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Occupational Dissimilarity between the American Indian/Alaska Native and the White Workforce in the Contemporary United States

Carolyn A. Liebler, Jacob Wise, and Richard M. Todd

Occupational structure is a useful social indicator. Group differences in occupational attainment may signal inefficiencies that significantly reduce economic productivity, such as labor market discrimination or suboptimal investment in education. Occupational differences can also mediate other adverse social and economic disadvantages because occupations differ in average pay, sensitivity to business cycles, health risks, prestige, status, and authority.

We analyze the occupational structure of the non-Hispanic American Indian and/or Alaska Native (AI/AN) workforce in the United States to understand this social indicator for this important but understudied group. We compare AI/AN occupational structures to those of the non-Hispanic white workforce and other specific comparison groups.[1] Racial, ethnic, and sex differences in occupational patterns have been documented and analyzed for decades,[2] but few studies have focused on the

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occupational structure of the AI/AN workforce. No other studies that we know of have examined occupations of both single-race and multiple-race AI/AN workers.

A detailed analysis of AI/AN occupational structure is timely in light of economic and social changes that have affected the AI/AN workforce in recent decades. The economies of many reservations and homeland areas have grown rapidly (albeit from a low base) in recent decades.[3] This growth directly affects many AI/ANs—about one-fifth of AI/AN individuals (single-race and multiple-race combined) lived on a reservation or other homeland as of 2010,[4] and at least as many lived in nearby counties.[5] Since 1970, tribal colleges have expanded significantly,[6] and there has been a general increase in AI/AN educational attainment (as we show in figure 6, below). At the same time, in the broader economy, the occupational distribution of the general workforce has changed significantly in response to deindustrialization and rising service employment.

Occupation and race are both time-specific concepts that undergo periodic changes in measurement. This adds to the value of our updated analysis of links between occupation and race. Partly as a result of the shift in the general occupational distribution, the Standard Occupational Classification system used by federal agencies and developed in 1977 was updated as of 1980, 2000, and 2010.[7] Meanwhile, in 1997 the federal government broadened the 1977 definition of AI/AN to include Central and South American Indigenous people and began to require that multiple-race responses be allowed.[8] In the censuses of 2000 and 2010, individuals were instructed to "mark one or more" races. In the 2010 Census, there were about 2.3 million individuals who reported AI/AN as well as another race or races, and 2.9 million who identified as single-race AI/AN.[9]

In this paper, we address three research questions about AI/AN occupational stratification. First, is the occupational distribution of AI/AN workers different from that of whites, now and since 1980? Using decennial census data and the American Community Survey, we show that it is and that AI/AN workers share many occupational patterns long observed among other racial and ethnic minorities. We find that the pattern of occupational dissimilarity between AI/AN workers and white workers is stronger among men than among women (although still significant among women). We do not find that AI/AN occupational dissimilarity has declined substantially since 1980, though results about changes over time are relatively tenuous due to changes in measurement (mentioned above) and racial identification (discussed below).

Second, in which occupations are AI/AN workers underrepresented relative to white workers? In which are they overrepresented? We make comparisons between single-race white workers, single-race AI/AN workers, and multiple-race AI/AN workers, including sex-specific comparisons. Using Census 2000 and the 2008–2012 American Community Survey (ACS), we find that AI/AN workers of both sexes are generally overrepresented in low-skilled occupations and underrepresented in high–skilled occupations, relative to white workers. This distinction is less pronounced for multiple-race AI/AN workers than for single-race AI/AN workers.

Third, we ask: do standard demographic factors account for the underrepresentation of AI/AN workers in high-education occupations, relative to white workers?

Among the observable factors that may account for sex-specific AI/AN-white occupational differences (including age, location, and language proficiency), we find that gaps in educational attainment are the most important. Controlling for individual differences in these factors reduces the degree of AI/AN underrepresentation in high-education occupations, but fails to fully account for it. We regard the remaining occupational structure differences between AI/AN and white workers as a call for more research on the deeper social and economic issues that continue to restrain the well-being of AI/AN workers.

Complex Issues of Defining Who Is in the AI/AN Population

We use US Census Bureau data for this study because of its level of coverage of "the AI/AN population," but who is in the census-defined population and who is excluded? The Census Bureau uses the current federal definition of "American Indian or Alaska Native," which is "A person having origins in any of the original peoples of North and South America (including Central America), and who maintains tribal affiliation or community attachment."[10] Maintenance of tribal affiliation or community attachment is not checked in any way, however; responses to the census are (usually) given by individuals in the privacy of their homes. The elements that go into self-definition are distinct from the types of procedures and checks used by most tribes to determine tribal enrollment status eligibility. Therefore, someone in the census self-identified as AI/AN may or may not be enrolled in a tribe or even have tribal affiliation or community attachment.[11]

Censuses and surveys also have issues of undercounting, which can exclude AI/AN people from studies such as ours.[12] Undercounts are higher in rural areas because standard enumeration strategies rely on mailing addresses and door-to-door follow-ups.[13] Those AI/ANs who live in cities are not usually residentially segregated,[14] which may be part of why neighbors of non-responsive households are unlikely to report AI/AN individuals as AI/AN.[15]

Note that people who reported AI/AN (whether single-race or multiple-race) in one census or survey did not necessarily give the same race report in another census or survey.[16] Several studies show a net increase in the AI/AN population that can only be due to a change in how individuals reported their race.[17] There is also evidence that some who reported AI/AN in 1990 reported a non-AI/AN race in 2000,[18] a response change that also happens in other racial groups.[19] In acknowledgment of response change, we urge readers to interpret our samples as point-in-time populations of people who self-reported (or were reported by someone else in their home) as American Indian or Alaska Native to the Census Bureau.

Previous Studies

In their landmark 1967 study *The American Occupational Structure*, Peter Blau and Otis Dudley Duncan documented basic occupational differences between whites and nonwhites (94% of whom were "Negro") in the 1960s in the United States.[20] After ranking seventeen occupations primarily by the median income and education of incumbents in 1962, they found that the occupation status typical for non-whites was not only different from that of whites but also "far inferior to that of whites." Although lower educational attainment explained part of this difference, it remained large "even when the lower social origin, education, and first occupation of Negroes [had] been taken into account." Furthermore, "the difference between mean occupational status of whites and nonwhites increase[d] with higher educational levels."[21] The occupational differences both illustrated and exacerbated social inequalities between whites and non-whites.

Blau and Duncan's key results have been confirmed in multiple subsequent studies: minority workers have different occupational patterns than majority workers, with minority workers generally holding lower status or lower paid occupations.[22] The lower educational attainment of minorities explains much of the occupation gap, but not all of it.[23] Comparisons of people with similar human capital shows that racial and ethnic disparities within occupational subcategories rise, or at least do not steadily decline, at higher levels of education and skill.[24]

There have been several expansions on Blau and Duncan's findings. In the United States, Tomaskovic-Devey and colleagues[25] find that the degree of racial/ethnic occupational separation declined most rapidly in the 1970s "during the peak period of regulatory enforcement" and then "stalled or nearly stalled," though other researchers report evidence of further declines.[26] In Australia, the degree of racial/ethnic occupational dissimilarity is substantially lower in the female Indigenous workforce than in the male Indigenous workforce.[27]

Although the literature on US racial and ethnic differences in occupational structure is long and rich, few results are available for the AI/AN workforce. A notable exception is recent (2012) work by Olga Alonso-Villar, Coral Del Rio, and Carlos Gradin. These researchers included "Native Americans" among the six racial/ethnic groups in their study using the 2007 ACS data. They defined "Native Americans" as non-Hispanic individuals who reported one of the following as their single race: American Indian, Alaska Native, Native Hawaiian, or another Pacific Islander group. They classified all individuals who reported a Hispanic ethnicity as "Hispanic" (regardless of their race response) and included all non-Hispanic multiracial individuals in the "other" category. They found substantial occupational dissimilarity between "Native Americans" and the overall population (about to the same degree as for other minority groups), with "Native Americans ... concentrated in lower-paid occupations."[28] They also found mostly higher occupational segregation for Native American women than Native American men, though this result did not hold in their regression analyses of the differences in a segregation index across 260 regional labor markets in the United States.[29]

Our research is similar to that conducted by Alonso-Villar, Del Rio, and Gradin (ADG), but is different in at least five ways that allow us to build on their results. First, our analysis is more narrowly focused on the AI/AN[30] workforce, as opposed to "Native Americans"[31] and five other race/ethnic groups. Accordingly, we do not benchmark relative to the overall workforce, a technique ADG introduced to facilitate simultaneous comparisons of multiple racial/ethnic groups. Instead, we rely mainly on the familiar Index of Dissimilarity, with the white workforce as our comparison group. Second, we implement recently developed statistical tests to assess the significance of the differences in dissimilarity we report.[32] Third, because occupational patterns remain quite different by sex, when we present occupational dissimilarity results by sex, we compare only within sexes (e.g., AI/AN women versus white women) rather than comparing to the overall workforce of both sexes, as in ADG. Fourth, we examine not only the single-race AI/AN workforce but also present separate results for the multiple-race AI/AN workforce. ADG studies only single-race AI/ANs; they include multiple-race AI/ANs in an "other" category that includes a variety of groups. Because single-race AI/ANs are not representative of the entire AI/AN group,[33] the omission of multiple-race AI/ANs can introduce bias. Finally, when modeling factors associated with occupational differences, we use an education-based ranking of occupations as the dependent variable (rather than regional differences), so that our regressions directly shed light on factors related to the tendency for AI/AN workers to be concentrated in low-skill sectors.

Data

We focus our analyses on the American Community Survey five-year pooled sample from 2008–2012, which hereafter we will refer to as 2010, its middle year. For a few analyses, we draw on other public-use datasets collected by the Census Bureau: decennial census data from 1980, 1990, and 2000 (5% samples). We accessed all data through IPUMS-USA.[34] We used person weights (the PERWT variable) to create statistics that are nationally representative of persons in the United States. in that year.[35] Throughout the paper we include all workers ages sixteen and over.[36] We used the statistical software *R* for all analyses.[37]

Our ability to detect changes over time in occupational dissimilarity is limited by changes in categorizations over time mentioned above. Specifically, the race categorization system has changed substantially, allowing us to begin tracking the multiple-race responses separately from single-race responses in 2000. As noted above, the AI/AN category does not include an entirely consistent set of individuals across the decades even before this change allowing multiple-race reporting. In addition, the categorization of occupations was changed fundamentally between the 1990 Census and the 2000 Census, and was modified again by 2010.[38]

To measure "occupation group," we used a twenty-six-category constructed variable that attempts to map the earlier occupational categories into the contemporary categories.[39] Changes in definitions as well as the evolving nature of jobs make perfect mapping impossible, though cross-time differences in measurement are reduced by using only twenty-six categories. We present the occupation groups in descending order of "occupational education," as shown in table 3, below.

Our focus in this research is on two categories of (non-Hispanic) AI/AN workers: those who reported being single-race American Indian or Alaska Native, and those who reported being American Indian or Alaska Native in combination with one or more other races. People who report AI/AN and Hispanic are especially unlikely to give the same race response in another census but are likely to consistently report being Hispanic.[40] We show results for Hispanic single-race and multiple-race AI/ANs only in table 1 and table 8; in table 2, we combine Hispanic AI/ANs with other Hispanic people.

Results

Research question 1: Is the AI/AN occupational distribution different from that of whites?

In table 1 we show a race-specific disaggregation of the US labor force in 2000 and 2010, where each category (except where noted) includes only people who were single-race and non-Hispanic. From the results in table 1 we see that there are relatively few AI/AN workers; AI/AN single-race and multiple-race individuals together comprised 1.43 percent of the (age sixteen and older) labor force.[41] In most of our analyses, we compare single-race AI/AN and multiple-race AI/AN workers to the largest race group in the workforce—single-race, non-Hispanic whites—who made up about two-thirds of the workforce in 2010 (table 1).

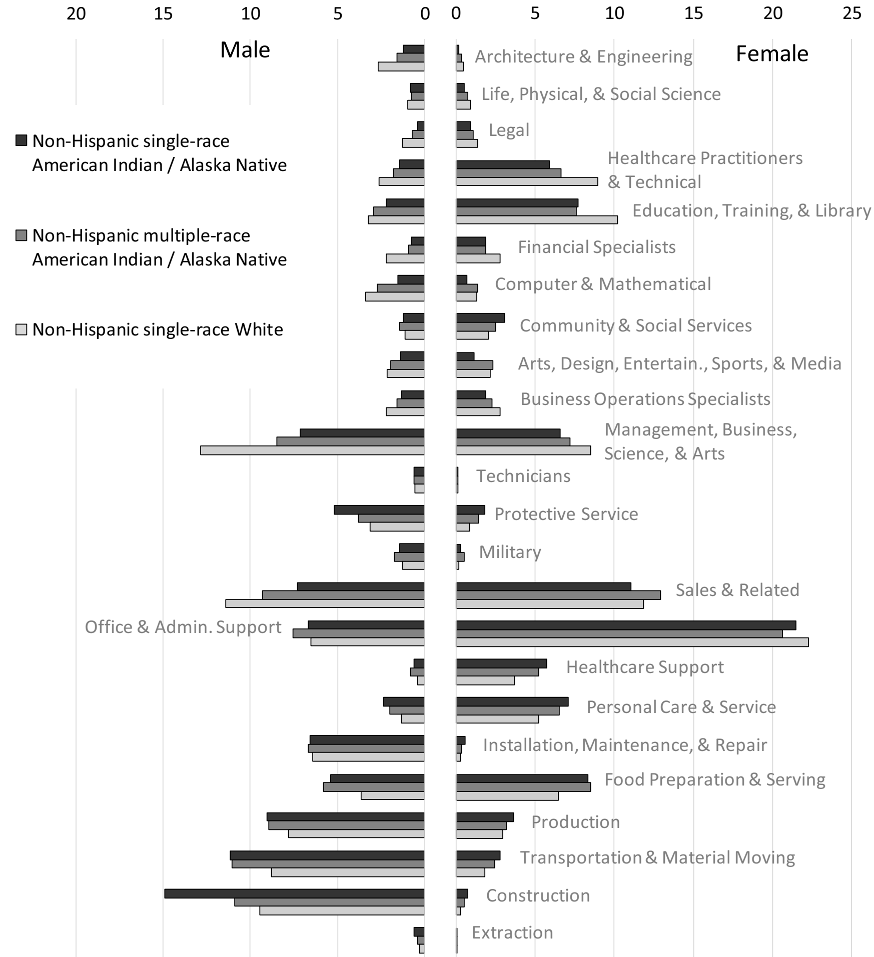
Table 1
Percentage breakdown of the labor force by race, 2000 and 2010

Race	2000	2010
American Indian/Alaska Native (AIAN) groups		
Non-Hispanic single-race AIAN	0.66	0.58
Non-Hispanic multiple-race AIAN	0.55	0.58
Hispanic single- or multiple-race AIAN	0.19	0.27
Other groups*		
White	72.71	65.99
Black or African American	10.57	11.45
Asian or Pacific Islander	3.75	5.14
Some Other Race or multiple races	1.09	1.04
Hispanic^	10.48	14.95
Total in the labor force	100	100

Note: Labor force participants must be sixteen years or older.
* All groups are single-race non-Hispanic unless specified.
^ "Hispanic" includes all people of Hispanic origin (besides AIAN), regardless of race(s)

Our first research question is: Is the occupational distribution of AI/AN workers different from that of single-race white workers, now and since 1980? We begin to address this question using figure 1, in which we plot the distribution of the workforce in 2010 across occupation groups, separating out the results by sex and by race group.

Some general patterns are evident. The distribution of women across occupations is very different from the distribution of men, and differences by sex are generally large relative to differences by race, which motivates our decision to present results



For example: 1.2% of single-race AIAN male workers were in an architecture or engineering field in 2010, as compared to 1.6% of multiple-race AIAN male workers and 2.7% of white male workers.

Figure 1: *Percent of workers in each race group who worked in each type of occupation in 2010, by race and sex*

separately for men and women. Multiple-race AI/AN workers have an occupational distribution that is generally between that of single-race AI/AN workers and white workers; the share for multiple-race AI/AN workers lies between the shares for single-race AI/AN and white workers in eighteen of the twenty-six career categories for men and seventeen of twenty-six for women. Also noteworthy is a tendency toward underrepresentation of all AI/AN workers of both sexes in traditional "white-collar" occupation categories, such as management, financial specialists, and legal professions, and their overrepresentation in traditional "blue/pink-collar" fields such as construction, healthcare support, and building/grounds cleaning and maintenance.

Table 2

Index of dissimilarity (and standard errors) for workers in 26 occupation categories, split by race/Hispanic origin and decade

	AIAN		AIAN+		Asian/PI		African American		Hispanic		Remainder	
1980	17.79	(0.37)			16.55	(0.21)	21.62	(0.08)	20.50	(0.10)	9.98	(2.00)
1990	18.16	(0.32)			15.97	(0.14)	20.35	(0.06)	22.43	(0.09)	14.91	(2.03)
2000	16.54	(0.27)	10.15	(0.47)	17.78	(0.12)	19.09	(0.08)	23.30	(0.07)	10.07	(0.31)
2010	16.47	(0.38)	9.92	(0.55)	18.13	(0.11)	19.00	(0.07)	24.14	(0.07)	10.33	(0.35)

Note: Comparisons are to non-Hispanic single-race whites.
AIAN = Non-Hispanic American Indian /Alaska Native (1980, 1990) and non-Hispanic single-race American Indian/Alaska Native (2000, 2010)
AIAN+ = Non-Hispanic multiple-race American Indian/Alaska Native
Hispanic = all workers of Hispanic origin (including AIAN), regardless of race(s)

Figure 1 presents a mixed answer to our first research question—whether the occupational distribution of AI/AN workers is different from that of white workers. On the one hand, the patterns suggest broad racial similarities in how workers in each sex sort across the groups. The occupations that account for large (small) shares of workers within one racial group tend to also account for large (small) shares within the other groups (e.g., construction is a large occupation for men of all three of the race groups). On the other hand, the racial differences in shares within many occupations appear large, at least proportionately (e.g., the share of single-race AI/AN men in construction is over 50% greater than the corresponding white share), raising the possibility that within-occupation share differences add up to a pattern of dissimilarity.

For a more rigorous test, we use data across all the occupations in figure 1 to calculate an overall index of occupational dissimilarity between each AI/AN group and the corresponding group of single-race white workers.[42] This index can be interpreted as a percentage that represents the proportion of workers who would need to change careers in order to make the AI/AN and white occupational distributions identical. In 2010, the index is about 16.5 percent for single-race AI/AN workers and about 10 percent for multiple-race AI/AN workers. Furthermore, both percentages are very significantly different from zero ($p < 0.001$ for both), according to the likelihood ratio test described by Allen and colleagues.[43]

In table 2, we show this index of dissimilarity for AI/AN and other race/ethnic groups over four decades, for males and females combined, compared to whites. All of the index values in the table are significantly different from zero. As in 2010, there is less dissimilarity to single-race white workers in 2000 for multiple-race AI/AN workers than for single-race AI/AN workers. For both 2000 and 2010, the degree of dissimilarity for single-race AI/AN workers is closer to that of African American or Asian/Pacific Islander workers than to the value for multiple-race AI/AN workers, and is about halfway between the values of multiple-race AI/AN workers and Hispanic workers.

The degree of AI/AN occupational dissimilarity from whites changed little between 2000 and 2010 and we see no clear AI/AN trend overall since 1980. This is in contrast to the small but steady decrease for African Americans and the steady increase for Hispanics. However, the change in the census race question and occupational classification undermines strong intertemporal comparisons.

Men and women tend to choose different occupations (as highlighted in fig. 1) and thus may have different within-sex occupational dissimilarities. Accordingly, we also calculate the dissimilarity index (AI/AN vs. white) separately for men and women in 2010. Similar to the findings reported by Taylor for the distribution of Indigenous Australian workers across broad occupational categories, we find a lower occupational dissimilarity index between single-race AI/AN women and white women (14.5%) than between single-race AI/AN men and white men (19.8%), and this difference is statistically significant. However, for women as well as men, the answer to our first question is the same—AI/AN workers have a different occupational distribution than white workers.

We are also interested in whether the overall difference between AI/AN and white workers' occupations varies by place. Dissimilarity indices for single-race AI/AN and multiple-race AI/AN workers appear to vary substantially by location within the United States. In figure 2, we show the occupational index of dissimilarity for single-race AI/AN people and multiple-race AI/AN people in thirteen regions.[44]

The single-race AI/AN occupational dissimilarity index is higher in areas with relatively many AI/AN workers than in areas with relatively few of them. For single-race AI/AN workers, the Southwest and North Carolina stand out as having the highest degree of occupational dissimilarity with whites in the same region. Alaska, California, and the Basin-Mountain, Northern Plains, and Great Lakes regions also show high levels of occupational dissimilarity between whites and single-race AI/AN workers. For multiple-race AI/AN workers, Alaska and the Northern Plains stand out as regions of higher occupational dissimilarity from local whites.

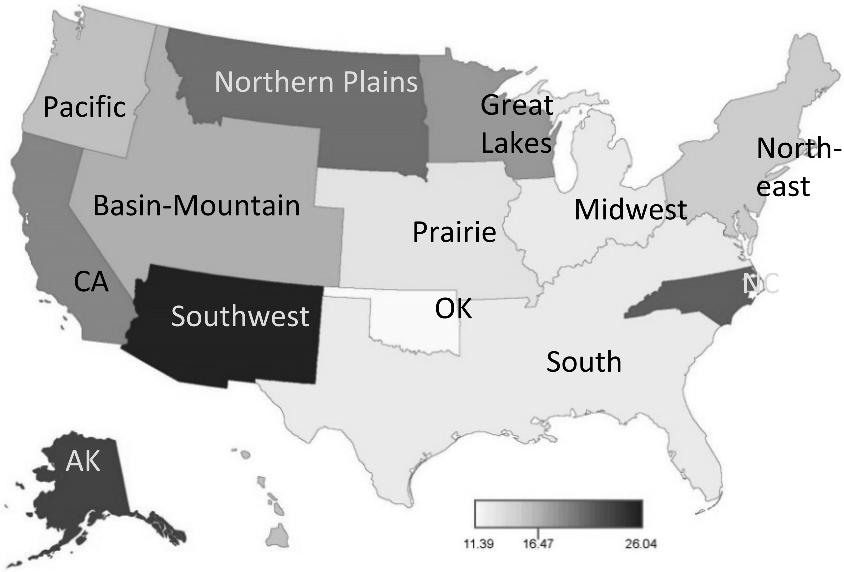
We found significant disparities between single-race AI/AN and multiple-race AI/AN workers in the Southwest and North Carolina (tests not shown). In the South, the dissimilarity from local whites is relatively low for both AI/AN groups, and in Alaska the dissimilarity is relatively high for both.[45]

In sum, our analyses show that the answer to our first question is clear: the AI/AN occupational distribution was significantly different from the white occupational distribution in 2010 and each of the three preceding decades. There are also notable variations in occupational distributions by single- or multiple-race, by sex, across time, and by geographic location.

Research question 2: In which occupations are AI/AN workers over- and underrepresented relative to white workers?

To begin answering this question, we return to figure 1. The occupational categories there are ordered by the fraction of incumbents who had completed at least one year of college, based on the data from 2010 (for all workers)—in other words, in order

Panel A: Occupational dissimilarity between AIAN workers and white workers

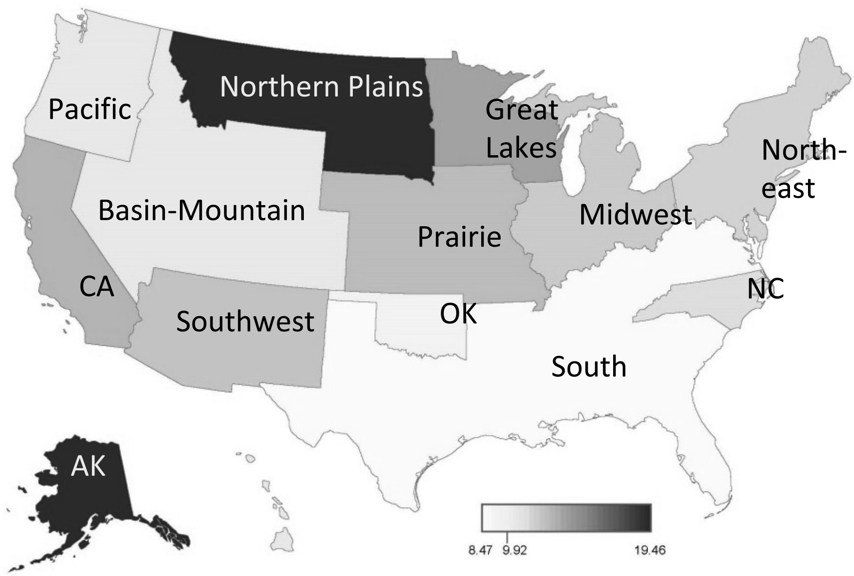


	D	SE
Alaska (AK)	23.52	2.71
Basin-Mountain	17.34	2.83
California (CA)	19.56	2.22
Great Lakes	18.66	3.22
Midwest	12.76	3.22
North Carolina (NC)	21.51	2.82
Northeast (NE)	15.14	2.95
Northern Plains	20.81	2.71
Oklahoma (OK)	11.39	2.15
Pacific	15.98	2.76
Prairie	13.33	4.13
South	12.33	1.80
Southwest	26.04	1.02
Entire US	16.47	0.38

Note: These regional aggregations are defined and justified in Eschbach (1992).
AIAN = Non-Hispanic single-race American Indian/Alaska Native
AIAN+ = Non-Hispanic multiple-race American Indian/Alaska Native
White = Non-Hispanic single-race white

Figure 2. *Occupational dissimilarity indices (D) by region.*

Panel B: Occupational Dissimilarity between AIAN+ workers and white workers



	D	SE
Alaska (AK)	19.46	5.63
Basin-Mtn. (BM)	10.56	3.94
California (CA)	13.15	2.07
Great Lakes (GL)	13.90	4.62
Midwest (M)	11.94	2.16
North Carolina (NC)	11.55	4.65
Northeast (NE)	11.67	1.95
Northern Plains (NP)	19.42	5.74
Oklahoma (OK)	9.68	2.72
Pacific (PA)	10.62	2.87
Prairie (PR)	12.90	3.41
South (S)	8.47	1.54
Southwest (SW)	12.55	4.94
Entire US	9.92	0.55

Note: These regional aggregations are defined and justified in Eschbach (1992).
AIAN = Non-Hispanic single-race American Indian/Alaska Native
AIAN+ = Non-Hispanic multiple-race American Indian/Alaska Native
White = Non-Hispanic single-race white

Figure 2. *cont.*

of "occupational education." For example, 92.9 percent of workers in architecture and engineering occupations had attended college. This was the highest rate of college attendance by labor force participants in any of the occupation groups, so it is at the

Table 3
Occupational education and occupational income by occupation group, all workers in 2010

Occupation Group	Occupational Education*		Occupational Income**	
Architecture & Engineering	high	93%	high	$ 78,296
Life, Physical & Social Science	high	92%	high	$ 60,251
Legal	high	92%	high	$ 92,550
Healthcare Practitioners & Technical	high	90%	high	$ 67,493
Education, Training & Library	high	90%		$ 39,477
Financial Specialists	high	90%	high	$ 66,827
Computer & Mathematical	high	90%	high	$ 72,010
Community & Social Services	high	88%		$ 38,332
Arts, Design, Entertainment, Sports & Media	high	81%		$ 37,760
Business Operations Specialists	high	80%	high	$ 58,952
Management, Business, Science & Arts	high	76%	high	$ 76,252
Technicians		63%		$ 49,100
Protective Service		61%		$ 44,791
Military		59%		$ 43,189
Sales & Related		55%		$ 36,657
Office & Administrative Support		54%		$ 29,813
Healthcare Support		48%		$ 22,451
Personal Care & Service		45%		$ 14,393
Installation, Maintenance & Repair		38%		$ 39,324
Food Preparation & Serving		33%		$ 14,383
Production		28%		$ 32,429
Transportation & Material Moving		28%		$ 29,042
Construction		26%		$ 29,982
Extraction		22%		$ 49,235
Building & Grounds Cleaning & Maintenance		22%		$ 17,563
Farming, Fishing & Forestry		17%		$ 18,955

* Percentage of workers in this occupation group who completed at least one year of college. Occupation groups with "high education" in later analyses are ones in which at least 75% of incumbents have completed at least one year of college.
** Average wage and salary income of workers in this occupation group. Most occupations with high occupational education also have high occupational income.

top of the chart. Those in the farming, fishing, and forestry occupation category, shown at the bottom, had the lowest percentage of incumbents who attended college (16.9%). See table 3 for details.

With this ordering, figure 1 suggests a racial occupation gap related to education, with AI/AN workers overrepresented towards the bottom (low-education occupations) and underrepresented at the top. To investigate the statistical significance of this apparent link between race and the educational ranking of occupations, we display in figure 3 an index based on the ratio of the single-race AI/AN employment proportion to the employment proportion of the white workforce (for men and women combined). Specifically, for single-race AI/AN workers our index for any single occupation takes the value (expressed as a percentage):

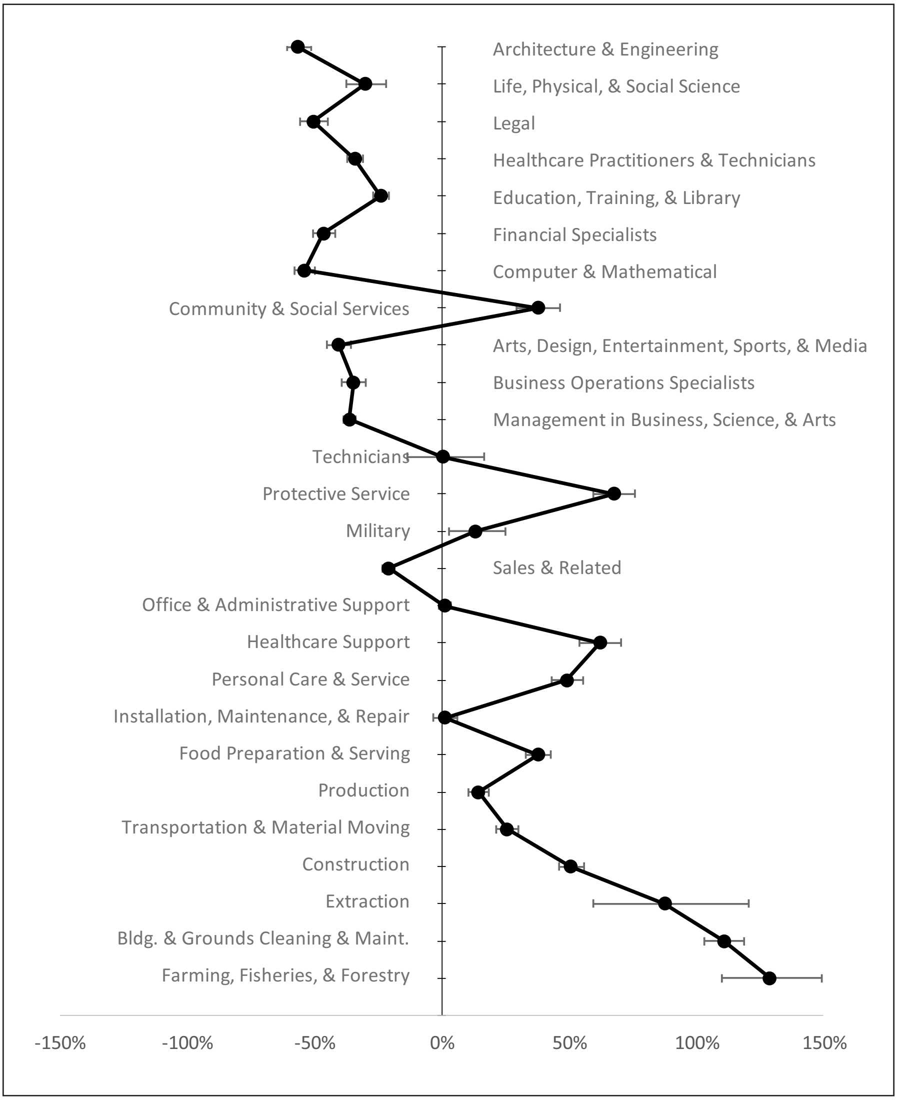
$$\frac{\text{(share of single-race AI/AN workers in the occupation)}}{\text{(share of white workers in the occupation)}} - 1$$

Figure 3 includes thin lines showing the 95 percent confidence interval for each career category and maintains the education-based ordering of the careers. In the careers in the bottom half of the occupational education distribution, where individuals typically have less education, there is generally overrepresentation of AI/AN workers. This tendency disappears for careers in the middle, whose incumbents tend to have moderate levels of education, and transitions to underrepresentation in fields where higher levels of education are common.

The ratios in figure 3 display a distinct "tilt" in the occupational representation of single-race AI/AN workers. In nine of the ten lowest categories on the education scale, there is statistically significant overrepresentation of single-race AI/AN workers. In fields such as building and grounds cleaning there are twice as many single-race AI/AN workers employed, relative to the proportion of whites in that sector (i.e., the index exceeds 100%). Single-race AI/AN individuals are underrepresented in ten of the top eleven most highly educated occupation categories (the exception being community and social services). For legal professions in particular, there were 50 percent fewer single-race AI/AN workers (our "parity" index is -50.45 percent) than there would have been if their occupational participation were proportional to participation by single-race whites.

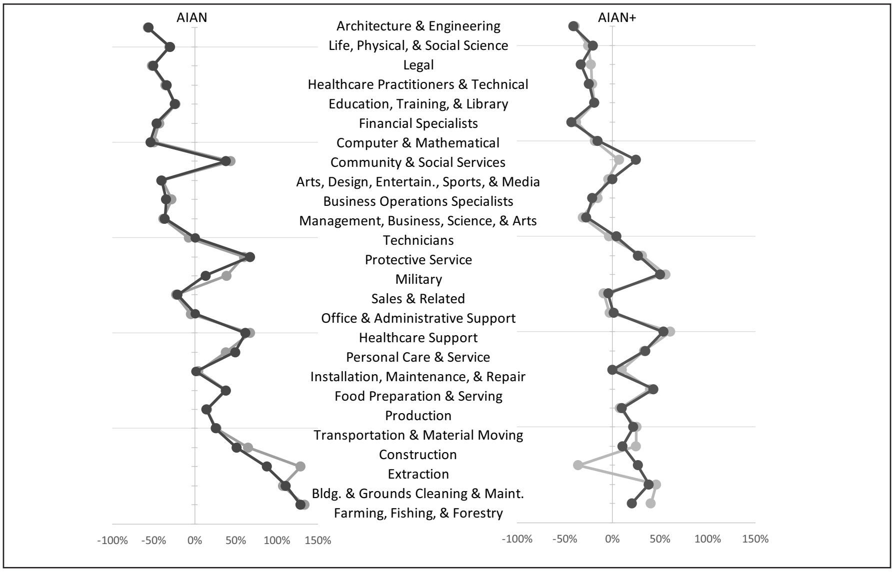
We expand these statistics in figure 4 to include multiple-race AI/AN workers and to include data for both 2000 and 2010. The results for multiple-race AI/AN workers (in the right-hand panel) show a pattern of statistically significant, education-based occupational disparity that is qualitatively similar to the pattern for single-race AI/AN workers in the left-hand panel (as seen by the visual "tilt" of both panels). However, the pattern is quantitatively milder for multiple-race AI/AN workers than single-race AI/AN workers. In both panels of figure 4, the observed changes in career categories between 2000 and 2010 are small (with the largest differences, like those in extraction occupations, mainly due to small cell counts).

Figure 5 is parallel to figure 3 but is separated by gender, comparing female single-race AI/AN workers to female white workers (and male multiple-race AI/AN workers to male white workers). Low cell-counts hinder interpretation for some categories. For



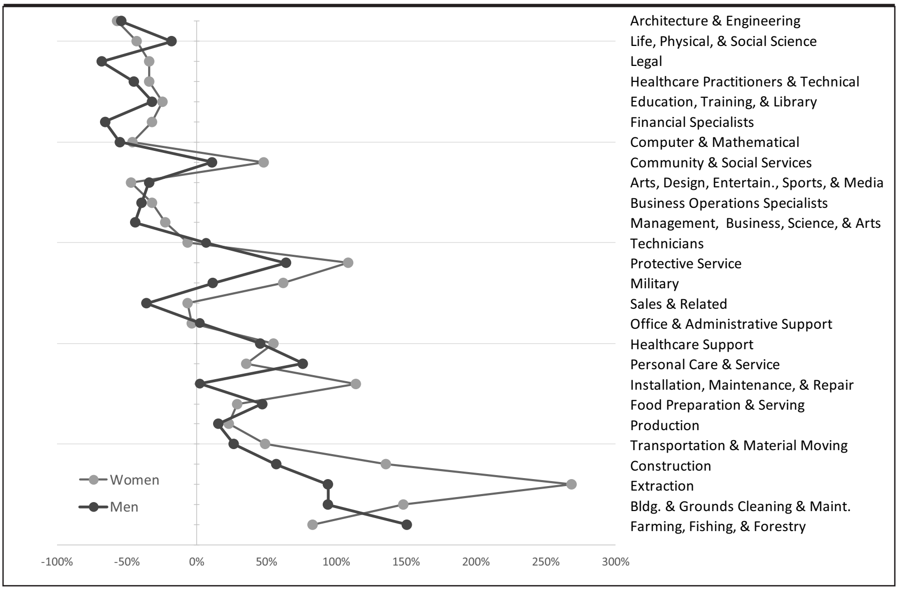
* Difference relative to proportional representation. Calculations and style based on that of John Fox in "Effect Displays in R for Generalised Linear Models," *Journal of Statistical Software* 8, no. 15 (2003): 1–27.

Figure 3. *Under-/overrepresentation of non-Hispanic single-race American Indian/Alaska Native workers in each occupation group, 2010*



Notes: Lighter lines represent 2000 and darker lines represent 2010 (2008-12 ACS).
AIAN = Non-Hispanic single-race American Indian/Alaska Native.
AIAN+ = Non-Hispanic multiple-race American Indian / Alaska Native.
All values are statistically significantly different from zero except: Community & Social Services (AIAN+ in 2000); Arts, Design, etc (AIAN+ in 2000 & 2010); Technicians (AIAN & AIAN+ in 2000 & 2010); Office & Admin. Support (AIAN & AIAN+ in 2010); and Installation, etc. (AIAN & AIAN+ in 2010).

Figure 4: *Under-/overrepresentation of non-Hispanic single-race and multiple-race AI/AN workers in 2000 and 2010, by occupation group*



Notes: All values are statistically significantly different from zero except: Community & Social Services (men); Technicians (women & men); Office & Administrative Support (men); and Installation, Maintenance & Repair (men).

Figure 5: *Under-/overrepresentation of non-Hispanic single-race American Indian/Alaska Native workers in 2010, by sex*

example, we estimated that female single-race AI/AN workers were 268 percent overrepresented in the extraction group; however, because few women work in extraction in either race, our 95 percent confidence interval for this estimate ranges from 76 to 654 percent. The basic pattern is the same as figure 3, but a few subtleties emerge. For example, AI/AN underrepresentation in the legal professions is larger for men than for women. Also, although AI/AN workers overall are overrepresented in protective services, this is even more true for AI/AN women relative to white women than it is for AI/AN men relative to white men.

Adjusting the Dissimilarity Index for Educational Attainment

To explore the relationship between education and occupation further, we calculated the AI/AN-white indices of dissimilarity within each of five education categories: less than high school, high school degree, some college or associates degree, bachelors degree, and more than a bachelors degree. We show these results for 2010 in table 4. For example, 12.23 percent of single-race AI/AN workers in the lowest education category would need to change fields in order for their occupational distribution to match that of white

Table 4
Occupational dissimilarity index in 2010 comparing non-Hispanic single-race and multiple-race AI/AN workers to non-Hispanic single-race white workers with similar education

	AIAN					
	Male workers		**All workers**		**Female workers**	
All Education Levels	19.77	(0.58)	16.47	(0.38)	14.47	(0.53)
No High School Degree	11.98	(2.25)	12.23	(1.69)	13.60	(2.44)
High School Graduate	13.64	(1.02)	12.95	(0.74)	12.90	(1.16)
Some College or Associate's Degree	12.91	(1.85)	10.97	(1.17)	11.43	(1.41)
Bachelor's Degree	18.18	(2.94)	13.70	(2.05)	8.97	(2.78)
More than a Bachelor's Degree	12.43	(4.29)	9.79	(2.81)	9.72	(3.41)
	AIAN+					
	Male workers		**All workers**		**Female workers**	
All Education Levels	12.61	(0.78)	9.92	(0.55)	10.32	(0.73)
No High School Degree	9.40	(3.00)	7.86	(2.44)	7.45	(3.33)
High School Graduate	7.29	(1.66)	7.69	(1.15)	10.24	(1.46)
Some College or Associate's Degree	7.60	(2.15)	6.88	(1.32)	9.01	(1.58)
Bachelor's Degree	13.03	(2.72)	10.87	(1.85)	8.27	(2.57)
More than a Bachelor's Degree	12.50	(3.34)	8.48	(2.27)	8.84	(2.80)

Note: Standard Errors are shown in parentheses.
AIAN = Non-Hispanic single-race American Indian/Alaska Native
AIAN+ = Non-Hispanic multiple-race American Indian/Alaska Native
White = Non-Hispanic single-race white

workers in the same education category. Again in table 4 we find that all occupational dissimilarity values represent a statistically significant dissimilarity between (single-race and multiple-race) AI/AN workers and white workers ($p < 0.001$).

From the calculated statistics shown in table 4 we notice that racial comparisons restricted to like-educated workforce members often produce a smaller index of occupational dissimilarity than for the general workforce (shown in the last row). This indicates that differences in educational attainment partly explain the high overall occupational dissimilarity between the AI/AN workforce and the white workforce. However, the index of dissimilarity is still quite high within education categories, especially among individuals with a bachelor's degree but no further education.[46] Also, in each educational category, the results for multiple-race AI/AN workers again lie between the results for white and single-race AI/AN workers.[47]

AI/AN Worker Underrepresentation: A Formal Test

Figures 3, 4, and 5 already show a statistically significant pattern of AI/AN overrepresentation in low-education occupations and underrepresentation in high-education occupations. To provide a clear test of this overall tendency, we construct a binomial regression model, predicting the probability that a given individual is employed in a highly educated field (the binomial "success") or not. In defining highly educated fields, we sort military workers (an industry) back into their original occupation groups. We code "high" education fields as "architecture and engineering" through "management in business, science, and arts" and "low" education fields as "technicians" through "farming, fishing, and forestry"; see table 3. This dichotomy roughly corresponds to careers with a higher/lower fraction of college-educated participants than in the general workforce. In table 3 we also show the occupational income (average income of incumbents) of each of the twenty-six broad occupation groups, which illustrates that ranking occupations by income instead of education would result in a generally similar definition of high-ranked versus low-ranked occupations.

For the binomial regression analyses, first we created a basic regression predicting whether a worker is in a high-education occupation based only on their race response; see table 5. The coefficient estimate for the intercept (– 0.502) implies that a white worker in the year 2010 had a $e^{-0.502}/(1 + e^{-0.502}) = 37.71$ percent chance of being employed in a highly educated field. The coefficient for multiple-race AI/AN workers

Table 5
Binomial regression predicting employment in a highly educated field,* for 2010

	Estimate	SE	z value	Pr(>|z|)	
(Intercept)	-0.502	0.001	-565.0	<2e-16	***
AIAN	-0.625	0.011	-58.29	<2e-16	***
AIAN+	-0.396	0.010	-38.87	<2e-16	***

AIAN = Non-Hispanic single-race American Indian/Alaska Native
AIAN+ = Non-Hispanic multiple-race American Indian/Alaska Native
* A field with high occupational education, as shown in Table 3

(− 0.396) implies an $e^{-0.396} - 1 = -32.70$ percent difference in the odds of a multiple-race AI/AN worker being in a highly educated field relative to the odds for whites. Thus, a multiple-race AI/AN worker in the labor force has 28.95 percent probability[48] of being employed in a highly educated field. The results also show that single-race AI/AN workers have an even lower probability, just 24.47 percent, of being employed in a highly educated field.

Notably, the Wald-tests (comparing each coefficient to zero, to which the p-values included refer) and the relative size of the standard errors in table 5 provide a clear answer to our second question. They show that there are statistically significant racial differences consistent with our earlier visualizations: Both single-race and multiple-race AI/AN workers are significantly more likely to be employed in low-education fields relative to whites, with the disparity significantly smaller for the multiple-race AI/AN group.

Research question 3: Do standard demographic factors account for occupational disparity?

Having established that the occupational distribution of AI/AN workers differs from that of single-race white workers and is tilted toward low-education fields, we now turn to our third research question: do standard demographic factors account for the underrepresentation of AI/AN workers in high-education occupations (relative to white workers)? To answer this question, we add additional explanatory variables, beyond race, to the regression framework introduced in the previous section.

Measures of educational achievement are, on the one hand, natural variables to add because of the obvious ties between education attainment and many occupations. On the other hand, using an individual's education to predict whether they are in a high-education occupation may seem circular and thus merits some discussion. To define the dependent variable in our regressions, we classify occupations as high- or low-education based on whether a high or low percentage of incumbents have at least some college education. Thus, on average over the full sample of whites and AI/AN workers, there must be a positive overall average relationship between an individual's education attainment and whether that person is in a high- or low-education field. However, it need not automatically be true that each additional level of education will further increase the odds that an individual will hold a high-education occupation. Nor must individual education be related to occupation on average in the AI/AN portion of our sample: this population is very small relative to the white population and thus has little influence on how occupations are ranked. Therefore, the race coefficients in a regression of occupational outcome (high- or low-education field) on individuals' race and education can meaningfully show that (holding the effects of individuals' educational attainment constant) AI/AN workers are less likely to hold high-education occupations than white workers.[49]

Other factors besides educational attainment may also be related to whether a person has a high-education occupation. For example, compared to jobs in rural areas, proportionately more jobs in metropolitan areas require high levels of education.

Because multiple-race AI/AN workers are more likely than single-race AI/AN workers to live in metropolitan areas,[50] controlling for location may account for some of the differences in outcomes between these two groups. In table 6 we show basic

TABLE 6
LABOR FORCE PARTICIPANTS IN 2010, BY RACE

Race	N	Mean	SD	Min	Max
Female					
AIAN	54,534	0.4988	0.500	0	1
AIAN+	45,154	0.4963	0.500	0	1
White	5,397,814	0.4687	0.499	0	1
Lives in a Metro Area					
AIAN	54,534	0.5045	0.500	0	1
AIAN+	45,154	0.7216	0.448	0	1
White	5,397,814	0.7353	0.441	0	1
Lives in a Homeland					
AIAN	54,534	0.6361	0.481	0	1
AIAN+	45,154	0.3007	0.459	0	1
White	5,397,814	0.1774	0.382	0	1
Age					
AIAN	54,534	39.5640	13.636	16	94
AIAN+	45,154	39.2964	14.131	16	94
White	5,397,814	42.3989	14.246	16	95
Not English-Proficient					
AIAN	54,534	0.0060	0.077	0	1
AIAN+	45,154	0.0041	0.064	0	1
White	5,397,814	0.0049	0.070	0	1

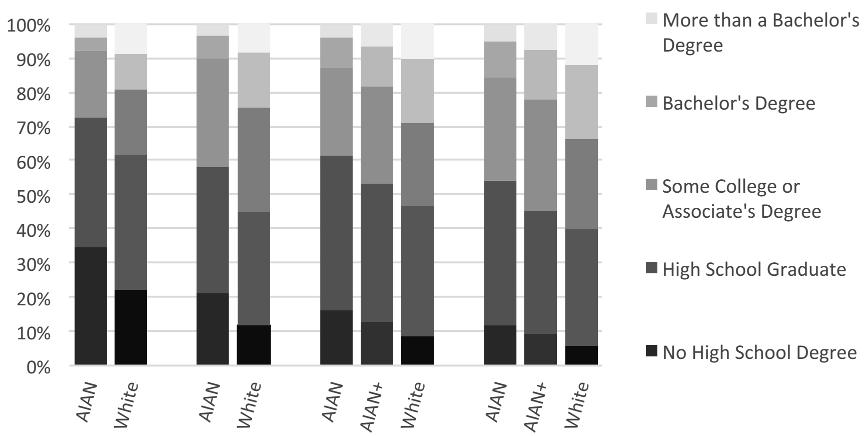
Race	N	No High School Degree	High School Graduate	Some College or Assoc.	Bachelor's Degree	More than Bachelor's Degree
Educational Attainment						
AIAN	54,534	12%	42%	30%	11%	5%
AIAN+	45,154	9%	36%	33%	14%	8%
White	5,397,814	6%	34%	26%	22%	12%

Note: We report weighted statistics (using PERWT in IPUMS-USA) and the unweighted N.
AIAN = Non-Hispanic single-race American Indian / Alaska Native
AIAN+ = Non-Hispanic multiple-race American Indian / Alaska Native
White = Non-Hispanic single-race white

summary statistics on the variables we use in our calculations, including sex, location in a metropolitan area, presence of an American Indian or Alaska Native homeland in the individual's Public Use Microdata Area,[51] age, English proficiency, and educational attainment.

We next show (in fig. 6) a plot of the educational attainment of single-race AI/AN, multiple-race AI/AN, and white workers in 1980, 1990, 2000, and 2010, because it is a primary independent variable of interest. Note that these data include multiple-race responses only in 2000 and 2010.

We see in figure 6 that, compared to whites in each year, a lower proportion of AI/AN labor force participants completed each educational level. In 2000 and 2010, both single-race and multiple-race AI/AN workers are more highly concentrated in the high school-graduate category than are whites, with fewer college degrees and greater numbers without high school education. We can also see a general increase in graduation rates for all groups over time. Although AI/ANs are keeping up with overall educational increases, they are not catching up to close the gaps. The AI/AN labor force in aggregate is more educated today than in 1980, but AI/AN workers are still less educated than white workers.



AIAN = Non-Hispanic American Indian/Alaska Native (1980, 1990) and non-Hispanic single-race American Indian/Alaska Native (2000, 2010)
AIAN+ = Non-Hispanic multiple-race American Indian/Alaska Native
White = Non-Hispanic white (1980–1990) and non-Hispanic single-race white (2000–2010)

Figure 6: *Educational attainment of labor force participants by race, 1980–2010*

Our predictors of a worker being employed in a highly educated field include those shown in table 6 as well as age squared. In table 7, we show our results of a single binomial regression model in terms of fitted coefficients, net of interaction effects, with separate columns for men and women as a way of displaying interaction effects.[52] As in

Table 7
Adjusted binomial regression predicting employment in a highly educated field,* for 2010

	Male workers			Female workers		
	Estimate	**SE**		**Estimate**	**SE**	
(Intercept)	-4.4954	0.0136	***	-4.3760	0.0147	***
AIAN	-0.2935	0.0186	***	-0.0752	0.0161	***
AIAN+	-0.1825	0.0175	***	-0.0944	0.0160	***
High school graduate	1.0581	0.0095	***	1.3205	0.0113	***
Bachelor's degree	2.8712	0.0097	***	3.0272	0.0115	***
More than a Bachelor's	4.1782	0.0105	***	4.3453	0.0125	***
In a metropolitan area	0.1517	0.0025	***	0.1517	0.0025	***
In a homeland	-0.0171	0.0028	***	-0.0171	0.0028	***
Age	0.0836	0.0005	***	0.0836	0.0005	***
Age2	-0.0008	0.0000	***	-0.0008	0.0000	***
Not proficient in English	-0.9483	0.0183	***	-0.9483	0.0183	***

AIAN = Non-Hispanic single-race American Indian/Alaska Native
AIAN+ = Non-Hispanic multiple-race American Indian/Alaska Native
* A field with high occupational education, as shown in Table 3

table 5, the sum of coefficients in table 7 are the log-odds of a particular worker being employed in a highly educated field.

Regardless of race, education is the best predictor of employment in a high-education field, and we show in figure 6 that AI/AN workers lag in education relative to white workers. This means that differences in education between AI/AN men and white men are responsible for a significant share of the differences between AI/AN and white men's occupational structure. The same patterns are evident for women. The education coefficients increase sharply with each level of educational attainment for both men and women, and these increases are statistically significant.[53] The effect of education on the odds of working in a highly educated field is stronger for women than for men. Age predicts a maximum probability of high-education employment just above age fifty, falling off quadratically. Living in a metropolitan area, not living near a homeland,[54] and being proficient in English are also statistically significant predictors of working in a "highly educated field," although their coefficients show much smaller effects than for education.

After adjusting for these other factors, including educational attainment, all the race coefficients are smaller than their values in the previous race-only regression (table 5). However, all the race group coefficients remain statistically different from zero, implying that the factors we considered did not fully account for the underrepresentation of AI/AN workers in high-education occupations. Compared to the disparities for AI/AN men, disparities between AI/AN women and white women are much smaller, or more nearly eliminated, after controlling for our additional factors, but even they remain statistically significant.[55]

One difference within the AI/AN workforce itself does disappear with our additional controls. Comparing female single-race AI/AN workers to female multiple-race AI/AN workers, the difference in their log-odds (and thus probability) of being in a high-education occupation is no longer statistically significant in our adjusted regression (with the additional explanatory variables). This is not true for male AI/AN workers.[56] For males, we can only say that the differences between single- and multiple-race AI/AN workers are substantially smaller in the adjusted model (table 7) than in the unadjusted model (table 5). This indicates that much, but not all, of the observed difference in employment in a high- or low-education field between single- and multiple-race male AI/AN workers is accounted for by the additional factors included in table 6.

Because the absolute counts for Hispanic American Indians or Alaska Natives are significantly smaller, we exclude them from the bulk of our analyses. However, in table 8 we show the fitted coefficients for two regression models that include the Hispanic AI/AN group (combining single-race Hispanic AI/AN workers and multiple-race Hispanic AI/AN workers). When compared to white workers, the disparity in education-ranked occupational outcomes is much larger for Hispanic AI/AN workers than for either of the non-Hispanic AI/AN groups in the "unadjusted" regression, which includes only race/ethnicity explanatory variables. All non-Hispanic AI/AN-white disparities are smaller than Hispanic AI/AN-white disparities after adjusting for the other covariates, but none are fully accounted for (each coefficient is statistically different from zero). When comparing non-Hispanic to Hispanic AI/AN workers, we find results that differ by sex. Among AI/AN women, the Hispanic AI/AN coefficient in the adjusted model is still statistically and materially larger than the coefficients for non-Hispanic AI/AN workers. Among men, however, the statistical difference between Hispanic AI/AN workers and single-race AI/AN workers disappears in the adjusted model.

Conclusion

Do standard demographic factors account for occupational disparity between AI/AN workers and white workers? Our analysis shows that the answer is "no, not completely," at least for the factors we consider. The raw data on occupational distribution by race reveals a clear disparity between AI/AN workers and white workers that has been present since at least 1980. AI/AN workers, both single-race and multiple-race, are underrepresented in high-education fields like management, financial services, and legal professions, relative to white workers. AI/AN workers are significantly overrepresented in low-education fields like construction, healthcare support, and food preparation. These differences are especially strong when the comparisons are limited to working men.

Table 8
Unadjusted and adjusted binomial regressions predicting employment in a highly educated field,* for the year 2010, including Hispanic AIANs

	Estimate	SE	z value	Pr(>|z|)	
(Intercept)	-0.502	0.0010	-564.9	<2e-16	***
AIAN	-0.625	0.0110	-58.28	<2e-16	***
AIAN+	-0.4.00	0.0100	-38.86	<2e-16	***
Hispanic AIAN	-0.948	0.0170	-55.23	<2e-16	***

	Male workers			Female workers		
	Estimate	SE		Estimate	SE	
(Intercept)	-4.4942	0.0135	***	-4.3748	0.0147	***
AIAN	-0.2856	0.0186	***	-0.0681	0.0161	***
AIAN+	-0.1832	0.0175	***	-0.0953	0.0160	***
Hispanic AIAN	-0.3189	0.0289	***	-0.2325	0.0274	***
High school graduate	1.0531	0.0095	***	1.3151	0.0113	***
Bachelor's degree	2.8666	0.0096	***	3.0225	0.0115	***
More than a Bachelor's	4.1753	0.0105	***	4.3416	0.0124	***
In a metropolitan area	0.1558	0.0025	***	0.1558	0.0025	***
In a homeland	-0.0186	0.0028	***	-0.0186	0.0028	***
Age	0.0839	0.0005	***	0.0839	0.0005	***
Age2	-0.0008	0.0000	***	-0.0008	0.0000	***
Not proficient in English	-0.9845	0.0179	***	-0.9845	0.0179	***
Mostly proficient in English	-0.5448	0.0113	***	-0.5448	0.0113	***

AIAN = Non-Hispanic single-race American Indian / Alaska Native
AIAN+ = Non-Hispanic multiple-race American Indian / Alaska Native
Hispanic AIAN = Hispanic single- or multiple-race American Indian / Alaska Native
* A field with high occupational education, as shown in Table 3

We find that AI/AN-white race-group differences in educational attainment are the single most important explanatory factor in predicting whether a worker is in an occupation group with relatively high education in 2010. Accounting for differences in educational outcomes and other factors markedly reduces all the race coefficients relative to their values in a race-only regression, but the race coefficients remain statistically different from zero. In other words, education and demographic characteristics cannot fully explain the AI/AN-white differences in working in a highly educated field. Measured factors explain much (for men) or all (for women) of the tendency for single-race AI/AN workers to be less likely than their multiple-race AI/AN counterparts to work in a high-education field.

Although American Indians and Alaska Natives have improved their educational attainment in the past decades, white educational levels have also been increasing, and the education gap remains. Over the same decades, the aggregate occupational dissimilarity of the AI/AN workforce seems to have changed little, though data issues prevent us from being certain. Our findings suggest that further efforts to close racial gaps in educational attainment can play an important role in narrowing the occupational dissimilarity between white workers and AI/AN workers, thus improving lives and eliminating potential inefficiencies in how jobs are allocated.

Other factors causing occupational dissimilarity can also be addressed. For example, Amy Peterson and Kristine West find that on average college completion boosts the earnings of AI/AN workers significantly (relative to those with only a high-school education) but less than for white workers and that this disparity persists after controlling for numerous observable demographic factors. They raise the possibility that labor market discrimination plays a role, but note that the effect could also be due to unobservable differences in factors such as the quality of K–12 schooling or the extent of labor market networking and mentorship.[57] Alessia Liebert tracks Minnesota college students who enter the Minnesota employment market and finds that college degrees completed after age thirty are less effective in closing racial gaps, a condition relatively common among AI/AN workers in her sample but one we could not control for here. She concludes that "Policies aimed at increasing educational attainment are most effective when they target individuals early in their working life, especially before age 30."[58] In addition, a disproportionate share of AI/AN workers live on or near American Indian reservations—locations where, as Akee, Mykerezi, and Todd show, employment opportunities are skewed toward a few large service sectors such as arts/entertainment/recreation (including casinos), food and accommodations, and public administration (i.e., government).[59] Not surprisingly, then, Liebert finds that AI/AN workers in her sample have a "very high concentration … in jobs in tribal government," which may skew their occupational choices and opportunities.[60]

Although further research is clearly needed to untangle the factors driving the many differences in occupational and earnings outcomes for AI/AN adults, some policy options may be tentatively offered now. We have already endorsed efforts to close racial gaps in education generally. Some tribes have taken specific steps to help young AI/AN workers learn about and gain mentoring in well-paid occupations. Tribes such as the Makah, Coeur d'Alene, Chickasaw, Saginaw Chippewa, and Tigua of Ysleta del Sur Pueblo expose their youth to information about prospective careers or work experience, often via internships or summer jobs in tribal government or tribally owned enterprises.[61] The Makah program specifically promotes science and technical education via a Fisheries Management internship that includes both hands-on and academic components.[62] The Indigenous Food and Agriculture Initiative at the University of Arkansas School of Law conducts a multiday Native Youth in Food and Agriculture leadership summit each summer.

A second policy option would be to reduce the total cost of training for these occupations. In light of their finding that returns to a college education are not as high for AI/AN workers as for white workers, Peterson and West discuss the value of compensating AI/AN graduates via loan forgiveness programs, perhaps including tribal programs that target certain occupations or jobs.[63] Some tribes are already linking scholarships with subsequent employment.[64] These and similar efforts seem well-targeted, but could be strengthened by research to assess their short- and long-term outcomes. A third policy path involves looking for opportunities to diversify reservation economies and thereby provide a broader array of career opportunities for AI/AN workers living on or near homelands. Akee, Mykerezi, and Todd showed that reservation employment opportunities are skewed to a narrow range of casino and government related sectors.[65]

Inequalities in occupational incumbency create and exacerbate inequalities in pay, health, authority, and opportunities for advancement. Using these and other paths, efforts to reduce occupational disparities between AI/AN workers and white workers are likely to have important positive effects on the AI/AN workers themselves, as well as their families and communities.

Notes

1. We group Hispanic individuals by their ethnicity, regardless of race, and omit them from all race categories except where explicitly noted. Unless otherwise indicated, we will hereafter use the term "white" to refer to non-Hispanic whites and will drop the "non-Hispanic" qualifier for other race groups as well. We use "race" to mean the person's answer to the census race question.

2. For example, Peter Blau and Otis Dudley Duncan, *The American Occupational Structure* (New York: The Free Press, 1967).

3. Randall K. Q. Akee and Jonathan B. Taylor, "Social and Economic Change on American Indian Reservations: A Databook of the US Censuses and the American Community Survey 1990–2010," May 15, 2014, http://taylorpolicy.com/us-databook/.

4. Tina Norris, Paula Vines, and Elizabeth Hoeffel, "The American Indian and Alaska Native Population: 2010," 2010 Census Briefs C2010BR-10, 2012, https://www.census.gov/prod/cen2010/briefs/c2010br-10.pdf

5. See Nancy Pindus, Thomas Kingsley, Jennifer Biess, Diane Levy, Jasmine Simington, and Christopher Hayes, "Housing Needs of American Indians and Alaska Natives in Tribal Areas: A Report from the Assessment of American Indian, Alaska Native, and Native Hawaiian Housing Needs" (US Department of Housing and Urban Development, Office of Policy Development and Research, 2017) https://www.huduser.gov/portal/publications/HNAIHousingNeeds.html. A study of employers and jobs on and near reservations found that "reservations have a similar sectoral distribution of employer establishments but have significantly fewer of them in nearly all sectors, especially when the area population is below 15,000 (as it is on the vast majority of reservations and for the majority of the reservation population)." See Randall Akee, Elton Mykerezi, and Richard Todd, "Reservation Employer Establishments: Data from the US Census Longitudinal Business Data Set," Center for Indian Country Development Working Paper No. 2017-02 (Federal Reserve Bank of Minneapolis, 2017, 3) https://www.minneapolisfed.org/indiancountry/research-and-articles/cicd-working-paper-series/reservation-employer-establishments-data-from-the-us-census-longitudinal-business-database].

6. American Indian Higher Education Consortium, "Tribal Colleges: An Introduction," 1999, http://www.aihec.org/who-we-serve/docs/TCU_intro.pdf.

7. Alissa Emmel and Theresa Cosca, "The 2010 SOC: A Classification System Gets an Update," *Occupational Outlook Quarterly* 54, no. 2 (2010): 13–19, https://www.bls.gov/careeroutlook/2010/summer/art02.pdf.

8. US Office of Management and Budget, "Revisions to the Standards for the Classification of Federal Data on Race and Ethnicity," *Federal Register Notice* (October 30, 1997), https://obamawhitehouse.archives.gov/omb/fedreg_1997standards.

9. Norris, et al., "American Indian and Alaska Native Population."

10. US Office of Management and Budget, "Revision to the Standards."

11. For characteristics of AI/AN census respondents who did not report a tribe in 1990, see Carolyn Liebler's "American Indian Ethnic Identity: Tribal Nonresponse in the 1990 Census," *Social Science Quarterly* 85, no. 2 (2004): 310–23, https://doi.org/10.1111/j.0038-4941.2004.08502006.x. For parallel work about Census 2000, see Carolyn A. Liebler and Meghan Zacher, "American Indians without Tribes in the Twenty-First Century," *Ethnic and Racial Studies* 36, no. 11 (2013): 1910–34, https://doi.org/10.1080/01419870.2012.692800.

12. See Carol Chiago Lujan, "American Indians and Alaska Natives Count: The US Census Bureau's Efforts to Enumerate the Native Population," *American Indian Quarterly* 38, no. 3 (2014): 319–41, https://doi.org10.5250/amerindiquar.38.3.0319; and Jennifer Williams, "The 2010 Decennial Census: Background and Issues" (Washington, DC: Congressional Research Service, 2011).

13. See Heather Fallica, Sarah Heimel, Geoff Jackson, and Bei Zhang, "2010 Census Update Enumerate Operations Assessment: Update Enumerate Production, Update Enumerate Quality Control, Remote Update Enumerate, and Remote Alaska," 2010 Census Program for Evaluations and Experiments (Washington, DC: US Census Bureau, 2012), https://www2.census.gov/programs-surveys/decennial/2010/program-management/5-review/cpex/2010-memo-245.pdf; Shelley Walker, Susanna Winder, Geoff Jackson, and Sarah Heimel, "2010 Census Non-response Follow-up Operations Assessment," 2010 Census Planning Memoranda Series No. 190 (Washington, DC: US Census Bureau, 2012), https://census.gov/content/dam/Census/library/publications/2012/dec/2010_cpex_190.pdf

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20. Blau and Duncan, *American Occupational Structure*, 207.

21. Ibid., 209, 210.

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24. Taylor, "Measuring the Occupational Segregation of Australia's Indigenous Workforce"; Alonso-Villar, et al., "The Extent of Occupational Segregation in the United States."

25. Donald Tomaskovic-Devey, Catherine Zimmer, Kevin Stainback, Corre Robinson, Tiffany Taylor, and Tricia McTague, "Documenting Desegregation: Segregation in American Workplaces by Race, Ethnicity, and Sex, 1966–2003," *American Sociological Review* 71, no. 4 (2006): 565–88, https://doi.org/10.1177%2F000312240607100403.

26. Queneau, "Changes in Occupational Segregation" and "Trends in Occupational Segregation"; Maia and Sakamoto, "Occupational Structure and Socioeconomic Inequality."

27. Taylor, "Measuring the Occupational Segregation of Australia's Indigenous Workforce."

28. Alonso-Villar, Del Rio, and Gradin, "The Extent of Occupational Segregation in the United States," 190.

29. Ibid., 194, 198–200. Note that the indices used by ADG compare each gender to the overall workforce of men plus women, thereby combining differences within gender-by-race (e.g., AI/AN women compared to all women), differences between genders within race (e.g., AI/AN women compared to AI/AN men), and differences across race and gender (e.g., AI/AN women compared to non-AI/AN men).

30. We focus on non-Hispanic single-race and multiple-race AI/ANs (separately) in comparison to non-Hispanic single-race whites. We provide information about Hispanic single-race and multiple-race AI/ANs in table 8.

31. ADG include single-race Hawaiians and Pacific Islanders in "Native American," but we combine these groups with single-race Asians in the category we label "Asian/PI."

32. Rebecca Allen, Simon Burgess, Russell Davidson, and Frank Windmeijer, "More Reliable Inference for the Dissimilarity Index of Segregation," *The Econometrics Journal* 18, no. 1 (2015): 40–66, https://doi.org/10.1111%2Fectj.12039.

33. Carolyn Liebler and Andrew Halpern-Manners, "A Practical Approach to Using Multiple-Race Response Data: A Bridging Method for Public Use Microdata," *Demography* 45, no. 1 (2008): 143–55, https://doi.org/10.1353/dem.2008.0004.

34. Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Mathew Sobek, Integrated Public Use Microdata Series: Version 6.0 (Minneapolis: University of Minnesota, 2015) (machine-readable database), https://usa.ipums.org/usa/.

35. Thomas Lumley, "Analysis of Complex Survey Samples," *Journal of Statistical Software* 9, no. 8 (2004): 1–19, https://doi.org/10.18637/jss.v009.i08.

36. Because young workers have often not completed their education, we have checked that the conclusions based on the regression results we report below are robust to limiting our sample to workers age 25 and up. Results for the older workers are consistent with those reported here.

37. Thomas Lumley, "Survey: Analysis of Complex Survey Samples," *R* (software), package version 3.30, 2014.

38. Norris, Vines, and Hoeffel, "American Indian and Alaska Native Population: 2010."

39. We use the 26 summary categories in OCC2010 in IPUMS-USA, but recoded workers whose industry was reported as "military" to the military occupation category. OCC2010 recodes all occupations into a 2010 framework. For a disaggregation of the 26 occupation categories, see https://usa.ipums.org/usa-action/variables/OCC2010#codes.

40. Liebler, Bhaskar, and Porter, "Joining, Leaving, and Staying."

41. AI/AN single-race and multiple-race individuals comprised 1.51% of the population ages 16 and older in 2010 (authors' calculations).

42. Specifically, we calculate the widely used Duncan index *D*, defined as follows: For *n* occupations, we compute the statistic $D = \frac{1}{2}\sum_{i=1}^{n} |A_i/A - B_i/B|$, where *A* (or *B*) is the total number of individuals of type A (or type B) and *Ai* (or *Bi*) is the number of Type A (or B) individuals in occupation *i*. This widely used index goes back at least to Blau and Duncan, but it has properties that can be undesirable; see Martin Watts, "Occupational Gender Segregation: Index Measurement and Econometric Modeling," *Demography* 35, no. 4 (1998): 489–96, https://doi.org/10.2307/3004016. As a check on the robustness of our results, we also compute the alternative indices *Ip* proposed by T. Karmel and M. MacLachlan) and *A* (proposed by Maria Charles and David Grusky in 1995). We note when our results are sensitive to the choice of index. See T. Karmel and M. MacLachlan, "Occupational Sex Segregation-Increasing or Decreasing," *Economic Record* 64, no. 3 (1988): 187–95, https://doi.org/10.1111/j.1475-4932.1988.tb02057.x; and Maria Charles and David Grusky, "Models for Describing the Underlying Structure of Sex Segregation," *American Journal of Sociology* 100, no. 4 (1995): 931–71, https://doi.org/10.1086/230605.

43. Allen, Burgess, Davidson, and Windmeijer, "More Reliable Inference." In addition to this formal test, we report standard errors. The IPUMS microdata includes a SUBSAMP variable, indexing all person level observations into 100 representative subsamples of the full data, each 1 percent of the entire data set. To estimate standard errors for the index of dissimilarity, we calculate the index value on each subsample (*Xi*) and the entire data set (*X*), then compute:

$$\mathrm{SE}(X) = \frac{1}{\sqrt{100}}\sqrt{\frac{1}{100}\sum_{i=1}^{100}(Xi - X)^2}$$

44. Karl Eschbach justified combining states into these regions for analyses of AI/ANs. See "Shifting Boundaries: Regional Variation in Patterns of Identification as American Indian," PhD diss., Harvard University, 1992.

45. In the Northern Plains, dissimilarity appears relatively high for multiple-race AI/AN workers relative to whites (higher than for single-race AI/AN workers in five other regions and nearly on par with single-race AI/AN dissimilarity nationally), and yet the dissimilarity for single-race AI/AN workers there appears noticeably higher than that for multiple-race AI/AN workers. However, this example also illustrates the limitations of our regional results: neither of these apparent results

for the Northern Plains is statistically significant, due to a small number of observations and thus large standard errors (shown in parentheses in fig. 2).

46. The Karmel and MacLachlan index for individual education groups is also usually equal to or lower than for the general workforce, but in this case the exception is for the least-educated group (those who did not complete high school). The Charles and Grusky index parallels the index of dissimilarity for single-race AI/AN workers, except for the most highly educated group, where it is not defined due to the index's reliance on logarithms and the null total of AI/AN incumbents in with college degrees in some occupation categories. For multiple-race AI/AN workers, the Charles and Grusky index for the two extreme education outcomes exceeds the overall index (and is not defined for the bachelor's degree category).

47. For the Karmel and MacLachlan index, we find much less dissimilarity for multiple-race AI/AN workers, compared to single-race AI/AN workers in the three lowest education groups, but slightly more dissimilarity in the two most highly educated groups. We cannot compare single-race and multiple-race AI/AN values of the Charles and Grusky index for the two college groups because there are some occupations in which there are no single- or multiple-race AI/AN incumbents who have college experience. We find that the Charles and Grusky index for the no-HS group has a higher value for multiple-race AI/AN workers than for single-race AI/AN workers.

48. $e^{(-0.502+(-0.396))}/(1+e^{(-0.502+(-0.396))}) = 0.2895 = 28.95\%$.

49. In addition, our discussion of table 3 noted that a ranking of occupations by income rather than education would be quite similar.

50. Pindus, et al., "Housing Needs."

51. See the IPUMS USA variable HOMELAND and Carolyn Liebler, "Homelands and Indigenous Identities in a Multiracial Era," *Social Science Research* 39, no. 4 (2010): 596–609, https://doi.org/10.1016/j.ssresearch.2010.02.003.

52. Although it has two columns, table 7 shows a single model that includes interaction terms that allow race and education effects to be different among men than they are among women. Other variables are not interacted with sex and thus have the same value in both columns.

53. We found limited evidence that educational effects differ by race. In a regression (not shown) with race and education interactions, the interactions of race and HS and race and BA were not significant, implying no AI/AN-white difference in the effect of education for those levels of attainment. We did find evidence that advanced degrees (more than a bachelor's degree) had a somewhat lower effect on occupational outcome for single-race AI/AN and multiple-race AI/AN workers than for white workers, but this race effect was small relative to the baseline effect of an advanced degree on workers generally.

54. Our data do not specifically identify whether an individual lives within homeland, only whether a homeland is present in their PUMA. However, the fact that the presence of a homeland in the PUMA is associated with lower odds of being in a high-education occupation is consistent with the possibility that the limited sectoral distribution of jobs on reservations shown in Akee, Mykerezi, and Todd in "Reservation Employer Establishments" also limits the occupational opportunities of AI/AN workers on or near reservations. Further research with more detailed datasets would be required to confirm this possibility.

55. The general pattern is that multiple-race AI/AN workers are intermediate between white workers and single-race AI/AN workers, but this is not true for female AI/AN workers in table 7. We have no explanation for this difference.

56. $p = 0.000013$ for men, and $p = 0.39$ for women.

57. Amy Peterson and Kristine West, "Returns to Higher Education for American Indian and Alaskan Native Students," Federal Reserve Bank of Minneapolis Center for Indian Country Development Working Paper No. 2018-03 (Federal Reserve Bank of Minneapolis, 2017, 3).

58. Alessia Liebert, "A Good Job after College," *Minnesota Employment Review* (July 2016), https://mn.gov/deed/newscenter/publications/review/july-2016/good-job-after-college.jsp.

59. Akee, et al., "Reservation Employer Establishments."

60. Liebert, "A Good Job after College."

61. See NCAI Partnership for Tribal Governance, "Workforce Development: Building the Human Capacity to Rebuild Tribal Nations: Ysleta del Sur Pueblo" (Washington, DC: National Congress of American Indians, 2015); and "Workforce Development: Building the Human Capacity to Rebuild Tribal Nations: Coeur d'Alene Tribe" (Washington, DC: National Congress of American Indians, 2016); as well as NCAI Policy Research Center, "Higher Education Workforce Development: Leveraging Tribal Investments to Advance Community Goals," Tribal Insights brief (Washington, DC: National Congress of American Indians, 2012).

62. NCAI Policy Research Center, "Higher Education Workforce Development."

63. Peterson and West, "Returns to Higher Education for American Indian and Alaskan Native Students."

64. NCAI Policy Research Center, "Higher Education Workforce Development."

65. Akee, et al., "Reservation Employer Establishments."