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Dissimilarity on the Career Path: The Occupational Structure of the American Indian/Alaska Native Workforce

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Abstract

We analyze the occupational structure of the non-Hispanic American Indian/Alaska Native (AIAN) workforce in the United States, relative to the non-Hispanic White workforce, using public-use census microdata. AIAN workers are generally overrepresented in low-skilled occupations and underrepresented in high-skilled occupations, relative to White workers. This pattern is stronger among men than among women and stronger among single-race AIANs than multiple-race AIANs. AIAN occupational dissimilarity does not appear to have declined substantially since 1980. Controlling for individual differences in factors such as education, age, location, and language proficiency accounts for a significant proportion of AIAN underrepresentation in high-education occupations.

Introduction

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 Alaska Native (AIAN) workforce in the United States, relative to the non-Hispanic White workforce and other specific comparison groups.[1] Although racial and ethnic differences in occupational patterns have been documented and analyzed for decades (e.g., Blau and Duncan 1967), few studies have focused on the occupational structure of the AIAN

[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.

workforce, and none that we know of have separately examined both AIAN workers who identify as single-race and AIAN workers who identify as multiple-race.

A detailed analysis of AIAN occupational structure is timely in light of economic and social changes that have affected the AIAN workforce in recent decades. The economies of many reservations and homeland areas have grown rapidly (albeit from a low base) in recent decades (Akee and Taylor 2014). This growth directly affects many AIANs - about one-fifth of AIAN individuals (single-race and multiple-race combined) lived on a reservation or other homeland as of 2010 (Norris, Vines, and Hoeffel 2012). Since 1970, tribal colleges have expanded significantly,[2] and there has been a general increase in AIAN educational attainment (Figure 5, below). In the broader economy, the occupational distribution of the general workforce has changed significantly in response to deindustrialization and rising service employment.

Measurement changes have also added to the value of an update on occupation and race. Partly as a result of the shift in the general occupational distribution, the Standard Occupational Classification system used by federal agencies was developed in 1977 and updated as of 1980, 2000, and 2010 (Emmel and Cosca 2010). In 1997, the federal government broadened the definition of AIAN to include Central and South American indigenous people and required that multiple-race responses be allowed (Office of Management and Budget 1997). 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 identified as AIAN in combination with another race or races, as well as 2.9 million who identified as AIAN alone (Norris, Vines, and Hoeffel 2012).[3]

In this paper, we address three research questions about non-Hispanic AIAN occupational stratification. First, is the occupational distribution of AIAN workers different from that of Whites, now and since 1980? We show that it is and that AIAN workers share many occupational patterns long-observed among other racial or ethnic minorities. We find that the pattern of occupational dissimilarity between AIAN workers and White workers is stronger among men than among women (although still significant among women). We do not find that AIAN occupational dissimilarity has declined substantially since 1980, though results about changes over time are relatively tenuous due to changes in measurement and racial identification (see Liebler, Bhaskar, and Porter 2016).

Second, in which occupations are AIAN workers underrepresented relative to White workers? In which are they overrepresented? We compare single-race Whites to single-race and multiple-race AIAN workers. Using Census 2000 and the 2008-2012 American Community Survey (ACS), we find that AIAN workers

[2] www.aihec.org/who-we-serve/docs/TCU_intro.pdf.

[3] Note that people who reported AIAN (alone or in combination with another race) in 2010 did not necessarily give the same race report in another census or survey (Liebler, Bhaskar, and Porter 2016). Ours is a study of the populations who reported AIAN at each measured point in time.

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 AIAN workers than for single-race AIAN workers.

Third, we ask: Do standard demographic factors account for the underrepresentation of AIAN workers in high-education occupations (relative to White workers)? Among the observable factors that may account for AIAN-White 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 AIAN underrepresentation but fails to fully account for it. We regard the remaining occupational structure differences we find between AIAN and White workers as a sign that deeper social and economic issues may continue to restrain the well-being of the AIAN population.

Previous Studies

In their landmark study *The American Occupational Structure*, Blau and Duncan (1967) documented basic occupational differences between Whites and non-Whites (94 percent of whom were "Negro" in their sample (p. 207)). After ranking 17 occupations primarily by the median income and education of incumbents in 1962 (p. 26), 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" (p. 209). 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" (p. 209). Furthermore, "the difference between mean occupational status of whites and nonwhites increase[d] with higher educational levels" (p. 210).

Blau and Duncan's key themes have been confirmed in multiple subsequent studies. Different occupational patterns for minority workers as opposed to majority workers have been found repeatedly, with minority workers generally holding lower status or lower paid occupations. Recent examples for the U.S. include Queneau (2005, 2009), Alonso-Villar, Del Rio, and Gradin (2012), and Gori Maia and Sakamoto (2012). Parallel results for Brazilian minorities (Gori Maia and Sakamoto 2012) and Australian aboriginals (Taylor 1994) have also been reported. Minorities' lower educational attainment explains much of the gap, but not all of it (for example, see Leicht 2008 and Gori Maia and Sakamoto 2012). Racial and ethnic disparities within occupational subcategories rise, or at least do not steadily decline, with increasing education or skill level (Taylor 1994 and Alonso-Villar, Del Rio, and Gradin 2012).

There have been several expansions on Blau and Duncan's findings. In the U.S., Tomaskovic-Devey et al. (2006) 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 (Queneau 2005 and 2009, and Gori Maia and Sakamoto 2012). Also, the degree of racial/ethnic occupational dissimilarity is substantially lower in the female indigenous workforce than in the male indigenous workforce in Australia (Taylor 1994).

Although the literature on U.S. racial and ethnic differences in occupational structure is long and rich, few results are available for the AIAN workforce. A notable exception is recent work by Alonso-Villar, Del Rio, and Gradin (2012). 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, Hawaiian, or other Pacific Islander. They classified all individuals who reported a Hispanic ethnicity as "Hispanic" (regardless of their race response) and included all non-Hispanic multi-racial 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" (p. 190). They also found mostly higher occupational segregation for Native American women than Native American men (p. 194),[4] though this result did not hold in their regression analyses of the differences in a segregation index across 260 regional labor markets in the U.S. (pp. 198-200).

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 AIAN workforce, as opposed to "Native Americans"[5] and five other race/ethnic groups. Accordingly, we do not benchmark relative to the overall workforce, a technique ADG introduce to facilitate simultaneous comparisons of multiple racial/ethnic groups. Instead we rely mainly on the familiar Index of Dissimilarity, with the (non-Hispanic) White workforce as our comparison group. Second, we implement recently developed statistical tests to assess the significance of the differences in dissimilarity we report.[6] Third, because occupational patterns remain quite different by sex, when we present occupational dissimilarity results by sex, we compare only within sexes (e.g., AIAN 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 AIAN workforce but also present separate results for the multiple-race AIAN workforce. ADG study only single-race AIANs; they include multiple-race AIANs in a broader "other" category. This may introduce bias because single-race AIANs are not representative of the entire AIAN group (Liebler and Halpern-Manners 2008). Finally, when modeling factors associated with occupational differences, we use an education-based ranking of occupations

[4]Note that these indices compare each gender to the overall workforce of men plus women, thereby combining differences within gender-by-race (e.g., AIAN women compared to all women), differences between genders within race (e.g., AIAN women compared to AIAN men), and differences across race and gender (e.g., AIAN women compared to non-AIAN men).

[5]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."

[6]Allen, Burgess, Davidson, and Windmeijer (2015).

as the dependent variable (rather than regional differences), so that our regressions directly shed light on factors related to the tendency for AIAN 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 also use additional public-use data sets collected by the Census Bureau: decennial census data from 1980, 1990, and 2000 (5 percent samples). We accessed all data through the IPUMS USA project at the University of Minnesota (Ruggles et al., 2015). We used weights (PERWT in IPUMS) to create statistics that are nationally representative of persons (Lumley 2004).

Our ability to detect changes over time in occupational dissimilarity is limited by changes in categorizations over time. The race categorization system has changed substantially. Since 2000, the Census has invited respondents to report multiple races and included multiple-race responses in the data, allowing us to begin tracking the multiple-race responses separately from single-race responses. There is evidence suggesting that the AIAN category does not include a consistent set of individuals across the decades.[7] In addition, the categorization of occupations was fundamentally changed between the 1990 Census and the 2000 Census and was modified again by 2010 (Norris, Vines, and Hoeffel 2012). Although we have used a constructed variable that attempts to map the earlier occupational categories into the contemporary categories,[8] changes in definitions as well as the evolving nature of jobs in the economy make perfect mapping impossible. This adds to the difficulties of interpreting change over time in dissimilarity indices, especially before and after 2000.

Throughout the paper we include all workers age 16 and over. 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.

Our focus in this research is on two categories of AIAN workers: those who reported being non-Hispanic American Indian or Alaska Native alone (AIANa), and those who reported being non-Hispanic American Indian or Alaska Native in combination with one or more other races (AIANc). We show results for Hispanic AIANs only in Table 1 and an appendix; elsewhere, we combine Hispanic AIANs with other Hispanics.

[7] Several studies show a net increase in the AIAN population that can only be due to change in race response (e.g., Passel 1997; Liebler and Ortyl 2014) and there is evidence that some who reported AIAN in 1990 reported a non-AIAN race in 2000 (Liebler and Ortyl 2014). Also between 2000 and 2010 there was considerable change over time in how individuals report their race(s); that is, a high proportion reported AIANa or AIANc race in 2000 or 2010 but not both (Liebler Bhaskar, and Porter 2016).

[8] We used the OCC2010 variable in the IPUMS USA microdata, which recodes all occupations into a 2010 framework.

In the appendix, we report regression results that include Hispanic AIAN individuals. People who report AIAN and Hispanic are especially unlikely to give the same race response in another census but are likely to consistently report being Hispanic (Liebler, Bhaskar, and Porter 2016).

Table 1: Percentage breakdown of the (age 16+) labor force by race, over time.

	Race	2000	2010
1	White	72.71	65.99
2	African American	10.57	11.45
3	Hispanic	10.48	14.95
4	Asian/PI	3.75	5.14
5	Remainder	1.09	1.04
6	AIANa	0.66	0.58
7	AIANc	0.55	0.58
8	Hispanic AIAN	0.19	0.27
	Total	100.00	100.00

Results

Is the AIAN Occupational Distribution Different from that of Whites?

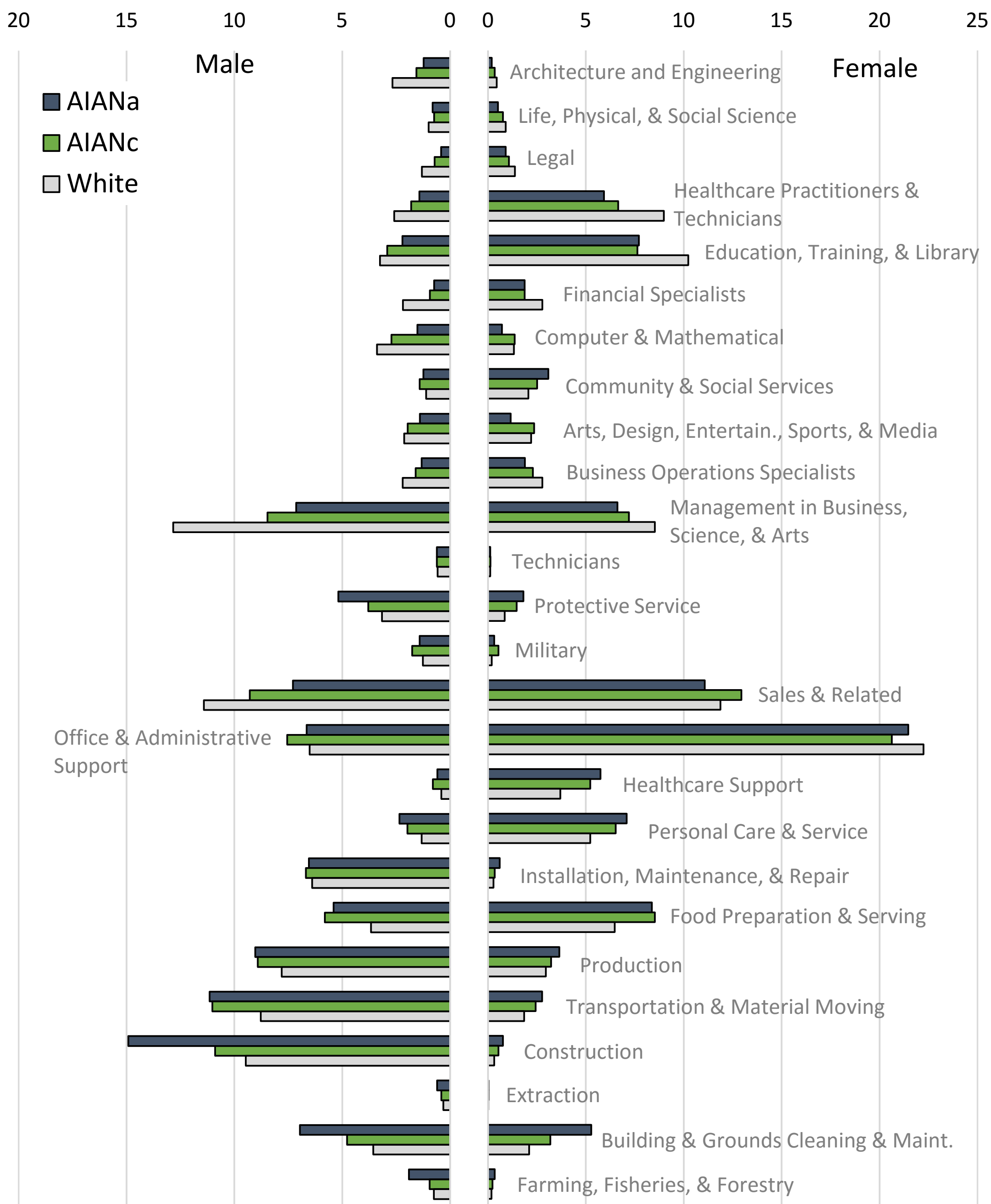
In Table 1 we show a breakdown of the U.S. labor force in 2000 and 2010 by race, where each category (except where explicitly listed) is single-race and non-Hispanic. From the results in Table 1 we see that there are relatively few AIAN workers—AIAN single-race and multiple-race individuals together comprised 1.43 percent of the (age 16+) *labor force* but 1.63 percent of the population in 2010 (authors' calculations). In most of our analyses, we compare AIANa and AIANc individuals to the largest race group in the workforce: single-race, non-Hispanic Whites.

Our first research question is: Is the occupational distribution of AIAN 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 26 occupation groups, separating out the results by sex and for non-Hispanic AIAN alone, AIAN in combination, and White.[9]

Some general patterns are evident. Females and males are very differently distributed across occupations, and differences by sex are generally large relative to differences by race. Multiple-race AIANs have an occupational distribution that is generally between that of single-race AIANs and Whites; the share for AIANc lies between the shares for AIANa and White in 18 of the 26 career categories for men and 17 of 26 for women. Also noteworthy is a tendency toward underrepresentation of AIANa and AIANc workers of

[9] We categorized individuals whose industry (not occupation) was reported as "military" to the military category, before assigning individuals to occupation groups. We then assigned the remaining individuals to their occupation group, if any, as reported by the Census Bureau.

Figure 1: Percent of workers of that race group who worked in each type of occupation in 2010, for non-Hispanic single-race AIANs (AIANa), multiple-race AIANs (AIANc), and Whites, separated by sex.



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. With respect to our first research question—whether the occupational distribution of AIAN workers is different from White workers—Figure 1 presents a mixed picture of gross similarity overall (for each sex) but also many differences occupation-by-occupation.

Further analysis shows that the answer to our first question is clear: the AIAN occupational distribution was significantly different from the White occupational distribution in 2010 and each of the three preceding decades. To arrive at this conclusion, we use data across all the occupations in Figure 1 to calculate an overall index of occupational dissimilarity between each AIAN group and the corresponding group of single-race White workers.[10] 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 AIAN and White occupational distributions identical. In 2010, the index is about 16.5 percent for AIANa workers and about 10 percent for AIANc 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 (Allen et al. 2015).

Table 2 shows this index of dissimilarity for AIAN and other racial/ethnic groups over four decades, for males and females combined, compared to non-Hispanic Whites. All of the index values in the table are significantly different from zero. As in 2010, dissimilarity to single-race Whites in 2000 is smaller for AIANc workers than for AIANa workers. For both 2000 and 2010, the degree of dissimilarity for AIANa workers is closer to that of African American or Asian/Pacific Islander workers than to the value for AIANc workers, and is about halfway between the values of AIANc workers and Hispanic workers.

Table 2: Index of dissimilarity (and standard errors) for 26 occupation categories, split by race/Hispanic origin and decade. Comparisons are to single-race, non-Hispanic Whites, for whom the index of dissimilarity (from themselves) is automatically zero.

	AIANa*	AIANc*	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)

*For 1980 and 1990 we report the AIAN data under the AIANa column (the Census did not allow multiple-race responses until 2000).
**All Hispanics are grouped together.

[10] Specifically, we calculate the widely used Duncan index D, defined as follows: For n occupations, we compute the statistic $D = (1/2)\sum_{i=1}^{n} |A_i/A - B_i/B|$, where A (or B) is the total number of individuals of type A (or type B) and A_i (or B_i) is the number of Type A (or B) individuals in occupation i. This widely used index goes back at least to Blau and Duncan (1967), but it has properties that can be undesirable (Watts 1998). As a check on the robustness of our results, we also compute the alternative indices I_p (proposed by Karmel and MacLachlan 1988) and A (proposed by Charles and Grusky 1995). We note when our results are sensitive to the choice of index.

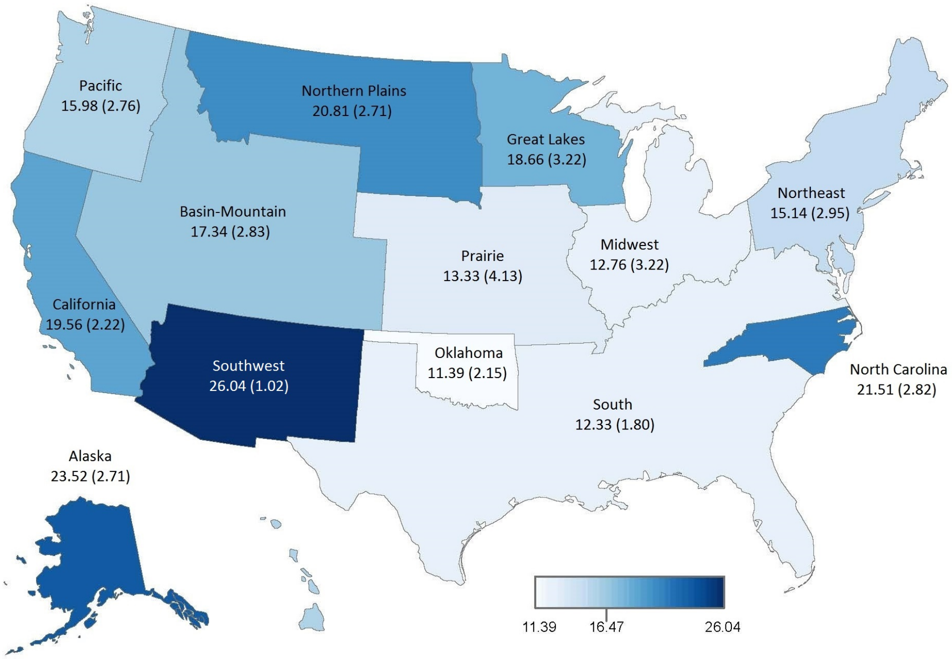
For 1980 and 1990 in Table 2, we show the AIAN data under the AIANa column, even though the Census did not allow multiple-race responses in those years. As discussed above, this makes intertemporal comparisons difficult. Nonetheless, we see that the degree of AIAN occupational dissimilarity from Whites changed little between 2000 and 2010 and see no clear AIAN trend overall since 1980. This is in contrast to the small but steady decrease for African Americans and the steady increase for Hispanics.

Men and women tend to choose different occupations (as highlighted in Figure 1) and thus may have different within-sex occupational dissimilarities. Accordingly, we also calculate the AIANa-White dissimilarity index separately for men and women in 2010. Similar to the findings reported by Taylor (1994) for the distribution of indigenous Australian workers across broad occupational categories, we find a lower occupational dissimilarity index between AIANa women and White women (14.5 percent) than between AIANa men and White men (19.8 percent), and this difference is statistically significant. However, for women as well as men, the answer to our first question is the same—AIAN workers have a different occupational distribution than single-race White workers.

We are also interested in whether the overall difference between AIAN and White workers' occupations varies by place. In Figure 2 we show the occupational index of dissimilarity for AIANa people in 13 regions (defined and discussed by Eschbach 1992). Dissimilarity indices for AIANa and AIANc workers appear to vary substantially by region within the U.S., and the AIANa occupational dissimilarity index is higher in areas with relatively many AIAN workers than in areas with relatively few of them. For AIANa 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 AIANa-White dissimilarity. For multiple-race AIAN workers, Alaska and the Northern Plains stand out as regions of higher occupational dissimilarity from local Whites.

There were very disparate results for AIANa versus AIANc workers in the Southwest and North Carolina (and we find these AIANa-AIANc gaps to be statistically significant, in tests not shown). In the South the dissimilarity from local Whites is relatively low for both AIAN groups, and in Alaska the dissimilarity is relatively high for both. In the Northern Plains, dissimilarity appears relatively high for AIANc workers relative to Whites (higher than for AIANa workers in five other regions and nearly on par with AIANa dissimilarity nationally), and yet the dissimilarity for AIANa workers there appears noticeably higher than that for AIANc 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 Figure 2).

Figure 2: Occupational dissimilarity indices by region, in the form: Index (SE)
(Blue = AIANa, Green = AIANc, with nationwide statistics indicated in the scale)



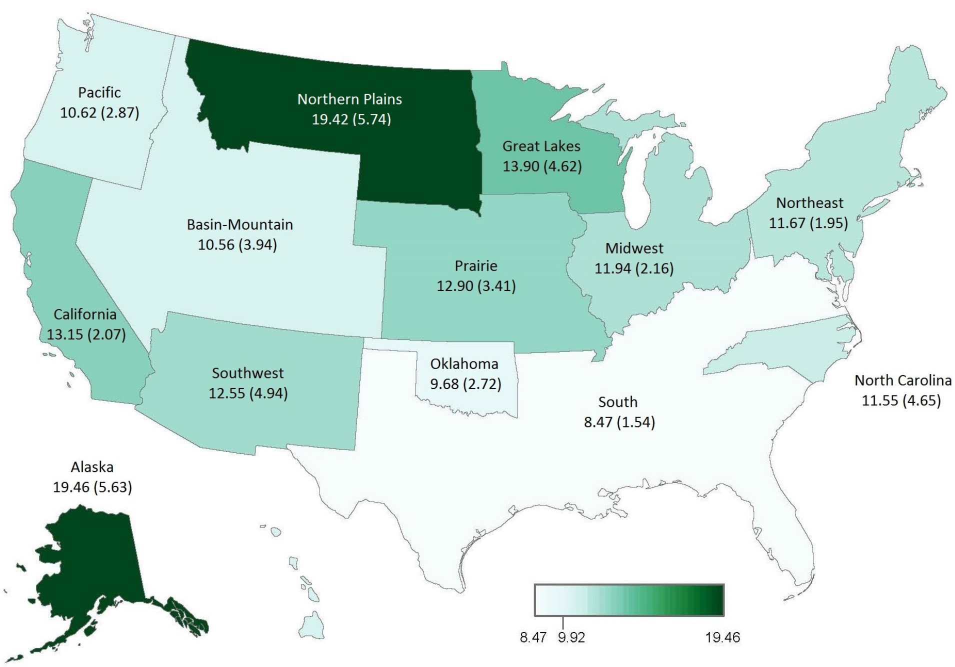


Table 3: Occupational education and occupational income by occupation group (all workers, 2008-2012 ACS).

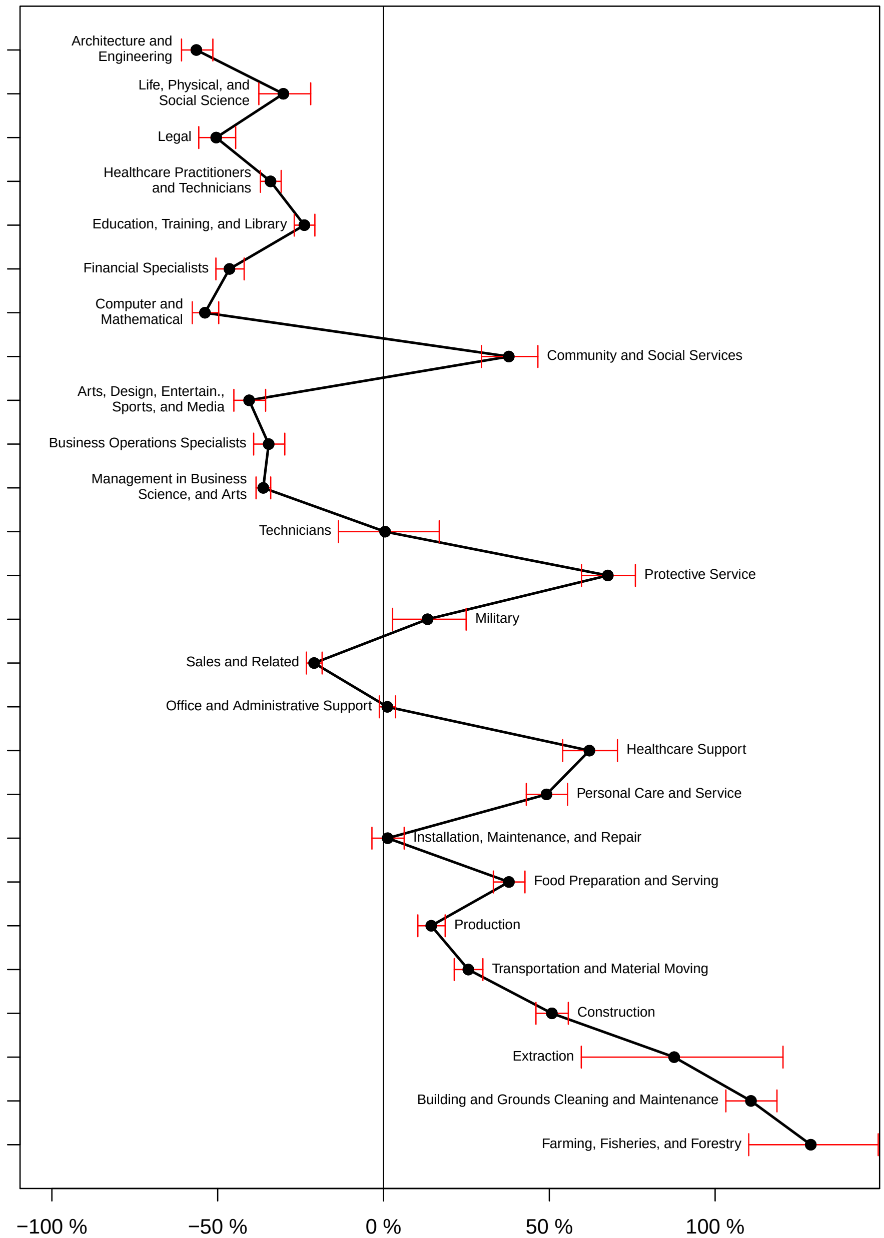
Occupation Group	Occupational Education		Occupational Income	
Architecture and Engineering	high	93%	high	$85,155
Life, Physical, and Social Science	high	92%	high	$68,781
Legal	high	92%	high	$115,592
Healthcare Practitioners and Technicians	high	90%	high	$75,637
Education, Training, and Library	high	90%	low	$43,963
Financial Specialists	high	90%	high	$76,898
Computer and Mathematical	high	90%	high	$76,918
Community and Social Services	high	88%	low	$43,022
Arts, Design, Entertainment, Sports, and Media	high	81%	low	$49,298
Business Operations Specialists	high	80%	high	$68,255
Management in Business, Science, and Arts	high	76%	high	$87,336
Technicians	low	63%	low	$52,601
Protective Service	low	61%	low	$48,859
Military	low	59%	low	$44,328
Sales and Related	low	55%	low	$43,321
Office and Administrative Support	low	54%	low	$32,855
Healthcare Support	low	48%	low	$24,817
Personal Care and Service	low	45%	low	$20,723
Installation, Maintenance, and Repair	low	38%	low	$43,477
Food Preparation and Serving	low	33%	low	$15,747
Production	low	28%	low	$35,266
Transportation and Material Moving	low	28%	low	$33,464
Construction	low	26%	low	$36,669
Extraction	low	22%	low	$52,030
Building and Grounds Cleaning and Maintenance	low	22%	low	$22,281
Farming, Fisheries, and Forestry	low	17%	low	$22,249

Over- and Under-representation in Occupations

Our second research question is: In which occupations are AIAN workers underrepresented relative to White workers? In which are they overrepresented? 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). For example, 92.9 percent of members of the architecture and engineering profession attended college. This was the highest rate of college attendance by labor force participants in any of the occupation groups, so it is shown at the top. Those in the farming, fisheries, and forestry category, shown at the bottom, had the lowest percentage of incumbents who attended college (16.9 percent). See Table 3 for details.

With this ordering, Figure 1 suggests an occupational gap based on education. To investigate the statistical significance of the differences in occupational participation, we display in Figure 3 an index based on the ratio of the AIAN-alone employment proportion to the employment proportion of the White workforce (for men and women combined). Specifically, for AIANa workers our index for any single occupation takes

Figure 3: Under-/over-representation of AIAN alone, 2010.
(Difference relative to proportional representation. Calculations and style based on Fox 2003).



the value:

$$\frac{\text{(share of AIANa workers in the occupation)}}{\text{(share of White workers in the occupation)}} - 1$$

In Figure 4, we also show a parallel index for AIANc workers. Figure 3 includes thin red 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, where individuals typically have less education, there is generally overrepresentation of AIAN 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 AIAN workers. In nine of the ten lowest categories on the education scale, there is statistically significant overrepresentation of AIANa workers. In fields like building and grounds cleaning there are twice as many AIANa workers employed, relative to the proportion of Whites in that sector (i.e., the index exceeds 100 percent). In the most highly educated occupation categories, AIANa individuals are underrepresented in ten of the top eleven (the exception being community and social services). For legal professions in particular, there are 50 percent fewer AIANa workers (index of -50.45 percent) employed than one would expect if AIANa participation were proportional to participation by single-race Whites.[11]

We expand these statistics in Figure 4 to include workers reporting an AIAN race in combination with other races and to include data for both 2000 and 2010. The results for AIANc individuals in the right-hand panel show a pattern of statistically significant, education-based occupational disparity that is qualitatively similar to the pattern for AIANa individuals in the left-hand panel (as seen by the visual "tilt" of both panels). However, the pattern is quantitatively milder for AIANc workers than AIANa 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," mainly due to small cell counts).

Adjusting the Dissimilarity Index for Educational Attainment

To further explore the relationship between education and occupation, we calculated the AIAN-White indices of dissimilarity within each of five education categories: less than high school, high school degree, some college or associate's degree, bachelor's degree, and more than a bachelor's degree. We show these results for 2010 in Table 4. For example, 12.23 percent of single-race AIAN workers in the lowest education category would

[11] We have also produced a version of Figure 3 (included in an appendix) that shows men and women separately. The basic pattern is the same but a few subtleties emerge. For example, AIAN underrepresentation in the legal professions is larger for men than for women. Also, although AIAN workers overall are overrepresented in protective services, this is even more true for AIAN women relative to white females than it is for AIAN men relative to white men.

Figure 4: Under-/over-representation of AIAN over time.
Filled circles represent statistically significant (non-zero) values.

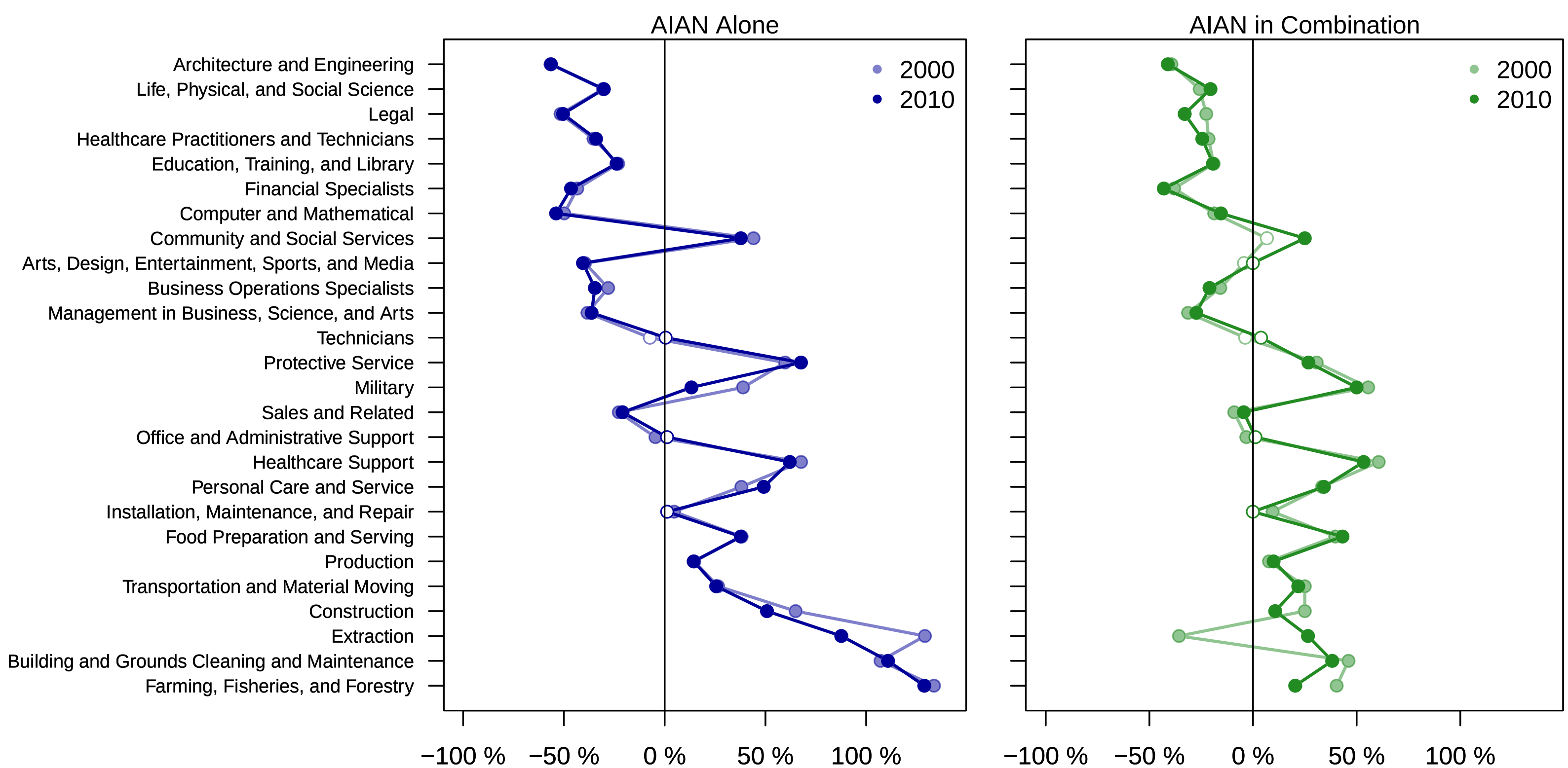


Table 4: Occupational dissimilarity index (and standard errors) by race and education in 2010.

	AIANa	AIANc	White
No HS Deg.	12.23 (1.69)	7.86 (2.44)	0
HS Grad	12.95 (0.74)	7.69 (1.15)	0
Some College	10.97 (1.17)	6.88 (1.32)	0
BA	13.70 (2.05)	10.87 (1.85)	0
BA+	9.79 (2.81)	8.48 (2.27)	0
All	16.47 (0.38)	9.92 (0.55)	0

need to change fields in order for their occupational distribution to match that of the least-educated White workers. We again find that all occupational dissimilarity values for both AIAN groups in Table 4 represent a statistically significant dissimilarity from Whites ($p < 0.001$).

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 AIAN 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.[12] Also note that the results for AIAN in combination again lie between the results for Whites and AIAN alone for each educational category.[13]

In Which Occupations Are AIAN Workers underrepresented: A Formal Test

Figures 3 and 4 already show a statistically significant pattern of AIAN 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 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

[12] 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 AIANa workers, except for BA+, where it is not defined due to a zero cell count. For AIANc workers, the Charles and Grusky index for the two extreme education outcomes, No HS and BA+, exceeds the overall index (and is not defined for the BA category).

[13] For the Karmel and MacLachlan index, we find much less dissimilarity for AIANc workers, compared to AIANa workers, in the three lowest education groups but slightly more dissimilarity in the BA and BA+ groups. We cannot produce both AIANa and AIANc values of the Charles and Grusky index for the two college groups, due to its reliance on logarithms and the null total of AIANc incumbents in certain occupations. We find that the Charles and Grusky index for the No HS group has an AIANc value that exceeds the AIANa value.

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	***
AIANc	-0.396	0.010	-38.87	<2e-16	***
AIANa	-0.625	0.011	-58.29	<2e-16	***

26 broad occupation groups. Ranking occupations by income instead of education would result in a generally similar definition of high-ranked versus low-ranked occupations.

In Table 5 we show the results of a basic regression predicting whether a worker is in a high-education occupation based only on their race response. The coefficient estimate for the intercept (-0.502) implies that a White worker in the year 2010 had a $e^{-0.502}/(1 + e^{-0.502}) = 37.71\%$ chance of being employed in a highly educated field. The coefficient for AIANc workers implies an $e^{-0.396} - 1 = -32.70\%$ difference in the log-odds of being in a highly educated field relative to the odds for the comparison group (Whites). Thus an AIANc worker in the labor force has a probability of 28.95 percent of being employed in a highly educated field. The results also imply that AIANa individuals in the labor force 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, for 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 AIANa and AIANc are significantly predisposed toward employment in low-education fields relative to Whites, with the disparity significantly smaller for the AIANc group.

Do Standard Demographic Factors Account for Occupational Disparity?

Having established that the occupational distribution of AIAN 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 AIAN 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 AIAN workers, there must be a positive overall average relationship between individual education attainment and whether an individual 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 AIAN portion of our sample—this population is very small relative to the White portion and thus has little influence on how occupations are ranked. So 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) AIAN workers are less likely to hold high-education occupations than Whites.[14]

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. In Table 6 we show basic 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,[15] age, English proficiency, and educational attainment.

Table 6: Summary statistics for the year 2010 (labor force participants), based on person weights. The reported N is unweighted.

	Race	N	Mean	SD	Min	Max
Female	White	5,397,814	0.4687	0.4990	0	1
	AIANc	45,154	0.4963	0.5000	0	1
	AIANa	54,534	0.4988	0.5000	0	1
Metro Area	White	5,397,814	0.7353	0.4412	0	1
	AIANc	45,154	0.7216	0.4482	0	1
	AIANa	54,534	0.5045	0.5000	0	1
Homeland	White	5,397,814	0.1774	0.3820	0	1
	AIANc	45,154	0.3007	0.4586	0	1
	AIANa	54,534	0.6361	0.4811	0	1
Age	White	5,397,814	42.3989	14.2460	16	95
	AIANc	45,154	39.2964	14.1305	16	94
	AIANa	54,534	39.5640	13.6356	16	94
Not English Proficient	White	5,397,814	0.0049	0.0696	0	1
	AIANc	45,154	0.0041	0.0642	0	1
	AIANa	54,534	0.0060	0.0773	0	1

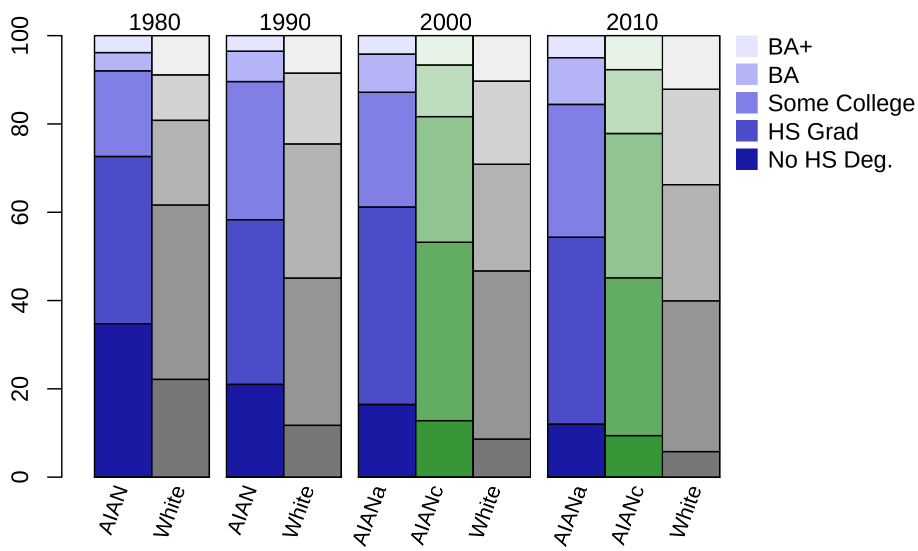
	Race	N	No HS Deg.	HS Grad	Some College	BA	BA+
Educational Attainment	White	5,397,814	6%	34%	26%	22%	12%
	AIANc	45,154	9%	36%	33%	14%	8%
	AIANa	54,534	12%	42%	30%	11%	5%

Because it is a primary independent variable of interest, we next (in Figure 5) show a plot of the educa-

[14] In addition, our discussion of Table 3 noted that a ranking of occupations by income rather than education would be quite similar.

[15] See the IPUMS USA variable HOMELAND and Liebler 2010.

Figure 5: Educational attainment of labor force participants by race, over time.



tional attainment of AIANa, AIANc, and White workers in 1980, 1990, 2000, and 2010. Note that the public census data only include multiple-race responses in 2000 and 2010.

We see in Figure 5 that, compared to Whites in each year, a lower proportion of AIAN labor force participants completed each educational level. In 2000 and 2010, AIANa and AIANc workers are both more highly concentrated in the high school graduate category than 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 American Indians and Alaska Natives are keeping up with overall educational increases, they are not catching up to close the gaps. The AIAN labor force in aggregate is more educated today than in 1980, but AIAN workers are still less educated than White workers.

Our predictors of a worker being employed in one of the "highly educated fields" include those shown in Table 6 as well as age squared. In Table 7, we show our results in terms of fitted coefficients, net of interaction effects, with separate columns for men and women as a way of displaying interaction effects.[16] As in Table 5, the coefficients in Table 7 sum to the log-odds of a particular individual being employed in a highly educated field.

Regardless of race, education is the best predictor of employment in a high-education field, and we

[16] 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.

Table 7: Fully adjusted binomial regression predicting employment in a highly educated field, for 2010.

	Men			Women		
	Estimate	SE		Estimate	SE	
(Intercept)	-4.4954	0.0136	***	-4.3760	0.0147	***
Race "AIANc"	-0.1825	0.0175	***	-0.0944	0.0160	***
Race "AIANa"	-0.2935	0.0186	***	-0.0752	0.0161	***
"Education" HS Grad	1.0581	0.0095	***	1.3205	0.0113	***
"Education" BA	2.8712	0.0097	***	3.0272	0.0115	***
"Education" BA+	4.1782	0.0105	***	4.3453	0.0125	***
Metro Area	0.1517	0.0025	***	0.1517	0.0025	***
Homeland	-0.0171	0.0028	***	-0.0171	0.0028	***
Age	0.0836	0.0005	***	0.0836	0.0005	***
Age^2	-0.0008	0.0000	***	-0.0008	0.0000	***
Not Proficient in English	-0.9483	0.0183	***	-0.9483	0.0183	***

show in Figure 5 that AIAN workers lag in education relative to White workers. This means differences in education between AIAN men and White men are responsible for a significant share of the differences between AIAN 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.[17] 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 50, falling off quadratically. Living in a metropolitan area, not living near a homeland, and being proficient in English also are 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 AIAN workers in high-education occupations. Compared to the disparities for AIAN men, disparities between AIAN women and White women are much smaller, or more nearly eliminated, after controlling for our additional factors, but even they remain statistically significant.[18] Thus, the answer to our third research question is "no," at least for the factors we consider.

One difference within the AIAN workforce itself does disappear with our additional controls. Comparing female AIANa workers to female AIANc 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

[17] 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 AIAN-White difference in the effect of education for those levels of attainment. We did find evidence that advanced degrees (BA+) had a somewhat lower effect on occupational outcome for AIANa and AIANc workers than for White workers, but this race effect was small relative to the baseline effect of an advanced degree on workers generally.

[18] The general pattern is that AIANc individuals are intermediate between Whites and AIANa individuals, but this is not true for AIAN women in Table 7. We have no explanation for this difference.

the additional explanatory variables). This is not true for male AIAN workers.[19] For males, we can only say that the differences between single- and multiple-race 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 AIANa and AIANc workers is accounted for by the additional factors in Table 6.

Conclusion

The raw data on occupational distribution by race reveals a clear disparity between AIAN workers and White workers that has been present since at least 1980. AIAN workers, both single-race and multiple-race, are underrepresented in high-education fields like management, financial services, and legal professions, relative to White workers. AIAN 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.

We find that race-group differences in educational attainment are the single most important explanatory factor behind the race-group differences in 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 they are all still statistically different from zero. These demographic factors also explain much (for men) or all (for women) of the tendency for AIANa workers to be less likely than their AIANc counterparts to work in a highly educated field.

Though American Indians and Alaska Natives have improved their educational attainment in the past decades, White educational levels have also been increasing, and AIANs have not closed the gap. Over the same decades, the aggregate occupational dissimilarity of the AIAN workforce seems to have changed little (though data issues prevent us from being certain). Although unmeasured factors also contribute to these occupational dissimilarities, 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 AIAN workers, thus improving lives and eliminating potential inefficiencies in how jobs are allocated.

Appendix A: Hispanic AIAN

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 the appendix table we show the fitted coefficients

[19] $p = 0.000013$ for men, and $p = 0.39$ for women.

for two regression models that include the Hispanic AIAN group (combining Hispanic AIANa with Hispanic AIANc). When compared to White workers, the disparity in education-ranked occupational outcomes is much larger for the Hispanic AIAN group than for either of the non-Hispanic AIAN groups in the "unadjusted" regression, which includes only race/ethnicity explanatory variables. All non-Hispanic AIAN-White disparities are smaller than Hispanic AIAN-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 AIAN workers, we find results that differ by sex. Among AIAN women, the Hispanic AIAN coefficient in the adjusted model is still statistically and materially larger than the coefficients for non-Hispanic AIAN workers. Among men, by contrast, the statistical difference between Hispanic AIAN workers and single-race AIAN workers disappears in the adjusted model.

Appendix Table: Unadjusted and fully adjusted binomial regressions predicting employment in a highly educated field, for the year 2010, including Hispanic AIANs.

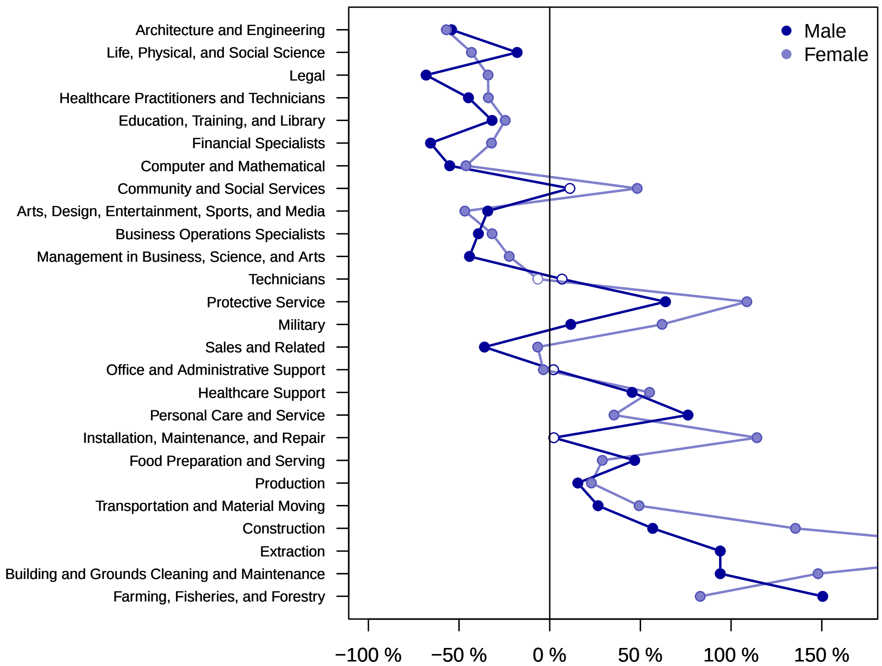
	Estimate	(SE)	z value	Pr(>|z|)	
(Intercept)	-0.502	0.001	-564.9	<2e-16	***
Race "AIANc"	-0.400	0.010	-38.86	<2e-16	***
Race "Hispanic AIAN"	-0.948	0.017	-55.23	<2e-16	***
Race "AIANa"	-0.625	0.011	-58.28	<2e-16	***

	Men			Women		
	Estimate	SE		Estimate	SE	
(Intercept)	-4.4942	0.0135	***	-4.3748	0.0147	***
Race "AIANc"	-0.1832	0.0175	***	-0.0953	0.0160	***
Race "Hispanic AIAN"	-0.3189	0.0289	***	-0.2325	0.0274	***
Race "AIAN"	-0.2856	0.0186	***	-0.0681	0.0161	***
"Education" HS Grad	1.0531	0.0095	***	1.3151	0.0113	***
"Education" BA	2.8666	0.0096	***	3.0225	0.0115	***
"Education" BA+	4.1753	0.0105	***	4.3416	0.0124	***
Metro Area	0.1558	0.0025	***	0.1558	0.0025	***
Homeland	-0.0186	0.0028	***	-0.0186	0.0028	***
Age	0.0839	0.0005	***	0.0839	0.0005	***
Age^2	-0.0008	0.0000	***	-0.0008	0.0000	***
Not Proficient in English	-0.9845	0.0179	***	-0.9845	0.0179	***
Mostly-Proficient	-0.5448	0.0113	***	-0.5448	0.0113	***

Appendix B: Under-/over-representation of AIAN by Gender

Here we present a version of Figure 3, separated by gender, comparing AIANa women to White women, and AIANa men to White men. Low cell counts hinder interpretation for some categories. For example, AIANa women were estimated to be 268 percent overrepresented in the extraction group; because few women work in extraction in either race, the 95 percent confidence interval for this estimate ranges from 76 to 654 percent.

Appendix Figure: Under-/over-representation of AIAN alone, 2010 by gender.
(Filled circles represent statistically significant (non-zero) values.)



Appendix C: Standard Error Estimation

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 (X_i) and the entire data set (X), then compute:

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

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