placement courses in high school.

Thus, the focus of this research is to examine the effect of grade level at the time of identification on proportional representation in gifted programs. Further, this research seeks to explore the quantitative effect of early identification on Black, Latinx, and Native American students.

14.3 Purpose

In this study, I address the gap in literature by examining gifted identification rates of Black, Latinx, and Native American students in the state of Washington. A longitudinal model was used to examine identification rates for gifted services in Washington public school districts. The NAGC programming standards (2012) advocate for early identification with appropriate services. In this paper, I aim to examine the influence of when gifted identification begins in a district on the overall rates of proportional identification for Black, Latinx, and Native American students. Further, I aim to examine how rurality moderates this influence.

14.4 Research Questions

1. To what extent are Black, Latinx and Native American students underrepresented in gifted programs in the state of Washington compared to their Asian and White peers from the academic years 2002-2003 through 2011-2012?

2. To what extent does the grade in which gifted identification begins relate to the proportional representation of Black, Latinx, and Native American students in gifted programs?

3. To what extent does the grade in which gifted services begin relate to the rates of proportional representation of cohorts Black, Latinx, and Native American student population in gifted programs over time?

4. To what extent does rurality relate to the proportional representation of Black, Latinx and Native American students and their rate of representation over time in gifted programs?

CHAPTER 15. WASHINGTON LITERATURE REVIEW

15.1 Underrepresentation in Gifted Education

Black, Latinx, and Native American children are underrepresented in gifted education programs across the United States (Yoon & Gentry, 2009). In the case of Washington, Yoon and Gentry (2009) found that Black, Latinx, and Native American children were consistently identified at a proportional rate of .5 in the state between 2002 and 2006. This means that in a Washington school district the students were identified for gifted services at half the rate of their inclusion in general populations.

Henfield, Moore, and Wood (2008) examined the issues facing Black students in gifted education programs using Critical Race Theory. Twelve Black students participating in gifted education programs were interviewed. The authors found that students faced identity issues with being labeled gifted. Further, the participants related experiences of how teachers treated them differently based on their race. Ford and Grantham (2003) stated that this differential treatment was one of the underlying causes for underrepresentation of Black students in gifted education programs. Esquierdo and Arreguin-Anderson (2012) examined the identification of Latinx students in Texas. The authors found that Latinx students were underidentified compared to Asian and White students. The authors noted that given Texas's large Latinx population, and its growth trajectory in the coming decades, further disenfranchisement of Latinx gifted students is unsustainable. Native American students are also underidentified compared to Asian and White students (Yoon & Gentry, 2009). In a study examining the causes for underidentification of Native American students, Gentry, Fugate, Wu, and Castellano (2014) worked with tribal members from the Diné, Ojibwe, and Lakota nations to assess causes for underrepresentation of

Native American students in gifted education programs. The authors found that in addition to ethnicity, rurality, and underlying poverty, communication style, learning preferences, and cultural differences impede identification of Native American students for gifted education.

15.1.1 School Readiness

School readiness refers to a student’s reading, math, and general knowledge skills upon entering kindergarten and is one of the underlying causes of the excellence gap (Davoudzadeh, McTernan, & Grimm, 2015). In a study examining the effects of school readiness on performance in mathematics in high school, Watts, Duncan, Siegler, and Davis-Kean (2014) found that school readiness predicted math performance up to age 15. The authors used an auto-regressive moving average model to examine the National Institute of Child Health and Human Development Study of Early Child Care and Youth Development data set. Interestingly, the authors found that the effect of school readiness diminished over time. Instead, the authors discovered that students who made substantial gains in early elementary had the highest levels of math achievement regardless of initial school readiness (Watts et al., 2014).

Duncan, et al. (2007) used meta-analytic techniques to analyze the effect of school readiness on later academic achievement. In the study, Duncan et al. found that mathematic readiness, followed by literacy skills, upon entering kindergarten was the strongest predictor for academic success in third grade in comparison to socioemotional behaviors (e.g. internalizing/externalizing problems and social skills). Geary, Hoard, Nugent, and Bailey (2013) found that early numeracy in kindergarten predicted mathematical achievement in thirteen-year-old students. The authors found that early knowledge of the number system was critical to math achievement in later grades. Campbell, Ramey, Pungello, Sparling, and Miller-Johnson (2002) examined the effect of school readiness on 111 preschoolers from 109 Black, Latinx, and Native

American families and found that preschoolers with greater school readiness had greater achievement in school and were more likely to attend a four-year university.

15.1.2 Identification of Underrepresented Students

How to accurately identify a diverse student group for gifted services has been contested subject among scholars in gifted education (Erwin & Worrell, 2012; Lohman, 2005; Lohman & Nicpon, 2012; Naglieri & Ford, 2003; Pfeiffer, 2012). IQ tests are one of the most widespread means of identification for gifted services in the United States (Pfeiffer, 2012). The concern is that IQ tests are biased against underrepresented groups. Pfeiffer (2012) argued that the bias is apparent in that the tests do not identify black, Latinx and Native American children at a rate similar to their Asian and White peers. In contrast to Pfeiffer (2012), Erwin & Worrell (2012) stated that an IQ test measures the constructs it is meant to measure. Any perceived bias in the test is due to variables that the test cannot control such as school readiness, the effect of poverty on achievement, household environments rather than an inherent bias in the test.

Other scholars state that teacher perceptions of underrepresented student populations is a cause for underrepresentation (Esquierdo & Arreguin-Anderson, 2012; McBee, 2006; Stambaugh & Ford, 2015). McBee (2006) analyzed the accuracy of referral methods in the state of Georgia. He found that teachers identified underrepresented and low socioeconomic (SES) students at a lower rate than Asian and White students. McBee also found that teacher nominations were a poorer gauge of success for identification than achievement. Esquierdo and Arreguin-Anderson (2012) stated that underrepresentation is due to cultural differences in the manifestation of gifted behavior that can make predominately white teachers unable to identify talent accurately in diverse student groups. Finally, Stambaugh and Ford (2015) argued that microaggressions on the part of teachers act as a deterrent towards Black, Latinx, and Native American student participation and identification in gifted programs.

Briggs, Reis, and Sullivan (2008) qualitatively analyzed 25 programs to assess best practices for identifying diverse students for gifted education services. They found that successful programs (1) modified identification procedures, (2) provided additional program support, (3) selected and designed curriculum that would lead to student success, (4) built connection with parents, and (5) used culturally sensitive practices. These districts implemented professional development throughout their schools to bring awareness to the problem of underrepresentation and implement strategies to rectify it.

15.1.3 Early Identification of Gifted Students

Early identification has been advocated by gifted scholars throughout the history of the field (Fatouros, 1986; Ford, 2010; Gay, 1978; McCoach, Kehle, Bray, & Siegle, 2001; Pfeiffer, 2001; Worrell & Erwin, 2011). Gay (1978) noted that early identification of Black students was critical to their success and retention in gifted programs. The author stated that Black students were underrepresented in gifted programs, and if not identified early, their likelihood of identification would decrease over time. In contrast, Ford (2010) described the problem of early identification of Black students in terms of poverty. Ford stated that school readiness issues stemming from poverty can make early identification of Black students difficult. A school that begins identification of students in early elementary years is at risk of misidentifying Black students from poverty as non-gifted.

Fatouros (1986) described the issues surrounding early identification. The author stated that identifying young children could prove difficult due immaturity of the students. The author suggested that identifying children after preschool would provide educators with better results.

Regardless, Worrell and Erwin (2011) stressed the importance of early identification in their overview of best practices in gifted education. Black, Latinx, and Native American populations are not the only group to benefit from early identification procedures. McCoach, Kehle, Bray, & Siegle (2001) argued that early identification is also beneficial to twice-exceptional learners. In almost all cases, scholars recommend early identification.

15.1.4 Retention of Underrepresented Students

In response to the dilemma of unequal school readiness, scholars developed different testing measures to circumvent differences in school readiness. These measures range from teacher rating scales (Gentry, Peters, Pereira, McIntosh, & Fugate, 2015; Ryser & McConnell, 2004) to intelligence tests with non-verbal components (Lohman, Korb, & Lakin, 2008, Naglieri & Ford, 2003). After identification, retention of Black, Latinx, and Native American students is critical to their subsequent talent development.

Landis and Reschly (2013) conducted a synthesis of the literature on gifted underachievement and found that cognitive engagement was one factor that studies had in common as an explanation for underachievement. The authors noted that students who became alienated from their academic pursuits were at greater risk for non-retention. Cavilla (2017) interviewed three Black students in an urban gifted program who were at risk of non-retention. The author found that disengagement from learning and unmet social-emotional needs were primary causes for underachievement.

Other scholars argued that the causes for lack of retention are due to structural issues within public education rather than socio-emotional issues. Ford (2014) argued that de-facto segregation and cultural biases against underrepresented students act as barriers to retention in gifted programs. Stambaugh and Ford (2015) explained the cultural biases facing black students including continual micro-aggressions in gifted programs, which can lead to the disengagement noted by Cavilla (2017).

Gentry (2009) argued that identification was not sufficient to retain Black, Latinx, and Native American students in gifted education program. Instead, a continuum of services must be provided along with identification. The NAGC programing standards describe that programming for gifted education must be sufficient and account for the specific needs of gifted students. With regard to Black, Latinx, and Native American students, that means that in conjunction with inclusive identification methods, programming must be provided appropriate for students from underrepresented groups to help retain them in these programs (NAGC Programing Standard 5.1, 2012).

15.2 Rurality

The United States Government defines rural based on locale in relation to urban centers and population density: rural fringe, rural distant and rural remote. Rural fringe communities are those within 5 miles of a major population center and defined as rural by the U.S. Census. Rural distant communities are those within 5-25 miles of a major population center and defined as rural by the U.S. Census. Rural remote communities are those greater than 25 miles from a major population center and defined as rural by the U.S. Census (NCES, 2016).

15.2.1 Rural Gifted Education

Rural school communities can struggle to meet the needs of gifted students due to limited resources (Cross & Burney, 2005). Further, Black, Latinx, and Native American students can be further underidentified compared to other locales (Pendarvis & Wood, 2009). Rural educators often do not have access to the same resources and training that educators from other locales have due to remoteness and/or lack of financial resources (Azano, Callahan, Missett, & Brunner, 2014).

15.2.2 Washington Rurality

Washington is a state dominated by a major population center in the Seattle metropolitan area where 60% (4,302,210) of the population of the state resides (U.S. Census, 2010). Other major population centers are the Portland Area, Vancouver Area, and Spokane Area. According to the U.S. census (2010), 16.9% of the Washington's population is classified as living in rural areas of the state. As such, Washington is a state of extreme areas of population density and vast tracts of sparsely populated areas.

In addition, Washington state contains two of the largest (in terms of land area) Indian Reservations in the United States. In the northeastern part of the state is the Colville Reservation. In the southwestern area of the state is the Yakama Nation Reservation. In total, there are 28 Indian reservations in the state, all located within rural areas (Governor's Office of Indian Affairs, 2015).

15.3 Gifted Education in Washington State

Legislators in the state of Washington defined gifted children as highly capable learners. The legislature defines a highly capable learner as:

> A student who has been assessed to have superior intellectual ability as demonstrated by one or more of the multiple criteria in WAC [Washington Administrative Code] 392-170-040. These students exhibit high capability in intellectual and/or creative areas, possess an unusual leadership capacity, or excel in specific academic fields, thereby requiring services beyond the basic programs provided by schools. Outstanding abilities are present

> in students from all cultural groups, across all economic strata, and in all areas of human endeavor. (WAC392-170-035)

The three areas for identification recognized by the state of Washington are cognitive ability, specific academic achievement, and exceptional creativity.

Cognitive ability is defined by the state as “complete range of intellectual functions referred to as intellect, intelligence, or mental abilities, and including such psychological concepts as thinking, abstract reasoning, problem solving, verbal comprehension, and numerical facility” (Washington Administrative Code 392-170-040). Specific academic achievement is defined as “obtained results on an achievement test appropriate to discriminate academic performance at high levels of achievement in one or more of the following content areas: reading, mathematics, social studies, language arts or science” (Washington Administrative Code 392-170-040, p. X). Finally, exceptional creativity is defined as “demonstration of unique or outstanding creative products and/or the demonstration of unusual problem-solving ability or other learning characteristics which indicate to teachers, parents, or classmates that the student has the intellectual potential to perform academically at a level significantly higher than the norm for chronological grade level” (Washington Administrative Code 392-170-040).

15.3.1 Identification for Inclusion in Highly Capable Programs

The state also includes standards for assessment for the three categories of giftedness. For a child to be identified as highly capable through cognitive ability, the child must demonstrate a score on a standardized test in the top 10 percent. Washington state legislators specifically suggest the use of the Cognitive Ability Test (CogAT, Lohman, 2011), Raven Progressive Matrices (Raven, 2000), the Wechsler Intelligence Scale for Children (Kaufman, 1994), or the Otis-Lennon School Ability Test (Otis, 1993). The school district determines the test used to measure student cognitive ability and is not limited to the four previously mentioned instruments. The most commonly used test for cognitive ability was the CogAT, with 42% of districts using it (Office of the Superintendent, 2009). Specific academic achievement is determined by a student's performance in the top five percent in a specific content area on a standardized test. It should be noted that specific area refers to performance on a state assessment test or another assessment test (e.g. Iowa Test of Basic Skills) rather than on a cognitive ability test like the CogAT. Finally, exceptional creativity is demonstrated by manifesting behavioral characteristics associated with exceptional creativity (Office of the Superintendent, 2009). The state provides examples of creativity checklists that a district could use: Structure of Intellect-Divergent Thinking Short Form (Meeker, Meeker, & Roid, 1985), Structure of Intellect-Form L (Meeker et al., 1985), Torrance Tests of Creative Thinking (Torrance, 1972), and Renzulli Checklist (Renzulli, Hartman, & Callahan, 1971).

15.3.2 Structure of Highly Capable Programs

The state legislature does not provide a defined mandate for how highly capable programs should be structured within a district. The state mandates that each child identified be given an Individualized Education Plan (IEP) (Washington Administrative Code 392-170-078). The state suggests strategies to fulfill the agreed upon IEP including cluster grouping, curriculum compacting, content enrichment, problem-based learning, learning contracts, tiered assignments, learning centers, differentiated instruction, flexible grouping, flexible pacing, flexible scheduling, content acceleration, advanced grade level placement, independent student and collaborative/cooperative arrangements (Office of the Superintendent, 2009).

Unlike programming in elementary schools, which vary widely across the state, in secondary grades gifted programming is more similar across school districts. Throughout the state, honors classes are used starting in middle school. In high school, districts add advanced placement courses provide services for gifted youth (Office of the Superintendent, 2009).

School districts are given autonomy to structure their gifted programs as they deem fit. This includes, not only the identification measures used and the programming available, but also when a child is identified and when programming begins (Office of the Superintendent, 2009). This means districts can begin to identify children in kindergarten or wait as late as high school to identify and provide services.

15.3.3 Funding for Highly Capable Programs

Washington funds its gifted programs using a weighting scheme. Districts are provided funds for each student enrolled in the district and additional funds for students identified as gifted based on a weight determined by the legislature. It is important to note that this additional funding weight is capped at a maximum of 2.314 percent of a district's enrollment (Office of the Superintendent, 2009). This funding is calculated by assessing the cost of hiring a teacher to provide gifted programming. A provision to the education bill to provide additional funding for students identified over the cap was vetoed by the governor in 2009 (Office of the Superintendent, 2009) Any additional resources used for gifted programming must be acquired from local sources of revenue (e.g., revenue from property taxes).

CHAPTER 16. WASHINGTON METHODS

16.1 Sample

Data were obtained from the Washington State Education Research and Data Center through the Office of the Washington Superintendent of Public Instruction. The dataset includes enrollment data for all 296 school districts in Washington state. Of the 296 school districts, 255 school districts report have highly capable programs. Of the 255 school districts that report having highly capable programs, 80 are designated as rural by the National Center for Education Statistics (NCES, 2016).

The Washington State Education Research and Data Center data are collected through the Comprehensive Education Data and Research System (CEDARS). Districts are required to report enrollment data annually to the CEDARS system. These data are compiled and made available through the Office of the Superintendent of Public Instruction Data Gateway in aggregated (across the state) and disaggregated (across school districts) forms. The complete dataset used in this study spans 2002-2003 through 2011-2012 school years for a total of 10 years.

16.2 Variables

The dependent variable is the log transformed odds ratio of identification for a gifted cohort in a school district. A cohort is defined as the group of students in the same grade level in a given year within the same school district. The initial year had 13 cohorts (Kindergarten through grade 12) with each of the following nine years adding an additional cohort. In total, this led to 11,628 observations (repeated measures of cohorts).

The dependent variable is the log transformed odds ratio of identification for a school district in a given year. In total, this led to 2234 observations (repeated measures of cohorts). 63 school districts did not report gifted identification rates for every academic year between 2002-2003 and 2011-212. The number of repeated measures for these districts ranged from 3 to 9. These districts were all rural districts as identified by the NCES.

Because rates of identification are the dependent variable, an odds ratio is an appropriate statistic to examine in these analyses (Bland & Atman, 2000). An odds ratio was calculated for each cohort in a school district per year. These odds ratios compare the identification of underrepresented groups (Black, Latinx, and Native American students) to non-underrepresented groups (Asian and White American students) using the following formula:

$$OR_{T,N} = \left(\frac{p(\mathrm{gifted}|\mathrm{B/L/N})_{T,N}}{1 - p(\mathrm{gifted}|\mathrm{B/L/N})_{T,N}}\right)\left(\frac{1 - p(\mathrm{gifted}|\mathrm{A/W})_{T,N}}{p(\mathrm{gifted}|\mathrm{A/W})_{T,N}}\right)$$

Where *T* indexes time points and *N* represents districts. The notation B/L/N refers to Black, Latinx, and Native American Students and W/A to Asian and White students.

A subset of odds ratios was calculated using the same methods as the odds ratio calculations for the overall rate of underrepresentation. The difference between the overall odds ratios and the subset odds ratios are that instead of including all underrepresented groups, each subset odds ratio will report an individual comparison of Black, Latinx, and Native American students to Asian and White students.

Further, Washington is a state divided between dense population centers around the Seattle bay area and sparsely populated rural areas in the eastern part of the state. Odds ratios can lead to biased results in models formulating a statistic from ratios derived from varying sample sizes. Smaller populations produce less sensitive odds ratios (Nurminen, 1995). This means that an odds ratio becomes increasingly discrete as the associated sample size diminishes. For example, an odds ratio taken on a population of 20 students has only 19 probable combinations of odds from which to calculate a ratio. As the initial population increases, so does the number of probable combinations (and thus gradients). A weighting strategy was used to create the best possible model.

The weighting strategy used employed analytic weights (Dupraz, 2013). In this case, each school district is weighted by the total number of students in that district in a given year. For example, in 2006, Odessa school district had 197 students enrolled and Kittitas School District had 676 students enrolled. The corresponding weights for the calculated odds ratio for Odessa school district in 2006 would be 197 and for Kittitas School District it would be 676. Following this, all weights were normalized such that their sum is equal to one.

For ethnicity specific dependent variables, an analytic weight was calculated based on the total number of students in that district of a given ethnicity in a given year. For example, in 2006, Odessa school district had 7 Hispanic students enrolled, 1 Black student and no Native Americans. Its corresponding analytic weight would be 7 for Hispanic students, 1 for Black students and 0 for Native Americans. Again, a reader should note that following this, all weights were normalized such that their sum is equal to one.

16.2.1 Predictors

Modeling was used to explain the relationship between proportional representation and time of identification for services. The following predictors were used in the model: (a) the grade in which the school district begins identification and services for students identified as gifted in that school district (*grade*), and (b) rural designation of a school district (*rurality*).

16.2.1.1 Grade

Grade is defined as the grade at which the school district begins identification and services for students identified as gifted in that school district. This is treated as a continuous variable. Each school district begins identification at a particular grade. This variable is coded as that grade level (e.g., kindergarten, first, second, third) where kindergarten was coded as 0, first grade as 1, second grade as 2, third grade as 3, fourth grade as 4, fifth grade as 5, and sixth grade as 6, etc. In interpretation of this variable a reader should consider each unit as years until receiving services. For example, 3rd grade, coded as 3, has 3 academic years before receiving services. A child identified in third grade would not receive services in kindergarten, first, and second grades.

16.2.1.2 Rurality

This variable is a dichotomous indicator. A school identified as rural is coded as a 1 and non-rural schools are coded as 0. Rurality is determined by using the federal National Center for Education Statistics locale codes. A district given the locale code of 41, 42, 43 was coded as rural.

16.2.2 Covariates

The percentage of students identified as gifted in a district was included as a covariate in the model. This variable controlled for the possibility of overall identification rates influencing proportional identification and retention of Black, Latinx, and Native American students (Lakin, 2016; Plucker et al., 2013). The percentage of students identified as gifted could affect identification rates of a district in two possible ways. The first is, as Lakin (2016) describes, that increased screening rates for gifted services identifies more students as gifted. Secondly, Plucker et al. (2013) remarked on the excellence gap. If there is a gap in excellence, identification rates can be influenced where in a 1% change in the overall identification rate does not equate to a similar change in the identification of underrepresented students. This is due to giftedness being normally distributed rather than uniformly distributed.

16.2.3 Dependence

The model has two sources of dependence. If the sources of dependence are not addressed, biased estimates will be produced (Faraway, 2014). The first source of dependence is due to serial correlation of time. Serial correlation can occur from prior history of the school district or changes in statewide policy. This issue of dependence it addressed through the inclusion of the random and fixed variable for year. The second source of dependence is through the repeated measures design. Odds ratios are nested under school districts.

16.2.3.1 Year

Year. A second time variable was coded to control for the effect of time across all district. In this case, the academic school year 2002-2003 is coded as zero, 2003-2004 as one, 2004-2005 as two, and so on with the 2011-2012 academic school year coded as nine.

16.2.3.2 District

Another source of dependence is that odds ratios are also clustered under school districts. In the analysis, the intercept is allowed to vary by district.

16.3 Analysis

Because the model contains repeated measures of odds ratios over time a generalized linear mixed effect model (GLMM) is appropriate. The following model was used in this analysis:

$$\left(Y_{tij}\right) = \alpha + \beta_1(grade_i) + \beta_2(rural_i) + \beta_4(year_t) + \beta_5(gifted_{ti}) + \beta_7(grade_i)(year_{ti}) + \left[u_{00i} + u_{1ij}(year_{ti})\right] + e_{tij}$$

Where (Y_i) is a district's log odds ratio of identification and α indicates the intercept. Where *i* is the *i*th school district and *j* is a measure of school district *i* in year *t*.

A Wald *t* was used as the test statistic to provide probability values for regression coefficients. A Wald *t* is an appropriate test statistic when using a GLMM. A Satterthwaite approximation was used to calculate the degrees of freedom necessary to compute the Wald *t*. (Satterthwaite, 1946; Verbeke & Molenberghs, 2009). A Satterthwaite approximation is a more robust calculation of pooled variance. The pooled standard error calculation assumes equal variances. In the case of mixed models where variance can be attributed to fixed and random effects, this is unlikely. In contrast, a Satterthwaite approximation does not assume equal variances and so is appropriate for GLMM's (Satterthwaite, 1946).

Model fit was assessed to ascertain the relationship between time and the dependent variable (i.e., if the relationship is linear or otherwise). To assess model fit, the Bayesian information criterion (BIC) was used. The purpose of model fitting is to determine the "true" model within a limited combination of regressors as opposed to trying to determine the best fit of covariates among all available variables offered by the data repository in the Office of the Superintendent of Public Instruction. In this case, a completely unknown model is not assumed and thus the BIC is a more appropriate fit index than the Akaike information criterion (Burnham & Anderson, 2004).

Model effect sizes were calculated with a generalized version of R^2 called Ω^2 . In mixed models, R^2 calculations can lead to misspecification of model effect sizes. A generalized version of R^2, as suggested by Xu (2003), was used to assess model effect size.

16.3.1 Model Assumptions

The assumption of normality of the dependent variable was addressed by a log transformation of the odds ratio (Faraway, 2014). Further, the assumption of constant variance of random effects was addressed by analyzing residual plots. Finally, the assumption of independent observations was addressed through the GLMM. Observations are not independent. Repeated measures are taken from cohorts since the data are longitudinal. Further, cohorts are nested within schools. This violation of independence is addressed through the use of random and fixed effects in model fitting by allowing intercepts and slopes to vary in a GLMM.

CHAPTER 17. WASHINGTON RESULTS

17.1 Demographics

During the time frame of the study, the number of students enrolled in the Washington state public education system increased from 1,015,968 in the 2002-2003 academic school year to 1,043,536 in the 2011-2012 academic school year. However, upon closer examination, only the percentage of Latinx students increased during this time frame, from 11.6% in 2002-2003 to 19.6% of the total enrollment in 2011-2012. Full demographic results can be seen in Table 1.

Table 1
General Enrollment in public schools by race

Academic Year	Total Public K-12 Enrollment	Percent Asian	Percent Black	Percent Latinx	Percent Native American	Percent White
2002-2003	1,015,968	7.6	5.6	11.6	2.7	72.5
2003-2004	1,021,309	7.8	5.7	12.3	2.8	71.4
2004-2005	1,020,959	7.9	5.7	12.8	2.8	70.3
2005-2006	1,013,189	7.9	5.7	13.7	2.8	69.2
2006-2007	1,026,682	7.8	5.6	14.0	2.7	67.5
2007-2008	1,031,846	7.8	5.5	14.7	2.7	66.2
2008-2009	1,040,750	7.9	5.5	15.3	2.6	64.8
2009-2010	1,036,135	7.9	5.6	16.1	2.5	63.7
2010-2011	1,041,892	7.1	4.7	18.8	1.7	61.3
2011-2012	1,043,536	7.1	4.6	19.6	1.6	60.2

Enrollment for the High Ability Program increased from 48,983 (4.8% of total enrollment) in the 2002-2003 academic school year to 55,093 (5.5% of total enrollment) in the 2011-2012 academic school year. Full High Ability Program demographic results are depicted in Table 2.

Table 2
Gifted Enrollment in public schools by race

Academic Year	Total K-12 HAP Enrollment	Percent Asian	Percent Black	Percent Latinx	Percent Native American	Percent White
2002-2003	48,983	8.1	2.1	7.5	1.2	81.0
2003-2004	50,460	8.1	2.1	6.5	1.2	81.2
2004-2005	35,607	10.9	2.6	5.8	1.4	79.3
2005-2006	34,416	12.4	2.2	8.2	1.4	77.1
2006-2007	49,190	12.7	2.3	9.5	1.3	75.8
2007-2008	50,224	13.7	2.3	7.0	1.2	77.2
2008-2009	46,190	14.0	2.8	7.2	1.3	74.7
2009-2010	47,819	16.0	3.0	6.7	1.1	73.2
2010-2011	56,075	15.4	3.9	8.5	1.0	70.5
2011-2012	55,093	14.8	3.7	8.3	1.1	72.8

Of the 296 school districts in Washington state, 255 school districts reported having highly capable programs. Of these districts, 140 are designated by the NCES as rural school districts. Washington allows districts to decide when to begin identification and programming for gifted students. A breakdown of grades at which identification begins by district can be seen in Table 3.

Table 3
Starting Grades of Highly Capable Programs by Number of School Districts

Grade	K	1	2	3	4	5	6	7	8	9	10	11	12	None
n	28	37	37	63	52	11	14	2	1	3	3	1	2	46
%	9.5	12.5	12.5	21.3	17.6	3.7	4.7	<.1	<.1	.1	.1	<.1	<.1	15.5

During the timeframe of the study, the percentage of Asian students enrolled in Washington state public schools decreased from 7.6% of enrollment to 7.1% of enrollment. The percentage of Asian students identified for gifted services increased from 8.1% to 14.8% in the time frame. See Figure 1 for full demographic trends.

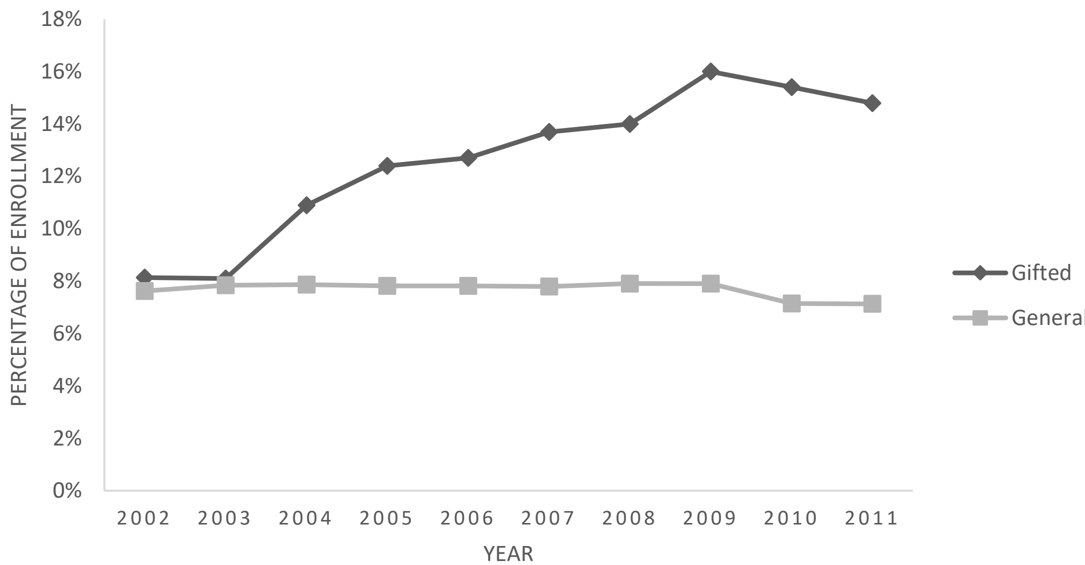

Figure 1. Percentage of Asian students enrolled in K-12 public schools and in the highly capable program throughout the state.

Between the 2002-2003 academic year and 2011-2012 academic year, the percentage of Black students enrolled in Washington state public schools decreased from 5.6% of enrollment to 4.6% of enrollment. The percentage of Black students identified for gifted services increased from 2.1% to 3.6% in the time frame. See Figure 2 for full demographic trends.

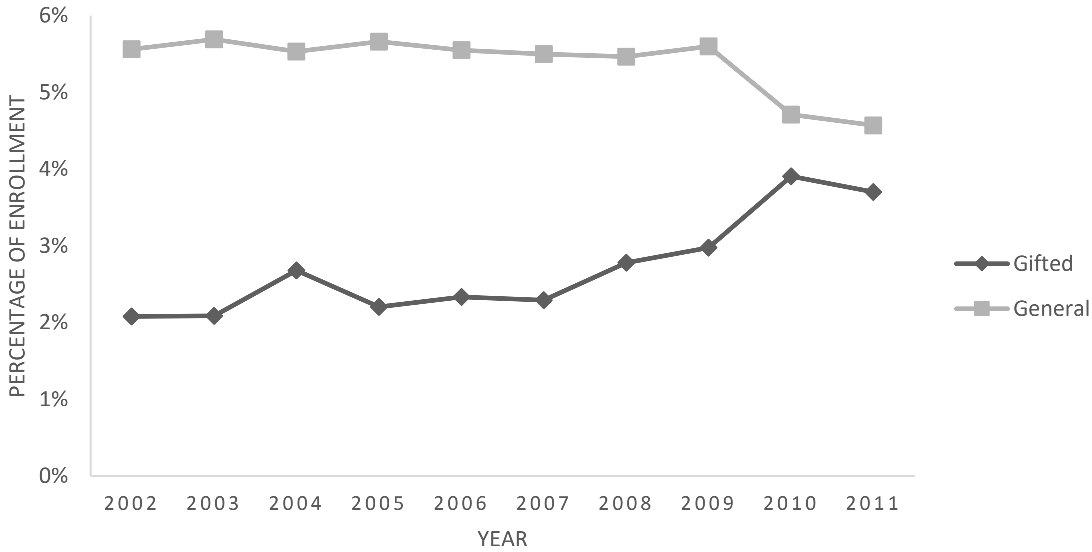

Figure 2. Percentage of Black students enrolled in K-12 public schools and in the highly capable program throughout the state.

Between the 2002-2003 academic year and 2011-2012 academic year, the percentage of Latinx students enrolled in Washington state public schools increased from 11.6% of enrollment to 19.6% of enrollment. The percentage of Latinx students identified for gifted services increased from 7.5% to 8.3% in the time frame. See Figure 3 for full demographic trends.

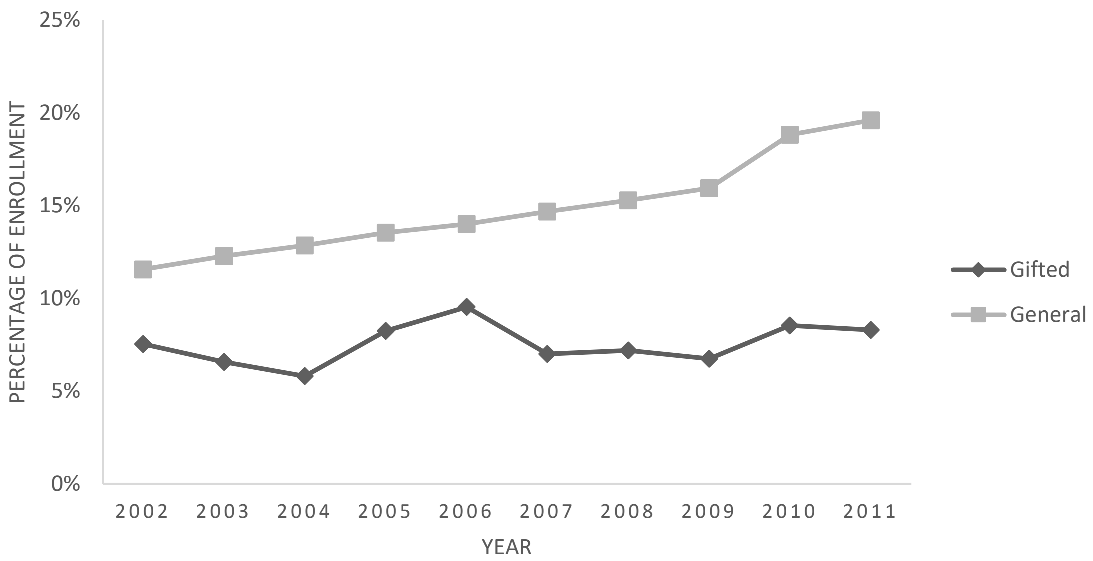

Figure 3. Percentage of Latinx students enrolled in K-12 public schools and in the highly capable program throughout the state.

Between the 2002-2003 academic year and 2011-2012 academic year, the percentage of Native American students enrolled in Washington state public schools decreased from 2.7% of enrollment to 1.6% of enrollment. The percentage of Native American students identified for gifted services decreased from 1.2% to 1.1% in the time frame. See Figure 4 for full demographic trends.

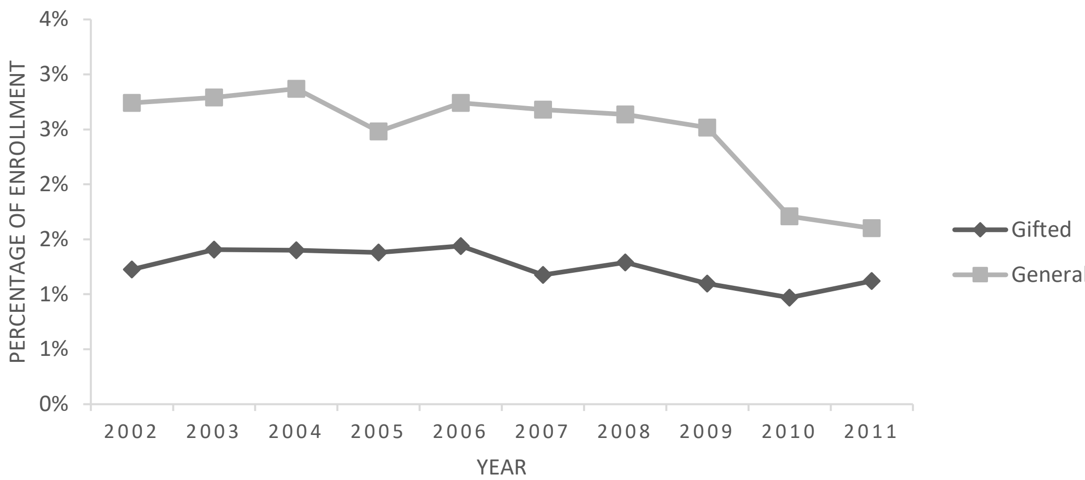

Figure 4. Percentage of Native American students enrolled in K-12 public schools and in the highly capable program throughout the state.

During the timeframe of the study, the percentage of White students enrolled in Washington state public schools fell from 72.5% of enrollment to 60.2% of enrollment. The percentage of White students identified for gifted services decreased from 81.0% to 65.2% in the time frame. See Figure 5 for full demographic trends.

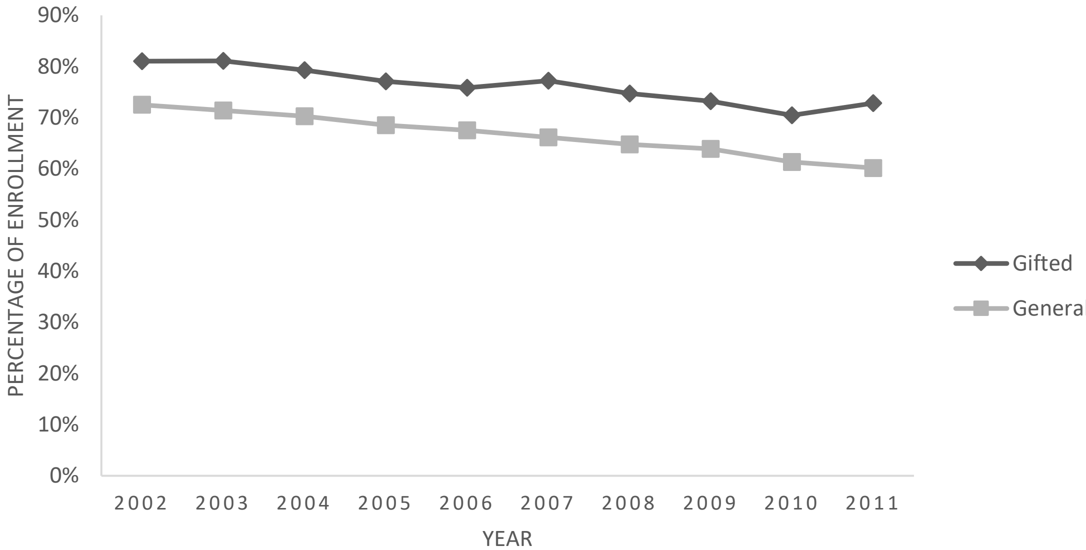

Figure 5. Percentage of White students enrolled in K-12 public schools and in the highly capable program throughout the state.

The odds ratio for the likliehood of identification of Black, Latinx, and Native American students for gifted services compared to Asian and White students ranged from .34 in the 2008-2009 academic school year to .47 in the 2002-2003 academic school year. This means that Black, Latinx, and Native American students were at best nearly half as likely to be identified as gifted as Asian and White students. See Figure 6 for full trends.

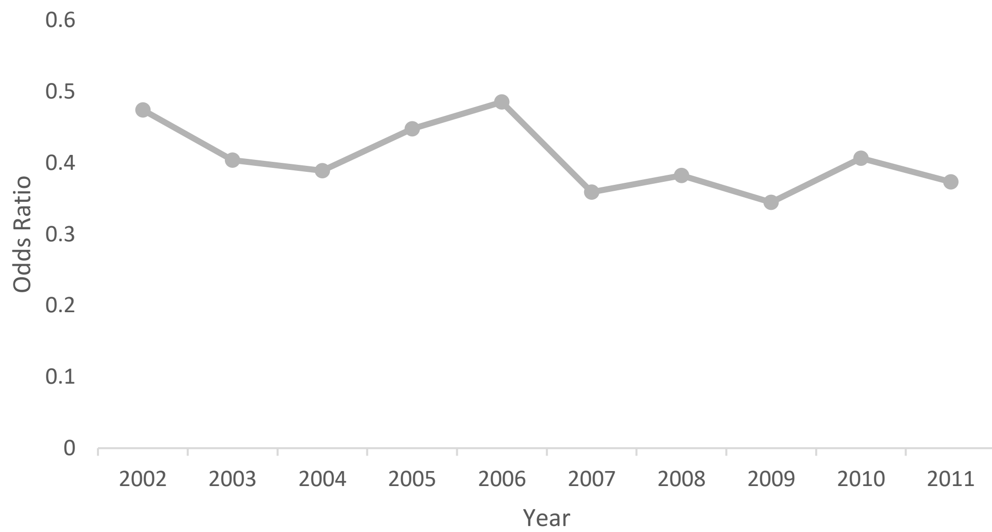

Figure 6. The odds ratio of identification Black, Latinx, and Native American students for gifted services compared to Asian and White students between the 2002-2003 academic school year and the 2011-2012 academic school year.

17.2 Model Diagnostics and Fit

An initial examination of the intraclass correlation (ICC) demonstrated that observations were clustered (*ICC* = .69). This provided evidence that a generalized linear mixed effect model was the appropriate model structure for analysis (Faraway, 2014). The residual plots were examined and suggested that constant variance was maintained for both fixed and random effects. An analysis of the QQ-plot before the use of a log transformation provided strong evidence that the odds ratios distributions were not normal. Following the log transformation, the dependent variable was approximately normally distributed.

Finally, the linear time variable for year was tested for best fit. The Bayesian Information Criteria (*BIC*) was assessed for a model containing a linear and squared term for time. The model with the linear term (*BIC* = 2783.44) had better fit than the model with the square term for time (*BIC* = 2796.70).

17.3 Full Model

The odds ratios for Black, Latinx, and Native American students ranged from 0.34 to 0.49 during the time frame of the study (see Figure 6). What this means is that the odds for Black, Latinx, and Native American students (the ratio of students identified as gifted to not identified) was 34% to 49% of the odds for Asian and White students. In other words, if 4 out of 10 Asian and White students was identified as gifted, then the odds would be 4 to 6 (or 2 to 3). This would mean that in the same school, if the odds ratio was .49, the odds for Black, Latinx, and Native American students would roughly be 2.5 to 7.5 (or 1 to 3). In the model, the time variable, *year*, ($\exp(\beta) = 1.00$, $p = .64$) was not a significant predictor. Of the main effect for *grade* ($\exp(\beta) = 1.02$, $p = .03$) and *rurality* ($\exp(\beta) = 1.07$, $p < .01$) were significant predictors. This result suggests that school districts that identify students in later grades, identify students at a more proportional level (2% per grade level after kindergarten). Further, this result suggests that in Washington state, underrepresented students in rural school districts are identified at a 7% higher relative rate than in non-rural areas. Finally, when the interactions with *grade* and the time variable were examined, the interaction was not a significant predictor ($\exp(\beta) = 1.00$, $p = .18$).

The random slope for *year* (*Variance* < 0.01, *SD* = 0.01) had a correlation of .52 with the random intercept of *district* (*Variance* = 0.01, *SD* = 0.08). This suggests that for schools that had higher levels of proportional identification, the negative effect of year was mitigated. In other words, school districts that proportionately identified students largely maintained those levels of identification through the time frame of the study. Model effect size was $\Omega^2 = .17$. Full model results can be seen in Table 4.

Table 4
Regression results for the overall odds ratio

Fixed Effects	Exp (β)	*SE*	*Wald T*	*p*
Year	0.99	0.01	1.05	.30
Grade	1.02	0.01	2.15	.03
Percentage Gifted	1.23	0.03	7.02	< .01*
Rurality	1.07	0.01	2.62	< .01*
Grade*Year	1.00	0.01	1.40	.18
Random Effects	Variance	*SD*	*Corr*	
District	0.01	0.08		
Year	< 0.01	0.01	-.52	
Residual	19.24	4.38		

Note. **p* < .05

17.4 Black Students

The odds ratios for Black students ranged from .30 to .68 during the time frame of the study. *Grade* (exp(β) = 1.02, p = .21) and the time variable (exp(β) = 0.99, p = .36) were not significant predictors in the model. Further, rural school district identified Black students at the same rate as non-rural districts (exp(β) = 1.02, p = .60). Finally, the interaction between *grade* and *year* was not a significant predictor (exp(β) = 1.00, p = .32).

The random intercept for *district* had a variance component of 0.07 (*SD* = 0.27). In comparison, the random slope for *year* had a variance component of 0.01 (*SD* = 0.04) and had a correlation with the intercept of .92. Finally, the remaining residual variance was 41.34 (*SD* = 2.33). This suggests that further random effects could be included in the model. Model effect size was Ω^2 = .18. Full model results for Black students can be seen in Table 5.

Table 5

Regression results for Black students

Fixed Effects	Exp (β)	*SE*	*Wald T*	*p*
Year	0.99	0.01	0.92	.36
Grade	1.02	0.01	1.25	.21
Percentage Gifted	1.44	0.08	5.15	< .01*
Rurality	1.07	0.01	0.52	.69
Grade*Year	1.00	0.01	0.99	.32
Random Effects	Variance	*SD*	*Corr*	
District	0.07	0.27		
Year	< 0.01	0.04	.92	
Residual	41.34	6.43		

Note. *$p < .05$

17.5 Latinx Students

Within the time frame of the study, odds ratios for proportional identification ranged from .33 to .58. In the model with the subset of odds ratios for Latinx students, *grade* ($\exp(\beta)$ = 1.02, p = .07) was not a significant predictor. In contrast, the time variable ($\exp(\beta)$ = 0.98, p < .01) was a significant predictor. The significance of the time variable provides evidence, that during the time frame of the study, proportional identification for Latinx students decreased by 2% annually. Finally, rurality was a significant predictor for Latinx students ($\exp(\beta)$ = 1.06, p = .02). This suggests that Latinx students are identified at 6% higher relative rates than their Latinx peers in non-rural areas.

When the interaction between *advancement* and *year* is examined, the results demonstrated a significant predictor of proportional representation for Latinx students ($\exp(\beta)$ = 1.01, p = .04). This provides evidence that school districts that began to provide services in later years were able to maintain levels of proportional identification for Latinx students than were school districts that began identifying students in earlier grade levels.

For random effects, the random intercept for *district* account had a variance total of 0.01 (*SD* = 0.11). The random slope for *year* accounted for < 0.01 of residual variance (*SD* = 0.02) with a correlation with the intercept of .54. Residual variance was 12.20 (*SD* = 3.49). Finally, model effect size was Ω_0^2 = .22. Full model results for Latinx students can be seen in Table 6.

Table 6
Regression results for Latinx students

Fixed Effects	Exp (β)	*SE*	*Wald T*	*p*
Year	0.98	0.01	3.19	< .01*
Grade	1.02	0.01	1.35	.18
Percentage Gifted	1.48	0.05	9.72	< .01*
Rurality	1.06	0.02	2.39	.02
Grade*Year	1.01	0.02	2.02	.04
Random Effects	Variance	*SD*	*Corr*	
District	0.01	0.11		
Year	< 0.01	0.02	.52	
Residual	12.20	3.49		

Note. *p < .05

17.6 Native American Students

During the time frame of the study, odds ratios for proportional identification rates ranged from .35 to .47 for Native American students. In the model with the subset of odds ratios for Native American students, *grade* (exp(β) = 1.00, p = .80) was not a significant predictor. The time variable (exp(β) = 1.02, p = .03) was a significant predictor. In contrast to Latinx students, the significance of the time variable provides evidence, that during the time frame of the study, proportional identification for Native American students increased by 2% annually. Rurality was not a significant predictor for Native American students (exp(β) = 1.00, p = .90).

When the interaction between *advancement* and *year* is examined, the results demonstrated a significant predictor of proportional representation for Latinx students (exp(β) = 1.01, p = .04). This provides evidence that school districts that began to provide services in later years were able to maintain levels of proportional identification for Latinx students than were school districts that began identifying students in earlier grade levels.

For random effects, the random intercept for *district* account had a variance total of 0.05 (*SD* = 0.22). The random slope for *year* accounted for < 0.01 of residual variance (*SD* = 0.03) with a correlation with the intercept of .79. Residual variance was 5.44 (*SD* = 2.33). Model effect size was Ω^2 = .24. Full model results for Native American students can be seen in Table 7.

Table 7

Regression results for Native American students

Fixed Effects	Exp (β)	*SE*	*Wald T*	*p*
Year	1.02	0.01	2.26	.03
Grade	1.00	0.01	0.26	.80
Percentage Gifted	1.55	0.06	9.65	< .01*
Rurality	1.00	0.03	0.12	.90
Grade*Year	1.00	0.01	0.37	.71
Random Effects	Variance	*SD*	*Corr*	
District	0.05	0.22		
Year	< 0.01	0.03	.79	
Residual	5.44	2.33		

Note. *p < .05

CHAPTER 18. WASHINGTON DISCUSSION

18.1 Research Question One

With regard to question one: *To what extent are Black, Latinx and Native American students underrepresented in gifted programs in the state of Washington compared to their Asian and White peers from the academic years 2002-2003 through 2011-2012?* Aligned with the findings of Yoon and Gentry (2009), Black, Latinx, and Native American students are underrepresented in gifted programs in Washington state. The odds ratio of identification for underrepresented students was .47 2002, reaching a low point of .34 in 2009 then returning to .37 in 2011. This means that, at best, Black, Latinx, and Native American students were represented at nearly half the rate of Asian and White students.

Of particular note, Native American students were identified at lower rates when controlling for other variables in the regression model in the time frame of the study. Considering the large number of Indian reservations within the state (including two of the largest in the U.S.), this fact is disconcerting. Gentry et al. (2014) described how poverty, rurality, and race coupled with communication style, cultural and learning differences may result underrepresentation for Native American students in schools where teachers lack requisite understanding of culture. In a state where the definition of a gifted student is inclusive and programming is diverse, the level of underrepresentation for Native American students is difficult to explain. To further accentuate this point, odds ratios can be sensitive to sample size in smaller populations. Native American students make up the smallest portion of students, demographically, yet their range of odds ratio for representation was also the smallest. This provides evidence that despite a small population within the state, this did not bias estimates.

18.2 Research Question Two

With regard to question two: *To what extent does the grade in which gifted services begin influence the proportional representation of Black, Latinx, and Native American students in gifted programs?* In an examination of the main effects for program commencement, the overall odds ratio for Black, Latinx, and Native American student representation in gifted programs increased as program identification was delayed. This result suggests that school districts that began identifying students and providing services earlier, had worse overall rates of identification for Black, Latinx, and Native American students than school districts who began identifying students at later grades. In other words, this result suggests that a school that begins providing services in sixth grade will have over a 10% greater rate of proportional identification than one that begins in kindergarten.

An initial examination of this result puts it in contention with the best practices in identification for the NAGC (2012). A best practice is early identification of students from underrepresented populations. The fact that the school districts in Washington that identified earlier had lower rates of proportional identification is worrisome. The underlying cause could be differences in school readiness. Children that enter school with less school readiness than their peers are likely to not be identified as gifted even if that child had the potential to be identified, all else being equal (Kaufman, 1994; Pfeiffer & Petscher, 2008). This is indicative of the structural barriers described by Esquierdo and Arreguin-Anderson (2012) and Ford (2010 & 2014). In contrast to the work of Worrell and Erwin (2011), who strongly favored early identification, school districts which identified earlier had larger gaps in proportional identification. Identifying children earlier is a greater indication of that child's school readiness than the child's ability. Watts et al. (2014) noted that the benefit of school readiness on achievement diminished over time. It is likely that this advantage is extended to performance on identification measures. In other words, as a child grows older, the benefit of school readiness on whether they will be identified as gifted diminishes. This in turn benefits students who do not have similar levels of school readiness. As noted by Ford (2010) students from traditionally underrepresented populations are less likely to enter school with high levels of school readiness. Thus, these same children are more likely to benefit from identification procedures which are less biased towards school readiness (i.e. early elementary grades where school readiness has the greatest effect).

The results from the analysis provide evidence that the grade level a school district begins providing services and identification has no bearings on the proportional identification of Black students. Cavilla (2017) and Ford (2010) would argue that regardless of when identification happens, the inherent bias against Black students in the structure of U.S. schools would impede efforts at proportional identification.

Similar results were found for Latinx students. The grade level that a school district began identifying students for had no bearing on the level of proportional identification of Latinx students. Much like Stambaugh and Ford (2015) described the structural barriers limiting identification of Black students as gifted, Esquierdo and Arreguin-Anderson (2012) described those pertaining to Latinx students. These results suggest that the low levels of identification of Latinx students across Washington exist irrespective of when school districts implement programs.

Like Black and Latinx students, Native American students had low levels of identification irrespective of the grade level that a school began identifying students. Gentry et al. (2014) described the structural barriers to inclusion for Native American students. These results provide evidence that these barriers surmount any disadvantage or advantage offered by school readiness.

The results provide a contradictory case. As a whole, grade level is significant predictor of representation of Black, Latinx, and Native American students. When disaggregated into composite parts, the significance vanishes. Rather than a theoretical issue, the cause for this is likely statistical. The analysis including all underrepresented students had more power to detect an effect. In contrast, disaggregating the odds ratio into its composite groups (Black, Latinx, and Native American) diminished the overall power. For example, a school district might have 50 Black students and 25 Native American students but no Latinx students. In this case, the overall power is maximized for underrepresented students but would be lost for Latinx students. This is likely to be the underlying cause for the change in significance between the aggregate and disaggregated results.

In essence, the best that can be said is that there is no effect. The alternative is that the effect of early identification is detrimental to proportional identification. In all, either result would corroborate the arguments of Gagné (2011). Gagné argued that proportional identification was not a meaningful goal in comparison to other goals of gifted education. The resources spent on developing early identification methods could instead be used to develop the inherent talent in individual students.

18.3 Research Question Three

With regard to question three: *To what extent does the grade in which gifted services begin influence the rates of proportional representation of a cohort's Black, Latinx, and Native American student population in gifted programs over time?* The results from this study provide evidence that, over time, the grade level in which a school level begins identifying students does not affect its overall rates of proportional identification over time. During the time frame of the study, those schools which identified students later (despite having high rates of proportional identification) did not see their rates of proportional identification increase relative to schools that identified earlier. In other words, in 2002, the gap in proportional representation between schools that identified students later rather than earlier was a 2% increase for each grade level delayed. Ten years later, it was still 2%. This result aligns with the works of authors who have pointed out the structural issues that impede identification (Cavilla, 2017; Esquierdo & Arreguin-Anderson, 2012; Ford, 2014; Gentry et al., 2014; Stambaugh & Ford, 2015). Esquierdo and Arreguin-Anderson (2012) and Ford (2010) described the ongoing lack of representation of Black and Latinx students. The authors described a stagnation in identification rates. Esquierdo and Arreguin-Anderson (2012) described how in Texas, Latinx students were identified at low rates with the gap in representation being unlikely to be closed in the upcoming decade (2010's). In Washington, the evidence from this student provides evidence that the stagnation in identification rates seen across the nation (Yoon & Gentry, 2009) and in Texas are systemic in Washington as well.

When examined by individual ethnicity, Latinx students saw increased levels of identification as cohorts advanced through grade levels. Programs that began services in later grades had increased rates of proportional identification over time of one percent annually. In other words, a school district that identifies in fifth grade as opposed to kindergarten experienced an increase of 50% over the time frame of the study in comparison to the school district that identified in kindergarten. Of note, though, that this change would not lead to a close in representation over the time frame of the study. Even with a 100% increase, the gap in representation would not be closed.

Caution must be taken when interpreting this result though. The *p* value associated with the result was .04 (with the unrounded *p* value of .0447). Further, Black and Latinx students did not see a similar result. The composite statistic also was not significant. This does not mean that the result is not indicative of a true effect, only that caution must be approached in interpreting it. Given the strong downward trend (2% decrease annually) in proportional identification of Latinx students in the time frame of the study, the result is more indicative of schools being able to maintain proportional rates of identification rather than experience an increase. Given the rather weak statistical evidence, this findings' place in the literature is tenuous. Regardless, it does provide evidence that aligns with the work of Gormley, Phillips, and Gayer (2008) who noted the detrimental effect of lack of school readiness on identification rates of underrepresented students. Since Latinx students enter into school with less school readiness on average than their peers, it is not surprising that those school districts which identified at later dates would have a more proportionately reflective make-up of their identified gifted student population than school districts which identified earlier.

18.4 Research Question Four

With regard to question four: *To what extent does rurality influences the proportional representation of Black, Latinx and Native American students and their rate of representation over time in gifted programs?* Rural school districts largely had greater rates of representation of Black, Latinx, and Native American students than their non-rural peers. This rate of representation ranged from an increase of 6% to 7% for underrepresented students. This finding contrasts the work of Pendarvis and Wood (2009) who stated that Black, Latinx, and Native American students were further underidentified compared to non-rural locales. Though the finding is statistically significant, its relatively low effect size makes drawing practical significance difficult. Further, when considering such low proportional identification rates (0.30 to 0.40), a 7% increase would only amount to an increase of 0.30 to 0.32. The reality, though, is that a 6% increase can equate to an extra student being identified in a rural locale where they might not have been in a non-rural locale.

18.5 Limitations

A limitation to this study is that this analysis only encompasses one state. Although the policies instituted by Washington state make it ideal for examining the effects of when students are identified for gifted services and proportional representation over time, gifted education policies are not uniform across the United States. This limits inference that can be drawn from this study.

Another limitation is the sensitivity of the odds ratio to smaller sample sizes. When an odds ratio is calculated using smaller sample sizes it has the potential to be biased in one direction compared to an odds ratio calculated from a large sample size ($n > 100$). For example, in a school district with only 10 Latinxs, an average 5% identification rate might or might not identify one of those children as gifted. If they are identified then there is a 10% identification rate and if not, there is a 0%. This has the potential to create biased results. To alleviate this, a weighting strategy within stratum was used in conjunction with a dichotomous indicator variable in model fitting. This strategy mitigates the potential for bias but the possibility still exists.

As shown by Winsler et al. (2013), early intervention can improve rates of identification and representation for children identified during early elementary years. Without information at the student level on which students received early intervention to include as a variable in the model, it is possible that this variable has a nuisance effect upon the model. In which case, the estimates obtained have potential to be too conservative.

Another limitation is due to the unit of observation. Odds ratios calculated from school counts are unable to account for individual student movement. For example, there is no way to determine an increase in annual measures of an odds ratio is due to true increased rates of identification within the school district or if a student moved to the district. This limitation is accounted for partially through weighting. Those districts most sensitive to the movement of a few individuals are weighted down in the regression (i.e. smaller districts). Conversely, districts that are not as sensitive to student movement were weighted higher.

A final limitation is due to the structure of the data. The Office of the Superintendent of Public Instruction data sets do not contain student specific data. Due to this, it is impossible to know if the make-up of any cohort is the same throughout all their reported data periods. Firstly, students move into and out of districts. Secondly, it is possible for a student who moves out of a gifted program to be replaced by a student that is demographically similar. Aggregated data at the district level has the potential to bias estimates. This limits the potential inference that could be made from the study.

18.6 Implications

This research provides state legislators and school district administrators with a benchmark on how the current policies enacted at the district level influence representation of Black, Latinx, and Native American students in gifted services. Further, this research can influence future policy decision by providing clarity on how identification practices influence Black, Latinx, and, Native American representation in gifted programming. Additionally, it uncovers disturbing trends of identification inequities in rural schools that are even worse than the overall findings, underscoring how at risk of being overlooked these children are if they go to a rural school.

Finally, this research contributes to the overall body of research concerning underrepresentation of Black, Latinx, and Native American students in gifted programming. Early identification with appropriate services is a NAGC standard (2008). This research provides longitudinal evidence to the efficacy of early identification procedures, but underscores the need for culturally responsive practices to retain students from underserved groups who are identified in early grades.

18.7 Future Research

One area of future research is to examine those school districts who were successful in identifying Black students for gifted education. The results of the regression provided evidence that there were school districts who succeeded in identifying proportional numbers of Black students for Washington state's highly capable program. Examining what policies and programming these school districts use would provide insight into helping close the gap in excellence. A second area of research is to examine why rural districts had greater difficulties maintaining levels of proportional identification after identifying students in early grades. The NAGC (2012) suggests that early identification is critical to identifying a diverse population for gifted services. Though there is a gap between the overall identification rates between rural and non-rural schools, the declining rates of proportional identification is troubling. Finally, extending this study across other states would allow for greater generalizations to be made.

CHAPTER 19. WASHINGTON CONCLUSION

Early identification of students for gifted services is considered a best practice in gifted education programming (NAGC, 2012). The findings from this study provide evidence that the relationship between age of identification and underrepresentation in gifted programs is nuanced. Just implementing early identification is unlikely to close the gap in representation between Black, Latinx, and Native American students with their Asian and White peers. What the findings do suggest is that grade of identification has a positive, albeit small, influence on representation rates. Though it does not completely close the gap in representation by itself, early identification is a necessary cornerstone in bridging the gap in representation.

CHAPTER 20. CONCLUSION

Taken together, these three case studies provide strong evidence that Black, Hispanic, and Native American students are underrepresented in gifted programs. At the minimum, the results demonstrate that underrepresentation is still an issue in Florida, Indiana, and Washington State. Though this is the case, the aggregated findings suggest that an optimistic outlook should be maintained.

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