Exploring the American Indian/ Alaska Native 8th Grade Patterns in Mathematics Achievement in Arizona and South Dakota

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EXPLORING THE AMERICAN INDIAN/ALASKA NATIVE 8TH GRADE PATTERNS IN MATHEMATICS ACHIEVEMENT IN ARIZONA AND SOUTH DAKOTA

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School reports mandated by NCLB demonstrated that AI/AN students have the lowest achievement among focal subgroups. What has not yet been investigated are the achievement differences among AI/AN students: public low density school students scored significantly higher than public high density school students who scored significantly higher than BIE school students on the NAEP 8th grade mathematics achievement test in 2009. The NIES data made it possible to reliably estimate and investigate these differences. Nine derived risk factors and seven risk indices were created using both NAEP and NIES student, teacher, and school questionnaire data. Chi-square and OLS regression analyses were performed to better understand the achievement patterns between states and across school density types within states. The final OLS regression models were more similar across states within school density types than across school density types within a state. Four out of the six final models captured the data well with the adjusted R-squared values ranging from 0.31-0.38 (the other two final models had adjusted R-squared values of 0.24 and 0.11). The results of the OLS regression models in five of the six strata showed that the *NAEP Social/physical risk index* was significantly associated with lower student achievement. The final model for the South Dakota BIE school students included completely different predictors than the

final models for the other five strata, possibly related to the extreme poverty on the reservations in South Dakota. There was a discrepancy in most strata between the number of students labeled as being ELL and the number of students who stated they spoke a language other than English at home at least half of the time or more. These and other results suggest that schools should focus on forming stronger connections with the students' families both because of language barriers and parents' previous experiences in school.

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Introduction

A Brief History of AI/AN Education in the United States. According to the US Census Bureau (2009), there are 2.5 million American Indian (AI) and Alaska Natives (AN) in the US, which is 0.8% of the total US population. Historically, the AI/AN people have benefited the least from educational institutions in the United States. Instead of allowing them to maintain their own education systems that incorporated their Native languages and cultures, nonindigenous people have tried to "civilize" the AI/AN people since their arrival to the Americas in 1492 by forcing them to learn European skills, knowledge, language, values, religion, attitudes, and customs (Trujillo & Alston, 2005).

In the 1600s, missionaries established boarding schools as a way to use formal education to try to assimilate the AI/AN people. AI/AN children were removed from their tribes and families and sent to these schools to be taught non-Indian ways. The children were punished if they were caught speaking their Native languages. In the 1700s, boarding schools gained support. By the 1800s, they had multiplied as the US government became more involved in developing an educational system for the AI/AN people (Dehyle & Swisher, 1997; Tippeconnic & Swisher, 1992).

In 1819, Congress authorized the President to establish education programs for AI/ANs. In 1824, the Department of War, without Congressional authorization, created an Office of Indian Affairs and within it, the Bureau of Indian Affairs (BIA). (Congress formally founded the BIA in the Department of War in 1834.) In 1849, the BIA was transferred to the newly created Department of the Interior, where it remains today. The BIA has evolved from imposing Federal policies designed to overcome and eradicate the AI/AN people (through the implementation of boarding schools) to promoting AI/AN self-determination (U.S. Department of the Interior, 2014). The BIA is the oldest federal agency that has remained continuously intact; however, it has come under criticism and calls for reform and even elimination almost since inception. In spite of this, for tribal advocates, it has become a symbol of the federal government's commitment to tribal sovereignty and the individual well-being of AI/ANs. This commitment is often referred to as the federal trust responsibility to Indians, which has been exercised primarily by the BIA (McCarthy, 2004).

The trust responsibility is a result of over 400 treaties over the course of almost 100 years (1778-1871) in which the AI/AN people ceded close to one billion acres of land in exchange for the Federal Government agreeing to provide, in perpetuity, for the health, education, and well-being of AI/AN people who are members of federally recognized tribes. This unique relationship between the AI/AN people and the Federal Government was founded on the AI/AN people trusting the Federal Government to fulfill the promises that were given in exchange for land, including educational services (Dehyle & Swisher, 1997; National Conference of State Legislatures, 2008; Trujillo & Alston, 2005).

However, the Meriam Report of 1928, *The Problem of Indian Administration*, pointed out to the Federal Government that AI/AN schools were "distinctly below the accepted social and educational standards of school systems in most cities and the better rural communities" (Hopkins, 2008, p. 346). Ultimately, the boarding schools failed. At which point, assimilationists felt that integrating AI/AN students with White students in public schools would be a better way to accomplish their goal of ridding them of their ethnic identity, which they felt was inferior (Dehyle & Swisher, 1997).

Over time, the government has been fickle in their support of AI/AN needs in the public school classroom. In the 1930s, there was support for incorporating AI/AN culturally-related material into the public school curriculum (Tippeconnic & Swisher, 1992). The passage of the Johnson O'Malley Act in 1934 provided supplemental funding to public schools to ensure that AI/AN children would receive the educational opportunities that would not otherwise be provided by the public schools in order to meet the unique needs of AI/AN students (Oglala Sioux Tribe, 2011). However, in the 1950s, the Federal Government terminated services to AI/AN people and moved away from Indian-related curriculum. A shift back to "Indianness" in the classroom occurred again in the 1960s and 1970s (Tippeconnic & Swisher, 1992), which is when the most change and growth in AI/AN education in the US occurred (from 1960 to 1977) compared to any previous time period (Havighurst, 1978).

Two major historical occurrences happened in the 1960s, which ended the assimilation focus of federal Indian policy and began the shift toward tribal self-determination: the civil rights movement and the changes in social and political culture that followed and President Johnson's attempt to ameliorate the problem of race and poverty in the US through the Great Society program, the War on Poverty, and the civil rights legislation of the 1960s (Nagel, 1995). All of these political developments were aimed at improving the lives of non-White and impoverished peoples. AI/ANs were able to capitalize on these movements towards equality of all peoples by obtaining increased federal spending on Indian affairs (Nagel, 1995).

The Civil Rights Act of 1964 commissioned the Coleman Report of 1966 to examine the lack of equal educational opportunities for students of all races in public schools in the US (Independence Hall Association, 2013; New York State Archives, 2006). While the Coleman Report was being generated, the Elementary and Secondary Education Act (ESEA) of 1965 was passed, which provided major funding to public and non-public schools to meet the educational needs of low-income students (New York State Archives, 2006). The establishment of the National Assessment of Educational Progress (NAEP) in 1969 continued the focus on equal education opportunities by administering federally-funded, periodic national sample surveys of student academic achievement (New York State Archives, 2006; Ravich, 2002).

Also during the 1960s, American Indians were also able to gain more involvement and control in schools. In 1968, President Johnson stipulated that AI/AN school boards be established at federal AI/AN schools. AI/AN participation in public school boards also increased in the late 1960s (Tippeconnic, 1999). Additionally, the Kennedy Report, *Indian Education: A national tragedy-a national challenge*, released in 1969, recommended increased AI/AN parental and community participation in AI/AN education programs (Tippeconnic, 1999; U.S Senate, 1969). Further, the Kennedy Report reiterated the failure of the Federal Government to provide equal opportunity education to AI/AN students, which was previously reported in the Meriam Report (Tippeconnic, 1999). Specifically,

> Public school findings included the lack of Indian participation or control; coursework which rarely recognized Indian history, culture, or language;

> and anti-Indian attitudes on the part of school administrators and teachers. Federal schools were found to be grossly underfinanced, deficient in academic performance, unsatisfactory in quality and effectiveness of instruction, seriously deficient in guidance and counseling programs, and characterized by a rigid and impersonal environment (U.S. Senate, 1969, abstract).

The results of the Kennedy Report, in part, led to the passage of the Indian Education Act of 1972, which allocated funds to public schools to meet the culturally-related educational needs of AI/AN students. Mandated parental committees allowed parents to become more involved. The Indian Education Act also provides services and funds over and above what is provided by the BIA (Tippeconnic, 1999). This legislation continues to be reauthorized under the ESEA (U. S. Department of Education, 2005).

Another landmark legislation that was passed in the 1970s was the Indian Self-Determination and Education Assistance Act of 1975, which authorized the Federal Government to enter into "638" contracts with AI/AN tribes and tribal organizations for tribal operation of the federal programs, including education, that were operating on the reservations (Tippeconnic, 1999; Trujillo & Alston, 2005). The Indian Education Act in 1972 and the Indian Education and Self-Determination Act in 1975 allowed AI/AN people to incorporate their languages and culture back into the schools that were under their control (Deyhle & Swisher, 1997).

A national education reform movement was sparked by the call to action in the 1983 report *A Nation at Risk*, which used available data to show that the US was experiencing unsatisfactory or declining achievement scores. This movement again steered away from the inclusion of "Indianness" in the classroom and instead shifted the focus to establishing standards to be assessed by standardized testing. Thus, began the era of accountability through testing, which remains in effect today (Tippeconnic & Swisher, 1992; New York State Archives, 2006).

In the 1990s, two significant reports were written about the condition of AI/AN education in the US and offered solutions to problems identified. The first was *Indian Nations At Risk: An Educational Strategy for Action*, which was compiled by the Indian Nations At Risk Task Force and was based on hearings, school visits, and commissioned papers (U.S. Department of Education, 1991; Deyhle & Swisher, 1997). The second was *The Final Report of the White House Conference*, which included 113 resolutions adopted by the delegates who attended the White House Conference on Indian Education in January 1992, regarding the need for basic research, applied research, and development of new programs and materials (Deyhle & Swisher, 1997). In 1998, President Clinton signed Presidential Executive Order 13096, which called for a comprehensive federal AI/AN education policy that would improve academic performance, reduce dropout rates, and create a federal research agenda to evaluate promising teaching strategies and the role of Native language and culture in curriculum (Fixico, 2012).

Continuing with the standards-based accountability approach that began in the 1980s, President George W. Bush signed the No Child Left Behind Act of 2001 (NCLB), a reauthorization of ESEA, which applied pressure on states to ensure that all students met state standards for proficiency in English/Language arts and mathematics by the end of the 2013-2014 school year (Nelson et. al., 2009). NCLB requires annual state assessments to be administered in certain subjects and grades and the results to be disaggregated by major racial and ethnic groups in addition to economically disadvantaged students, students with disabilities, and students with limited English proficiency (Nelson et. al., 2009). NCLB data pinpointed areas in which AI/AN students were not achieving at levels that would lead to academic success. The accountability requirements of the law have been able to highlight the failures of school systems to adequately meet the needs of their AI/AN students (Trujillo & Alston, 2005).

Studies conducted using NCLB data showed early on that AI/AN students scored lower on these assessments than all other student sub-populations (Nelson et. al., 2009). In response to these results, President George W. Bush revoked President Clinton's Executive Order 13096 and signed Executive Order 13336 on April 30, 2004 "to assist American Indian and Alaska Native students in meeting the challenging student academic standards of the No Child Left Behind Act of 2001 (Public Law 107–110) in a manner that is consistent with tribal traditions, languages, and cultures" (p. 1). Section 3 of the Order states that the Secretary of Education, in coordination with an interagency working group on AI/AN education, will conduct a multiyear study of AI/AN education in relation to the challenging student academic standards of the No Child Left Behind Act of 2001 (Exec. Order No. 13336, 2004). This multiyear study is called the National Indian Education Study (NIES). Since 2011, NIES has been authorized under Executive Order 13592, Improving American Indian and Alaska Native Educational Opportunities and Strengthening Tribal Colleges and Universities, which was issued to improve education efforts for AI/AN students across the US (National Center for Education Statistics, 2012). NIES and NAEP data were used in this dissertation.

Description of the problem

To date, NIES has been conducted in 2005, 2007, 2009, and 2011. From 2005-2009, NIES results were reported in two parts. Part I was based on the National Assessment of Educational Progress (NAEP)[1] achievement test results in English/Language arts and in mathematics in the 4^{th} and 8^{th} grades. In order to create a large enough sample size to be able to analyze the NAEP data from AI/AN students at a state level, schools in states with higher proportions of AI/AN students were chosen at a higher rate than they typically would be for standard NAEP assessments (Grigg et. al., 2010).

The 2005, 2007, 2009, and 2011 NAEP results have shown achievement gaps (i.e., differences in proficiency rates) between AI/AN students and all other students at both grade levels in English/Language arts and mathematics. In English/Language arts, the achievement gap in grade 8 increased four percentage points from 2005 (when there was a 14-percentage point gap) to 2007 (when there was an 18-percentage point gap). In mathematics, the achievement gap in grade 8 increased three percentage points from 2005 (when there was a 16-percentage point gap) to 2007 (when there was a 19-percentage point gap) (Nelson et. al., 2009). In 2011, grade 8 AI/AN students scored 19 points lower, on average, in mathematics than all other students. In comparison to 2005 and 2009, average mathematics scores for grade 8 AI/AN students did not change significantly in 2011 compared to 2005 and 2009 (National Center for Education Statistics, 2011).

[1] NAEP provides a common measure of what students in the United States know and can do in a variety of subjects (Gorman, 2010).

Part II of NIES was reported separately and included information from the NAEP background questionnaires in addition to special NIES background questionnaires created specifically to understand AI/AN student educational context and experiences. Both the NAEP and NIES background questionnaires have a student version, a teacher version, and a school version, which were administered to all 4th and 8th grade AI/AN students who participated in NAEP, their English/Language arts and mathematics teachers, and their school administrators. Additionally, there was a short NAEP questionnaire completed for students in the sample who had disabilities and another short NAEP questionnaire completed for those with limited English proficiency. These questionnaires were completed by a special education teacher, bilingual education/ESL teacher, or someone on staff at the school who was most familiar with the student. The results of all of the questionnaires were linked to the achievement data, except in the first administration of NIES in 2005. The NIES questionnaires contain questions specific to AI/AN culture and customs in relation to education and experiences in mathematics and English/Language arts that might affect student achievement (National Center for Education Statistics, 2014).

In order to increase the sample size for the questionnaire data, all students completed the same student questionnaire regardless of which achievement test they completed (English/Language arts, mathematics, or science). Therefore, the AI/AN students who participated in the NAEP science assessment completed the special NIES student background questionnaire, even though the science assessment results were not included in Part I of NIES and the questionnaire questions were about the students' educational experiences or interest in English/Language arts and mathematics, not science (National Center for Education Statistics, 2011a).

The purpose of the NAEP and NIES background questionnaires is to understand the context in which 4th and 8th grade AI/AN students learn English/Language arts and mathematics, to identify factors or circumstances related to higher achievement levels, and to statistically account for the observed differences in achievement based on demographic variables and attitudes towards learning. Understanding the context in which the students who participated in NIES learn English/Language arts and mathematics provides a more in-depth understanding of the patterns in AI/AN achievement scores found in Part I of NIES.

What is striking about the NAEP results is that when the AI/AN achievement scores are disaggregated by school density type (i.e., the percentage of AI/AN students in public schools in addition to the percentage of students in Bureau of Indian Education schools), achievement differences are evident among subgroups of the AI/AN student population – differences that have not yet been investigated. The 2009 NAEP results showed that average English/Language arts and mathematics scores for AI/AN students in both the 4th and 8th grades were significantly higher for students in public low density schools (less than 25% of the students in the school are AI/AN) than in public high density schools (25% or more of the students are AI/AN)[2], and significantly higher in both low and high density schools than in Bureau of Indian Education (BIE) schools (Grigg et. al., 2010).

[2] Public low and high density schools were defined by the Office of Indian Education (National Center for Education Statistics, 2011a).

BIE schools are federally funded elementary and secondary schools. The BIE was formerly known as the Office of Indian Education Programs (OIEP) under the BIA until 2006 when it became a separate bureau under the Department of the Interior (U.S. Department of the Interior, 2013). The BIE is responsible for educating 48,000 AI/AN children in 183 elementary, secondary, residential and peripheral dormitories on 64 reservations across 23 states. Of these schools, 130 are tribally controlled and 53 schools are operated by the BIE (Bureau of Indian Education, 2016). There are approximately 2,500 eighth grade students in 110 BIE schools (National Center for Education Statistics, 2011a). The focus of this dissertation was to explore the patterns in 8th grade mathematics achievement among AI/AN students in public low density schools, public high density schools, and BIE schools using both NAEP and NIES data.

Purpose & Research questions

The purpose of this dissertation was to explore the within and between state patterns in 8th grade mathematics achievement among AI/AN students in Arizona and South Dakota in public low density, public high density, and BIE schools using the 2009 NAEP achievement and questionnaire data in combination with the 2009 NIES questionnaire data. Using the questionnaire data, factors associated with the higher mathematics achievement scores of students in public low density schools as compared to students in public high density and BIE schools in Arizona and South Dakota were investigated. Additionally, the factors associated with the higher mathematics achievement scores of students in public high density schools in South Dakota as compared to students in BIE schools in South Dakota were examined. It is important to learn more about the characteristics of the students, teachers, and schools and how the context in which these students are learning differs among the three school density types in both states in order to better understand the AI/AN achievement patterns.

Arizona and South Dakota and the 2009 NIES data were the focus of this dissertation because these two states had significant differences in achievement both among and within school density types. When this dissertation was initiated, the most recent restricted-use NIES dataset available was 2009. Since then, 2011 data have become available. The same twelve states with higher proportions of AI/AN students were selected to participate in the 2009 and 2011 NIES. The NAEP Data Explorer (US Department of Education, IES, NCES, 2015) shows that only data from two states met the NAEP reporting standards[3] in 8th grade mathematics for each of the three school density types in each year. In 2009, Arizona and South Dakota were the two states that met the reporting standards. In 2011, New Mexico and South Dakota were the two states that met the reporting standards. In the 2011 data, there were no significant differences in the scores among the three school density types in New Mexico. There were also no significant differences between the scores in each state in each school density type. The only significant differences were among the school density types in South Dakota. Therefore, in order to have the ability to examine both between and within state differences among the three school density types, the 2009 NIES and NAEP 8th grade mathematics data for Arizona and South Dakota were used for this dissertation.

[3] NAEP reporting standards require a minimum of 62 students in a subgroup from at least five primary sampling units (i.e., each metropolitan area is a single PSU while smaller contiguous counties are merged in order to have a minimum population of about 50,000 people) (US Department of Education, IES, NCES, 2012a).

Arizona is 14th among all states in total population with 6.6 million people, while South Dakota is 46th among all states with 812,383 people. In Arizona, 296,810 people (4.5%) identified as AI/AN while in South Dakota, 69,865 people (8.6%) identified as AI/AN (US Census Bureau, 2009). Most of the AI/AN students in Arizona live in counties that border or encompass AI/AN reservations (Arizona Department of Education, 2012). A list of federally recognized tribes in Arizona and South Dakota can be found in Appendix 1.

Eighth grade was chosen because middle school is an important time in education for AI/AN students because many have fallen behind non-AI/AN students by the time they enter high school (Crawford et. al, 2010). The mathematics assessment was chosen over the English/Language arts assessment because the results are not as confounded by how well the students speak English.

In order to develop the research questions for this dissertation, the NAEP Data Explorer was used to learn more about 8th grade mathematics achievement in 2009 on NAEP for all students, as well as for AI/AN students, in Arizona and South Dakota. Table 1.1 shows the mean achievement scores for all students in Arizona and South Dakota by school-reported race. The achievement scores for all students in each state are shown first followed by the achievement scores by school-reported race between and within each state.

Table 1.1: *8th grade mathematics achievement in 2009 for all students and by school-reported race in Arizona and South Dakota using the NAEP Data Explorer*							
	ALL STUDENTS	White	Black	Hispanic	Asian American/ Pacific Islander	AI/AN	More than one race
Arizona	277	292	269[b]	265 [b]	295	254 [b,c]	-
South Dakota	291[a]	295	-	268 [d]	-	266 [a,d]	-

[a] Significantly higher than Arizona
[b] Significantly lower than Whites and Asian/Pacific Islander in Arizona
[c] Significantly lower than Blacks and Hispanics in Arizona
[d] Significantly lower than Whites in South Dakota

On the 8th grade mathematics NAEP assessment in 2009, which tested only students in public schools in the US, students in South Dakota scored significantly higher than students in Arizona (291 and 277, respectively). Arizona had the 13th lowest score of all 50 states and South Dakota had the 8th highest score of all 50 states. The other significant difference between the two states was that AI/AN students in South Dakota scored significantly higher (266) than AI/AN students in Arizona (254). It is interesting to note that the achievement differences between all students in South Dakota and Arizona (14 points, on average) and AI/AN students in each state (12 points, on average) were almost equal. There were no significant differences in the achievement of the other races between the states. The achievement variation between the two states may be driven by the AI/AN achievement differences.

In Arizona, Black and Hispanic students (269 and 265, respectively) scored significantly lower than White and Asian/Pacific Islander students (292 and 295, respectively) while AI/AN students (254) scored significantly lower than Whites, Asian/Pacific Islanders, Blacks, and Hispanic students.

In South Dakota, Hispanics students (268) and AI/AN students (266) scored significantly lower than White students (295). There was no significant difference between the scores of Hispanic and AI/AN students in South Dakota.

Table 1.2 shows the differences in AI/AN students 8th grade mathematics achievement in Arizona and South Dakota between students in public schools and students in BIE schools using the NAEP Data Explorer.

Table 1.2: *8th grade mathematics achievement for AI/AN students in public schools and BIE schools in Arizona and South Dakota using the NAEP Data Explorer*

	Public	BIE
Arizona	254	249
South Dakota	266 [a,b]	247

[a] Significantly higher than Arizona
[b] Significantly higher than BIE schools

In Arizona, there was no significant difference in AI/AN student achievement on the NAEP 8th grade mathematics assessment between students in public and students in BIE schools. However, students in public schools in South Dakota scored significantly higher than students in BIE schools.

Table 1.3 shows the differences in AI/AN students' 8th grade mathematics achievement in Arizona and South Dakota by all three school density types using the NAEP Data Explorer.

Table 1.3: *8th grade mathematics achievement for AI/AN students by school density type in Arizona and South Dakota using the NAEP Data Explorer*			
	Public Low Density	Public High Density	BIE
Arizona	263 [a]	249	249
South Dakota	276 [a,c]	260 [b,c]	247

[a] Significantly higher than public high density and BIE schools
[b] Significantly higher than BIE schools
[c] Significantly higher than Arizona

In Arizona and South Dakota, AI/AN students in public low density schools scored significantly higher on the 8th grade mathematics assessment than both students in public high density and BIE schools (14 points, on average, in Arizona and 16 points and 29 points, on average, in South Dakota, respectively). In South Dakota, AI/AN students in public high density schools scored significantly higher than students in BIE schools (13 points, on average). Students in South Dakota public low and high density schools scored significantly higher than students in Arizona public low and high density schools (13 points and 11 points, on average, respectively). Again, it is interesting to note that the achievement differences both between and across states and school density types closely mirrored the achievement differences between students of all races in each state and also between AI/AN students as a group in each state in Table 1.1 (except for the achievement difference of 29 points, on average, between South Dakota public low density and BIE school students).

As stated previously, the overall pattern in the 2009 NIES data was that the average reading and mathematics scores for AI/AN students in both the 4th and 8th grades were significantly higher for students in public low density schools than in public high density schools and significantly higher in both low and high density schools than in BIE schools (Grigg et. al., 2010). The data for South Dakota AI/AN students followed this pattern for 8th grade mathematics, but the data for Arizona AI/AN students did not, and therefore, warrant further examination as to what factors might be associated with this pattern that do not follow the norm. In Arizona, the 8th grade mathematics scores were significantly higher for students in public low density schools than in public high density schools and BIE schools, but the scores for students in public high density schools were not significantly higher than the scores for students in BIE schools. Why did the overall data pattern and the data pattern for South Dakota show significant differences in achievement between public high density schools and BIE schools, but the data pattern for Arizona did not? The expectation would have been that the public high density schools in Arizona would have scored significantly higher than BIE schools, but they scored the same.

Before stating the research questions, several terms must be defined. Single background questionnaire items associated with achievement were referred to as *individual items*. Multiple individual items thought to be related to the same construct were statistically combined into what was termed *derived risk factors*. The purpose of the derived risk factors was to take an in depth look across the states and school density types at specific constructs mentioned in the literature as being associated with achievement: attitudes toward mathematics, how much AI/AN traditions and culture was incorporated into the lives of the students both in and out of school, and school climate. Lastly, the individual items and derived risk factors were used to create several *risk indices* for which each student was assigned one point for each individual item and derived risk factor that applied to them. These risk indices were used as independent predictors of achievement. Higher values on the risk indices were expected to be associated with lower levels of achievement.

Research questions.

RQ1a. How do the distributions of the individual items and derived risk factors from the NAEP background questionnaires and school administration records differ among the three school density types in each state?

RQ1b. How do the distributions of the individual items and derived risk factors from the NIES background questionnaires differ among the three school density types in each state?

RQ2a. To what extent do the distributions of risk indices based on the individual items and derived risk factors from the NAEP background questionnaires and school administration records differ between states and among the three school density types?

RQ2b. To what extent do the distributions of risk indices based on the individual items and derived risk factors from the NIES background questionnaires differ between states and among the three school density types?

RQ3a: To what extent are the risk indices created using the NAEP background questionnaires and school administration records associated with AI/AN 8th grade mathematics achievement in each of the school density types in each state?

RQ3b: To what extent are the risk indices created using the NIES background questionnaires associated with AI/AN 8th grade mathematics achievement and what is their incremental contribution to explained variance after accounting for the NAEP risk indices in each of the school density types in each state?

RQ4: How can the answers to the previous questions inform AI/AN education policy? What additional policy implications can be drawn from comparisons both within and between the school density types in each of these states?

This analysis consisted of four main phases. The first phase comprised looking for interesting patterns identified in the literature by examining the descriptive data from the background questionnaires using cross tabulations and tests of independence. The second was to understand better the differences in the distributions of the risk indices, comprising variables that have been shown in the literature to be associated with achievement. The third was to identify risk indices that were related to higher 8th grade mathematics achievement in one school density type as compared to another within each state and to understand the impact of the student body composition on the between and within state differences in achievement using ordinary least squares (OLS) regression. The fourth was to synthesize the results as they relate to policy implications.

Significance of the Study

Much of the existing literature on factors related to student achievement or achievement gaps (which will be discussed in more depth in Chapter 2) does not even include data on AI/AN students because the sample sizes are too small to analyze separately. The extant literature on AI/AN achievement, specifically, is based on national studies that did not oversample AI/AN students or describe the experiences of students from one school or one tribe, which cannot be generalized to students outside of that school or tribe. NIES is a rich, untapped well of background data and achievement information about AI/AN students and their learning environments. It provides researchers with a national dataset with a large enough sample size for AI/AN students (i.e., enough power) to make meaningful conclusions. Examining the achievement of AI/AN students using a robust, national dataset conveys more information than currently exists in the literature about the risk factors in AI/AN students' learning environments that play a role in achievement. For the purposes of this dissertation, it allowed the researcher to draw within state inferences for Arizona and South Dakota, as well as make between state comparisons in order to explore the various AI/AN achievement differences.

The report written by Grigg et. al. (2010) on the NIES 2009 assessment results revealed that school density type is a risk factor related to AI/AN achievement. There are no published articles that use the NIES datasets to examine the AI/AN achievement differences by school density type. In an effort to reduce the achievement disparities, it is important to understand the differences in achievement based on the percentage of AI/AN students in the school. This dissertation contributes information to the current literature on risk factors associated with differences in AI/AN 8^{th} grade mathematics achievement by school density type.

The goal of this dissertation was to use the NIES 2009 mathematics achievement data and the NAEP and NIES questionnaire data for Arizona and South Dakota to describe the educational environments of different groups of AI/AN students in two different states and to uncover risk factors that are associated with the AI/AN 8^{th} grade mathematics achievement in these two states to help inform policy.

These data were examined through three lenses: each of the six groups of students (i.e., three school density types in both states), comparisons of the three school density types within each state, and comparisons of the three school density types between each state. The importance of examining the AI/AN achievement differences was due to the ongoing emphasis on student achievement outcomes and ensuring that all students have an equal opportunity for higher quality education.

A review of the literature, presented in detail in Chapter Two, describes several in-home and at-school risk factors shown to be related to achievement for students of all backgrounds, for minority students, and for AI/AN students specifically. In addition, three topics are discussed more in depth as to how they affect AI/AN education: culture, English-language learners, and having a disability. The findings from this dissertation could be a starting point towards policy initiatives that could lead to improving the overall performance of AI/AN students and beginning to close the gap between AI/AN students and students of other racial backgrounds.

Chapter Two

"Individual student achievement is an outcome of factors that affect the child, the teacher, and the classroom (Hosp & Reschly, 2004, p. 187)". This chapter provides an overview of the literature regarding some of the many risk factors that have been found to be associated with student achievement for students of all races in addition to some specific risk factors associated with minority students' achievement, including AI/AN students.

Studies have been conducted to try to understand achievement differences and improve achievement outcomes (Ladner & Hammons, 2001). However, as mentioned previously, due to small sample sizes, AI/AN students have not always been represented in these studies. Additionally, studies that have been conducted with just AI/AN students have not included risk factors associated with achievement for all races (Lipska & Adams, 2004; Whitbeck et. al., 2001). Therefore, this chapter is not solely focused on AI/AN achievement literature, but on the broader achievement literature, in order to gather a fuller understanding of which risk factors related to the achievement of all students, and specifically AI/AN students, are relevant to 8th grade mathematics achievement for AI/AN students in South Dakota and Arizona.

Since this was an exploratory analysis and many different variables were tested in the models, what follows is neither an exhaustive review of all risk factors associated with achievement, nor is it an exhaustive review of the literature for each risk factor. Core literature on each risk factor has been included in order to justify its importance and, thus, inclusion in this dissertation.

According to Rothstein (2004), the consensus in the early 2000s among social science researchers is that home background risk factors account for about two thirds of the variation in achievement while school risk factors account for about one third. Therefore, both student/home background and school risk factors were examined in this dissertation.

The chapter consists of three main components: general student/home risk factors associated with achievement (financial capital, human capital, social capital, attitude toward and self-confidence in mathematics), general school risk factors associated with achievement (socioeconomic status, school climate, teacher quality, and student body composition), and risk factors associated with low achievement for minorities, including AI/AN students. Both student and school-level risk factors are discussed, with a focus on the literature related to the importance of incorporating culture into learning, being an English-language learner, and being labeled as a student with a disability. Although the general student and school risk factors are extremely important and must be included to make this dissertation comprehensive, more emphasis is placed on the issues specific to the achievement of AI/AN students, as that is the focus of this dissertation.

Student risk factors associated with achievement

Home background overview. Home background (such as parental income, parental education, and family structure) is known to be associated with school achievement (Magnuson & Duncan, 2006; Parcel & Dufur, 2001; Muller, 1995; Entwistle & Alexander, 1988; Stevenson & Baker, 1987). Coleman (1988) defines home background as consisting of three components that may be used as a resource to enhance the academic success of a child: financial capital, human capital, and social capital. He defines financial capital as a family's wealth or income. It provides the child with a home to study, materials for learning, and financial resources to ease family problems. Human capital refers to the learned skills and knowledge that each person obtains throughout their lifetime. Parents' education provides the potential for a cognitive environment for the child that aids in learning. Social capital refers to relationships among people, both at home and in the community. One aspect of this is the amount of time and effort spent by parents with the child on intellectual matters. Coleman asserts that it is critical to have the support of both human capital and social capital in order to have an impact on the educational outcomes of children. In other words, parents' human capital may not increase the achievement of their children if the parents are not an important part of their children's lives (both their physical presence in the home and the attention they provide to their children).

Family structure can affect social capital (i.e., the relationship between parents and children). The more siblings in the home, the more diluted the adult attention to each child, especially in single-parent homes (Coleman, 1988). In 2011, only 52% of AI/AN children lived in two-parent households compared to 75% of Whites (Aud et. al., 2012). In his meta-analysis of 845 studies, Hattie (2009) found the overall effect size (difference between two means) for family structure and achievement was small (d=0.17). Although family structure is an important aspect of social capital, it cannot be measured using the NIES dataset. How AI/AN students are affected by each of the three forms of capital and the relationship between each form of capital and mathematics achievement is discussed next.

Financial Capital. Minority children are disproportionately poor. Poverty is associated with a number of risk factors that hinder development and, later, school preparedness such as low birth weight, poor nutrition, and higher rates of exposure to toxins such as lead, alcohol, and tobacco (National Research Council, 2002). AI/AN children, in particular, are more likely to be exposed prenatally to high levels of alcohol and tobacco (National Research Council, 2002).

Living in poverty increases everyday life stresses that are associated with low achievement (Crawford et al, 2010). In 2007, 33% of AI/AN children were living in poverty (Aud et. al., 2010). That number increased in 2011 when 36% of AI/AN children were living in poverty, second only to Black children (39%). At the same time, 34% of Hispanic children, 30% of Native Hawaiian/Pacific Islander children, and 13% of White and Asian children were living in poverty (Aud et. al., 2013). The median income of AI/AN households in 2011 was $35,192 compared to $50,502 for the whole nation (U.S. Census Bureau, 2012). In their report on indicators related to the gap in educational participation and attainment among racial/ethnic groups, Ross et. al. (2012) stated that, in 2010, the poverty rate for children under the age of 18 who were living with a female parent without a spouse living in the home was significantly higher for AI/AN children (53%) than for children of all other racial/ethnic groups (with the exception of Black children, 51%, and Hispanic children, 50%, among which the differences were not significantly different).

Sirin (2005) conducted a meta-analysis of 58 studies and found a strong relationship between academic achievement and parental income (mean effect size of r = 0.29 or d = 0.58). Using data from the National Longitudinal Survey of Youth (NLSY) on 4,412 children matched to their mothers (2,401 mothers), Dahl and Lochner (2008) sought to determine the impact of family income on student achievement based on the earned income tax credit increases from 1988-2000. Overall, they found a $1000 increase in income was associated with an increase in mathematics scores by 6% of a standard deviation. For minority children (only Black and Hispanic children were included in this study), the achievement gains were significantly greater (8% of a standard deviation) than that of White children (1% of a standard deviation) with an increase in income. Additionally, achievement for children with mothers with a high school diploma or less increased significantly (5% of a standard deviation) with an increase in income compared to children with mothers who had some college or more (0% of a standard deviation).

In an examination of the impact of family income, parental education, and parental occupation (three main indicators of SES) on achievement, Hattie (2009) reviewed four meta-analyses comprising 499 studies and determined an overall effect size of d=0.57, which he concluded means that SES has a notable influence on a student's achievement. Hattie considered effect sizes above d=0.40 to be significant. For AI/AN students, low SES is associated with low academic achievement (DeVoe & Darling-Churchill, 2008; Gilbert, 2000). In fact, AI/AN students' academic success is more strongly associated with SES than it is for other races (Crawford et. al., 2010).

Unfortunately, the NIES dataset does not include information on family income. Instead, student eligibility for the National School Lunch Program (NSLP) was used as an indicator of low income. Children who are eligible for free meals are those whose families have incomes below 130 percent of the poverty level (from July 1, 2008 to June

30, 2009, 130 percent of the poverty level was $27,560 for a family of four). Children who are eligible for reduced-price meals are those whose families have incomes between 130 and 185 percent of the poverty level ($39,220 for the same period mentioned previously). However, some schools choose to provide free meals to all students whether or not each individual student is eligible, which means these schools have high percentages of eligible students and report all students as eligible for free lunch (National Center for Education Statistics, 2011a). Therefore, in addition to NSLP eligibility, another variable was used to examine the role of family financial capital.

When datasets do not contain information on family income, surrogate variables are used to indicate SES. As mentioned above, in addition to family income, parental education (discussed further in the next section) and parental occupation (also not captured in the NIES dataset) are also used as SES indicators and should be considered as separate variables as each measures different aspects of SES (Magnuson & Duncan, 2006; Sirin, 2005; White, 1982).

Home resources are a fourth indicator of SES. Home resources include household possessions such as books, computers, a study room, and after-school and summer tutoring (Sirin, 2005). Trends in International Mathematics and Science Study (TIMSS), an international mathematics and science assessment given to nationally representative samples of fourth and eighth grade students in 63 countries, has consistently found that students who have more than 100 books in the home have higher achievement in mathematics. Additionally, they have found that having study aids such as a computer, Internet connection, their own room, or a study desk/table also are positively associated with achievement in mathematics (Mullis et. al., 2012; Mullis et. al., 2008).

For the purposes of this dissertation and the limitations of measuring financial capital using the NIES data, eligibility for NSLP and the number of books in the home were employed as proxy measures of financial capital in the analysis.

Human Capital. Although there are different components of human capital, as it relates to student achievement, human capital is measured using parents' education (Coleman, 1988). The more education a student's parents have, the better the student's mathematics achievement (Mullis et al, 2012; Magnuson & Duncan, 2006; Sirin, 2005). In 2010, more Asians (59%) and Whites (44%) had parents with a bachelor's degree or higher compared to Black (20%), Native Hawaiian/Pacific Islander (18%), American Indian (18%), Hispanic (16%), and Alaska Native (16%) children (Ross et. al., 2012). Having a mother who has less than a high school education is associated with low academic achievement for AI/AN students (Devoe & Darling-Churchill, 2008).

Historically, TIMSS has found strong positive relationships between level of parents' education and their children's academic success (Mullis et. al., 2012; Mullis et. al., 2008). Sirin (2005) conducted a meta-analysis of 58 studies and also found a strong relationship between academic achievement and parental education (mean effect size of $r = 0.30$ or $d = 0.60$).

A derived variable included in the NIES dataset using the highest level of education received by either parent represented human capital in this dissertation.

Social Capital. Parental involvement in school activities is related to school performance (Stevenson & Baker, 1987; Parcel & Dufur, 2001), specifically AI/AN student achievement (Leveque, 1994; Kratochwill et. al, 2004; Willeto, 1999).

Parental involvement in school activities can be defined as parental membership and attendance at meetings and activities of a parent-teacher organization (Muller, 1995; Stevenson & Baker, 1987; Ho & Willms, 1986); participation in parent-teacher conferences (Stevenson & Baker, 1987); frequency that parents contact the school about their child's academic performance or program during the year; and whether parents volunteer at the school (Muller, 1995; Ho & Willms, 1986).

Examining data from the National Education Longitudinal Study (NELS), which was based on a sample of 24,599 eighth-grade students and their parents and teachers in public and private schools in the United States, Ho & Willms (1996) identified four dimensions of parental involvement: home discussion (talk with mother, talk with father, discuss school program, discuss activities), school communication (school contacts parents, parents contact school), home supervision (limit TV time, limit going out, monitor homework, home after school), and school participation (volunteer at school, participate in PTO). They studied the relationship of each dimension with achievement and found that home discussion accounted for the largest increase in mathematics and English/Language arts achievement. Specifically, students whose parents discussed school-related activities at home and helped children plan their academic programs had an increase in achievement of approximately 12% of a standard deviation.

According to Hattie's (2009) synthesis of 36 meta-analyses including 2,211 studies on contributions from the home, parental aspirations and expectations for their children's academic achievement had the strongest effect on achievement (*d* = 0.80), while discussing school progress, helping with homework, and interest in schoolwork had a moderate effect on achievement (*d*=0.38).

To examine parental involvement using the NIES dataset, the following student background questions were included in the analysis: *how often does family help with your schoolwork*; *during 8th grade, how many times have you talked to a family member about the classes you should take in high school or about what you want to do after high school*; and *how often do you talk about things you have studied in school with someone in your family*. The school background question regarding *the extent to which low family involvement is a problem at the school* was included in the *school climate* derived risk factor.

Attitude Toward and Self-Confidence in Mathematics. TIMSS has found a positive association between having a positive attitude toward mathematics (i.e., I enjoy learning mathematics; mathematics is boring; I like mathematics) and having self-confidence in learning mathematics (i.e., I usually do well in mathematics; mathematics is harder for me than for many of my classmates; I am just not good at mathematics; I learn things quickly in mathematics) and mathematics achievement (Mullis et al, 2008). Students with more positive attitudes toward mathematics have substantially higher mathematics achievement (Mullis et al, 2012), as do students with more self-confidence in mathematics (Mullis et al, 2008). The relationships between having a positive attitude toward mathematics and mathematics achievement and self-confidence in mathematics and mathematics achievement are reciprocal. In other words, students who have higher achievement in mathematics are more likely to have positive attitudes towards mathematics and more self-confidence in mathematics (Mullis et al, 2012).

Analyzing three meta-analyses of student attitudes toward school comprising 288 studies, Hattie (2009) found that attitudes toward mathematics (e.g., liking or disliking mathematics, thinking mathematics is easy or difficult, believing one is good or bad at mathematics, and tending to engage in or avoid mathematics activities) were related to mathematics achievement with an overall effect size of d=0.36. It is important to note that student attitudes and achievement are correlated (Hattie, 2009).

School-level Risk Factors Associated with Achievement.

Socioeconomic status. School SES is usually measured using the percentage of students in the school who are eligible for free or reduced-price lunch programs (Sirin, 2005). In 2011, 31% of AI/AN students attended high-poverty public schools[4] compared to 6% of White students while just 11% of AI/AN students attended low-poverty public schools[5] compared to 33% of White students (Ross et. al., 2012).

In a meta-analysis of 101 studies, White (1982) compared the relationship between the SES of the school and the SES of the parents on academic achievement and found that the SES at the school level (mean r = 0.68) was more important than the SES at the individual student level (mean r = 0.25). However, both a student level and school-level SES variable (i.e., percent of school eligible for NSLP) were included in this analysis to see if this conclusion held true for this dataset.

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[4] High-poverty schools were defined as having more than 75% of students eligible for free or reduced-price lunch.

[5] Low-poverty schools were defined as having 25% or fewer students eligible for free or reduced-price lunch.

Using a large, Midwestern, urban school district with 133 schools that served about 96,000 students (58% White, 36% African American, and 6% Other), Vanderhaar & Muñoz (2006) found a statistically significant association between schools' poverty concentration levels and students' achievement scores. Schools with a low concentration of free or reduced-priced lunch students (11.8-42.3%) had significantly higher mean scores on the Comprehensive Test of Basic Skills (CTBS) Total Battery and the Total Academic Index (TAI) than schools with medium low concentration (42.4-62.7%), medium high concentration (62.8-76.8%), and high concentration (76.9-97.9%). They found that concentrated poverty had a moderate effect size of 0.31 on the CTBS scores and 0.37 on the TAI scores.

The school background questionnaire question asking the percentage of students in the school eligible for free or reduced-priced lunch was used as a proxy for school SES in this analysis. This variable was dichotomized in the analysis of research question 1a as follows: 76% or more eligible national school lunch program (i.e., high-poverty schools) and 75% or less eligible for national school lunch program (i.e., other schools).

School Climate. A school's climate is extremely important to successful student outcomes (Cohen et. al., 2009; Phillips, 1997; Stewart, 2007). There is much literature surrounding school climate and its definition in each study often varies.

Based on their extensive review of the literature on school climate, Zullig et. al. (2010) determined that there were five common aspects of school climate that have been measured over time: order, safety, and discipline (e.g., students feel safe, respect peers and authority, know disciplinary policies); academic outcomes (e.g., recognition of accomplishments, satisfaction with classes, performance evaluations); social relationships (e.g., student relationships with teachers and peers, support of school staff); school facilities (e.g., inside temperature, noise level, condition of school), and school connectedness (e.g., engaged learners, students feel valued for their input).

Using principal, teacher, and student questionnaires and reading and mathematics achievement data on the Iowa Tests of Basic Skills from several hundred Chicago public elementary schools from 1990-1997, Bryk et. al. (2010) examined the core elements in the organization of a school that appeared to increase its ability to improve student engagement and learning. They defined school climate as how safe the students feel in and around the school and the number of classroom disruptions reported by the teachers (i.e., safety and order in the school). Also included in the definition were whether teachers press students to work hard and do their homework, whether teachers can be counted on to help students and notice when they are having trouble, and how often students make fun of each other, disrupt one another, and work hard at getting good grades (i.e., academic support and press). They found that schools with strong ties to parents and the local community were able to create a safer and more orderly environment because these connections enhanced students' participation in school and raised achievement goals. Additionally, they found that over half the schools that reported problems with school safety and order did not improve student attendance over the seven-year period of the study.

Phillips (1997) defined academic climate as teachers' expectations for students, the percentage of students enrolled in algebra in 8th grade, and the amount of time students spent doing homework. She found that a school's academic climate was positively related to mathematics achievement in a sample of 5,659 mostly African

American middle-class, suburban, middle school students. Using data from 24,599 eighth grade students from the NELS, Muller (1998) also found that teacher expectations were associated with student achievement.

In terms of the relationship between school climate and achievement, TIMSS has found:

- students with the highest mathematics achievement were most often in schools that emphasized academic success: rigorous curricular goals, effective teachers, students who desire to do well, and parental support.
- students in schools with discipline and safety problems had lower achievement.
- a negative relationship between 8th grade students' reports of being bullied and average mathematics achievement: students who reported "almost never" being bullied had an average mathematics achievement 32 points higher than students who reported being bullied weekly (Mullis et. al, 2012).

Analyzing data from a sample of 11,999 tenth grade students enrolled in 715 high schools from the second wave of the NELS in 1990, Stewart (2007) found that schools in which there were clearer expectations about the school's mission, greater cooperation among teachers and administrators, and stronger support for students were associated with higher levels of achievement.

Based on these data, the following school background questionnaire questions were included in this analysis:

- Considering all of the students in your school, to what extent is each of the following a problem in your school
    - Student absenteeism

- Student tardiness
- Drug or alcohol use by students
- Physical conflicts among students
- Bullying
- Low student aspirations
- Low teacher expectations
- Low family involvement

Teacher Quality. With the passage of NCLB in 2001, all teachers were required to be "highly qualified" by the 2005-2006 academic year. Highly qualified means the teacher must have a bachelor's degree, full state certification or licensure, and demonstrate knowledge in each subject they teach by having majored in the subject they teach, having credits equivalent to a major in the subject, passing a state-developed test, meeting the requirements for High, Objective, Uniform State Standard of Evaluation (HOUSSE)[6], having an advanced certification from the state, or holding a graduate degree (US Department of Education, 2004). In South Dakota, once initial certification is obtained, teachers must also complete an approved Indian studies course (South Dakota Department of Education, 2014). The Arizona Department of Education does not list this type of requirement on their website.

Teacher quality has a stronger relationship to the achievement of minority students than majority students, especially at higher grades (Coleman, 1966). Schools with more low-income, minority students are less likely to have experienced, well-trained teachers (National Research Council, 2002). It is difficult to retain teachers in schools

[6]HOUSSE is only for teachers who had already been teaching when NCLB was passed and states decide the terms of proof, which may include teaching experience and professional development and knowledge of the subject obtained over time in the field (US Department of Education, 2004).

serving AI/AN children because many of the schools are isolated in rural areas, the teacher salaries are low, poverty is high, and there are linguistic and cultural differences (National Indian Education Association, 2008; Trujillo & Alston, 2005).

In a national review of teacher qualifications as they relate to student achievement, Darling-Hammond (2000) analyzed data on student achievement and characteristics from 44 states participating in state NAEP in reading and mathematics and linked it to data on public school teacher qualifications and other school inputs from the Schools and Staffing Surveys (SASS). She found that student characteristics such as poverty, English-language learner, and minority status were positively correlated with teacher qualifications. In other words, students who were less socially advantaged had teachers who were less likely to have full certification and a degree in their field and were more likely to have entered the field without certification. She also found that teacher quality characteristics (e.g., certification status and degree in the field) were very significantly and positively correlated with student outcomes. Even after controlling for student poverty and being an English-language learner, Darling-Hammond (2000) found that there was still a strong, significant relationship between teacher quality and student achievement. Specifically, the most significant predictor of student achievement in reading and mathematics was the proportion of well-qualified teachers (i.e., those with full certification and a major in the field they teach) in a state, which was even more powerful than teachers' education levels (e.g., master's degree).

Student body composition. Coleman (1966) found that after controlling for students' socioeconomic status (SES), the differences in the characteristics of the schools (e.g., curriculum, teachers, facilities, and student body composition), only accounted for a small proportion of the differences in student achievement for majority students and Asian students. On the other hand, he found the achievement of other minority students depended more on the characteristics of the school. Specifically, he found that if minority students (except for Asian students) from homes without a strong educational background were enrolled in schools with students from homes with a strong education background, the minority students' achievement was likely to be greater. For example, 10.79% of the variance in verbal achievement for Puerto Rican 9th graders was accounted for by student body composition while 0.05-0.31% of the variance in verbal achievement for Puerto Rican 9th graders was accounted for by school facilities, curriculum, teacher quality, and teacher attitudes. For AI/AN 9th graders in Coleman's study, 4.76% of the variance in verbal achievement was accounted for by student body composition while 0.16-0.89% was accounted for by school facilities, curriculum, teacher quality, and teacher attitudes. For Black and Mexican 9th graders, 4.05% and 3.64%, respectively, of the variance in verbal achievement was accounted for by student body composition while 0-1.18% of the variance was account for by school facilities, curriculum, teacher quality, and teacher attitudes. Lastly, for Asian and White 9th graders, 3.48% and 1.69%, respectively, of the variance in verbal achievement was accounted for by student body composition while 0.02-0.27% of the variance was account for by school facilities, curriculum, teacher quality, and teacher attitudes.

Using information on students' economic home backgrounds provided by school principals, in 2011, TIMSS found that students attending schools in which a greater percentage of students were from relatively affluent socioeconomic backgrounds had higher average mathematics achievement than students in schools with peers from lower socioeconomic backgrounds (Mullis et. al, 2012). Thus, the home background (both educational background and SES) of the students in the school and school context of the student body have a strong relationship with achievement.

Risk Factors for Low Achievement of AI/AN Students.

Overview. In the Early Childhood Longitudinal Study, Birth Cohort (ECLS-B), the gap between AI/AN children and all other children became apparent as early as 4 years of age. At age 4, substantially smaller percentages of AI/AN children exhibited language, literacy, mathematics, and color identification skills compared to all other children. For example, 19% of AI/AN children were able to identify letters by their shapes and sounds compared to 33% of all children; 41% of AI/AN children demonstrated proficiency in identifying numbers and shapes compared to 66% of all children; and 43% of AI/AN children were able to identify five out of five colors compared to 64% of all children (DeVoe & Darling-Churchill, 2008).

However, at a 2005 workshop on improving the academic performance among AI/AN students, Dr. David Grissmer stated that one issue with studying AI/AN achievement is that the sample sizes are not large enough to make conclusions that are generalizable to all AI/AN students. The example he gave was that the data collected by the Early Childhood Longitudinal Survey (ECLS) only included 400 AI/AN children. The data he presented at the workshop indicated that AI/ANs generally have the largest gap with White students at the beginning of kindergarten, but that the gap decreases as schooling progresses. He attributes the gap to family characteristics and community characteristics. He stated that family characteristics such as parental education, the learning environment in the home, and number of siblings account for approximately half of the gap for AI/AN students (National Institutes of Health, 2005).

In his commentary on the condition of AI/AN education in the US for the Journal of American Indian Education, Beaulieu (2000) asserted that schools that have a high number of AI/AN students typically have extremely high student and staff mobility and students who attend these schools have been disproportionately affected by violence and substance abuse, which negatively impacts school readiness and an individual's capacity to learn. Additionally, he professed that schools serving AI/AN students typically do not provide staff with adequate professional development or curricular development to meet the unique cultural needs of the students and to support continuous improvement in the capacity to meet those needs.

DeVoe and Darling-Churchill (2008) examined the educational attainment of and challenges facing AI/AN children through employing data on a number of educational achievement indicators over the past 20 years. The results showed differences remain between AI/AN students and students of other racial/ethnic groups on certain risk factors. For example, the early reading and mathematics skills of children of any racial group with at least one of the following risk factors tend to lag behind the skills of children with no risk factors: living in a single-parent family, living in poverty, having a mother who has less than a high school education, and having parents whose primary language is not English. These risk factors are much more common among racial/ethnic minorities, including AI/ANs, than among White families. In particular, a higher percentage of AI/AN children than White children live in a single-parent family, live in poverty, have a mother who has less than a high school education, and have parents whose primary language is not English (DeVoe & Darling-Churchill, 2008), which places AI/AN students at more risk of struggling academically than White children. Living in poverty, being an English-language learner, and being a minority are significantly and negatively correlated with student outcomes (Darling-Hammond, 2000).

In order to understand how certain risk factors are related to high educational attainment among AI/AN students, Rindone (1988) surveyed 107 Navajo college graduates (identified from 1983-1986 graduate rosters from the Navajo Division of Higher Education in Window Rock, AZ) about their family characteristics, educational background, SES, language background, and demographic information. She found that 66% had family incomes below $10,000 with 49% having family incomes of $5,999 or less, including income from rug weaving, jewelry making, and other crafts. The most frequently listed occupation for fathers was “laborer” and “housewife” for mother. Half of the respondents (50%) indicated that they came from traditional families in which Navajo was the predominant language (48% of the respondents reported being monolingual Navajo speakers) and the Navajo way was followed by family members. Only 9% reported that their teacher used Navajo in the classroom, meaning instruction was primarily in English. Just over half of the respondents (55%) stated their fathers had completed less than six years of schooling and 52% reported their mothers had completed less than six years of schooling. Only 10% had fathers who were college graduates or had attended some college and only 9% had mothers who were college graduates or had attended some college. Thus, this group of AI/AN men and women were able to overcome potentially adverse achievement effects from living in poverty, being an English-language learner, and having parents with very little education. Eighty percent or more of the respondents indicated that their parents were born on the reservation and were married. Fifty-three percent of the respondents stated their teacher encouraged them to succeed in school. Rindone postulated that for Navajo families, a stable family life with traditional values may be an important factor that relates to achievement, in addition to teacher aspirations. Finally, 34% of respondents stated that the single factor that contributed to their high academic success was their own motivation while 45% reported it was encouragement from parents and other family members.

Several studies have examined the impact of multiple risk factors, including comparing quality (i.e., type of risk factor) to quantity (i.e., number of risk factors) to see if one carries more weight than the other (Deater-Deckard, Dodge, Bates, & Pettit, 1998; Gutman, Sameroff, & Eccles, 2002; Rutter, 1979; Sameroff, Seifer, Baldwin, & Baldwin, 1993). Rutter (1979), in a well-known study, sampled 10-year olds to investigate whether the quality or quantity of risk factors led to a psychiatric disorder. He studied six risk factors and found that it was not any particular risk factor but the number of risk factors that was more likely to lead to a psychiatric disorder. He found that psychiatric risk rose from 2% in families with zero or one risk factor to 20% in families with four or more risk factors.

Sameroff, Seifer, Baldwin, & Baldwin (1993) analyzed 10 risk factors to examine the effects of a child's environment on IQ of children at 4- and 13-years old. The sample comprised 152 families of varied race (99 families were White, 52 were Black, and 1 was Puerto Rican) who participated in the Rochester Longitudinal Study at both time points. They found that having multiple risk factors was related to child IQ at 4 and 13 years even after controlling for SES and race and that for families with three or more risk factors, the pattern of risk was less important than the number of risk factors at both time points.

Deater-Deckard, Dodge, Bates, & Pettit (1998) followed a sample of 466 European American and 100 African American boys and girls from ages 5 to 10 to see whether individual items and the number of risk factors predicted children's externalizing behaviors throughout middle childhood. They used 20 risk variables from four domains: child, sociocultural, parenting, and peer-related. All four domains of risk variables made significant unique contributions to predicting the outcome variable. Additionally, the number of risk factors present, no matter which ones they were, were predictive of the outcome variable. Although, they concluded that even though using the cumulative number of risks as a predictor is more parsimonious, it is still important to understand individual differences in the presence or absence of each risk factor to predict externalizing behavior issues.

To look at the effect of multiple risk factors on achievement, Gutman, Sameroff, and Eccles (2002) interviewed 837 African American 7th grade students and their mothers and found that as the number of risk factors increased from 0-10, these students had lower grade point averages, more absences, and lower achievement test scores.

Several studies have linked the incorporation of students' culture and language into educational programs to increased achievement (Gilbert, 2000; Leveque, 1991; Powers, Potthoff, Bearinger, and Resnick, 2003; Sherman, 2002; Willeto, 1999). The importance of culture and how it relates to AI/AN achievement is discussed next.

The Importance of Culture in AI/AN Educational Achievement. Cultural discontinuity theory states that the mismatch between the traditional culture of AI/AN homes and the mainstream culture at school can create academic difficulties for AI/AN students (Huffman, 2010). Traditional AI/AN culture offers a more holistic approach to learning and understanding the world, which is not the traditional model of instruction in most schools (Fenimore-Smith, 2009). In mainstream contexts, the focus is on the independent representation of self (i.e., striving towards individual goals and achievements and assertiveness) in order to gain academic success while AI/AN people focus on the interdependent representation of the self, which emphasizes the importance of community and developing trusting relationships with teachers in order to attain academic success (Fryberg et. al., 2013). For example, to the Navajo, success is communal and family is of great importance while White people value individual careers and economic prosperity (Deyhle, 1995).

In order to examine how these cultural differences relate to AI/AN students' academic performance, Fryberg et.al. (2013) administered a series of questionnaires, including those related to culture identification, to 115 AI/AN students in grades 6-11. The students attended a school on a reservation in Canada in which all the teachers were White and the governing board required the school to conform to the provincially mandated curricula. Their teachers answered five questions regarding each student's assertiveness as an indicator of a valued cultural characteristic of mainstream education. They found that the AI/AN students who identified highly with either AI/AN culture or White culture (regardless of whether or not the students were perceived as assertive by their teachers) had higher grades, which is evidence that culture is a protective factor in education. Their results lend credence to the belief that the academic underperformance of AI/AN students is not simply an indication of "deficits" in the students' ability to learn but, at least in part, of culture differences that do not foster success for all students. This can be an important distinction in the effort to develop schools that promote the educational attainment of AI/AN students.

Deyhle (1995) conducted a 10-year ethnographic study following young Navajos as they navigated the school system. She found that Navajo students who identified with their home culture were more successful students, while those with little connection to their culture who were not accepted by their White peers because they were not White had the greatest risk of low academic achievement. Deyhle concluded that schools should incorporate Native culture and language into the classroom in order to achieve equity and increase Navajo students' academic success.

After reviewing hundreds of studies on the schooling of minority youth (e.g., Asian, African American, Latino, AI/AN), Tharpe (2006) and his colleagues determined that the most effective school pedagogies (i.e., those resulting in higher achievement) were those used in AI/AN classrooms that involved traditional cultural patterns of activity and interaction.

There is empirical evidence in the literature that culturally based education (CBE) programs, with strong Native language programs influence a student's academic development in a positive way (Demmert, 2001; Demmert & Towner, 2003). Culturally-based education includes recognition of and use of AI/AN languages; pedagogy that stresses traditional cultural characteristics; pedagogy in which teaching strategies link together traditional AI/AN culture with current methods of learning; curriculum based on traditional culture and that recognizes the importance of Native spirituality; and a strong Native community participation – parent, elders, other community resources – in educating children and in curriculum, planning, and operation of school/community activities (Demmert & Towner, 2003).

Several small studies have been conducted looking at the impact of incorporating culture into the curriculum. Zwick and Miller (1996) used a posttest-only, quasi-experimental design to examine achievement differences in two fourth grade classes in one school district in Montana. The students in the two classes had similar characteristics, although these were not described, and statistical analysis showed these classes to be representative of all fourth graders in the district. The experimental class used a culturally-sensitive, activity-based, outdoor science curriculum while the control class used traditional textbook and classroom science education. There were 24 students in the experimental class, of whom 10 were American Indian and 14 were non-Indian, and 25 students in the control class, of whom 12 were American Indian and 13 were non-Indian. The American Indian students in the experimental group had significantly higher achievement scores on the California Achievement Test than the American Indian students in the control group, who did not receive the culturally-sensitive curriculum. There was no difference in the achievement scores between the American Indian students and non-Indian students in the culturally-sensitive curriculum group.

Similarly, Lipska and Adams (2004) used a pre-posttest, quasi-experimental design to conduct a study looking at the implementation of a culturally-based mathematics curriculum in 15 urban and rural classes in Alaska. There were 180 students (109 in the treatment group and 71 in the control group) in eight classes in the urban group in Fairbanks. There were 78 students (51 in the treatment group and 27 in the control group) in seven classes in the rural Yup'ik group. The 6th grade Yup'ik students in the urban school treatment group gained the most from using this curriculum, but the students in the rural school treatment group also outperformed the students in the rural school control group. No effect sizes were reported.

A study by Whitbeck et. al. (2001) examined factors related to school success for a sample of 196 fifth-eighth grade American Indian children from three reservations in the upper Midwest. The regression model included age, gender, family structure, parental occupation and income, maternal warmth, extracurricular activities (i.e., team or club member), enculturation, and self-esteem. Enculturation was a multidimensional construct defined as involvement in traditional AI activities (e.g., tribal Powwows, use of tribal language, beading, ricing[7], spear fishing), identification with AI culture (e.g., how much they participated in AI culture, how much they lived by this culture, and if they felt they were successful in their Native culture), and traditional spiritual involvement (e.g., how often they participated in traditional spiritual activities and the importance of traditional spiritual values to how they led their life). In the final model, enculturation, self-esteem, participation in clubs, maternal warmth and supportiveness, and age were all statistically significant predictors of the academic success of 5th- 8th grade children.

The AI/AN communities in both Arizona and South Dakota are working hard to incorporate their cultures into the school systems via legislation in their respective states. The 2006 Arizona Indian Education Act mandated that an Office of Indian Education be established in the Arizona Department of Education. The Office of Indian Education, among other things, is expected to provide technical assistance to schools and Indian

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[7] Ricing played a central role in tribal life as wild rice was the main source of food. Wild rice plants grow in water. To harvest wild rice, two people paddled in a canoe to the rice plants. One used long poles to move through the rice beds while the other used ricing sticks, or knockers. One stick was used to pull in as many stalks as possible over the edge of the canoe and the other was used to knock the kernels into the bottom of the canoe (Ojibwe Wild Rice, 2012).

nations to develop, implement, and evaluate culturally appropriate curricula and instructional materials that are aligned with the state standards; consult the tribes regarding education; and distribute annual AI/AN education status reports to the tribes (Arizona Department of Education, 2015a). Other legislation was revised in 2005 requiring AI/AN history to be incorporated into existing Arizona curricula (Justia US Law, 2015a) and again in 2014 requiring instruction in Arizona AI/AN history to be included in history courses for at least one year in secondary grades and one year in high school (Justia US Law, 2015b). In 2012, an AI/AN Language Certification Policy was unanimously adopted, which enables Native language speakers to be certified to teach their Native languages in Arizona classrooms (Arizona Department of Education, 2015b).

The South Dakota 2007 Indian Education Act mandates the following:

- the establishment of an Office of Indian Education to spread awareness and appreciation of South Dakota's unique American Indian culture among South Dakota's students and public school staff
- certain teachers must complete a South Dakota Indian Studies course
- the Department of Education and the Indian Education Advisory Council will incorporate South Dakota American Indian history and culture into the curriculum
- the implementation of a South Dakota American Indian language revitalization program (South Dakota Office of Indian Education, 2007).

In order to develop course materials in South Dakota American Indian history and culture, the South Dakota Office of Indian Education was granted funding from the

Indian Land Tenure Foundation to develop the Oceti Sakowin[8] Essential Understandings and Standards. The purpose of this project was to give school districts in South Dakota basic knowledge about the Oceti Sakowin. First, the core concepts needed to understand and teach the Oceti Sakowin history and culture were developed. Next, the essential understandings and standards were created. The project was completed in 2011. From 2012-2015, the essential understandings and standards were used for curriculum development with examples of how the Common Core, the state standards, and the Oceti Sakowin standards could be taught together (South Dakota Office of Indian Education, 2015).[9]

Incorporating culture into the school environment is important. But, cultural differences can be magnified when students don't speak the language of the school. The next section highlights academic challenges that occur when students are English-language learners.

English-language learners (ELLs). "Students who enter school with limited proficiency in English are among those at highest risk for school failure (National Research Council, 2002, pg. 195)". This is a pervasive issue for AI/AN students. In 2011, 27% of AI/ANs ages 5 years and older spoke a language other than English at home compared to 21% for the nation as a whole. More specifically, in 2011, 68% of the residents of Navajo Nation Reservation and Off-Reservation Trust Land in Arizona, New Mexico, and Utah ages 5 years and older spoke a language other than English at home

[8] The proper name for the people in the Sioux tribe is Oceti Sakowin (Akta Lakota Museum & Cultural Center, n.d.). All eight tribes of South Dakota are Sioux.
[9] It is imperative to be mindful of the dates of these legislative acts in both states. Many are after 2009 (the year in which the data used in this dissertation was collected) or just before (i.e., 2006 and 2007). Therefore, it is likely that any relationships between culture and achievement would not be apparent in these data or even for several years.

(US Census Bureau, 2012). Almost 60% of BIE school students have limited English proficiency compared to 8% of public school students (U.S. General Accounting Office, 2001).

The language or languages spoken at home and how they are used are important risk factors in subsequent school achievement. Children are likely to be at an initial disadvantage learning mathematics if their knowledge of proficiency in the language of instruction is substantially lower than the expected level for their age (Mullis et. al., 2012). Students who do not speak the language of the test (and therefore the language of instruction) at home have lower 8th grade mathematics achievement than those who speak it more often (DeVoe & Darling-Churchill, 2008; Mullis et al, 2008). Additionally, many English-language learners come from families with low SES. Thus, not speaking English at home is compounded by the effects of poverty (National Research Council, 2002).

For children who do not speak English at home, one disadvantage of not having enough instruction in both English and the child's native language is that several studies have shown a relationship between being an English-language learner and being labeled as having a disability (which is discussed further in the next section). Using student databases from 11 urban school district in CA, Artiles et. al. (2002) determined that ELL students were overrepresented in special education programs, specifically in later grades (i.e., grades five through twelve). In 8th grade during the 1998-1999 school year, 15% of the total student population were English-language learners, mostly Latino. Of those, 43% were in special education. They found that ELL students were almost twice as likely to be placed in special education as English-proficient students in secondary grades. Additionally, they found that ELLs who were receiving the least support in their primary language were more likely to be placed in special education than ELLs in programs with greater native-language support.

Similarly, Figeroa & Newsome (2006) reviewed 19 psychological reports written by six different school psychologists to assess Asian, Hispanic, and Pacific Islander English-language learners for special education eligibility in a small, urban elementary school district (approximately 2,000 students) in California. They found that these school psychologists did not follow the specifications of federal law requiring that testing be selected and administered in a way that was nondiscriminatory (e.g., racially, culturally, or sexually) and gave these students a diagnosis of specific learning disability when these students just needed more help developing their bilingual ability.

Samson & Lesaux (2009) used a nationally representative subsample of children from the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K) to understand more about proportional representation, identification rates, and predictors of language minority (LM) children in special education. In their study, 2,470 children who were designated as LM (i.e., a language other than English is spoken at home) were compared with 8,517 children who were designated as L1 (i.e., only English is spoken at home). They found that, when controlling for SES, teacher ratings of language and literacy skills were the strongest predictor of placement in special education in kindergarten, first grade, and third grade.

More about the impact of being a student with a disability is discussed next.

Students with Disabilities. "The disproportionate representation of minority students is among the most critical and enduring problems in the field of special education (Skiba et. al., 2008, p 264)." For minorities, overrepresentation in special education is just one aspect of the denial of access to educational opportunities (Losen & Orfield, 2002).

This issue is not new. In his critique of the special education field in 1968, Dunn pointed out that a disproportionate number of minority students were placed in separate classrooms for special education, which remains a persistent issue several decades later (Artiles & Trent, 1994; Hosp & Reschly, 2004). In 1979, and again in 1999, the National Research Council was commissioned to conduct a study to determine the factors accounting for the disproportionate representation of minority students in special education programs (National Research Council, 2002). In their review published in 2002, the National Research Council stated that the students who need and can benefit from special education programs were not correctly being identified due to the subjectivity of the referral process (most students are referred by a teacher) and the shortcomings of the assessment process (i.e., the scores of students not familiar with standardized testing or with the demands of classrooms may be lower than their true ability).

Despite the improvements to the laws and regulations governing special education with the passage of the Individuals with Disabilities Education Act (IDEA) in 1975, minority children with disabilities often experience inadequate services, low-quality curriculum and instruction, and unnecessary isolation from their nondisabled peers (Losen & Orfield, 2002). Moving students out of general education classrooms and into separate special education classrooms tends to work to the disadvantage of the slow learners and underprivileged students. Achievement improves for these students when surrounded by children from white, middle class homes (Dunn, 1968; Fierros & Conroy, 2002). For some children, receiving inappropriate services may be more harmful than receiving none at all (Losen & Orfield, 2002).

AI/AN students are overreferred for special education, which can make enrollment in special education a risk factor for AI/AN students because it can retard student achievement if the student does not need it. Those AI/AN students with a general learning disability are more likely to be enrolled in special education if the students are not progressing academically as fast as their peers (National Conference of State Legislatures, 2008). The following data show the disproportionate enrollment of AI/AN students in special education.[10]

- Among the more common special education designations (e.g., general learning disability), AI/AN students are 96% more likely than students of other racial and ethnic groups to be identified as having a disability (National Conference of State Legislatures, 2008).
- In 2007, 14% of AI/AN children received services under IDEA compared to 12% of Black students, 9% of Hispanic students, 8% of White students, and 5% of Asian/Pacific Islander students (Aud et al, 2010).
- In 2005, 15% of AI/AN 8th graders were categorized as students with disabilities meaning they had or were in the process of receiving Individualized Education Plans (IEP), compared to 9% of all non-AI/AN 8th graders (National Indian Education Association, 2008).

[10] This list is simply sharing data and is not implying wrongdoing. It is possible that AI/AN students are more likely than students of other races to truly need special education services because they may have more risk factors than students of other races.

- According to the 2005 Census, AI/AN students living in states with high concentrations of AI/AN children were 73% more likely than students of other racial and ethnic groups to be enrolled in special education services (National Conference of State Legislatures, 2008).
- In 2005, AI/AN students ages 6 through 21 were 1.8 times more likely to receive special education services for specific learning disabilities than same-age students all other racial/ethnic groups combined (US Department of Education, OSEP, 2010).
- The BIE records for the 2000–2001 school year show that about 21% of BIE students are enrolled in special education compared to 13% of public school students and 8% of Department of Defense students (another school system for which the federal government is responsible) (U.S. General Accounting Office, 2001).

A number of risk factors may contribute to the disproportionality: race, test bias, poverty, special education designation procedures, inequity in general education (e.g., curriculum/instruction; classroom management; teacher quality; quality and availability of resources), issues of behavior management, and cultural mismatch/cultural reproduction (i.e., a symptom of a broader disconnect between mainstream educational culture and the cultural orientations of communities of color, which was discussed previously) (Skiba et al., 2008; Losen & Orfield, 2002; Oswald et. al., 2002; Ladner & Hammons, 2001). Achievement is a strong predictor of referral for assessment and once a student is referred, he/she is likely to be found eligible for special education services (Hosp & Reschly, 2004).

"In practice, it can be quite difficult to distinguish internal child traits that require the ongoing support of special education from inadequate opportunity or contextual support for learning and behavior (National Research Council, 2002, pg. 3)." Currently, there are no assurances that minority students from disadvantaged backgrounds will be given the opportunity to have exposure to high-quality instruction and classroom management that minimizes chaos before being placed in a special education program (National Research Council, 2002).

Using district-level data from Texas and Florida, Ladner and Hammons (2001) found that the differences in African American and White rates of eligibility for special education rose in direct proportion to the percentage of the teachers who were White, especially in districts in which 60% or more of the student body was White. Additionally, Ladner & Hammons (2001) concluded that the percentage of minority students in a district was the driving force in determining special education rates. (Minority students included Black, Hispanic, and Asian students. There were not enough AI/AN students to draw conclusions about the group separately.) They found that race was more strongly associated with special education rates than spending-per-pupil, class size, or poverty. Districts with high percentages of minority students placed fewer of their students in special education programs, regardless of school location (i.e., urban or rural) or poverty level.

The following is a summary by Ladner & Hammons (2001) of other researchers' explanations for why the racial composition of the district is a key predictor of special education enrollment.

- Many public schools are designed to serve white middle-class students, which poses an additional challenge for minority students.
- Many white teachers interpret lack of academic progress among minorities a deficiency because they are not trained to recognize and deal with learning differences, or they are unaware of them.
- Minority students are compared against a standard model based on White, middle-class norms.

Additionally, Ladner & Hammons (2001) found that in districts in which the faculty members were predominantly from a minority group, three to four times fewer minority students were enrolled in special education as compared to the reduction in the number of White students enrolled in special education in the same district. Minorities do not have lower special education rates than Whites in these districts, but the rates drop greatly in districts with minority faculty while those of White students experience only a slight decrease. Therefore, the districts with a lower difference in special education rates were the ones in which less than 20% of the faculty members were White.

Similarly, using data from all 67 school districts in Florida, Serwatka et. al. (1995) found that as the percentage of African American teachers increased, overrepresentation of African American students in special education classes, specifically the emotionally disturbed category, decreased.

Shifrer et. al. (2011) analyzed a sample of 10,847 students within 546 high schools from the Education Longitudinal Study of 2002 to describe national patterns in learning disability identification. They concluded that lower average SES accounted for the disproportionate identification of African American and Hispanic students as learning disabled (there were too few AI/AN students in the sample to make meaningful conclusions). It is possible that teachers experience difficulty determining whether or not AI/AN students are disabled when they are unable to assess them in their Native languages (National Institutes of Health, 2005; Klingner & Harry, 2006).

Hankes et. al. (2012) conducted a study in which they aimed to increase mathematics test scores of AI/AN students identified as learning disabled in Wisconsin in part by teaching their teachers how to use culturally responsive methods when teaching mathematics (i.e., lessons were not rushed, lessons involved solving real life problems, manipulatives were used, students worked in groups, and classroom discussion was mostly conversational with the teacher facilitating the lesson). Professional development was provided to 30 teachers responsible for teaching mathematics to AI/AN students identified as learning disabled from eight Wisconsin school districts serving AI/AN students (22 special education teachers and eight regular education teachers). The authors believed that since students identified as learning disabled possess average or better reasoning ability, they should be able to achieve academically with appropriate instruction. After testing 43 target students in grades 3-8 in the fall of 2008 and the spring of 2009, they found significant improvement in problem solving performance (fall mean score of 6.58 with a standard deviation of 3.92; spring mean score of 9.23 with a standard deviation of 3.70, $t = 4.24$, $\alpha < .01$). Additionally, they found that the mathematics achievement results on the state test for 56 target students in grades 4-8 increased significantly from 2008-2009 after the teachers implemented some of tools learned in the professional development workshops (2008 mean score of 1.68 with a standard deviation of 0.88; 2009 mean score of 2.02 with a standard deviation of 0.96, $\alpha = 0.001$) (Hankes et. al., 2012).

Summary of the Literature Review

To date, there is no publication of a large-scale analysis that explores the differences in achievement among AI/AN students. The present study offers an opportunity to start filling this gap in the literature. Current general and AI/AN specific literature points to several risk factors that are associated with achievement: family SES, parental education, parental involvement in school activities, attitude toward and self-confidence in mathematics, lack of adequate school funding, school climate, teacher quality, the importance of incorporating culture into learning, being an English-language learner, and being labeled as a student with a disability. These risk factors can be directly captured by or derived from the NIES 2009 questionnaire data. Because AI/AN students were oversampled in the NIES dataset, sample size is much less of a limitation in this dissertation, as it is in most of the existing AI/AN achievement literature.

Much of the literature stresses the importance of incorporating culture into the academic experience of AI/AN students or students needing to have a strong association with culture in order to improve educational outcomes. The NIES questionnaires contain many questions about how much AI/AN culture each student is exposed to in their daily lives both in and out of school and provides a unique opportunity to use a large dataset to explore claims in the literature about the risk factors found to be related to AI/AN achievement. However, it may be too soon to measure the impact of any legislation requiring culturally-related materials in the schools. Therefore, analyses that involved culturally-related risk factors were analyzed separately within each of the three school density types in each state because it was expected that there would be differences between the amount of AI/AN culture incorporated into the school milieu in a public low density school as compared to a BIE school.

The methodology used to address the research questions of this dissertation is presented in detail in Chapter Three.

Chapter Three

The focus of this dissertation was understanding and documenting the characteristics that were associated with the 8th grade mathematics achievement scores of the AI/AN students in each of the three school density types in Arizona and South Dakota and then discerning the policy implications associated with these differences. The study utilized the 2009 NAEP achievement data and the 2009 NAEP and NIES questionnaire data submitted by the students, their teachers, and their school administrators. The risk factors identified in the literature review were used in several different analyses in order to examine patterns and relationships in AI/AN 8th grade mathematics achievement in these two states from different perspectives.

As stated in Chapter 1, for the purposes of this dissertation, single background questionnaire items associated with achievement will be referred to as *individual items*. Multiple individual items thought to be related to the same construct were statistically combined into what will be termed *derived risk factors*. The purpose of constructing the derived risk factors was to take an in-depth look across the states and school density types at specific constructs mentioned in the literature as being associated with achievement: attitudes toward mathematics, how much AI/AN traditions and culture was incorporated into the lives of the students both in and out of school, and school climate. Lastly, the individual items and derived risk factors were used to create several *risk indices* for which each student was assigned one point for each individual item and derived risk factor that applied to them. These risk indices were then used as independent predictors of achievement. Higher values on the risk indices were expected to be associated with lower levels of achievement. For example, the literature states that having a mother who has less than a high school education is associated with lower achievement. Therefore, students whose mothers have less than a high school education were assigned one point. These individual items, derived risk factors, and risk indices were included in different types of analyses in order to describe the home and learning environments of the AI/AN students, to identify student, teacher, and school characteristics associated with AI/AN students' achievement in each school density type in each state, and then to uncover any significant differences among the school density types and between states.

The report by Grigg et. al. (2010) on the NIES 2009 assessment results showed systematic differences in AI/AN 8th grade mathematics achievement by school density type: public low density (less than 25 percent of the students were AI/AN); public high density (25 percent or more of the students were AI/AN), and Bureau of Indian Education (BIE) schools. As stated previously, only data from Arizona and South Dakota met the NAEP reporting standards[11] in 8th grade mathematics for all three school density types. In this chapter, the methodology used to address the following research questions is discussed:

- **RQ1a.** How do the distributions of the individual items and derived risk factors from the NAEP background questionnaires and school administration records differ among the three school density types in each state?

[11] NAEP reporting standards require a minimum of 62 students in a subgroup from at least five primary sampling units (i.e., schools) (Institute of Education Sciences, 2012).

- **RQ1b.** How do the distributions of the individual items and derived risk factors from the NIES background questionnaires differ among the three school density types in each state?
- **RQ2a.** To what extent do the distributions of risk indices based on the individual items and derived risk factors from the NAEP background questionnaires and school administration records differ between states and among the three school density types?
- **RQ2b.** To what extent do the distributions of risk indices based on the individual items and derived risk factors from the NIES background questionnaires differ between states and among the three school density types?
- **RQ3a:** To what extent are the risk indices created using the NAEP background questionnaires and school administration records associated with AI/AN 8th grade mathematics achievement in each of the school density types in each state?
- **RQ3b:** To what extent are the risk indices created using the NIES background questionnaires associated with AI/AN 8^{th} grade mathematics achievement and what is their incremental contribution to explained variance after accounting for the NAEP risk indices in each of the school density types in each state?
- **RQ4:** How can the answers to the previous questions inform AI/AN education policy? What additional policy implications can be drawn from

comparisons both within and between the school density types in each of these states?

The discussion of the methodology used to address these questions is divided into two sections. The first includes a description of the dataset used to perform the analyses: the 2009 NAEP achievement and questionnaire data and the NIES questionnaire data. The second offers a description of the quantitative data analysis procedures that were used in this dissertation.

Description of the dataset

The first NAEP assessment was administered in 1973. The purpose of NAEP is to continually measure trends in the academic achievement of nationally representative samples of elementary and secondary students in the US in various subjects (e.g., reading, mathematics, science, writing, U.S. history, geography, civics, etc.) in order to evaluate the condition and progress of education in the US (National Assessment Governing Board, 2008).

As described in Chapter 1, NIES was commissioned by President Bush in 2004 and was first conducted in 2005. NIES uses NAEP achievement and questionnaire data in addition to a special background questionnaire created for NIES specifically related to AI/AN students and their educational experiences to describe the state of education for AI/AN students in the US (National Center for Education Statistics, 2011a).

The data for the analyses reported in this dissertation were from two restricted-use datasets obtained from the National Center for Education Statistics (NCES). One dataset was for main NAEP and included the test scores and questionnaire data for everyone who completed the NAEP mathematics assessment and questionnaire in 2009. This dataset was used to further describe the setting in which AI/AN students learn. The other dataset was for NIES and contained the 2009 NIES questionnaire results for AI/AN students who completed the 2009 NAEP mathematics assessment in addition to their 2009 NAEP mathematics assessment and questionnaire results.[12]

Target population. The target population of NIES is AI/AN students in 4th and 8th grades across the US. In order to obtain more detailed reporting of performance for these groups of students, the samples of AI/AN students who participated in NIES 2009 were augmentations of the sample of AI/AN students who were selected to participate in the 2009 NAEP reading and mathematics assessments. In addition, 100% of the BIE schools and students were included in the sample, although not all of the BIE schools participated (National Center for Education Statistics, 2011a). For the purposes of this dissertation, only data associated with 8th grade mathematics in Arizona and South Dakota were utilized.

Information from a total of 26,247 AI/AN students who were administered the 2009 NAEP mathematics achievement test from the 12 states selected to participate in NIES 2009 was available in the dataset (see Table 3.1).

[12] A second NIES dataset was available containing only the 2009 NIES questionnaire data from the students who participated in the English/Language arts, mathematics, and science portions of NAEP. However, because the outcome variable for research question three was mathematics achievement, the mathematics achievement dataset linked to the questionnaire data for those students who participated in the mathematics assessment only was used for this dissertation.

Table 3.1: *Number (percentage of total) of AI/AN students participating in NIES 2009 (weighted) by State*[13]

State	Number (percentage of total) of AI/AN students (weighted)
Alaska	1848 (7%)
Arizona	*4744 (18%)*
Minnesota	980 (4%)
Montana	1059 (4%)
New Mexico	2598 (10%)
North Carolina	1598 (6%)
North Dakota	727 (3%)
Oklahoma	7869(30%)
Oregon	951 (4%)
South Dakota	*1399 (5%)*
Utah	546 (2%)
Washington	1928 (7%)
Total Number AI/AN students (weighted)	26,247

In the 2009 administration of NAEP, six states had sufficient samples of AI/AN students to report state-level data without oversampling: Alaska, Montana, New Mexico, North Dakota, Oklahoma, and South Dakota. Schools in the other six states were oversampled: Arizona, Minnesota, North Carolina, Oregon, Utah, and Washington (Grigg et. al., 2010). Students from Arizona and South Dakota made up 23% of the total number of AI/AN students participating in NIES in 2009 (18% from Arizona and 5% from South Dakota).

Sample design. The sampling plan for the 2009 NAEP assessments (i.e., Part I of NIES) was a two-stage design. First, schools were sampled. The sampling frame for school sample selection was a comprehensive list of operating public schools in each

[13] This table was created using the overall student weight (ORIGWT). It is a frequency of the variable FIPSAI (state code for AI/AN students) with the following filters: RPTSAMP=1 (in reporting sample=1), SCHTBIE=1 (public/BIE schools=1), and SDRACEM=5 (AI/AN students=5).

jurisdiction that is assembled each year by the National Center for Education Statistics (NCES) called the Common Core of Data (CCD) file. The list of schools is stratified based on school location, extent of minority enrollment, state-based achievement scores, and median income of the area in which the school is located (US Department of Education, IES, NCES, 2011). Each sampled school was asked to provide a list of all enrolled students in the grade(s) of interest. Next, using these lists, a random sample of students was drawn from each school. On these student lists, schools reported each student's race/ethnicity based on information from official school records. For NIES Part II, the schools that reported having (at least one) AI/AN students enrolled in 4^{th} or 8th grade were identified. All identified AI/AN students in the sampled schools were asked to complete the special NIES background questionnaire. Again, all BIE schools were asked to participate (National Center for Education Statistics, 2011a).

Because each school that participated and each student who was assessed only represented a portion of the population of interest and because simple random sampling was not employed, sampling weights were calculated so that appropriate inferences could be made from the student samples to the respective target populations from which they were drawn. Sampling weights account for the disproportionate representation in the selected sample due to the oversampling of schools with high concentrations of students from certain minority groups and the lower sampling rates of students who attend very small, nonpublic schools. Standard statistical procedures cannot be used with NAEP data without using the weights because of the complex sampling scheme (i.e., each student does not have an equal probability of being selected to participate). Therefore, all analyses included the appropriate weights (National Center for Education Statistics, 2011b).

Test booklets

Content domains. For test design purposes, items can be characterized with respect to two dimensions: mathematical content and cognitive demand (i.e., item complexity). There were five content areas: number properties and operations (including computation and understanding of number concepts); measurement (including use of instruments, application of processes, and concepts of area and volume); geometry (including spatial reasoning and applying geometric properties); data analysis, statistics, and probability (including graphical displays and statistics); and algebra (including representations and relationships) (National Center for Education Statistics, 2011b). The item distribution for each content domain is described in Table 3.2.

Table 3.2: *Percentage distribution of items on the 2009 8th grade NAEP mathematics assessment and content area*

Content area	%
Number Properties and Operations	20
Measurement	15
Geometry	20
Data Analysis, Statistics, and Probability	15
Algebra	30

Source. National Assessment Governing Board, 2008, p. 6.

Item complexity. Items in the NAEP assessment were classified as having low, moderate, or high mathematical complexity. Half of the testing time was devoted to moderate complexity items while the other half was evenly split between high complexity and low complexity items. Low complexity items involved recall or recognition of mathematical concepts or procedures. Moderate complexity items required students to bring together concepts and processes from various domains to decide what to do and how to do it. High complexity items took more time to complete because they entailed using reasoning, planning, analysis, judgment, and creative thought (National Assessment Governing Board, 2008).

The mathematics assessment used three types of item formats: multiple-choice, short constructed response, and extended constructed response. Half of the testing time was allocated to multiple-choice items while the other half was reserved for the two types of constructed response items. Because it would take too long to administer every item to every student, a matrix sampling design was used so that each student was only tested for 50 minutes (i.e., two 25-minute blocks or sets of items). Each block contained 15-18 questions depending on how many multiple-choice and constructed response items were included. Matrix sampling means that representative samples of students are administered different or overlapping sets of items. Therefore, not every student took the same assessment and no student answered all the items. The purpose of this design is to increase coverage across a broader range of objectives than would be possible if each student was administered the same items. This design also minimizes the time burden for each individual student (National Assessment Governing Board, 2008). It also means NAEP does not provide individual scores for each student.

Background questionnaires

In addition to the booklet containing two sets of mathematics items, each AI/AN student also completed the standard NAEP student background questionnaire and a NIES student background questionnaire. The NAEP student background questionnaire asked questions about their home backgrounds and their experiences learning mathematics. The NIES student background questionnaire asked questions specific to their AI/AN background, how much AI/AN culture was incorporated into their home life and school life, and their attitudes toward learning English/language arts and mathematics. The mathematics teachers of the students tested, in addition to the principals of the schools of the students tested, also completed a NAEP background questionnaire and a NIES background questionnaire. The NAEP teacher background questionnaire asked about the teachers' preparation to teach, training activities they participated in, and their classroom organization and instruction. The NIES teacher background questionnaire asked about the classroom experiences of their AI/AN students. The NAEP school background questionnaire provided information about the school characteristics and policies and the structure of the mathematics classrooms and program. The NIES school background questionnaire gathered information about the schools that serve AI/AN students such as inclusion of AI/AN languages and culture in the curriculum and interactions between the school and the AI/AN community (US Department of Education, IES, NCES, 2014; US Department of Education, IES, NCES, 2012b).

Scaling

In order to create a common scale on which to compare performance across groups of students when students completed different sets of items, Item Response Theory (IRT) was used by a NAEP contractor. IRT scaling uses a student's responses to the test items in order to estimate the student's location on a latent scale that corresponds to a one-dimensional construct, in this case, mathematics ability. The three-parameter logistic IRT model was used to scale the multiple-choice questions. The two-parameter logistic IRT model was used to scale the short constructed-response questions that were scored as acceptable or unacceptable (i.e., partial credit was not given). The generalized partial credit model was used to scale the short constructed-response and extended constructed-response questions that were scored using three-level and four-level rubrics (respectively). The results for the assessment were reported using the NAEP mathematics composite scale. Performance was first scaled separately in each of the five mathematics content areas using a scale ranging from 0-500. The composite score was then generated using a weighted combination of these subscales (National Center for Education Statistics, 2011b).

Plausible values

Because of the matrix sampling design, not enough responses were available from each student to estimate his or her mathematics proficiency with sufficient accuracy. Therefore, proficiency values, or "plausible values," were randomly drawn for each student from a posterior distribution based on a fitted latent regression model that employed both the student's responses to the mathematics items and a specified set of principal components based on responses to the background questions. Student achievement on NAEP is represented by five plausible values calculated for each student for each of the five mathematics content domains in addition to five plausible composite values. The composite scale is a weighted combination of the separate calibrations of the five content domain subscales. (National Center for Education Statistics, 2011b). The five plausible composite values were used in analyses involving mathematics scores as the outcome variable.

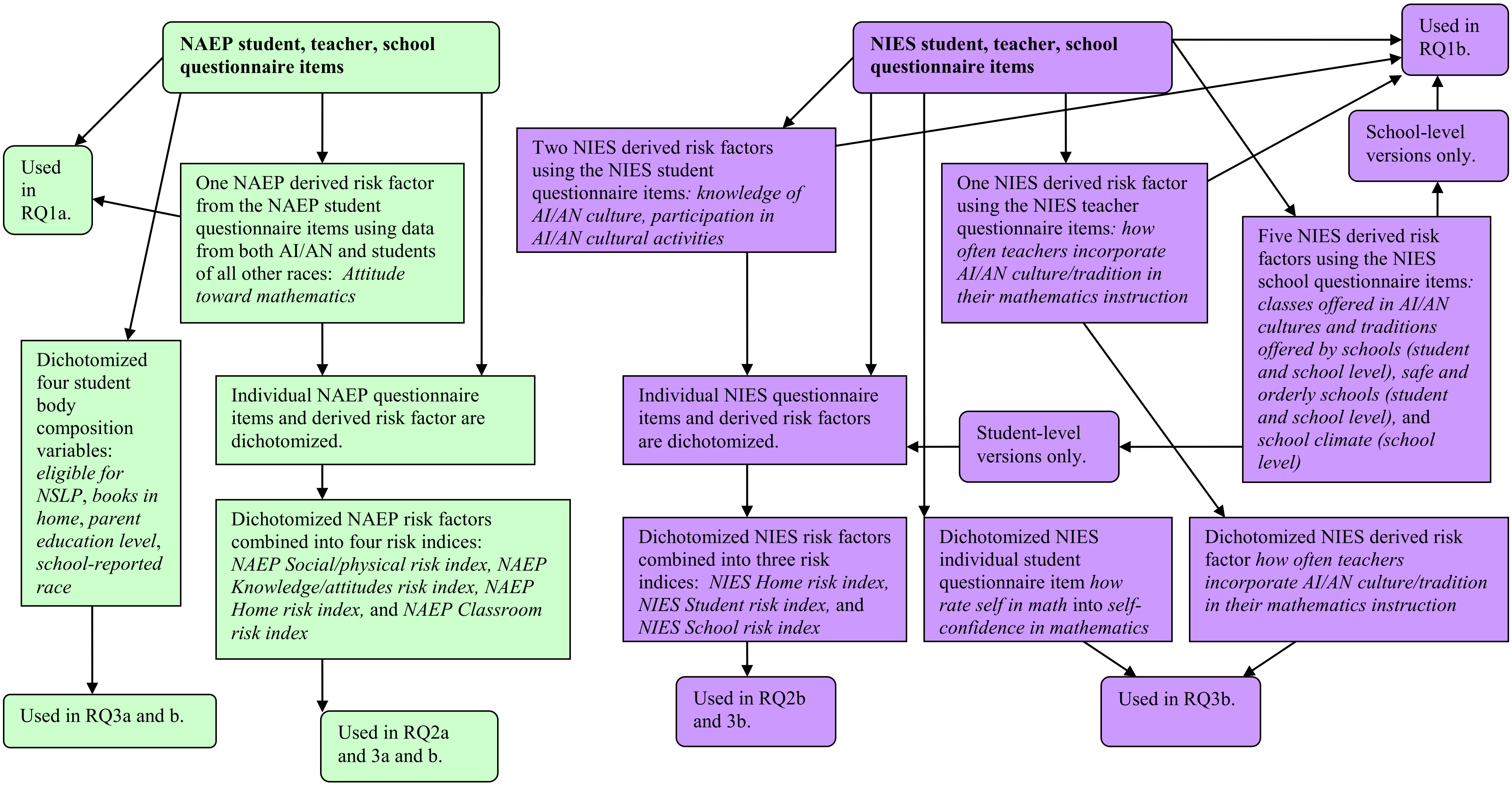
Data Analysis Procedures

As stated previously, the restricted-use dataset for the NIES 2009 grade 8 mathematics achievement test results comprising students, teacher, and school NAEP and NIES questionnaire responses was used for this analysis. The main NAEP 2009 restricted-use dataset was also obtained for two reasons: to provide more contextual information about the learning environments of AI/AN students and because the NIES 2009 dataset does not include school weights, which were needed in order to run the school-level cross tabulations in research questions 1a and b.[14] Data from only Arizona and South Dakota were used. Only public schools and BIE schools were included in the dataset. Records of SD/ELL students who were originally sampled but were later deemed unable to be assessed were removed. The restricted-use dataset offered the analyst the opportunity to retain the original coding for items coded as multiple response, not attempted, omitted, illegible, off task, or not-rateable or change them to missing. For the purposes of this dissertation, it was not necessary to differentiate between an item coded as multiple response, not attempted, etc. Therefore, all of these responses were coded as missing. Figure 3.1 displays a flowchart of how the NAEP and NIES student, teacher, and school questionnaire items were used. For research question 1a, the NAEP questionnaire and school administration items were used. For research question 1b, the NIES questionnaire items were used. Some NAEP and NIES items were used "as is" while others were combined into derived risk factors. For research questions 2 and 3, all items and derived risk factors were dichotomized and the responses were added together to form risk indices. Appendix B lists all 70 individual items that were used throughout

[14] The school weights were also intended to be used in an HLM model. However, there was not enough variation between schools to justify using HLM, which will be discussed further in research question 3a.

the analyses for this dissertation, based on the literature review described in Chapter 2. The results of data preparation are described next and documented in Appendices C and D.

Figure 3.1: Flowchart of how the NAEP (in green) and NIES (in purple) student, teacher, and school questionnaire data were used.



Missing values. Seven of the 48 items used in the OLS regression analyses had more than 5% missing data. The highest level of missingness occurred in three items in which 16-25% of the data were missing: *mother's education level* in the *NAEP Home risk index* (25% overall for AI/AN students because 24% of students answered "I don't know", which was coded as missing for purposes of this analysis, but the missingness varied among school density types in each state), *highly-qualified teacher this year* in the *NAEP Classroom risk index* (16% overall for AI/AN students, but this varied among school density types in each state), and *parent education level* (18% overall for AI/AN students, but this varied among school density types in each state from 14-23%). Due to the missingness of *mother's education level*, 22-31% of the data were missing on the *NAEP Home risk index* in Arizona and 25-60% of the data were missing in South Dakota. Due to the missingness of the *highly-qualified teacher this year* item, 4-30% of the data were missing on the *NAEP Classroom risk index* in Arizona and 7-13% of the data were missing in South Dakota.

The two derived risk factors and one individual item that comprised the *NIES School risk index* had about 10% missing data: *safe and orderly schools – student level* (8%); *classes offered – student level* (10%); and *percentage of AI/AN teachers in the school – student level* (10%). The level of missing data in the *NIES School risk index* varied across school density types in each state from 7-21%.

Lastly, the NIES derived risk factor *teacher incorporated AI/AN culture into mathematics instruction* had 9% missing data overall, which varied by school density type in each state from 4-29%. The remaining 41 items used in the OLS regression analyses had 0.1-3.5% missing data overall, among AI/AN students.

According to Sterne et. al. (2009), missing data in predictor variables do not cause bias using listwise deletion, if the data were missing for reasons unrelated to the outcome variable. However, it was decided that, in addition to listwise deletion, conditional mean substitution would be implemented for all 48 items used in the OLS regression models in order to test the impact of the missing data and make comparisons between the results of the OLS regression analyses using listwise deletion and conditional mean substitution. Multiple imputation was considered; however, it is best to include the outcome variable when performing multiple imputation (Sterne et. al., 2009). The outcome variable for the OLS regressions in this dissertation consisted of five plausible values. In fact, plausible values are not actually outcome variables, but a way of representing the relationship between the independent variables and a latent proficiency variable. They are not the latent proficiency variable itself. Technically, this means that if data are imputed for missing predictor values, the data should be re-scaled and the plausible values re-calculated with the imputed data. However, this was outside the scope of this dissertation.

As stated previously, all of the OLS regression analyses for research questions 3a and b were run using both listwise deletion and conditional mean substitution (based on state and school density type) for the 48 items used in the OLS regression models. Means were computed for each subgroup (e.g., each of the six strata for both AI/AN students and students of all other races, when applicable) and substituted for missing values. The weighted N's for AI/AN students in each stratum, with no missing data, were as follows: Arizona public low density schools (N=1619); Arizona public high density schools (N=2459); Arizona BIE schools (N=665); South Dakota public low density schools (N=354); South Dakota public high density schools (N=601); South Dakota BIE schools (N=443). Only listwise deletion (and not conditional mean substitution) was implemented in research questions 1a, 1b, 2a, and 2b.

Creating the Derived Risk Factors

Before conducting analyses for any of the research questions, nine derived risk factors were created using items from the NAEP and NIES student, teacher, and school questionnaires in order to take an in-depth look across the states and school density types at specific constructs mentioned in the literature as being associated with achievement. Statistical methods were used to see how many items thought to be on the same topic could be combined to form a meaningful derived risk factor.

Combining individual items that may be related reduced the total number of variables included in the analyses and helped to minimize collinearity problems. It also facilitated the description of broader topics that required more information than could be provided by a single question. Factor analysis was used to create the derived risk factors in order to ensure that the values that were combined all had just one single factor in common. Factor analysis is a data reduction technique that aims to account for the correlations between the values (Kim & Mueller, 1978).

Principal components analysis could also have been used. Principal components analysis and factor analysis are similar in that they both seek to reduce the dimensionality of a set of observed variables. A key difference between these two techniques is that principal component analysis focuses on explaining the total variance (i.e., including the error variance) while factor analysis partitions the total variance into common, unique, and error variance and only tries to explain the common variance (Dunteman, 1989).

Principal components analysis is a way to transform a set of observed variables into another set of variables in order to account for as much variance as possible in the data (Kim & Mueller, 1978).

Factor analysis is more appropriate to use when one is trying to create derived risk factors that can be interpreted easily and linked back to the literature, as is the case in this analysis. Principal components would be appropriate if the purpose was just to reduce dimensionality and there was no preconceived notion as to which items might be statistically related. Factor analysis was employed for this analysis because the values to be combined were expected to share a lot of variance based on the literature review and factor analysis focuses solely on the common variation. The values did share a lot variance, so creating one derived risk factor for each construct opposed to using several items for each construct resulted in a more parsimonious analysis.

If the goal of this analysis was to, for example, see how much of the variation in achievement is accounted for by a certain item, it might make sense to run a principal components analysis on all the items in the background questionnaire, leaving out the item of interest. In this case, the purpose of the principal components analysis would be to include information about the other background variables in the model while reducing collinearity. The principal components would be added to the model first to see if the variable of interested accounted for a significant amount of variance above and beyond that accounted for by the principal components. In this analysis, the focus was not interpreting the components but including as much information as possible from the other background variables without introducing collinearity issues. In the analysis for this dissertation, it was very important that the results of the dimensionality reduction were interpretable and tied to the literature review. Therefore, factor analysis was more appropriate.

Because there are so many background variable contrasts created in order estimate the NAEP population-structure models (which are the basis for estimating the posterior distributions of scales' scores for groups of students), NAEP utilizes principal components analysis to remove the number of variables that have very little variance and variables that are highly collinear with other variables. The principal component scores are used as predictor variables to estimate the population-structure model (National Center for Education Statistics, 2008). Again, principal components analysis is used by NAEP in order to reduce dimensionality among all variables. The purpose of the dimensionality reduction analysis for this dissertation was to reduce the collinearity among specific sets of variables that have been shown to be related to achievement in the literature, which can be done using factor analysis.

The first derived risk factor, *attitude toward mathematics*, was developed using the NAEP student questionnaire data and responses from both AI/AN students and students of all other races from both states combined. The other eight derived risk factors were developed using the NIES student, teacher, and school questionnaire data and responses from just AI/AN students from both states combined.

A few of the NIES derived risk factors were related to AI/AN culture. Much of the AI/AN literature focuses on the importance of incorporating culture into the curriculum in order to improve achievement. Therefore, not being exposed to AI/AN culture could be considered a risk factor for low achievement for AI/AN students.

Using the NIES student questionnaire, two culture-related risk factors were derived: *knowledge of AI/AN culture* and *participation in AI/AN cultural activities*. From the NIES teacher questionnaire, one culturally-based derived risk factor was created regarding *how often teachers incorporate AI/AN culture/tradition into their mathematics instruction*. From the NIES school questionnaire, a culturally-based derived risk factor related to *how many classes in AI/AN cultures and traditions were offered by schools* was created in addition to a *school climate* derived risk factor.

For the NIES school questionnaire items, derived risk factors were formed at both the school level and the student level. The school-level version was used in research question 1b. However, since there was not enough variation between schools to use HLM, the student-level version was also calculated and used in the OLS regression models in research question 3b.

Interestingly, when factor analysis was used to analyze the school climate items using school-level data, two distinct derived risk factors emerged: *safe and orderly schools* and *school climate*. Whereas, when factor analysis was used to analyze the school climate items using student-level data, only one derived risk factor emerged from the same set of items: *safe and orderly schools*. See Appendix C for more details.

After conducting a principal axis factor analysis, a reliability analysis was performed. The reliability of the derived risk factors was estimated using Cronbach's alpha. Typically, an alpha level of 0.70 or higher is considered to be adequate. An attempt was made to improve the reliability of each derived risk factor by reviewing the Item-Total Statistics to see if deleting any of the individual items used to create the derived risk factor would improve the reliability. The final alpha levels for all of the derived risk factors were above 0.7.

Once a decision was reached as to which items formed a single, reliable derived risk factor, the numerical labels associated with the responses to each item in the derived risk factor were averaged for each student. The only derived risk factor for which the values were not averaged together was classes in AI/AN cultures and traditions offered by schools. The values for this derived risk factor were summed.

Using means of Likert scale responses can be difficult to interpret because the differences between the response options in the scale are not meaningful. For example, there is no way to measure the differences between a person answering “strongly agree” that he/she likes mathematics, a person answering “agree” that he/she likes mathematics, and a person answering “disagree” that he/she likes mathematics. Although these responses are ordinal (ranked) and it is clear that “strongly agree” is better than “agree” and that “agree” is better than “disagree”, it is not clear if the difference between “strongly agree” and “agree” is the same as the difference between “agree” and “disagree”. By average the responses, ordinal data are being treated as if it were interval data.

Instead of using the mean, another option is to use the Rasch model to create the derived risk factors. The Rasch model takes into account the item difficulty and the student’s ability to form the scale. Thus, the result provides more information about the items and student’s ability than a mean value. However, the NAEP and NIES questionnaires were not built to create Rasch scales. Suen (1990) proposed a formula to determine the minimum requirements for Rasch scaling: (number of items) x (number of response categories – 1) ≥ 20. Six derived risk factors using student-level data were created for OLS regression models used in this dissertation. One set of questions had two response categories; four had four response categories; and one had five response categories. The derived risk factor with two response categories, *classes in AI/AN cultures and traditions offered by schools,* comprised eight items. Using the formula (8x1), there were not enough categories or items to create a Rasch scale. Of the derived risk factors with four response categories, two were made up of three items (*knowledge of AI/AN culture* and *participation in AI/AN cultural activities*), one was made up of five items (*attitude toward mathematics*), and one was made up of eight items (*safe and orderly schools*). Using the formula for the four response categories, the derived risk factor would have needed to comprise at least seven items. Only the derived risk factor for *safe and orderly schools* met this criterion. Using the formula for the set of questions with five response categories (*teachers incorporate AI/AN culture into the mathematics instruction*), the derived risk factor would have need to comprise at least five items. However, the *teachers incorporate AI/AN culture into the mathematics instruction* derived risk factor only had four items. Therefore, Rasch scaling could only be reliably applied to one of the six derived risk factors (*safe and orderly schools*).

According to Norman (2010), parametric statistics can be used to analyze data from Likert scales because they are robust to violations of the assumptions that the data are interval data and normally distributed. Additionally, he states that Likert scales consisting of sums across many items will be interval data and that tests such a Pearson and Spearman correlations have been shown to be robust to skewness and nonnormality.

Thus, it was determined that using the mean to calculate each derived risk factor was acceptable.

Based on logic and the distribution of the data, the means of the student responses to each item in the derived risk factor were divided into three categories (i.e., high, medium, and low). For the most part, the category with the highest value was linked to higher achievement in the literature (e.g., positive attitude toward mathematics and being surrounded by AI/AN culture and tradition). The *safe and orderly schools* and *school climate* derived risk factors were based on NIES school questionnaire items that asked the principals to what extent something was a problem in the school (e.g., bullying, low student aspirations, etc.). Therefore, high values on these derived risk factors were linked to lower achievement in the literature (i.e., being in a school in which bullying and low student aspirations is a big problem in the school is linked to lower achievement).

Validity testing was done by looking at the correlations among the individual items that comprised each derived risk factors and 8th grade mathematics achievement in addition to the percent of variance in 8th grade mathematics achievement accounted for by the component variables (R-square) in a multiple regression equation (Olson, Martin, & Mullis, 2008). Data from both states and all three school density types were combined for these analyses. Validity testing was not done within each state and school density type so that just one version of each derived risk factor could be created and used across all six strata.

The overall student sampling weight was used for all but the school-level derived risk factors, for which the overall school sampling weight was used.

Because the response options for all of the variables used in the factor analyses were ordinal level, the Spearman correlation coefficient was used instead of the Pearson correlation coefficient.

Each derived risk factor was calculated using both listwise deletion and conditional mean substitution. The three-level categorical derived risk factors using listwise deletion only were used in the cross tabulations in research questions 1a and 1b (see Appendix C for more detailed information on how each of the derived risk factors were created). Next, each derived risk factor was converted into a dichotomous variable for inclusion in the risk indices used in questions 2a and 2b (using listwise deletion only) and 3a and 3b (using both listwise deletion and conditional mean substitution), which are described next.

Creating the Risk Indices

Before it was possible to answer the second and third research questions, the derived risk factors discussed previously, in addition to several individual questionnaire items chosen to be incorporated into the risk indices based on the theoretical and empirical evidence presented in Chapter 2, needed to be dichotomized so that several NAEP and NIES risk indices could be created. The purpose of creating the risk indices was to understand the differences among student profiles across each of the three school density types in each state using as many items as possible in the most parsimonious manner.

Using both theoretical and empirical approaches, each individual questionnaire item and derived risk factor was dichotomized. A “1” represented the risk factor (e.g., being absent 3 or more days in the last month or being identified as being ELL or having a disability). The other, non-missing response options were recoded as "0" (i.e., not having the risk factor).

In contrast to the three-level derived risk factors, high scores (i.e., a value of "1") on the dichotomous risk factors were associated with lower achievement. For example, in the dichotomized version of the three-level derived risk factor *attitude toward mathematics*, the category "do not like/somewhat like learning mathematics" was coded as a "1" or a risk factor, which was associated with lower achievement in the literature while in the three-level derived risk factor version of *attitude toward mathematics*, a high score of "3" meant "like learning mathematics", which was associated with higher achievement in the literature.

Two different criteria were used to determine if each of the dichotomized items/derived risk factors could be considered a "risk factor" (Gutman et.al., 2002). The first criterion was that there was a correlation between each dichotomized item/derived risk factor and the outcome variable, AI/AN 8th grade mathematics achievement. The second criterion was that there was a significant difference in the outcome variable between AI/AN students who had the risk factor compared to those who didn't. A two-sample *t*-test was used to see if the dichotomized risk factors in each risk index discriminated between those who had the risk factor and those who didn't. For example, was there a statistically significant difference in 8th grade mathematics achievement for AI/AN students whose mothers had not completed high school and those whose mothers had at least completed high school?

Next, the risk index for each student was created by adding up the number of risk factors (i.e., “1”s) from each individual item and derived risk factor for the student. The more points assigned to a student, the greater the value of the risk index for the student.

Four risk indices were calculated using NAEP questionnaire data and school administration records for AI/AN students from both states and all school density types combined. The scales for the NAEP risk indices ranged from 0-5, based on the number of dichotomized items and derived risk factors comprising the risk index.

- NAEP Knowledge/attitudes (*having a clear understanding of what the mathematics teacher was asking* and *attitudes toward mathematics*; scale ranged from 0-2)
- NAEP Social/physical (*being ELL*, *having a disability*, *number of days absent*; scale ranged from 0-3)
- NAEP Home (*mother’s education level*, *how often talk about studies at home*, *number of books in the home*, *eligibility for National School Lunch Program*, and *how often a language is spoken at home other than English*; scale ranged from 0-5)
- NAEP Classroom (*level of mathematics class* and *highly-qualified teacher this year*; scale ranged from 0-2).

Three more risk indices were created using the NIES questionnaire data for AI/AN students from both states and all school density types combined. The scales for the NIES risk indices ranged from 0 to 3, based on the number of dichotomized items and derived risk factors comprising the risk index.

- NIES Student (*participation in AI/AN activities* and *knowledge of AI/AN culture*; scale ranged from 0-2)[15]
- NIES Home (*how often does family help with schoolwork* and *how often talk to family about classes to take in high school/future*; scale ranged from 0-2)
- NIES School (*safe and orderly schools*, *classes offered in AI/AN topics*, *percent of AI/AN teachers in the school*; scale ranged from 0-3).

Teachers incorporate AI/AN culture into the mathematics instruction was the only classroom-related NIES predictor. Therefore, this derived risk factor was included in the OLS regression individually instead of in a risk index. Additionally, the individual item *self-confidence in mathematics* was also included individually since it didn't fit well within any of the other three NIES risk indices.

Correlations among the individual items and derived risk factors within each risk index were tested, in addition to the correlations among the risk indices, to check that the categorizations of the risk factors were sensible and that the directionality was correctly understood. The correlations between each of the risk indices and the NAEP 8th grade mathematics score were examined in order to validate each risk index.

In order to demonstrate that compressing the data into risk indices didn't result in the loss of too much information, principal components analyses were run within each risk index comprising more than two items to see if the risk index was a good

[15] *Participation in AI/AN activities* and *knowledge of AI/AN culture*, did not discriminate between students who had the risk factor and those who didn't have the risk factor, even after adjusting the cutpoints. However, a decision was made to include them in the *NIES Student risk index* because culture is very important to AI/AN people and to see if the *NIES Student risk index* accounted for variation in achievement when analyzed by state and density type (which, in certain strata, it did account for variation in achievement when entered into the model on its own).

representation of the items within it. The assumption was that the primary factor in each risk index would account for a significant amount of variation, which would show that the risk index was a representation of the items and derived risk factors within it. More detailed information about how the NAEP and NIES risk indices, the NIES individual item (*self-confidence in mathematics*), the NIES derived risk factor (*teachers incorporate AI/AN culture into the mathematics instruction*), and the five student body composition variables (*White/Asian*, *Hispanic/Black*, *highest level of parent education*, *number of books in the home*, and *eligibility for NSLP*, which are detailed further below in the description research question 3a) were created can be found in Appendix D.

Research question 1a: *How do the distributions of the individual items and derived risk factors from the NAEP background questionnaires and school administration records differ among the three school density types in each state?*

In order to begin to form a picture of and describe the characteristics of the AI/AN students and their learning environments in each of the three school density types in each state, several sets of cross tabulations were calculated using individual items and derived risk factors from the NAEP background questionnaires and school administration records that have been shown in the literature to be related to achievement. Cross tabulations were used to show the relationship between two variables. In most cases, tests of independence were conducted to see which individual items and derived risk factors were associated with school density type in each state in order to understand better the differences in achievement among the six strata. The overall student sampling weights were used for all the cross tabulation analyses except for the school-level cross tabulations. The overall school sampling weights were used for the school-level cross tabulations.

Chi-square is the statistic used to test for independence between categorical variables. If there is no relationship between the risk factors, the frequency counts in each cell should be similar to the frequency counts for the total sample (i.e., the expected frequencies and observed frequencies are similar). A large discrepancy between the expected and observed counts would suggest that the risk factors are not independent. There should be at least five observations in each cell (Howell, 2007). The chi-square value was provided for descriptive purposes only because NAEP data do not conform to the assumption that the data were obtained through simple random sampling. NAEP data are clustered within schools, which means the chi-square value is a conservative estimate because the students within a school are more like each other. Similarly, the *p*-value was given as an indication of significance; however, it is simply suggestive due to the clustering of the sample and the need to use sampling weights because of unequal probabilities of selection.

Based on the literature review, six sets of cross tabulations were run using the NAEP background questionnaires and school administration records to see how the individual items and derived risk factors varied across school density types in each state. Three sets of cross tabulations were run using data from the main NAEP dataset (i.e., comparing AI/AN students with students of all other races): *attitude toward mathematics* (derived using the NAEP student questionnaire), *opportunity to learn the material on the NAEP assessment based on the mathematics class the student was taking in 2009* (from the NAEP student questionnaire), and *the number of minorities labeled as having a disability* (from school administration records).

The fourth set of cross tabulations were split into parts A and B and were run using data from only the AI/AN students. Part A looked at the percent of AI/AN students in each school density type in each state who were *labeled as having a disability* and/or *being ELL* (from school administration records). Part B examined the percent of AI/AN students who stated they *never or hardly ever clearly understood what the teacher asked* (from the NAEP student questionnaire) among the AI/AN students who were labeled as *having a disability* and/or *being ELL* (from school administration records). A fifth set of cross tabulations was run that included both a student characteristic and a teacher characteristic: the relationship between *having a disability* (from the school administration records) and the *race of the teaching force* (from the NAEP teacher questionnaire). A sixth set of cross tabulations was run that included both a student characteristic and a school characteristic: whether or not poverty (based on the *percent of students in the school who were eligible for NSLP* from the NAEP school questionnaire) was associated with the number of AI/AN students *labeled as having a disability* and the number of students *labeled as being ELL* (from school administration records).

Research Question 1b: *How do the distributions of the individual items and derived risk factors from the NIES background questionnaires differ among the three school density types in each state?*

To build on research question 1a, six more sets of cross tabulations were run using individual items and derived risk factors from the NIES background questionnaires that have been shown in the literature to be related to achievement. The purpose of these cross tabulations was to see how these individual items and derived risk factors varied across school density types in each state. In most cases, tests of independence were conducted to see which risk factors/derived risk factors were associated with school density type in each state in order to understand better the differences in achievement among the six strata. Chi-square values were calculated.

Three sets of cross tabulations were related to AI/AN culture at the student level: comparisons of *knowledge of AI/AN culture* and *participation in AI/AN cultural activities* across strata (from the NIES student questionnaire) and comparisons of how often *teachers incorporate AI/AN culture/tradition into their mathematics instruction* across strata (from the NIES teacher questionnaire). Two sets of cross tabulations were created using school-level data: comparisons of the number of *classes offered in AI/AN cultures and traditions* across strata (from the NIES school questionnaire) and how many AI/AN students were in *safe and orderly schools* (from the NIES school questionnaire). The final cross tabulation was run to look at the distribution of different *types of school funding* (from the NIES school questionnaire), not just funding geared towards AI/AN students, across the six strata.

Research Question 2a: *To what extent do the distributions of risk indices based on the individual items and derived risk factors from the NAEP background questionnaires and school administration records differ between states and among the three school density types?*

Four 2x2 tables were created comparing the results of the four NAEP risk indices described above (the *NAEP Knowledge/attitude risk index*; the *NAEP Social/physical risk index*; the *NAEP Home risk index*; and the *NAEP Classroom risk index*) by state and race. Histograms of the distributions of risk index scores were plotted in each cell.

Additionally, eight 2x3 tables were created comparing student race by school density type with one table for each of the four NAEP risk indices in each state. Histograms of the distributions of risk index scores were plotted in each cell.

Research Question 2b: *To what extent do the distributions of risk indices based on the individual items and derived risk factors from the NIES background questionnaires differ between states and among the three school density types?*

One 2x3 table was created comparing each state by each of the three NIES risk indices described previously (the *NIES Student risk index*; the *NIES Home risk index*; and the *NIES School risk index*). Histograms of the distributions of risk index scores were plotted in each cell.

Three 2x3 tables were created comparing state by school density type for each of the three NIES risk indices. Histograms of the distributions of risk index scores were plotted in each cell.

Research Question 3a: *To what extent are the risk indices created using the NAEP background questionnaires and school administration records associated with AI/AN 8th grade mathematics achievement in each of the school density types in each state?*

The original plan was to use hierarchical level modeling (HLM) to see which of the risk indices created using the NAEP background questionnaires and school administration records were associated with 8^{th} grade mathematics achievement in each of the six strata. HLM was to be used instead of ordinary least squares (OLS) regression because, by virtue of the sampling design, students were nested in classrooms/schools. Nesting would affect the analysis of the data if the model used did not account for the hierarchical structure of the data (Raudenbush & Bryk, 2002; Bickel, 2007).

When data are nested, it means that the individuals in a group (e.g., classroom or school) share the context of the group and, therefore, are more likely to be similar to each other on the outcome of interest than a random sample of individuals in the US or than individuals in other groups would be. For example, the students in one mathematics classroom tend to be more similar to each other than to students in another mathematics classroom because they have the same teacher. Similarly, classrooms in the same school tend to be more similar to each other than classrooms from different schools. Not all of the similarities between the individuals or classrooms can be observed using OLS regression because the similarities become part of the error term. Therefore, the error terms for individuals in a group or classrooms in a school are no longer independent or uncorrelated in the group, which violates the independence assumption of single-level models. The consequence of having correlated errors is that the traditional standard errors for the regression coefficients tend to be smaller than they should be, which means that the *t*-statistic would be larger and significant differences would be found more often (Raudenbush & Bryk, 2002; Bickel, 2007).

In order to gauge the impact of nesting, the intraclass correlation coefficient (ICC) was calculated within each stratum. The ICC is the proportion of variability in mathematics achievement that is between groups (i.e., students and schools, in this case). The greater the proportion of the total variability between groups, the higher the ICC and the greater the impact of nesting. As it happens, the ICCs within each stratum were too low to justify using HLM, which means there was not enough variation between schools to warrant using multi-level modeling. ICCs should be 0.25 or higher. The ICCs were as follows: Arizona public low density – 0.03; Arizona public high density – 0.007; Arizona BIE – 0.096; South Dakota public low density – 0.049; South Dakota public high density – 0.034; South Dakota BIE – 0.13.[16] Therefore, OLS regression was used instead.

Model building: NAEP questionnaire/school administration records risk indices. Six OLS regression models were created: one for each of the school density types in each state. The following NAEP risk indices were entered into the level 1 model one at a time: the *NAEP Knowledge/attitudes risk index*; the *NAEP Social/physical risk index*; the *NAEP Home risk index*; and the *NAEP Classroom risk index*. The significant risk indices ($p \leq 0.05$) remained in the model. Interactions were added into the model for any NAEP risk indices significantly related to achievement in order to estimate the main effect of each NAEP risk index without regard to any overlapping covariation with the other NAEP risk indices (Deater-Deckard, Dodge, Bates, & Pettit, 1998). None of the interactions were significant and, therefore, were not included in the final models for

[16] The ICCs were checked for each state (i.e., combining the three density types together). For Arizona, the ICC was 0.057. However, for South Dakota, the ICC was 0.25. An HLM analyses for South Dakota only with indicators for school density type was started, but the reliability estimates were very low, so it was decided to only use OLS regression for all analyses.

each stratum. This process was repeated six times for each of the school density types in each state.

Once the NAEP risk indices were vetted, individual student body composition variables (described next) were entered into just the four public school OLS regression models. BIE schools enroll only AI/AN students, which was why the individual student body composition risk factors were not included in the two BIE school models.

To represent student body composition, several dummy variables were created using the main NAEP student-level data (i.e., the data for students of all races in each state): SES (i.e., student *eligibility for the National School Lunch Program* and the *number of books in the home*), *parental education* (derived variable created by NAEP in which the highest level of education of either parent was chosen as the level of parent education for the student), and *school-reported race*[17] for each student in each public school. Student body composition defined as family SES and parental education has been found to be associated with minority student achievement (Coleman, 1966; Mullis et. al, 2012).

Additionally, Table 1.1 showed that students of all races in South Dakota scored significantly higher than students of all races in Arizona on the 8the grade NAEP mathematics achievement test. South Dakota students were White, Hispanic, or AI/AN. Arizona students were White, Black, Hispanic, Asian American/Pacific Islander, and AI/AN. An immediate difference shows: Arizona had a more diverse student body than

[17] Many students do not fit into one racial bucket very cleanly. For the purposes of these analyses, the NAEP guidelines on reporting student race will be followed. NAEP collects data on both student-reported race and school-reported race. Prior to 2002, NAEP reported student-reported race. However, beginning in 2002, a decision was made to use school-reported race, supplemented by student-reported race only if school data were missing (National Center for Education Statistics, 2011b). Therefore, the NAEP school-reported variable, SDRACEM, was used for these analyses.

South Dakota. There was no significant difference between the scores of White students in Arizona (292), Asian American/Pacific Islander students in Arizona (295), and White students in South Dakota (295). There was no significant difference between the scores of Hispanic students between the two states. The only differences were that AI/AN students in Arizona scored significantly lower than AI/AN students in South Dakota and Black students scored significantly lower than White students in both states and Asian American/Pacific Islander students in Arizona. Therefore, the differences in achievement between students in both states overall and between public low and high density school students in each state may be related to student body composition (i.e., SES, parental education, and race).

The main NAEP student-level data for student *eligibility for the National School Lunch Program*, *the number of books in the home*, *parental education*, and *school-reported student race* was used to describe the student body composition of the schools attended by AI/AN students. The data for each of these student-level items were aggregated to the school level to obtain the proportion of students in each school with an entry of "1" for that item. For these school-level contextual variables, having a "1" was associated with higher achievement in the literature. For example, having more than 100 books in the home is associated with higher achievement (Mullis et. al., 2012; Mullis et. al., 2008). Appendix D includes more detailed information on how the student body composition variables were created.

These individual student body composition risk factors were entered one at a time into the model with the significant NAEP risk indices and remained in the model if they were significant. The purpose was to see if any of the student body composition variables accounted for significant differences in 8th grade mathematics achievement over and above that which was account for by the NAEP risk indices. Appendix E shows the step-by-step model building process using listwise deletion for the NAEP questionnaire and school administration records. Appendix G shows the step-by-step model building process using conditional mean substitution for the NAEP questionnaire and school administration records.

Research Question 3b: *To what extent are the risk indices created using the NIES background questionnaires associated with AI/AN 8th grade mathematics achievement and what is their incremental contribution to explained variance after accounting for the NAEP risk indices in each of the school density types in each state?*

OLS regression was used to see which of the risk indices created using the NIES background questionnaires were associated with 8th grade mathematics achievement in each of the six strata and what their incremental contribution was to the explained variance after accounting for the NAEP risk indices. None of the student body composition variables remained significant in the final NAEP models, so these variables were not incorporate into the NAEP/NIES models.

Model building: NIES predictors. Each of the NIES predictors were entered into an OLS regression model one at a time to see which ones were significantly associated with achievement: the *NIES Student risk index*, the *NIES Home risk index*, the *NIES School risk index*, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*, and the NIES individual item *self-*

confidence in mathematics. This process was repeated six times for each of the school density types in each state.

Model building: NAEP and NIES predictors. Once the NIES predictors were vetted, six new models were created. First, the significant NAEP risk indices from research question 3a were added to the model. Next, the significant NIES predictors were added one at a time to see how much variation in achievement was accounted for by the NIES predictors over and above that which was accounted for by the NAEP risk indices. The significant NAEP and NIES predictors remained in the model. Interactions were added into the model for any of the NAEP and NIES predictors significantly related to achievement in order to estimate the main effect of each predictor without regard to any overlapping covariation with the other NAEP and NIES predictors (Deater-Deckard, Dodge, Bates, & Pettit, 1998). None of the interactions were significant and were, therefore, not included in the final models for each stratum. This process was repeated six times for each of the school density types in each state. Appendix F shows the step-by-step model building process using listwise deletion for the NAEP and NIES items. Appendix H shows the step-by-step model building process using conditional mean substitution for the NAEP and NIES items.

Building the models using the student, teacher, and school questionnaire questions allowed for maximum usage of the questionnaire responses related to factors that have been shown in the literature to be relevant to achievement. At each step of the model building process, the results described how much variation in achievement was accounted for by each variable entered into the models. Comparisons were made using the final models in each of the six strata to determine the most important factors related to achievement and how they varied by school density type and state.

Research Question 4: *How can the answers to the previous questions inform AI/AN education policy? What additional policy implications can be drawn from comparisons both within and between the school density types in each of these states?*

The policy implications of the answers to the previous research questions were discussed (mainly research question 3). Additional cross tabulations were run. The consistency of fitted models across cells was considered. For example, were the same risk factors significant in each stratum? Were the risk factors in the same order of importance in each stratum? The mean differences and regression coefficients between the school density types in a high performing state (South Dakota) and a low performing state (Arizona) and among the school density types in each state were examined to see what policy changes might be made to decrease the achievement differences among AI/AN students. For example, did Arizona public high density, Arizona BIE, and South Dakota BIE students have more risk factors? Did South Dakota AI/AN students overall have fewer risk factors than Arizona AI/AN students overall?

Chapter Four

This chapter presents the results from the analyses conducted to answer the research questions. The weighted sample size from Arizona was 4,738 students (1,619 from public low density schools; 2,460 from public high density schools; and 659 from BIE schools). The weighted sample size from South Dakota was 1,399 students (355 from public low density schools; 601 from public high density schools; and 443 from BIE schools).

First, the NAEP and NIES derived risk factors were created (see Appendix C). Next, to address the first research question, several cross tabulations were generated and tests of independence were performed using the NAEP and NIES derived risk factors and NAEP and NIES individual items. To address the second research question, NAEP and NIES risk indices were calculated using the NAEP and NIES derived risk factors and individual items (see Appendix D) and several tables with within-cell histograms were developed to examine the differences among the risk indices in each state and in each of the school density types. Next, to answer the third research question, OLS regression modeling was used to examine the relationships between the NAEP and NIES risk indices, NIES individual item, NIES derived risk factor, and 8th grade mathematics achievement. Lastly, to answer the fourth research question, the results from the first three research questions were synthesized as they relate to policy implications.

Research Question 1a: Results from cross tabulations using NAEP individual items and derived risk factors

In an effort to reduce the number of tables, cross tabulations on the same topic that were run separately in each state and/or for each school density type were combined into one table. The data for all cross tabulations created for research questions 1a were weighted using the overall student weight (ORIGWT).

Cross tabulation #1: attitude toward mathematics. The purpose of this set of cross tabulations was to understand differences and similarities in attitude toward mathematics between AI/AN students and students of all other races and among AI/AN students in each school density type in each state using the derived risk factor on *attitude toward mathematics*. The students of all other races in public schools only (because no students of other races attended BIE schools) who participated in NAEP in Arizona and South Dakota were identified in the main NAEP dataset. Students of all other races/schools were filtered out of the dataset. The students of all other races were merged with the NIES students and assigned a school density type based on whether the school he/she attended was labeled as a public low or high density school in the NIES dataset (the NAEP dataset does not include a school density type variable).

The first goal of this analysis was to compare attitudes toward mathematics of AI/AN students to the attitudes toward mathematics of students of all other races across the two public school density types. Since attitude toward mathematics has been linked to higher achievement (Mullis et. al., 2008), based on the overall NAEP 8th grade mathematics achievement test results shown in Table 1.3, students of all other races and AI/AN students in public low density schools in both states (or at least in South Dakota) were expected to like learning mathematics more than AI/AN students in public high density and BIE schools in both states.

A second goal was to look at AI/AN students only to see if AI/AN students in public low density schools were more likely to have more positive attitudes toward mathematics than AI/AN students in public high density and BIE schools in each state.

A test of independence was run within the public low and high density schools (since there were no BIE students who were not AI/AN) in each state comparing AI/AN students to students of all other races on their attitudes toward mathematics. The null hypothesis was that there was no relationship between type of student and attitude toward mathematics in each school density type in each state. The alternative hypothesis was that there was a relationship between type of student and attitude toward mathematics in each school density type in each state.

Additionally, a test of independence was run within the school density types, across categories, in each state just among the AI/AN students to see if AI/AN students in public low density schools were more likely to have a more positive attitude toward mathematics than AI/AN students in public high density and BIE schools in each state. The null hypothesis was that there was no relationship between school density type and attitude toward mathematics for AI/AN students in each state. The alternative hypothesis was that there was a relationship between school density type and attitude toward mathematics for AI/AN students in each state.

Table 4.1 shows comparisons between AI/AN students and students of all other races by state and public school density type. It also shows comparisons among AI/AN students only, by state and school density type.

Table 4.1: *Percent (number) of AI/AN students and students of all other races by attitude toward mathematics in each state and school density type*			
	Like learning mathematics	Somewhat like learning mathematics	Do not like learning mathematics
Arizona public low density school students (N=26,819; 7% of the data were missing)			
AI/AN students (n=1,572)	43% (670)	47% (743)	10% (159)
Students of all other races (n=25,247)	39% (9,909)	46% (11,718)	14% (3,620)
Notes. X^2 (2) = 23, $p < 0.001$[18]			
Arizona public high density school students (N=3,122; 3.8% of the data were missing)			
AI/AN students (n=2,397)	51% (1,227)	42% (994)	7% (176)
Students of all other races (n=725)	41% (298)	39% (285)	20% (142)
Notes. X^2 (2) = 94, $p < 0.001$			
Arizona BIE school students (N=4,601; 3% of the data were missing)[19]			
AI/AN students (n=632)	57% (360)	36% (225)	7% (47)
Notes. X^2 (4) = 49, $p < 0.001$[20]			
South Dakota public low density school students (N=4,789; 4% of the data were missing)			
AI/AN students (n=345)	38% (130)	42% (144)	21% (71)
Students of all other races (n=4,444)	40% (1787)	45% (1987)	15% (670)
Notes. X^2 (2) = 7, $p = 0.025$			
South Dakota public high density school students (N=797; 6% of the data were missing)			
AI/AN students (n=571)	47% (270)	37% (212)	16% (89)
Students of all other races (n=226)	40% (91)	50% (112)	10% (23)
Notes. X^2 (2) = 11, $p = 0.004$			
South Dakota BIE school students (N=1,327; 5% of the data were missing)[21]			
AI/AN students (n=411)	44% (181)	45% (186)	11% (44)
Notes. X^2 (4) = 20, $p < 0.001$[22]. Values are based upon weighted estimates.			

[18] The Pearson chi-square value was provided for descriptive purposes only because NAEP data do not conform to the assumption that the data were obtained through simple random sampling. NAEP data are clustered within schools, which means the chi-square value is a conservative estimate because the students within a school are more like each other. Similarly, the *p*-value was given as an indication of significance; however, it is simply suggestive due to the clustering of the sample and the need to use sampling weights because of unequal probabilities of selection.

[19] This was the N and missing data percentage for all the AI/AN students in Arizona.

[20] This was the Pearson chi-square value for just the AI/AN students in Arizona, comparing each of the three school density types.

[21] This was the N and missing data percentage for all the AI/AN students in South Dakota.

[22] This was the Pearson chi-square value for just the AI/AN students in South Dakota, comparing each of the three school density types.

There was a high level of association between type of student and attitude toward mathematics in public low and high density schools in Arizona and South Dakota and among AI/AN students in all three school density types. Surprisingly, AI/AN students in Arizona public low and high density schools were more likely to report liking to learn mathematics than students of all other races, and AI/AN students in BIE schools in Arizona were more likely to like learning mathematics than AI/AN students in public low and high density schools. AI/AN students in public high density schools in South Dakota were more likely to like learning mathematics than students of all other races in South Dakota while AI/AN students in public low density schools in South Dakota were more likely to not like learning mathematics compared to students of all other races in South Dakota.

Cross tabulation #2: opportunity to learn the material on NAEP assessment. The purpose of this set of cross tabulations was to examine differences in the opportunity to learn the material on the 8th grade NAEP mathematics assessment between AI/AN students and students of all other races and among AI/AN students in each school density type in each state.

As shown in Table 3.2, half of the NAEP 8th grade mathematics assessment questions involved geometry and algebra. Differences in achievement scores could be related to the opportunity to learn the material on the test for those students who were not enrolled in geometry or algebra classes. The expectation was that those students who had higher NAEP 8th grade mathematics scores (i.e., students of all other races and AI/AN students in public low density schools) would be taking geometry/algebra classes.

The original idea was to compare the percent of AI/AN students taking geometry and algebra to the percent of students of all other races taking geometry and algebra across each school density type. However, in each density type, so few students of any race were taking geometry (5%) and algebra II that these categories were combined. Additionally, the Algebra I and Intro to algebra/pre-algebra categories were separated. It was presumed that students taking a 1-year Algebra I course would be learning material comparable to what students in the 2nd year of a 2-year Algebra I course would be learning; therefore, these categories were combined. Twenty-two percent of the students were taking a 1-year Algebra I course, while 1% of the students were in their 2nd year of a 2-year Algebra I course. Furthermore, it was decided that students taking Intro to algebra/pre-algebra (26% of the students were taking one of these classes) would be learning material comparable to what students in the 1st year of a 2-year Algebra I course (1% of the students were taking this class) would be learning; therefore, these categories were combined. The "other mathematics class" category included: basic or general 8th grade mathematics (30% of students were taking this class), integrated or sequential mathematics (1% of students were taking this class), and other mathematics class (7% of students were taking this class).

A test of independence was run within each public school density type in each state comparing AI/AN students to students of all other races on the type of math class taken in 2009. The null hypothesis was that there was no relationship between type of student and type of math class taken in each school density type in each state. The alternative hypothesis was that there was a relationship between type of student and type of math class taken in each school density type in each state.

Additionally, a test of independence was run within the school density types, across categories, in each state just among the AI/AN students to see if AI/AN students in public low density schools were more likely to have been exposed to the geometry and algebra material on the NAEP assessment. The null hypothesis was that there was no relationship between school density type and type of math class taken for AI/AN students in each state. The alternative hypothesis was that there was a relationship between school density type and type of math class taken for AI/AN students in each state.

Table 4.2 shows comparisons between AI/AN students and students of all other races by state and public school density type. It also shows comparisons among AI/AN students only, by state and school density type.

Table 4.2: *Percent (number) of AI/AN students and students of all other races by mathematics class taking this year in each state and school density type*				
	Geometry/ Algebra II	Algebra I (1-year course)/ Algebra I (2nd year)	Algebra I (1st year)/ Intro to Algebra/ pre-algebra	Other mathematics class
Arizona public low density school students (N=27,788; 3% of the data were missing)				
AI/AN students (n=1,576)	6% (92)	17% (272)	41% (649)	36% (563)
Students of all other races (n=26,212)	9% (2466)	24% (6292)	28% (7352)	39% (10,102)
Notes. X^2 (3) = 141, p < 0.001				
Arizona public high density school students (N=3,162; 3% of the data were missing)				
AI/AN students (n=2,424)	10% (247)	24% (570)	30% (721)	37% (886)
Students of all other races (n=738)	15% (111)	23% (166)	31% (231)	31% (230)
Notes. X^2 (3) = 17, p = 0.001				
Arizona BIE school students (N=4,636; 2% of the data were missing)[23]				
AI/AN students (n=636)	10% (62)	15% (94)	27% (170)	49% (310)
Notes. X^2 (6) = 121, p < 0.001[24]				
South Dakota public low density school students (N=4,859; 3% of the data were missing)				
AI/AN students (n=345)	0% (0)	13% (43)	39% (135)	48% (167)
Students of all other races (n=4,514)	3% (137)	30% (1349)	25% (1122)	42% (1906)
Notes. X^2 (3) = 73, p < 0.001				
South Dakota public high density school students (N=822; 3% of the data were missing)				
AI/AN students (n=588)	6% (37)	19% (114)	30% (179)	44% (258)
Students of all other races (n=234)	3% (7)	27% (62)	42% (99)	28% (66)
Notes. X^2 (3) = 25, p < 0.001				
South Dakota BIE school students (N=1,364; 3% of the data were missing)[25]				
AI/AN students (n=431)	10% (42)	12% (53)	29% (123)	49% (213)
Notes. X^2 (6) = 52, p < 0.001[26] Values are based upon weighted estimates.				

[23] This was the N and missing data percentage for all the AI/AN students in Arizona.
[24] This was the Pearson chi-square value for just the AI/AN students in Arizona, comparing each of the three school density types.
[25] This was the N and missing data percentage for all the AI/AN students in South Dakota.
[26] This was the Pearson chi-square value for just the AI/AN students in South Dakota, comparing each of the three school density types.

The majority of all students in all density types in both states were taking Algebra I (1st year), Intro to Algebra, pre-algebra, or another math class. There was still a high level of association between type of student and mathematics class taken this year in public low and high density schools in Arizona and South Dakota and among AI/AN students in all three school density types.

Surprisingly, AI/AN students in public low density schools in Arizona were more likely to be taking Algebra I (1st year)/Intro to Algebra/pre-algebra compared to students of all other races, who were more likely to be taking another mathematics class. AI/AN students and students of all other races in public low density schools in South Dakota were more likely to be taking another mathematics class. In fact, a higher percentage of AI/AN students in all three school density types in both states (almost 50% for BIE school students in Arizona and South Dakota and AI/AN students in South Dakota public low density schools) were taking another mathematics class, except for public low density schools students in Arizona, who, as stated previously, were more likely to be taking Algebra I (1 yr course)/Algebra I (2nd year). Additionally, a higher percentage of AI/AN students in South Dakota public low and high density schools were taking another math class compared to AI/AN students in Arizona public low and high density schools.

All of these results were unexpected since students of all other races scored significantly higher on the NAEP 8th grade mathematics achievement test than AI/AN students and AI/AN students in South Dakota public low and high density schools students scored higher on the NAEP 8th grade mathematics achievement test than AI/AN students in Arizona public low and high density schools.

Although the percentages were small, students of all other races in public low and high density schools in Arizona and public low density schools in South Dakota were more likely to be taking geometry/algebra II compared to AI/AN students, which was not surprising. However, it was unexpected that a higher percentage of students overall in Arizona were taking geometry/algebra II compared to students in South Dakota and that AI/AN students in public high density and BIE schools in Arizona were more likely to be taking geometry/algebra II compared to AI/AN students in public low density schools in Arizona while AI/AN students in BIE schools in South Dakota were more likely to be taking geometry/algebra II compared to AI/AN students in public low and high density schools in South Dakota.

Cross tabulation #3: number of minorities labeled as having a disability. Because the literature shows that AI/AN students are more likely to be labeled as having a disability (Aud et. al., 2010; National Conference of State Legislatures, 2008; National Indian Education Association, 2008; US Department of Education, OSEP, 2010; US General Account Office, 2001), the purpose of this set of cross tabulations was to see how many minorities, especially AI/AN students, were labeled as having a disability and how this might differ across the three school density types in each state

A test of independence was run within just the two public school density types[27] in each state comparing the percent of students in each race who were labeled as having a disability.[28] The null hypothesis was that there was no relationship between race and being labeled as having a disability in each school density type in each state. The alternative hypothesis was that there was a relationship between race and being labeled as

[27] BIE schools were not included in this analysis because they are not as diverse as the public schools.
[28] These cross tabs only included students identified as having a disability (IEP=1) so a comparison could be made between the number of students identified as having a disability and race.

having a disability in each school density type in each state. Table 4.3 shows comparisons between AI/AN students and students of all other races by state and public school density type.

Additionally, a test of independence was run across the three school density types[29] in each state just among the AI/AN students to see if there were differences in being labeled as having a disability across school density types in each state. The null hypothesis was that there was no relationship between school density type and being labeled as an AI/AN student with a disability in each state. The alternative hypothesis was that there was a relationship between school density type and being labeled as an AI/AN student with a disability in each state. Table 4.4 shows comparisons among AI/AN students with and without a disability by state and school density type.

[29] BIE schools were included in this analysis to see how many AI/AN students in BIE schools were labeled as having a disability compared to AI/AN students in public schools.

Table 4.3: *Percent (number) of students with a disability (IEP=1) by school-reported race in each state and public school density type*[30]

	White	Black	Hispanic	Asian American/ Pacific Islander	AI/AN
	Arizona (N=3,734/28,244; no missing data)				
Public low (n=3,329/25,404)	12% (1518/12,231)	18% (205/1150)	13% (1293/9670)	0% (0/1047)	24% (313/1306)
Public high (n=405/2,840)	8% (33/434)	0% (0/24)	24% (54/228)	0% (0/12)	15% (318/2142)
	South Dakota (N=644/5,207; no missing data)				
Public low (n=553/4,456)	12% (441/3787)	14% (22/161)	22% (31/139)	0% (0/73)	20% (59/296)
Public high (n=91/751)	18% (34/185)	0% (0/13)	100% (3/3)	0% (0/3)	10% (54/547)
Notes. Values are based upon weighted estimates.					

AI/AN students in public low density schools in Arizona were more likely to be identified as having a disability compared to students of all other races; however, Hispanics were more likely to be identified as having a disability in pubic high density schools in Arizona and public low and high density schools in South Dakota (although AI/AN students in public low density schools in South Dakota were a close second). All Hispanic students in public high density schools were identified as having a disability (3 of 3). No Asian American/Pacific Islander or Black students were identified as having a disability.

[30] Comparisons among AI/AN students across school density types in each state are shown in Table 4.6.

Table 4.4: *Percent (number) of AI/AN students in Arizona and South Dakota by disability and school density type*		
	With disability	Without disability
	Arizona (N=4,738; no missing data)	
Public low (n=1,619)	19% (313)	81% (1306)
Public high (n=2,460)	13% (318)	87% (2142)
BIE (n=659)	13% (87)	87% (572)
Notes. X^2 (2) = 33, p < 0.001		
	South Dakota (N=1,399; no missing data)	
Public low (n=355)	17% (59)	83% (296)
Public high (n=601)	10% (54)	90% (547)
BIE (n=443)	20% (89)	80% (354)
Notes. X^2 (2) = 27, p < 0.001 Values are based upon weighted estimates.		

There was a high level of association between being identified as having a disability and school density type for AI/AN students in Arizona and South Dakota. Among AI/AN students, students in public low density schools in Arizona were more likely to be identified as having a disability compared to students in public high density and BIE schools in Arizona. Students in public low density and BIE schools in South Dakota were more likely to be identified as having a disability compared to students in public high density schools. Public high density school students were least likely to be identified as having a disability compared to AI/AN students in any other school density type in either state.

Cross tabulation #4A: AI/AN students with/without disability/ELL. The fourth set of cross tabulations has two parts. Part A examined the percent (number) of AI/AN students in each school density type in each state who were identified as having a disability, being ELL, having a disability and being ELL, or having neither a disability nor being ELL, using the variable that classifies students as being in only one of these four discrete categories (SDELL).

The purpose of this cross tabulation was to see how many AI/AN students were identified as having a disability and being ELL across school density types in both states. The justification for this cross tabulation was: as stated previously, AI/AN students are more likely to be labeled as having a disability (Aud et. al., 2010; National Conference of State Legislatures, 2008; National Indian Education Association, 2008; US Department of Education, OSEP, 2010; US General Account Office, 2001), students identified as being ELL have lower achievement compared to students who speak the language of the test (DeVoe & Darling-Churchill, 2008; Mullis et. al., 2012; National Research Council, 2002, pg. 195), and more AI/AN students, specifically, BIE school students, have limited English proficiency (U.S. General Accounting Office, 2001). Table 4.5 shows comparisons among AI/AN students with and without a disability and ELL or not ELL by state and school density type. No test of independence was performed.

Table 4.5: *Percent (number) of AI/AN students in Arizona and South Dakota with and without a Disability and ELL or not ELL by school density type*				
	Not ELL or Disability	ELL & Disability	ELL	Disability
	Arizona (N=4,729; no missing data)			
Public low (n=1,619)	81% (1306)	0% (0)	0% (0)	19% (313)
Public high (n=2,459)	80% (1975)	5% (120)	7% (167)	8% (197)
BIE (n=651)	54% (350)	7% (45)	33% (214)	7% (42)
	South Dakota (N=1,399; no missing data)			
Public low (n=355)	83% (296)	0% (0)	0% (0)	17% (59)
Public high (n=601)	84% (503)	3% (15)	7% (44)	7% (39)
BIE (n=443)	80% (354)	0% (0)	0% (0)	20% (89)
Notes. Values are based upon weighted estimates.				

No AI/AN students in public low density schools in either state were identified as being ELL while close to 20% of the public low density school students in each state were identified as having a disability (19% in Arizona and 17% in South Dakota). Unexpectedly, no AI/AN students in South Dakota BIE schools were identified as being ELL. In Arizona BIE schools, 33% of AI/AN students in Arizona BIE schools were identified as being ELL (which is not surprising based on the percentages in the literature).

AI/AN students in public low density schools in both states and AI/AN students in public high density schools in both states had similar percentages of students in each of the four categories while students in BIE schools in both states had very different percentages in each of the four categories. Students in BIE schools in South Dakota had percentages similar to public low density school students in both states while students in BIE schools in Arizona had very different percentages due to the previously mentioned high percentage of students who were identified as being ELL.

Cross tabulation #4B: AI/AN students with/without disability/ELL and don't understand what teacher asks. The purpose of cross tabulation 4B was to see if there was a relationship between not understanding what the teacher asks and being labeled as having a disability and/or being ELL. The notion was that if the student was not proficient in the language of the school, it might be difficult to understand the mathematics teacher, which might, in turn, affect mathematics achievement test outcomes. Only 2.7% of 6,028 students in all school density types in both states answered "never/hardly ever" to whether or not they *clearly understand what the mathematics teacher asks*. Therefore, this option was combined with "sometimes" (which 32.9% of the students chose) to create these cross tabulations.

A test of independence was run within each school density type in each state to compare the percent of AI/AN students who don't understand what the teacher asks and being identified as having a disability and/or being ELL. The null hypothesis was that there was no relationship between not understanding what the teacher asks and being identified as having a disability and/or being ELL in each school density type in each state. The alternative hypothesis was that there was a relationship between not understanding what the teacher asks and being identified as having a disability and/or being ELL in each school density type in each state. Table 4.6 shows comparisons among AI/AN students between those who have been identified as having a disability and/or being ELL and how often the student *clearly understands what the teacher asks* by state and school density type.

Table 4.6: *Percent (number) of AI/AN students by disability/ELL and how often the student clearly understands what teacher asks in each state and school density type*

	Not ELL or Disability	ELL and Disability	ELL	Disability
	Arizona public low density school students (N=1,572; 3% of the data were missing)			
Never/hardly ever/ sometimes understand teacher (n=507)	33% (425)	0% (0)	0% (0)	28% (82)
Often/always/almost always understand teacher (n=1,065)	67% (858)	0% (0)	0% (0)	72% (207)
Notes. X^2 (1) = 2, p =0.118				
	Arizona public high density school students (N=2,451; 0.3% of the data were missing)			
Never/hardly ever/sometimes understand teacher (n=935)	36% (711)	43% (52)	48% (80)	47% (92)
Often/always/almost always understand teacher (n=1,516)	64% (1255)	57% (68)	52% (87)	54% (106)
Notes. X^2 (3) = 17, p =0.001				
	Arizona BIE school students (N=627; 5.7% of the data were missing)			
Never/hardly ever/sometimes understand teacher (n=243)	34% (119)	73% (29)	38% (76)	50% (19)
Often/always/almost always understand teacher (n=384)	66% (228)	28% (11)	62% (126)	50% (19)
Notes. X^2 (3) = 24, p < 0.001				
	South Dakota public low density school students (N=348; 1.8% of the data were missing)			
Never/hardly ever/ sometimes understand teacher (n=106)	26% (74)	0% (0)	0% (0)	54% (32)
Often/always/almost always understand teacher (n=242)	74% (215)	0% (0)	0% (0)	46% (27)
Notes. X^2 (1) = 19, p < 0.001				
	South Dakota public high density school students (N=595; 1% of the data were missing)			
Never/hardly ever/sometimes understand teacher (n=223)	39% (193)	73% (11)	22% (9)	26% (10)
Often/always/almost always understand teacher (n=372)	61% (307)	27% (4)	78% (32)	74% (29)
Notes. X^2 (3) = 15, p = 0.002				
	South Dakota BIE school students (N=421; 5% of the data were missing)			
Never/hardly ever/sometimes understand teacher (n=178)	42% (140)	0% (0)	0% (0)	44% (38)
Often/always/almost always understand teacher (n=243)	58% (195)	0% (0)	0% (0)	56% (48)
Notes. X^2 (1) = 0.2, p = 0.688 Values are based upon weighted estimates.				

Overall, among students who were not identified as being ELL or having a disability, an unexpectedly low percentage of students, ranging from 58-74% across strata, reported often/always/almost always *clearly understanding what the mathematics teacher asks*. There was still a statistically significant association between clearly understanding what the mathematics teacher asks and being identified as having a disability/being ELL for AI/AN students in each school density type in each state, except for public low density school students in Arizona and BIE school students in South Dakota.

Surprisingly, the majority of students in public low density schools in Arizona (about 70%) reported often/always/almost ways *clearly understanding what the mathematics teacher asks* regardless of whether or not the student was identified as having a disability while a low percentage of BIE school students in South Dakota reported often/always/almost always *clearly understanding what the mathematics teacher asks* regardless of whether or not the student was identified as having a disability (56% and 58%, respectively).

Among students who were identified as having both a disability and being ELL, BIE school students in Arizona and public high density school students in South Dakota were much more likely (73%) to report never/hardly ever/sometimes *clearly understanding what the mathematics teacher asks* while just under half of the public high density schools students in Arizona who were identified as having both a disability and being ELL reported never/hardly ever/sometimes *clearly understanding what the mathematics teacher asks*.

Among ELL students, public high density school students in South Dakota were most likely to report often/always/almost ways *clearly understanding what the mathematics teacher asks* (78%), BIE school students in Arizona had the next highest percentage of students who reported often/always/almost ways *clearly understanding what the mathematics teacher asks* while public high density school students in Arizona were least likely to report often/always/almost ways *clearly understanding what the mathematics teacher asks* (only 52%).

Among students identified as having a disability, approximately half of the students in public high density and BIE schools in Arizona and public low density and BIE schools in South Dakota reported never/hardly ever/sometimes *clearly understanding what the mathematics teacher asks*. Students identified as having a disability in public low density schools in Arizona and public high density schools in South Dakota were much more likely to report often/always/almost ways *clearly understanding what the mathematics teacher asks*.

Cross tabulation #5: AI/AN students identified as having a disability and teacher race. The purpose of this set of cross tabulations was to investigate whether there was evidence in this dataset to support the finding from Skiba et. al. (2008) that AI/AN students were more likely to be labeled as having a disability when the teaching force comprised more White teachers and less likely to be labeled as having a disability when the teaching force comprised more AI/AN teachers.

A test of independence was run within each school density type in each state to compare the percent of AI/AN students who have a disability and teacher reported race. The null hypothesis was that there was no relationship between *having a disability* and *teacher race* in each school density type in each state. The alternative hypothesis was that there was a relationship between *having a disability* and *teacher race* in each school density type in each state. Table 4.7 shows comparisons among AI/AN students only, with and without a disability and teacher race by state and school density type.

Table 4.7: *Percent (number) of AI/AN students with and without a disability by teacher race in each state and school density type*				
	Students whose teachers identify as White	Students whose teachers identify as AI/AN	Students whose teachers identify as White and AI/AN	Students whose teachers identify as a race other than White or AI/AN
	Arizona public low density school students (N=1,481; 9% of the data were missing)			
With disability (n=289)	18% (251)	0% (0)	0% (0)	45% (38)
Without disability (n=1,192)	82% (1146)	0% (0)	0% (0)	55% (46)
Notes. X^2 (1) = 37, p < 0.001				
	Arizona public high density school students (N=2,226; 10% of the data were missing)			
With disability (n=264)	18% (178)	7% (86)	0% (0)	0% (0)
Without disability (n=1,962)	82% (811)	93% (1151)	0% (0)	0% (0)
Notes. X^2 (1) = 64, p < 0.001				
	Arizona BIE school students (N=496; 25% of the data were missing)			
With disability (n=68)	15% (9)	13% (51)	0% (0)	22% (8)
Without disability (n=428)	85% (49)	87% (350)	0% (0)	78% (29)
Notes. X^2 (2) = 2, p = 0.294				
	South Dakota public low density school students (N=310; 13% of the data were missing)			
With disability (n=48)	15% (48)	0% (0)	0% (0)	0% (0)
Without disability (n=262)	85% (262)	0% (0)	0% (0)	0% (0)
Notes. N/A				
	South Dakota public high density school students (N=572; 4.8% of the data were missing)			
With disability (n=51)	10% (47)	0% (0)	10% (4)	0% (0)
Without disability (n=521)	90% (401)	100% (44)	90% (38)	100% (38)
Notes. X^2 (3) = 9, p = 0.024[31]				
	South Dakota BIE school students (N=390; 12% of the data were missing)			
With disability (n=73)	19% (31)	18% (42)	0% (0)	0% (0)
Without disability (n=317)	81% (128)	82% (189)	0% (0)	0% (0)
Notes. X^2 (1) = 0.1, p = 0.744 Values are based upon weighted estimates.				

[31]Three cells (37.5%) have an expected count less than 5. The minimum expected count is 3.39. Re-running the cross tab using the Monte Carlo option, the chi-square value is still significant, p = 0.026, which means there is a high level of association between being identified as having a disability and teacher race for public high density students in South Dakota.

There was a high level of association between being identified as *having a disability* and *teacher race* for public low density school students in Arizona and public high density school students in Arizona and South Dakota. There was no statistically significant association between being identified as *having a disability* and *teacher race* for BIE school students in Arizona and South Dakota or public low density school students in South Dakota (where 100% of the students had teachers who reported being White). Students in public high density schools in South Dakota were the only group who had 42 (7%) teachers identify as both White and AI/AN.

In public low density schools in Arizona, approximately half of the students whose teachers identified as a race other than White or AI/AN were labeled as having a disability while only 18% of students whose teachers identified as White were labeled as having a disability. In public low density schools in South Dakota, all of the AI/AN students had teachers who identified as White; 15% of the students were identified as having a disability. There were no students in public low density schools in Arizona or South Dakota who had teachers who identified as AI/AN.

As expected, in public high density schools in Arizona, students whose teachers identified as White were labeled as *having a disability* at a higher rate (twice as often) compared to students whose teachers identified as AI/AN. There were no students in public high density schools in Arizona who had teachers who identified as a race other than White or AI/AN. Interestingly, in public high density schools in South Dakota, students whose teachers identified as White were labeled as *having a disability* at the same rate as students whose teachers identified as White and AI/AN. No students whose teachers identified as AI/AN or a race other than White or AI/AN were labeled as *having a disability*.

In Arizona BIE schools, students whose teachers identified as White or AI/AN were labeled as *having a disability* at almost the same rate. Students whose teachers identified as a race other than White or AI/AN were labeled as *having a disability* at a higher rate. In South Dakota BIE schools, students whose teachers identified as White or AI/AN were labeled as *having a disability* at almost the same rate.

According to these results, across all six strata, students whose teachers identified as White were labeled as having a disability at a consistently similar rate. In public high density schools in both Arizona and South Dakota, students whose teachers identified as White were labeled as *having a disability* at a higher rate than students whose teachers identified as AI/AN (which is what the literature states) while in BIE schools in both states, students whose teachers identified as White or AI/AN were labeled as *having a disability* at a similar rate. Interestingly, students whose teachers identified as White and AI/AN (only in South Dakota public high density schools) were labeled as *having a disabili*ty at the same rate as students whose teachers identified as White. Students in Arizona public low density and BIE schools whose teachers identified as a race other than White or AI/AN were labeled as *having a disability* at a higher rate than students in those schools whose teachers identified as White or AI/AN. Although, none of the 38 students in South Dakota public high density schools whose teachers identified as a race other than White or AI/AN were labeled as *having a disability*.

Cross tabulation #6: AI/AN students in high poverty schools and disability/ELL.

The purpose of this set of cross tabulations was to see if AI/AN students in high poverty schools were more likely to be identified as having a disability or being ELL than AI/AN students not in high poverty schools (Shifrer et. al., 2011).

A test of independence was run within each school density type in each state to compare the percent of AI/AN students in schools in which *76% or more of the students were eligible for NSLP* and had a disability and/or were ELL to the percent of AI/AN students in all other schools who had a disability and/or were ELL. The null hypothesis was that there was no relationship between the poverty level of the school and having a disability and/or being ELL in each school density type in each state. The alternative hypothesis was that there was a relationship between the poverty level of the school and having a disability and/or being ELL in each school density type in each state.

Table 4.8 shows comparisons among AI/AN students in schools in high and low poverty schools by state and school density type.

Table 4.8: *Percent (number) of AI/AN students in each school density type in Arizona and South Dakota by whether or not 76% or more of the students are eligible for the National School Lunch Program and disability/ELL*				
	Student w/disability	ELL	Both SD and ELL	Neither SD nor ELL
	Arizona public low density school students (N=1,504; 7% of the data were missing)			
AI/AN Students in schools with ≥ 76% of students eligible for NSLP (n=290)	31% (89)	0% (0)	0% (0)	69% (201)
AI/AN Students in schools with < 76% of students eligible for NSLP (n=1,214)	17% (203)	0% (0)	0% (0)	83% (1011)
Notes. X^2 (1) = 29, $p < 0.001$				
	Arizona public high density school students (N=2,459; no missing data)			
AI/AN Students in schools with ≥ 76% of students eligible for NSLP (n=1,961)	7% (130)	7% (141)	6% (108)	81% (1582)
AI/AN Students in schools with < 76% of students eligible for NSLP (n=498)	14% (67)	5% (26)	2% (12)	79% (393)
Notes. X^2 (3) = 3, $p < 0.001$				
	Arizona BIE school students (N=593; 11% of the data were missing)			
AI/AN Students in schools with ≥ 76% of students eligible for NSLP (n=593)	6% (35)	36% (214)	8% (45)	50% (299)
AI/AN Students in schools with < 76% of students eligible for NSLP (n=0)	0% (0)	0% (0)	0% (0)	0% (0)
	South Dakota public low density school students (N=321; 9% of the data were missing)			
AI/AN Students in schools with ≥ 76% of students eligible for NSLP (n=0)	0% (0)	0% (0)	0% (0)	0% (0)
AI/AN Students in schools with < 76% of students eligible for NSLP (n=321)	16% (52)	0% (0)	0% (0)	84% (269)
	South Dakota public high density school students (N=552; 8% of the data were missing)			
AI/AN Students in schools with ≥ 76% of students eligible for NSLP (n=451)	8% (36)	8% (36)	3% (15)	81% (364)
AI/AN Students in schools with < 76% of students eligible for NSLP (n=101)	0% (0)	3% (3)	0% (0)	98% (98)
Notes. X^2 (3) = 17, $p = 0.001$				
	South Dakota BIE school students (N=366; 17% of the data were missing)			
AI/AN Students in schools with ≥ 76% of students eligible for NSLP (n=366)	22% (82)	0% (0)	0% (0)	78% (284)
AI/AN Students in schools with < 76% of students eligible for NSLP (n=0)	0% (0)	0% (0)	0% (0)	0% (0)
Notes. Values are based upon weighted estimates.				

All of the students in BIE schools in Arizona and South Dakota were in high poverty schools (i.e., 76% or more of the students were eligible for NSLP) while all of the students in public low density schools in South Dakota were in low poverty schools (i.e., less than 76% of the students were eligible for NSLP); therefore, no comparisons could be made within these strata. However, there was still a high level of association between being identified as having a disability/being ELL and the poverty level of the school in public low and high density schools in Arizona and in public high density schools in South Dakota.

In Arizona public low density schools, more AI/AN students were in low poverty schools. As expected, AI/AN students in high poverty, public low density schools in Arizona were more likely to be identified as having a disability compared to students in low poverty, public low density schools in Arizona.

In Arizona and South Dakota public high density schools, more AI/AN students were in high poverty schools. Surprisingly, AI/AN students in these high poverty, public high density schools in Arizona were less likely to be identified as having a disability but more likely to be identified as having both a disability and being ELL (although the percentages were small) compared to students in low poverty, public high density schools in Arizona while AI/AN students in high poverty, public high density schools in South Dakota were more likely to be identified as having a disability or being ELL or both (although the numbers were small) compared to students in low poverty, public high density schools in South Dakota.

Summary of the NAEP questionnaire and school administration data cross tabulations. The cross tabulations responding to research question 1a did not always follow the expected achievement pattern in which students of all other races and AI/AN students in public low density schools were more likely to have the characteristics that have been found to be associated with higher achievement in the literature. For example, overall, AI/AN students were more likely to like learning mathematics (which is positive, but unexpected, since attitude toward mathematics is linked to higher mathematics achievement, but AI/AN students historically have low mathematics achievement), most students of all other races were taking another math class (not geometry or algebra), and Hispanic students were more likely to be identified as having a disability compared to students of all other races. On the other hand, some results were as expected. AI/AN students in public high density schools in Arizona and South Dakota were more likely to be identified as having a disability if their teacher was White. AI/AN students in high poverty, public low density schools in Arizona and high poverty, public high density schools in South Dakota were more likely to be identified as having a disability compared to students in low poverty schools in Arizona. Other interesting results were that no AI/AN students in BIE schools in South Dakota were identified as being ELL and a relatively low percentage of AI/AN students who were not identified as being ELL or having a disability across all six strata reported often/always/almost always *clearly understanding what the mathematics teacher asks*.

Research Question 1b: Results from cross tabulations using NIES individual items and derived risk factors

The purpose of cross tabulations 7-10 were to see how much AI/AN students were being immersed in AI/AN culture, as this may be a protective factor when it comes to learning and achievement. In other words, when AI/AN culture is incorporated into AI/AN students' lives and the school curriculum, it has been associated with higher achievement (Demmert, 2001; Demmert & Towner, 2003; Deyhle, 1995; Fryberg et. al., 2013; Lipska and Adams, 2004; Tharpe, 2006; Whitbeck et. al., 2001; Zwick and Miller, 1996). In an effort to reduce the number of tables, cross tabulations on the same topic that were run separately in each state and/or for each school density type were combined into one table.

Cross tabulation #7: Knowledge of AI/AN culture. The purpose of this set of cross tabulations was to see how much knowledge of AI/AN culture the AI/AN students in each school density type in each state had using the derived risk factor on *knowledge of AI/AN culture*.

A test of independence was run within the school density types, across categories, in each state to see if there were differences in students' *knowledge of AI/AN culture*. The null hypothesis was that there was no relationship between school density type and students' *knowledge of AI/AN culture* in each state. The alternative hypothesis was that there was a relationship between school density type and students' *knowledge of AI/AN culture* in each state. Table 4.9 shows comparisons among AI/AN students' *knowledge of AI/AN culture* by state and school density type.

Table 4.9: *Percent (number) of AI/AN students in Arizona and South Dakota by knowledge of AI/AN culture* by school density type*			
	A lot	Some	A little/nothing
	Arizona (N=4,636; 2% of the data were missing)		
Public low (n=1574)	9% (140)	45% (714)	46% (720)
Public high (n=2,418)	15% (359)	53% (1271)	33% (788)
BIE (n=647)	15% (91)	53% (345)	33% (211)
Notes. X^2 (4) = 87, $p < 0.001$			
	South Dakota (N=1,330; 4.9% of the data were missing)		
Public low (n=337)	10% (32)	35% (119)	55% (186)
Public high (n=587)	12% (71)	58% (341)	30% (175)
BIE (n=406)	12% (48)	53% (215)	35% (143)
Notes. X^2 (4) = 61, $p < 0.001$ Values are based upon weighted estimates.			

*combination of the following three questions asked to students: "How much do you know about each of the following: Your American Indian or Alaska Native history, Your American Indian or Alaska Native traditions and culture (way of life, customs), and Issues today that are important to American Indian or Alaska Native people".

There was a high level of association between *knowledge of AI/AN culture* and school density type for students in Arizona and South Dakota. Surprisingly, overall, only 9-15% of AI/AN students across strata knew a lot about AI/AN culture with slightly more public high density and BIE school students reporting knowing a lot about AI/AN culture in both states compared to students in public low density schools in both states.

Public low density school students in South Dakota were more likely to know a little/nothing about AI/AN culture compared to public high density and BIE school students in both states while public high density and BIE school students in both states were more likely to know something about AI/AN culture. Public low density school students in Arizona were equally as likely to know some or a little/nothing about AI/AN culture. Interestingly, the students in public high density and BIE schools in Arizona have the same percentages in each category while slightly more public high density school students in South Dakota have some knowledge of AI/AN culture compared to BIE school students in South Dakota.

Cross tabulation #8: Participation in AI/AN cultural activities. The purpose of this set of cross tabulations was to see how much AI/AN students in each school density type in each state participated in AI/AN cultural activities using the derived risk factor on *participation in AI/AN cultural activities*.

A test of independence was run within the school density types, across categories, in each state to compare students' *participation in AI/AN cultural activities*. The null hypothesis was that there was no relationship between school density type and students' *participation in AI/AN cultural activities* in each state. The alternative hypothesis was that there was a relationship between school density type and students' *participation in AI/AN cultural activities* in each state. Table 4.10 shows comparisons among AI/AN students' *participation in AI/AN cultural activities* by state and school density type.

Table 4.10: *Percent (number) of AI/AN students in Arizona and South Dakota by participation in AI/AN cultural activities* by school density type*			
	Several times a year	At least once a year	Never/every few years
	Arizona (N=4,631; 2.4% of the data were missing)		
Public low (n=1,574)	7% (115)	35% (551)	58% (908)
Public high (n=2,420)	16% (385)	40% (977)	44% (1058)
BIE (n=637)	16% (101)	40% (255)	44% (281)
Notes. X^2 (4) = 108, p < 0.001			
	South Dakota (N=1,327; 5.1% of the data were missing)		
Public low (n=344)	10% (35)	28% (97)	62% (212)
Public high (n=577)	22% (128)	42% (244)	36% (205)
BIE (n=406)	21% (85)	38% (154)	41% (167)
Notes. X^2 (4) = 64, p < 0.001 Values are based upon weighted estimates.			

*combination of the following three questions asked to students: "How often have you participated in each of the following: Ceremonies and gatherings for people from your AI/AN group; ceremonies and gatherings that bring people together from many different AI tribes or AN groups; other AI/AN activities"

There was a high level of association between *participation in AI/AN cultural activities* and school density type for students in Arizona and South Dakota. Similar to Table 4.9, although a low percentage of students in both states overall participated in cultural activities several times a year, public low density school students in both states were less likely to participate in AI/AN cultural activities several times a year compared to public high density and BIE school students in both states. Additionally, more AI/AN students in public high density and BIE schools in South Dakota (approximately 22%) participated in cultural activities several times a year compared to the percentage of students who had a lot of knowledge of AI/AN cultural activities (12%) from Table 4.9.

The percentages of students in public high density and BIE schools in Arizona who participated in cultural activities several times a year compared to the percentage of students who had a lot of knowledge of AI/AN cultural activities was approximately the same (about 15%).

Also similar to Table 4.9, AI/AN students in public low density schools in Arizona and South Dakota were more likely to never participate or participate every few years in AI/AN cultural activities compared to students in public high density and BIE schools in both states.

Interestingly, and similar to Table 4.9, the students in public high density and BIE schools in Arizona have the same percentages in each category while slightly more public high density school students in South Dakota participated in AI/AN cultural activities compared to BIE school students.

Cross tabulation #9: Teachers incorporate AI/AN culture/tradition into their mathematics instruction. The purpose of this set of cross tabulations was to understand the percent of AI/AN students whose teachers incorporated AI/AN culture and tradition into their mathematics instruction in each school density type in each state using the derived risk factor on *teachers incorporating AI/AN culture/tradition into their mathematics instruction*.

A test of independence was run within the school density types, across categories, in each state to compare how often teachers incorporated AI/AN culture/tradition into their mathematics instruction. The null hypothesis was that there was no relationship between school density type and how often teachers incorporated AI/AN culture/tradition into their mathematics instruction in each state. The alternative hypothesis was that there was a relationship between school density type and how often teachers incorporated AI/AN culture/tradition into their mathematics instruction in each state. Table 4.11 shows comparisons among AI/AN students by state and school density type.

Table 4.11: *Percent (number) of AI/AN students in Arizona and South Dakota by how often teachers incorporate AI/AN culture/tradition into their mathematics instruction in each school density type*

	Once/month or more	At least once/year	Never
	Arizona (N=4,345; 8% of the data were missing)		
Public low (n=1,550)	0% (0)	16% (240)	85% (1310)
Public high (n=2,320)	23% (527)	33% (759)	45% (1034)
BIE (n=475)	46% (216)	48% (228)	7% (31)
Notes. X^2 (4) = 1200, $p < 0.001$			
	South Dakota (N=1,240; 11% of the data were missing)		
Public low (n=314)	1% (3)	10% (30)	90% (281)
Public high (n=554)	25% (140)	26% (144)	49% (270)
BIE (n=372)	16% (58)	50% (184)	35% (130)
Notes. X^2 (4) = 269, $p < 0.001$ Values are based upon weighted estimates.			

There was a high level of association between how often *teachers incorporated AI/AN culture/tradition into their mathematics instruction* and school density type for students in Arizona and South Dakota. Not surprisingly, AI/AN students in public low density schools in Arizona and South Dakota were more likely to have teachers who reported they never incorporated AI/AN culture/tradition into their mathematics instruction compared to students in public high density and BIE schools. However, surprisingly, AI/AN students in public high density schools in both states were also more likely to have teachers who reported they never incorporated AI/AN culture/tradition into their mathematics instruction. Only 7% of students in BIE schools in Arizona but, surprisingly, 35% of students in BIE schools in South Dakota had teachers who reported they never incorporated AI/AN culture/tradition into their mathematics instruction.

As expected, BIE school students in Arizona were more likely to have teachers who reported they incorporated AI/AN culture/tradition into their mathematics instruction once/month or more compared to public low and high density school students. However, public high density school students in South Dakota were more likely to have teachers who reported they incorporated AI/AN culture/tradition into their mathematics instruction once/month or more compared to public low density and BIE school students.

Cross tabulation #10: Classes offered in AI/AN cultures and traditions – school level. The purpose of this set of cross tabulations was to examine how many classes were offered to students in AI/AN cultures and traditions in each school density type in each state using the derived risk factor on *classes offered in AI/AN cultures and traditions*.

A test of independence was run across each school density type in each state to compare how many schools offered classes in AI/AN cultures and traditions. The null hypothesis was that there was no relationship between school density type and the number of schools that offer classes in AI/AN cultures and traditions in each state. The alternative hypothesis was that there was a relationship between school density type and the number of schools that offer classes in AI/AN cultures and traditions in each state. Table 4.12 shows the percent (number) of schools in each school density type in each state that offer classes in oral language, written language, history of tribe, traditions/customs, arts/crafts/music, tribal/village government, and current events/issues. The overall school weight (SCHWT) was used for this set of cross tabulations.

Table 4.12: *Percent (number) of schools that offered classes in the following areas*

	Oral language	Written language	History of tribe	Traditions/ customs	Arts/crafts/ music	Tribal/village government	Current events/ issues
	Arizona						
Public low	17% (20/118)	16% (18/116)	71% (82/116)	66% (77/116)	41% (47/116)	23% (27/118)	38% (44/115)
Public high	73% (30/41)	53% (21/40)	93% (38/41)	93% (38/41)	85% (35/41)	73% (30/41)	93% (38/41)
BIE	95% (19/20)	68% (13/19)	100% (20/20)	100% (20/20)	95% (19/20)	74% (14/19)	89% (16/18)
	South Dakota						
Public low	26% (11/42)	24% (10/42)	83% (35/42)	79% (33/42)	64% (27/42)	31% (13/42)	46% (19/41)
Public high	45% (9/20)	50% (10/20)	70% (14/20)	65% (13/20)	70% (14/20)	37% (7/19)	50% (10/20)
BIE	100% (15/15)	100% (15/15)	100% (15/15)	100% (15/15)	100% (15/15)	73% (11/15)	93% (14/15)

Notes. Values are based upon weighted estimates.

Not surprisingly, BIE schools in Arizona and South Dakota are more likely to offer instruction in all seven content areas compared to public low and high density schools. In fact, BIE schools in South Dakota offered the most instruction in these seven content areas compared to schools in all other school density types in either state while Arizona public low density schools offered the least amount of AI/AN classes compared schools in any other school density type in either state.

In Arizona, public high density and BIE schools offered significantly more instruction in these seven content areas than public low density schools, which was not consistently the case in South Dakota where a similar percentage of public low density schools offered instruction in history of the tribe, traditions/customs, and arts/crafts/music compared to public high density and BIE schools. Table 4.13 shows the number of schools that offer instruction in 7 content areas, 3-6 content areas, and 2 or fewer content areas by state and school density type.

Table 4.13: *Percent (number) of schools in Arizona and South Dakota by how much instruction in AI/AN culture and traditions was offered by school density type*

	7 content areas	3-6 content areas	2 or fewer content areas
	Arizona (N=173; 13% of the data were missing)		
Public low (n=114)	7% (8)	44% (50)	49% (56)
Public high (n=41)	44% (18)	49% (20)	7% (3)
BIE (n=18)	67% (12)	33% (6)	0% (0)
Notes. X^2 (4) = 59.91, $p < 0.001$[a]			
	South Dakota (N=75; 12% of the data were missing)		
Public low (n=41)	15% (6)	49% (20)	37% (15)
Public high (n=19)	37% (7)	26% (5)	37% (7)
BIE (n=15)	73% (11)	27% (4)	0% (0)
Notes. X^2 (4) = 19.91, $p = 0.001$[b] Values are based upon weighted estimates.			

[a] One cell (11.1%) had an expected count lower than 5.
[b] Two cells (22.2%) had an expected count lower than 5.

Similar to Table 4.12, BIE schools in Arizona and South Dakota were more likely to offer instruction in all seven content areas compared to public low and high density schools and did not have any schools that offered two or fewer content areas. Public low density schools in Arizona and public high density schools in South Dakota were more likely to offer instruction in two or fewer content areas while public high density schools in Arizona and public low density schools in South Dakota were more likely to offer 3-6 content areas.

Cross tabulation #11: School Climate – school level. The purpose of this set of cross tabulations was to understand the school climate in each school density type in each state using the derived risk factors on *safe and orderly schools* and *school climate*. School climate has been shown to be associated with achievement (Bryk et. al., 2010; Cohen et. al., 2009; Muller, 1998; Phillips, 1997; Stewart, 2007).

As shown in Appendix C, when the derived risk factor for *school climate* was developed using school-level data, two distinct derived risk factors emerged: *safe and orderly schools* and *school climate*. Table 4.14 shows comparisons among AI/AN schools by state and school density type for *safe and orderly schools*. A test of independence was run across each school density type in each state to compare how many schools were safe and orderly. The null hypothesis was that there was no relationship between school density type and *safe and orderly schools* in each state. The alternative hypothesis was that there was a relationship between school density type and *safe and orderly schools* in each state.

Table 4.15 shows comparisons among AI/AN schools by state and school density type for *school climate*. A test of independence was run across each school density type in each state to compare how many schools had a positive school climate. The null hypothesis was that there was no relationship between school density type and *school climate* in each state. The alternative hypothesis was that there was a relationship between school density type and *school climate* in each state. The overall school weight (SCHWT) was used for both tables.

Table 4.14: *Percent (number) of safe and orderly schools*[32] *in Arizona and South Dakota by school density type*			
	Safe and Orderly	Somewhat safe and orderly	Not safe and orderly
	Arizona (N=178; 10.6% of the data were missing)		
Public low (n=117)	21% (25)	67% (78)	12% (14)
Public high (n=41)	5% (2)	71% (29)	24% (10)
BIE (n=20)	0% (0)	85% (17)	15% (3)
Notes. X^2 (4) = 13, p = 0.012 [a]			
	South Dakota (N=76; 10.6% of the data were missing)		
Public low (n=42)	26% (11)	69% (29)	5% (2)
Public high (n=20)	10% (2)	65% (13)	25% (5)
BIE (n=14)	0% (0)	43% (6)	57% (8)
Notes. X^2 (4) = 21, p < 0.001 [b] Values are based upon weighted estimates.			

[a] Two cells have an expected count less than 5.
[b] Four cells have an expected count less than 5.

There was a high level of association between *safe and orderly schools* and school density type for students in Arizona and South Dakota. The schools in all strata were more likely to be somewhat safe and orderly except South Dakota BIE schools, which were more likely to be not safe and orderly. As expected, in Arizona and South Dakota, more public low density schools were safe and orderly compared to public high

[32] Safe and orderly schools means to what extent did the principal of the school think the following were a problem in the school: student misbehavior in class, physical conflicts among students, and bullying.

density and BIE schools. Surprisingly, no BIE schools in Arizona or South Dakota were safe and orderly.

Table 4.15: *Percent (number) of schools in Arizona and South Dakota by school climate[33] and school density type*			
	Positive School Climate	Moderate School Climate	Negative School Climate
	Arizona (N=179; 10.1% of the data were missing)		
Public low (n=118)	4% (5)	61% (72)	35% (41)
Public high (n=41)	51% (21)	49% (20)	0% (0)
BIE (n=20)	20% (4)	65% (13)	15% (3)
Notes. X^2 (4) = 57, $p < 0.001$[a]			
	South Dakota (N=75; 11.8% of the data were missing)		
Public low (n=42)	2% (1)	62% (26)	36% (15)
Public high (n=20)	35% (7)	60% (12)	5% (1)
BIE (n=13)	39% (5)	46% (6)	15% (2)
Notes. X^2 (4) = 19, $p < 0.001$[b] Values are based upon weighted estimates.			

[a] Two cells have an expected count less than 5.
[b] Four cells have an expected count less than 5.

There was a high level of association between *school climate* and school density type for students in Arizona and South Dakota. The schools in all strata were more likely to have a moderate school climate, except for Arizona public high density in which just under half had a moderate school climate and just over half had a positive school climate. Surprisingly, no public high density schools in Arizona had a negative school climate and

[33] School climate consisted of questions asked of the principal of the school regarding to what extent each of the following were a problem in the school: student health, student drug/alcohol use, low parent involvement, low student aspirations, low teacher aspirations. Negative school climate means many of these issues were a big problem in the school.

only one school in public high density schools in South Dakota had a negative school climate.

Compared to Table 4.14 where public low density schools in Arizona and South Dakota were more likely to have safe and orderly schools, public low density schools in both states were more likely to have a negative school climate and very few had a positive school climate compared to public high density and BIE schools. Public high density schools in Arizona and South Dakota were more likely to have a positive school climate but not be safe and orderly. BIE schools in both states were more likely to have schools with a positive school climate than negative school climate but had no schools that were safe and orderly.

Cross tabulation #12: distribution of school funding across school density types – school level. The purpose of this cross tabulation was to offer further description of the types of schools AI/AN students in these two states attended and to observe any differences in the following types of school funding across the three school density types in each state: National School Lunch Program (NSLP), Title I funds, Title II funds, Title III funds, Title VII (Indian Education Formula Grants) funds, Title VII (Discretionary Grant) funds, IDEA funds, Impact Aid, Johnson-O'Malley funds, and other funding sources related to AI/AN education (e.g., grants, donations, tuition, etc.). No test of independence was performed. The overall school weight (SCHWT) was used.

Table 4.16: *Percent (number) of AI/AN students in schools with funding from sources that provide educational services and support for AI/AN students (both funding designed specifically for AI/AN education and funding intended for broader use)*

	Title I [a]	Title II [b]	Title III [c]	Title VII, Indian Ed [d]	Title VII, Discretionary [e]	IDEA [f]	Impact Aid [g]	Johnson-O'Malley [h]	Other funding sources related to AI/AN education[i]
	Arizona								
Public low	51% (43/85)	60% (50/84)	48% (37/77)	41% (35/85)	28% (24/85)	68% (58/85)	8% (7/85)	19% (16/86)	10% (8/83)
Public High	100% (39)	100% (31)	100% (31)	90% (28/31)	84% (26/31)	93% (37/40)	69% (27/39)	82% (32/39)	36% (14/39)
BIE	100% (19)	95% (18/19)	61% (11/18)	79% (15/19)	39% (7/18)	100% (19)	6% (1/17)	17% (3/18)	50% (9/18)
	South Dakota								
Public low	40% (12/30)	63% (19/30)	17% (5/29)	45% (13/29)	20% (6/30)	83% (25/30)	40% (12/30)	30% (9/30)	7% (2/30)
Public High	93% (14/15)	80% (12/15)	53% (8/15)	80% (12/15)	60% (9/15)	87% (13/15)	93% (14/15)	73% (11/15)	20% (3/15)
BIE	100% (13)	100% (13)	33% (4/12)	92% (11/12)	55% (6/11)	100% (13)	27% (3/11)	17% (2/12)	46% (6/13)

Notes. Values are based upon weighted estimates.

[a] provided to schools with high numbers of children from low-income families (U.S. Department of Education, 2011)

[b] provided to schools to improve the quality of teachers and principals (U.S. Department of Education, 2009)

[c] provided to schools to close the achievement gap for people for whom English is not their first language (U.S. Department of Education, 2011)

[d] Indian Education Formula Grant funding (provided to schools to address culturally-related academic needs to AI/AN students) (U.S. Department of Education, 2010)

[e] Discretionary Grant funding (which includes a professional development program that provides funding to train qualified Indian individuals to work in the school and demonstration grants that provide funding for school readiness programs for AI/AN students) (U.S. Department of Education, 2003)

[f] ensures services are provided to children with disabilities (U.S. Department of Education, n.d.)

[g] provides funding to school districts that have lost property tax revenue due to the parcels of land within their boundaries that are owned by the Federal government, including Indian lands (U.S. Department of Education, 2008)

[h] provides supplemental funds to meet the unique needs of AI/AN students in public schools (Oglala Sioux Tribe, 2011)

[i] e.g., grants, donations, tuition, etc.

Principals from public low density schools in both states reported receiving significantly less Title I and Title II funding compared to principals in public high density and BIE schools in both states (almost 100%). One can surmise from this that public high density and BIE schools in both states were more likely to have high numbers of children from low-income families and a greater need to improve the quality of teachers and principals compared to students in public low density schools.

A higher percentage of principals in public high density schools in both states reported receiving Title III funding (provided to schools to close the achievement gap for people for whom English is not their first language). This may mean that public high density schools in both states were more diverse than the other schools density types and had a lot of other students (not just AI/AN students) who did not speak English as their first language. This seems especially true for Arizona where twice as many schools in each school density type were receiving this type of funding compared to South Dakota.

Not surprisingly, in both states, a higher percentage of principals in public high density and BIE schools reported receiving Title VII, Indian Education Formula Grant funding (provided to schools to address culturally related academic needs to AI/AN students) compared to public low density schools. Additionally, in both states, a higher percentage of principals from public high density schools reported receiving Title VII, Discretionary Grant funding (which includes a professional development program that provides funding to train qualified AI/AN individuals to work in the school and demonstration grants that provide funding for school readiness programs for AI/AN students). BIE schools received the next highest percentage while public low density schools received the lowest percentage of this type of funding.

More principals from public high density schools in Arizona reported receiving the funding from all of these types grants compared to public low density and BIE schools in Arizona, except for IDEA funding, which provides services for children with disabilities (100% of the BIE school principals reported receiving IDEA funding while 93% of the public high density school principals reported receiving IDEA funding), and other funding sources related to AI/AN education (e.g., grants, donations, tuition, etc.). More principals from public low density schools in both states reported receiving IDEA funding than any other type of funding.

More principals in public high density schools in both states reported receiving Impact Aid funding, which must mean these schools were in districts that included Indian lands within their boundaries (or other land owned by the Federal government). Only about 7% of principals in public low density and BIE schools in Arizona were in schools in districts that included Indian lands or other land owned by the Federal government. In South Dakota, twice as many schools in each school density type were receiving this type of funding compared to Arizona.

Not surprisingly, a higher percentage of public high density school principals in both states (about 78%) reported receiving Johnson-O'Malley funding (supplemental funds to meet the unique needs of AI/AN students in public schools).

Summary of the NIES questionnaire cross tabulations. Similar to the results of the NAEP questionnaire and school administration record cross tabulations in research question 1a, not all of the results for the NIES questionnaire cross tabulations for research question 1b were expected. Overall, fewer AI/AN students were immersed in AI/AN culture at home than was expected with only 7-22% knowing a lot about AI/AN culture and participating in AI/AN cultural activities several times a year. Although, as expected, public high density and BIE school students were more immersed in AI/AN culture at school compared to public low density school students (i.e., having teachers who were more likely to reported they incorporated AI/AN culture/tradition into their mathematics instruction and were in schools that were more likely offer instruction in all seven content areas).

It was surprising that the results of the two school climate cross tabulations were not more similar. For example, public low density schools in Arizona and South Dakota were more likely to have safe and orderly schools but a negative school climate while no BIE schools in either state were safe and orderly but only 15% had a negative school climate.

Based on funding received, public high density and BIE schools in both states were more likely to enroll high numbers of children from low-income families and have a greater need to improve the quality of teachers and principals compared to students in public low density schools. Public high density schools in both states were more diverse than the other school density types and had a lot of other students (not just AI/AN students) who did not speak English as their first language. A higher percentage of public high density and BIE schools reported receiving funding to address culturally related academic needs to AI/AN students and to train qualified AI/AN individuals to work in the school. A high percentage of schools in all strata received funding for students with disabilities. More public high density schools in both states were in districts that included Indian lands within their boundaries (or other land owned by the Federal government).

Research Question 2a: Distributions of scores from the NAEP risk indices

The *NAEP Knowledge/attitudes risk index* comprised one individual item and one derived risk factor: *how often you feel you have a clear understanding of what your mathematics teacher is asking you to do* and *attitude toward mathematics*. The N for this risk index was 5,922 with 3.6% missing data (created using data from just AI/AN students). Having zero risk factors on this risk index meant that the student often had a clear understanding of what the mathematics teacher was asking and liked mathematics. Having one risk factor on this risk index meant that the student either didn't have a clear understanding of what the mathematics teacher was asking or didn't like/somewhat liked mathematics. Having two risk factors on this risk index meant that the student didn't have a clear understanding of what the mathematics teachers was asking and did not like/somewhat liked mathematics.

The *NAEP Social/physical risk index* comprised three individual items: *the student is identified as being ELL, the student is identified as having a disability,* and *the number of days absent in the last month*. The N for this risk index was 6,097 with 0.8% missing data (created using data from just AI/AN students). Having zero risk factors on this risk index meant that the student was not identified as being ELL or having a disability and the student was absent 0-2 days in the last month. Having three risk factors on this risk index meant that the student was identified as being ELL and having a disability and the student was absent three or more days in the last month.

The *NAEP Home risk index* comprised five individual items: *mother's education level, number of books in the home, eligibility for the National School Lunch Program, how often people in your home talk to each other in a language other than English,* and *how often you talk about things you have studied in school with someone in your family*. The N for this risk index was 4,394 with 28.5% missing data (created using data from just AI/AN students). The reason for the high percentage of missing data was because 24% of the AI/AN students answered "I don't know" to mother's education level. Having zero risk factors on this risk index meant that the student's mother continued her education after graduating high school, there were 26 or more books in the home, the student was not eligible for NSLP and didn't not speak a language other than English at home, and often talked about things he/she had studied in school with someone in his/her family. Having five risk factors on this risk index meant that the student's mother had less than a high school education or had graduated high school, there were 25 books or less in the home, the student was eligible for NSLP and spoke a language other than English at home at least half the time or more, and didn't talk about things he/she had studied in school with someone in his/her family.

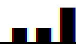
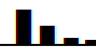
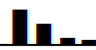
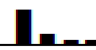
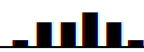
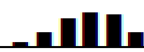
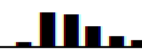
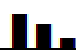
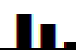
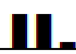
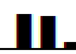
The *NAEP Classroom risk index* comprised two individual items: *mathematics class enrolled in this year* and *being taught by a teacher who stated he/she was a highly-qualified teacher this year*. The N for this risk index was 5,043 with 18% missing data (created using data from just AI/AN students). The reason for the high percentage of missing data was because 16% of the *highly-qualified teacher this year* variable responses were missing. Having zero risk factors on this risk index meant that the student was taking a geometry/algebra class and that the student had a teacher who stated he/she was a highly-qualified teacher this year. Having one risk factor on this risk index meant that the student either wasn't taking a geometry/algebra class or the student wasn't being taught by a teacher who stated he/she was a highly-qualified teacher this year.

Having two risk factors on this risk index meant that the student wasn't taking a geometry/algebra class and wasn't being taught by a teacher who stated he/she was a highly-qualified teacher this year.

The distributions of scores from all four of the NAEP risk indices were created using the overall student weight (ORIGWT). The scores in each cell are shown from lowest to highest (left to right, respectively). The number of students in each group was normalized to a number between 0 and 9[34] and then plotted in a bar graph in each cell of the table. Table 4.17 shows the distribution of scores on each of the four NAEP risk indices by state and race (AI/AN students vs. students of all other races). A summary of themes from the NAEP risk indices follows these tables.

[34] Each number was divided by the largest number in the group, which was multiplied by 9, and then rounded.

Table 4.17: *Distribution of scores on the four NAEP risk indices by state and race*

	AI/AN students	Students of all other races
NAEP Knowledge/attitudes risk index (0-2)*		
Arizona	(n=4,601; 3% missing data) 	(n=25,951; 7% missing data) 
South Dakota	(n=1,321; 5.6% missing data) 	(n=4,667; 4.7% missing data) 
NAEP Social/physical risk index (0-3)**		
Arizona	(n=4,720; 0.5% missing data) 	(n=27,232; 2.4% missing data) 
South Dakota	(n=1,377; 1.6% missing data) 	(n=4,786; 2.3% missing data) 
NAEP Home risk index (0-5)***		
Arizona	(n=3,505; 26.1% missing data) 	(n=21,146; 24.2% missing data) 
South Dakota	(n=889; 36.4% missing data) 	(n=4,106; 16.1% missing data) 
NAEP Classroom risk index (0-2)****		
Arizona	(n=3,774; 20.4% missing data) 	(n=24,466; 12.3% missing data) 
South Dakota	(n=1,269; 9.3% missing data) 	(n=4,577; 6.5% missing data) 

Notes. Values are based upon weighted estimates.

**how often you feel you have a clear understanding of what your mathematics teacher is asking you to do and attitude toward mathematics*

***the student is ELL, the student has a disability, and the number of days absent in the last month*

****mother's education level, number of books in the home, eligibility for the National School Lunch Program, how often people in your home talk to each other in a language other than English, and how often you talk about things you have studied in school with someone in your family*

*****mathematics class enrolled in this year and being taught by a highly qualified teacher*

The distribution of scores on the *NAEP Knowledge/attitudes risk index* for students of all other races between states was similar. The distribution of scores of AI/AN students between states was very different. Surprisingly, the group who had the most risk factors across all four risk indices was AI/AN students in South Dakota, of whom most had two risk factors on the *NAEP Knowledge/attitudes risk index*, which meant most of the AI/AN students in South Dakota did not feel they had a clear understanding of what the mathematics teachers was asking and did not like learning mathematics.

Students of all other races had the least number of risk factors across all four risk indices. On the *NAEP Social/physical risk index*, most students of all other races had 0 risk factors on this risk index. Most AI/AN students had 0 or 1 with a small percentage having two risk factors and a smaller number of students in Arizona having all three risk factors. More AI/AN students in Arizona had one risk factor on the *NAEP Social/physical risk index* compared to students of all other races on this risk index. No students in South Dakota had all three risk factors. Most likely this was because only 4% of the AI/AN students in South Dakota were identified as being ELL (as shown in Table 4.6, no students in South Dakota public low density or BIE schools were identified as being ELL).

Overall, more students of all other races in both states had fewer risk factors on the *NAEP Home risk index* compared to AI/AN students in both states. Most of the AI/AN students in both states had 3 or 4 risk factors while most of the students of all other races in both states had 1 or 2 risk factors. AI/AN students in South Dakota had more risk factors on this risk index (and more students with five risk factors) compared to students of all other races in both states while students of all other races in South Dakota had the least number of risk factors on the *NAEP Home risk index*. As stated previously, it is important to note that there was a high percentage of missing data in the *NAEP Home risk index* (ranging from 16-36%) due to 24% of students (overall) stating "I don't know" to the mother's education level question.

The distributions of scores between the two states and races on the *NAEP Classroom risk index* were similar: more students had 0 or 1 risk factor while very few had two risk factors on this risk index. More AI/AN students in South Dakota had one risk factor on the *NAEP Classroom risk index* compared to AI/AN students in Arizona, who were more likely to have zero risk factors. More students of all other races in South Dakota had one risk factor (either not taking Algebra or Geometry or not having a teacher who stated he/she was a highly-qualified teacher this year) on the *NAEP Classroom risk index* compared to students of all other races in Arizona. It is important to note that there was a high percentage of missing data in the *NAEP Classroom risk index* (ranging from 6-20%) due to 16% of the *highly-qualified teacher this year* data being missing.

Tables 4.18 and 4.19 show the distribution of scores on each of the four NAEP risk indices in each state by race and school density type.

Table 4.18: *Distribution of scores on the NAEP risk indices by Race and School Density Type in Arizona*

	Public low density	Public high density	BIE
NAEP Knowledge/attitudes risk index* (0-2)			
AI/AN students	(n=1,572; 2.9% missing data)	(n=2,397; 2.5% missing data)	(n=632; 5% missing data)
Students of all other races	(n=25,226; 7% missing data)	(n=725; 7.7% missing data)	(0 students of all other races)
NAEP Social/physical risk index (0-3)**			
AI/AN students	(n=1,619; 0% missing data)	(n=2,459; 0% missing data)	(n=641; 3.6% missing data)
Students of all other races	(n=26,468; 2.4% missing data)	(n=765; 2.6% missing data)	(0 students of all other races)
NAEP Home risk index* (0-5)**			
AI/AN students	(n=1,115; 31.2% missing data)	(n=1,917; 22% missing data)	(n=473; 28.9% missing data)
Students of all other races	(n=20,546; 24.2% missing data)	(n=600; 23.6% missing data)	(0 students of all other races)
NAEP Classroom risk index** (0-2)**			
AI/AN students	(n=1,553; 4.1% missing data)	(n=1,714; 30.3% missing data)	(n=507; 23.8% missing data)
Students of all other races	(n=24,184; 10.8% missing data)	(n=282; 64.1% missing data)	(0 students of all other races)

Notes. Values are based upon weighted estimates.

**how often you feel you have a clear understanding of what your mathematics teacher is asking you to do and attitude toward mathematics*

***the student is ELL, the student has a disability, and the number of days absent in the last month*

****mother's education level, number of books in the home, eligibility for the National School Lunch Program, how often people in your home talk to each other in a language other than English, and how often you talk about things you have studied in school with someone in your family*

*****mathematics class enrolled in this year and being taught by a highly qualified teacher*

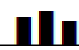
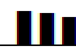
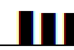
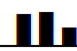
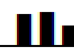
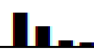
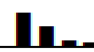
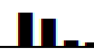
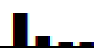
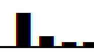
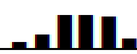
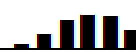
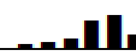
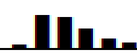
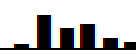
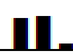
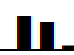
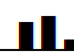
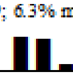
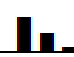
On the *NAEP Knowledge/attitudes risk index*, unexpectly, BIE school students had the least amount of risk factors among all students in each school density type in Arizona. More students in public schools had one or two risk factors compared to BIE school students, which meant the student either didn't have a clear understanding of what the mathematics teacher was asking or the student didn't like learning mathematics.

Students of all other races had the least number of risk factors (most had zero) on the *NAEP Social/physical risk index* while most AI/AN students had one risk factor on this risk index. None of the AI/AN students in public low density schools or students of all other races in public high density schools in Arizona had all three risk factors on the *NAEP Social/physical risk index*. More BIE school students had one or two risk factors compared to students of all other races (meaning the student was identified as being either ELL, having a disability, or was absent 3 or more days in the last month).

Students of all other races had fewer risk factors on the *NAEP Home risk index* compared to AI/AN students. In fact, students of all other races in public high density schools in Arizona had the least number of risk factors on this risk index (i.e., more students had two risk factors). AI/AN students in public low and high density schools in Arizona had about the same number of risk factors on this risk index (with slightly more public high density school students having four risk factors) while BIE school students had the most risk factors on this risk index (two, three, or four risk factors). The risk factors in the *NAEP Home risk index* were *mother's education level*, *number of books in the home*, *eligibility for the National School Lunch Program*, *how often people talk in your home in a language other than English* and *how often you talk about things you studied in school with someone in your family*. There was a high amount of missing data in the *NAEP Home risk index* for Arizona students (22-31%).

AI/AN students in public low density schools and students of all other races in public low and high density schools in Arizona had the least amount of risk factors on the *NAEP Classroom risk index*: most students had zero risk factors, some had one risk factor, and very few had two risk factors. Again, BIE school students had the most risk factors overall on the *NAEP Classroom risk index* (mostly one risk factor). AI/AN students in public high density schools in Arizona had the highest number of students with two risk factors (either not taking algebra/geometry or not having a teacher who stated he/she was a highly-qualified teacher this year). There was a big range of missing data in the *NAEP Classroom risk index* for Arizona students (4-30% for AI/AN students and 11-64% for students of all other races).

Table 4.19: *Distribution of scores on the NAEP risk indices by Race and School Density Type in South Dakota*

	NAEP Knowledge/attitudes risk index* (0-2)		
	Public low density	Public high density	BIE
AI/AN students	(n=345; 2.7% missing data) 	(n=571; 4.9% missing data) 	(n=405; 8.7% missing data) 
Students of all other races	(n=4,440; 4.6% missing data) 	(n=227; 6.61% missing data) 	(0 students of all other races)
	NAEP Social/physical risk index** (0-3) (no one in South Dakota had all three risk factors)		
AI/AN students	(n=351; 0.9% missing data) 	(n=591; 1.7% missing data) 	(n=434; 2% missing data) 
Students of all other races	(n=4,553; 2.2% missing data) 	(n=233; 3.9% missing data) 	(0 students of all other races)
	NAEP Home risk index*** (0-5)		
AI/AN students	(n=276; 24.6% missing data) 	(n=444; 26.2% missing data) 	(n=178; 59.8% missing data) 
Students of all other races	(n=3,899; 16.2% missing data) 	(n=207; 14.7% missing data) 	(0 students of all other races)
	NAEP Classroom risk index**** (0-2)		
AI/AN students	(n=328; 7.3% missing data) 	(n=554; 7.8% missing data) 	(n=386; 12.9% missing data) 
Students of all other races	(n=4,359; 6.3% missing data) 	(n=218; 10.3% missing data) 	(0 students of all other races)
Notes. Values are based upon weighted estimates.			

**how often you feel you have a clear understanding of what your mathematics teacher is asking you to do and attitude toward mathematics*
***the student is ELL, the student has a disability, and the number of days absent in the last month*
****mother's education level, number of books in the home, eligibility for the National School Lunch Program, how often people in your home talk to each other in a language other than English, and how often you talk about things you have studied in school with someone in your family*
*****mathematics class enrolled in this year and being taught by a highly qualified teacher*

AI/AN students in South Dakota had more risk factors on the *NAEP Knowledge/attitudes risk index* compared to students of all other races with BIE school students having the most risk factors on this risk index (i.e., more students had two risk factors) compared to students of all other races.

No one in South Dakota had all three risk factors on the *NAEP Social/physical risk index* and very few had two risk factors. Students of all other races had fewer risk factors on the *NAEP Social/physical risk index* compared to AI/AN students in South Dakota. BIE school students had more risk factors (i.e., more students had one risk factor) on the *NAEP Social/physical risk index* compared to students of all other races in the public school density types.

Overall, students of all other races in South Dakota had fewer risk factors on the *NAEP Home risk index* compared to AI/AN students. BIE school students had the highest number of risk factors on this risk index compared to students of all other races in public low and high density schools (i.e., more students had three and four risk factors). Unfortunately, 60% of the data were missing for BIE school students in South Dakota on the *NAEP Home risk index*.

Overall, students of all other races in South Dakota had fewer risk factors on the *NAEP Classroom risk index* compared to AI/AN students. BIE school students had the highest number of risk factors on the *NAEP Classroom risk index* with slightly more students with 1 or 2 risk factors compared to students of all other races in public low and high density schools.

Summary of the distributions of the NAEP risk indices. Not surprisingly, students of all other races had fewer risk factors on each of the NAEP risk indices compared to AI/AN students. BIE school students had the highest number of risk factors on all the NAEP risk indices in both states and across all the school density types, except for the *NAEP Knowledge/attitudes risk index*. BIE school students in Arizona had the lowest number of risk factors on the *NAEP Knowledge/attitudes risk index* compared to all other AI/AN students in both states and school density types. There was a substantial amount of missing data on the *NAEP Home risk index* because of the mother's education level variable, which varied by state and school density type from 15-60%. Similarly, there was a substantial amount of missing data on the *NAEP Classroom risk index* because of the *highly-qualified teacher this year* variable, which varied by state and school density type (6-13% in South Dakota and 4-64% in Arizona).

Research Question 2b: Distributions of scores from the NIES risk indices

The *NIES Student risk index* comprised two derived risk factors: *participation in AI/AN cultural activities* and *knowledge of AI/AN culture.* The N for this risk index was 5,934 with 3.4% missing data. Having zero risk factors on this risk index meant that the student participated in AI/AN cultural activities and had knowledge of AI/AN culture. Having one risk factor on this risk index meant that the student either didn't participate very much in AI/AN cultural activities or didn't have very much knowledge of AI/AN culture. Having two risk factors on this risk index meant that the student didn't participate very much in AI/AN cultural activities and didn't have very much knowledge of AI/AN culture.

The *NIES Home risk index* comprised two individual items: *how often the student's family helps with homework* and *how often the student talks to his/her family about classes and his/her future*. The N for this risk index was 5,971 with 2.8% missing data. Having zero risk factors on this risk index meant that the student's family often helped with homework and the student often talked with family about classes and his/her future. Having one risk factor on this risk index meant that either the student's family didn't help very much with homework or the student didn't often talk to his/her family about classes and his/her future. Having two risk factors on this risk index meant that the student's family didn't help very much with homework and the student didn't often talk to his/her family about classes and his/her future.

The *NIES School risk index* comprised two derived risk factors and one individual item: *safe and orderly schools, classes offered in AI/AN topics,* and *percent of AI/AN teachers in the school*. The N for this risk index was 5,298 with 13.8% missing data. Having zero risk factors on this risk index meant that the student was in a safe and orderly school, had a lot of instruction in AI/AN topics, and had a high percentage of AI/AN teachers in the school. Having three risk factors on this risk index meant that the student was not in a safe and orderly school, did not have a lot of instruction in AI/AN topics, and had a low percentage of AI/AN teachers in the school.

The distributions of scores from the three NIES risk indices were created using the overall student weight (ORIGWT). The scores in each cell are shown from lowest to highest (left to right, respectively). The number of students in each group was normalized to a number between 0 and 9[35] and then plotted in a bar graph in each cell of the table. Table 4.20 shows the distribution of scores on all three of the NIES risk indices in each state. A summary of themes from the NIES risk indices follows the tables.

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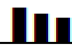
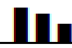
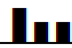
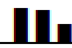
[35] Each number was divided by the largest number in the group, which was multiplied by 9, and then rounded.

Table 4.20: *Distribution of scores on NIES risk indices by State*

	NIES Student Risk Index* (0-2)	NIES Home Risk Index** (0-2)	NIES School Risk Index*** (0-3)
Arizona	(n=4,617; 2.7% missing data) 	(n=4,609; 2.8% missing data) 	(n=4,157; 12.4% missing data) 
South Dakota	(n=1,317; 5.8% missing data) 	(n=1,362; 2.6% missing data) 	(n=1,141; 18.5% missing data) 
Notes. Values are based upon weighted estimates.			

* *participation in AI/AN cultural activities* and *knowledge of AI/AN culture*

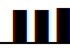
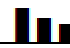
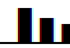
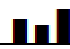
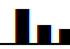
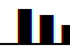
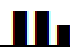
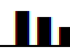
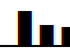
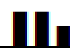
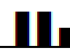
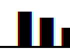
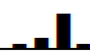
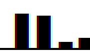
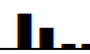
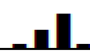
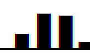
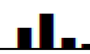
** *how often the student's family helps with homework* and *how often the student talks to his/her family about classes and his/her future*

*** *safe and orderly schools, classes offered in AI/AN topics,* and *percent of AI/AN teachers in the school*

The distributions of scores on the *NIES Student risk index* and the *NIES Home risk index* were very similar. More students in Arizona and South Dakota had zero risk factors on the *NIES Student risk index* and the *NIES Home risk index* with a steady decrease in the number of students with one and two risk factors on these two indices with the exception of students in South Dakota who had a similar number of students with one and two risk factors on the *NIES Student risk index*. More students in Arizona had 0, 1, or 2 risk factors on the *NIES School risk index* while most students in South Dakota had 1 or 2 risk factors on the *NIES School risk index*. Twelve percent of the data were missing in Arizona and 19% of the data were missing in South Dakota on the *NIES School risk index*. Among all the AI/AN students in both states, within the *NIES School risk index*, the *safe and orderly schools* derived risk factor had 8% missing data, *classes offered in AI/AN topics* derived risk factor had 10% missing data, and the *percent of AI/AN teachers in the school* had 10% missing data.

Table 4.21 shows the distribution of scores for each risk index by state and school density type.

Table 4.21: *Distribution of scores on the NIES risk indices by state and school density type*

	Public low density	Public high density	BIE
NIES student risk index* (0-2)			
Arizona	(n=1,574; 2.8% missing data) 	(n=2,408; 2.1% missing data) 	(n=635; 4.5% missing data) 
South Dakota	(n=337; 4.8% missing data) 	(n=577; 4.1% missing data) 	(n=403; 9% missing data) 
NIES home risk index (0-2)**			
Arizona	(n=1,551; 4.2% missing data) 	(n=2,409; 2.1% missing data) 	(n=650; 2.3% missing data) 
South Dakota	(n=337; 4.8% missing data) 	(n=595; 1.1% missing data) 	(n=431; 2.9% missing data) 
NIES school risk index* (0-3)**			
Arizona	(n=1,316; 18.8% missing data) 	(n=2,288; 7% missing data) 	(n=553; 16.8% missing data) 
South Dakota	(n=316; 10.9% missing data) 	(n=475; 21% missing data) 	(n=350; 21.1% missing data) 

Notes. Values are based upon weighted estimates.

* *participation in AI/AN cultural activities* and *knowledge of AI/AN culture*

** *how often the student's family helps with homework* and *how often the student talks to his/her family about classes and his/her future*

*** *safe and orderly schools, classes offered in AI/AN topics,* and *percent of AI/AN teachers in the school*

More public low density school students in both states had two risk factors on the *NIES Student risk index* compared to public high density and BIE school students, meaning more public low density school students did not participate in AI/AN cultural activities often and did not have a lot of knowledge of AI/AN culture. Not surprisingly, most public high density and BIE school students had zero risk factors on the *NIES Student risk index*. Public high density school students in South Dakota actually had the lowest number of risk factors on the *NIES Student risk index*.

Again, more public low density school students in both states had more risk factors on the *NIES Home risk index* compared to public high density and BIE school students, meaning more students' families never/hardly ever/once or twice a month helped with homework and more students never/one time talked to his/her family about classes and his/her future. Surprisingly, public high density school students in South Dakota had almost the same distribution of risk factors as the public low density school students (the public high density school students had slightly fewer students with two risk factors compared to public low density school students). Public high density school students in Arizona and BIE school students in South Dakota had the same distribution of risk factors on this risk index while BIE school students in Arizona had fewer students with one risk factor compared to all other school density types in both states, which meant BIE school students in Arizona had the least number of risk factors on this risk index compared to all other school density types in both states.

The most variation in the distribution of scores on the risk indices occurred within each school density type in each state on the *NIES School risk index*. Interestingly, and similar to the *NIES Home risk index*, more Arizona BIE school students had zero risk factors on the *NIES School risk index* compared to any other school density type in either state.

The *NIES School risk index* had the most missing data of the three NIES risk indices varying from 7-21% by stratum. Public low density school students in both states had similar distributions on the *NIES School risk index* with most students having 2 risk factors and none having 0 or 3 risk factors (because all the students were in schools that were safe and orderly and in which 25% or less of the teachers were AI/AN). Public high density school students in Arizona mostly had 0 or 1 risk factors with some having 2 or 3 risk factors while public high density school students in South Dakota mostly had 1 or 2 risk factors with some having 0 or 3 risk factors. Most of the Arizona BIE school students had zero risk factors and none had 2 or 3 on this risk index while most of the South Dakota BIE school students had one risk factor on this risk index and none had three (because all the students were in school that offered 5 or more classes in AI/AN culture/tradition).

Summary of the distributions of the NIES risk indices. As expected, public high density and BIE school students had the least number of risk factors on the *NIES Student* and *Home risk indices* while the public low density school students had the most. Arizona BIE school students had the least number of risk factors on the *NIES Home* and *School risk index* compared to students of all other races on all other NIES risk indices. The *NIES School risk index* had the most missing data of the three NIES risk indices varying from 7-21% by stratum.

Research Question 3a: Results from OLS regressions of NAEP 8th grade mathematics achievement on NAEP risk indices and student body composition variables

Six OLS regression models, one for each of the school density types in each state, were created using the NAEP risk indices and student body composition variables using AM software[36]. The purpose of research question 3a is to see which of the risk indices created using the NAEP background questionnaires and school administration records are associated with 8th grade mathematics achievement in each of the six strata.

[36] All regressions were conducted using AM software. AM is a statistical software package specially designed for analyzing data from complex, large-scale sampling designs that are not based on random sampling of a population, such as NAEP. The software uses plausible values to estimate achievement scores and replicate weights to provide correct standard errors (American Institutes for Research, 2006).

Each risk index was grand mean centered (i.e., the mean of each risk index was calculated and then subtracted from each student's risk on that index), thus, the interactions were also grand mean centered. The following risk indices were entered into the model one at a time:

- *NAEP Knowledge/attitudes risk index - clear understanding of math teacher*, *attitude toward mathematics*
- *NAEP Social/physical risk index - ELL*, *disability*, *days absent*
- *NAEP Home risk index - mother's education level*, *number of books in home*, *eligibility for NSLP*, *talk language other than English at home*, *talk to family about school*
- *NAEP Classroom risk index - level of math class* and *highly-qualified teacher this year*

The significant risk indices remained in the model and were entered into the model in order of the proportion of variance accounted for (largest to smallest).

Next, five school-level dummy variables, created using the main NAEP student-level data (i.e., the data for students of all races in each state), were entered into the public low and high density school models one at a time to represent student body composition. Since these were used as contextual variables at the school level, the data for each of these student-level variables were aggregated to the school level to get the proportion of students in each school with an entry of "1" for each of the following:

- *number of students eligible for the National School Lunch Program* for AI/AN students and students of all other races – aggregated to school level (1. not eligible, 0. eligible)

- *number of books in the home* for AI/AN students and students of all other races - aggregated to school level (1. more than 100 books, 0. 100 books or less)
- *parental education* for AI/AN students and students of all other races – aggregated to the school level (1. graduate college, 0. less than college education)
- *school-report student race* for AI/AN students and students of all other races – aggregated to school level - Hispanic/Black (1. yes, 0. no) and White/Asian American/Pacific Islander (1. yes, 0. no). AI/AN was used as the reference group.

These individual student body composition risk factors were entered into the model one at a time and remained in the model if they were significant. These variables were not included in the BIE school models since there were no students of other races in those schools. The purpose of including these variables was to see if any of them accounted for significant differences in 8th grade mathematics achievement over and above that which was account for by the NAEP risk indices. Interactions were added into the model for any of the NAEP risk indices and/or student body composition variables that were significantly related to achievement in order to estimate the main effect of each risk factor index without regard to any overlapping covariation with the other risk indices. None of the interactions were significant; therefore, they were not included in the final models in each stratum.

This process was repeated six times, for each of the school density types in each state. Appendix E describes the step-by-step process for each model using listwise deletion for the NAEP risk indices. Appendix G describes the step-by-step process for each model using conditional mean substitution for the NAEP risk indices. Table 4.22 shows the final models in each stratum using listwise deletion.

Table 4.22: *Final Results of OLS regression models using NAEP 8th grade mathematics achievement regressed on NAEP risk indices and student body composition variables for each stratum using listwise deletion*			
	Final model –Arizona public low density school students		
	z	*B*	*SE B*
NAEP Social/ physical	-4.03	-31.17	7.73
NAEP Knowledge/ attitudes	-2.33	-14.45	6.2
Notes. Adjusted R^2= 0.31 (p < 0.001)			
	Final model – Arizona public high density school students		
NAEP Social / physical	-7.93	-19.13	2.41
NAEP Home	-3.13	-6.05	1.93
Notes. Adjusted R^2= 0.23 (p < 0.001)			
	Final model - Arizona BIE school students		
NAEP Social / physical	-7.31	-18.89	2.58
NAEP Knowledge / attitudes	-4.73	-12.43	2.63
Notes. Adjusted R^2= 0.32 (p < 0.001)			
	Final model – South Dakota public low density school students		
NAEP Social/ physical	-4.75	-25.56	5.34
NAEP Knowledge/attitudes	-2.87	-10.62	3.7
Notes. Adjusted R^2= 0.38 (p < 0.001)			
	Final model – South Dakota public high density school students		
NAEP Social / physical	-4.18	-16.68	3.99
NAEP Home	-4.93	-9.55	1.94
Notes. Adjusted R^2= 0.23 (p < 0.001)			
	Final model – South Dakota BIE school students		
NAEP Classroom	-2.72	-11.94	4.38
Notes. Adjusted R^2= 0.07 (p= 0.009) Values are based upon weighted estimates.			

All of the final models for the NAEP risk indices using both listwise deletion and conditional mean substitution included the *NAEP Social/physical risk index*, except for the final model for South Dakota BIE school students, which only included the *NAEP Classroom risk index*. Although 13% of the data were missing using listwise deletion for the *NAEP Classroom risk index* for South Dakota BIE school students, using conditional mean substitution, the results were the same: only the *NAEP Classroom risk index* was significant.

Surprisingly, the final models for Arizona public low density and BIE school students included the same NAEP risk indices using both listwise deletion and conditional mean substitution: the *NAEP Social/physical* and the *NAEP Knowledge/attitudes risk indices*.

The final model for South Dakota public low density school students was the only final model that included a student body composition variable: *Hispanic/Black*. However, the *Hispanic/Black* variable had a very high standard error (33.51 for listwise deletion and 32.44 for conditional mean substitution), which was well above the standard errors for all of the other coefficients (the highest being 7.73 for the *NAEP Social/physical risk index* in the final model for the Arizona public low density school students), and was associated with about a 100-point decrease in mathematics score, on average. The final model without the *Hispanic/Black* variable using both listwise deletion and conditional mean substitution contained the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index*, which matched the final model for the Arizona public low density school students and seemed plausible. The final models that included the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index* accounted for 38% (listwise deletion) and 37% (conditional mean substitution) of the variation in NAEP 8th grade mathematics achievement, which was slightly higher than the final models that included the *NAEP Social/physical risk index* and *Hispanic/Black* (36% and 35%, respectively). Therefore, the final model that included the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index* was determined to be a better fit for South Dakota public low density school students.

Not surprisingly, the final models for the public high density schools in both states also included the same NAEP risk indices using listwise deletion: the *NAEP Social/physical* and the *NAEP Home risk indices*. However, using conditional mean substitution, the final model for South Dakota public high density schools also included the *NAEP Knowledge/attitudes risk index*. Although, the *NAEP Knowledge/attitudes risk index* only account for an additional 2% of variance in achievement for the South Dakota public high density school students, so it wasn't adding very much to the model.

Summary of results from OLS regressions of NAEP 8th grade mathematics achievement on NAEP risk indices and student body composition variables. All of the final models for the NAEP risk indices contained the *NAEP Social/physical risk index*, except for the final model for South Dakota BIE school students, which only included the *NAEP Classroom risk index*. Surprisingly, the final models for Arizona and South Dakota public low density school students were the same as the final model for Arizona BIE school students. In all of the final models, a one-unit increase in the NAEP risk index was associated with a significant decrease in NAEP 8^{th} grade mathematics achievement. No student body composition variables were fitted into the final models.

All of the final models using the NAEP risk indices accounted for 23-36% of the variation in NAEP 8^{th} grade mathematics achievement (25-35% in the conditional mean substitution models), except for the *NAEP Classroom risk index* in the final model for the South Dakota BIE schools, which only account for 7% of the variance (9% in the conditional mean substitution model).

Research Question 3b: Results from OLS regressions of NAEP 8th grade mathematics achievement on NAEP risk indices, student body composition variables, NIES risk indices, NIES derived risk factor, and NIES individual item

Similar to research question 3a, six OLS regression models, one for each of the school density types in each of the states, were created using the NIES and NAEP risk indices. The difference between questions 3a and 3b is that 3a examined the NAEP questionnaires, school administration records, and student body composition variables while 3b looked at the NIES questionnaires and incorporated them into the results from research question 3a. The purpose of research question 3b is to see which of the NIES and NAEP risk indices were associated with 8th grade mathematics achievement in each of the six strata and what the incremental contribution of the NIES risk indices were to explained variance after accounting for the NAEP risk indices.

As described previously, listwise deletion and conditional mean substitution were used. Each NIES risk index, the NIES individual item, and the NIES derived risk factor were grand mean centered (i.e., the mean of each risk index/factor was calculated and then subtracted from each student's risk on that index/factor), thus, the interactions were also grand mean centered. The following risk indices and predictors were entered individually into a model with achievement (five plausible values) as the outcome variable:

- *NIES Student Risk Index - participation in AI/AN culture, knowledge of AI/AN culture*
- *NIES Home Risk Index - family helps with schoolwork, talk to family about future*

- NIES individual item - *Self-confidence in mathematics* - *how do you rate yourself in math:* very good, good, average, poor (see Appendix D for more information on how this item was dichotomized)
- NIES derived risk factor - *Teachers incorporate AI/AN culture/tradition into their mathematics instruction* - once/month or more, at least once/year, never (see creation of derived risk factor in Appendix C for more information).
- *NIES School Risk Index* - *safe and orderly schools*, *classes offered in AI/AN topics*, *percent of AI/AN teachers in the school*

Once the NIES predictors were vetted, six new models were created. First, the significant NAEP risk indices from research question 3a were added to the model (no student body composition variables remained in the final models for research question 3a; therefore, none were included in research question 3b). Then, the significant NIES predictors were added one at a time to see how much variation in achievement could be accounted for by the NIES predictors -- over and above that which was accounted for by the NAEP risk indices. Interactions were added into the model for any of the risk indices, individual item, and derived risk factor significantly related to achievement in order to estimate the main effect of each risk factor index, individual item, and derived risk factor without regard to any overlapping covariation with the other risk indices.

This process was repeated six times for each of the school density types in each state. Appendix F describes the step-by-step process for each model using listwise deletion for the NAEP 8th grade mathematics achievement regressed on NAEP and NIES predictors. Appendix H describes the step-by-step process for each model using conditional mean substitution. Table 4.23 shows the final models in each stratum using listwise deletion.

Table 4.23: *Final Results of OLS regression models using the NAEP 8th grade mathematics achievement regressed on NAEP and NIES risk indices, NIES individual item, and NIES derived risk factor for each stratum using listwise deletion*

	Final model –Arizona public low density school students		
	z	*B*	*SE B*
NAEP Social/ physical	-4.03	-31.17	7.73
NAEP Knowledge/ attitudes	-2.33	-14.45	6.2
Notes. Adjusted R^2= 0.31 (p < 0.001)			
	Final model – Arizona public high density school students		
NAEP Social / physical	-6.36	-17.37	2.73
NAEP Home	-2.65	-5.92	2.23
NIES individual item *self-confidence in mathematics*	-2.99	-11.73	3.92
Notes. Adjusted R^2= 0.24 (p = 0.002)			
	Final model - Arizona BIE school students		
NAEP Social / physical	-5.36	-16.82	3.14
NAEP Knowledge/ attitudes	-4.51	-13.07	2.9
NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*	2.34	11.25	4.81
Notes. Adjusted R^2= 0.35 (p < 0.001)			
	Final model – South Dakota public low density school students		
NAEP Social/ physical	-4.75	-25.56	5.34
NAEP Knowledge/attitudes	-2.87	-10.62	3.7
Notes. Adjusted R^2= 0.38 (p < 0.001)			
	Final model – South Dakota public high density school students		
NAEP Social / physical	-3.63	-15.43	4.26
NAEP Home	-4.55	-9.07	1.99
NIES individual item *self-confidence in mathematics*	-4.09	-18.66	4.56
NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*	3.04	16.43	5.4
Notes. Adjusted R^2= 0.38 (p < 0.001)			
	Final model – South Dakota BIE school students		
NAEP Classroom	-2.32	-10.45	4.5
NIES School	2.00	8.84	4.4
Notes. Adjusted R^2= 0.11 (p= 0.02) Values are based upon weighted estimates.			

Interestingly, using listwise deletion, the final models for Arizona and South Dakota public high density and BIE school students included NIES predictors while the final models for Arizona and South Dakota public low density schools did not. (Using conditional mean substitution, South Dakota public high density schools also did not include any NIES predictors.)

Similar to research question 3a, all of the final models using the NAEP and NIES predictors using both listwise deletion and conditional mean substitution included the *NAEP Social/physical risk index*, except for the final model for South Dakota BIE school students, which included the *NAEP Classroom* and *NIES School risk indices*. Although 13% of the data were missing using listwise deletion for the *NAEP Classroom risk index* and 21% of the data were missing using listwise deletion for the *NIES School risk index* for South Dakota BIE school students, using conditional mean substitution, the results were the same: the *NAEP Classroom* and *NIES School risk indices* were both significant. For South Dakota BIE school students, a one-unit unit increase in the *NAEP Classroom risk index* (not taking algebra or geometry for *mathematics class this year* and not being taught by a teacher who stated he/she was a *highly-qualified teacher*) was associated with an 11-point decrease in mathematics score (14 points using conditional mean substitution), on average. A one-unit increase in the *NIES School risk index* (not being in a *safe and orderly school* and having 25% or less of the *teachers in the school identifying as AI/AN*[37]) was associated with a 9-point increase in mathematics score (8 points using conditional mean substitution), on average. These two risk indices explained 11% of the variation in mathematics achievement (13% using conditional mean substitution).

[37] None of the BIE school students in South Dakota were in schools that offered four classes or less in AI/AN culture.

The final NAEP model, shown in Table 4.24, which included only the *NAEP Classroom risk index*, accounted for 7% of the variation in achievement (9% using conditional mean substitution). Thus, adding the *NIES School risk index* increased the amount of variation accounted for in mathematics achievement 4% over and above that which was accounted for by the NAEP risk index for students in South Dakota BIE schools.

For Arizona BIE school students, in addition to the *NAEP Social/physical* and the *NAEP Knowledge/attitudes risk indices* (same as the final model in research question 3a), the final model also included the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*. For Arizona BIE school students, for each unit increase in the *NAEP Social/physical risk index* (*having a disability*, *being ELL*, and *being absent 3 or more days in the last month*), their mathematics score, on average, decreased 17 points (19 points using conditional mean substitution). For each unit increase in the *NAEP Knowledge/attitudes risk index* (not liking math/somewhat *liking math*, and never/hardly ever/sometimes *clearly understanding what the mathematics teacher is asking*), their mathematics score, on average, decreased 13 points (12 points using conditional mean substitution). Surprisingly, for each unit increase in the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*, their mathematics score, on average, increased 11 points (14 points using conditional mean substitution). This means having a *teacher who incorporated AI/AN culture/tradition into their mathematics instruction* at least once a year or never increased achievement, on average, by 11 points. These two NAEP risk indices and NIES derived risk factor explained 35% of the variation in mathematics achievement (37% using conditional mean substitution).

The final NAEP model, shown in Table 4.24, which included the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index*, accounted for 32% of the variation in achievement (34% using conditional mean substitution). Thus, adding the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* increased the amount of variation account for in mathematics achievement 3% over and above that which was accounted for by the NAEP risk indices for students in Arizona BIE schools.

For Arizona public high density school students, in addition to the *NAEP Social/physical* and the *NAEP Home risk indices* (same as the final model in research question 3a), the final model using listwise deletion also included the NIES individual item, *self-confidence in mathematics*. For Arizona public high density school students, for each unit increase in the *NAEP Social/physical risk index* (*having a disability*, *being ELL*, and *being absent 3 or more days in the last month*), their mathematics score, on average, decreased 17 points (23 points using conditional mean substitution). For each unit increase in the *NAEP Home risk index* (having a mother who didn't finish high school or graduated high school, having 0-25 *books in the home*, being *eligible for the NSLP*, *speaking a language other than English at home* at least half of the time or more, and never/hardly ever/every few weeks *talk about studies at home*), their mathematics score, on average, decreased 6 points. For each unit increase in the NIES individual item *self-confidence in mathematics*, their mathematics score, on average, decreased 12 points (13 points using conditional mean substitution). This means that rating themselves in mathematics as poor or average was associated, on average, with a 12-point decrease in achievement. These two NAEP risk indices and NIES predictor explained 24% of the variation in mathematics achievement using listwise deletion.

Interestingly, using conditional mean substitution, the *NAEP Home risk index* was no longer significant after adding the NIES individual item *self-confidence in mathematics* (a response on the *NAEP Home risk index* was missing for 22% of the Arizona public high density school students using listwise deletion), which meant the final model using conditional mean substitution was more parsimonious. It also accounted for slightly more variation in achievement than the final model using listwise deletion (28% vs. 24%). However, since the final models for all the other strata used listwise deletion and the final model for South Dakota public high density schools also included the *NAEP Home risk index*, a decision was made that the final model for Arizona public high density school students would be the version using listwise deletion, which included the *NAEP Social/physical risk index*, the *NAEP Home risk index*, and the NIES individual item *self-confidence in mathematics*.

The final NAEP model for Arizona public high density school students using both listwise deletion and conditional mean substitution accounted for 1% more variation in achievement over and above that which was accounted for by the NAEP risk indices when the NIES individual item *self-confidence in mathematics* was added to the model.

For South Dakota public high density school students, using conditional mean substitution, the final model remained the same as in research question 3a, with no NIES predictors: *NAEP Social/physical*, *NAEP Home*, and *NAEP Knowledge/attitudes risk indices*. However, using listwise deletion, in addition to *the NAEP Social/physical* and the *NAEP Home risk indices* (same as the final model in research question 3a), the final model also included both the NIES individual item *self-confidence in mathematics* and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*. These two NAEP risk indices and NIES predictors explained 38% of the variation in mathematics achievement using listwise deletion while the *NAEP Social/physical*, *NAEP Home*, and *NAEP Knowledge/attitudes risk indices* explained only 25% of the variance using conditional mean substitution. Therefore, the model using listwise deletion was chosen as the final model.

For South Dakota public high density school students, for each unit increase in the *NAEP Social/physical risk index* (*having a disability*, *being ELL*, and *being absent 3 or more days in the last month*), their mathematics score was associated with a decrease in achievement of 15 points, on average. For each unit increase in the *NAEP Home risk index* (having a mother who didn't finish high school or graduated high school, having 0-25 *books in the home*, being *eligible for the NSLP*, *speaking a language other than English at home* at least half of the time or more, and never/hardly ever/every few weeks *talk about studies at home*), their mathematics score was associated with a decrease in achievement of 9 points (5 points using conditional mean substitution), on average. For each unit increase in the NIES individual item *self-confidence in mathematics*, their mathematics score was associated with a decrease in achievement of 19 points, on average. For each unit increase in the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*, their mathematics score was associated with an increase in achievement of 16 points, on average. Thus, rating yourself as poor or average in mathematics was associated, on average, with a 19-point decrease in achievement and having a *teacher who incorporated AI/AN culture/tradition into their mathematics instruction* at least once a year or never was associated, on average, with an increase in achievement of 16 points.

The final NAEP model for South Dakota public high density school students from Table 4.24 included the *NAEP Social/physical risk index* and the *NAEP Home risk index* and accounted for 23% of the variation in achievement. Thus, adding the NIES risk factors *self-confidence in mathematics* and *teachers incorporate AI/AN culture/tradition into their mathematics instruction* increased the amount of variation account for in mathematics achievement 15% over and above that which was accounted for by the NAEP risk indices.

As stated previously, the final models for students in Arizona and South Dakota public low density schools did not include any NIES predictors. As in research question 3a, the final models for Arizona and South Dakota public low density school students included the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitude risk index*. For Arizona public low density school students, for each unit increase in the *NAEP Social/physical risk index* (*having a disability*, *being ELL*, and *being absent 3 or more days in the last month*), their mathematics score was associated, on average, with a decrease in achievement of 31 points (32 points using conditional mean substitution) and for each unit increase in the *NAEP Knowledge/attitudes risk index* (not liking math/somewhat *liking math,* and never/hardly ever/sometimes *clearly understanding what the mathematics teacher is asking*), their mathematics score was associated, on average, with a decrease in achievement of 15 points. These two risk indices explained 31% of the variation in mathematics achievement.

For South Dakota public low density school students, for each unit increase in the *NAEP Social/physical risk index* (*having a disability*, *being ELL*, and *being absent 3 or more days in the last month*), their mathematics score was associated, on average, with a decrease in achievement of 26 points (25 points using conditional mean substitution) and for each unit increase in the *NAEP Knowledge/attitudes risk index* (not liking math/somewhat *liking math,* and never/hardly ever/sometimes *clearly understanding what the mathematics teacher is asking*), their mathematics score was associated, on average, with a decrease in achievement of 11 points. These two risk indices explained 38% of the variation in mathematics achievement (37% using conditional mean substitution).

Summary of results from OLS regressions of NAEP 8th grade mathematics achievement on NAEP and NIES risk indices, the NIES individual item, and the NIES derived risk factor. Similar to research question 3a, all of the final models using the NAEP and NIES predictors using both listwise deletion and conditional mean substitution included the *NAEP Social/physical risk index*, except for the final model for South Dakota BIE school students, which included the *NAEP Classroom* and *NIES School risk indices*. Interestingly, using listwise deletion, the final models for Arizona and South Dakota public high density and BIE school students included NIES predictors while the final models for Arizona and South Dakota public low density schools did not include any NIES predictors. In each case, the addition of the NIES risk index/individual item/derived risk factor increased the amount of variation accounted for in mathematics achievement over and above that which was accounted for by the NAEP risk index. Similar to research question 3a, a one-unit increase in the NAEP risk index resulted in a significant decrease in NAEP 8th grade mathematics achievement. However, a one-unit increase in the NIES risk index and derived risk factor related to AI/AN-specific topics (*NIES School risk index* and NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*) resulted in a significant increase in NAEP 8th grade mathematics achievement. This was not the case with the NIES individual item *self-confidence in mathematics*, which was asked in the NIES questionnaire but is known in the literature to be significantly associated with achievement for students of all races (Mullis et al, 2008; Mullis et al, 2012; Hattie, 2009).

Four out of the six final models captured the data well with the adjusted R-squared values in each model ranging from 0.31-0.38. The adjusted R-squared value for the final model for the Arizona public high density school students was 0.24. The adjusted R-squared value for final model for the South Dakota BIE school students was 0.11.

Research Question 4: Policy implications

A number of interesting results and policy implications have emerged from these analyses. Some of the results followed the pattern of achievement while others did not. As a reminder, South Dakota public low density school students scored significantly higher than South Dakota public high density and BIE school students and all AI/AN students in Arizona. South Dakota public high density school students scored significantly higher than South Dakota BIE school students and Arizona public high density and BIE school students. Arizona public low density school students scored significantly higher than Arizona public high density and BIE school students.

First, the risk indices in research question 2 were reviewed to see if there were any patterns that followed the achievement differences. Not surprisingly, students of all other races had fewer risk factors on each of the NAEP risk indices compared to AI/AN students. Also, BIE school students in both states had the highest number of risk factors on all but one of the NAEP risk indices. The BIE school students in Arizona had the least number of risk factors on the *NAEP Knowledge/attitudes risk index* (which included the derived risk factor *attitude toward mathematics* and the individual item *clear understanding of what mathematics teacher is asking*) compared to public low and high density school students in both states and BIE school students in South Dakota.

It was expected that South Dakota AI/AN students overall would have fewer risk factors than Arizona AI/AN students overall, but this was not the case. Similarly, the students with the lowest NAEP 8th grade achievement test score across the six strata (Arizona public high density school students, Arizona BIE school students, and South Dakota BIE school students) did not have more risk factors.

Next, the regression coefficients were examined to see if they followed the pattern of achievement. The regression coefficients for Arizona public low density school students were associated with a larger decrease in achievement compared to the coefficients for South Dakota public low density school students on both the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index*, which is consistent with the achievement pattern of South Dakota public low density school students scoring significantly higher than Arizona public low density school students. In other words, these two risk indices were associated with a larger decrease in achievement for Arizona public low density school students compared to public low density school students in South Dakota. No other comparisons could be made because no other final models were the same (i.e., comparable).

Finally, the results of the NAEP and NIES predictors in the final regression models were compared and additional cross tabulations were run. A discussion of the policy implications from those results, both within and across strata, is discussed next.

Results within school density type, across states: Public low density schools and the interpretation of the significant risk indices in the OLS regression models. The final NAEP risk index models from research question 3a showed that for students in public low density schools in both states, the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index* explained a significant amount of the variance in achievement. These final models remained the same for the public low density schools in both states even when the NIES predictors were introduced. In each school density type, the *NAEP Social/physical risk index* was associated with the largest decrease in achievement (31 points and 26 points, on average) followed by the *NAEP Knowledge/attitudes risk index* (14 and 11 points, on average). As stated previously, the regression coefficients for Arizona were larger than those for South Dakota.

The NAEP Social/physical risk index. The *NAEP Social/physical risk index* included whether the student was identified as *being ELL*, *having a disability*, and if the student was *absent 3 or more days in the last month*. Table 4.6 showed that there were no students in public low density schools who were identified as *being ELL*. Table 4.24 shows that in Arizona public low density schools, 32% of students *spoke a language other than English at home* at least half of the time or more while in South Dakota public low density schools, 8% of students *spoke a language other than English* at home at least half of the time or more, which means it is possible there are students in Arizona (at least) who might benefit from ELL services.

Table 4.24: *Percent (number) of AI/AN students in Arizona and South Dakota by how often the student stated that a language other than English is spoken at home by school density type**		
	Half of the time/ All or most of the time	Never/ Once in a while
	Arizona (N=4,683)	
Public low (n=1619)	32% (520)	68% (1099)
Public high (n=2421)	71% (1741)	29% (679)
BIE (n=643)	77% (492)	24% (151)
	South Dakota (N=1,349)	
Public low (n=354)	8% (29)	92% (325)
Public high (n=587)	21% (119)	80% (462)
BIE (n=406)	22% (91)	78% (323)
Notes. Values are based upon weighted estimates.		

**percentages for public high density and BIE school students will be referenced in the next sections.*

Among the public low density school students (where no one is labeled as being ELL), Table 4.6 shows that in Arizona public low density schools, 19% of the students were identified as *having a disability* and in South Dakota public low density schools, 17% of the students were identified as *having a disability*. As mentioned in the literature review in Chapter 2, Artiles et. al. (2002) found that ELL students are overrepresented in special education programs and that ELLs who were receiving the least amount of support in their primary language were more likely to be placed in special education than be given ELL services. It would be interesting to know if any of the students labeled as having a disability in the public low density schools should be receiving ELL services instead (or also).

Lastly, regarding the *number of days absent in the last month*, Table 4.25 shows that 38% of Arizona public low density school students stated they were absent 3 days or more in the last month and 29% of South Dakota public low density school students stated they were *absent 3 days or more in the last month*. Since the *number of days absent* contained the highest percentages of students in each of these strata, it is possible that this is where the focus of policy changes should rest for public low density schools in both states: figuring out how to work with students who are frequently absent to engage them in school so they have the opportunity to learn the material.

Table 4.25: *Percent (number) of AI/AN students in Arizona and South Dakota by student reported number of days absent in the last month by school density type**

	3 or more	0-2
	Arizona (N=4,734)	
Public low (n=1619)	38% (622)	62% (997)
Public high (n=2459)	38% (934)	62% (1525)
BIE (n=656)	30% (196)	70% (460)
	South Dakota (N=1,376)	
Public low (n=351)	29% (103)	71% (248)
Public high (n=591)	27% (157)	73% (434)
BIE (n=434)	34% (146)	66% (288)
Notes. Values are based upon weighted estimates.		

**percentages for public high density and BIE school students will be referenced in the next sections.*

The NAEP Knowledge/attitudes risk index. The *NAEP Knowledge/attitudes risk index* was also associated with achievement for public low density school students. This risk index included how often the student *clearly understood what the mathematics teacher was asking* and the students' *attitude toward mathematics*.

In terms of *attitude toward mathematics*, Table 4.1 showed that 56% of Arizona public low density school students and 61% of South Dakota public low density school students did not like/somewhat *like math*. Table 4.26 shows that about 31% of students in Arizona and South Dakota public low density schools never/hardly ever/sometimes *clearly understood what the mathematics teacher was asking*.

Table 4.26: *Percent (number) of AI/AN students in Arizona and South Dakota by how often the student clearly understands what the mathematics teacher is asking by school density type**

	Never/hardly ever/sometimes	Often/Always/Almost always
	Arizona (N=4,664)	
Public low (n=1572)	32% (507)	68% (1065)
Public high (n=2451)	38% (935)	62% (1516)
BIE (n=641)	38% (242)	62% (399)
	South Dakota (N=1,365)	
Public low (n=348)	31% (106)	70% (242)
Public high (n=595)	38% (223)	63% (372)
BIE (n=422)	42% (178)	58% (244)
Notes. Values are based upon weighted estimates.		

**percentages for public high density and BIE school students will be referenced in the next sections.*

Combining these results with the number of students absent 3 or more days in the last month, Table 4.27 shows that of Arizona public low density school students who were *absent 3 or more days in the last month* and never/hardly ever/*sometimes clearly understand what the mathematics teacher is asking*, 91% did not like/somewhat like *math*. For South Dakota public low density school students, it was 100% of the students.

Table 4.27: *Percent (number) of AI/AN students in Arizona and South Dakota public low density schools by number of days absent/how clearly the student understands what the mathematics teacher is asking/attitude toward math by school density type*

	Do not like math/ Somewhat like math	Like math
	Arizona public low density school students (N=234)	
Absent 3 or more days in the last month & Never/Hardly ever/sometimes understands what the mathematics teacher is asking	71% (165)	30% (69)
	South Dakota public low density school students (N=34)	
Absent 3 or more days in the last month & Never/Hardly ever/sometimes understands what the mathematics teacher is asking	100% (34)	0% (0)

Notes. Values are based upon weighted estimates.

Again, focusing on students who are absent 3 or more days in the last month and figuring out the reasons why they are absent so often may reveal how to get these students more engaged in school/learning.

Results within school density type across states: Public high density schools and the interpretation of the significant risk indices in the OLS regression models. For public high density schools in both states, the *NAEP Social/physical risk index*, the *NAEP Home risk index*, and the NIES individual item *self-confidence in mathematics* were significantly associated with achievement. Additionally, for public high density schools in South Dakota, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* was also significantly associated with achievement.

Arizona public high density schools. Similar to the public low density school strata, for public high density school students in Arizona, the *NAEP Social/physical risk index* was associated with the largest decrease in achievement (17 points, on average). In Arizona public high density schools, 12% of the students were identified as *being ELL* in Table 4.7; 13% were identified as *having a disability* in Table 4.7; and 38% of the students were *absent 3 or more days in the last month* in Table 4.27. The NIES individual item *self-confidence in mathematics* (53% of the Arizona public high density school students had low *self-confidence in mathematics*, rating themselves as poor or average in mathematics) was associated with the next largest decrease in achievement (12 points, on average). And, finally, the *NAEP Home risk index* was associated with a 6-point decrease in achievement, on average. In Arizona public high density schools, 87% of the students were *eligible for NSLP*, 62% had 25 *books of less in the home*, 52% never/hardly ever/every few weeks *talk about studies at home*, 42% had mothers who had didn't finish high school/graduated high school, and 71% *spoke a language other than English at home* at least half of the time or more from Table 4.26.

Although 71% of the students stated *speaking a language other than English at home* at least half the time or more, as mentioned previously, Table 4.7 showed only 12% of the students were classified as *being ELL*. The following results were found among the students who stated *speaking a language other than English at home* at least half the time or more: 6% were labeled as *having a disability*; 7% were labeled as *being ELL*; 5%

were labeled as having both a disability and being ELL; and 83% were not labeled as having a disability or being ELL.

Additionally, 58% of the students who were *absent 3 or more days in the last month* had low *self-confidence in mathematics* while 75% of the students who were *absent 3 or more days in the last month* and were identified as *being ELL*, had low *self-confidence in mathematics*. Finally, 51% of the students who were *absent 3 or more days in the last month* and *spoke a language other than English at home* at least half of the time or more, had low-*self confidence in mathematics*.

The conclusion for Arizona public high density school students is to work with students who are frequently absent to engage them in school so they have the opportunity to learn the material and to work with students who speak a language other than English at home to assess whether or not they would benefit from the services offered to students identified as being ELL.

South Dakota public high density schools. Unlike the results mentioned thus far, for public high density school students in South Dakota, the *NAEP Social/physical risk index* was not associated with the largest decrease in achievement. The NIES individual item *self-confidence in mathematics* (50% of the students had low *self-confidence in mathematics*) was associated with the largest decrease in achievement (19 points, on average). The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into mathematics instruction* (64% of students had *teachers who incorporate AI/AN culture/tradition into the mathematics instruction* never or at least once a year) was associated with a 16-point increase in achievement, on average. The *NAEP Social/physical risk index* (10% of the students were identified as *being ELL* in Table 4.7;

10% were identified as *having a disability* in Table 4.7; and 27% were *absent 3 or more days in the last month* in Table 4.27) was associated with a 15-point decrease in achievement, on average. And, finally, the *NAEP Home risk index* (90% were *eligible for NSLP*; 57% had 25 *books or less in the home*; 39% never/hardly ever/every few weeks *talk about studies at home*; 36% had mothers who had didn't finish high school/graduated high school; and 20% *spoke a language other than English at home* at least half of the time or more) was associated with a 9-point decrease in achievement, on average. Table 4.25 shows that the *NAEP Social/physical risk index* and the NIES individual item and derived risk factor had similar associations with achievement with the *NAEP Home risk index* have a slightly lower association.

Similar to public high density schools in Arizona, 64% of the students who were *absent 3 or more days in the last month* had low *self-confidence in mathematics*. Interestingly, 71% of students who had low *self-confidence in mathematics* had *teachers who incorporated AI/AN culture/tradition into their mathematics instruction* never or at least once a year. Although, 67% of students with high *self-confidence in mathematics* also had *teachers who incorporated AI/AN culture/tradition into their mathematics instruction* never or at least once a year. Therefore, this connection is not as meaningful as it first appeared. Regardless, understanding how *teachers incorporate AI/AN culture/tradition into their mathematics instruction* would be an important undertaking since not incorporating AI/AN culture/tradition into the mathematics instruction was associated with a 16-point increase in mathematics instruction, on average, instead of a decrease. Incorporating culture into the curriculum is intended to be a protective factor for AI/AN students (Demmert, 2001; Demmert & Towner, 2003; Deyhle, 1995;

Fenimore-Smith, 2009; Fryberg et. al., 2013; Huffman, 2010; Lipska & Adams, 2004; Tharpe, 2006; Whitbeck et. al., 2001; Zwick and Miller, 1996), which is why this risk factor was included in the analysis.

If possible, it might be helpful for South Dakota public high density schools and Arizona BIE schools to see how Arizona public high density school teachers are incorporating AI/AN culture/tradition into their mathematics curriculum since this derived risk factor was not significantly associated with achievement for Arizona public high density school students and that was the only difference in the final models for the public high density schools in each state.

Also, similar to Arizona public high density school students, public high density school students in South Dakota were from high poverty families with little support at home to talk about their studies, which was associated with a decrease in achievement. As mentioned previously, only 10% of the students were identified as *being ELL*; however, 20% of them *spoke a language other than English at home*.

Unlike in the public low density schools, the *NAEP Social/physical risk index*, the *NAEP Home risk index*, and the NIES individual item *self-confidence in mathematics* were not associated with a larger decrease in achievement for Arizona students, the regression coefficients were close to the same or slightly higher for these predictors for South Dakota students.

Results within school density type across states: BIE schools and the interpretation of the significant risk indices in the OLS regression models.

Arizona BIE schools. For Arizona BIE school students, similar to public low density school strata, the *NAEP Social/physical risk index* and the *NAEP*

Knowledge/attitudes risk index were significant in the final OLS regression model and the *NAEP Social/physical risk index* was associated with the largest decrease in achievement (17 points, on average) followed by the *NAEP Knowledge/attitudes risk index* (13 points, on average). However, for Arizona BIE schools, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* also was also significant (and was associated with an 11-point increase in achievement, on average). Table 4.7 shows that 40% of Arizona BIE school students were identified as *being ELL* while Table 4.26 shows that 77% *spoke a language other than English at home* at least half of the time or more. This is another discrepancy between the number of students labeled as being ELL and the number of students who state that they speak a language other than English at home at least half the time or more. Regarding the *number of days absent in the last month*, Table 4.27 shows that 30% of Arizona BIE school students were *absent 3 days or more in the last month*. Similar to public low density schools, the number of days absent is possibly where the focus of policy changes should be for Arizona BIE schools.

In terms of *attitude toward mathematics*, Table 4.1 showed that 41% of Arizona BIE school students did not like/somewhat *like math*. Table 4.28 shows that 38% of students in Arizona BIE schools never/hardly ever/sometimes *clearly understood what the mathematics teacher was asking*. Fifty-five percent of the Arizona BIE school students who were *absent 3 or more days in the last month*, never/hardly ever/sometimes *clearly understood what the mathematics teacher was asking* and did not like/somewhat *like math*. Again, focusing on students who are *absent 3 or more days in the last month* and figuring out the reasons why they are absent so often may reveal how to get these students more engaged in school/learning.

Similar to South Dakota public high density school students, for Arizona BIE school students, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* was significantly associated with achievement. Having *teachers who incorporated AI/AN culture/tradition into their mathematics instruction* never or at least once a year (56% of students, as shown in Table 4.13) actually increased achievement for Arizona BIE school students. It may be that Arizona BIE schools and South Dakota public high density schools need to examine how culture is being incorporated by the teachers in order for it to act as a protective factor and increase achievement instead of decrease achievement.

South Dakota BIE schools. Unlike the results from the other five strata, the significant risk indices in the final model for the South Dakota BIE schools were the *NAEP Classroom risk index* and the *NIES School risk index*. Within *the NAEP Classroom risk index*, Table 4.3 shows that 49% of the students were taking another mathematics class. Twenty percent were being taught by a teacher who stated he/she was not highly-qualified or a highly-qualified teacher in only one subject. Each of these risk factors was associated with a decrease in achievement for South Dakota BIE school students. Within the *NIES School risk index* for South Dakota BIE school students, 45% of the students were in schools that were not safe and orderly and 33% of the students were in schools in which 25% or less of the teachers were AI/AN. None of the students were in schools that offered four classes or less in AI/AN culture. Each of these risk factors was associated with an increase in achievement, which is hard to explain because not being in a school that is safe and orderly should decrease, not increase achievement. Likewise, being in a school in which 25% or less of the teachers were AI/AN should lead to a decrease, not increase, in achievement.

Regarding the students in schools that were not safe and orderly, 78% were in schools in which *misbehavior* was a moderate/large problem in the school; 72% were in schools in which *bullying* was a moderate/large problem in the school; 71% were in schools in which *low student aspirations* were a moderate/large problem; 67% were in schools in which *physical conflict* was a moderate/large problem in the school; 59% were in school in which *low family involvement* was a moderate/large problem; 58% were in schools in which *drug/alcohol use* was a moderate/large problem; 34% were in schools in which *health* was a moderate problem in the school (no students were in schools in which health was a large problem); and 29% were in schools in which *low teacher expectations* was a moderate problem (no students were in schools in which *low teacher expectations* was a large problem). It is hard to see how these numbers could lead to an increase in achievement. Although, this type of an outcome can occur in cross-sectional studies and, thus, argues for caution against over-interpretation of the results.

For South Dakota BIE school students, it may be important to focus on the *mathematics class* the student is taking, having the student taught by a teacher who stated he/she was a *highly-qualified teacher this year*, reducing *misbehavior*, *bullying*, *physical conflict*, *drug/alcohol use*, and increasing *student aspirations* and *family involvement* (even though not being in a safe and orderly school increased achievement).

Based on Tables 4.16 and 4.17, which displayed the distribution of *safe and orderly schools* and *school climate* at the school level in each stratum, policy changes in

South Dakota BIE schools may need to focus on *student misbehavior*, *bullying*, and *physical conflict* first and foremost among all the individual items in the *safe and orderly schools* and *school climate* derived risk factors. Table 4.16 showed that no South Dakota BIE schools were *safe and orderly* (schools in which *student misbehavior*, *bullying*, and *physical conflict* were not a large problem in the school) while Table 4.17 showed that only 15% of South Dakota BIE schools had a negative *school climate* (i.e., *student health*, student *drug/alcohol use*, *low parent involvement*, *low student aspirations*, *low teacher aspirations* were not a large problem in the school).

Although the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index* were not significant for the South Dakota BIE school students, a cross tabulation was run showing that 75% of the South Dakota BIE school students who were *absent 3 or more days in the last month* and never/hardly ever/sometimes *clearly understood what the mathematics teacher was asking*, did not like/somewhat *like math*.

Summary of the policy implications. The themes emerging from this policy analysis are:

- Students of all other races had fewer risk factors on each of the NAEP risk indices compared to AI/AN students.
- BIE school students in both states had the highest number of risk factors on all but the *NAEP Knowledge/attitudes risk*.
- South Dakota AI/AN students overall did not have fewer risk factors than Arizona AI/AN students overall.

- Students with the lowest NAEP 8th grade achievement test score across the six strata (Arizona public high density school students, Arizona BIE school students, and South Dakota BIE school students) did not have more risk factors.
- The regression coefficients for Arizona public low density school students were associated with a larger decrease in achievement compared to the coefficients for South Dakota public low density school students on both the *NAEP Social/physical risk index* and the *NAEP Knowledge/attitudes risk index*. This result is consistent with the achievement pattern of South Dakota public low density school students scoring significantly higher than Arizona public low density school students.
- There is a potential under-identification of students needing ELL services due to the discrepancy in the percentage of students labeled as *being ELL* and the much higher percentage of students who *spoke a language other than English at home* at least half of the time or more.
- There were a high percentage of students who were *absent 3 or more days in the last month*.
- There is a potential misclassification of public low density school students in each state as *having a disability* instead of *being ELL* (or, perhaps, needing both types of services).
- Approximately half of the students in public high density school students in each state have low *self-confidence in mathematics*.
- South Dakota BIE schools need to have a completely different policy focus than all the other strata, focusing on *student misbehavior*, *bullying*, *physical conflict*,

employing *highly-qualified teacher*, and enabling students to enroll in more difficult *mathematics classes*.

Chapter Five

The goal of this chapter is to provide further insights into the various achievement differences among AI/AN students in Arizona and South Dakota based on the results found in Chapter 4. The focus will be on the extent to which the results from research questions 1, 2, and 3 follow the NAEP 8th grade mathematics achievement test patterns both among school density types within each state and within each school density type between the two states.

As a reminder, South Dakota students of all races scored significantly higher on the 8th grade NAEP mathematics assessment in 2009 than Arizona students of all races. In fact, as stated in Chapter 1, the overall achievement differences between all students in South Dakota and Arizona (14 points) and between all AI/AN students in each state (12 points) were almost equal. Additionally, between states within school density types, South Dakota AI/AN students scored significantly higher than Arizona AI/AN students in public low and high density schools (13 points and 11 points, respectively). Among the school density types within each state, South Dakota public low density school students scored significantly higher (16 points) than South Dakota public high density school students who scored significantly higher (13 points) than South Dakota BIE school students. (Thus, South Dakota public low density school students scored 29 points higher than South Dakota BIE school students). Arizona public low density school students scored significantly higher (14 points) than both Arizona public high density and BIE school students. However, there were no significant differences in achievement scores among students in Arizona public high density and BIE schools and South Dakota BIE schools.

Again, as mentioned in Chapter 1, it is interesting to note that, except for the 29-point achievement difference between South Dakota public low density and BIE school students, the achievement differences both between and across states and school density types closely mirrored the achievement differences between students of all races in each state and also between AI/AN students as a group in each state (11- to 14-point differences in achievement among the strata). It was unexpected that South Dakota BIE school students did not score significantly higher than Arizona BIE schools students and that Arizona public high density school students did not score significantly higher than Arizona BIE school students. It was most surprising that there were no significant differences in achievement among Arizona public high density and BIE school students and South Dakota BIE school students.

What follows in this chapter is a general review of the study and the findings, a discussion of the added value of NIES over and above what NAEP provides, policy implications both among and between school density types in each state, limitations of the study, and recommendations for future research.

Overview of the Study and General Findings

This study comprised four main research questions. Each will be described and the results highlighted.

The first research question called for comparisons of the distributions of the responses to individual items, as well as of the derived risk factors from the NAEP and NIES background questionnaires and school administration records among and between the three school density types in each state using cross tabulations and tests of independence.

Some unexpected results were found with regard to the first research question. For example, overall, AI/AN students were more likely to like learning mathematics than students of all other races (which is surprising because *attitude toward mathematics* is typically linked to higher mathematics achievement, but AI/AN students historically have had low mathematics achievement) and most students of all other races were taking another math class (not geometry or algebra). A higher percentage of students overall in Arizona were taking geometry/algebra II compared to students in South Dakota. AI/AN students in public high density and BIE schools in Arizona were more likely to be taking geometry/algebra II compared to AI/AN students in public low density schools in Arizona. AI/AN students in BIE schools in South Dakota were more likely to be taking geometry/algebra II compared to AI/AN students in public low and high density schools in South Dakota. One might have assumed that the higher scoring students (e.g., students of all other races, AI/AN students in public low and high density schools in South Dakota, and AI/AN students in public low density schools) would have been taking geometry/algebra II and not the reverse.

Some other interesting results from the first research question were that no AI/AN students in public low density schools in both states and BIE schools in South Dakota were identified as being ELL and a relatively low percentage of AI/AN students, who were not identified as being ELL or having a disability, across all six strata reported often/always/almost always clearly understanding what the mathematics teacher asked. Additionally, no AI/AN students in public low density schools in Arizona or South Dakota or BIE school students in South Dakota were labeled as being ELL. These findings point to an important conclusion of this dissertation, discussed in more depth later in this chapter; namely, that there may be an under-identification of AI/AN students who might benefit from ELL services.

The second research question compared the distributions of the risk indices created using the NAEP and NIES background questionnaires and school administration records among and between the three school density types in each state using within cell histograms. Having a risk factor was associated with lower achievement. Therefore, the more risk factors a student had on any given risk index, the lower the student's achievement score (on average).

As expected, the results of the second research question showed that students of all other races had fewer risk factors on each of the NAEP risk indices compared to AI/AN students. It was also not surprising that the BIE school students had the highest number of risk factors on all the NAEP risk indices in both states and across all the school density types (except on the *NAEP Knowledge/attitudes risk index*[38]), since BIE school students had the lowest achievement scores in both states.

The U.S. Commission on Civil Rights published a report in July 2003 describing the when hundreds of millions of dollars in deferred maintenance backlog of BIE schools have forced AI/AN students to continue to go to school in old, deteriorating buildings, even though the government has a binding trust obligation to provide them (as discussed in Chapter 1). This means AI/AN students are left with deteriorating school facilities, underpaid teachers, inferior curricula, discrimination, outdated learning tools, and cultural isolation. Their housing structures are substandard and overcrowded. One in five reservation homes does not have complete plumbing. AI/ANs face higher rates of

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[38] BIE school students in Arizona had the lowest number of risk factors on the *NAEP Knowledge/attitudes risk index* compared to all other AI/AN students in both states and school density types.

hunger and poverty compared to the general population. It would be hard for most people to succeed academically under these conditions. As stated in Chapter 2, there is a strong relationship between academic achievement and socioeconomic status (Sirin, 2005; Dahl and Lochner, 2008; Hattie, 2009) and AI/AN students' academic success is more strongly associated with SES than it is for other races (Crawford et. al., 2010).

The results of the second research question also showed that public high density and BIE school students had the least number of risk factors on the *NIES Student* and *Home risk indices*, whereas the public low density school students had the most. The *NIES Student risk index* comprised *AI/AN knowledge of* and *participation in AI/AN cultural activities*; therefore, these results are not unexpected (i.e., it is not surprising that public low density school students had less AI/AN knowledge of and participation in AI/AN cultural activities). However, with regard to the *NIES Home risk index*, this is an interesting result. The *NIES Home risk index* consisted of the individual items: *how often family helps with homework* and *how often the student talks to family about classes to take in high school and their future*. Since family/parent involvement in a student's education is generally associated with higher achievement, and public low density school students had higher achievement scores than public high density and BIE school students, this result was unexpected.

Since South Dakota AI/AN students scored significantly higher than Arizona AI/AN students, one might have expected South Dakota AI/AN students to have had fewer risk factors. However, South Dakota AI/AN students only had fewer risk factors than Arizona AI/AN students on two risk indices: the *NAEP Social/physical risk index* and the *NIES Home risk index*. Based on these varying results from research question two, it would not have been possible to predict the achievement patterns observed.

The third research question explored the association between the NAEP and NIES risk indices, the student body composition variables, one individual NIES item, one NIES derived risk factor, and 8th grade mathematics achievement in each school density type in each state using OLS regression modeling. Model building began in each of the six strata by entering each NAEP risk index, student body composition variable, and NIES predictors separately into a regression model to determine which variables significantly predicted achievement on their own. Next, combinations of these significant variables were entered into regression models to establish which combination of variables remained significant in each of the six strata. Final models using only the significant NAEP risk indices (since none of the student body composition variables remained significant when included with the significant NAEP risk indices) were constructed first. Next, the NIES predictors were added, one at a time, into the final NAEP models. The intent was to determine whether or not the NIES predictors accounted for variation in achievement over and above that which was accounted for by the NAEP risk indices.

For the most part, the final models in each stratum (i.e., school density type) were more similar between states than across school density types within each state. Four out of the six final models captured the data well with the adjusted R-squared values in each model ranging from 0.31-0.38. The adjusted R-squared value for the final model for the Arizona public high density school students was 0.24. The adjusted R-squared value for final model for the South Dakota BIE school students was 0.11.

As described later in this chapter, the final model for the South Dakota BIE school students was completely different than any of the other final models as it was the only one to include the *NAEP Classroom risk index* and the *NIES School risk index* and no other predictors. The other five final regression models included the *NAEP Social/physical risk index*; three included the *NAEP Knowledge/attitude risk index*; two included the *NAEP Home risk index*; two included the NIES individual item *self-confidence in mathematics*; and two included the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction.*

The *NAEP Social/physical risk index* comprised whether the student was identified as *being ELL*, *having a disability*, and how many *days they were absent in the last month*. This risk index was significant even for the public low density schools in each state, which had no students who were identified as *being ELL*. Additionally, in four of the five strata (not South Dakota public high density schools[39]), the *NAEP Social/physical risk index* was associated with the largest decrease in achievement compared to the other significant variables remaining in the final models.

Unlike the final models using just the NAEP risk indices from research question 3a, which were almost all the same across school density types in each state, only the public low density schools in each state had the same final models in research question 3b (i.e., no NIES predictors remained significant when the NAEP risk indices were included in the model). The final models in the public high density and BIE school strata had varying degrees of differences based on which NIES predictor(s) remained significant.

[39] For South Dakota public high density school students, having low *self-confidence in mathematics* was associated with a larger decrease in achievement (19 points) compared to the *NAEP Social/physical index*, which was associated with a 15-point decrease in achievement.

Consistently, across all six strata, each risk factor in the NAEP risk indices corresponded to a significant decrease in NAEP 8^{th} grade mathematics achievement, as expected. The NIES individual item, *self-confidence in mathematics*, was not specific to AI/AN students (i.e., students of all races can be measured on their self-confidence in mathematics) and performed as expected (i.e., low self-confidence was associated with lower achievement). However, a one-unit increase in a NIES predictor related to AI/AN-specific topics related to achievement (*NIES School risk index* and NIES risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*) was associated with a significant increase in NAEP 8^{th} grade mathematics achievement, which was unexpected because having a risk factor was hypothesized to be associated with a decrease in achievement.

In the case of the NIES risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction*, having a teacher who incorporated AI/AN culture/tradition into their mathematics instruction at least once a year or never (the risk factor) was associated with an increase in achievement instead of a decrease achievement for students in Arizona BIE schools and South Dakota public high density schools. This type of an outcome can occur in cross-sectional studies and, thus, argues for caution against over-interpretation of the results.

An alternative explanation for this result might be found in a study by Fenimore-Smith (2009), who conducted a qualitative analysis of the first two years of a charter high school on an Indian reservation in the Northwest. The school did not experience the success they expected by incorporating culturally-based education. There was unanticipated resistance from the students in participating in cultural activities (e.g., classes that focused on cultural crafts, drumming, and singing) because the students felt it was intimidating and not relevant to mainstream society. Additionally, the parents and community were not as involved in the operation of the school as much as was foreseen, and the teachers found it hard to incorporate culture into existing school frameworks in order to pass the State assessments, which 79% of the students did not pass. Tying the results of the NIES risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* to the results of this study, it may be that employing a "culturally sensitive" pedagogy does not have much impact, if it is not done well. Successfully incorporating culture into the curriculum may be difficult in some cases and take more than two years.

Additionally, for each unit increase in the *NIES School risk index* for South Dakota BIE school students, students' NAEP 8th grade mathematics achievement score also increased. The *NIES School risk index* included *safe and orderly schools*, *percentage of AI/AN teachers in the school*, and *classes offered in AI/AN culture/tradition*. There were no South Dakota BIE school students who were in schools that offered fewer than five classes in AI/AN culture/tradition. Therefore, having one of the risk factors in the *NIES School risk index* meant being in a BIE school in South Dakota that was either not safe and orderly or in which 25% or less of the teachers were AI/AN. Each of these risk factors was associated with an increase in mathematics achievement.

It was unexpected that the *NAEP Home risk index* was not significantly associated with achievement in any of the other strata since all of the variables included in this risk index (*mother's education*, *eligibility for NSLP*, *number of books in the home*, *talking* *about studies at home*, and *language spoke at home other than English*) have been shown in the literature to be associated with achievement for students of all other races. Clearly, the focus should be on the *NAEP Social/physical risk index* (whether the student has a *disability*, is *labeled as ELL*, and was *absent 3 or more days in the last month*), which was associated with a larger decrease in achievement compared to all the other predictors in all the strata except South Dakota public high density and BIE schools.

Similarly, it was disappointing that the *NIES Home risk index* (*family never/hardly ever/once or twice a month helps with homework* and *never/one time talked to family about classes should take in high school or future plans after high school*) was not significant in any of the final models. It significantly predicted achievement individually for South Dakota public high density and BIE school students (see Appendices F and H for more details), but it didn't remain significant in the final model for either stratum. (The final model for South Dakota public high density schools included the *NAEP Home risk index*, but the final model for South Dakota BIE schools did not.) This risk index was intended to be a proxy for family involvement, which is typically related to achievement (Hattie, 2009; Kratochwill et. al, 2004; Leveque, 1994; Parcel & Dufur, 2001; Stevenson & Baker, 1987; Willeto, 1999).

Since the risk factors in the *NIES Home risk index* were not AI/AN-specific topics related to achievement, it would be interesting to know if the risk factors in the *NIES Home risk index* might have played a more significant role if they had been combined with the *NAEP Home risk index* (instead of being analyzed separately to see the impact on achievement of the NIES risk indices over and above the NAEP risk indices). Table D.71 shows that these two risk indices had a positive, low correlation with each other (*p*

= 0.22), which means they may not be measuring the same underlying construct and should remain separate. Regardless, it may be that, although family involvement is significantly associated with achievement for other races, the significant predictors found in this dissertation are what are pertinent to AI/AN students.

The student body composition variables turned out not to be significant predictors of achievement over and above that which was accounted for by the NAEP risk indices. This result was unforeseen because, as mentioned in Chapter 3, Table 1.1 showed that Arizona had a more diverse, lower achieving student body than South Dakota. Thus, the hypothesis was that student body composition may be associated with the differences in achievement between students in both states overall and between public low and high density school students in each state. However, this was not the case. The student body composition variables might have had a larger impact had more schools been included in the sample, a point discussed further in the study limitations.

The indicator for *Hispanic/Black* did enter the final model for South Dakota public low density schools, but the standard error of the regression coefficient (33.51) was almost five times larger than the largest coefficient across all the other final models (which was 7.73, the regression coefficient for the *NAEP Social/physical risk index* for Arizona public low density school students). Therefore, the variable was deemed unstable and it was decided that the *NAEP Knowledge/attitudes risk index* was a better fit.

The fourth research question synthesized the results from the first three research questions, included some additional cross tabulations, and offered policy implications, which are discussed later in this chapter. A major revelation from the policy analysis was the vast discrepancies across all strata between the number of students who stated they spoke a language other than English at home at least half the time or more and the number of students labeled as being ELL. Table 4.26 shows that, for each school density type, much higher percentages of AI/AN students in Arizona spoke a language other than English at home at least half the time or more compared to AI/AN students in South Dakota. In Arizona, the difference between the percent of students labeled as being ELL and the percentage of students who stated speaking a language other than English at home at least half the time or more ranged from 32% (Arizona public low density schools) to 59% (Arizona public high density schools). In South Dakota, the difference between the percent of students labeled as being ELL and the percentage of students who stated speaking a language other than English at home at least half the time or more ranged from 8% (South Dakota public low density schools) to 22% (South Dakota BIE schools). It is possible that not all of the students who spoke a language other than English at home at least half the time or more need ELL services, especially in Arizona.

Added value of NIES

This dissertation would not have been possible without NIES. What NIES provides, over and above NAEP, is the capability to disaggregate the AI/AN students among the three school density types. Without the added sample size among AI/AN students that NIES supplies, detailed examination of AI/AN achievement differences would not have been possible, as NAEP alone cannot offer this.

When the NIES predictors remained significant in the final models, their addition to the model accounted for a larger percent of variation in achievement (marginally in most cases) over and above that which was accounted for by NAEP risk indices alone.

The additional percent of variation accounted for by the NIES predictors ranged from 1% in the Arizona public high density school model (*self-confidence in mathematics*), 3% in the Arizona BIE school model (*teachers incorporate AI/AN culture/tradition into their mathematics instruction*), and 4% in the South Dakota BIE school model (*NIES School risk index*) to 15% in the South Dakota public high density school model (*self-confidence in mathematics* and *teachers incorporate AI/AN culture/tradition into their mathematics instruction*). Recall that the NIES predictors were not significant in the public low density school models.

One might consider removing any questions not specific to AI/AN students from the NIES questionnaires and incorporating them into the NAEP questionnaires (i.e., *self-confidence in mathematics* and the questions from the *NIES Home risk index*). However, it would be important to retain the AI/AN culture/tradition questions from the NIES questionnaires in order to follow trends in achievement patterns based on the amount of AI/AN culture/tradition surrounding the students, which is a very important issue for the AI/AN people.

Based on the literature review and qualitative information about life on a reservation, it might be worthwhile to add the following questions to the NIES student and/or school background questionnaires to see if any are related to achievement: the number of siblings in the student's family, the number of siblings the student lives with, the number of people who live in the same house as the student, the number of adults in the home who work, and the length of time it takes for the student to get from home to school.

Looking at the results both within a school density type across states and within a state and across school density types, there is more of a discernable pattern across states within a school density type. Therefore, the bulk of the policy implications focus on the former. A short description of the latter is included next.

Policy implications based on school density type within each state

The achievement pattern among the school density types in each state was that Arizona public low density school students scored significantly higher than Arizona public high density and BIE school students and that South Dakota public low density school students scored significantly higher than South Dakota public high density school students who scored significantly higher than South Dakota BIE school students.

In Arizona, the final OLS regression model in each school density type included the *NAEP Social/physical risk index*. This risk index was associated with lower achievement in public low density schools (-31 points, on average) compared to public high density and BIE schools (about -17 points, on average). The final OLS regression models in the public low density and BIE schools both also contained the *NAEP Knowledge/attitudes risk index*. The final OLS regression model for the BIE schools contained a third predictor: the NIES derived risk factor. In addition to the *NAEP Social/physical risk index*, the final OLS regression model for the public high density schools also included the *NAEP Home risk index* and the NIES individual risk factor.

There is not a discernible, meaningful pattern across school density types in Arizona. One might have expected the final OLS regression models for the public high density and BIE schools to be the same based on the achievement results. Surprisingly, the public low density and BIE school final models contained the same significant predictors, except, for the BIE school model, the NIES derived risk factor was also significant.

Similarly, across school density types in South Dakota, there was no obvious pattern. There were fewer similarities in the final OLS regression models in South Dakota than in Arizona. The public low and high density schools both contained the *NAEP Social/physical risk index*, but that is where the similarities end. The achievement results showed that, in South Dakota, public low density school students scored significantly higher than public high density and BIE schools and public high density school students scored significantly higher than BIE school students. It is possible that the fact that the final OLS regression models were very different in each of the school density types in South Dakota is reflective of this achievement pattern.

Policy implications based on comparisons within school density type between the two states

The achievement pattern being examined is South Dakota public low and high density school students scoring significantly higher than Arizona public low and high density school students with no significant differences in achievement scores between Arizona and South Dakota BIE school students.

Public low density schools. It is interesting and, perhaps, not unexpected that the final models for the public low density schools in each state contained the same two significant NAEP predictors and did not change when the NIES predictors were added to the model. In other words, the NIES predictors did not add any information to the models over and above what was accounted for by the NAEP risk indices. This makes sense since AI/AN students in public low density schools are surrounded by 75% or more students of other races, not fellow AI/AN students. Therefore, their school settings are much different than those of public high density and BIE school students. There are no AI/AN teachers in their schools, not many classes in AI/AN culture/tradition are offered, teachers are not incorporating AI/AN culture/tradition into their mathematics instruction, etc.

South Dakota public low density school students scored significantly higher than Arizona public low density schools students on the NAEP 8th grade mathematics achievement test, which parallels the pattern for the states as a whole (South Dakota students of all races scored significantly higher than Arizona students of all races). This achievement difference was evident in the fact that the two significant risk indices in both of the final public low density school models were associated with a larger decrease in achievement for Arizona public low density school students and a smaller decrease in achievement for South Dakota public low density school students.

As stated previously, it was interesting to note that the *NAEP Social/physical risk index* (*having a disability*, *being ELL*, and *being absent 3 or more days in the last month*) was significantly associated with achievement in public low density schools in both states since no AI/AN students in public low density schools in either state were identified as being ELL. However, according to Table 4.6, Arizona public low density school students were more likely to be identified as having a disability compared to Arizona public high and BIE school students. South Dakota public low density school students[40] were more likely to be identified as having a disability compared to South Dakota public high

[40] South Dakota BIE school students were also more likely to be identified as having a disability compared to South Dakota public high density school students and South Dakota BIE school students also had no students who were labeled as being ELL.

density school students. Table 4.7 shows that even though AI/AN students in Arizona and South Dakota public low density schools were not identified as being ELL, almost the same percentage of Arizona and South Dakota public high density school students were identified as having a disability, being ELL, and having both a disability and being ELL as Arizona and South Dakota public low density school students had of just students identified as having a disability (19% and 17%, respectively).

As stated in Chapter 4, there is a discrepancy between the percent of students who spoke a language other than English at home at least half the time or more and the number of students labeled as being ELL. No students in public low density schools were labeled as being ELL, even though 32% of the students in Arizona and 8% of the students in South Dakota stated speaking a language other than English at home at least half the time or more.

Based on these results (being more likely to be identified as having a disability and the discrepancy between how often a language other than English is spoken at home and being labeled as being ELL), there may be an under-identification or even mis-identification of ELL students in public low density schools (i.e., students labeled as having a disability who would benefit from ELL services instead, or also). It is possible that this under-identification of ELL students is a more important issue for public low density school students and that is why no NIES predictors were significant in the public low density school models.

Additionally, being absent 3 or more days in the last month was an issue for public low density school students. Table 4.27 showed that 38% of the students in Arizona public low density schools were absent 3 or more days in the last month and

29% of the student in South Dakota public low density schools were absent 3 or more days in the last month.

Public high density schools. Both final models for public high density schools contained the *NAEP Social/physical* and *NAEP Home risk indices* and the NIES individual item *self-confidence in mathematics*. The final model for South Dakota public high density school students also included the NIES derived risk factor *teacher incorporates AI/AN culture/tradition into their mathematics curriculum*. Interestingly, public high density schools in each state had similar percentages of students whose teachers stated incorporating AI/AN culture/tradition into their mathematics curriculum never or at least once a year (60% for Arizona public high density school students and 64% for South Dakota public high density school students); however, this derived risk factor was not a significant predictor for Arizona public high density school students, which is the only difference in the final models for the public high density schools.

One difference that stood out between the public high density school students was that 71% of public high density school students in Arizona spoke a language other than English at home at least half the time or more while only 21% of public high density school students in South Dakota spoke a language other than English at home at least half the time or more. This difference may be associated with the significant difference in achievement scores between Arizona public high density school students and South Dakota public high density school students (South Dakota public high density school students scored significantly higher than Arizona public high density school students), especially since Table 4.7 showed that only 12% of public high density school students in Arizona were identified as being ELL. This is an interesting finding since Table 4.18

showed that 100% of the students in public high density schools in Arizona were in schools that reported receiving Title III funding (provided to schools to close the achievement gap for people for whom English is not their first language). It may be that the public high density schools in Arizona, specifically, should consider reallocating some of their Title III money to ensuring that all of the students who qualify for ELL services have been identified, if they have not done that already.

Half of the public high density school students in both states (53% in Arizona and 50% in South Dakota) had low *self-confidence in mathematics*, rating themselves as poor or average in mathematics. For public high density school students in South Dakota, this risk factor was associated with the largest decrease in achievement compared to the other significant risk factors in the final model.

The *NAEP Home risk index* was significantly associated with achievement only for public high density school students in both states. In Arizona, Table 4.26 showed that 87% of the students were eligible for NSLP, 62% had 25 books or less in the home, 52% never/hardly ever/every few weeks talk about studies at home, 42% had mothers who didn't finish high school/graduated high school, and 71% spoke a language other than English at home at least half of the time or more. In South Dakota, 90% of the students were eligible for NSLP; 57% had 25 books or less in the home; 39% never/hardly ever/every few weeks talk about studies at home; 36% had mothers who had didn't finish high school/graduated high school; and 20% spoke a language other than English at home at least half of the time or more. Each of the risk factors in this risk index was associated with a decrease in achievement for Arizona public high density school students and South Dakota public high density school students.

BIE schools. In research question 3a, using only the NAEP risk indices, Arizona BIE schools had the same final model as Arizona and South Dakota public low density schools. While the Arizona and South Dakota public low density school models remained the same in research question 3b, the NIES derived risk factor *teacher incorporates AI/AN culture/tradition in mathematics instruction* was significantly associated with mathematics achievement for Arizona BIE school students (in addition to the *NAEP Social/Physical risk index* and the *NAEP Knowledge/attitudes risk index*). Similar to South Dakota public high density school students, having a teacher who never or at least once a year *incorporated AI/AN culture/tradition in their mathematics instruction* was associated with an increase in achievement. For Arizona BIE school students, it was associated with an 11-point increase in achievement, on average. For South Dakota public high density school students, it was associated with a 16-point increase in achievement, on average. There was no significant difference between the NAEP 8th grade mathematics achievement results for Arizona public high density school students and Arizona BIE school students. However, their final models are very different. The only similarity was that they both include the *NAEP Social/physical risk index*.

It was interesting that the OLS regression results for the South Dakota BIE school students did not include any of the predictors that made it into the final models for all the other strata. South Dakota BIE school students also did not perform as expected on the NAEP 8th grade mathematics achievement test. In other words, South Dakota students overall, AI/AN students in South Dakota overall, and AI/AN students in public low and high density schools in South Dakota scored significantly higher than Arizona students.

However, there was no significant difference in the NAEP 8th grade mathematics scores between South Dakota BIE school students and Arizona BIE school students. Thus, it may not be surprising that the OLS regression results for South Dakota BIE schools were much different from the results in all the other strata.

No AI/AN students in South Dakota BIE schools were identified as being ELL, whereas, 33% of AI/AN students in Arizona BIE schools were identified as being ELL. Overall, a much lower percentage of AI/AN students in South Dakota were labeled as being ELL and spoke a language other than English at home at least half of the time or more compared to AI/AN students in Arizona. Table 4.26 showed that 22% of South Dakota BIE school students spoke a language other than English at home at least half of the time or more (77% for Arizona BIE school students).

It is interesting because to be classified as ELL in South Dakota, one of the four requirements of the South Dakota Department of Education is that the student is AI/AN (in addition to being between ages 3-21; enrolled in school; and have enough difficulty speaking, reading, writing or understanding English to not score in the proficient level on the state tests, be able to achieve successfully in an English-speaking classroom, or participate fully in society) (South Dakota Department of Education, 2016). A definition of an ELL, specifying that the student be AI/AN, was not found on the Arizona Department of Education website (Arizona Department of Education, 2016). It is possible that being an AI/AN student in South Dakota provides students with ELL services at a younger age, so by the time the student is in 8th grade, he/she is proficient in English. However, being labeled as being ELL was still associated with a decrease in achievement for AI/AN students in South Dakota public high density schools.

Table 4.9 showed more AI/AN students in South Dakota BIE schools had teachers who identified as AI/AN (41% of students had teachers who identified as White and 59% had teachers who identified as AI/AN). It is possible that these teachers spoke the Native language of those students who didn't speak fluent English and could, therefore, teach them in their Native language, which was why they were not classified as being ELL. Although, more students in Arizona BIE schools (81%) had teachers who identified as AI/AN (12% had teachers who identified as White and 7% had teachers who identified as a race other than White or AI/AN) and a higher percentage of them were labeled as ELL (33%), so the hypothesis that having a teacher who speaks your Native language may lead to fewer students requiring ELL services may not be true.

It is also interesting that the *NAEP Social/physical risk index* was not significant for South Dakota BIE school students as it was for Arizona and South Dakota public low density school students, who also had no students who were identified as being ELL. It further suggests that the South Dakota BIE students seem to have different needs than the rest of the AI/AN students.

Looking at the poverty estimates for Arizona and South Dakota provided by the US Census Bureau for 2009 (Figures 5.1 and 5.3, respectively), Arizona has more children ages 5 to 17 in poverty in metropolitan, micropolitan, and "other areas" compared to the US. South Dakota has fewer children ages 5 to 17 in poverty in metropolitan and micropolitan areas compared to the US, but they have more children in poverty in "other areas" than the US. When you compare the maps provided by the US Census Bureau (2010) of school age children in poverty in 2009 by school district to a map of reservation locations in each state (Figures 5.2 and 5.4) from the US Geological

Survey from 2014, there is a more distinct match between the percent of children in poverty in school districts on reservations in South Dakota than in Arizona. Although there is a high percentage of children in poverty in school districts on reservations in Arizona, there are also other school districts in Arizona that are not on reservations that also have a high percentage of children in poverty. In other words, poverty may be more concentrated on reservations in South Dakota than in Arizona, which might help explain the different needs South Dakota BIE school students may have.

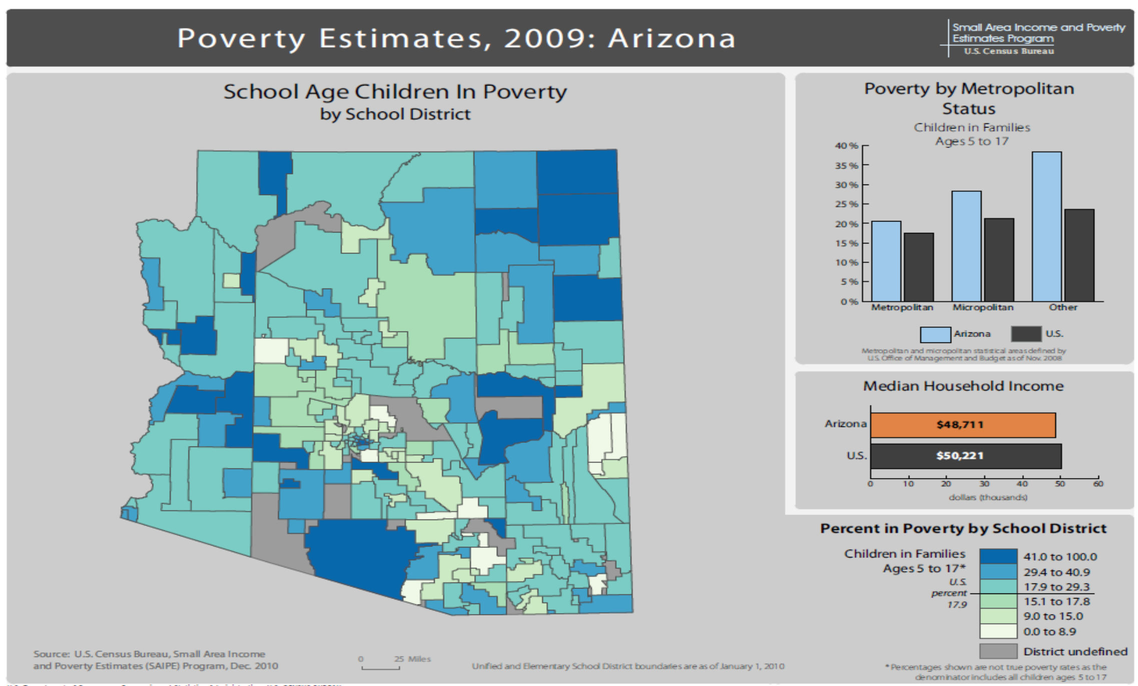

Figure 5.1: Poverty Estimates, 2009: Arizona
Source: US Census Bureau, 2010.

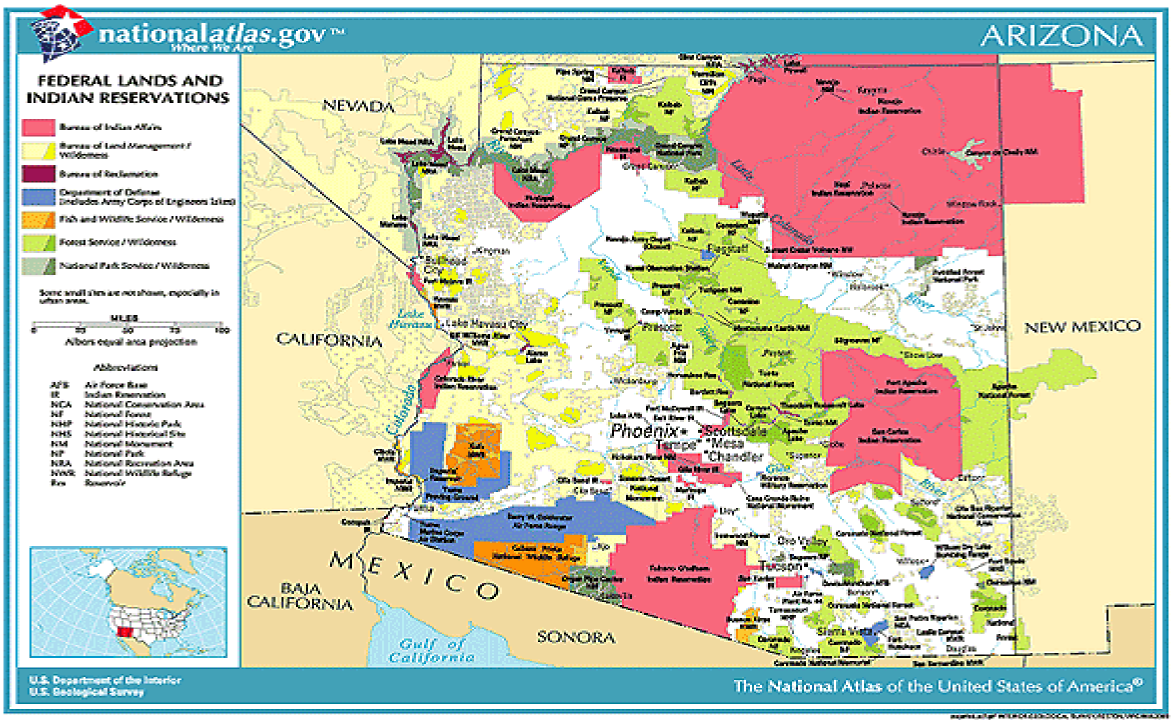

Figure 5.2: Arizona Indian Reservations
Source: US Geological Survey, 2014.

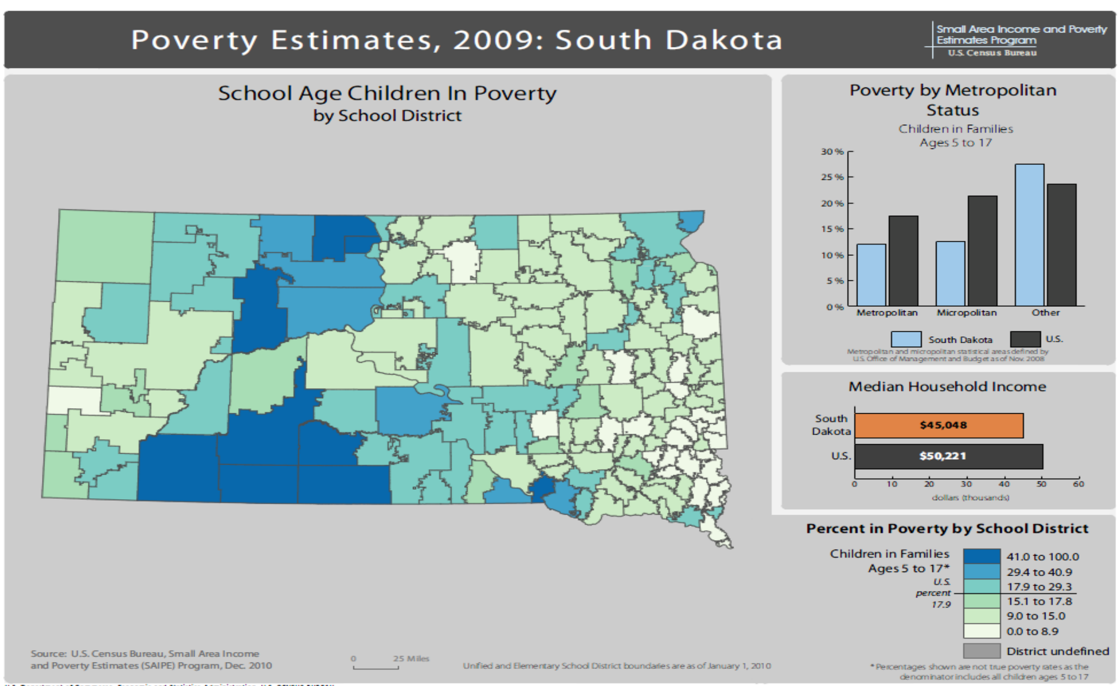

Figure 5.3: Poverty Estimates, 2009: South Dakota
Source: US Census Bureau, 2010.

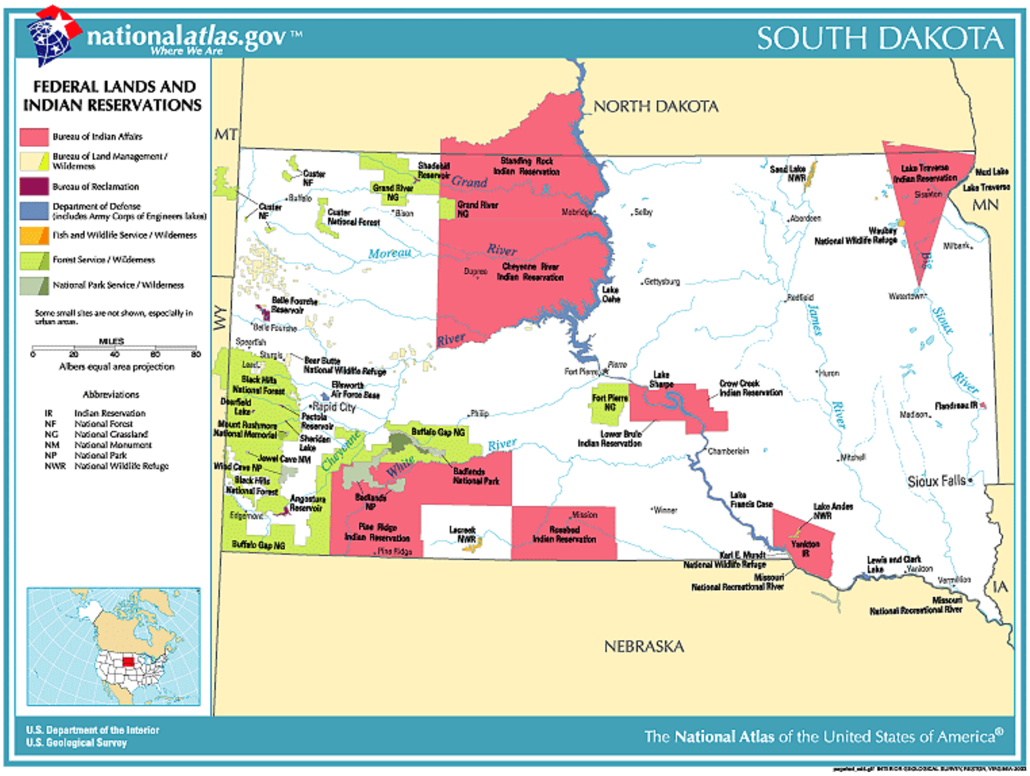

Figure 5.4: South Dakota Indian Reservations
Source: US Geological Survey, 2014.

There doesn't seem to be a clear explanation as to why Arizona public high density school students did not score significantly higher than Arizona BIE school students, as the overall NIES 2009 achievement pattern suggests (discussed in Chapter 1). The final regression model for Arizona public high density school students more closely resembles the final regression model for South Dakota public high density school students and BIE school students had more risk factors than Arizona public high density school students. It may be that Arizona BIE school students scored higher than expected, as their final regression model more closely resembled that of the public low density schools. This explanation would mean South Dakota BIE school students scored exceptionally low, which may be viable for the following reasons: their final regression model was completely different from that of all the other strata, they unexpectedly had the same achievement scores as Arizona public high density and BIE school students, there was a 29-point achievement difference between South Dakota public low density and BIE school students, and the percent of school age children in poverty in South Dakota seems to be concentrated in reservation lands.

Summary of policy implications.

The NIES data offer larger samples of AI/AN students, which allow for more in-depth analyses of the AI/AN student population both across strata between states and within strata across states. The analyses performed throughout this dissertation have uncovered both anomalies (such as the potential under-identification of students needing ELL services) and additional information describing variations in achievement specific to AI/AN students (such as being absent more than 3 days in the last month and having low self-confidence in mathematics). The six most important findings of this dissertation are described next.

1. **Understand the associations among students who are labeled as having a disability, being ELL, and are absent 3 or more days in the last month and achievement.**

The *NAEP Social/physical risk index* (*having a disability*, *being ELL*, and *being absent 3 or more days in the last month*) was significantly associated with lower student achievement across all strata except South Dakota BIE schools. Based on the history of AI/AN education in the US, schools may need to think of creative, meaningful ways to engage AI/AN parents in their children's education. Many AI/AN parents do not have positive view of education in the US, based on their knowledge of and experience with boarding schools (as described in Chapter 1), which may be associated with the high rate of absenteeism of their children (Maxwell, 2013). Improving the relationship between schools and AI/AN families (as described further below in #4) may also help to increase school attendance.

2. Focus on identifying all students who may benefit from receiving disability and/or ELL services.

Across all strata, Table 4.8 showed that, overall, among students who were not identified as being ELL or having a disability, a surprisingly low percentage of students, ranging from 58-74% across strata, reported often/always/almost always clearly understanding what the mathematics teacher asked. This may be an important area to focus on for policymakers. This result could be due to AI/AN students being well-below grade level in mathematics. Although, many were taking low-level mathematics classes and were still not clearly understanding what the mathematics teacher was asking. One explanation is that there are students who should be identified as being ELL or as having a disability who have not been classified as such and, therefore, are not getting enough specialized help. For example, almost the same percentage of students in Arizona public low density schools (67% vs. 72%) and South Dakota BIE schools (58% vs. 56%) reported never/hardly ever/sometimes clearly understanding what the mathematics teacher asks regardless of whether or not the student was identified as having a disability. This is important to investigate since the *NAEP Social/physical risk index*, which included whether the student was identified as having a disability or being ELL, was significantly associated with achievement in every stratum except South Dakota BIE schools. And because the *NAEP Knowledge/attitudes risk index*, which included whether the student clearly understood what the mathematics teacher was asking, was significantly associated with achievement in three of the six strata. One suggestion to delve into this deeper would be to add more in-depth questions onto the next NIES survey to try to uncover exactly what is holding the students back from understanding the mathematics teacher more often.

Additionally, schools in all six strata might consider methods for confirming that all students who speak a language other than English at home at least half of the time or more do not need ELL services due to the discrepancy in most strata between the number of students labeled as being ELL and the number of students who stated they spoke a language other than English at home at least half of the time or more. A language barrier could be contributing to AI/AN students having lower achievement scores.

3. Find ways to increase self-confidence in mathematics.

In addition to absenteeism rates and under-identification of ELL students, public high density schools in both states may want to think about ways to increase the self-confidence in mathematics for AI/AN students as about half of them have low self-confidence in mathematics (increasing attendance may help to increase self-confidence in mathematics). Dweck (2006) presents two mindsets: fixed and growth. The growth mindset is the belief that you can develop and improve your abilities through practice and effort. A fixed mindset is the belief that your abilities are predetermined and mostly unalterable. Teaching students how to embrace a growth mindset can increase their achievement.

4. Explore how to better connect a student's home life and school life.

Additionally, public high density schools need to understand that the achievement of their AI/AN students was associated with a decrease in achievement for the *NAEP Home risk index* (having a mother who didn't finish high school or graduated high school, having 25 or fewer *books in the home*, being *eligible for the NSLP*, *speaking a language other than*

English at home at least half of the time or more, and never/hardly ever/every few weeks *talk about studies at home*). This result might suggest that schools should focus on forming stronger connections with the students' families both because of language barriers and parents' previous experiences in school.

One barrier to getting AI/AN parents involved in their children's education is that the parents may support education but not necessarily the assimilatory goals of mainstream public schools (Dehyle & Swisher, 1997). This can be understood through structural inequality theory, which states that the educational difficulties experienced by AI/ANs stem from extended periods of discrimination by the dominant society, as mentioned previously, which has led the AI/ANs to distrust the educational institution that was created for, and by, the dominant society (Huffman, 2010).

Another major barrier to parents contributing to achievement is when parents do not speak the language of the school. This has two meanings: English language ability and the culture and politics of the school. Using the Early Childhood Longitudinal Study-Kindergarten Cohort (because this is the time when parents start interacting with schools), Turney & Kao (2009) analyzed data from 12,954 White, Black, Hispanic, and Asian parents of kindergarteners to examine the barriers to parent involvement at their children's schools. (Data on AI/ANs was deleted from the dataset because the sample size was too small to analyze separately.) They found that English language ability was an important predictor of parents' perceived barriers. Parents whose primary language was not English were generally more likely to report that meeting times at the school were inconvenient, the school did not make them feel welcome, and meetings were conducted only in English. Not surprisingly, parents whose primary language was not English were found to have lower levels of involvement in school.

Clinton, Hattie, and Dixon (2007) conducted a five-year study of five of the lowest SES schools (approximately 1800 students) in New Zealand in order to improve educational outcomes for students, in part, by using former teachers as home-school liaisons who taught the parents “the language of schooling”. They focused on these schools because the language of schooling is particularly difficult for those from lower income families. These parents had found it difficult to get involved in school because they lacked confidence, had negative school experiences themselves, and had a limited understanding of what learning is about. The barrier of not knowing the language of schooling is that these parents are not able to use effective methods to encourage their children to meet their educational expectations. By teaching the parents the language of schooling, the liaisons taught them the nature of learning in today’s classrooms, how to speak to teachers and school staff, and how to help their children engage in learning. Involving the parents increased their expectations of their children and almost doubled the gain in the students’ attitudes toward mathematics compared to the control group of students (d=0.58 compared to d=0.29) (Hattie, 2009; Clinton et. al, 2007).

Being sensitive to and trying to break through the barriers some families may have with both speaking English and not understanding “the language of schooling” because of their own experiences in school may go a long way to improving AI/AN students’ achievement and improving attendance among AI/AN students.

5. **Determine how to successfully incorporate AI/AN culture/tradition into the curriculum.**

For Arizona BIE school students and South Dakota public high density school students, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* was significantly associated with achievement. Even though having a teacher who incorporated AI/AN culture/tradition into their mathematics instruction frequently was associated with a decrease in achievement, Arizona BIE schools and South Dakota public high density schools should still examine how culture is being incorporated by the teachers and discuss how to use it effectively as a protective factor to increase achievement, perhaps by offering professional development in this area. If possible, it might be helpful for Arizona BIE and South Dakota public high density schools to see how Arizona public high density school teachers are incorporating AI/AN culture/tradition into their mathematics curriculum since this derived risk factor was not significantly associated with achievement for Arizona public high density school students and that was the only difference in the final models for the public high density schools in each state.

6. **South Dakota BIE schools have different needs.**

The risk indices significantly associated with achievement for South Dakota BIE school students were completely different than the risk indices significantly associated with achievement for all other strata, which fits with the unexpected performance of South Dakota BIE school students whose achievement scores were not significantly different from Arizona public high density and BIE school students. For South Dakota BIE school students, the data suggest focusing on the mathematics class the students are taking (i.e., increasing the level of difficulty as 32% of the students were taking basic, general grade 8 mathematics and 16% were taking another math class), having the students taught by highly-qualified teachers, and reducing misbehavior, bullying, and physical conflict.

Special issues for the AI/AN people.

AI/AN student achievement in federal (BIE) schools is lower than anywhere else. In public high density schools on reservations, AI/AN achievement is higher than in BIE schools, but it is much lower than in schools with fewer AI/AN students. In high achieving states such as Oklahoma, AI/AN students are more evenly distributed among schools whereas in low achieving states, such as Arizona, AI/AN students are more likely to attend schools that have higher concentrations of AI/AN students (National Conference of State Legislatures, 2008). Thus, it may not be surprising that the AI/AN students in public low density schools scored significantly higher than those in public high density and BIE schools.

As described in Chapter 1 and mentioned earlier in this chapter, the relationship between the AI/AN people and the US government is different than that of any other subgroup. They are the only racial subgroup to give up much of their land in exchange for protection and support from the US government. But, the US government has not fulfilled its trust responsibilities, which has left the AI/AN people in crisis for years with high rates of poverty, poor educational achievement, substandard housing, and high rates of disease and illness (U.S. Commission on Civil Rights, 2003). Based on the results of this dissertation, the poor educational achievement appears to be more evident for BIE school students, especially in South Dakota.

As described in Chapter 1, the AI/AN people have struggled between self-determination and assimilation since nonindigenous people arrived in the Americas in 1492. Culture, tradition, and revitalizing languages that are on the verge of being lost are very important to the AI/AN people. Focusing on self-determination while trying to meet state reporting standards for achievement must be challenging. Although the findings of this dissertation are important, they must be understood in the overall context of the lives of AI/AN people in the US. Making changes and seeing improvements in achievement outcomes may seem like a difficult task, especially when hundreds of millions of dollars in deferred maintenance backlog of BIE schools have forced AI/AN students to continue to go to school in old, deteriorating buildings (U.S. Commission on Civil Rights, 2003). But, it is important to continue to focus on the specific needs of AI/AN students and how they can be met in order to improving achievement outcomes for AI/AN students.

Study limitations

Multiplicity. Multiplicity issues occur when many different models are applied to the same data. Excessive Type I errors may arise. Therefore, caution must be taken in over-interpreting the reported *p*-values.

Data. The following data limitations will be addressed in this section: missing data, limited sample size, using a dataset from 2009, losing data variability by collapsing variable categories, and the limits of using cross-sectional data.

Missing data. Seven of the 48 items used in the OLS regression analyses had more than 5% missing data. The highest level of missingness occurred in three items:

mother's education level in the *NAEP Home risk index* (25% overall for AI/AN students because 24% of students answered "I don't know", but this varied among school density types in each state), *highly-qualified teacher this year* in the *NAEP Classroom risk index* (16% overall for AI/AN students, but this varied among school density types in each state), and *parent education level* (18% overall for AI/AN students, but this varied among school density types in each state from 14-23%). Due to the missingness of *mother's education level*, 22-31% of the data were missing on the *NAEP Home risk index* in Arizona and 25-60% of the data were missing in South Dakota. Due to the missingness of the *highly-qualified teacher this year* item, 4-30% of the data were missing on the *NAEP Classroom risk index* in Arizona and 7-13% of the data were missing in South Dakota. The level of missing data in the *NIES School risk index* varied across school density types in each state from 7-21% due to missing data in *safe and orderly schools* (8%), *classes offered* (10%), and the *percentage of AI/AN teachers in the school* (10%). Lastly, the NIES derived risk factor *teacher incorporated AI/AN culture into mathematics instruction* had 9% missing data overall, which varied by school density type in each state from 4-29%.

It was validating to see that there was not much of a difference between the OLS regression final models using listwise deletion and conditional mean substitution. For example, 13% of the data in the *NAEP Classroom risk index* and 21% of the data in the *NIES School risk index* were missing for South Dakota BIE school students; however, the results of the OLS regression were the same using listwise deletion and conditional mean substitution in which both of these risk indices remained significant.

The remaining 41 items used in the OLS regression analyses had 0.1-3.5% missing data overall, among AI/AN students. Additionally, the *NAEP Social/physical risk index*, which was significant in five of the six strata, only had 0-3.6% missing data across the five strata.

Limited sample size. Because many of the schools were very small, only a few students were sampled in many NIES schools. There were enough students in each school density type to make comparisons across strata, but it was not possible to run analyses separating the school data from the student data because there were not enough schools or students in the schools to create enough variation between schools.

Using a dataset from 2009. Although the results from one subsequent NIES administration have been published (for the 2011 administration), the 2009 results had several interesting and significant differences between states, with South Dakota and Arizona having achievement differences both between and among the school density types. In 2011, Arizona no longer had achievement differences among the school density types and the only other state with sufficient sample size to meet the reporting requirements was New Mexico, which did not have any significant differences among the school density types.

Losing data variability by collapsing variable categories. All of the variables in this analysis were combined in some way and/or dichotomized. Variation in data is lost when variables are collapsed. However, it was important to create the derived risk factors in order to be able to comment on the results from the derived risk factors such as *attitude toward mathematics* and *school climate* and relate them back to the literature review. Additionally, several of the risk indices proved to be strong predictors of achievement.

Limits of using cross-sectional data. Using cross-sectional data means capturing information at a specific point in time. It does not support inferences regarding cause and effect but, rather, is descriptive and suggestive. Therefore, caution needs to be taken in applying these results to inform policy.

Future research

The findings from this dissertation have shown that AI/AN students in each of the school density types in each state have unique needs and that even within a group of students (e.g., AI/AN students) there are many different needs to be met. This dynamic is evident in the differences in NAEP 8th grade mathematics scores among AI/AN students in each school density type in each state that have not yet been captured in the achievement literature.

A future study might consider combining some of the NAEP and NIES predictors that were not AI/AN-specific topics related to achievement to see if the results more clearly follow the pattern of achievement differences. For example, combining the *attitude toward mathematics* derived risk factor and the *self-confidence toward mathematics* individual item might form a strong predictor of NAEP 8th grade mathematics achievement, especially since the NIES individual item *self-confidence toward mathematics* and the *NAEP Knowledge/attitudes risk index* had a correlation of 0.49. Similarly, it is possible that using principal axis factor analysis to combine the *NAEP Home risk index* and the *NIES Home risk index*, as mentioned earlier in this chapter, might have resulted in a risk index with a stronger association with achievement.

The ability to refine the risk indices would allow for informative longitudinal analyses of the NIES data across administrations of the test. Additionally, if some of the risk factors were combined, it would be interesting to examine which of the following was associated with a larger decrease in achievement: a particular risk factor or the number of risk factors in a student's life. For example, which of the following is associated with a larger decrease in achievement for students in South Dakota BIE schools: poverty, a different risk factor, or the number of risk factors?

Even though this analysis employed as many as 70 variables, there are many other individual items in the NAEP and NIES student, teacher, and school questionnaires that were not included that might be associated with achievement (e.g., *how hard the student tried on the NAEP 8th grade achievement test*, *how important it was to do well on the test*, *how hard the test was compared to other tests the student has taken*, *the student's plans the first year after high school*, *how many years the teacher has been teaching*, *professional development for teachers*, etc.). There are other variables in the questionnaires (e.g., *amount of community participation in schools*) that might be risk factors and might be relevant to AI/AN student achievement but were not included in this dissertation because they were not as much of the focus in the literature as the variables included in this dissertation. In fact, all of the questions in all of the background questionnaires were administered because they are expected to have some relevance to achievement.

It would also be interesting to see what the results of the NAEP risk indices would be looking at other subgroups (i.e., Hispanics and Blacks). It is possible that these results might be universal across subgroups, especially those who speak a language other than English at home at least half of the time or more.

Finally, running the analyses using other states and more current data might be revealing, such as using the 2011 NIES data to compare New Mexico and South Dakota. There were no significant differences in achievement among the three school density types in New Mexico and there were no significant differences between the school density types in each state. It would also allow comparisons between the results of this analysis for South Dakota in 2009 and in 2011.

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Appendix A: List of Federally recognized tribes in Arizona and South Dakota

Table A1: *Federally recognized tribes in Arizona*
1. Ak-Chin Indian Community
2. Cocopah Indian Tribe
3. Colorado River Indian Tribes
4. Fort McDowell Yavapai Nation
5. Fort Mojave Indian Tribe
6. Fort Yuma-Quechan Tribe
7. Gila River Indian Community
8. Havasupai Tribe
9. Hopi Tribe
10. Hualapai Tribe
11. Navajo Nation
12. Kaibab-Paiute Tribe
13. Pascua Yaqui Tribe
14. Salt River Pima-Maricopa Indian Community
15. San Carlos Apache Tribe
16. San Juan Southern Paiute Tribe
17. Tohono O'odham Nation
18. Tonto Apache Tribe
19. White Mountain Apache Tribe
20. Yavapai-Apache Nation
21. Yavapai-Prescott Indian Tribe

Adapted from: Native Languages of the Americas (1998-2011). Native American Tribes of Arizona. Retrieved January 6, 2012 from http://www.native-languages.org/arizona.htm.

Table A2: *Federally recognized tribes in South Dakota*
1. Cheyenne River Sioux Tribal Council
2. Crow Creek Sioux Tribe
3. Flandreau Santee Sioux Tribe
4. Lower Brule Sioux Tribe
5. Oglala Sioux Tribe
6. Rosebud Sioux Tribe
7. Sisseton-Wahpeton Sioux Tribe
8. Yankton Sioux

Adapted from: Native Languages of the Americas (1998-2011). Native American Tribes of South Dakota. Retrieved January 6, 2012 from http://www.native-languages.org/sdakota.htm.

Appendix B: Items used in the analyses for this dissertation

Table B1: *Items used in the analyses for this dissertation*			
	Item name in dataset	Topic area/question	Original response options
	School administration record items		
1.	DENSBIE	BIE/public school AI density indicator	1. Public, low density; 2. Public, high density; 3. BIE school
2.	FIPSAI	FIPS location code for American Indian students	4. Arizona; 46. South Dakota
3.	SDELL	Student classified as SD or ELL	1. Student with disability; 2. ELL; 3. Both SD and ELL; 4. Neither SD nor ELL
4.	LEP	Student classified as ELL	1. ELL; 2. Not ELL; 8. Omitted
5.	IEP	Student classified as having a disability, which includes students with an Individualized Educational Program (IEP), for reasons other than being gifted or talented or students with a Section 504 Plan (FROM DISABILITY QUESTIONNAIRE INSTRUCTIONS).	1. Student with disability; 2. Not student with disability; 8. Omitted
6.	SDRACEM	Race/ethnicity (from school administration records)	1. White; 2. Black; 3. Hispanic; 4. Asian Amer/Pacif Isl; 5. AI/AN; 6. Unclassified
7.	SLUNCH1	Student classified as being eligible for National School Lunch Program	1. Eligible; 2. Not eligible; 3. Info not available
	Student questionnaire items		
8.	B013801 (VB331335)	FINANCIAL CAPITAL About how many books are there in your home?	1. 0-10 books; 2. 11-25 books; 3. 26-100 books; 4. more than 100 books; 8. Omitted; 0. Multiple
9.	B003501	How far in school did your mother go?	1. Did not finish h.s; 2. Graduated h.s.; 3. Some ed after h.s.; 4. Graduated college; 7. I don't know; 8. Omitted; 0. Multiple

10.	PARED	HUMAN CAPITAL Parental education level (from 2 questions – highest level of education between mother and father)	1. Did not finish h.s; 2. Graduated h.s.; 3. Some ed after h.s.; 4. Graduated college; 7. I don't know; 8. Omitted; 0. Multiple
11.	B018201 (VB331451)	How often do people in your home talk to each other in a language other than English?	1. Never; 2. Once in a while; 3. About half the time; 4. All or most of the time
12.	M824901 (VC497573)	How often do you feel you have a clear understanding of what your math teacher is asking you to do?	1. Never or hardly ever; 2. Sometimes; 3. Often; 4. Always or almost always
13.	IBI9301	SOCIAL CAPITAL How often does family help with your schoolwork?	1. Never or hardly ever; 2. Once or twice a month; 3. Once or twice a week; 4. Every day or almost every day
14.	IB19601	SOCIAL CAPITAL During 8th grade, how many times have you talked to a family member about the classes you should take in high school or about what you want to do after high school?	1. Never; 2. One time; 3. Two or three times; 4. Four or more times
15.	B017451	SOCIAL CAPITAL How often do you talk about things you have studied in school with someone in your family?	1. Never or hardly ever; 2. Once every few weeks; 3. About once a week; 4. Two or three times a week; 5. Every day
		Derived risk factor "Attitude toward mathematics" using the following seven items	
16-19.	(M824902/VC497574) (M824903/VC497575) (M824904/VC497576) (M824905/VC497577)	How often do you feel the following way in your math class? • Math work is too easy (M824902/VC497574) • Math work is challenging (reverse coded) (M824903/VC497575) • Math work is engaging and	1. Never or hardly ever; 2. Sometimes; 3. Often; 4. Always or almost always

		interesting (M824904/VC497576) • I am learning (M824905/VC497577)	
20-22.	(M820901/VC189707) (M820905/VC189711) (M820904/VC189710)	Please indicate how much you disagree or agree with the following statements. • Math is fun (M820901/VC189707) • Math is favorite subject (M820905/VC189711) • Like math (M820904/VC189710)	1. Strongly disagree; 2. Disagree; 3. Agree; 4. Strongly agree
23.	IBI7601	<u>Self-confidence in math</u> How do you rated yourself in mathematics? (p. 37)	1. Poor; 2. Average; 3. Good; 4. Very good
24.	B018101	<u>Opportunity to Learn</u> How many days were you absent from school in the last month? (p. 52)	1. None; 2. 1 or 2 days; 3. 3 or 4 days; 4. 5 to 10 days; 5. More than 10 days
25.	M815701	<u>Opportunity to Learn</u> What math class are you taking this year?	1. Geometry; 2. Algebra II; 3. Algebra I (one-year course); 4. First year of a two-year Algebra I Course; 5. Second year of a two-year Algebra I Course; 6. Introduction to algebra or pre-algebra; 7. Basic or general eighth-grade math; 8. Integrated or sequential math; 9. Other math class
		Derived risk factor "Knowledge of AI/AN culture" using the following three items	
26-28.	IB18501- IB18503	<u>Knowledge of AI/AN culture</u> How much do you know about each of the following? • Your American Indian or Alaska Native history (IB18501)	1. Nothing; 2. A little; 3. Some; 4. A lot

		• Your American Indian or Alaska Native traditions and culture (way of life, customs) (IB18502) • Issues today that are important to American Indian or Alaska Native people (IB18503)	
		Derived risk factor "Participation in AI/AN cultural activities" using the following three items	
29-31.	IB18601- IB18603	<u>Participation in AI/AN cultural activities</u> How often have you participated in each of the following? • Ceremonies and gatherings for people from your AI tribe or AN group (IB18601) • Ceremonies and gatherings that bring people together from many different AI tribes or AN groups (IB18602) • Other AI or AN activities (IB18603)	1. Never; 2. Every few years; 3. At least once a year; 4. Several times a year
Teacher questionnaire items			
32.	T096601 (VC309886)	This school year, are you a Highly Qualified Teacher (HQT) according to your state's requirements?	1. Yes; 2. In at least 1 subject that I teach; 3. No; 8. Omitted; 0. Multiple
33.	BA21201 (VB331331)	Which of the following best describes you?	1. White
34.	BE21101 (VB331330)	Which of the following best describes you?	1. Hispanic
35.	BB21201 (VB331331)	Which of the following best describes you?	1. Black
36.	BC21201 (VB331331)	Which of the following best describes you?	1. Asian
37.	BE21201 (VB331331)	Which of the following best describes you?	1. Native Hawaiian/other Pacific Islander
38.	BD21201	Which of the following best	1. American

	(VB331331)	describes you?	Indian/Alaska Native
		Derived risk factor "Teachers incorporate AI/AN culture/tradition into their mathematics instruction" using the following six items	
39.	IT07301	To what extent do you integrate lessons and materials about American Indian or Alaska Native culture and history into your mathematics curriculum?	1. Never; 2. At least once a year; 3. At least once a month; 4. At least once a week; 5. Every day or almost every day
40.	IT06201	To what extent do you integrate lessons and materials about current issues affecting American Indian or Alaska Native people and communities into your mathematics curriculum?	1. Never; 2. At least once a year; 3. At least once a month; 4. At least once a week; 5. Every day or almost every day
41-44.	IT06301-IT06304	How often do you have your students do each of the following mathematics activities? • Solve mathematics problems that reflect situations found in American Indian or Alaska Native communities • Participate in activities that integrate mathematics with American Indian or Alaska Native themes (for example, use traditional symbols and designs to teach geometric concepts) • Study traditional American Indian or Alaska Native mathematics (for example, American Indian or Alaska Native systems of counting, estimating, and recording quantities) • Study mathematics within traditional American Indian or Alaska Native	1. Never; 2. At least once a year; 3. At least once a month; 4. At least once a week; 5. Every day or almost every day

		contexts (for example, American Indian or Alaska Native systems of astronomy and physics)	
School questionnaire risk factors			
45.	C051601 (VB608487)	<u>SES</u> Percent Eligible National School Lunch Program	1. 0%; 2. 1-5%; 3. 6-10%; 4. 11-25%; 5. 26-34%; 6. 35-50%; 7. 51-75%; 8. 76-99%; 9. 100%; 88. Omitted; 0. Multiple
		Derived risk factor "Safe and orderly schools" using the following set of eight items	
46-53.	IS05501, IS05502, IS05504, IS05506-IS05510,	Considering all of the students in your school, to what extent is each of the following a problem in your school? • Student absenteeism (IS05501) • Student tardiness (IS05502) • Drug or alcohol use by students (IS05504) • Physical conflicts among students (IS05506) • Bullying (IS05507) • Low student aspirations (IS05508) • Low teacher expectations (IS05509) • Low family involvement (IS05510)	1. Not at all; 2. Small extent; 3. Moderate extent; 4. Large extent
		Derived risk factor "Classes in AI/AN cultures and traditions are offered by schools" using the following set of seven items	
54-60.	IS05101-IS05107	Do students in your school receive instruction about American Indian or Alaska Native cultures in any of the following areas?	1. Yes; 2. No

		• Oral language (IS05101/VC963005) • Written language (IS05102/VC963007) • History of tribes or cultural groups (IS05103/VC963008) • Traditions and customs (IS05104/VC963009) • Arts, crafts, music, or dance (IS05105/VC963010) • Tribal or village government (IS05106/VC963013) • Current events and issues important to tribes or cultur groups (IS05107/VC96301	
61.	IS05902	<u>Culture in school</u> Please indicate what percentage of individuals at your school is described by each of the following statements: • AI/AN teachers at this school	1. 0%; 2. 1-5%; 3. 6-10%; 4. 11-25%; 5. 26-50%; 6. 51-75%; 7. 76-100%; 77. I don't know; 88. Omitted; 0. Multiple
62-70.	IS02401-IS02408, IS024011	For this school year, has funding from any of the following sources been used to provide educational services and support for American Indian or Alaska Native students? Some of the sources are designated specifically for American Indian or Alaska Native education, while others are intended for broader use. • Title I funds (compensatory ed) (IS02401) • Title II funds (Professional Improvement) (IS02402) • Title III or other bilingual or ESL/ELL funds (IS02403)	1. Yes; 2. No; 7. I Don't Know; 8. Omitted; 0. Multiple

		• Title VII, Indian Ed Formula Grant (IS02404) • Title VII, Discretionary Grant under Indian Education (IS02405) • IDEA funds (IS02406) • Impact Aid Program (IS02407) • Johnson-O'Malley Grant (IS02408) • Other funding sources related to American Indian or Alaska Native education (e.g., grants, donations, tuition, etc.) (IS024011)	

Appendix C: Creating the Derived Risk Factors

As stated in Chapter 3, each of the nine derived risk factor was calculated using both listwise deletion and conditional mean substitution. The version of each derived risk factor calculated using listwise deletion was used in research questions 1, 2, and 3 while the version of each derived risk factor calculated using conditional mean substitution (i.e., substituting the mean in each state and school density type for missing data) was used only for research question 3. This appendix describes the creation of each derived risk factor using listwise deletion followed by the recalculated results using conditional mean substitution.

Attitude toward mathematics. One derived risk factor was created using the NAEP student questionnaire data: *attitude toward mathematics*. The following seven items were tested to see how many would combine to form a derived risk factor:

- How often do you feel the following way in your mathematics class? *(1. Never or hardly ever; 2. Sometimes; 3. Often; 4. Always or almost always)*
    - Mathematics work is too easy. (M824902/VC497574)
    - Mathematics work is challenging. **(reverse coded)** (M824903/VC497575)
    - Mathematics work is engaging and interesting. (M824904/VC497576)
    - I am learning. (M824905/VC497577)
- Please indicate how much you disagree or agree with the following statements. *(1. Strongly disagree; 2. Disagree; 3. Agree; 4. Strongly agree)*
    - Mathematics is fun. (M820901/VC189707)
    - Mathematics is favorite subject. (M820905/VC189711)
    - Like mathematics. (M820904/VC189710)

First, the item *mathematics is challenging* was reversed coded. Next, principal axis factor analysis (PAF)[41] using Spearman's rho correlation coefficient was run using all seven items. Data from AI/AN students and students of all other races in both states combined were used to create this derived risk factor. The data were weighted using the overall student weight (ORIGWT). The sample size was 35,673, using listwise deletion. Two items (*mathematics work is too easy* and *mathematics is challenging*) had correlations less than 0.3 with all the other items. However, they were moderately correlated with each other (0.468). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.805, above the recommended value of 0.6. Bartlett's test of sphericity was significant (χ^2 (21) = 92434, p < .0001); therefore, this was not an identity matrix. This was also confirmed by the determinant, which was 0.075. The first two eigenvalues were greater than 1. Together they accounted for 66% of the total variance. Since the items loaded on two factors, varimax and oblimin rotations of the factor loading matrix were examined. The results of both types of rotations showed similar loadings on each factor. Table C1 shows the varimax rotation results. The items *mathematics is challenging* and *mathematics work is too easy* loaded highly on the second factor.

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[41] All PAF analyses were run in SPSS.

Table C1: *Rotated Factor Matrix[a] for attitude toward mathematics (all seven items)*

	Factor	
	1	2
Like mathematics	.839	
Mathematics is a favorite subject	.788	
Mathematics is fun	.768	
Mathematics work is engaging and interesting	.663	
I am learning	.455	
Mathematics is challenging reverse coded		.764
Mathematics work is too easy		.598

Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Notes. Values are based upon weighted estimates.

Next a reliability analysis[42] was run. Cronbach's alpha was 0.798. *Mathematics is challenging* was the only item of the seven in which the Cronbach's alpha would have been higher than 0.798 if the item was deleted ($\alpha = 0.817$).

Another PAF was conducted using Spearman's rho without the *mathematics is challenging* item. The sample size was 36,262. *Mathematics work is too easy* had correlations less than 0.3 with all the other items. The KMO value was 0.834. Bartlett's test of sphericity was significant (χ^2 (15) = 84400, $p < .0001$). The determinant was 0.098. One eigenvalue was greater than 1 and accounted for 54% of the total variance. Table C2 shows that *mathematics work is too easy* and *I am learning* were moderately associated with Factor 1.

[42] All reliability analyses were run in SPSS.

Table C2: *Factor Matrix[a] for attitude toward mathematics without mathematics is challenging*

	Factor
	1
Like mathematics	.871
Mathematics is a favorite subject	.829
Mathematics is fun	.786
Mathematics work is engaging and interesting	.644
I am learning	.450
Mathematics work is too easy	.331

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 6 iterations required.

Notes. Values are based upon weighted estimates.

Another reliability analysis was conducted with these six items. Cronbach's alpha was 0.817. If *I am learning* and *mathematics work is too easy* were deleted, Cronbach's alpha would have been higher than 0.817 ($\alpha = 0.821$ and $\alpha = 0.841$, respectively).

A final PAF was conducted using Spearman's rho without the *mathematics is challenging* and *mathematics work is too easy*. The sample size was 36,367. No items had correlations of less than 0.3. The KMO value was 0.820. Bartlett's test of sphericity was significant (χ^2 (10) = 80710, $p < .0001$). The determinant was 0.109. One eigenvalue was greater than 1 and accounted for 62% of the total variance. Table C3 shows that *I am learning* was moderately associated with Factor 1.

Table C3: *Factor Matrix[a] for final attitude toward mathematics derived risk factor without mathematics is challenging and mathematics is too easy*

	Factor 1
Like mathematics	.870
Mathematics is a favorite subject	.822
Mathematics is fun	.788
Mathematics work is engaging and interesting	.646
I am learning	.457

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 6 iterations required.

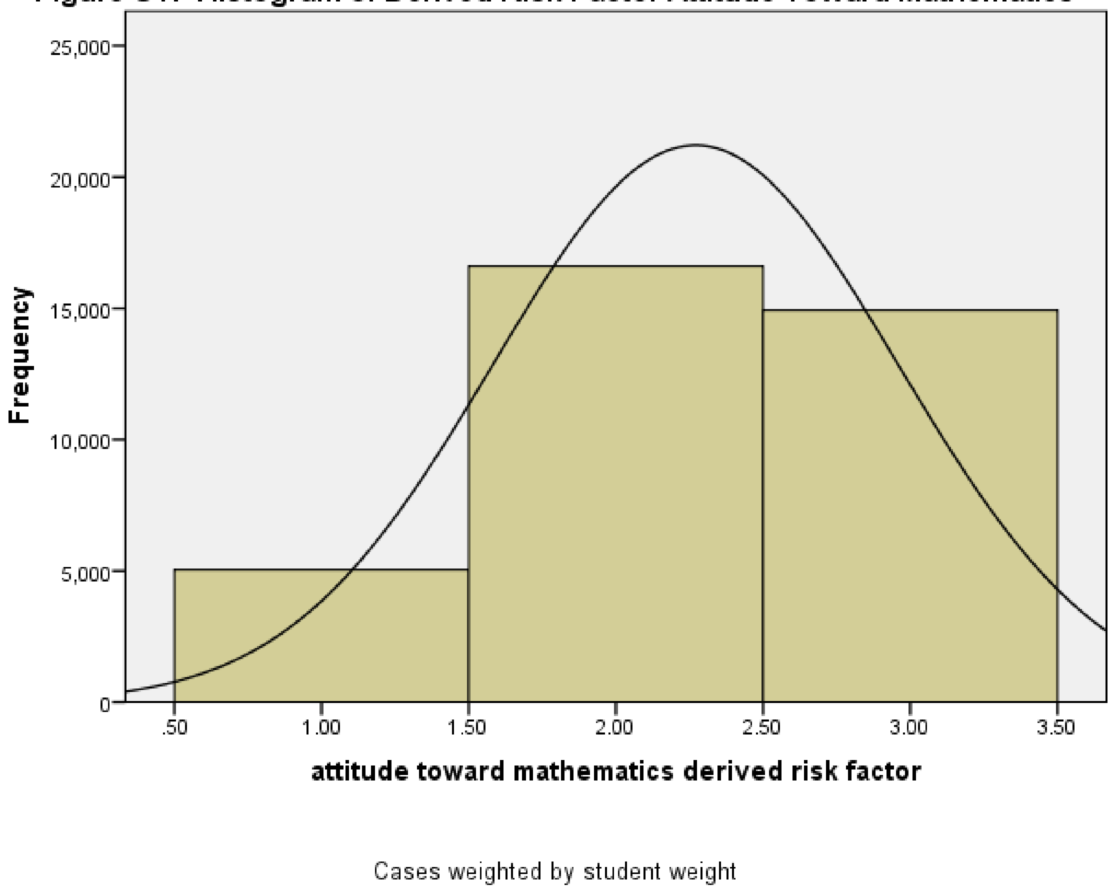
Notes. Values are based upon weighted estimates.

A final reliability analysis was conducted with these five items. Cronbach's alpha was 0.841. If *I am learning* was deleted, Cronbach's alpha would have been higher than 0.841 ($\alpha = 0.859$), but a decision was made to create the *attitude toward mathematics* derived risk factor using these five items that load on one factor for construct representation (*mathematics work is engaging and interesting*; *mathematics is fun*; *like mathematics*; *I am learning*; and *mathematics is a favorite subject*). The responses to these five items were added together and divided by five to get the mean *attitude toward mathematics* derived risk factor value for each student[43]. Next, the scores were divided into three categories based on logic and the distribution of the data: like learning mathematics (an average score equal to or greater than 3), somewhat like learning mathematics (an average score of 2 to 2.99), and do not like learning mathematics (an average score less than 2). The final derived risk factor included data for 37,921 students

[43] Chapter 3 describes an alternative to using the mean and why it is justified to use the mean in this dissertation.

(4.3% of the data were missing). Figure C1: Histogram of Derived Risk Factor Attitude Toward Mathematics shows the distribution of the data for the derived risk factor *attitude toward mathematics*.

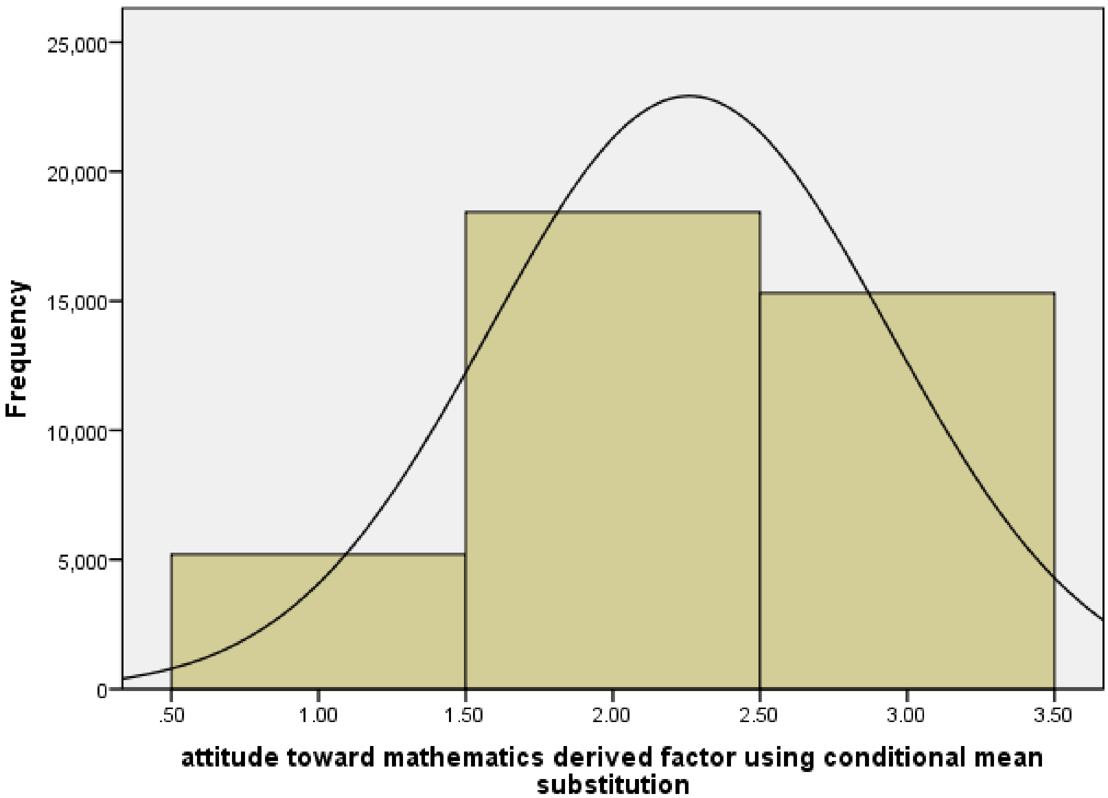
Figure C1: Histogram of Derived Risk Factor Attitude Toward Mathematics



The *8th grade mathematics achievement scores* were regressed on the final five individual items that comprised the *attitude toward mathematics* derived risk factor. The *attitude toward mathematics* derived risk factor accounted for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.09$, $F(5, 36{,}565) = 26.31$, $p < 0.001$. These five items had a 0.3 correlation with *8th grade mathematics achievement*.

Figure C2: Histogram of Derived Risk Factor Attitude Toward Mathematics using Conditional Mean Substitution shows the distribution of the data for the derived risk factor *attitude toward mathematics* using conditional mean substitution for any missing data.

Figure C2: Histogram of Derived Risk Factor Attitude Toward Mathematics using conditional mean substitution



Cases weighted by student weight

Using conditional mean substitution, the *attitude toward mathematics* derived risk factor accounted for a significant proportion of variance in *8th grade mathematics achievement* test scores, R^2 = 0.08, F(5, 38,933) = 25.3, p < 0.001. These five items had a 0.3 correlation with *8th grade mathematics achievement*, using conditional mean substitution.

Using the NIES student, teacher, and school questionnaires, several risk factors were derived. First, using the NIES student questionnaire, two student-level, culture-related risk factors were created.

Knowledge of AI/AN culture. The first NIES derived risk factor represented *knowledge of AI/AN culture* and was calculated using the following three items from the NIES student questionnaire:

- How much do you know about each of the following? *(1. Nothing; 2. A little; 3. Some; 4. A lot)*
  - Your American Indian or Alaska Native history (IB18501)
  - Your American Indian or Alaska Native traditions and culture (way of life, customs) (IB18502)
  - Issues today that are important to American Indian or Alaska Native people (IB18503)

A principal axis factor analysis (PAF) using Spearman's rho correlation coefficient was run. Data from just AI/AN students in both states combined were used to create this derived risk factor. The data were weighted using the overall student weight (ORIGWT). The sample size was 5,938, using listwise deletion. The three items were correlated between 0.430 and 0.485 with each other. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.676, slightly above the recommended value of 0.6. Bartlett's test of sphericity was significant ($\chi^2(3) = 3,385$, $p < 0.0001$); therefore, this was not an identity matrix. This was also confirmed by the determinant, which was 0.565. There was one eigenvalue greater than 1, which accounted for 64% of the total variance. The items loaded on one factor so no rotations were needed. Table C4 shows the unrotated results for the *knowledge of AI/AN culture* derived risk factor.

Table C4: *Factor Matrix[a] for Knowledge of AI/AN culture derived risk factor*

	Factor
	1
AI/AN history	.711
AI/AN traditions	.681
Issues in world important to AI/AN	.632

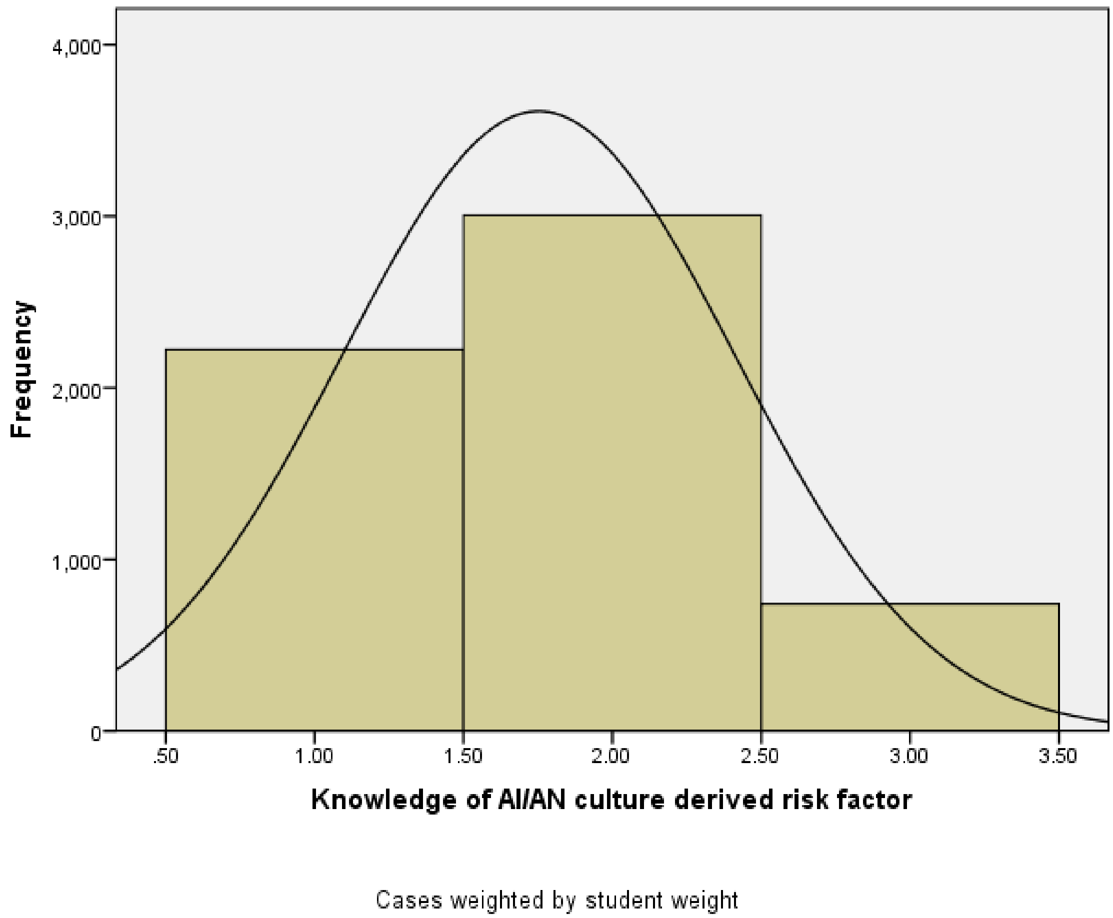
Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 9 iterations required.

Notes. Values are based upon weighted estimates.

A reliability analysis was conducted. Cronbach's alpha was 0.711. Cronbach's alpha would not have increased if any of the items were deleted. The responses to these three items were added together and divided by three to get the mean *knowledge of AI/AN culture* derived risk factor value for each student. Next, the scores were divided into three categories based on logic and the distribution of the data: a lot (an average score equal to or greater than 4), some (an average score of 3 to 3.99), and a little/nothing (an average score less than 2.99). The final derived risk factor included data for 5,969 students (2.2% of the data were missing). Figure C3: Histogram of Derived Risk Factor Knowledge of AI/AN Culture shows the distribution of the data for the *knowledge of AI/AN culture* derived risk factor.

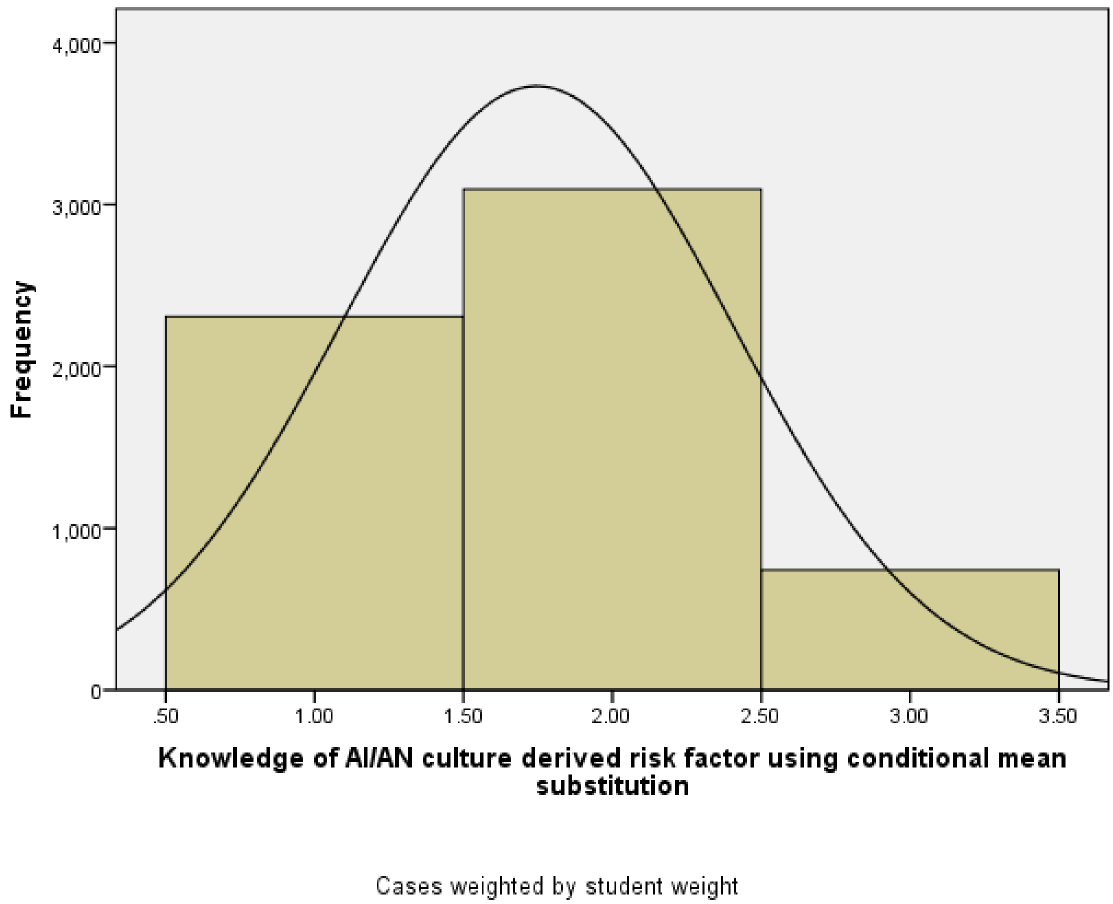
Figure C3: Histogram of Derived Risk Factor Knowledge of AI/AN Culture



A multiple regression of *8th grade mathematics achievement scores* on the three individual items showed that the *knowledge of AI/AN culture* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.01$, $F(3, 5{,}966) = 1.45$, $p = 0.24$. These three items had a 0.1 correlation with *8th grade mathematics achievement*.

Figure C4: Histogram of Derived Risk Factor Knowledge of AI/AN Culture using conditional mean substitution shows the distribution of the data for the derived risk factor *knowledge of AI/AN culture* using conditional mean substitution for any missing data.

Figure C4: Histogram of Derived Risk Factor Knowledge of AI/AN Culture using conditional mean substitution



Using conditional mean substitution, the *knowledge of AI/AN culture* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.01$, $F(3, 6{,}140) = 1.44$, $p = 0.24$. These three items had a 0.1 correlation with *8th grade mathematics achievement*, using conditional mean substitution.

Participation in AI/AN cultural activities. The *participation in AI/AN cultural activities* derived risk factor was created using the following three items from the NIES student questionnaire:

- How often have you participated in each of the following? *(1. Never; 2. Every few years; 3. At least once a year; 4. Several times a year)*
  - Ceremonies and gatherings for people from your AI tribe or AN group (IB18601)
  - Ceremonies and gatherings that bring people together from many different AI tribes or AN groups (IB18602)
  - Other AI or AN activities (IB18603)

A principal axis factor analysis (PAF) using Spearman's rho correlation coefficient was run. Data from just AI/AN students in both states combined were used to create this derived risk factor. The data were weighted using the overall student weight (ORIGWT). The sample size was 5,927, using listwise deletion. The three items were correlated between 0.557 and 0.659 with each other. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.711, above the recommended value of 0.6. Bartlett's test of sphericity was significant (χ^2 (3) = 6551, p < .0001); therefore, this was not an identity matrix. This was also confirmed by the determinant, which was 0.331. There was one eigenvalue greater than 1, which accounted for 74% of the total variance. The items loaded on one factor so no rotations were needed. Table C5 shows the unrotated results for the participation in AI/AN cultural activities derived risk factor.

Table C5: *Factor Matrix[a] for participation in AI/AN cultural activities*

	Factor
	1
Attend gatherings of many groups	.848
Attend ceremonies/gatherings of group	.777
Attend other AI/AN activities	.718

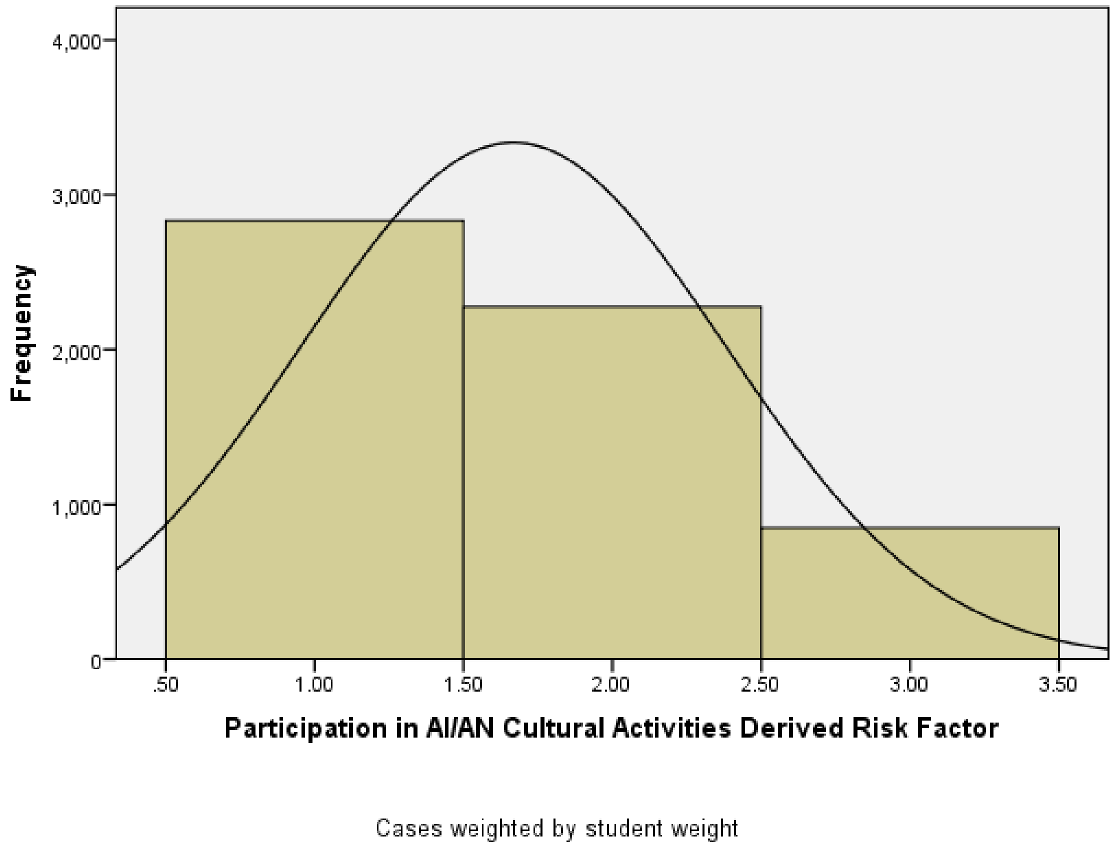
Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 11 iterations required.

Notes. Values are based upon weighted estimates.

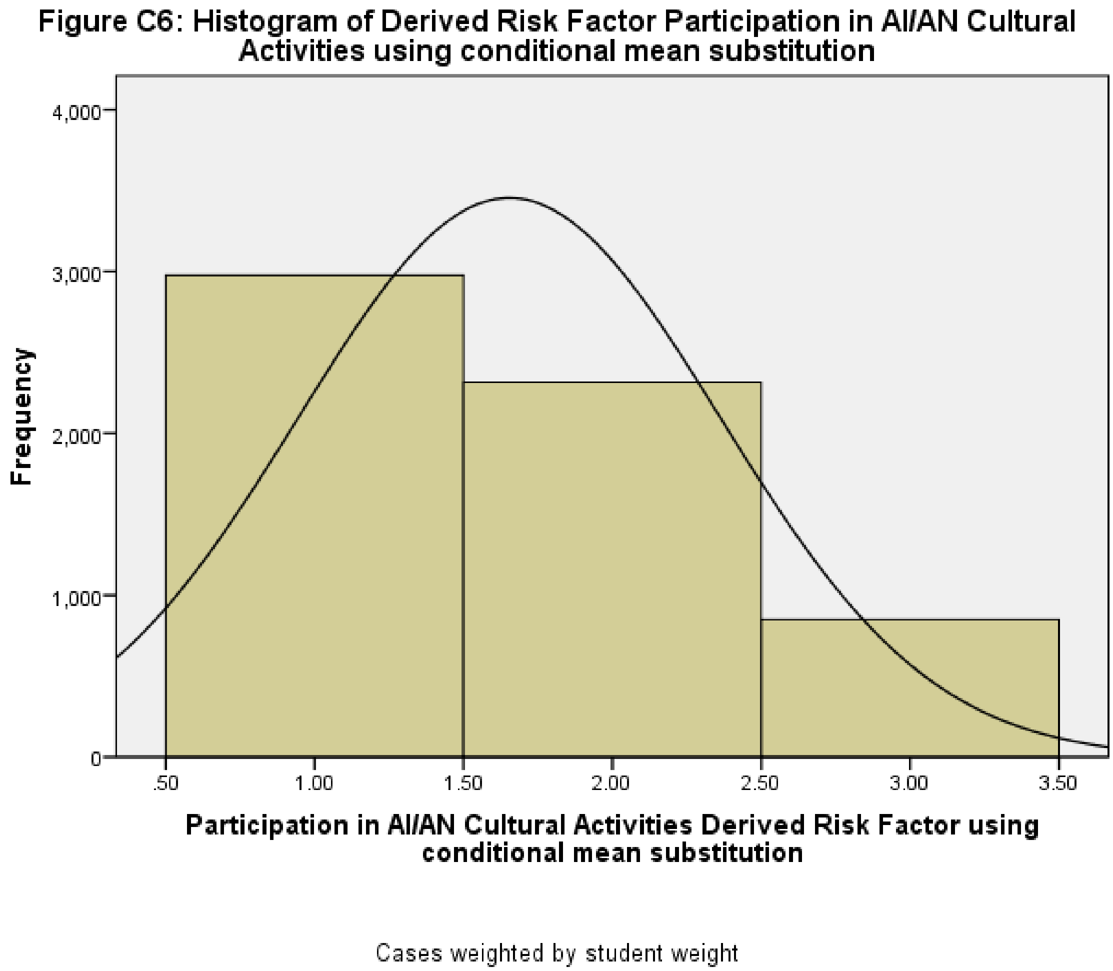
A reliability analysis was conducted. Cronbach's alpha was 0.826. Cronbach's alpha would not have increased if any of the items were deleted. The responses to these three items were added together and divided by three to get the mean *participation in AI/AN cultural activities* derived risk factor value for each student. Next, the scores were divided into three categories based on logic and the distribution of the data: several times a year (an average score equal to 4), at least once a year (an average score of 3 to 3.99), and never/every few years (an average score less than 2.99). The final derived risk factor included data for 5,959 students (3% of the data were missing). Figure C5: Histogram of Derived Risk Factor Participation in AI/AN Cultural Activities shows the distribution of the data for the *participation in AI/AN cultural activities* derived risk factor.

Figure C5: Histogram of Derived Risk Factor Participation in AI/AN Cultural Activities



A multiple regression of *8th grade mathematics achievement scores* on the three individual items showed that the *participation in AI/AN cultural activities* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.01$, $F(3, 5{,}956) = 0.87$, $p = 0.46$. These three items had a 0.1 correlation with *8th grade mathematics achievement*.

Figure C6: Histogram of Derived Risk Factor Participation in AI/AN Cultural Activities using conditional mean substitution shows the distribution of the data for the derived risk factor *participation in AI/AN culture* using conditional mean substitution for any missing data.



Using conditional mean substitution, the *participation in AI/AN cultural activities* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.01$, $F(3, 6{,}140) = 0.99$, $p = 0.4$. These three items had a 0.1 correlation with *8th grade mathematics achievement*, using conditional mean substitution.

Teachers incorporate AI/AN culture/tradition into their mathematics instruction. From the NIES teacher questionnaire, a culturally-based derived risk factor regarding how often *teachers incorporate AI/AN culture/tradition into their mathematics instruction* was created from the following six items:

- To what extent do you integrate lessons and materials about American Indian or Alaska Native culture and history into your mathematics curriculum? (*1. Never; 2. At least once a year; 3. At least once a month; 4. At least once a week; 5. Every day or almost every day)*
- To what extent do you integrate lessons and materials about current issues affecting American Indian or Alaska Native people and communities into your mathematics curriculum? (*1. Never; 2. At least once a year; 3. At least once a month; 4. At least once a week; 5. Every day or almost every day)*
- How often do you have your students do each of the following mathematics activities? (*1. Never; 2. At least once a year; 3. At least once a month; 4. At least once a week; 5. Every day or almost every day)*
    - Solve mathematics problems that reflect situations found in American Indian or Alaska Native communities
    - Participate in activities that integrate mathematics with American Indian or Alaska Native themes (for example, use traditional symbols and designs to teach geometric concepts)
    - Study traditional American Indian or Alaska Native mathematics (for example, American Indian or Alaska Native systems of counting, estimating, and recording quantities)
    - Study mathematics within traditional American Indian or Alaska Native contexts (for example, American Indian or Alaska Native systems of astronomy and physics)

A principal axis factor analysis (PAF) using Spearman's rho correlation coefficient was run. Data from just AI/AN students in both states combined were used to create this derived risk factor. The data were weighted using the overall student weight (ORIGWT). The sample size was 5,549, using listwise deletion. The only items with a correlation of less than 0.3 was the correlation between *study traditional AI/AN mathematics* and *solve mathematics problems reflecting typical AI/AN situation* with a correlation of 0.265. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.762, above the recommended value of 0.6. Bartlett's test of sphericity was significant (χ^2 (15) = 19261, $p < .0001$); therefore, this was not an identity matrix. This was also confirmed by the determinant, which was 0.031. There were two eigenvalues greater than 1, which accounted for 79% of the total variance. Since the items loaded on two factors, varimax and oblimin rotations of the factor loading matrix were examined. The results of both types of rotations had similar loadings on each factor. Table C6 shows the varimax rotation results. Although the unrotated factor matrix showed all six items loaded higher on factor 1, the varimax and oblimin results showed that *study traditional AI/AN mathematics* and *study mathematics within traditional AI/AN contexts* both loaded on factor 2 and *integrate mathematics with AI/AN themes* loaded almost equally on factors 1 and 2.

Table C6: *Rotated Factor Matrix[a] for teachers incorporate derived risk factor (all six items)*

	Factor	
	1	2
Integrate issues affecting AI/AN into mathematics curriculum	.864	
Solve mathematics problem reflecting typical AI/AN situation	.823	
Integrate AI/AN culture/history into mathematics curriculum	.690	.302
Study traditional AI/AN mathematics		.899
Study mathematics within traditional AI/AN contexts		.862
Integrate mathematics with AI/AN themes	.467	.522

Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Notes. Values are based upon weighted estimates.

A reliability analysis was conducted. Cronbach's alpha was 0.840. Cronbach's alpha would not have increase if any of the items were deleted. But, the decision was made to run another PAF using Spearman's rho without *study traditional AI/AN mathematics* and *study mathematics within traditional AI/AN contexts*. The sample size was 5,549. The correlations among the four items were higher, ranging from 0.436 and 0.727. The KMO value was 0.774. Bartlett's test of sphericity was significant (χ^2 (6) = 10174, p < .0001). The determinant was 0.160. One eigenvalue was greater than 1 and accounted for 69% of the total variance. Table C7 shows that these four items were moderately to strongly associated with factor 1.

Table C7: *Factor Matrix[a] for teachers incorporate AI/AN culture/tradition into their mathematics instruction (final version)*

	Factor
	1
Integrate issues affecting AI/AN into mathematics curriculum	.870
Solve mathematics problem reflecting typical AI/AN situation	.839
Integrate AI/AN culture/history into mathematics curriculum	.754
Integrate mathematics with AI/AN themes	.587

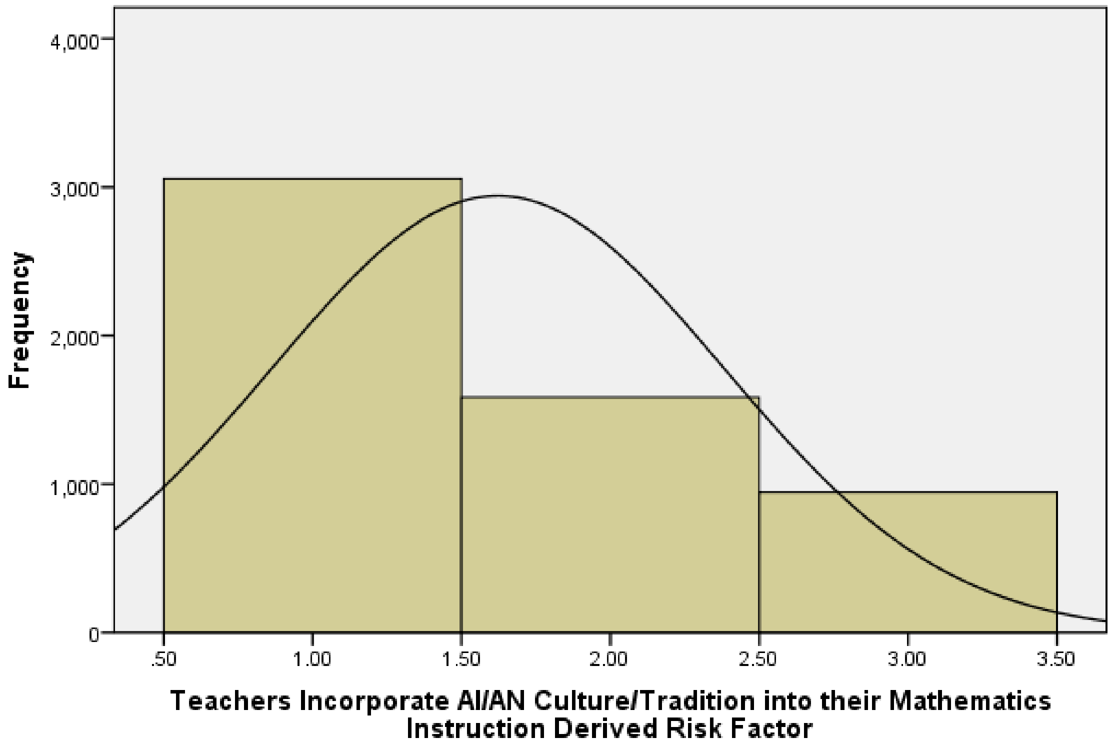
Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 7 iterations required.

Notes. Values are based upon weighted estimates.

A final reliability analysis was run. Cronbach's alpha was 0.835. Cronbach's alpha would not have increased if any of the items were deleted. The responses to these four items were added together and divided by four to get the mean *teachers incorporate AI/AN culture/tradition into their mathematics instruction* derived risk factor value for each student. Next, the scores were divided into three categories based on logic and the distribution of the data: once/month or more (an average score equal to or greater than 3), at least once/year (an average score of 2 to 2.99), and never (an average score less than 2). The final derived risk factor included data for 5,586 students (9.1% of the data were missing). Figure C7: Histogram of Derived Risk Factor Teachers incorporate AI/AN Culture/Tradition into their Mathematics Instruction shows the distribution of the data for *teachers incorporate AI/AN culture/tradition into their mathematics instruction* derived risk factor.

Figure C7: Histogram of Derived Risk Factor Teachers Incorporate AI/AN Culture/Tradition into their Mathematics Instruction

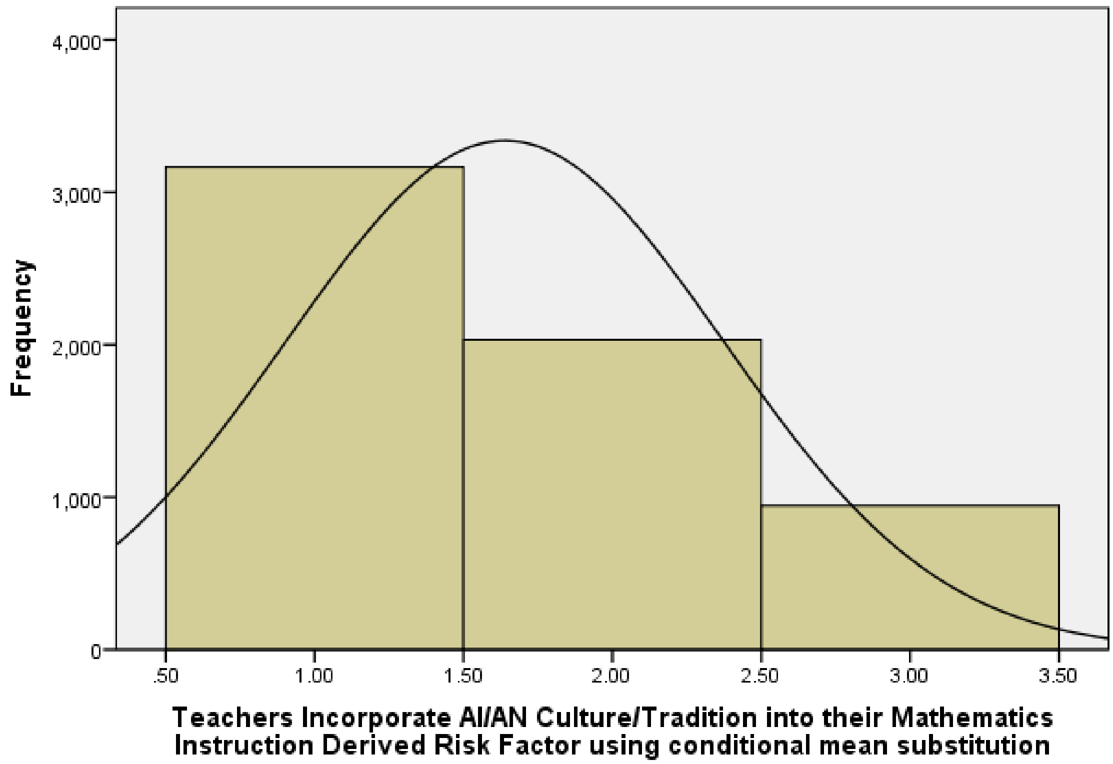


Cases weighted by student weight

A multiple regression of *8th grade mathematics achievement scores* on the four individual items showed that the *teachers incorporate AI/AN culture/tradition into their mathematics instruction* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.03$, $F(4, 5{,}582) = 1.74$, $p = 0.15$. These three items had a 0.17 correlation with *8th grade mathematics achievement*.

Figure C8: Histogram of Derived Risk Factor Teachers incorporate AI/AN Culture/Tradition into their Mathematics Instruction using conditional mean substitution shows the distribution of the data for the derived risk factor *teachers incorporate AI/AN* *culture/tradition into their mathematics instruction* using conditional mean substitution for any missing data.

Figure C8: Histogram of Derived Risk Factor Teachers Incorporate AI/AN Culture/Tradition into their Mathematics Instruction using conditional mean substitution



Cases weighted by student weight

Using conditional mean substitution, the *teachers incorporate AI/AN culture/tradition into their mathematics instruction* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.03$, $F(4, 6139) = 2.25$, $p = 0.07$. These three items had a 0.17 correlation with *8th grade mathematics achievement*, using conditional mean substitution.

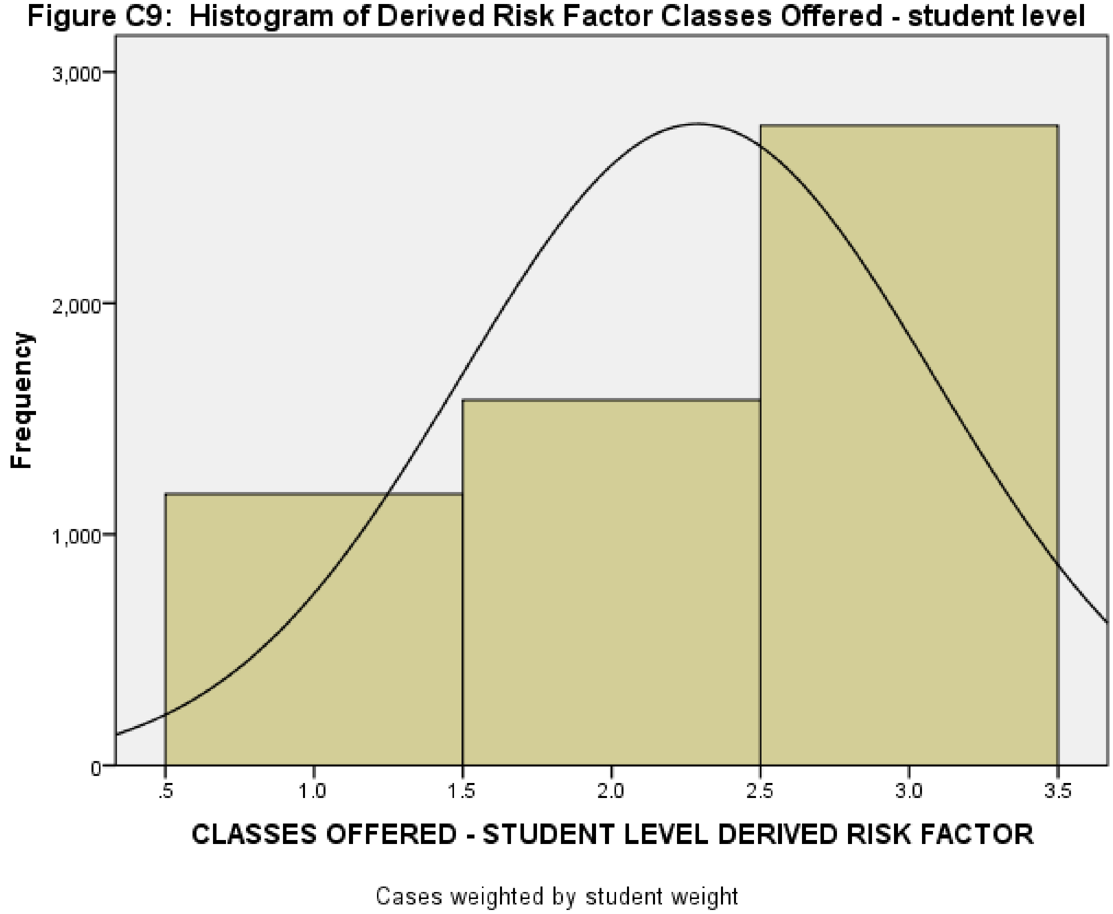
The *classes in AI/AN cultures and traditions are offered by schools* and the *safe and orderly schools* derived risk factors, which are described next, were based on questions asked of the school principals. The "student-level" versions of these derived risk factors were created using the student-level data and were used in the OLS regression analyses in research question 3b. The "school-level" versions of these derived risk factors (the descriptions of which follow the "student-level" versions) were used in the cross tabulations in research question 1b.

Classes in AI/AN cultures and traditions offered by schools- student level. From the NIES school questionnaire, a culturally-based derived risk factor relating to the number of *classes in AI/AN cultures and traditions offered by schools* was created based on the responses to the following seven items:

- Do students in your school receive instruction about American Indian or Alaska Native cultures in any of the following areas? *(1. Yes; 2. No)*
  - Oral language (IS05101/VC963005)
  - Written language (IS05102/VC963007)
  - History of tribes or cultural groups (IS05103/VC963008)
  - Traditions and customs (IS05104/VC963009)
  - Arts, crafts, music, or dance (IS05105/VC963010)
  - Tribal or village government (IS05106/VC963013)
  - Current events and issues important to tribes or cultural groups (IS05107/VC963014)

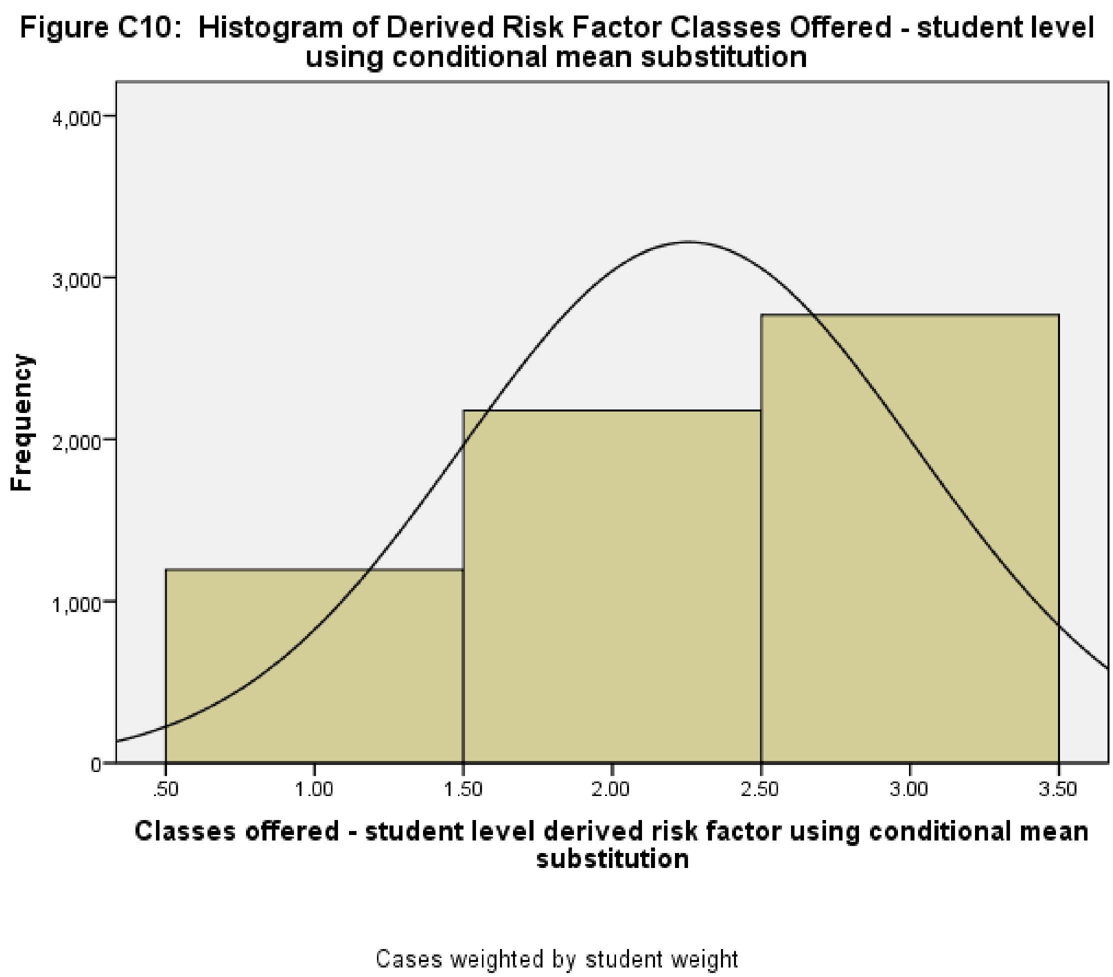
The number of "yes" responses for each question was added together for each student, which resulted in a *classes in AI/AN cultures and traditions offered by schools* derived risk factor. A high number of classes in AI/AN cultures and traditions offered by the school was represented by an average score equal to 7. A low number of classes in AI/AN cultures and traditions offered by the school was represented by an average score equal to or less than 2. A medium number of classes in AI/AN cultures and traditions offered by the school was indicated by an average score of greater than 2 but less than 7. The final derived risk factor included data for 5,524 students (10.1% of the data were missing). Figure C9: Histogram of Derived Risk Factor Classes Offered – student level shows the distribution of the data for the *classes offered* derived risk factor.

Figure C9: Histogram of Derived Risk Factor Classes Offered - student level



A multiple regression of *8th grade mathematics achievement scores* on the seven individual items showed that *the classes in AI/AN cultures and traditions offered by schools* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.04$, $F(7, 5{,}517) = 1.77$, $p = 0.11$. These seven items had a 0.2 correlation with *8th grade mathematics achievement*.

Figure C10: Histogram of Derived Risk Factor Classes Offered – student level using conditional mean substitution shows the distribution of the data for the derived risk factor *classes offered* using conditional mean substitution for any missing data.



A multiple regression of *8th grade mathematics achievement scores* on the seven individual items showed that the *classes offered in AI/AN cultures and traditions by schools* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.04$, $F(7, 6{,}136) = 1.93$, $p = 0.08$. These seven items had a 0.2 correlation with *8th grade mathematics achievement*.

Safe and orderly schools – student level. A school climate risk factor based on *safe and orderly schools* was derived using the data from the following ten questions:

- Considering all of the students in your school, to what extent is each of the following a problem in your school? *(1. Not at all; 2. Small extent; 3. Moderate extent; 4. Large extent)*
  - Student absenteeism (IS05501)
  - Student tardiness (IS05502)
  - Student health (IS05503)
  - Drug or alcohol use by students (IS05504)
  - Physical conflict (IS05505)
  - Physical conflicts among students (IS05506)
  - Bullying (IS05507)
  - Low student aspirations (IS05508)
  - Low teacher expectations (IS05509)
  - Low family involvement (IS05510)

A principal axis factor analysis (PAF) using Spearman's rho correlation coefficient was run. Data from just AI/AN students in both states combined were used to create this derived risk factor. The data were weighted using the overall student weight (ORIGWT). The sample size was 5,597, using listwise deletion. Both *student absenteeism* and *student tardiness* had correlations of less than 0.3 with several other items. *Low family involvement* and *student misbehavior* had a correlation of 0.267. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.787, above the recommended value of 0.6. Bartlett's test of sphericity was significant (χ^2 (45) = 30435.143, p < .0001); therefore, this was not an identity matrix. This was also confirmed by the determinant, which was 0.031. There were two eigenvalues greater than 1, which accounted for 63% of the total variance. Since the items loaded on two factors, varimax and oblimin rotations of the factor loading matrix were examined. The results of both types of rotations had similar loadings on each factor. The varimax and oblimin results showed that *student absenteeism* and *student tardiness* both loaded on factor 2 and *low family involvement* loaded almost equally on factors 1 and 2. Table C8 shows the varimax rotation results.

Table C8: *Rotated Factor Matrix[a] for safe and orderly schools derived risk factor – student level (all 10 items)*

	Factor	
	1	2
Problem in your school: physical conflict btw stud	.782	
Problem in your school: low student aspirations	.725	.323
Problem in your school: bullying	.715	
Problem in your school: student drug/alcohol use	.662	
Problem in your school: student misbehavior	.618	
Problem in your school: low teacher expectations	.608	.301
Problem in your school: student health	.592	
Problem in your school: student absenteeism		.912
Problem in your school: student tardiness		.759
Problem in your school: low family involvement	.425	.531

Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Notes. Values are based upon weighted estimates.

A reliability analysis was conducted. Cronbach's alpha was 0.883. Cronbach's alpha would not have increased if any of the items were deleted. But, the decision was made to run another PAF using Spearman's rho without *student absenteeism* and *student tardiness*. The sample size was 5,597. The only correlation less than 0.3 was still *low family involvement* and *student misbehavior* ($\alpha = 0.267$). The KMO value was 0.802. Bartlett's test of sphericity was significant (χ^2 (28) = 22260.824, $p < .0001$). The determinant was 0.019. One eigenvalue was greater than 1 and accounted for 54% of the total variance. Table C9 shows that these three items were moderately to strongly associated with factor 1.

Table C9: *Factor Matrix[a] for safe and orderly schools derived risk factor – student level (final version)*

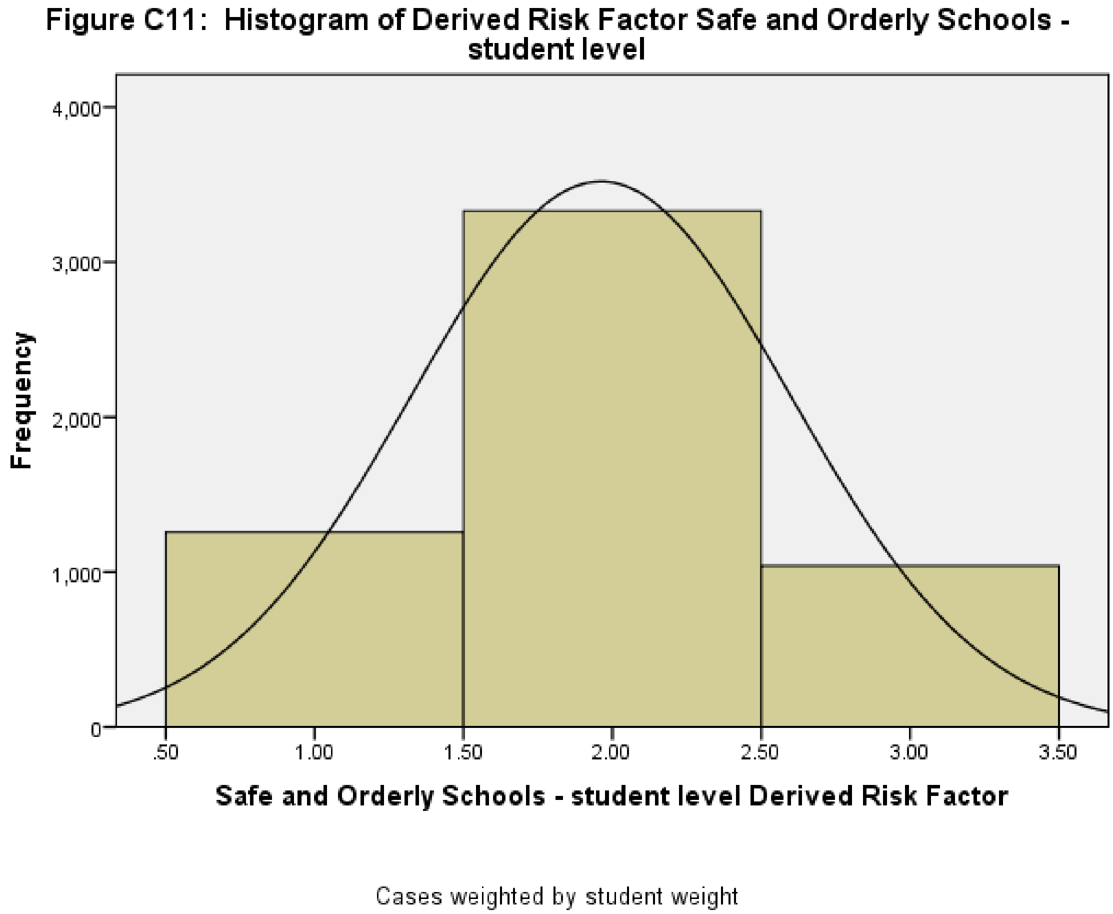
	Factor
	1
Problem in your school: low student aspirations	.811
Problem in your school: physical conflict btw stud	.782
Problem in your school: bullying	.709
Problem in your school: low teacher expectations	.688
Problem in your school: student drug/alcohol use	.678
Problem in your school: student health	.646
Problem in your school: student misbehavior	.617
Problem in your school: low family involvement	.577

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 5 iterations required.

Notes. Values are based upon weighted estimates.

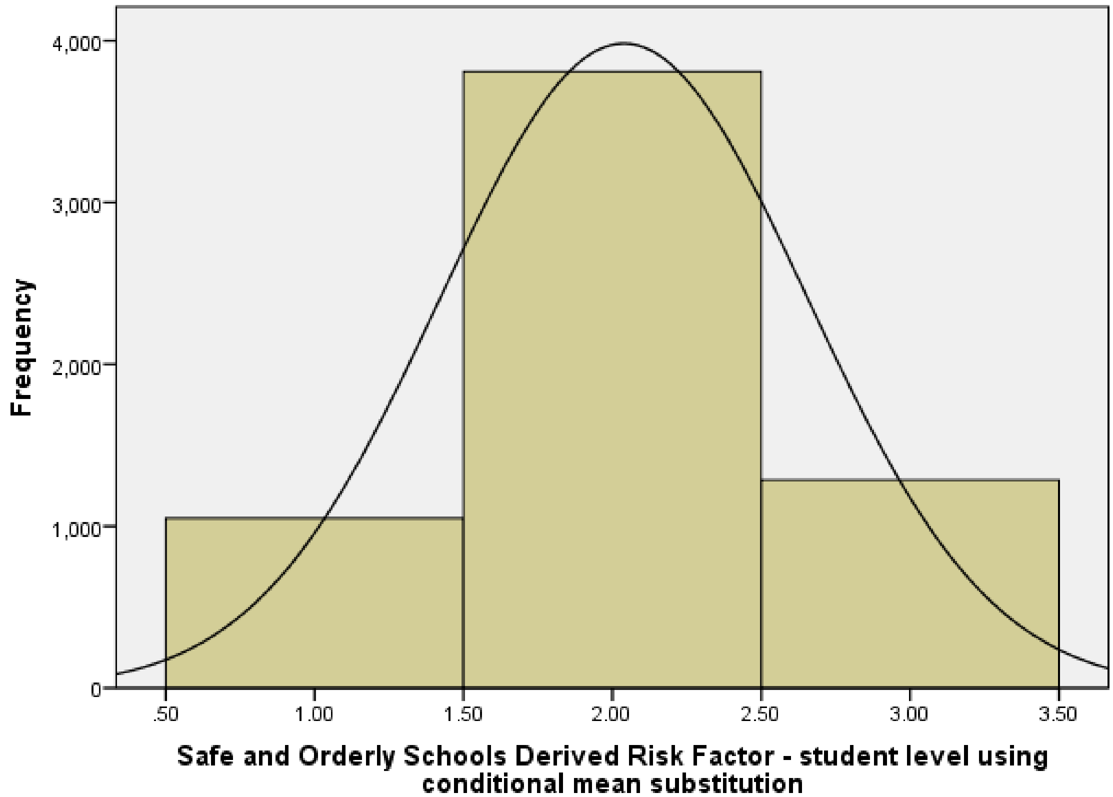
A final reliability analysis was run. Cronbach's alpha was 0.877. Cronbach's alpha would not have increased if any of the items were deleted. The responses to these eight items were added together and divided by eight to get the mean "safe and orderly schools" derived risk factor value for each student. Next, the scores were divided into three categories based on logic and the distribution of the data: safe and orderly (an average score less than 2), somewhat safe and orderly (an average score of 2 to 2.99), and not safe and orderly (an average score of equal to or greater than 3). The final derived risk factor included data for 5,628 students (8.4% of the data were missing). Figure C11: Histogram of Derived Risk Factor Safe and Orderly Schools – student level shows the distribution of the data for *safe and orderly schools* derived risk factor.



A multiple regression of *8th grade mathematics achievement scores* on the eight individual items that comprised the *safe and orderly schools* derived risk factor showed that this derived risk factor accounted for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.05$, $F(8, 5620) = 3.34$, $p = 0.003$. These eight items had a 0.22 correlation with *8th grade mathematics achievement*.

Figure C12: Histogram of Derived Risk Factor Safe and Orderly Schools – student level using conditional mean substitution shows the distribution of the data for the derived risk factor *safe and orderly schools – student level* using conditional mean substitution for any missing data.

Figure C12: Histogram of Derived Risk Factor Safe and Orderly School - student level using conditional mean substitution



Cases weighted by student weight

Using conditional mean substitution, this derived risk factor accounted for a significant proportion of variance in *8th grade mathematics achievement* test scores, R^2 = 0.05, $F(8, 6135) = 3.87$, $p = 0.001$. These eight items had a 0.22 correlation with *8th grade mathematics achievement*, using conditional mean substitution.

School-level versions of classes in AI/AN cultures and traditions offered by schools and safe and orderly schools. The following are the school-level versions of the *classes in AI/AN cultures and traditions offered by schools* and the *safe and orderly schools* derived risk factors that were created using the school data only. Again, these variations of these derived risk factor were used in the cross tabulations in research question 1b. Since school-level risk factors were not used in the OLS regression models (because the data did not meet the criteria to use HLM), a version using conditional mean substitution for each of these items was not calculated.

Table C10 shows the number of schools in each state and in each school density type using the overall school weight (SCHWT). There were a total of 284 schools: 199 in Arizona and 85 in South Dakota.

Table C10: *Percent (number) of schools in each state and in each school density type*

	Public Low Density	Public High Density	BIE
Arizona (n=199)	67% (133)	22% (43)	12% (23)
South Dakota (n=85)	52% (44)	28% (24)	20% (17)

Notes. Values are based upon weighted estimates.

Classes offered in AI/AN cultures and traditions by schools –school level. From the NIES school questionnaire, a culturally-based derived risk factor relating to how many *classes offered in AI/AN cultures and traditions by schools* was created based on the responses to the following questions:

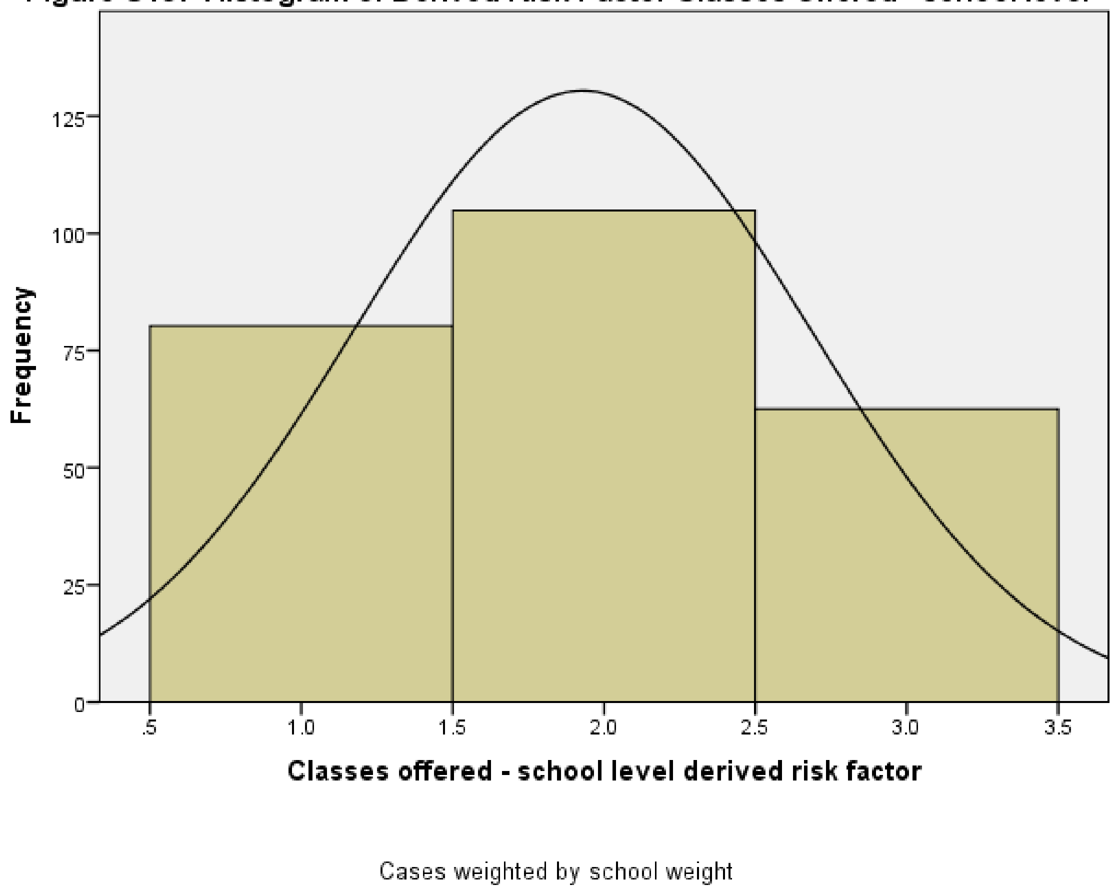
- Do students in your school receive instruction about American Indian or Alaska Native cultures in any of the following areas? *(1. Yes; 2. No)*
  - Oral language (IS05101/VC963005)
  - Written language (IS05102/VC963007)
  - History of tribes or cultural groups (IS05103/VC963008)
  - Traditions and customs (IS05104/VC963009)

- Arts, crafts, music, or dance (IS05105/VC963010)
- Tribal or village government (IS05106/VC963013)
- Current events and issues important to tribes or cultural groups (IS05107/VC963014)

The data were weighted using the overall school weight (SCHWT). One point was given for each "yes" response. The number of "yes" responses for each question was added together for each student, which resulted in a *classes offered in AI/AN cultures and traditions by schools* derived risk factor. A high number of content areas in AI/AN cultures and traditions offered by the school was represented by a score equal to 7. A low number of content areas in AI/AN cultures and traditions offered by the school was represented by a score equal to or less than 2. A medium number of content areas in AI/AN cultures and traditions offered by the school was indicated by a score of greater than 2 but less than 7. The final derived risk factor included data for 248 schools (12.7% of the data were missing). Figure C13: Histogram of Derived Risk Factor Classes Offered – school level shows the distribution of the data for the *classes offered – school level* derived risk factor.

A multiple regression of *8th grade mathematics achievement scores* on the seven individual items showed that the *classes offered in AI/AN cultures and traditions offered by schools* derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.1$, $F(7, 240) = 1.16$, $p = 0.34$. These seven items had a 0.2 correlation with *8th grade mathematics achievement*.

Figure C13: Histogram of Derived Risk Factor Classes Offered - school level



Safe and orderly schools – school level. A school climate risk factor based on *safe and orderly schools- school level* was derived using the school-level data from the following questions:

- Considering all of the students in your school, to what extent is each of the following a problem in your school? *(1. Not at all; 2. Small extent; 3. Moderate extent; 4. Large extent)*
  - Student absenteeism (IS05501)
  - Student tardiness (IS05502)
  - Student health (IS05503)

- Drug or alcohol use by students (IS05504)
- Physical conflict (IS05505)
- Physical conflicts among students (IS05506)
- Bullying (IS05507)
- Low student aspirations (IS05508)
- Low teacher expectations (IS05509)
- Low family involvement (IS05510)

A principal axis factor analysis (PAF) using Spearman's rho correlation coefficient was run. Data from the AI/AN schools in both states combined were used to create this derived risk factor. The data were weighted using the overall school weight (SCHWT). The sample size was 250, using listwise deletion. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.824, above the recommended value of 0.6. Bartlett's test of sphericity was significant (χ^2 (45) = 1146, $p < .0001$); therefore, this was not an identity matrix. This was also confirmed by the determinant, which was 0.009. There were three eigenvalues greater than 1, which accounted for 70% of the total variance. Since the items loaded on three factors, varimax and oblimin rotations of the factor loading matrix were examined. The results of both types of rotations had similar loadings on each factor, except for *bullying*. Table C11 shows the varimax rotation results. The varimax results showed that *bullying* loaded almost equally on factors 1 and 2. The pattern and structure matrices from the oblimin results showed that *bullying* loaded almost equally on factors 1 and 3. The varimax and oblimin results showed that *student drug/alcohol use*, *low student aspirations*, *low family involvement*, *student health*, and *low teacher expectations* all loaded on factor 1. *Physical conflict between students* and *student misbehavior* loaded on factor 2. And *student absenteeism* and *student tardiness* both loaded on factor 3.

Table C11: *Rotated Factor for Matrix[a] for Safe and Orderly Schools – school level*

	Factor		
	1	2	3
Problem in your school: student drug/alcohol use	.690		
Problem in your school: low student aspirations	.662	.328	
Problem in your school: low family involvement	.605	.275	.376
Problem in your school: student health	.604	.377	
Problem in your school: low teacher expectations	.585		
Problem in your school: bullying	.545	.453	
Problem in your school: physical conflict btw stud		.867	
Problem in your school: student misbehavior		.693	
Problem in your school: student absenteeism	.366		.817
Problem in your school: student tardiness			.728

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.
Notes. Values are based upon weighted estimates.

A reliability analysis was conducted. Cronbach's alpha was 0.881. Cronbach's alpha would not have increased if any of the items were deleted. But, the decision was made to run another PAF using Spearman's rho without *student absenteeism* and *student tardiness*. The sample size was 250. The KMO value was 0.823. Bartlett's test of sphericity was significant (χ^2 (28) = 878, p < .0001). The determinant was 0.028. Two eigenvalues were greater than 1 and accounted for 66% of the total variance. Since the items loaded on two factors, varimax and oblimin rotations of the factor loading matrix were examined. The results of both types of rotations had similar loadings on each factor. The varimax and oblimin results showed that *student drug/alcohol use*, *low* *student aspirations*, *low family involvement*, *student health*, and *low teacher expectations* all loaded on factor 1. *Physical conflict between students* and *student misbehavior* loaded on factor 2. And *bullying* still loaded almost equally on both factors 1 and 2. Table C12 shows the varimax rotation results.

Table C12: *Rotated Factor Matrix*[a] *for Safe and Orderly Schools – school level*

	Factor	
	1	2
Problem in your school: low student aspirations	.696	.350
Problem in your school: low family involvement	.663	.325
Problem in your school: student drug/alcohol use	.657	
Problem in your school: student health	.629	.406
Problem in your school: low teacher expectations	.620	
Problem in your school: bullying	.540	.466
Problem in your school: physical conflict btw stud		.889
Problem in your school: student misbehavior		.702

Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Notes. Values are based upon weighted estimates.

A decision was made to create two derived risk factors based on these results. Since *bullying* seemed more related to *physical conflict between students* and *student misbehavior in class*, these three items were assumed to form one derived risk factor, which was called *safe and orderly schools*, while the other items (*student drug/alcohol use*, *low student aspirations*, *low family involvement*, *student health*, and *low teacher expectations*) were assumed to form another derived risk factor, which was called *school climate*.

A final PAF using Spearman's rho was run for the *safe and orderly schools* and *school climate* derived risk factors. The final sample size for *safe and orderly schools* was 251. The KMO value was 0.671. Bartlett's test of sphericity was significant (χ^2 (3) = 226, p < .0001). The determinant was 0.403. One eigenvalue was greater than 1 and accounted for 70% of the total variance. Since the items loaded on one factor, no rotation was needed. Table C13 shows the unrotated results.

Table C13: *Factor Matrix[a] for safe and orderly schools derived risk factor- school level (final version)*

	Factor
	1
Problem in your school: physical conflict btw stud	.881
Problem in your school: student misbehavior	.730
Problem in your school: bullying	.617

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 16 iterations required.

Notes. Values are based upon weighted estimates.

The final sample size for the *school climate* was 250. The KMO value was 0.790. Bartlett's test of sphericity was significant (χ^2 (10) = 454, p < .0001). The determinant was 0.159. One eigenvalue was greater than 1 and accounted for 59% of the total variance. Since the items loaded on one factor, no rotation was needed. Table C14 shows the unrotated results.

Table C14: *Factor Matrix[a] for school climate derived risk factor- school level (final version)*

	Factor
	1
Problem in your school: low student aspirations	.784
Problem in your school: low family involvement	.749
Problem in your school: student health	.733
Problem in your school: student drug/alcohol use	.647
Problem in your school: low teacher expectations	.596

Extraction Method: Principal Axis Factoring.

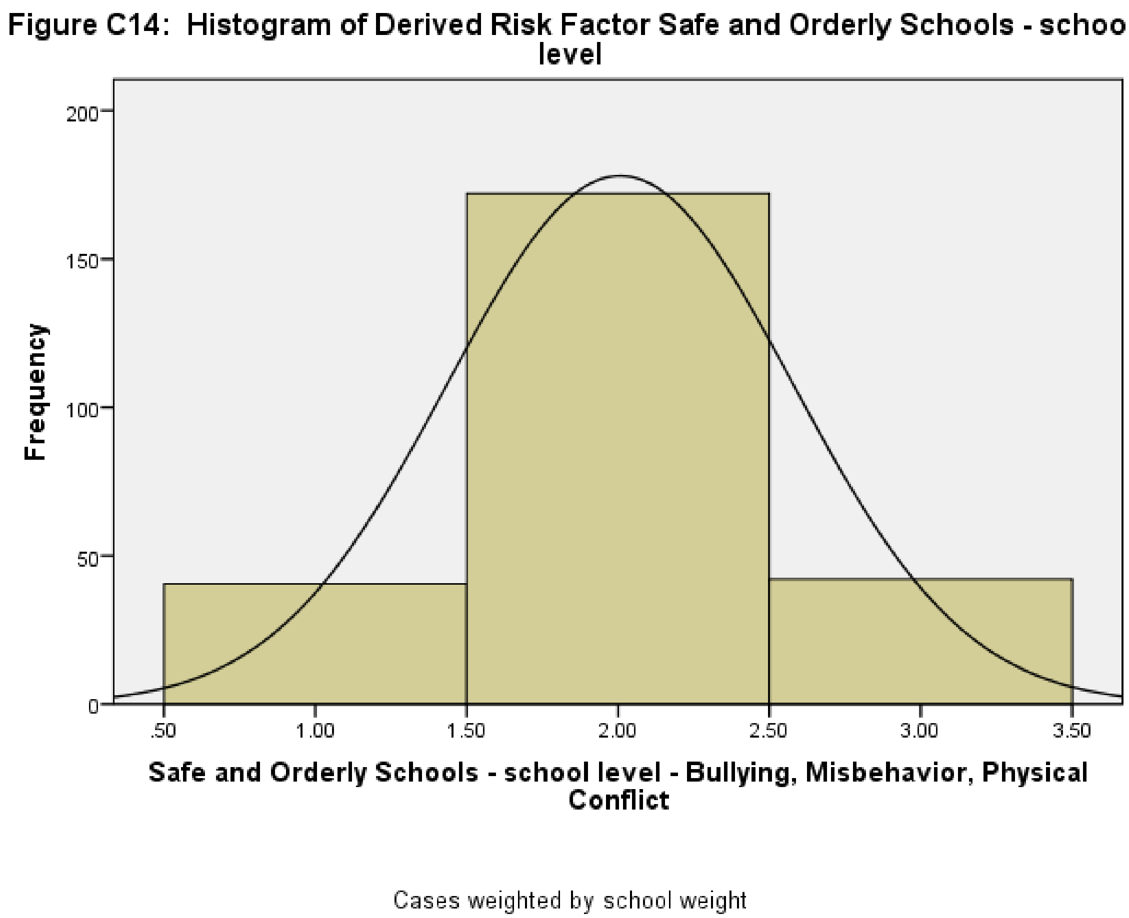
a. 1 factors extracted. 5 iterations required.

Notes. Values are based upon weighted estimates.

Final reliability analyses were run. Cronbach's alpha 0.814 for the *safe and orderly Schools* derived risk factor and 0.831 for the *school climate* derived risk factor. Cronbach's alpha would not have increased if any of the items were deleted.

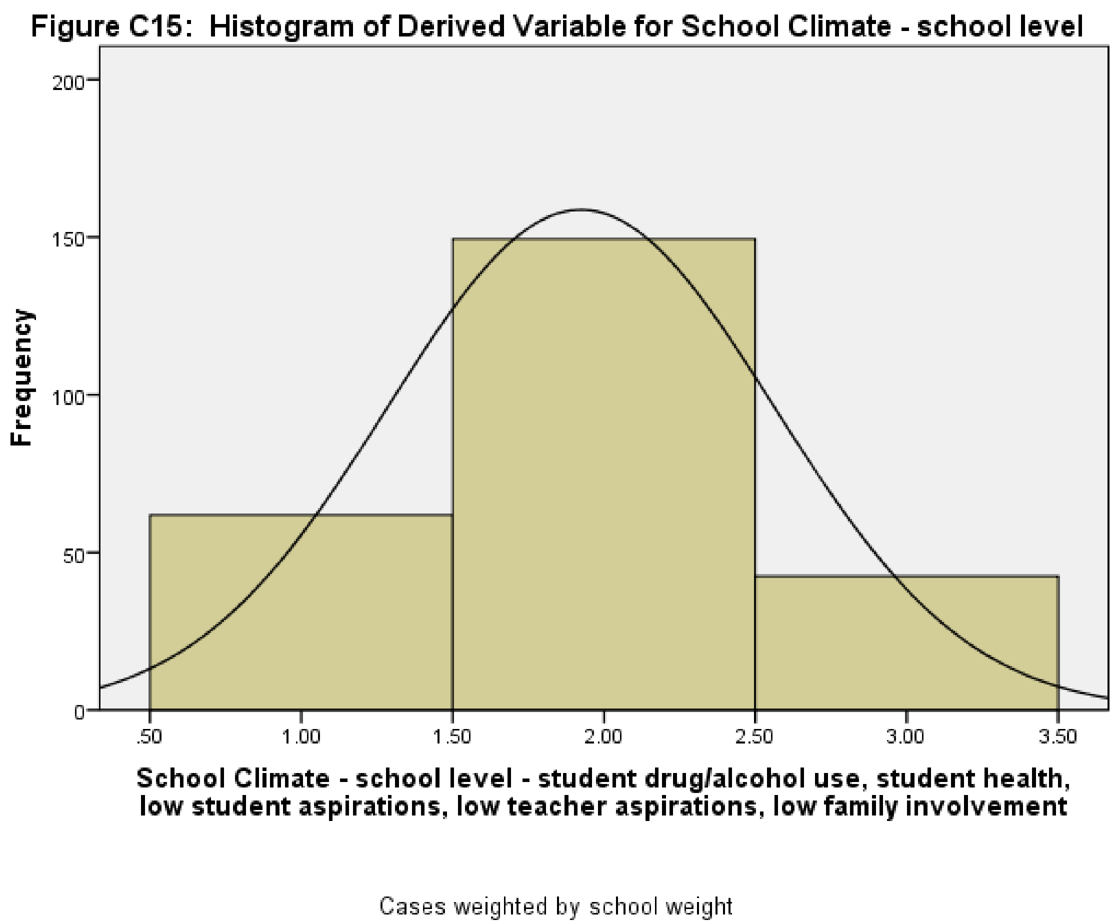
The responses to the three items in the *safe and orderly schools* derived risk factor were added together and divided by three to get the mean *safe and orderly schools* derived risk factor value for each school. Next, the scores were divided into three categories based on logic and the distribution of the data: safe and orderly schools (an average score less than 2), somewhat safe and orderly schools (an average score of 2 to 2.99), and not safe and orderly schools (an average score of equal to or greater than 3). The final derived risk factor included data for 255 schools (10.3% of the data were missing). Figure C14: Histogram of Derived Risk Factor Safe and Orderly Schools –

school level shows the distribution of the data for the *safe and orderly schools – school level* derived risk factor.



A multiple regression of *8th grade mathematics achievement scores* on the three individual items that comprised the *safe and orderly schools* derived risk factor showed that this derived risk factor accounted for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.09$, $F(3, 252) = 3.62$, $p = 0.02$. These seven items had a 0.3 correlation with *8th grade mathematics achievement*.

The responses to the five items in the *school climate* derived risk factor were added together and divided by five to get the mean *school climate* derived risk factor value for each school. Next, the scores were divided into three categories based on logic and the distribution of the data: positive school climate (an average score less than 2), moderate school climate (an average score of 2 to 2.99), negative school climate (an average score of equal to or greater than 3). The final derived risk factor included data for 254 schools (10.7% of the data were missing). Figure C15: Histogram of Derived Risk Factor for School Climate – school level shows the distribution of the data for the *school climate – school level* derived risk factor.



A multiple regression of *8th grade mathematics achievement scores* on the five individual items that comprised the *school climate* derived risk factor showed that this derived risk factor did not account for a significant proportion of variance in *8th grade mathematics achievement* test scores, $R^2 = 0.08$, $F(5, 249) = 2.23$, $p = 0.06$. These seven items had a 0.3 correlation with *8th grade mathematics achievement*.

Appendix D: Creating the Risk Indices

Similar to the derived risk factors, each risk index was calculated using both listwise deletion and conditional mean substitution using data for AI/AN students in both states and all school density types. The listwise deletion version of each risk index was calculated first and used in research question 2. For research question 3, the distribution of the data for each risk index was also recalculated using conditional mean substitution (i.e., substituting the mean for each state and school density type for missing data). For comparability purposes, the same cutoff points were used to calculate both the listwise deletion and conditional mean substitution versions of each risk index. This appendix describes the creation of the risk indices using listwise deletion followed by the recalculated results using conditional mean substitution. The four NAEP risk indices were created using the overall student weight (ORIGWT). The risk indices are shown below.

NAEP Knowledge/attitudes risk index.[44]

1. <u>How often do you feel you have a clear understanding of what your mathematics teacher is asking you to do? (from the NAEP Student questionnaire)</u> Table D1 shows the distribution of AI/AN student responses to the individual item regarding how often he/she clearly understands what the mathematics teacher is asking him/her to do (n=6028; 2% of the data were missing).

[44] This index was able to be formed because it had a moderate correlation between the two variables (>0.4). Otherwise, these two items would have been used as individual factors instead of used to create a risk index.

Table D1: *Clearly understand what teacher is asking*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never or hardly ever	166	2.7	2.8	2.8
	Sometimes	2024	32.9	33.6	36.3
	Often	2039	33.2	33.8	70.2
	Always/almost always	1798	29.3	29.8	100.0
	Total	6028	98.1	100.0	
Missing	Multiple	8	.1		
	Omitted	107	1.7		
	Total	115	1.9		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining "never or hardly ever" and "sometimes", as shown in Table D2.

Table D2: *Clearly Understand What Mathematics Teacher Is Asking Dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	OFTEN/ALWAYS/ALMOST ALWAYS	3838	62.5	63.7	63.7
	NEVER/HARDLY EVER/SOMETIMES	2190	35.7	36.3	100.0
	Total	6028	98.1	100.0	
Missing	System	115	1.9		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "never/hardly ever/sometimes" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test[45], a significant difference in mathematics achievement scores was found between

[45] Independent samples *t*-tests were run using AM software.

students who had the risk factor (never/hardly ever/sometimes clearly understanding what the mathematics teacher is asking) and those who didn't have the risk factor (often/always/almost always clearly understanding what the mathematics teacher is asking), t (6,026) = 3.7, $p < 0.001$[46], with students with the risk factor having lower scores than students without the risk factor. The correlation between *clearly understand what the mathematics teacher is asking* and *8th grade mathematics achievement* was 0.17.

Table D3 shows the dichotomized distribution of AI/AN student responses to the individual item regarding how often he/she *clearly understands what the mathematics teacher is asking him/her to do* using conditional mean substitution for any missing data. Using an independent samples t-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (never/hardly ever/sometimes clearly understanding what the mathematics teacher is asking) and those who didn't have the risk factor (often/always/almost always clearly understanding what the mathematics teacher is asking), t (6,141) = 3.52, $p = 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *clearly understand what the mathematics teacher is asking* and *8th grade mathematics achievement* was 0.17.

[46] As a reminder, the p-value was provided for descriptive purposes only because of the large sample sizes.

Table D3: *Clearly Understand What Mathematics Teacher Is Asking Dichotomized Using Conditional Mean Substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	often/always/almost always	3952	64.3	64.3	64.3
	never/hardly ever/sometimes	2190	35.7	35.7	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. Attitude toward mathematics (from the NAEP Student questionnaire). Table D4 shows the distribution of AI/AN student responses to the derived risk factor regarding their attitude toward mathematics (n=5928; 4% of the data were missing).

Table D4: *Attitude toward mathematics derived risk factor*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	do not like learning mathematics	585	9.5	9.9	9.9
	somewhat like learning mathematics	2504	40.8	42.2	52.1
	like learning mathematics	2839	46.2	47.9	100.0
	Total	5928	96.5	100.0	
Missing	System	215	3.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this derived risk factor by combining "do not like learning mathematics" and "somewhat like learning mathematics", as shown in Table D5.

Table D5: *Attitude toward mathematics dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	like mathematics	2839	46.2	47.9	47.9
	do not like mathematics/somewhat like mathematics	3089	50.3	52.1	100.0
	Total	5928	96.5	100.0	
Missing	System	215	3.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was “do not like/somewhat like learning mathematics” and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (do not like/somewhat like learning mathematics) and those who didn’t have the risk factor (like mathematics), t (5,926) = 3.5, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *attitude toward mathematics* and *8th grade mathematics achievement* was 0.2.

Table D6 shows the dichotomized distribution of AI/AN student responses to the derived risk factor *attitude toward mathematics* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (do not like/somewhat like learning mathematics) and those who didn’t have the risk factor (like mathematics), t (6,141) = 3.7, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *attitude toward mathematics* and *8th grade mathematics achievement* was 0.2.

Table D6: *Attitude toward mathematics dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	like math	2877	46.8	46.8	46.8
	do not like math/somewhat like math	3265	53.2	53.2	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

Using listwise deletion and an unweighted, tetrachoric correlation in R, these two individual items (*clear understanding of what your mathematics teacher is asking you to do* and *attitude toward mathematics*) that made up the *NAEP Knowledge/attitudes risk index* had a positive correlation, $r = 0.53$. Because this index forms a moderate correlation between the two items (>0.4), these two individual items were combined in the *NAEP Knowledge/attitudes risk index* instead of being used as factors in the OLS regression models in questions 3a and 3b. The correlation between the *NAEP Knowledge/attitudes risk index* and *8th grade mathematics achievement* was 0.22.

Using conditional mean substitution and an unweighted, tetrachoric correlation in R, these two individual items that made up the *NAEP Knowledge/attitudes risk index* had a positive correlation, $r = 0.49$. The correlation between the *NAEP Knowledge/attitudes risk index* and *8th grade mathematics achievement* was 0.22.

Since there were only two items in this risk index, a factor analysis could not be run; however, the moderate correlation of 0.53/0.49 shows that the *NAEP Knowledge/attitudes risk index* was a good representation of the items within it.

NAEP Social/physical risk index.

1. Student was ELL (from School Administration records). Table D7 shows the distribution of AI/AN student responses to the individual item regarding whether or not the student was ELL (n=6129; 0.2% of the data were missing).

Table D7: *Student was ELL*

		Frequency	Percent	Valid Percent	Cumulative Percent
	ELL	606	9.9	9.9	9.9
Valid	Not ELL	5523	89.9	89.9	99.8
	Total	6129	100.0	100.0	

Notes. Values are based upon weighted estimates.

The risk factor (i.e., equal to 1) was "ELL". Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (ELL) and those who didn't have the risk factor (not ELL), t (6,127) = 8.4, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *student was ELL* and *8th grade mathematics achievement* was 0.3.

Table D8 shows the dichotomized distribution of AI/AN student responses to the individual item *student was ELL* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (ELL) and those who didn't have the risk factor (not ELL), t (6,141) = 8.4, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *student was ELL* and *8th grade mathematics achievement* was 0.3.

Table D8: *Student was ELL using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	ELL	606	9.9	9.9	100.0
	Not ELL	5537	90.1	90.1	90.1
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. Student had a disability (from School Administration records). Table D9 shows the distribution of AI/AN student responses to the individual item regarding whether or not the student had a disability (n=6137; 0.1% of the data were missing).

Table D9: *Student had a disability*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Student with disability	919	15.0	15.0	15.0
	Not student with disability	5218	84.9	85.0	100.0
Total		6137	100.0		

Notes. Values are based upon weighted estimates.

The risk factor (i.e., equal to 1) was “Student with disability”. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (student with disability) and those who didn’t have the risk factor (not student with disability), t (6,135) = 7.0, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *student had a disability* and *8th grade mathematics achievement* was 0.4.

Table D10 shows the dichotomized distribution of AI/AN student responses to the individual item *student had a disability* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (student with disability) and those who didn't have the risk factor (not student with disability), $t\ (6{,}141) = 7.0$, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *student had a disability* and *8th grade mathematics achievement* was 0.4.

Table D10: *Student had a disability using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Student with disability	919	15.0	15.0	100.0
	Not student with disability	5224	85.0	85.0	85.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

3. <u>Number of days absent in the last month (from the NAEP Student questionnaire).</u>

   Table D11 shows the distribution of AI/AN student responses to the individual item regarding how many days he/she was absent last month (n=6111; 0.5% of the data were missing).

Table D11: *Days absent from school last month*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	1961	31.9	32.1	32.1
	1-2 days	1991	32.4	32.6	64.7
	3-4 days	1167	19.0	19.1	83.8
	5-10 days	645	10.5	10.6	94.3
	More than 10 days	347	5.6	5.7	100.0
	Total	6111	99.5	100.0	
Missing	Omitted	32	.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining “3-4 days, “5-10 days”, and “more than 10 days”, as shown in Table D12.

Table D12: *Days absent from school last month dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0-2 days	3952	64.3	64.7	64.7
	3 or more days	2159	35.1	35.3	100.0
	Total	6111	99.5	100.0	
Missing	System	32	.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was “3 or more days” and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (absent 3 or more days in the last month) and those who didn’t have the risk factor (absent 0-2 days in the last month), $t\ (6{,}109) = 3.7$, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *days absent from school last month* and *8th grade mathematics achievement* was 0.2.

Table D13 shows the dichotomized distribution of AI/AN student responses to the individual item *days absent from school last month* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (absent 3 or more days in the last month) and those who didn’t have the risk factor (absent 0-2 days in the last month), t (6,141) = 3.6, p = 0.001, with students with the risk factor having lower scores than students without the risk factor. The correlation between *days absent from school last month* and *8th grade mathematics achievement* was 0.2.

Table D13: *Days absent from school last month dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
	0-2 days	3984	64.9	64.9	64.9
Valid	3 or more days	2159	35.1	35.1	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

Using listwise deletion and an unweighted, tetrachoric correlation in R, *student was ELL* and *student had a disability* had a positive correlation, r = 0.24. *Student was ELL* and *days absent last month* had a negative correlation, r = -0.04. *Student had a disability* and *days absent last month* had a positive correlation, r = 0.11. The proportion of variance in factor 1 accounted for by these three items was 36%, which means that the *NAEP Social/physical risk index* was a moderate representation of the items within it. The correlation between the *NAEP Social/physical risk index* and *8th grade mathematics achievement* was 0.46.

Using conditional mean substitution and an unweighted, tetrachoric correlation in R, *student was ELL* and *student had a disability* had a positive correlation, r = 0.23. *Student was ELL* and *days absent last month* had a negative correlation, r = -0.04. *Student had a disability* and *days absent last month* had a positive correlation, r = 0.11. The proportion of variance in factor 1 accounted for by these three items was 35%, which means that the *NAEP Social/physical risk index* was a moderate representation of the items within it. The correlation between the *NAEP Social/physical risk index* and *8th grade mathematics achievement* was 0.47.

NAEP Home risk index.

1. Mother's education level (from the NAEP Student questionnaire). Table D14 shows the distribution of AI/AN student responses to the individual item regarding mother's education level (n=4620; 25% of the data were missing because 24% of the students selected "I don't know").

Table D14: *Mother's education level*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Did not finish high school	758	12.3	12.3	12.3
	Graduated high school	1420	23.1	23.1	35.4
	Some education after high school	1103	18.0	18.0	53.4
	Graduated college	1339	21.8	21.8	75.2
	Total	4620	75.2	100.0	
Missing	I Don't Know	1476	24.0	24.0	99.2
	Omitted	47	.8	.8	100.0
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining "did not finish high school", and "graduated high school", as shown in Table D15.

Table D15: *Mother's education level dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	some education after high school, graduated college	2442	39.8	52.9	52.9
	did not finish high school, graduated high school	2177	35.4	47.1	100.0
	Total	4620	75.2	100.0	
Missing	System	1523	24.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "did not finish high school/graduated high school" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (mother did not finish high school/graduated high school) and those who didn't have the risk factor (mother had some education after high school/graduated college), t (4,618) = 3.5, $p <$ 0.001, with students with the risk factor having lower scores than students without the risk factor. The correlation between *mother's education level* and *8th grade mathematics achievement* was 0.2.

Table D16 shows the dichotomized distribution of AI/AN student responses to the individual item *mother's education level* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (mother did not finish high school/graduated high school) and those who didn't have the risk factor (mother had some education after high school/graduated college), t (6,141) = 2.5, p = 0.02, with students with the risk factor having lower scores than students without the risk factor. The correlation between *mother's education level* and *8th grade mathematics achievement* was 0.1.

Table D16: *Mother's education level dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	some education after high school, graduated college	3965	64.6[47]	64.6	64.6
	did not finish high school, graduated high school	2177	35.4	35.4	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. <u>Number of books in the home (from the NAEP Student questionnaire)</u>. Table D17 shows the distribution of AI/AN student responses to the individual item regarding the number of books in the home (n=6096; 0.8% of the data were missing).

Table D17: *Books in home*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0-10 books	1337	21.8	21.8	21.8
	11-25 books	2185	35.6	35.6	57.3
	26-100 books	1839	29.9	29.9	87.3
	More than 100 books	735	12.0	12.0	99.2
	Total	6096	99.2	100.0	
Missing	Omitted	47	.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

[47] There was a much higher percentage here than in Table D15 because all of the conditional means fell above 2.54, which meant they were rounded up to 3 "some education after high school" and then coded a "0", not a risk factor.

The decision was made to dichotomize this individual item by combining “0-10 books” and “11-25 books”, as shown in Table D18.

Table D18: *Books in home dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
	26 or more books	2574	41.9	42.2	42.2
Valid	0-25 books	3522	57.3	57.8	100.0
	Total	6096	99.2	100.0	
Missing	System	47	.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was “0-25 books” and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (0-25 books in the home) and those who didn’t have the risk factor (26 or more books in the home), t (6,094) = 4.1, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *books in the home* and *8th grade mathematics achievement* was 0.2.

Table D19 shows the dichotomized distribution of AI/AN student responses to the individual item *books in the home* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (0-25 books in the home) and those who didn’t have the risk factor (26 or more books in the home), t (6,141) = 4.2, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *books in the home* and *8th grade mathematics achievement* was 0.2.

Table D19: *Books in home dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0-25 books	2574	41.9	41.9	41.9
	26 or more books	3569	58.1	58.1	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

3. Eligibility for the National School Lunch Program (from School Administration records).[48] Table D20 shows the distribution of AI/AN student responses to the individual item regarding eligibility for the National School Lunch Program (n=5926; 4% of the data were missing).

Table D20: *National School Lunch Program eligibility*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not eligible	1368	22.3	23.1	23.1
	Eligible	4558	74.2	76.9	100.0
	Total	5926	96.5	100.0	
Missing	Info not available	217	3.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The risk factor (i.e., equal to 1) was "eligible". Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between

[48] This was "yes" for students in schools that did not determine individual student eligibility for the NSLP and instead chose to provide free meals to all students. However, of the 14 principals who stated that their school participated in NSLP, all 14 also stated that student eligibility was determined individually (question16 from Part I of the main NAEP school questionnaire/C051401/VB556173=2).

students who had the risk factor (eligible for NSLP) and those who didn't have the risk factor (not eligible for NSLP), t (5,924) = 4.6, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *eligibility for NSLP* and *8th grade mathematics achievement* was 0.2.

Table D21 shows the dichotomized distribution of AI/AN student responses to the individual item *eligibility for NSLP* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (eligible for NSLP) and those who didn't have the risk factor (not eligible for NSLP), t (6,141) = 4.7, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *eligibility for NSLP* and *8th grade mathematics achievement* was 0.2.

Table D21: *National School Lunch Program eligibility using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not eligible	1368	22.3	22.3	22.3
	Eligible	4775	77.7	77.7	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

4. <u>How often people in your home talk to each other in a language other than English? (from the NAEP Student questionnaire)</u> Table D22 shows the distribution of AI/AN student responses to the individual item regarding how often people in your home talk to each other in a language other than English (n=6032; 2% of the data were missing).

Table D22: *Language other than English spoken in home*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never	1124	18.3	18.6	18.6
	Once in a while	1915	31.2	31.8	50.4
	Half the time	1497	24.4	24.8	75.2
	All or most of time	1496	24.4	24.8	100.0
	Total	6032	98.2	100.0	
Missing	Omitted	110	1.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining "half of the time" and "all or most of the time", as shown in Table D23.

Table D23: *Language Other Than English Spoken in Home Dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	NEVER/ONCE IN A WHILE	2993	48.7	49.6	49.6
	HALF THE TIME/ALL OR MOST OF THE TIME	3040	49.5	50.4	100.0
	Total	6032	98.2	100.0	
Missing	System	110	1.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "half of the time/all or most of the time" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (at least half of the time or more spoke a language other than English at home) and those who didn't have the risk factor (never/once in a while spoke a language other than English at home), t (6,030) = 2.4, p =

0.02, with students with the risk factor having lower scores than students without the risk factor. The correlation between *language other than English spoken at home* and *8th grade mathematics achievement* was 0.12.

Table D24 shows the dichotomized distribution of AI/AN student responses to the individual item *language other than English spoken in home* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (at least half of the time or more spoke a language other than English at home) and those who didn't have the risk factor (never/once in a while spoke a language other than English at home), $t\ (6{,}141) = 2.4$, $p = 0.02$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *language other than English spoken at home* and *8th grade mathematics achievement* was 0.13.

Table D24: *Language Other Than English Spoken in Home Dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	NEVER/ONCE IN A WHILE	3054	49.7	49.7	49.7
	HALF THE TIME/ALL OR MOST OF THE TIME	3089	50.3	50.3	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

5. <u>How often do you talk about things you have studied in school with someone in your family? (from the NAEP Student questionnaire)</u> Table D25 shows the distribution of AI/AN student responses to the individual item regarding how

often he/she talks about things he/she has studied in school with someone in his/her family (n=6117; 0.4% of the data were missing).

Table D25: *Talk about studies at home*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never or hardly ever	1789	29.1	29.3	29.3
	Every few weeks	1233	20.1	20.2	49.4
	About once a week	852	13.9	13.9	63.3
	2-3 times a week	997	16.2	16.3	79.6
	Every day	1246	20.3	20.4	100.0
	Total	6117	99.6	100.0	
Missing	Omitted	25	.4		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining "never or hardly ever" and "every few weeks", as shown in Table D26.

Table D26: *Talk about studies at home dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	about once a week or more	3095	50.4	50.6	50.6
	never hardly ever/every few weeks	3022	49.2	49.4	100.0
	Total	6117	99.6	100.0	
Missing	System	25	.4		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "never/hardly ever/every few weeks" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (talk about studies at home never/hardly ever/every few weeks) and those who didn't have the risk factor (talk about studies at home about once a week or more), t (6,115) = 3.7, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor.[49] The correlation between *talk about studies at home* and *8th grade mathematics achievement* was 0.17.

Table D27 shows the dichotomized distribution of AI/AN student responses to the individual item *talk about studies at home* using conditional mean substitution for any missing data. Using an independent samples t-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (talk about studies at home never/hardly ever/every few weeks) and those who didn't have the risk factor (talk about studies at home about once a week or more), t (6,141) = 3.7, $p < 0.001$, with students with the risk factor having lower scores than students without the risk factor. The correlation between *talk about studies at home* and *8th grade mathematics achievement* was 0.16.

Table D27: *Talk about studies at home dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	about once a week or more	3121	50.8	50.8	50.8
	never/hardly ever/every few weeks	3022	49.2	49.2	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

[49] This item was also dichotomized with the risk factor including those who responded "about once a week", but the t-test did not show a significant difference in the mathematics achievement scores between the two groups, t (6115) = 1.9, $p = 0.069$.

Table D28 shows the correlations among the five risk factors that comprised the *NAEP Home risk index* using listwise deletion and an unweighted, tetrachoric correlation in R.

Table D28: *Correlations among NAEP Home risk index items using listwise deletion*					
	Language at home other than English	Talk about studies	NSLP	Mother's education	Books in home
Language at home other than English	1.00	**0.03**	**-0.27**	**-0.06**	**-0.01**
Talk about studies	**0.03**	1.00	**-0.003**	**0.2**	**0.26**
NSLP	**-0.27**	**-0.003**	1.00	**0.25**	**0.24**
Mother's education	**-0.06**	**0.2**	**0.25**	1.00	**0.31**
Books in home	**-0.01**	**0.26**	**0.24**	**0.31**	1.00
Notes. Values are based upon weighted estimates.					

An unweighted principal components analysis in R using listwise deletion shows that the proportion of variance in factor 1 accounted for by these five items was 19%, which means that the *NAEP Home risk index* may be missing important items within it. The correlation between the *NAEP Home risk index* and *8th grade mathematics achievement* was 0.31.

Table D29 shows the correlations among the five risk factors that comprised the *NAEP Home risk index* using conditional mean substitution and an unweighted, tetrachoric correlation in R.

Table D29: *Correlations among NAEP Home risk index items using conditional mean substitution*					
	Language	Talk about studies	NSLP	Mother education	Books in home
Language	1.00	**-0.003**	**-0.24**	**-0.08**	**0.01**
Talk about studies	**-0.003**	1.00	**-0.003**	**0.15**	**0.24**
NSLP	**-0.24**	**-0.003**	1.00	**0.14**	**0.25**
Mother's education	**-0.08**	**0.2**	**0.14**	1.00	**0.18**
Books in home	**0.01**	**0.24**	**0.25**	**0.18**	1.00
Notes. Values are based upon weighted estimates.					

An unweighted principal components analysis in R using conditional mean substitution shows that the proportion of variance in factor 1 accounted for by these five items was 15%, which means that the *NAEP Home risk index* may be missing important items within it. The correlation between the *NAEP Home risk index* and *8th grade mathematics achievement* was 0.26.

NAEP Classroom risk index.

1. Mathematics class enrolled in this year (from the NAEP Student questionnaire). Table D30 shows the distribution of AI/AN student responses to the individual item regarding the mathematics class he/she is taking this year (n=5998; 2% of the data were missing).

Table D30: *Mathematics class taking now*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Geometry	286	4.7	4.8	4.8
	Algebra II	194	3.2	3.2	8.0
	Algebra I (1-yr course)	1105	18.0	18.4	26.4
	1st yr 2-yr Algebra I	116	1.9	1.9	28.4
	2nd yr 2-yr Algebra I	40	.7	.7	29.0
	Intro algebra, pre-algebra	1860	30.3	31.0	60.0
	Basic, general grade 8 mathematics	1825	29.7	30.4	90.5
	Integrated or sequential mathematics	12	.2	.2	90.7
	Other mathematics class	560	9.1	9.3	100.0
	Total	5998	97.6	100.0	
Missing	Multiple	38	.6		
	Omitted	106	1.7		
	Total	144	2.4		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by separating algebra and geometry classes from all other mathematics classes (i.e., combining “basic, general grade 8 mathematics”, “integrated or sequential mathematics”, and “other mathematics class”), as shown in Table D31.

Table D31: *Mathematics class taking now dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	geometry, algebra II, algebra I, intro to algebra/pre-algebra	3601	58.6	60.0	60.0
	basic grade 8 mathematics, integrated or sequential mathematics, other mathematics class	2397	39.0	40.0	100.0
	Total	5998	97.6	100.0	
Missing	System	144	2.4		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "basic, general grade 8 mathematics/ integrated or sequential mathematics/other mathematics class" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (were taking basic, general grade 8 mathematics/integrated or sequential mathematics/other mathematics class) and those who didn't have the risk factor (were taking geometry/algebra II/algebra I/Intro to algebra/pre-algebra), t (5,996) = 3.1, p = 0.003, with students with the risk factor having lower scores than students without the risk factor.[50] The correlation between *mathematics class taking now* and *8th grade mathematics achievement* was 0.14.

Table D32 shows the dichotomized distribution of AI/AN student responses to the individual item *mathematics class taking now* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in

[50] This item was also dichotomized with the risk factor including those who were taking "intro to algebra/pre-algebra". The *t*-test also showed a significant difference in the mathematics achievement scores between the two groups, t (5,996) = 2.2, p = 0.03. The decision was made to keep all classes related any type of algebra in the same category.

mathematics achievement scores was found between students who had the risk factor (were taking basic, general grade 8 mathematics/integrated or sequential mathematics/other mathematics class) and those who didn't have the risk factor (were taking geometry/algebra II/algebra I/Intro to algebra/pre-algebra), t (6,141) = 3.0, p = 0.004, with students with the risk factor having lower scores than students without the risk factor.[51] The correlation between *mathematics class taking now* and *8th grade mathematics achievement* was 0.14.

Table D32: *Mathematics class taking now dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	geometry, algebra II, algebra I, intro to algebra/pre-algebra	3746	61.0	61.0	61.0
	basic grade 8 mathematics, integrated or sequential mathematics, other mathematics class	2397	39.0	39.0	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. Being taught by a teacher who stated he/she was a highly-qualified teacher (from the NAEP Teacher questionnaire). Table D33 shows the distribution of students whose teacher stated on the main NAEP teacher individual item whether or not the teacher was a highly-qualified teacher this school year (n=5165; 16% of the data were missing).

[51] This item was also dichotomized with the risk factor including those who were taking "intro to algebra/pre-algebra". The t-test also showed a significant difference in the mathematics achievement scores between the two groups, t (62) = 2.2, p = 0.03. The decision was made to keep all classes related any type of algebra in the same category.

Table D33: *Highly-qualified teacher this year*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	4246	69.1	82.2	82.2
	1 subject	132	2.1	2.6	84.8
	No	787	12.8	15.2	100.0
	Total	5165	84.1	100.0	
Missing	Multiple	40	.7		
	Omitted	50	.8		
	System	888	14.5		
	Total	978	15.9		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining "no" and "Just in 1 subject", as shown in Table D34.

Table D34: *Highly-qualified teacher this year dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	highly-qualified teacher	4246	69.1	82.2	82.2
	not highly-qualified or just in 1 subject	919	15.0	17.8	100.0
	Total	5165	84.1	100.0	
Missing	System	978	15.9		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "not highly-qualified/just in 1 subject" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (having a teacher who stated he/she was not a highly-qualified teacher or having a teacher who stated he/she was a highly-qualified teacher in just one subject) and those who didn't have the risk factor (having a teacher who stated he/she was a highly-qualified teacher), t (5163) = 2.6, p = 0.01, with students with the risk factor having lower scores than students without the risk factor. The correlation between having a teacher who stated he/she was a *highly-qualified teacher this year* and *8th grade mathematics achievement* was 0.13.

Table D35 shows the dichotomized distribution of AI/AN student responses to the individual item *highly-qualified teacher this year* from the teacher questionnaire using conditional mean substitution for any missing data. Using an independent samples t-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (having a teacher who stated he/she was not a highly-qualified teacher or having a teacher who stated he/she was a highly-qualified teacher in just one subject) and those who didn't have the risk factor (having a teacher who stated he/she was a highly-qualified teacher), t (6,141) = 2.3, p = 0.025, with students with the risk factor having lower scores than students without the risk factor. The correlation between having a teacher who stated he/she was a *highly-qualified teacher this year* and *8th grade mathematics achievement* was 0.10.

Table D35: *Highly-qualified teacher this year dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	highly-qualified teacher	4506	73.3	73.3	73.3
	not highly-qualified or just in 1 subject	1637	26.7	26.7	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

Using listwise deletion and an unweighted, tetrachoric correlation in R, these two items (*mathematics class taking this year* and *highly-qualified teacher*) that make up the *NAEP Classroom risk index* had a low, positive correlation, $r = 0.17$. Since there were only two items in this risk index, a factor analysis could not be run. The low correlation of 0.17 shows that the *NAEP Classroom risk index* may not be a good representation of the items within it. The correlation between the *NAEP Classroom risk index* and *8th grade mathematics achievement* was 0.17.

Using conditional mean substitution and an unweighted, tetrachoric correlation in R, these two items that make up the *NAEP Classroom risk index* had a low, negative correlation, $r = -.04$. Since there were only two items in this risk index, a factor analysis could not be run. The low correlation of 0.04 shows that the *NAEP Classroom risk index* may not be a good representation of the items within it. The correlation between the *NAEP Classroom risk index* and *8th grade mathematics achievement* was 0.17.

Using Spearman's rho in SPSS and the overall student weight and pairwise deletion, the four NAEP risk indices were found to have low, positive correlations with each other as shown in Table D36 below. This outcome was encouraging because it means the four risk indices were not overlapping in content.

Table D36: *Correlations among the four NAEP risk indices using listwise deletion*

			NAEP Social/physical risk index	NAEP classroom risk index	NAEP Home risk index	NAEP knowledge/attitude risk index
Spearman's rho	NAEP social/physical risk index	Correlation Coefficient	1.000	**.078**	**.135**	**.073**
		Sig. (2-tailed)	.	.000	.000	.000
		N	6064	4979	4362	5863
	NAEP classroom risk index	Correlation Coefficient	**.078**	1.000	**.085**	**.019**
		Sig. (2-tailed)	.000	.	.000	.182
		N	4979	5004	3629	4869
	NAEP Home risk index	Correlation Coefficient	**.135**	**.085**	1.000	**.237**
		Sig. (2-tailed)	.000	.000	.	.000
		N	4362	3629	4377	4231
	NAEP knowledge/attitude risk index	Correlation Coefficient	**.073**	**.019**	**.237**	1.000
		Sig. (2-tailed)	.000	.182	.000	.
		N	5863	4869	4231	5891

Notes. Values are based upon weighted estimates.

Using Spearman's rho in SPSS and the overall student weight and conditional mean substitution, the four NAEP risk indices were found to have low, positive correlations with each other as shown in Table D37 below. This outcome was encouraging because it means the four risk indices were not overlapping in content.

Table D37: *Correlations among the four NAEP risk indices using conditional mean substitution*

			NAEP social/physical risk index	NAEP classroom risk index	NAEP Home risk index	NAEP knowledge/attitude risk index
Spearman's rho	NAEP social/physical risk index	Correlation Coefficient	1.000	**.060**	**.119**	**.076**
		Sig. (2-tailed)	.	.000	.000	.000
	NAEP classroom risk index	Correlation Coefficient	**.060**	1.000	**-.003**	**.049**
		Sig. (2-tailed)	.000	.	.835	.000
	NAEP Home risk index	Correlation Coefficient	**.119**	**-.003**	1.000	**.229**
		Sig. (2-tailed)	.000	.835	.	.000
	NAEP knowledge/attitude risk index	Correlation Coefficient	**.076**	**.049**	**.229**	1.000
		Sig. (2-tailed)	.000	.000	.000	.

Notes. Values are based upon weighted estimates.

The three NIES risk indices were created using the overall student weight (ORIGWT). These risk indices are shown below.

NIES Student risk index.

1. AI/AN participation (from the NIES Student questionnaire). Table D38 shows the distribution of AI/AN student responses to the derived risk factor regarding how often he/she participates in AI/AN culture activities (n=5959; 3% of the data were missing).

Table D38: *Participation In AI/AN Cultural Activities Derived Risk Factor*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	never/every few years	2832	46.1	47.5	47.5
	at least once a year	2278	37.1	38.2	85.7
	several times a year	850	13.8	14.3	100.0
	Total	5959	97.0	100.0	
Missing	System	183	3.0		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this derived risk factor by combining "at least once a year" and "several times a year", as shown in Table D39.

Table D39: *Participation in AI/AN activities dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	once/year or more	3128	50.9	52.5	52.5
	never/every few years	2832	46.1	47.5	100.0
	Total	5959	97.0	100.0	
Missing	System	183	3.0		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "never/every few years" and the rest of the non-missing responses were set to equal 0. However, using an independent samples *t*-test, no significant difference in mathematics achievement scores was found between students who had the risk factor (never/every few years participated in AI/AN activities) and those who didn't have the risk factor (participating in AI/AN activities once a year or more), $t\ (5{,}957) = 0.91$, $p = 0.37$. The correlation between *participation in AI/AN activities* and *8th grade mathematics achievement* was 0.04.

Table D40 shows the dichotomized distribution of AI/AN student responses to the derived risk factor *participation in AI/AN activities* using conditional mean substitution for any missing data. Using an independent samples *t*-test, no significant difference in mathematics achievement scores was found between students who had the risk factor (never/every few years participated in AI/AN activities) and those who didn't have the risk factor (participating in AI/AN activities once a year or more), $t\ (6{,}141) = 0.92$, $p = 0.36$. The correlation between *participation in AI/AN activities* and *8th grade mathematics achievement* was 0.04.

Table D40: *Participation in AI/AN activities dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	once/year or more	3165	51.5	51.5	51.5
	never/every few years	2978	48.5	48.5	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. <u>AI/AN knowledge (from the NIES Student questionnaire)</u>. Table D41 shows the distribution of AI/AN student responses to the derived risk factor regarding knowledge of AI/AN culture (n=5970; 2.8% of the data were missing).

Table D41: *Knowledge Of AI/AN Culture Derived Risk Factor*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	a little/nothing	2223	36.2	37.2	37.2
	some	3006	48.9	50.4	87.6
	a lot	741	12.1	12.4	100.0
	Total	5970	97.2	100.0	
Missing	System	173	2.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this derived risk factor by combining "a little" and "nothing", as shown in Table D42.

Table D42: *Knowledge of AI/AN culture dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	some/a lot	3747	61.0	62.8	62.8
	a little/nothing	2223	36.2	37.2	100.0
	Total	5970	97.2	100.0	
Missing	System	173	2.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "a little/nothing" and the rest of the non-missing responses were set to equal 0. However, using an independent samples *t*-test, no significant difference in mathematics achievement scores was found between students who had the risk factor (knowing a little/nothing of AI/AN culture) and those who didn't have the risk factor (knowing some/a lot of AI/AN culture), t (5,968) = 0.74, p = 0.46. The correlation between *knowledge of AI/AN culture* and *8th grade mathematics achievement* was 0.04.

Table D43 shows the dichotomized distribution of AI/AN student responses to the derived risk factor *knowledge of AI/AN culture* using conditional mean substitution for any missing data. Using an independent samples *t*-test, no significant difference in mathematics achievement scores was found between students who had the risk factor (knowing a little/nothing of AI/AN culture) and those who didn't have the risk factor (knowing some/a lot of AI/AN culture), t (6,141) = 0.47, p = 0.64. The correlation between *knowledge of AI/AN culture* and *8th grade mathematics achievement* was 0.03.

Table D43: *Knowledge of AI/AN culture dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	some/a lot	3836	62.4	62.4	62.4
	a little/nothing	2307	37.6	37.6	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

Using listwise deletion and an unweighted, tetrachoric correlation in R, these two items (*knowledge of AI/AN culture* and *participation in AI/AN activities*) that comprised the *NIES student risk index* had a positive correlation, r = 0.61. Since there were only two items in this risk index, a factor analysis could not be run; however, the high correlation of 0.61 shows that the *NIES student risk index* was a good representation of the items within it. The correlation between the *NIES Student risk index* and *8th grade mathematics achievement* was 0.04.

Using conditional mean substitution and an unweighted, tetrachoric correlation in R, these two items that comprised the *NIES student risk index* had a positive correlation, r = 0.59. Since there were only two items in this risk index, a factor analysis could not be run; however, the high correlation of 0.59 shows that the *NIES student risk index* was a good representation of the items within it. The correlation between the *NIES Student risk index* and *8th grade mathematics achievement* was 0.04.

Participation in AI/AN activities and *knowledge of AI/AN culture* did not discriminate between students who had the risk factor and those who didn't have the risk factor. The *NIES Student risk index* had a low correlation with *8th grade mathematics achievement*. Even so, a decision was made to include the *NIES Student risk index* in the OLS regression analyses because culture is very important to AI/AN people and to see if it accounted for variation in achievement when analyzed by state and density type (which, in certain strata, it did account for variation in achievement when entered into the model on its own).

NIES Home risk index.

1. <u>How often does family help with your schoolwork? (from the NIES Student questionnaire)</u> Table D44 shows the distribution of AI/AN student responses to the individual item regarding how often his/her family helps with schoolwork (n=5992; 2.5% of the data were missing).

Table D44: *How often family helps with your schoolwork*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never or hardly ever	1401	22.8	23.4	23.4
	Once or twice/month	1261	20.5	21.1	44.4
	Once or twice/week	2074	33.8	34.6	79.0
	Every day or almost	1256	20.4	21.0	100.0
	Total	5992	97.5	100.0	
Missing	Omitted	128	2.1		
	System	23	.4		
	Total	151	2.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining "never or hardly ever" with "once or twice/month", as shown in Table D45.

Table D45: *How Often Family Helps With Homework Dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	ONCE OR TWICE/WEEK OR MORE	3330	54.2	55.6	55.6
	NEVER/HARDLYEVER/ONCE OR TWICE A MONTH	2662	43.3	44.4	100.0
	Total	5992	97.5	100.0	
Missing	System	151	2.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "never/hardly ever/once or twice a month" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a marginally significant difference in mathematics achievement scores was found between students who had the risk factor (never/hardly ever/once or twice a month having family help with homework) and those who didn't have the risk factor (having family help with homework once or twice a week or more), t (5990) =1.94, p = 0.056, with those having the risk factor having lower scores than those without the risk factor. The correlation between *how often family helps with homework* and *8th grade mathematics achievement* was 0.08.

Table D46 shows the dichotomized distribution of AI/AN student responses to the individual item *how often family helps with homework* using conditional mean substitution for any missing data. Using an independent samples t-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (never/hardly ever/once or twice a month having family help with homework) and those who didn't have the risk factor (having family help with homework once or twice a week or more), t (6,141) =2.14, p = 0.036, with those having the risk factor having lower scores than those without the risk factor. The correlation between *how often family helps with homework* and *8th grade mathematics achievement* was 0.08.

Table D46: *How Often Family Helps With Homework Dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	ONCE OR TWICE/WEEK OR MORE	3460	56.3	56.3	56.3
	NEVER/HARDLYEVER/ ONCE OR TWICE A MONTH	2683	43.7	43.7	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. <u>During 8th grade, how many times have you talked to a family member about the classes you should take in high school or about what you want to do after high school? (from the NIES Student questionnaire)</u> Table D47 shows the distribution of

AI/AN student responses to the item regarding how many times he/she has talked to a family member about the classes he/she should take in high school or about what he/she wants to do after a high school (n=5980; 2.7% of the data were missing).

Table D47: *Talk about classes in HS or after: family*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never	619	10.1	10.3	10.3
	One time	1303	21.2	21.8	32.1
	Two or three times	1658	27.0	27.7	59.9
	Four or more times	2400	39.1	40.1	100.0
	Total	5980	97.3	100.0	
Missing	Multiple	3	.1		
	Omitted	137	2.2		
	System	23	.4		
	Total	163	2.7		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by combining “never” with “one time”, as shown in Table D48.

Table D48: *Talk About Classes Or Future With Family Dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	TWO OR MORE TIMES	4058	66.1	67.9	67.9
	NEVER/ONE TIME	1922	31.3	32.1	100.0
	Total	5980	97.3	100.0	
Missing	System	163	2.7		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "never/one time" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (never/one time talking about classes or the future with family) and those who didn't have the risk factor (talking with family two or more times about classes or the future), t (5,978) = 2.7, p = 0.009, with those having the risk factor having lower scores than those without the risk factor. The correlation between *talk about classes or future with family* and *8th grade mathematics achievement* was 0.12.

Table D49 shows the dichotomized distribution of AI/AN student responses to the individual item *talk about classes or future with family* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (never/one time talking about classes or the future with family) and those who didn't have the risk factor (talking with family two or more times about classes or the future), t (6,141) = 2.5, p = 0.02, with those having the risk factor having lower scores than those without the risk factor. The correlation between *talk about classes or future with family* and *8th grade mathematics achievement* was 0.11.

Table D49: *Talk About Classes Or Future With Family Dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	TWO OR MORE TIMES	4221	68.7	68.7	68.7
	NEVER/ONE TIME	1922	31.3	31.3	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

Using both listwise deletion and conditional mean substitution and an unweighted, tetrachoric correlation in R, these two items (*how often family helps with homework* and *talk about classes or future with family*) that comprised the *NIES Home risk index* had a positive correlation, $r = 0.44$. Since there were only two items in this risk index, a factor analysis could not be run; however, the moderate correlation of 0.44 shows that the *NIES Home risk index* was a good representation of the items within it. The correlation between the *NIES Home risk index* and *8th grade mathematics achievement* was 0.01.

NIES School risk index – student level.

1. <u>Safe and Orderly Schools –student level (from the NIES School questionnaire).</u>

   Table D50 shows the distribution of AI/AN student-level responses to the derived risk factor regarding safe and orderly schools (n=5628; 8.4% of the data were missing).

Table D50: *Safe and orderly schools – student level derived risk factor*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	26	.4	.5	.5
	1.25	113	1.8	2.0	2.5
	1.38	54	.9	1.0	3.4
	1.50	10	.2	.2	3.6
	1.63	108	1.8	1.9	5.5
	1.75	424	6.9	7.5	13.1
	1.88	305	5.0	5.4	18.5
	2.00	215	3.5	3.8	22.3
	2.13	435	7.1	7.7	30.0
	2.25	403	6.6	7.2	37.2
	2.38	622	10.1	11.1	48.2
	2.50	464	7.6	8.2	56.5
	2.63	474	7.7	8.4	64.9
	2.75	658	10.7	11.7	76.6
	2.88	59	1.0	1.1	77.7
	3.00	38	.6	.7	78.3
	3.13	324	5.3	5.8	84.1
	3.25	251	4.1	4.5	88.6
	3.38	462	7.5	8.2	96.8
	3.50	20	.3	.4	97.1
	3.63	94	1.5	1.7	98.8
	3.75	68	1.1	1.2	100.0
	Total	5628	91.6	100.0	
Missing	System	515	8.4		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this derived risk factor by designating average scores of 2.88 and higher as “moderate/large problem” (i.e., the principal rated at least six of the eight questions as a “3” or “4” and the others were two’s) and average scores of less than 2.88 as "not a problem/small extent" (i.e., the principal gave no more than two ratings of "4" among the eight questions), as shown in Table D51.

Table D51: *Safe and orderly schools- student level dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	not problem/ small extent	4311	70.2	77.4	77.4
	moderate/ large problem	1257	20.5	22.6	100.0
	Total	5569	90.7	100.0	
Missing	System	574	9.3		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "moderate/large problem" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (not being in a safe and orderly school) and those who didn't have the risk factor (being in a safe and orderly school), t (5,567) = 2.1, p = 0.04.[52] The correlation between *safe and orderly schools- student level* and *8th grade mathematics achievement* was 0.12.

Table D52 shows the dichotomized distribution of AI/AN student responses to the individual item *safe and orderly schools- student level* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (not being in a safe and orderly school) and those who didn't have the risk

[52] This item was also dichotomized using a cutoff of 2.75, but the t test did not show a significant difference in the mathematics achievement scores between the two groups, t (5,567) = 2.0, p = 0.05.

factor (being in a safe and orderly school), t (6,141) = 2.2, p = 0.03. The correlation between *safe and orderly schools- student level* and *8th grade mathematics achievement* was 0.09.

Table D52: *Safe and orderly schools – student level dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	not problem/ small extent	4858	79.1	79.1	79.1
	moderate/large problem	1285	20.9	20.9	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. <u>Classes offered in AI/AN cultures and traditions –student level (from the NIES School questionnaire)</u>. Table D53 shows the distribution of AI/AN student-level responses to the derived risk factor regarding number of classes offered about AI/AN cultures and traditions (n=5524; 10.1% of the data were missing).

Table D53: *Classes offered in AI/AN cultures and traditions – student level*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	633	10.3	11.5	11.5
	1.00	343	5.6	6.2	17.7
	2.00	199	3.2	3.6	21.3
	3.00	365	5.9	6.6	27.9
	4.00	313	5.1	5.7	33.5
	5.00	243	4.0	4.4	37.9
	6.00	660	10.7	11.9	49.9
	7.00	2768	45.1	50.1	100.0
	Total	5524	89.9	100.0	
Missing	System	619	10.1		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this derived risk factor by separating the total number of content areas related to AI/AN cultures and traditions offered by five or more content areas and less than five content areas, as shown in Table D54.

Table D54: *Classes offered in AI/AN cultures and traditions – student level dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
	5-7 content areas	3671	59.8	66.5	66.5
Valid	1-4 content areas	1853	30.2	33.5	100.0
	Total	5524	89.9	100.0	
Missing	System	619	10.1		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "less than 5 content areas about AI/AN cultures and traditions offered at the school" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (1-4 content areas) and those who didn't have the risk factor (5-7 content areas), t (5,522) = 2.5, $p = 0.02$.[53] The correlation between *classes offered in AI/AN cultures/traditions- student level* and *8th grade mathematics achievement* was 0.09.

Table D55 shows the dichotomized distribution of AI/AN student responses to the individual item *classes offered in AI/AN cultures and traditions – student level* using conditional mean substitution for any missing data. Using an independent samples *t*-test,

[53] This item was also dichotomized using a cutoff of 3 or less classes being the risk factor, but the t test did not show a significant difference in the mathematics achievement scores between the two groups, t (5,522) = 2.0, $p = 0.05$.

a significant difference in mathematics achievement scores was found between students who had the risk factor (1-4 content areas) and those who didn't have the risk factor (5-7 content areas), t (6,141) = 2.8, p = 0.006. The correlation between *classes offered in AI/AN cultures/traditions- student level* and *8th grade mathematics achievement* was 0.16.

Table D55: *Classes offered in AI/AN cultures and traditions- student level dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	5-7 content areas	4063	66.1	66.1	66.1
	1-4 content areas	2080	33.9	33.9	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

3. <u>Percentage of AI/AN teachers in the school – student level (from the NIES School questionnaire).</u> Table D56 shows the distribution of AI/AN student-level responses to the percent of AI/AN teachers in the school (n=5534; 9.9% of the data were missing).

Table D56: *Percentage of AI/AN teachers – student level*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0%	1403	22.8	25.3	25.3
	1-5%	777	12.7	14.0	39.4
	6-10%	352	5.7	6.4	45.7
	11-25%	443	7.2	8.0	53.8
	26-50%	910	14.8	16.4	70.2
	51-75%	435	7.1	7.9	78.1
	76-100%	1215	19.8	21.9	100.0
	Total	5534	90.1	100.0	
Missing	I Don't Know	75	1.2		
	Omitted	150	2.4		
	System	383	6.2		
	Total	609	9.9		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by separating the responses between 25% or less and more than 25% to coincide with the difference between the number of AI/AN students in public low density opposed to public high density schools, as shown in Table D57.

Table D57: *Percentage Of AI/AN Teachers- student level Dichotomized*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	26% or more	2559	41.7	46.2	46.2
	25% or less	2975	48.4	53.8	100.0
	Total	5534	90.1	100.0	
Missing	System	609	9.9		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was “25% or less of the teachers are AI/AN” and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (being in a school in which 25% or less of the teachers are AI/AN) and those who didn’t have the risk factor (being in a school in which more than 25% of the teachers are AI/AN), t (5,532) = 4.2, p = 0.001. The correlation between *percentage of AI/AN teachers in the school- student level* and *8th grade mathematics achievement* was 0.14.

Table D58 shows the dichotomized distribution of AI/AN student responses to the individual item *percentage of AI/AN teachers – student level* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (being in a school in which 25% or less of the teachers are AI/AN) and those who didn’t have the risk factor (being in a school in which more than 25% of the teachers are AI/AN), t (6,141) = 4.5, $p < 0.001$. The correlation between *percentage of AI/AN teachers in the school – student level* and *8th grade mathematics achievement* was 0.2.

Table D58: *Percentage Of AI/AN Teachers – student level Dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	26% or more	2830	46.1	46.1	46.1
	25% or less	3313	53.9	53.9	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

Using listwise deletion and an unweighted, tetrachoric correlation in R, *safe and orderly schools* and *percentage of AI/AN teachers* had a negative correlation, *r* = -0.4. *Safe and orderly schools* and *classes offered in AI/AN cultures and traditions* had a positive correlation, *r* = 0.23. *Percentage of AI/AN teachers* and *classes offered in AI/AN cultures and traditions* had a positive correlation, *r* = 0.86. The proportion of variance in factor 1 accounted for by these three items was 50%, which means that the *NIES School risk index* was a good representation of the items within it. The correlation between the *NIES School risk index* and *8th grade mathematics achievement* was 0.12.

Using conditional mean substitution and an unweighted, tetrachoric correlation in R, *safe and orderly schools* and *percentage of AI/AN teachers* had a negative correlation, *r* = -0.16. *Safe and orderly schools* and *classes offered in AI/AN cultures and traditions* had a negative correlation, *r* = -0.41. *Percentage of AI/AN teachers* and *classes offered in AI/AN cultures and traditions* had a positive correlation, *r* = 0.71. The proportion of variance in factor 1 accounted for by these three items was 56%, which means that the *NIES school risk index* was a good representation of the items within it. The correlation between the *NIES School risk index* and *8th grade mathematics achievement* was 0.16.

NIES predictors.

1. Self-confidence in mathematics (from the NIES Student questionnaire – "how do you rate yourself in mathematics?"). Table D59 shows the distribution of AI/AN student-level responses to the question *how do you rate yourself in mathematics* (n=5997; 2.4% of the data were missing).

Table D59: *NIES individual item self-confidence in mathematics*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00 - Poor	792	12.9	13.2	13.2
	2.00 - Average	2365	38.5	39.4	52.7
	3.00 – Good	2049	33.4	34.2	86.8
	4.00 – Very good	790	12.9	13.2	100.0
	Total	5997	97.6	100.0	
Missing	System	146	2.4		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this individual item by separating the responses between poor/average and good/very good, as shown in Table D60.

Table D60: *NIES individual item self-confidence in mathematics dichotomized factor*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00 (good/very good)	2839	46.2	47.3	47.3
	1.00 (poor/ average)	3158	51.4	52.7	100.0
	Total	5997	97.6	100.0	
Missing	System	146	2.4		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "poor/average" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (rating themselves as poor/average in mathematics) and those who didn't have the risk factor (rating themselves as good/very good in mathematics), *t*

(5,995) = 5.6, $p < 0.001$. The correlation between *self-confidence in mathematics* and *8th grade mathematics achievement* was 0.3.

Table D61 shows the dichotomized distribution of AI/AN student responses to the individual item *self-confidence in mathematics* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (rating themselves as poor/average in mathematics) and those who didn't have the risk factor (rating themselves as good/very good in mathematics), t (6,141) = 5.7, $p < 0.001$. The correlation between *self-confidence in mathematics* and *8th grade mathematics achievement* was 0.3.

Table D61: *NIES individual item self-confidence in mathematics dichotomized factor using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	good/very good	2914	47.4	47.4	47.4
	poor/average	3229	52.6	52.6	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. <u>Teachers incorporate AI/AN culture/tradition into their mathematics instruction (from the NIES Teacher questionnaire).</u> Table D62 shows the distribution of responses to the derived risk factor asking teachers how often they incorporate AI/AN culture/tradition into their mathematics instruction (n=5586; 9.1% of the data were missing).

Table D62: *NIES derived risk factor teachers Incorporate AI/AN culture/tradition into their mathematics instruction derived risk factor*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	1492	24.3	26.7	26.7
	1.25	271	4.4	4.9	31.6
	1.50	916	14.9	16.4	48.0
	1.75	377	6.1	6.7	54.7
	2.00	664	10.8	11.9	66.6
	2.25	362	5.9	6.5	73.1
	2.50	441	7.2	7.9	81.0
	2.75	118	1.9	2.1	83.1
	3.00	274	4.5	4.9	88.0
	3.25	348	5.7	6.2	94.2
	3.50	50	.8	.9	95.1
	3.75	214	3.5	3.8	98.9
	4.00	38	.6	.7	99.6
	4.25	21	.3	.4	100.0
	Total	5586	90.9	100.0	
Missing	System	557	9.1		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

The decision was made to dichotomize this derived risk factor by separating the responses between 2.25[54] (at least once a year/never) and lower and 2.50 and higher (at least once a month or more), as shown in Table D63.

[54] This was the value in which there were students in Arizona public low density schools coded as “0” (i.e., using a cutoff value of 2.50 meant all the Arizona public low density school students were coded as “1”) and the item still discriminated between the mathematics achievement coded as “0”and “1” (i.e., when the cutoff was 2.00, the item did not discriminate).

Table D63: *NIES derived risk factor teachers Incorporate AI/AN culture/tradition into their mathematics instruction dichotomized factor*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00 (at least once a month or more)	1504	24.5	26.9	26.9
	1.00 (at least once a year/never)	4082	66.4	73.1	100.0
	Total	5586	90.9	100.0	
Missing	System	557	9.1		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Therefore, the risk factor (i.e., equal to 1) was "2.25 or lower" and the rest of the non-missing responses were set to equal 0. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (teachers incorporate AI/AN culture/tradition into their mathematics instruction at least once a year/never) and those who didn't have the risk factor (teachers incorporate AI/AN culture/tradition into their mathematics instruction at least once a month or more), t (5,584) = 2.2, p = 0.03. The correlation between *teachers incorporate AI/AN culture/tradition into their mathematics instruction* and *8th grade mathematics achievement* was 0.1.

Table D64 shows the dichotomized distribution of AI/AN student responses to the individual item *teachers incorporate AI/AN culture/tradition into their mathematics instruction* using conditional mean substitution for any missing data. Using an independent samples *t*-test, a significant difference in mathematics achievement scores was found between students who had the risk factor (teachers incorporate AI/AN culture/tradition into their mathematics instruction at least once a year/never) and those who didn't have the risk factor (teachers incorporate AI/AN culture/tradition into their mathematics instruction at least once a month or more), t (6,141) = 2.3, p = 0.03. The correlation between *teachers incorporate AI/AN culture/tradition into their mathematics instruction* and *8th grade mathematics achievement* was 0.1.

Table D64: *NIES derived risk factor teachers Incorporate AI/AN culture/tradition into their mathematics instruction dichotomized factor using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	At least once a month or more	1694	27.6	27.6	27.6
	At least once a year/never	4449	72.4	72.4	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

Student body composition indicator items aggregated to the school level for OLS regression analysis.

The following five student body composition indicator items were created using data from students of all races that were aggregated to the school level to show the proportion of students in the school who possessed each characteristic in order to assess the student body composition in each of the four public school strata. The data shown below have already been aggregated to the school level and the results are shown for just AI/AN students/schools.[55]

1. Parent Education Level. Table D65 shows the distribution of responses using listwise deletion to the *parent education level* item (PARED) that was dichotomized so that

[55] Each item was aggregated to the school level using students of all races. It was then centered using data for students of all races. In the OLS regression analyses, only data for AI/AN students was included.

responses over 3.45 were coded as "1. graduated college". All other responses were coded "0. less than college education" (n=5039; 18% of the data were missing).

Table D65: *Parent education level for students of all races dichotomized using listwise deletion*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	less than college education	3355	54.6	66.6	66.6
	graduated college	1684	27.4	33.4	100.0
	Total	5039	82.0	100.0	
Missing	System	1104	18.0		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Table D66 shows the distribution of responses to the *parent education level* item for students of all races using conditional mean substitution.

Table D66: *Parent education level for students of all races dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	less than college education	4458	72.6	72.6	72.6
	graduated college	1684	27.4	27.4	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

2. <u>Eligibility for National School Lunch Program.</u> Table D67 shows the distribution of responses using listwise deletion to the *eligibility for NSLP* item (SLUNCH1) for students of all races that was dichotomized so that responses over 0.5 were coded as "1. not eligible". All other responses were coded "0. eligible" (n=5926; 3.5% of the data were missing).

Table D67: *Eligibility for NSLP using listwise deletion*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	eligible	4558	74.2	76.9	76.9
	not eligible	1368	22.3	23.1	100.0
	Total	5926	96.5	100.0	
Missing	System	217	3.5		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Table D68 shows the distribution of responses to the *eligibility for NSLP* item for students of all using conditional mean substitution.

Table D68: *Eligibility for NSLP using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	eligible	4775	77.7	77.7	77.7
	not eligible	1368	22.3	22.3	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

3. Books in home. Table D69 shows the distribution of responses using listwise deletion to the *books in the home* item for students of all races that was dichotomized so that responses over 0.5 were coded as "1. more than 100 books". All other responses were coded "0. 100 books or less" (n=6096; 0.8% of the data were missing).

Table D69: *Books in home dichotomized using listwise deletion*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	100 books or less	5361	87.3	87.9	87.9
	more than 100 books	735	12.0	12.1	100.0
	Total	6096	99.2	100.0	
Missing	System	47	.8		
Total		6143	100.0		

Notes. Values are based upon weighted estimates.

Table D70 shows the distribution of responses to the *books in the home* item for students of all races using conditional mean substitution.

Table D70: *Books in home dichotomized using conditional mean substitution*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	100 books or less	5407	88.0	88.0	88.0
	more than 100 books	735	12.0	12.0	100.0
	Total	6143	100.0	100.0	

Notes. Values are based upon weighted estimates.

4. Student race. Tables D71-D73 show the distribution of student race based on school records using the item SDRACEM (n=38,939; 0% of the data were missing). White and Asian American/Pacific Islander were combined because they were both high scoring groups, on average, and Hispanic and Black were combined because they were both low scoring groups, on average. Therefore, the two dummy race variables were: *Hispanic/Black* (1. yes, 0. no) and *White/Asian American/Pacific Islander* (1. yes, 0. no). AI/AN was used as the reference group. Each of these dummy race variables was aggregated to show the proportion of students in each school in each race category (e.g., the proportion of White/Asian American/Pacific Islander students

in the school was a separate variable from the proportion of Hispanic/Black students in the school, etc.). There were no missing data so conditional mean substitution was not used.

Table D71: *AI/AN vs. all other races*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	ALL OTHER RACES	32796	84.2	84.2	84.2
	AI/AN	6143	15.8	15.8	100.0
	Total	38939	100.0	100.0	

Notes. Values are based upon weighted estimates.

Table D72: *Hispanic/Black vs. not Hispanic/Black*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	not Hispanic/Black	25942	66.6	66.6	66.6
	Hispanic/Black	12997	33.4	33.4	100.0
	Total	38939	100.0	100.0	

Notes. Values are based upon weighted estimates.

Table D73: *White/Asian vs. not White/Asian*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	not White/Asian	19140	49.2	49.2	49.2
	White/Asian	19799	50.8	50.8	100.0
	Total	38939	100.0	100.0	

Notes. Values are based upon weighted estimates.

Using Spearman's rho in SPSS and the overall student weight and pairwise deletion, the four NAEP risk indices, the three NIES risk indices, the NIES individual item, the NIES derived risk factor, and three of the student body composition variables (the two race variables were not included because they were dichotomous) were found, for the most part, to have low correlations with each other, as shown in Table D74 below. This outcome was encouraging because it means the seven risk indices, two factors, and three of the student body composition variables were not overlapping in content. There were two low to moderation correlations. The NIES individual item *self-confidence in mathematics* and the *NAEP Knowledge/attitudes risk index* had a 0.487 correlation, which was not surprising since the NIES individual item *self-confidence in mathematics* and *attitude toward mathematics* had a 0.475 correlation (the NIES individual item *self-confidence in mathematics* and *clearly understands the teacher* had a 0.302 correlation). *Books in the home, eligibility for NSLP,* and *parent education level* had low to moderate correlations with the *NAEP Home risk index* (0.324 - 0.407), which is not surprising since *books in the home*, *eligibility for NSLP*, and *mother's education* were also included in the *NAEP Home risk index*. These similar sets of items were used for different purposes. In the risk index, the items were coded as risk factors (e.g., having 0-25 books in the home was a risk factor and equal to "1"). In the student body composition variables, the variables incorporated responses from AI/AN students and students of all other races and were coded in a positive way (e.g., "1" was equal to more than 100 books in the home to represent SES of the student body). Still, these correlations were not high enough to be of concern, especially since the regressions were done by entering one risk index/factor at a time and by using interaction terms.

Table D74: *Correlations among the four NAEP risk indices, three NIES risk indices, derived risk factor, individual item, and three student body composition variables using pairwise deletion*

		NAEP knowledge	NAEP social	NAEP home	NAEP classroom	NIES student	NIES home	NIES school	NIES ind. item *Self-confidence*	NIES derived risk factor *Teach incorp*	Parent education level	NSLP	Books in home
NAEP knowledge	Correlation Coefficient	1.000	.073**	.237**	.019	.161**	.181**	.116**	.487**	-.022	-.061**	.007	-.055**
	Sig. (2-tailed)	.	.000	.000	.182	.000	.000	.000	.000	.101	.000	.594	.000
	N	5891	5863	4231	4869	5728	5755	5063	5773	5361	4850	5708	5863
NAEP social	Correlation Coefficient	.073**	1.000	.135**	.078**	.080**	.021	-.042**	.146**	-.016	.007	.125**	-.044**
	Sig. (2-tailed)	.000	.	.000	.000	.000	.111	.002	.000	.227	.624	.000	.001
	N	5863	6064	4362	4979	5874	5909	5227	5933	5518	4997	5862	6036
NAEP home	Correlation Coefficient	.237**	.135**	1.000	.085**	.132**	.221**	-.034*	.141**	-.054**	-.341**	.407**	-.324**
	Sig. (2-tailed)	.000	.000	.	.000	.000	.000	.034	.000	.001	.000	.000	.000
	N	4231	4362	4377	3629	4278	4304	3818	4334	4066	4377	4377	4377
NAEP classroom	Correlation Coefficient	.019	.078**	.085**	1.000	.010	-.002	-.267**	.155**	-.022	-.059**	.082**	-.018
	Sig. (2-tailed)	.182	.000	.000	.	.486	.914	.000	.000	.130	.000	.000	.213
	N	4869	4979	3629	5004	4843	4875	4399	4886	4706	4094	4837	4979
NIES student	Correlation Coefficient	.161**	.080**	.132**	.010	1.000	.102**	.170**	.120**	.071**	-.020	-.046**	-.004
	Sig. (2-tailed)	.000	.000	.000	.486	.	.000	.000	.000	.000	.164	.001	.746
	N	5728	5874	4278	4843	5902	5841	5096	5841	5392	4868	5715	5871
NIES home	Correlation Coefficient	.181**	.021	.221**	-.002	.102**	1.000	.104**	.091**	-.083**	-.053**	-.004	-.037**
	Sig. (2-tailed)	.000	.111	.000	.914	.000	.	.000	.000	.000	.000	.733	.004
	N	5755	5909	4304	4875	5841	5940	5127	5928	5418	4905	5744	5909
NIES school	Correlation Coefficient	.116**	-.042**	-.034*	-.267**	.170**	.104**	1.000	-.033*	.088**	.033*	-.332**	.004
	Sig. (2-tailed)	.000	.002	.034	.000	.000	.000	.	.019	.000	.032	.000	.745
	N	5063	5227	3818	4399	5096	5127	5264	5148	4879	4344	5065	5221
NIES individual item *self-confidence*	Correlation Coefficient	.487**	.146**	.141**	.155**	.120**	.091**	-.033*	1.000	-.032*	-.048**	.043**	-.042**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.019	.	.018	.001	.001	.001
	N	5773	5933	4334	4886	5841	5928	5148	5964	5442	4938	5765	5933
NIES der. risk factor *Teacher incorporate*	Correlation Coefficient	-.022	-.016	-.054**	-.022	.071**	-.083**	.088**	-.032*	1.000	.080**	-.182**	-.029*
	Sig. (2-tailed)	.101	.227	.001	.130	.000	.000	.000	.018	.	.000	.000	.031
	N	5361	5518	4066	4706	5392	5418	4879	5442	5549	4584	5385	5515
Parent education level	Correlation Coefficient	-.061**	.007	-.341**	-.059**	-.020	-.053**	.033*	-.048**	.080**	1.000	-.221**	.078**
	Sig. (2-tailed)	.000	.624	.000	.000	.164	.000	.032	.001	.000	.	.000	.000
	N	4850	4997	4377	4094	4868	4905	4344	4938	4584	5015	4849	5015
NSLP	Correlation Coefficient	.007	.125**	.407**	.082**	-.046**	-.004	-.332**	.043**	-.182**	-.221**	1.000	-.123**
	Sig. (2-tailed)	.594	.000	.000	.000	.001	.733	.000	.001	.000	.000	.	.000
	N	5708	5862	4377	4837	5715	5744	5065	5765	5385	4849	5905	5862
Books in home	Correlation Coefficient	-.055**	-.044**	-.324**	-.018	-.004	-.037**	.004	-.042**	-.029*	.078**	-.123**	1.000
	Sig. (2-tailed)	.000	.001	.000	.213	.746	.004	.745	.001	.031	.000	.000	.
	N	5863	6036	4377	4979	5871	5909	5221	5933	5515	5015	5862	6064

Notes. Values are based upon weighted estimates.

Using Spearman's rho in SPSS and the overall student weight and conditional mean substitution, the four NAEP risk indices, the three NIES risk indices, the NIES individual item, the NIES derived risk factor, and three of the student body composition variables (the two race variables were not included because they were dichotomous) were found, for the most part to have low correlations with each other, as shown in Table D75 below. Similar to the previous table, this outcome was encouraging because it means the seven risk indices, two factors, and three of the student body composition variables were not overlapping in content. Using conditional mean substitution, the NIES individual item *self-confidence in mathematics* and the *NAEP Knowledge/attitudes risk index* had a slightly lower correlation of 0.467. In this case, the NIES individual item *self-confidence in mathematics* and *attitude toward mathematics* had a correlation of 0.466 and the NIES individual item *self-confidence in mathematics* and *clearly understands the teacher* had a 0.290 correlation. *Eligibility for NSLP* and *parent education level* had slightly lower correlations using conditional mean substitution (-0.267 and 0.361) with the *NAEP Home risk index*. However, *books in the home* and the *NAEP Home risk index* had a higher, moderate correlation of 0.612 using conditional mean substitution. Again, since the regression was done by entering one risk index/risk factor at a time and by using interaction terms, these correlations were not of much concern.

Table D75: *Correlations among the four NAEP risk indices, three NIES risk indices, derived risk factor, individual item, and three student body composition variables using conditional mean substitution (n=6143)*

		NAEP knowledge	NAEP social	NAEP home	NAEP classroom	NIES student	NIES home	NIES school	NIES ind. item *self-conf*	NIES der. risk factor *teach inc*	Parent education	NSLP	Books in home
NAEP knowledge	Correlation coefficient	1.000	**.076**	**.229**	**.049**	**.166**	**.164**	**.094**	**.467**	**-.007**	**-.070**	**-.001**	**.183**
	Sig. (2-tailed)	.	*.000*	*.000*	*.000*	*.000*	*.000*	*.000*	*.000*	*.587*	*.000*	*.957*	*.000*
NAEP social	Correlation coefficient	**.076**	1.000	**.119**	**.060**	**.078**	**.017**	**-.040**	**.142**	**.035**	**.002**	**.118**	**.122**
	Sig. (2-tailed)	*.000*	.	*.000*	*.000*	*.000*	*.194*	*.002*	*.000*	*.006*	*.866*	*.000*	*.000*
NAEP home	Correlation coefficient	**.229**	**.119**	1.000	**-.003**	**.144**	**.218**	**-.015**	**.171**	**-.004**	**-.267**	**.361**	**.612**
	Sig. (2-tailed)	*.000*	*.000*	.	*.835*	*.000*	*.000*	*.231*	*.000*	*.738*	*.000*	*.000*	*.000*
NAEP classroom	Correlation coefficient	**.049**	**.060**	**-.003**	1.000	**.019**	**.007**	**-.263**	**.152**	**-.145**	**.010**	**.054**	**.000**
	Sig. (2-tailed)	*.000*	*.000*	*.835*	.	*.142*	*.565*	*.000*	*.000*	*.000*	*.453*	*.000*	*.986*
NIES student	Correlation coefficient	**.166**	**.078**	**.144**	**.019**	1.000	**.082**	**.149**	**.110**	**.089**	**-.039**	**-.042**	**.007**
	Sig. (2-tailed)	*.000*	*.000*	*.000*	*.142*	.	*.000*	*.000*	*.000*	*.000*	*.002*	*.001*	*.600*
NIES home	Correlation coefficient	**.164**	**.017**	**.218**	**.007**	**.082**	1.000	**.077**	**.097**	**-.033**	**-.047**	**-.018**	**.070**
	Sig. (2-tailed)	*.000*	*.194*	*.000*	*.565*	*.000*	.	*.000*	*.000*	*.010*	*.000*	*.149*	*.000*
NIES school	Correlation coefficient	**.094**	**-.040**	**-.015**	**-.263**	**.149**	**.077**	1.000	**-.048**	**.263**	**.017**	**-.299**	**-.060**
	Sig. (2-tailed)	*.000*	*.002*	*.231*	*.000*	*.000*	*.000*	.	*.000*	*.000*	*.182*	*.000*	*.000*
NIES ind. item *self-confidence*	Correlation coefficient	**.467**	**.142**	**.171**	**.152**	**.110**	**.097**	**-.048**	1.000	**-.028**	**-.063**	**.037**	**.200**
	Sig. (2-tailed)	*.000*	*.000*	*.000*	*.000*	*.000*	*.000*	*.000*	.	*.026*	*.000*	*.003*	*.000*
NIES derived risk factor *teachers incorporate*	Correlation coefficient	**-.007**	**.035**	**-.004**	**-.145**	**.089**	**-.033**	**.263**	**-.028**	1.000	**.033**	**-.191**	**-.006**
	Sig. (2-tailed)	*.587*	*.006*	*.738*	*.000*	*.000*	*.010*	*.000*	*.026*	.	*.009*	*.000*	*.621*
Parent education	Correlation coefficient	**-.070**	**.002**	**-.267**	**.010**	**-.039**	**-.047**	**.017**	**-.063**	**.033**	1.000	**-.223**	**-.116**
	Sig. (2-tailed)	*.000*	*.866*	*.000*	*.453*	*.002*	*.000*	*.182*	*.000*	*.009*	.	*.000*	*.000*
NSLP	Correlation coefficient	**-.001**	**.118**	**.361**	**.054**	**-.042**	**-.018**	**-.299**	**.037**	**-.191**	**-.223**	1.000	**.105**
	Sig. (2-tailed)	*.957*	*.000*	*.000*	*.000*	*.001*	*.149*	*.000*	*.003*	*.000*	*.000*	.	*.000*
Books in home	Correlation coefficient	**.183**	**.122**	**.612**	**.000**	**.007**	**.070**	**-.060**	**.200**	**-.006**	**-.116**	**.105**	1.000
	Sig. (2-tailed)	*.000*	*.000*	*.000*	*.986*	*.600*	*.000*	*.000*	*.000*	*.621*	*.000*	*.000*	.

Notes. Values are based upon weighted estimates.

Appendix E: OLS Regression results for NAEP risk indices and student body composition variables using listwise deletion

Although interactions were tested whenever more than one significant predictor was included in a model, none of the interactions were significant; therefore, no interactions were included in any of the final models.

Arizona public low density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -15.82$, $z = -2.3$, $p = .02$ (N=1572; 3% of the data were missing). The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.09$, $F\ (1, 1570) = 5.2$, $p = 0.03$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -32.66$, $z = -4.2$, $p < 0.001$ (N=1619, there were no missing data). The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.24$, $F\ (1, 1617) = 17.92$, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -11.75$, $z = -2.4$, $p = 0.02$ (N=1115, 31.2% of the data were missing). The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.12$, F (1, 1113) = 5.6, $p = 0.02$.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -14.24$, $z = -1.5$, $p = 0.13$ (N=1553, 4.1% of the data were missing). The *NAEP (General) Classroom risk index (GCRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.04$, F (1, 1551) = 2.3, $p = 0.14$.

When each of the five student body composition variables was entered into a regression model alone, none significantly predicted *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools: *White/Asian* ($\beta = 4.7$, $z = 0.22$, $p = 0.83$); *Hispanic/Black* ($\beta = -10.67$, $z = -0.52$, $p = 0.6$); *books in home* ($\beta = 33.413$, $z = 1.02$, $p = 0.31$); *eligibility for NSLP* ($\beta = 18.52$, $z = 0.85$, $p = 0.39$[56]); *parent education level* ($\beta = 32.52$, $z = 1.22$, $p = 0.22$).

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools ($R^2 = 0.24$ and $R^2 = 0.12$, respectively). An interaction term for these two risk indices was also entered into this model (N=1115, 31.2% of the data were missing). The *NAEP (General) Social/physical risk index (GSRI)* was significant, but the *NAEP (General) Home risk index (GHRI)* and

[56] These values, although not significant, were much different from the NSLP values using conditional mean substitution, also not significant, because there was one Arizona public low density school (SCRPSU=C189) for which the majority of data were missing (18/27 student values missing), which means the mean value for the school using listwise deletion was 0.11 while the mean value for the school using conditional mean substitution was 0.71.

the interaction were not. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* was added to create Model 2 (R^2 = 0.09) with the *NAEP (General) Social/physical risk index (GSRI)* and the interaction of the two (N=1572; 3% of the data were missing). *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were significant but not the interaction. Therefore, Model 2, in which the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were significant, was used as the final model for Arizona public low density schools (N=1572; 3% of the data were missing) with no interaction term. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -31.17$, $z = -4.03$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -14.45$, $z = -2.33$, $p = 0.02$. These two risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.31$, $F(2, 1569) = 11.28$, $p < 0.001$.

Arizona public high density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -5.69$, $z = -2.19$, $p = 0.03$ (N=2397; 2.5% of the data were missing). However, the *NAEP (General) Knowledge/attitudes risk index (GKRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.02$, F (1, 2395) = 4.81, $p = 0.06$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -23.95$, $z = -11.08$, $p < 0.001$ (N=2459; there were no missing data). The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.25$, F (1, 2457) = 122.66, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -8.17$, $z = -3.03$, $p = 0.002$ (N=1917; 22% of the data were missing). The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.09$, F (1, 1915) = 9.15, $p = 0.02$.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -1.4$, $z = -0.35$, $p = 0.73$ (N=1714; 30% of the data were missing). The *NAEP (General) Classroom risk index (GCRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.002$, F (1, 1712) = 0.12, $p = 0.74$.

When each of the five student body composition variables was entered into a regression model alone, the only one that significantly predicted *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools was *eligibility for NSLP*: *eligibility for NSLP* (β =20.95, z = 2.16, p= 0.03)[57]; *White/Asian* (β = 11.27, z = 0.84, p= 0.4); *Hispanic/Black* (β = 28.7, z = 1.11, p= 0.27); *books in home* (β = 19.72, z = 0.71, p = 0.48); *parent education level* (β = 16.44, z = 1, p = 0.32)[58].

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools (R^2 = 0.25 and R^2 = 0.09, respectively). An interaction term for these two risk indices was also entered into this model. The two main effects were significant, but the interaction was not. For Model 2, the *NAEP (General) Knowledge/attitudes risk index (GKRI)* was added to the model (R^2 = 0.02) with the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* and the appropriate interactions (GKRI x GSRI, GKRI x GHRI, GSRI x GHRI, and GKRI x GSRI x GHRI). The *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* remained significant, but the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the interactions were not significant. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the interactions associated with it were removed from the model. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were added with NSLP and the appropriate interactions. The *NAEP (General) Social/physical risk index (GSRI)* and the *home x NSLP x social*

[57] This results was different from the conditional mean substitution results substitution (in which NSLP was not significant) because there was one AZ public high density school (SCRPSU=B589) with missing data and using conditional mean that student was coded as “1. not eligible”.

[58] This results was different from the conditional mean substitution results substitution (in which parent education was significant) because using listwise deletion, 14% of the data were missing and using conditional mean substitution, all those students were coded as having parents with the highest education of “less than graduated college”.

interaction were significant. Therefore, Model 1, in which the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were significant, was used as the final model for Arizona public high density schools (N=1917; 22% of the data were missing) with no interaction term. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -19.13$, $z = -7.93$, $p < 0.001$. The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -6.05$, $z = -3.13$, $p = 0.002$. These two risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.23$, $F\ (2, 1914) = 28.76$, $p < 0.001$.

Arizona BIE schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -14.42$, $z = -5.06$, $p < 0.001$ (N=632; 5% of the data were missing). The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.13$, $F\ (1, 630) = 25.55$, $p < 0.001$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -21.5$, $z = -8.2$, $p < 0.001$ (N=641; 3.6% of the data were missing). The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.26$, $F(1, 639) = 67.22$, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -7.5$, $z = -3.7$, $p < 0.001$ (N=473; 29% of the data were missing). The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.07$, $F(1, 471) = 13.72$, $p < 0.001$.

The *NAEP (General) Classroom risk index (GCRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -14.07$, $z = -3.57$, $p < 0.001$ (N=507; 24% of the data were missing). The *NAEP (General) Classroom risk index (GCRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.08$, $F(1, 505) = 12.73$, $p < 0.001$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were entered into the model first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools ($R^2 = 0.26$ and $R^2 = 0.13$, respectively). An interaction term for these two risk indices was also entered into this model. The two main effects were significant, but the interaction was not. For Model 2, the *NAEP (General) Classroom risk index (GCRI)* was added ($R^2 = 0.08$) and the appropriate interactions (GKRI x GSRI, GKRI x GCRI, GSRI x GCRI, and GKRI x GSRI x GCRI). *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP*

(General) Knowledge/attitudes risk index (GKRI) remained significant, but the *NAEP (General) Classroom risk index (GCRI)* and the interactions were not significant. The *NAEP (General) Classroom risk index (GCRI)* and the interactions associated with it were removed from the model. For Model 3, the *NAEP (General) Home risk index (GHRI)* was added ($R^2 = 0.07$) with the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the appropriate interactions (GSRI x GHRI, GSRI x GKRI, GHRI x GKRI, and GSRI x GHRI x GKRI). Only the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* remained significant. Therefore, Model 1, in which the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were significant, was used as the final model for Arizona BIE schools (N=616; 7% of the data were missing) with no interaction term. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β= -18.89, z = -7.31, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β= -12.43, z = -4.73, $p < 0.001$. These two risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.32$, F (2, 615) = 60.86, $p <$ 0.001.

South Dakota public low density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, β = -

14.26, z = -3.6, $p < 0.001$ (N=345; 2.7% of the data were missing). The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.13$, F (1, 343) = 12.93, $p < 0.001$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, β= -27.58, z = -5.18, $p < 0.001$ (N=351; 0.9% of the data were missing). The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.30$, F (1, 349) = 26.8, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, β = -9.51, z = -3.78, $p < 0.001$ (N=267; 25% of the data were missing). The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.13$, F (1, 265) = 14.3, $p < 0.001$.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, β = -7.9, z = -1.64, p = 0.1 (N=328; 7% of the data were missing). The *NAEP (General) Classroom risk index (GCRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for

AI/AN students in South Dakota public low density schools, $R^2 = 0.03$, $F(1, 326) = 2.69$, $p = 0.11$.

When each of the five student body composition variables was entered into a regression model alone, the only one that significantly predicted *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools was *Hispanic/Black*: *Hispanic/Black* ($\beta = -93.74$, $z = -2.74$, $p = 0.006$); *eligibility for NSLP* ($\beta = 15.14$, $z = 0.67$, $p = 0.5$; *White/Asian* ($\beta = -11.31$, $z = -0.62$, $p = 0.54$); *books in home* ($\beta = 1.96$, $z = 0.07$, $p = 0.95$); *parent education level* ($\beta = 21.55$, $z = 1.11$, $p = 0.27$). Unfortunately, the standard error for the *Hispanic/Black* coefficient was extremely high, 33.51. Therefore, a decision was made that this student body composition variable was not stable enough to include in the final model.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools ($R^2 = 0.30$ and $R^2 = 0.13$, respectively). An interaction term for these two risk indices was also entered into this model. Only the *NAEP (General) Social/physical risk index (GSRI)* was significant so the *NAEP (General) Home risk index (GHRI)* and the interaction were removed from the model. Model 2 included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* ($R^2 = 0.13$) and the appropriate interactions. The two main effects were significant, but the interactions were not significant. Therefore, Model 2, in which the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were significant, was used as the final model for South Dakota public low density schools (N=342; 3.5% of the data were missing) with no interaction term. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -25.56$, $z = -4.75$, $p < .001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -10.62$, $z = -2.87$, $p = 0.004$. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.38$, $F\ (2, 339) = 19.45$, $p < 0.001$.

South Dakota public high density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -14.43$, $z = -5.23$, $p < 0.001$ (N=571; 5% of the data were missing). The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.14$, $F\ (1, 569) = 27.37$, $p < 0.001$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -16.55$, $z = -4.18$, $p < 0.001$ (N=597; 1.7% of the data were missing). The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for

AI/AN students in South Dakota public high density schools, $R^2 = 0.10$, F (1, 595) = 17.5, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -9.77$, $z = -4.88$, $p < 0.001$ (N=444; 26% of the data were missing). The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.13$, F (1, 442) = 23.8, $p < 0.001$.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -8.46$, $z = -1.81$, $p = 0.07$ (N=554; 7.8% of the data were missing). Additionally, the *NAEP (General) Classroom risk index (GCRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.02$, F (1, 552) = 3.29, $p = 0.08$.

When each of the five student body composition variables was entered into a regression model alone, three significantly predicted *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools: *eligibility for NSLP* ($\beta = 25.75$, $z = 3.21$, $p= 0.001$); *books in home* ($\beta = 36.2$, $z = 2.09$, $p = 0.04$); *parent education level* ($\beta = 24.12$, $z = 2.45$, $p = 0.01$); *Hispanic/Black* ($\beta = 40.79$, $z = 0.73$, $p = 0.46$); *White/Asian* ($\beta = 18.58$, $z = 1.61$, $p= 0.11$).

For Model 1, the NAEP (General) Knowledge/attitudes index (GSRI) and the *NAEP (General) Home risk index (GHRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools ($R^2 = 0.14$ and $R^2 = 0.13$, respectively). An interaction term for these two risk indices was also entered into this model. Only the *NAEP (General) Home risk index (GHRI)* was significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)* was added to the model ($R^2 = 0.10$) with the *NAEP (General) Home risk index (GHRI)* and an interaction. The two main effects were significant, but the interaction was not significant. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and *parent education level* were included with no interaction terms. The risk indices were significant, but *parent education level* was not. For Model 4, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and *books in the home* were included with no interaction terms. The risk indices were significant, but *books in the home* was not. For Model 5, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and *eligibility for NSLP* were included with no interaction terms. The risk indices were significant, but *eligibility for NSLP* was not. Therefore, Model 2, in which the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were significant, was used as the final model for South Dakota public high density schools (N=439; 27% of the data were missing) with no interaction term. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -16.68$, $z = -4.18$, $p < 0.001$. The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -9.55$, $z = -4.93$, $p < 0.001$. These two risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.23$, $F(2, 437) = 18.34$, $p < 0.001$.

South Dakota BIE schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -9.11$, $z = -2.36$, $p = 0.02$ (N=405; 8.7% of the data were missing). The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.07$, $F(1, 403) = 5.56$, $p = 0.02$.

The *NAEP (General) Social/physical risk index (GSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -8.11$, $z = -1.5$, $p = 0.13$ (N=434; 2% of the data were missing). The *NAEP (General) Social/physical risk index (GSRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.04$, $F(1, 432) = 2.31$, $p = 0.14$.

The *NAEP (General) Home risk index (GHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -3.29$, $z = -0.89$, $p = 0.38$ (N=178; 60% of the data were missing). The *NAEP (General) Home risk index (GHRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.01$, $F(1, 176) = 0.79$, $p = 0.38$.

The *NAEP (General) Classroom risk index (GCRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -11.94$, $z = -2.72$, $p = 0.006$ (N=386; 13% of the data were missing). The *NAEP (General) Classroom risk index (GCRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.07$, F (1, 384) = 7.42, $p = 0.009$.

For Model 1, the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the *NAEP (General) Classroom risk index (GCRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools ($R^2 = 0.07$ and $R^2 = 0.07$). An interaction term for these two risk indices was also entered into the model. Only the *NAEP (General) Classroom risk index (GCRI)* was significant. For Model 2, even though it wasn't significant on its own, the *NAEP (General) Social/physical risk index (GSRI)* was added to the model ($R^2 = 0.04$) with the *NAEP (General) Classroom risk index (GCRI)* and an interaction term. Again, only the *NAEP (General) Classroom risk index (GCRI)* was significant. Therefore, the final model for South Dakota BIE schools only included the *NAEP (General) Classroom risk index (GCRI)*. As stated above, the *NAEP (General) Classroom risk index (GCRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -11.94$, $z = -2.72$, $p = 0.006$ (N=386; 13% of the data were missing). The *NAEP (General) Classroom risk index (GCRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.07$, F (1, 384) = 7.42, $p = 0.009$.

Appendix F: OLS Regression results for NAEP and NIES risk indices, NIES individual item, and NIES derived risk factor variables using listwise deletion

Although interactions were tested whenever more than one significant predictor was included in a model, none of the interactions were significant; therefore, no interactions were included in any of the final models.

Arizona public low density schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -5.1$, $z = -0.78$, $p = 0.44$ (N=1574; 2.8% of the data were missing). Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.01$, F (1, 1572) = 0.6, p = 0.44.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -4.66$, $z = -0.8$, $p = 0.42$ (N=1551; 4% of the data were missing). Additionally, the *NIES Home risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.007$, F (1, 1549) = 0.65, $p = 0.42$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -32.65$, $z = -2.8$, $p = 0.005$ (N=1551; 5% of the data were missing). Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade* *mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.15$, $F(1, 1549) = 7.83$, $p = 0.008$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -37.24$, $z = -3.52$, $p < 0.001$ (N=1550; 4% of the data were missing). Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.02$, $F(1, 1548) = 12.4$, $p = 0.001$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -4.02$, $z = -0.39$, $p = 0.7$ (N=1316; 19% of the data were missing). Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.003$, $F(1, 1314) = 0.15$, $p = 0.7$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions (GSRI x SELFCONF, GSRI x GKRI, GKRI x SELFCONF, GSRI x GKRI x SELFCONF). Only the *NAEP (General) Social/physical risk index (GSRI)* was significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions (GSRI x CLASS, GSRI x GKRI, GKRI x CLASS, GSRI x GKRI x CLASS). However, there was not enough variation in how often teachers incorporate AI/AN culture/tradition into their mathematics instruction in Arizona public low density schools. Only 1.9% of the students had teachers who incorporate AI/AN culture/tradition into their mathematics instruction at least once a year or more. Therefore, this risk factor was removed from the model. Thus, the final model for Arizona public low density schools did not include any NIES predictors. The final model included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and no interaction terms (N=1572; 3% of the data were missing). The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -31.17$, $z = -4.03$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -14.45$, $z = -2.33$, $p = 0.02$. These two risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.31$, $F\ (2, 1569) = 11.28$, $p < 0.001$.

Arizona public high density schools. The *NIES Student risk index (NSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -4.02$, $z = -2.09$, $p = 0.04$ (N=2408; 2% of the data were missing). However, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.008$, $F(1, 2406) = 4.36$, $p = 0.07$.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = 1.18$, $z = 0.4$, $p = 0.69$ (N=2409; 2% of the data were missing). Additionally, the *NIES Home risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.001$, $F(1, 2407) = 0.16$, $p = 0.7$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -16.9$, $z = -3.4$, $p = 0.001$ (N=2414; 2% of the data were missing). Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.06$, $F(1, 2412) = 11.52$, $p = 0.009$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -2.85$, $z = -0.53$, $p = 0.6$ (N=2320; 5.7% of the data were missing). Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.002$, $F(1, 2318) = 0.28$, $p = 0.61$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = 2.84$, $z = 1.22$, $p = 0.22$ (N=2288; 7% of the data were missing). Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.005$, $F(1, 2286) = 1.49$, $p = 0.26$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions (GSRI x SELFCONF, GSRI x GHRI, GHRI x SELFCONF, GSRI x GHRI x SELFCONF). All three main effects were significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the *NIES Student risk index (NSRI)* were entered with the appropriate interactions (GSRI x NSRI, GSRI x GHRI, GHRI x NSRI, GSRI x GHRI x NSRI). Only the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were significant. Therefore, the final model for Arizona public high density school students included the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) and no interaction terms. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -17.37$, $z = -6.36$, $p < 0.001$

(N=1907; 22.5% of the data were missing). The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, β = -5.92, z = -2.65, p = 0.008. The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, β = -11.73, z = -2.99, p = 0.003. These risk indices/factor also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, R^2 = 0.24, F (3, 1910) = 19.63, p = 0.002.

The final NAEP model from Table 4.24 included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* and accounted for 23% of the variation in achievement. Thus, adding the NIES individual item *self-confidence in mathematics* (SELFCONF) slightly increased the amount of variation account for in mathematics achievement to 24%.

Arizona BIE schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β= -4.44, z = -1.55, p = 0.12 (N=635; 4.5% of the data were missing). Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, R^2 = 0.01, F (1, 633) = 2.43, p = 0.12.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β = -2.3, z = -0.77, p = 0.44 (N=650; 2% of the data were missing). Additionally, the *NIES Home* *risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, R^2 = 0.003, F (1, 648) = 0.59, p = 0.44.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β = -15.8, z = -3.05, p = 0.002 (N=656; 1.4% of the data were missing). Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, R^2 = 0.06, F (1, 654) = 9.32, p = 0.003.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β = 22.5, z= 4.2, p < 0.001 (N=475; 29% of the data were missing). Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, R^2 = 0.10, F (1, 473) = 17.75, p < 0.001.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β = -9.38, z = -1.84, p = 0.07 (N=553; 17% of the data were missing). Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade* *mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.02$, $F(1, 551) = 3.4$, $p = 0.07$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions (GSRI x SELFCONF, GSRI x GKRI, GKRI x SELFCONF, GSRI x GKRI x SELFCONF). All three main effects were significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions (GSRI x CLASS, GSRI x GKRI, GKRI x CLASS, GSRI x GKRI x CLASS). All three main effects were significant. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, the NIES individual item *self-confidence in mathematics* (SELFCONF), and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions (GSRI x CLASS, GSRI x GKRI, GSRI x SELFCONF, GKRI x CLASS, GKRI x SELFCONF, CLASS x SELFCONF, CLASS x GKRI x GSRI, GSRI x GKRI x SELFCONF, CLASS x SELFCONF x GKRI, CLASS x SELFCONF x GSRI, CLASS x GKRI x GSRI x SELFCONF). Only the *NAEP (General) Social/physical risk index (GSRI)* and the NIES individual item *self-confidence in mathematics* (SELFCONF) were significant. When the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, the NIES individual item *self-confidence in* *mathematics* (SELFCONF), and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered into a model with no interactions, only the NIES individual item *self-confidence in mathematics* (SELFCONF) was not significant. Therefore, the final model for Arizona BIE school students included the *NAEP (General) Social/physical risk index (GSRI)*, the NAEP (General) Knowledge risk index (GKRI), and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) with no interactions. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -16.82$, $z = -5.36$, $p < 0.001$ (N=638; 3.6% of the data were missing). The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = 11.25$, $z = 2.34$, $p = 0.02$. These NAEP risk indices and NIES derived risk factor explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.35$, $F(3, 634) = 30.03$, $p < 0.001$.

The final NAEP model from Table 4.24 included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and accounted for 32% of the variation in achievement. Adding the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) to the model increased the variance accounted for by 3% to 35%.

South Dakota public low density schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = 1.12$, $z = 0.38$, $p = 0.7$ (N=337; 5% of the data were missing). Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.001$, F (1, 335) = 0.15, $p = 0.7$.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = 0.22$, $z = 0.06$, $p = 0.95$ (N=337; 5% of the data were missing). Additionally, the *NIES Home risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 < 0.001$, F (1, 335) = 0.003, $p = 0.95$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -22.99$, $z = -4.3$, $p < 0.001$ (N=344; 3% of the data were missing). Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.15$, F (1, 342) = 18.49, $p < 0.001$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, β= 24.1, $z = 2.78$, $p = 0.005$ (N=314; 11% of the data were missing). Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics* *instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.02$, $F(1, 312) = 7.75$, $p = 0.007$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = 5$, $z = 0.9$, $p = 0.36$ (N=316; 11% of the data were missing). Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.008$, $F(1, 314) = 0.85$, $p = 0.36$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions (GSRI x SELFCONF, GSRI x GKRI, GKRI x SELFCONF, GSRI x GKRI x SELFCONF). The *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the interaction between these two risk indices were significant. When these two risk indices were entered into a model with their interaction, the interaction was no longer significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions (GSRI x CLASS, GSRI x GKRI, GKRI x CLASS, GSRI x GKRI x CLASS). However, there was not enough variation in how often teachers incorporate AI/AN culture/tradition into their mathematics instruction in South Dakota public low density schools. Only 2.9% of the students had teachers who incorporate AI/AN culture/tradition into their mathematics instruction at least once a year or more. Therefore, this risk factor was removed from the model. Therefore, the final model for South Dakota public low density schools did not include any NIES predictors. The final model included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and no interaction terms (N=342; 3.5% of the data were missing). The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -25.56$, $z = -4.75$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -10.62$, $z = -2.87$, $p = 0.004$. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.38$, $F\ (2, 339) = 19.45$, $p < 0.001$.

South Dakota public high density schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = 1.7$, $z = 0.43$, $p = 0.67$ (N=577; 4% of the data were missing). Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.004$, $F\ (1, 575) = 0.18$, $p = 0.67$.

The *NIES Home risk index (NHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -8.31, z = -2.3, p = 0.02 (N=595; 1% of the data were missing). Additionally, the *NIES Home risk index (NHRI)* explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, R^2 = 0.04, F (1, 593) = 5.21, p = 0.03.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -21.19, z = -4.05, p < 0.001 (N=595; 1% of the data were missing). Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, R^2 = 0.11, F (1, 593) = 16.42, p < 0.001.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = 14.87, z = 2.43, p = 0.02 (N=554; 17% of the data were missing). Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, R^2 = 0.05, F (1, 552) = 5.89, p = 0.02.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = 4.1, z = 1.1, p = 0.26 (N=475; 21% of the data were missing). Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.01$, $F\ (1, 473) = 1.25$, $p = 0.27$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions (GSRI x SELFCONF, GSRI x GHRI, GHRI x SELFCONF, GSRI x GHRI x SELFCONF). All three main effects were significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions (GSRI x CLASS, GSRI x GHRI, GHRI x CLASS, GSRI x GHRI x CLASS). All three main effects were significant. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the *NIES Home risk index (NHRI)* were entered with the appropriate interactions (GSRI x NHRI, GSRI x GHRI, GHRI x NHRI, GSRI x GHRI x NHRI). Only the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were significant. For Model 4, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, the NIES individual item *self-confidence in mathematics* (SELFCONF), and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions (GSRI x CLASS, GSRI x GHRI, GSRI x SELFCONF, GHRI x CLASS, GHRI x SELFCONF, CLASS x SELFCONF, CLASS x GHRI x GSRI, GSRI x GHRI x SELFCONF, CLASS x SELFCONF x GHRI, CLASS x SELFCONF x GSRI, CLASS x GHRI x GSRI x

SELFCONF). All four main effects were significant. Therefore, the final model for South Dakota public high density school students included the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, the NIES individual item *self-confidence in mathematics* (SELFCONF), and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) and no interaction terms. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -15.43, z = -3.63, p < 0.001 (N=407; 32% of the data were missing). The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -9.07, z = -4.55, p < 0.001. The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -18.66, z = -4.09, p < 0.001. The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = 16.43, z = 3.04, p = 0.002. These risk indices/factors explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, R^2 = 0.38, F (4, 402) = 14.57, p < 0.001.

The final NAEP model from Table 4.24 included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* and accounted for 23% of the variation in achievement. Thus, adding the NIES predictors *self-confidence in mathematics (SELFCONF)* and *teachers incorporate AI/AN culture/tradition into their mathematics instruction (CLASS)* greatly increased the amount of variation account for in mathematics achievement to 38%.

South Dakota BIE schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -2.88$, $z = -0.84$, $p = 0.4$ (N=403; 9% of the data were missing). Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.008$, $F\ (1, 401) = 0.71$, $p = 0.4$.

The *NIES Home risk index (NHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = 6.2$, $z = 2$, $p = 0.047$ (N=431; 3% of the data were missing). Additionally, the *NIES Home risk index (NHRI)* explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.03$, $F\ (1, 429) = 3.93$, $p = 0.053$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -13.24$, $z = -2.48$, $p = 0.01$ (N=437; 17% of the data were missing). Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.06$, $F\ (1, 435) = 6.14$, $p = 0.02$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = 1.22, z = 0.15, p = 0.88 (N=372; 16% of the data were missing). Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.006, F (1, 370) = 0.02, p = 0.88.

The *NIES School risk index (NSCHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = 10.44, z = 2.2, p = 0.03 (N=350; 22% of the data were missing). Additionally, the *NIES School risk index (NSCHRI)* explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.06, F (1, 348) = 5.1, p = 0.03.

For Model 1, the *NAEP (General) Classroom risk index (GCRI)* and the *NIES Home risk index (NHRI)* were entered with the interaction between the two. Only the *NAEP (General) Classroom risk index (GCRI)* was significant. For Model 2, the *NAEP (General) Classroom risk index (GCRI)* and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the interaction between the two. Again, only the *NAEP (General) Classroom risk index (GCRI)* was significant. For Model 3, the *NAEP (General) Classroom risk index (GCRI)* and the *NIES School risk index (NSCHRI)* were entered with the interaction between the two. In Model 3, only the *NIES School risk index (NSCHRI)* was significant. However, when these two risk indices were entered into a model without an interaction, the *NAEP (General) Classroom risk index (GCRI)* was significant and the *NIES School risk index (NSCHRI)* was marginally significant. Therefore, the final model for South Dakota BIE school students included both of these risk indices. The *NAEP (General) Classroom risk index (GCRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -10.45$, $z = -2.32$, $p = 0.02$ (N=350; 22% of the data were missing). The *NIES School risk index (NSCHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = 8.84$, $z = 2$, $p = 0.045$. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $R^2 = 0.11$, $F\ (2, 348) = 4.3$, $p = 0.02$.

The final NAEP model from Table 4.24 included the *NAEP (General) Classroom risk index (GCRI)* and accounted for 7% of the variation in achievement. Thus, adding the *NIES School risk index (NSCHRI)* increased the amount of variation account for in mathematics achievement to 11%.

Appendix G: OLS Regression results for NAEP risk indices and student body composition variables using conditional mean substitution

Table G1: *Final Results of OLS regression models using NAEP 8th grade mathematics achievement regressed on NAEP risk indices and student body composition variables for each stratum using conditional mean substitution*

	Final model –Arizona public low density school students		
	z	*B*	*SE B*
NAEP (General) Social/ physical	-4.25	-31.61	7.4
NAEP (General) Knowledge/ attitudes	-2.33	-14.5	6.21
Notes. Adjusted R^2= 0.31 (p < 0.001)			
	Final model – Arizona public high density school students		
NAEP (General) Social / physical	-11.84	-22.82	1.93
NAEP (General) Home	-2.02	-4.31	2.13
Notes. Adjusted R^2= 0.27 (p < 0.001)			
	Final model - Arizona BIE school students		
NAEP (General) Social / physical	-7.94	-20.26	2.55
NAEP (General) Knowledge / attitudes	-4.64	-12.18	2.63
Notes. Adjusted R^2= 0.34 (p < 0.001)			
	Final model – South Dakota public low density school students		
NAEP (General) Social/ physical	-4.78	-24.92	5.21
NAEP (General) Knowledge/attitudes	-2.92	-10.76	3.69
Notes. Adjusted R^2= 0.37 (p < 0.001)			
	Final model – South Dakota public high density school students		
NAEP (General) Social / physical	-3.78	-14.92	3.95
NAEP (General) Knowledge / attitudes	-4.08	-12.21	2.99
NAEP (General) Home	-2.44	-4.77	1.95
Notes. Adjusted R^2= 0.25 (p < 0.001)			
	Final model – South Dakota BIE school students		
NAEP (General) Classroom	-3.44	-13.95	4.06
Notes. Adjusted R^2= 0.09 (p= 0.001)			
Notes. Values are based upon weighted estimates.			

Although interactions were tested whenever more than one significant predictor was included in a model, none of the interactions were significant; therefore, no interactions were included in any of the final models.

Arizona public low density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -15.95$, $z = -2.3$, $p = 0.02$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.09$, $F(1, 1617) = 5.27$, $p = 0.03$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -32.66$, $z = -4.2$, $p < 0.001$. The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.24$, $F(1, 1617) = 17.92$, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -11.74$, $z = -2.68$, $p = 0.007$. The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.10$, $F(1, 1617) = 7.16$, $p = 0.01$.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, β = -7.6, z = -1.1, p = 0.28. The *NAEP (General) Classroom risk index (GCRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, R^2 = 0.01, F (1, 1617) = 1.2, p = 0.28.

When each of the five student body composition variables was entered into a regression model alone, none significantly predicted *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools: *White/Asian* (β = 4.7, z = 0.22, p = 0.83); *Hispanic/Black* (β = -10.67, z = -0.52, p= 0.6); *books in home* (β = 36.92, z = 1.12, p = 0.26); *eligibility for NSLP* (β = 38.2, z = 1.35, p= 0.18); *parent education level* (β =38.20, z = 1.35, p = 0.18).

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools (R^2 = 0.24 and R^2 = 0.10, respectively). An interaction term for these two risk indices was also entered into this model. The *NAEP (General) Social/physical risk index (GSRI)* was significant, but the *NAEP (General) Home risk index (GHRI)* and the interaction were not. For Model 2, the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the *NAEP (General) Social/physical risk index (GSRI)* and the interaction were included. Both the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were significant but not the interaction term. Therefore, Model 2 was the final model (without the interaction term). The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade* *mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -31.61$, $z = -4.25$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -14.5$, $z = -2.34$, $p = 0.02$. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, adjusted $R^2 = 0.31$, F (2, 1617) = 12.2, $p < 0.001$.

Arizona public high density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -6.15$, $z = -2.28$, $p = 0.02$. However, the *NAEP (General) Knowledge/attitudes risk index (GKRI)* explained a marginally significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.02$, F (1, 2457) = 5.22, $p = 0.05$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -23.95$, $z = -11.08$, $p < 0.001$. The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.25$, F (1, 2457) = 122.66, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -6.8$, $z = -2.6$, $p = 0.009$. The *NAEP (General) Home risk index*

(GHRI) also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, R^2 = 0.05, F (1, 2457) = 6.7, p = 0.03.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, β = -4.8, z = -1.36, p = 0.73. The *NAEP (General) Classroom risk index (GCRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, R^2 = 0.01, F (1, 2457) = 1.85, p = 0.21.

When each of the five student body composition variables was entered into a regression model alone, the only one that significantly predicted *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools was *parent education level*: *eligibility for NSLP* (β = 26.37, z = 1.55, p= 0.12); *White/Asian* (β = 11.27, z = 0.84, p= 0.4); *Hispanic/Black* (β = 28.7, z = 1.11, p= 0.27); *books in home* (β = 20.1, z = 0.71, p = 0.48); *parent education level* (β = 20.87, z = 2.29, p = 0.02).

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools (R^2 = 0.25 and R^2 = 0.05, respectively). An interaction term for these two risk indices was also entered into this model. The two main effects were significant, but the interaction was not. For Model 2, the *NAEP (General) Knowledge/attitudes risk index (GKRI)* was added to the model with the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home* *risk index (GHRI)* and the appropriate interactions (GKRI x GSRI, GKRI x GHRI, GSRI x GHRI, and GKRI x GSRI x GHRI). Only the *NAEP (General) Social/physical risk index (GSRI)* and the *social x knowledge* interaction were significant (p=0.043). For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the *parent education level* variable were included with the appropriate interactions. Only the *NAEP (General) Social/physical risk index (GSRI)* and the *social x home x NSLP* interaction term (p=0.04) were significant. Therefore, the final model was Model 1 (the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* with no interactions. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, β = -22.82, z = -11.84, p < 0.001. The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, β = -4.31, z = -2.02, p = 0.04. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, adjusted R^2 = 0.27, F (2, 2456) = 65.91, p < 0.001.

Arizona BIE schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, β = -14.34, z = -5.09, p < 0.001. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, R^2 = 0.12, F (1, 663) = 25.94, p < 0.001.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -21.6$, $z = -8.5$, $p < 0.001$. The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.26$, $F(1, 663) = 72.97$, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -6.7$, $z = -3.5$, $p = 0.001$. The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.05$, $F(1, 663) = 12.04$, $p < 0.001$.

The *NAEP (General) Classroom risk index (GCRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -15.15$, $z = -4.03$, $p < 0.001$. The *NAEP (General) Classroom risk index (GCRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.08$, $F(1, 663) = 16.28$, $p < 0.001$.

Since there are no students of any other race other than AI/AN in BIE schools, the student body composition variables were not included.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools ($R^2 = 0.26$ and $R^2 = 0.12$, respectively). An interaction term for these two risk indices was also entered into this model. The two main effects were significant, but the interaction was not. For Model 2, the *NAEP (General) Classroom risk index (GCRI)* was added with the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the appropriate interactions (GKRI x GSRI, GKRI x GCRI, GSRI x GCRI, and GKRI x GSRI x GCRI). *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* remained significant, but the *NAEP (General) Classroom risk index (GCRI)* and the interactions were not significant. For Model 3, the *NAEP (General) Home risk index (GHRI)* was added with the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and the appropriate interactions (GSRI x GHRI, GSRI x GKRI, GHRI x GKRI, and GSRI x GHRI x GKRI). Only the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* remained significant. Therefore, the final model was Model 1 and included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* with no interactions. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -20.26$, $z = -7.94$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -12.18$, $z = -4.64$, $p < 0.001$. These two risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for

AI/AN students in Arizona BIE schools, adjusted $R^2 = 0.34$, $F(2, 662) = 68.83$, $p < 0.001$.

South Dakota public low density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -14.25$, $z = -3.6$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.13$, $F(1, 352) = 12.92$, $p < 0.001$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -27.28$, $z = -5.21$, $p < 0.001$. The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.30$, $F(1, 352) = 27.16$, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -9.81$, $z = -3.94$, $p < 0.001$. The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.13$, $F(1, 352) = 15.5$, $p < 0.001$.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -7.19$, $z = -1.53$, $p = 0.13$. The *NAEP (General) Classroom risk index (GCRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.02$, F (1, 352) = 2.34, $p = 0.13$.

When each of the five student body composition variables was entered into a regression model alone, the only one that significantly predicted *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools was *Hispanic/Black*: *Hispanic/Black* ($\beta = -93.74$, $z = -2.74$, $p = 0.006$); *eligibility for NSLP* ($\beta = 28.71$, $z = 1.53$, $p= 0.13$; *White/Asian* ($\beta = -11.31$, $z = -0.62$, $p= 0.54$); *books in home* ($\beta = 3.9$, $z = 0.14$, $p = 0.89$); *parent education level* ($\beta = 14.75$, $z = 0.65$, $p = 0.51$). Unfortunately, the standard error for the *Hispanic/Black* coefficient was extremely high, 32.44. Therefore, a decision was made that this student body composition variable was not stable enough to include in the final model.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions. Only the *NAEP (General) Social/physical risk index (GSRI)* and *social x knowledge* interaction ($p= 0.003$) were significant. For Model 2, only the *NAEP (General) Social/physical risk index (GSRI)* and the *social x knowledge* interaction were entered into the model. Only the risk index was significant. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions. However, there was not enough variation in how often teachers incorporate AI/AN culture/tradition into their mathematics instruction in South Dakota public low density schools. Only 2.9% of the students had teachers who incorporate AI/AN culture/tradition into their mathematics instruction at least once a year or more. Therefore, this risk factor was removed from the model. The final model for South Dakota public low density schools did not include any NIES predictors. The final model included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* only. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -24.92$, $z = -4.78$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -10.76$, $z = -2.92$, $p = 0.004$. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, adjusted $R^2 = 0.37$, F (2, 351) = 19.5, $p < .001$.

South Dakota public high density schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -15.01$, $z = -5.622$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.14$, F (1, 599) = 31.61, $p < 0.001$.

The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -16.64$, $z = -4.14$, $p < 0.001$. The *NAEP (General) Social/physical risk index (GSRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.10$, F (1, 599) = 17.1, $p < 0.001$.

The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -7.78$, $z = -3.9$, $p < 0.001$. The *NAEP (General) Home risk index (GHRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.07$, F (1, 599) = 15.38, $p < 0.001$.

The *NAEP (General) Classroom risk index (GCRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -7.8$, $z = -1.9$, $p = 0.06$. Additionally, the *NAEP (General) Classroom risk index (GCRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.02$, F (1, 599) = 3.6, $p = 0.06$.

When each of the five student body composition variables was entered into a regression model alone, three significantly predicted *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools: *eligibility for NSLP* ($\beta = 30.26$, $z = 2.68$, $p = 0.007$); *books in home* ($\beta = 36.32$, $z = 2.09$, $p = 0.04$);

parent education level (β = 25.81, z = 3.2, p = 0.001); *Hispanic/Black* (β = 40.79, z = 0.73, p = 0.46); *White/Asian* (β = 18.58, z = 1.61, p= 0.11).

For Model 1, the *NAEP (General) Knowledge/attitudes risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools (R^2 = 0.14 and R^2 = 0.07, respectively). An interaction term for these two risk indices was also entered into this model. Both risk indices were significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)* was added to the model with the *NAEP (General) Knowledge/attitudes risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* and the appropriate interactions. All three risk indices were significant. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and *eligibility for NSLP* were included with no interactions. Everything was significant. For Model 4, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and *parent education level* were included with no interactions. Everything was significant. For Model 5, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and *books in the home* were included with no interactions. Everything was significant, except *books in the home*. For Model 6, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, *parent education level*, and *eligibility for NSLP* were included with no interactions. Only the three risk indices were significant. Therefore, Model 2 will be the final model, without any interactions: the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GSRI)*, and the *NAEP (General) Home risk index (GHRI)*. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -14.92, z = -3.77, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -12.21, z = -4.08, $p < 0.001$. The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -4.77, z = -2.44, p = 0.02. These three risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, adjusted R^2 = 0.25, F (3, 597) = 23.36, $p < 0.001$.

South Dakota BIE schools. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = -9.07, z = -2.35, p = 0.02. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.07, F (1, 441) = 5.51, p = 0.02.

The *NAEP (General) Social/physical risk index (GSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South

Dakota BIE schools, β = -8.07, z = -1.5, p = 0.13. The *NAEP (General) Social/physical risk index (GSRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.03, F (1, 441) = 2.36, p = 0.13.

The *NAEP (General) Home risk index (GHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = -2.22, z = -1, p = 0.32. The *NAEP (General) Home risk index (GHRI)* also did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.01, F (1, 441) =1, p = 0.32.

The *NAEP (General) Classroom risk index (GCRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = -13.95, z = -3.44, p = 0.001. The *NAEP (General) Classroom risk index (GCRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.09, F (1, 441) = 11.82, p = 0.001.

Since there are no students of any other race other than AI/AN in BIE schools, the student body composition variables were not included.

For Model 1, the *NAEP (General) Classroom risk index (GCRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and were entered first because they accounted for the largest proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools (R^2 = 0.09 and R^2 = 0.07, respectively). An interaction term for these two risk indices was also entered into the model. Only the *NAEP (General) Classroom risk index (GCRI)* was significant. Therefore, the final model for South Dakota BIE schools only included the *NAEP (General) Classroom risk index (GCRI)*. As stated above, the *NAEP (General) Classroom risk index (GCRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, $\beta = -13.95$, $z = -3.44$, $p = 0.001$. The *NAEP (General) Classroom risk index (GCRI)* also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, adjusted $R^2 = 0.09$, $F\ (1, 441) = 11.82$, $p = 0.001$.

Appendix H: OLS Regression results for NAEP and NIES risk indices, NIES individual item, and NIES derived risk factor using conditional mean substitution

Table H1: *Final Results of OLS regression models using NAEP 8th grade mathematics achievement regressed on NAEP and NIES risk indices, NIES individual item, and NIES derived risk factor for each stratum using conditional mean substitution*

	Final model –Arizona public low density school students		
	z	*B*	*SE B*
NAEP Social/ physical	-4.25	-31.61	7.4
NAEP Knowledge/ attitudes	-2.34	-14.5	6.21
Notes. Adjusted R^2= 0.31 ($p < 0.001$)			
	Final model – Arizona public high density school students		
NAEP Social / physical	-10.19	-22.54	2.21
NIES individual item *self-confidence in mathematics*	-2.85	-12.5	4.38
Notes. Adjusted R^2= 0.28 ($p < 0.001$)			
	Final model - Arizona BIE school students		
NAEP Social / physical	-7.52	-18.88	2.51
NAEP Knowledge/ attitudes	-4.51	-11.71	2.6
NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS)	2.96	13.88	4.69
Notes. Adjusted R^2= 0.37 ($p < 0.001$)			
	Final model – South Dakota public low density school students		
NAEP Social/ physical	-4.78	-24.92	5.21
NAEP Knowledge/attitudes	-2.92	-10.76	3.69
Notes. Adjusted R^2= 0.37 ($p < 0.001$)			
	Final model – South Dakota public high density school students		
NAEP Social / physical	-3.77	-14.92	3.95
NAEP Knowledge / attitudes	-4.08	-12.21	2.99
NAEP Home	-2.44	-4.77	1.95
Notes. Adjusted R^2= 0.25 ($p < 0.001$)			
	Final model – South Dakota BIE school students		
NAEP Classroom	-3.59	-14.02	3.91
NIES School	2.24	8.13	3.63
Notes. Adjusted R^2= 0.13 (p= 0.001)			
Notes. Values are based upon weighted estimates.			

Although interactions were tested whenever more than one significant predictor was included in a model, none of the interactions were significant; therefore, no interactions were included in any of the final models.

Arizona public low density schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -4.5$, $z = -0.7$, $p = 0.48$. Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.009$, $F\ (1, 1617) = 0.5$, $p = 0.48$.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -4.31$, $z = -0.78$, $p = 0.43$. Additionally, the *NIES Home risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.007$, $F\ (1, 1617) = 0.6$, $p = 0.44$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $\beta = -31.1$, $z = -2.6$, $p = 0.009$. Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.14$, $F\ (1, 1617) = 6.75$, $p = 0.01$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, β = -37.95, z = -3.68, $p < 0.001$. Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.02$, $F(1, 1617) = 13.54$, $p < 0.001$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, β = -1.1, z = -0.12, $p = 0.9$. Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, $R^2 = 0.001$, $F(1, 1617) = 0.01$, $p = 0.9$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions. Only the *NAEP (General) Social/physical risk index (GSRI)* was significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions. However, there was not enough variation in how often teachers incorporate AI/AN culture/tradition into their mathematics instruction in Arizona public low density schools. Only 1.9% of the students had teachers who incorporate AI/AN culture/tradition into their mathematics instruction at least once a year or more. Therefore, this risk factor was removed from the model. Therefore, the final model for Arizona public low density schools did not include any NIES predictors. The final model included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)*. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, β = -31.61, z = -4.25, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, β = -14.5, z = -2.34, p = 0.02. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public low density schools, adjusted R^2 = 0.31, F (2, 1616) = 12.2, $p < 0.001$.

Arizona public high density schools. The *NIES Student risk index (NSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, β = -4.35, z = -2.14, p = 0.03. However, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, R^2 = 0.01, F (1, 2457) = 4.56, p = 0.07.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, β = 1.64, z = 0.56, p = 0.58. Additionally, the *NIES Home risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.001$, $F\ (1, 2457) = 0.31$, $p = 0.6$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -18.24$, $z = -4.1$, $p < 0.001$. Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.07$, $F\ (1, 2457) = 16.81$, $p = 0.003$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -4.56$, $z = -0.83$, $p = 0.4$. Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.004$, $F\ (1, 2457) = 0.69$, $p = 0.43$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = 2.78$, $z = 1.28$, $p = 0.2$. Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics* *achievement scores* for AI/AN students in Arizona public high density schools, $R^2 = 0.005$, $F(1, 2459) = 1.65$, $p = 0.24$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions. The *NAEP (General) Social/physical risk index (GSRI)* and the NIES individual item *self-confidence in mathematics* (SELFCONF) were significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the *NIES Student risk index (NSRI)* were entered with the appropriate interactions. The *NAEP (General) Social/physical risk index (GSRI)* and the *NIES student x social* interaction term (p=0.02) were significant. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the NIES individual item *self-confidence in mathematics* (SELFCONF), and the *NIES Student risk index (NSRI)* were entered with the appropriate interactions. Only the *NAEP (General) Social/physical risk index (GSRI)* and the NIES individual item *self-confidence in mathematics* (SELFCONF) were significant. Therefore, the final model for Arizona public high density school students included the *NAEP (General) Social/physical risk index (GSRI)* and the NIES individual item *self-confidence in mathematics* (SELFCONF). The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -22.54$, $z = -10.19$, $p < 0.001$. The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, $\beta = -12.5$, $z = -2.85$, $p = 0.004$. This risk index and risk factor explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona public high density schools, adjusted $R^2 = 0.28$, F (2, 2456) = 66.97, $p < 0.001$.

The final NAEP model from Table G.1 included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Home risk index (GHRI)* and accounted for 27% of the variation in achievement. Therefore, removing the *NAEP (General) Home risk index (GHRI)* and adding the NIES individual item *self-confidence in mathematics* (SELFCONF) slightly increased the amount of variation account for in mathematics achievement to 28%.

Arizona BIE schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -4.65$, $z = -1.66$, $p = 0.1$. Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.01$, F (1, 663) = 2.74, $p = 0.1$.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -1.6$, $z = -0.55$, $p = 0.59$. Additionally, the *NIES Home risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.002$, F (1, 663) = 0.3, $p = 0.59$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -16$, $z = -3.1$, $p = 0.002$. Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.06$, F (1, 663) = 9.6, $p = 0.003$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = 21.7$, $z = 4.2$, $p < 0.001$. Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.08$, F (1, 663) = 17.32, $p < 0.001$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -6.06$, $z = -1.21$, $p = 0.23$. Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.007$, F (1, 663) = 1.46, $p = 0.23$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions. All three of the main effects were significant. For Model 2, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions. All three of the main effects were significant. For Model 3, the *NAEP*

(General) Social/physical risk index (GSRI), the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS), and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions. Only the *NAEP (General) Social/physical risk index (GSRI)* and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were significant. However, when these four risk indices/factors were entered into a model without interactions, only the NIES individual item *self-confidence in mathematics* (SELFCONF) was not significant. Therefore, the final model for Arizona BIE school students included the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS). The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -18.88$, $z = -7.52$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = -11.71$, $z = -4.51$, $p < 0.001$. The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $\beta = 13.88$, $z = 2.96$, $p = 0.003$. These risk indices and risk factor explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in Arizona BIE schools, $R^2 = 0.37$, $F(3, 661) = 47.78$, $p < 0.001$.

The final NAEP model from Table G.1 included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* and accounted for 34% of the variation in achievement. Adding the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) to the model increased the variance accounted for by 3% to 37%.

South Dakota public low density schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = 1.9$, $z = 0.67$, $p = 0.5$. Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.004$, F (1, 352) = 0.44, $p = 0.5$.

The *NIES Home risk index (NHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = 0.36$, $z = 0.09$, $p = 0.93$. Additionally, the *NIES Home risk index (NHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 < 0.001$, F (1, 352) = 0.009, $p = 0.93$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -21.77$, $z = -4.1$, $p < 0.001$. Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for

AI/AN students in South Dakota public low density schools, $R^2 = 0.13$, F (1, 352) = 16.62, $p < 0.001$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, β = 24.41, $z = 2.81$, $p = 0.005$. Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $R^2 = 0.02$, F (1, 352) = 7.9, $p = 0.007$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = 2.14$, $z = 0.38$, $p = 0.7$. Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, R^2 = 0.003, F (1, 352) = 0.14, $p = 0.71$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions. Only the *NAEP (General) Social/physical risk index (GSRI)* and *social x knowledge* interaction (p= 0.003) were significant. For Model 2, only the *NAEP (General) Social/physical risk index (GSRI)* and the *social x knowledge* interaction were entered into the model. Only the risk index was significant. For Model 3, the *NAEP (General)*

Social/physical risk index (GSRI), the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions. However, there was not enough variation in how often teachers incorporate AI/AN culture/tradition into their mathematics instruction in South Dakota public low density schools. Only 2.9% of the students had teachers who incorporate AI/AN culture/tradition into their mathematics instruction at least once a year or more. Therefore, this risk factor was removed from the model. The final model for South Dakota public low density schools did not include any NIES predictors. The final model included the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* only. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -24.92$, $z = -4.78$, $p < 0.001$. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, $\beta = -10.76$, $z = -2.92$, $p = 0.004$. These two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public low density schools, adjusted $R^2 = 0.37$, $F\ (2, 351) = 19.5$, $p < .001$.

South Dakota public high density schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = 1.34$, $z = 0.33$, $p = 0.74$. Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.003$, F (1, 599) = 0.11, $p = 0.75$.

The *NIES Home risk index (NHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -8.38$, $z = -2.3$, $p = 0.02$. Additionally, the *NIES Home risk index (NHRI)* explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.04$, F (1, 599) = 5.27, $p = 0.03$.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -20.6$, $z = -4.03$, $p < 0.001$. Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.10$, F (1, 599) = 16.23, $p < 0.001$.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = 15.86$, $z = 2.62$, $p = 0.009$. Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.05$, F (1, 599) = 6.86, $p = 0.01$.

The *NIES School risk index (NSCHRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = 4.52$, $z = 1.3$, $p = 0.2$. Additionally, the *NIES School risk index (NSCHRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $R^2 = 0.01$, $F(1, 599) = 1.66$, $p = 0.2$.

For Model 1, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the appropriate interactions (GSRI x SELF CONF, GSRI x GKRI, GKRI x SELF CONF, GSRI x GHRI, GHRI x GKRI, GHRI x SELF CONF, GSRI x GKRI x SELF CONF, GSRI x GKRI x GHRI, GSRI x GHRI x SELF CONF, GHRI x GKRI x SELF CONF, GSRI x GHRI x GKRI x SELF CONF). The *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the *knowledge x home x self-confidence* interaction ($p = 0.02$) were significant. When these two risk indices and interaction were entered alone into Model 2, all three remained significant. For Model 3, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) were entered with the appropriate interactions (GSRI x CLASS, GSRI x GKRI, GKRI x CLASS, GSRI x GHRI, GHRI x GKRI, GHRI x CLASS, GSRI x GKRI x CLASS, GSRI x GKRI x GHRI, GSRI x GHRI x CLASS, GHRI x GKRI x CLASS, GSRI x GHRI x

GKRI x CLASS). The three risk indices were significant, but the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) was not. For Model 4, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and the *NIES Home risk index (NHRI)* were entered with the appropriate interactions (GSRI x NHRI, GSRI x GKRI, GKRI x NHRI, GSRI x GHRI, GHRI x GKRI, GHRI x NHRI, GSRI x GKRI x NHRI, GSRI x GKRI x GHRI, GSRI x GHRI x NHRI, GHRI x GKRI x NHRI, GSRI x GHRI x GKRI x NHRI). Only the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* were significant. For Model 5, the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, the *NAEP (General) Knowledge/attitudes risk index (GKRI)*, and *knowledge x home x self-confidence* interaction term were entered into the model and only the *NAEP (General) Social/physical risk index (GSRI)* and the *NAEP (General) Knowledge/attitudes risk index (GKRI)* remained significant. Therefore, the final model for South Dakota public high density school students did not include any NIES predictors. The final model included the *NAEP (General) Social/physical risk index (GSRI)*, the *NAEP (General) Home risk index (GHRI)*, and the *NAEP (General) Knowledge/attitudes risk index (GKRI)*. The *NAEP (General) Social/physical risk index (GSRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, $\beta = -14.92$, $z = -3.77$, $p < 0.001$. The *NAEP (General) Home risk index (GHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -4.77, z = -2.44, p = 0.02. The *NAEP (General) Knowledge/attitudes risk index (GKRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, β = -12.21, z = -4.08, $p <$ 0.001. These three risk indices also explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota public high density schools, adjusted R^2 = 0.25, F (3, 597) = 23.36, $p < 0.001$.

South Dakota BIE schools. The *NIES Student risk index (NSRI)* did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β= -4.01, z = -1.28, p = 0.2. Additionally, the *NIES Student risk index (NSRI)* did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.01, F (1, 441) = 1.65, p = 0.2.

The *NIES Home risk index (NHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = 6.5, z = 2.14, p = 0.03. Additionally, the *NIES Home risk index (NHRI)* explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.03, F (1, 441) = 4.6, p = 0.04.

The NIES individual item *self-confidence in mathematics* (SELFCONF) significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = -13.33, z = -2.46, p = 0.01. Additionally, the NIES individual item *self-confidence in mathematics* (SELFCONF) explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.06, F (1, 443) = 6.04, p = 0.02.

The NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not significantly predict the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = 2.14, z = 0.29, p = 0.78. Additionally, the NIES derived risk factor *teachers incorporate AI/AN culture/tradition into their mathematics instruction* (CLASS) did not explain a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.005, F (1, 441) = 0.08, p = 0.78.

The *NIES School risk index (NSCHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = 8.04, z = 2.21, p = 0.03. Additionally, the *NIES School risk index (NSCHRI)* explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, R^2 = 0.04, F (1, 441) = 4.87, p = 0.03.

For Model 1, the *NAEP (General) Classroom risk index (GCRI)* and the *NIES Home risk index (NHRI)* were entered with the interaction between the two. Only the *NAEP (General) Classroom risk index (GCRI)* was significant. For Model 2, the *NAEP (General) Classroom risk index (GCRI)* and the NIES individual item *self-confidence in mathematics* (SELFCONF) were entered with the interaction between the two. Again, only the *NAEP (General) Classroom risk index (GCRI)* was significant. For Model 3, the *NAEP (General) Classroom risk index (GCRI)* and the *NIES School risk index (NSCHRI)* were entered with the interaction between the two. Both main effects were significant. Therefore, Model 3 was the final model for South Dakota BIE school students and included the *NAEP (General) Classroom risk index (GCRI)* and the *NIES School risk index (NSCHRI)*. The NAEP (General) Classroom significantly predicted the *8th grade* *mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = -14.02, z = -3.6, p < 0.001. The *NIES School risk index (NSCHRI)* significantly predicted the *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, β = 8.13, z = 2.24, p = 0.025. Additionally, these two risk indices explained a significant proportion of variance in *8th grade mathematics achievement scores* for AI/AN students in South Dakota BIE schools, adjusted R^2 = 0.13, F (2, 439) = 7.76 p = 0.001.

The final NAEP model included only the *NAEP (General) Classroom risk index (GCRI)* and accounted for only 9% of the variation in achievement. Therefore, adding the *NIES School risk index (NSCHRI)* increased the amount of variation account for in mathematics achievement for AI/AN students in South Dakota BIE schools to 13%.