Online Appendices for: “Employment Discrimination against Indigenous Peoples in the United States: Evidence from a Field Experiment”

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Contents:

1. Additional Details About the Experimental Design
2. Pre-Analysis Plan
3. The “Heckman-Siegelman” Critique and the Neumark (2012) Correction
4. Robustness Checks
5. Additional Details and Results from the Resume Surveys
6. Additional Details and Results from the Name Survey
7. Secondary Data Analysis of Discrimination using the Current Population Survey
8. Sample Resumes and Cover Letters
9. Additional Socioeconomic Status Statistics by Native American Tribal Group
10. Additional References Not Included in Main Paper

**Online Appendix A: Additional Details About the Experimental Design**

**Language as a Racial Signal**

Here we provide additional details on how we determined which Indigenous languages were appropriate, in which circumstances, to signal Indigenous status. We used Indigenous languages to signal Indigenous status in some cases for most (but not all) of the tribal groups since Indigenous language use varies by tribal group. We used two approaches to determine which languages are spoken by which tribal groups. The first was to ascertain the languages historically spoken by the tribe. The second was to determine which Indigenous languages are spoken by individuals who live on the Indian reservation associated with the tribe.

While not all individuals from a tribe live or have lived on a reservation, this was the only data-driven approach for us to investigate language use by the tribal group. Online Appendix Table A1 presents the languages that we selected for each American Indian tribal group and the proportion of individuals who report speaking this language at home and live on the associated reservations, using Census data. We did not use language to signal Indigenous status for individuals from the Osage or Blackfeet tribes since Indigenous language use by these tribes is very low (less than 1% for Osage) or sufficiently uncommon (less than 10% for Blackfeet).

**First Names as a Racial Signal**

Using first names is a natural way to signal minority status in audit-correspondence studies. This approach is evident and easy for gender (for names that are gender-specific and well-known), but signaling race by name is more complicated. For race, names are used to signal African-American status (e.g., Bertrand and Mullainathan, 2004), Arab, Muslim, or Middle Eastern descent (e.g., Rooth, 2010), Turkish or Moroccan descent (e.g., Baert and De Pauw, 2014), and Asian, Roma, Ashkenazi Jewish, African, Indian, and Pakistani descent, among others (Booth, Leigh, and Varganova, 2012; Fershtman and Gneezy, 2001; McGinnity and Lunn, 2011; Oreopoulos, 2011), and caste (e.g., Siddique, 2011). Using names as a signal improves external validity since names are required. However, first names can signal socioeconomic status in some cases, which some argue (Fryer and Levitt 2004) is the case in studies such as Bertrand and Mullainathan (2004).

We settled on three male names: Kekoa, Ikaika, and Keoni, and one female name: Maile. Malia also appeared on the top 100 list of names for girls, but we avoided using this name in case it sent a different signal given that this is the name of President Obama’s daughter. We also did not use Alana since it is also a name of Irish origin. We opted not to use Leilani as there was some evidence that this name is common for those who are not Native Hawaiian.

**Last Names as a Racial Signal**

For those who identify as AIAN only, AIAN-specific last names are not common, but they are also not unusual. From our Census data, there are 268 last names where at least 80% of those with that name identified as AIAN only. Further, 5.5% of individuals who identified as AIAN only have one of these 268 last names.[[1]](#footnote-1) A broader list of names where at least 30% of those with the name identified as AIAN only has 660 names, and 11.0% of those who identified as AIAN only have one of these 660 names.

To determine feasible last names, we first extracted a list of 268 last names that met the criteria where at least 80% of the people with those last names identified as AIAN alone. We then narrowed this list to 12 AIAN-specific last names that had at least 0.2 people per 100,000 with that last name. Finally, we selected four last names from this list where we could identify the tribal group (Navajo): Begay (5.96 people per 100,000, 94.98% identified as AIAN alone), Yazzie (5.16, 96.10%), Benally (1.87, 95.99%), and Tsosie (1.80, 96.23%).[[2]](#footnote-2)

There are costs and benefits to this last name signal. Last names have the benefit of being a natural signal, since one cannot realistically put a different last name on the resume, but one could refuse to disclose relevant experience or skills that signal Indigenous status (e.g., the volunteer or language signals, discussed earlier) or applicants may re-phrase the experience in attempts to obscure racial signals. However, it may be less likely that employers understand that these are Native American last names relative to, say, understanding African-American first names, making the last name signal weaker. We investigate this in the robustness section and our resume survey (Online Appendix E) and name survey (Online Appendix F).

Another issue with using last names as a signal of race is that they are a weaker signal for women since they may take the last name from her spouse. This is especially an issue given the increase in interracial marriages after the 1970s (Fryer 2007). Thus, if discrimination against Native American women occurs less than for men, using the last name as the only signal, then this suggests that discrimination is weaker for women, that this is a weaker signal of race for women, or both. In contrast, using Native Hawaiian first names as the only signal may present a different set of implications. A Native Hawaiian first name and a non-Native Hawaiian last name (although Native Hawaiian last names appear uncommon) may imply that the applicant is multi-racial or it may separately or additionally imply interracial marriage for female applicants. However, we do not find discrimination regardless of gender or the signal used.

**Phone Numbers and Email Addresses**

We purchased phone numbers for our applicants from the companies *Vumber* and *GoTo Phone*. These appear the same as regular phone numbers but have the benefit that they do not require physical phones and store all the voicemails into a central account. We gave each phone number a typical and generic voicemail greeting that instructs the caller to leave a detailed message after the tone. When employers called, they did not always leave a message that provided enough information to match them to an exact applicant (let alone the job ad). Assigning a unique phone number to every job application would solve this problem but was not feasible. We purchased enough phone numbers to assign unique numbers to bins of job applicants defined by city, race (white or Indigenous), and occupation (retail sales, server, kitchen staff, janitor, and security, with janitor and security pooled into one set of numbers). This resulted in 88 unique phone numbers. With all of these numbers and other matching methods (discussed below), it was highly unlikely that we could not assign a response to an applicant.

We bought domains to create a large number of email addresses such that each applicant almost always had a unique email address, which allowed us to match, almost perfectly, the email responses to job applications.

**Working with Research Assistants on Data Collection**

We continually worked with the research assistants to standardize their job search methods so that each research assistant conducted their search the same way in each city and occupation and applied the same criteria to identify appropriate jobs. In addition to providing an instruction sheet (available upon request) and updating it when we learned about additional confusing cases, we supervised the research assistants in a few ways. These included direct supervision of research assistants (e.g., working nearby them and checking their work in person occasionally), an online forum where research assistants could post questions and receive quick answers, and regular meetings of the entire research team to discuss procedures and clarify ambiguities.

To check that our research assistants followed the guidelines, we required for one week early on that all research assistants saved every job ad that they opened, instead of just saving the job ads that they deemed eligible to apply to. For each ad, research assistants either saved it as a rejected ad or an eligible ad and for rejected ads they indicated why they rejected them. This allowed us to spot-check their work and make suggestions for improvement.

**Sending Out Applications**

Once research assistants determined that a job was eligible to apply to, they entered information about the job into a spreadsheet. They entered the job ID number (unique to each job posting), day and city for the job posting, occupation, email address for the application, subject line to be used (e.g., whether the employer requested a particular subject line; otherwise we randomized subject lines that were realistic), and whether the employer requested a resume in Microsoft Word format rather than PDF (by default we sent resumes as PDF documents). We then used Python and SQL code created by Nanneh Chehras for Neumark, Burn, Button, and Chehras (2018) to email these job applications automatically with a delay of a few hours between emails to the same employer. We ran the code at least twice per week, usually on set days (e.g., Monday and Thursday); though, we often ran it daily to minimize the time between finding the job and applying to it.

 Each day was randomly assigned a different pair of resumes in terms of skill levels, employed or unemployed, and the gender of the applicants, as these factors are set to be the same within resume pairs. Within each pair, we randomized the application ordering of the two resumes. To distinguish further resumes in a pair further, we randomly name the computer files slightly differently. One resume in the pair was named “FirstLastResume,” where First and Last were the applicant’s first and last names, and the other resume was named “ResumeFirstLast.”

**Matching Responses to Jobs and Applications**

Responses to job applications could be received by email or by phone. All email responses forwarded to a central email account, and all voicemails forwarded to that same account as email attachments. A research assistant then read each email and listened to each voicemail to code the response. We anticipated that the email or voicemails received would not always be enough to match the response to a specific job ad. However, we designed the email addresses and chose phone numbers in a way to improve our ability to match responses to specific applications and job ads.

Matching responses to specific applications and job advertisements was easier if the response from the employer was through email. If the employer replied directly to the original application email (sent to the employer through an email relay system), then the email response contained the unique ID number for the job ad. Each job ID number provides a one-to-one match to a job ad. However, if employers responded directly to the individual (by typing in the email address rather than hitting reply), then we did not observe this job ID. In this case, we used other information from the email, such as the company name or type, job ad title, and location. While our email addresses were not perfectly unique,[[3]](#footnote-3) we also looked through records of which applications used which email addresses, and for which job ads, to narrow down the likely matches.

Voicemail responses conveyed less information which made matching more difficult, but usually possible. Based on how we assigned phone numbers, we always knew the city and Indigenous status of the applicant, and we almost always knew the occupation (only janitor and security jobs got the same phone numbers). We then used information in the voicemail message itself to try to match to an exact applicant or job advertisement. We assigned first and last names such that the combination of phone number and first or last name gave us the unique job applicant (except in a few cases for janitor or security). This improved our matching since employers almost always mentioned the first or last name of the applicant they called.

However, since we assign each pair of applicants to a particular day of the month, these applicants may apply to multiple jobs. Given this, additional information was required to make a match to a specific job advertisement. The additional information that helped us make a match was often the phone number of the employer and in the content of their voicemail message (e.g., they mention their employer by name).

When we could not match to a job ad, we matched to the next most specific level, which was the applicant.[[4]](#footnote-4) This still allows us to run all of our regressions, including those with resume control variables. The only restriction, which is irrelevant in our case, is that these observations would need to be dropped if we wanted to use any information from the job ads.

Online Appendix Table A1 – Non-English Languages and Indian Reservations

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Indian Reservation | Tribal Group | Population | % Who Speak an “Other” Language | Language Assigned |
| Blackfeet Indian Reservation and Off-Reservation Trust Land, MT | Blackfeet | 10,037 | 8.1 | None |
| Fort Apache Reservation, AZ | Apache | 13,179 | 54.4 | Apache |
| Navajo Nation Reservation and Off-Reservation Trust Land, AZ-NM-UT | Navajo | 161,009 | 67.2 | Navajo |
| Osage Reservation, OK | Osage | 45,257 | 0.7 | None |
| Pine Ridge Reservation, SD-NE | Oglala Lakota | 17,165 | 22.8 | Lakota |
| San Carlos Reservation, AZ | Apache | 9,145 | 33.9 | Apache |
| Tohono O’odham Nation Reservation and Off-Reservation Trust Land, AZ | Tohono O’odham | 9,154 | 33.7 | Pima |

Notes: Our data source is the U.S. Census Bureau (2014). “Other” language is a language other than English, Spanish, or an Indo-European or an Asian or Pacific Island language. The “Language Assigned” column corresponds to the language column in Table 1.

Online Appendix Table A2 - Rural City and Reservation Matches for the Rural Control for Indian Reservation Upbringing

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Matching Urban City | Matching Reservation | Driving Distance | Control Rural Town | Driving Distance |
| Albuquerque | Navajo | 3 h 26 m | Holbrook, AZ | 3 h 19 m |
| Albuquerque | Fort Apache | 4 h 23 m | Eagar, AZ | 3 h 12 m |
| Albuquerque | San Carlos | 6 h 18 m | Willcox, AZ | 5 h 14 m |
| Billings | Blackfeet | 5 h 32 m | Polson, MT | 5 h 55 m |
| Oklahoma City | Osage | 2 h 11 m | Newkirk, OK | 1 h 49 m |
| Phoenix | Navajo | 5 h 27 m | Fredonia, AZ | 5 h 17 m |
| Phoenix | Fort Apache | 2 h 59 m | Taylor, AZ | 2 h 56 m |
| Phoenix | San Carlos | 2 h 30 m | San Manuel, AZ | 2 h 2 m |
| Phoenix | Tohono O'odham | 2 h 13 m | Ajo, AZ | 1 h 48 m |
| Sioux Falls | Pine Ridge | 5 h 8 m | Wall, SD | 4 h 1 m |

Notes: We determined the distances between the city and the Indian reservation and the rural town using Google Maps.

Online Appendix Table A3 – Demographics of Occupations for Men Aged 25-35

|  |  |  |
| --- | --- | --- |
| Occupation | Proportion of Entire Race | Ratio to White |
| White | AIAN | NHPI | AIAN | NHPI |
| Driver/sales workers and truck drivers 53-3030 | 3.04% | 3.07% | 4.41% | 3.17% | 1.38% |
| Construction laborers 47-2061 | 2.80% | 2.04% | 3.74% | 2.29% | 1.27% |
| Managers, all other (11-9199) | 2.55% | 1.22% | 2.62% | 1.50% | 0.98% |
| First-line sups./managers of retail sales workers 41-1011 | 2.36% | 1.92% | 1.81% | 2.54% | 0.73% |
| **Retail salespersons 41-2031** | 2.18% | 0.83% | 0.46% | 1.19% | 0.20% |
| **Grounds maintenance workers 37-3010** | 2.06% | 2.36% | 2.11% | 3.59% | 0.97% |
| Carpenters 47-2031 | 1.97% | 1.90% | 1.75% | 3.02% | 0.84% |
| Laborers & freight, stock, and material movers, hand 53-7062 | 1.90% | 3.02% | 3.65% | 4.99% | 1.83% |
| **Cooks 35-2010** | 1.65% | 3.73% | 2.51% | 7.07% | 1.44% |
| **Janitors and building cleaners 31-201X** | 1.49% | 1.68% | 2.00% | 3.55% | 1.28% |
| Automotive service technicians and mechanics 49-3023 | 1.34% | 1.22% | 2.74% | 2.85% | 1.94% |
| Software developers, apps. and systems software 15-113X | 1.23% | 1.01% | 0.00% | 2.57% | 0.00% |
| Sales representatives, wholesale and manufacturing 41-4010 | 1.21% | 0.55% | 0.30% | 1.41% | 0.24% |
| Electricians 47-2111 | 1.19% | 1.14% | 0.94% | 3.00% | 0.75% |
| Miscellaneous agricultural workers 45-2090 | 1.18% | 0.65% | 0.14% | 1.72% | 0.11% |
| Stock clerks and order fillers 43-5081 | 1.14% | 1.09% | 0.68% | 2.98% | 0.57% |
| Customer service representatives 43-4051 | 1.09% | 1.39% | 1.20% | 3.98% | 1.05% |
| Accountants and auditors 13-2011 | 1.08% | 0.01% | 0.69% | 0.03% | 0.61% |
| Welding, soldering, and brazing workers 51-4120 | 1.05% | 1.64% | 0.96% | 4.90% | 0.87% |
| Police and sheriff's patrol officers 33-3051 | 1.03% | 0.96% | 0.52% | 2.95% | 0.48% |
| Production workers, all other 51-9199 | 0.98% | 1.93% | 0.44% | 6.18% | 0.43% |
| Elementary and middle school teachers 25-2020 | 0.95% | 0.46% | 0.60% | 1.53% | 0.59% |
| Pipelayers, plumbers, pipefitters, and steamfitters 47-2150 | 0.95% | 0.74% | 0.23% | 2.43% | 0.23% |
| **Waiters and waitresses 35-3031** | 0.94% | 0.57% | 0.08% | 1.89% | 0.08% |
| Food service managers (11-9051) | 0.88% | 0.29% | 1.01% | 1.02% | 1.09% |
| Painters, construction and maintenance 47-2141 | 0.87% | 0.54% | 0.38% | 1.94% | 0.41% |
| General and operations managers (11-1021) | 0.86% | 0.47% | 1.51% | 1.71% | 1.66% |
| Lawyers, Judges, magistrates, and other jud. workers 23-1011 | 0.86% | 0.38% | 0.00% | 1.38% | 0.00% |
| Miscellaneous assemblers and fabricators 51-2090 | 0.86% | 1.43% | 1.98% | 5.24% | 2.20% |
| Construction managers (11-9021) | 0.84% | 0.16% | 0.00% | 0.59% | 0.00% |
| **Cashiers 41-2010** | 0.84% | 1.26% | 0.50% | 4.69% | 0.56% |
| First-line sups./managers of non-retail sales workers 41-1012 | 0.81% | 0.05% | 1.93% | 0.20% | 2.26% |
| Postsecondary teachers 25-1000 | 0.77% | 0.13% | 1.29% | 0.52% | 1.58% |
| Marketing and sales managers (11-2020) | 0.77% | 0.00% | 0.14% | 0.00% | 0.17% |
| First-line sups./managers of prods. and oper. workers 51-1011 | 0.77% | 0.33% | 0.53% | 1.33% | 0.66% |
| … of construction trades and extraction workers 47-1011 | 0.76% | 1.43% | 0.27% | 5.93% | 0.34% |
| **Security Guards and Gaming Surveillance Officers** | 0.74% | 1.44% | 2.74% | 6.14% | 3.53% |
| Heating, A/C, and fridge mechanics and installers 49-9021 | 0.72% | 0.43% | 0.25% | 1.87% | 0.33% |

Notes: This data comes from all months of the 2015 Current Population Survey. We weight these estimates using population weights. We sort occupations by the decreasing share of white men that have this occupation out of all white men.

Online Appendix Table A4 – Demographics of Occupations for Women Aged 25-35

|  |  |  |
| --- | --- | --- |
| Occupation | Proportion of Entire Race | Ratio to White |
| White | AIAN | NHPI | AIAN | NHPI |
| Elementary and middle school teachers 25-2020 | 4.61% | 1.27% | 2.19% | 1.12% | 0.44% |
| Registered nurses 29-1141 | 4.27% | 1.66% | 4.11% | 1.57% | 0.89% |
| Secretaries and administrative assistants 43-6010 | 3.23% | 1.45% | 4.36% | 1.81% | 1.24% |
| **Cashiers 41-2010** | 2.65% | 3.30% | 3.25% | 5.03% | 1.13% |
| **Waiters and waitresses 35-3031** | 2.65% | 0.80% | 0.47% | 1.22% | 0.16% |
| First-line supervisors/managers of retail sales workers 41-1011 | 2.21% | 1.60% | 3.44% | 2.92% | 1.44% |
| Customer service representatives 43-4051 | 2.16% | 2.01% | 2.43% | 3.76% | 1.04% |
| **Retail salespersons 41-2031** | 2.00% | 1.94% | 1.50% | 3.91% | 0.69% |
| Nursing, psychiatric, and home health aides 31-1010 | 1.87% | 2.94% | 4.34% | 6.36% | 2.14% |
| Managers, all other (11-9199) | 1.87% | 0.82% | 1.77% | 1.77% | 0.87% |
| Child care workers 39-9011 | 1.65% | 1.79% | 1.01% | 4.37% | 0.56% |
| Receptionists and information clerks 43-4171 | 1.59% | 1.34% | 4.29% | 3.40% | 2.49% |
| Maids and housekeeping cleaners 37-2012 | 1.47% | 2.41% | 2.88% | 6.65% | 1.81% |
| Accountants and auditors 13-2011 | 1.43% | 0.49% | 2.03% | 1.38% | 1.31% |
| Office clerks, general 43-9061 | 1.38% | 1.39% | 3.06% | 4.07% | 2.04% |
| Preschool and kindergarten teachers 25-2010 | 1.32% | 0.60% | 0.43% | 1.85% | 0.30% |
| Hairdressers, hairstylists, and cosmetologists 39-5012 | 1.27% | 0.79% | 0.27% | 2.52% | 0.20% |
| Secondary school teachers 25-2030 | 1.24% | 0.39% | 1.08% | 1.29% | 0.80% |
| First-line sups./mngrs. of office and admin. support 43-1011 | 1.21% | 0.83% | 2.99% | 2.77% | 2.29% |
| Health diag. and treating practitioner support techs. 29-2050 | 1.17% | 0.63% | 0.00% | 2.18% | 0.00% |
| Counselors 21-1010 | 1.09% | 0.48% | 0.23% | 1.77% | 0.20% |
| Medical assistants 31-9092 | 1.07% | 0.89% | 1.07% | 3.35% | 0.92% |
| Designers 27-1020 | 1.04% | 0.15% | 0.63% | 0.60% | 0.56% |
| Personal and home care aides 39-9021 | 1.03% | 2.01% | 3.98% | 7.86% | 3.56% |
| Food service managers (11-9051) | 1.02% | 1.10% | 1.82% | 4.36% | 1.65% |
| Social workers 21-1020 | 1.02% | 0.71% | 0.00% | 2.84% | 0.00% |
| **Cooks 35-2010** | 1.00% | 1.11% | 1.81% | 4.49% | 1.67% |
| Bookkeeping, accounting, and auditing clerks 43-3031 | 1.00% | 0.66% | 0.08% | 2.66% | 0.07% |
| Postsecondary teachers 25-1000 | 0.97% | 0.12% | 0.53% | 0.52% | 0.50% |
| Marketing and sales managers (11-2020) | 0.93% | 0.03% | 0.00% | 0.12% | 0.00% |
| Human resource workers 13-1070 | 0.91% | 0.10% | 1.39% | 0.45% | 1.41% |
| Teacher assistants 25-9041 | 0.90% | 0.99% | 1.65% | 4.42% | 1.69% |
| Financial managers (11-3031) | 0.87% | 0.74% | 0.19% | 3.44% | 0.20% |
| **Bartenders 35-3011** | 0.81% | 0.32% | 0.86% | 1.61% | 0.98% |
| Other teachers and instructors 25-3000 | 0.80% | 0.05% | 1.26% | 0.24% | 1.46% |
| Lawyers, Judges, magistrates, and other jud. workers 23-1011 | 0.78% | 0.06% | 0.00% | 0.32% | 0.00% |
| Licensed practical and licensed vocational nurses 29-2061 | 0.76% | 0.54% | 0.20% | 2.90% | 0.24% |
| **Janitors and building cleaners 31-201X** | 0.75% | 0.40% | 1.03% | 2.17% | 1.27% |

Notes: See the notes to Online Appendix Table A3. We sort occupations by the decreasing share of white women that have this occupation out of all white women.

**Online Appendix B: Pre-Analysis Plan**

 Before putting this experiment into the field, we filed a pre-analysis plan (PEP) and registered it with the American Economic Association’s Randomized Control Trial Registry (socialscienceregistry.org).[[5]](#footnote-5) Our goal was to pre-specify any variables, models, sample sizes, or decisions that could easily be data mined.

In this experiment, there is only one outcome – callbacks – so there is little to no risk of a typical data mining issue where a researcher can select a subset of outcome variables that show statistically significant results (Olken 2015). We did, however, pre-specify a few things. First, we specified how we could code callbacks by including ambiguous responses with callbacks (e.g., “We reviewed your application, and we have some questions for you.”), as done in previous work (e.g., Neumark, Burn, and Button, forthcoming.) We also chose to pre-specify some control variables and models to avoid less pivotal possibilities of data mining, such as choosing resume control variables or models specifically to affect the results. This sort of decision of which control variables or model to use, and how that could lead to p-hacking or data mining, is not unique to our study by any means. While it is not common to pre-specify these, it has been done before with some benefit (e.g., Neumark, 2001) and we wanted to be upfront about decisions that we knew made the most sense to take beforehand. In this pre-analysis plan we sought to commit to approaches to prevent possibilities of data mining or p-hacking whenever we could while also not tying our hands too much in ways that would negatively affect our ability to conduct this research later (see Olken, 2015, p. 71 and Lahey and Beasley, 2018, for some useful discussion of the costs of pre-analysis plans.) In retrospect, we believe that we struck a good balance, but we did pre-specify a few things that we really should not have (e.g., probit models instead of linear probability models), but this did force us to be transparent about our deviations from our pre-analysis plan and justify those deviations.

In this pre-analysis plan, we pre-specified the way callbacks would be coded, the primary models and tabulations, and the main control variables. We also committed to using a particular sample size, in addition to using all our data, for our main results to mitigate concerns of data mining if our sample size exceeded the minimum sample size required based on the power analysis. As shown in Online Appendix Table B1, our main results are virtually identical using the smaller sample size of 8,422, suggested by our power analysis.

We primarily adhered to the core of the pre-analysis plan but made a few minor deviations. The first minor deviation is in our full controls (see Table 6, column (3)), in which we planned to include indicator variables for each company used on the resume in our vector of full controls.[[6]](#footnote-6) Including these company indicator variables ended up making interpretation of the coefficients on $Reservation Job$ and $Rural Job $impossible since some companies are assigned based on if the applicant had an upbringing and job on an Indian Reservation or in a small rural town. For this reason, we do not include these company indicator variables in the full controls regression in Table 6, column (3). However, our estimates outside of those for $Reservation Job$ and $Rural Job$ do not change when we add company indicator variables (online Appendix Table B2.)

The second minor deviation is in the statistical model that we used to run regressions. We originally specified using a probit, but we later learned that it is problematic to interpret interactions in a probit model (Ai and Norton 2003). For this reason, we switched to presenting the main results from a linear probability model. However, our results are similar using a probit (see Appendix Tables D6 through D9).

The third minor deviation is in weighting our results. In our pre-analysis plan, we considered our population-weighted estimates to be the preferred specification. Since we now realize that there is more than one way to weight the estimates, we instead include the unweighted estimates in the main paper for ease of presentation. However, we present main estimates with and without all types of weighting in Online Appendix D. Our results never differ in a meaningful way regardless of how we weight, if at all.

Online Appendix Table B1 – Callback Estimates by Race and Indian Reservation Upbringing – Results by Sample Size

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  |  (1) | (2) |
| Native American | -0.003 | -0.004 |
|  | (0.010) | (0.009) |
| … x Reservation | -0.007 | -0.000 |
|  | (0.013) | (0.012) |
| … x Reservation x Reservation Job | -0.009 | 0.006 |
|  | (0.018) | (0.016) |
| Alaska Native | -0.008 | 0.005 |
|  | (0.046) | (0.035) |
| Native Hawaiian | -0.009 | -0.003 |
|  | (0.018) | (0.013) |
| Non-Reservation Rural | -0.025\* | -0.016 |
|  | (0.013) | (0.013) |
| … x Rural Job | 0.006(0.018) | 0.002(0.018) |
|  | N=8,422 | N=13,516 |

Notes: See the notes to Table 6. All regressions use the regular controls (Column (2) of Table 6). Column (1) uses the first 8,422 observations, per our power analysis calculation. Column (2) uses all observations. Significantly different from zero at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*).

Online Appendix Table B2 – Callback Estimates by Race and Indian Reservation Upbringing – Full Controls vs. Full Controls plus Company Indicators

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  |  (1) | (2) |
| Native American | -0.005 | 0.005 |
|  | (0.009) | (0.010) |
| … x Reservation | -0.000 | -0.004 |
|  | (0.012) | (0.013) |
| … x Reservation x Reservation Job | 0.005 | N/A |
|  | (0.016) |  |
| Alaska Native | 0.003 | 0.013 |
|  | (0.035) | (0.034) |
| Native Hawaiian | -0.002 | -0.005 |
|  | (0.013) | (0.016) |
| Non-Reservation Rural | -0.015 | 0.001 |
|  | (0.013) | (0.014) |
| … x Rural Job | 0.002(0.018) | N/A |

Notes: N=13,516. See the notes to Table 6. Both regressions include the full controls (Column (2) of Table 6). Column (2) includes the added company indicator variables, which removes the separate effects of reservation job and rural job since it controls for each possibly company that could be listed for those. Significantly different from zero at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*).

**Online Appendix C: The “Heckman-Siegelman” Critique and the Neumark (2012) Correction**

**Introduction and Theoretical Model**

Audit-Correspondence (AC) studies suffer from the “Heckman-Siegelman critique” (Heckman, 1998; Heckman and Siegelman, 1993). The critique is that while AC studies control for average differences in observable characteristics (what is included in the application), discrimination estimates can still be biased through the variance of unobservable characteristics (what is not seen on the resume). Neumark (2012) shows how this can occur using a model of hiring decisions, which we summarize very briefly here following the notation of Neumark, Burn, and Button (2016).

Assume that productivity depends linearly and additively on two characteristics: observable (on the resume) characteristics, which are denoted XI and unobservable characteristics (not on the resume), which are denoted as XII. Let N denote Indigenous (“Native”) applicants and let W denote white applicants. AC studies standardize XI to be the same for N and W at some level XI\*, such that XIN = XIW = XI\*. Let γ be an additional linear, additive, term that reflects discrimination against Indigenous Peoples. This term can either reflect taste discrimination, where the productivity of Indigenous Peoples is undervalued, or statistical discrimination, where firms believe that the average unobservable characteristics are different between groups (i.e., that E(XIIN) ≠ E(XIIW)). AC studies seek to estimate γ as a linear function of XI and an indicator for race (N).

Applicants are given an interview (T = 1) if expected productivity exceeds a threshold, c:

|  |  |
| --- | --- |
| $$T\left(X^{I\*}, X\_{N}^{II}\right)| \left(N=1\right)= 1 if β\_{1}X^{I\*}+X\_{N}^{II}+γN>c$$$$T\left(X^{I\*}, X\_{W}^{II}\right)| \left(N=0\right)= 1 if β\_{1}X^{I\*}+X\_{W}^{II}>c$$ | [C1] |

If XIIN and XIIW are normally distributed with means of zero and standard deviations of σIIN and σIIW, respectively, then the interview offer probability is:

|  |  |
| --- | --- |
| $$Φ\left[(β\_{1}X^{I\*}+γN-c\right)/σ\_{N}^{II}] if N= 1$$$Φ\left[(β\_{1}X^{I\*}-c\right)/σ\_{W}^{II}] if N= 0$. | [C2] |

The Heckman critique arises because it is not possible to identify γ unless the ratio between σIIN and σIIW is known. To illustrate why this is the case, suppose that Indigenous people have a larger variance of unobservables (i.e., σIIN > σIIW). This is likely the case as evidence suggests that other racial minorities also have a larger variance of unobservables (e.g., Neumark, 2012). For firms that require very productive workers (c is high), and the standardized observables on the resumes are of somewhat low quality, then the larger variance for Indigenous applicants means that they are more likely to pass this high standard than white applicants. This negatively biases the estimate of γ. This bias becomes more positive when the interview standard is lower, or the observables are standardized at a higher level. Regardless, the estimate of γ is a function of the ratio of σIIN to σIIW, and to the level of standardization of the observables (XI\*).

Neumark (2012) develops a method to address this by using different quality standardizations that are introduced when quality features are added to the applicants. This allows γ to be identified under the assumption that β1 is equal for Indigenous and white applicants. Neumark (2012) also shows that if there are multiple added quality features then there is an over-identification test that can be used to test this assumption.

**Quality Features**

Any resume or applicant feature that shifts the quality of the resume in the eyes of the employer can be used in the Neumark (2012) correction. Of course, one can randomly add quality features using resume randomization tools (Lahey and Beasley, 2018, 2009) and then let the data “speak” about what features, according to the employer, boost quality (Lahey and Beasley, 2018). However, we feel that it is essential to incorporate some quality features beforehand that are believed to affect callback rates, with the goal to ensure that there is enough variation in applicant quality in order for this correction to be sufficiently powered. This is crucial since the Neumark (2012) correction requires significantly more power than the standard uncorrected analysis.

In this experiment, we made half of the applicants high-quality and half of them low-quality by assigning four of five quality elements to the high-quality applicants. So as not to take identifying variation away from detecting the effects of Indigenous status, we assign either all resumes within a set sent to an employer to be high or low quality, but the four randomly chosen quality elements can vary between resumes sent to the same employer. Like Neumark, Burn, and Button (forthcoming), we chose which quality elements to include based on what is commonly listed on actual resumes or in job applications. These five quality elements are fluency in Spanish as a second language, a more detailed cover letter (e.g., an additional two or so sentences on their cover letter that briefly summarizes their work experience), the lack of typos in the cover letter (that is, resumes without this quality feature have either a missing comma after the opening line, a missing period at the end of the first sentence, or a misspelled word somewhere on the cover letter), and two occupation-specific skills. All high-quality resumes randomly receive all but one of these skills. This allows for some variation to identify the effects of each quality feature separately.

For retail jobs, the occupation-specific skills are knowledge of programs used to monitor inventory (VendPOS, AmberPOS, and Lightspeed), the ability to learn new programs, and experience with Microsoft Office applications. For janitor, this is a certificate in using particular machines and a certification in janitorial and cleaning sciences. For security, this is CPR and First Aid and stating that they are licensed in their state. For server, this is CPR, First Aid, and experience with point-of-service (POS) software used in food service. For kitchen staff, this is CPR, First Aid, and a certificate or training in food safety. An example of some of these skills are shown in the resume examples later in this appendix, and additional resumes are available upon request.

Of course, not all added quality features will have a positive effect,[[7]](#footnote-7) and some other randomly added features (e.g., certain employers, template styles) might have positive or negative effects. Neumark (2012) shows the iterative process to select from among the resume features to be used in the Neumark (2012) correction. This mirrors the process outlined in Lahey and Beasley (2018) for letting the data “speak” about which features actually affect callback rates.

Online Appendix Table C1 – Heteroskedastic Probit Estimates

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Combined** | **Retail** | **Server** | **Kitchen** | **Security** | **Janitor** |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | Common quality features | All quality features | All quality features | All quality features | All quality features | All quality features |
| *A. Probit estimates*  |  |  |  |  |  |  |
| Indigenous (marginal) | 0.003(0.006) | 0.009(0.013) | 0.003(0.012) | -0.003 (0.011) | 0.014(0.021) | 0.002(0.014) |
| *B. Heteroskedastic probit estimates*  |  |  |  |  |  |  |
| Indigenous (marginal) | 0.001(0.006) | 0.009(0.013) | 0.004(0.011) | -0.006 (0.010) | 0.014(0.021) | 0.002(0.014) |
| Overidentification test: ratios of coefficients on quality features for Indigenous relative to white are equal (p-value, Wald test) | 0.993 | 1.000 | 1.000 | 0.999 | 0.693 | 0.992 |
| Standard deviation of unobservables, Indigenous/white | 0.911 | 1.003 | 1.037 | 0.858 | 1.015 | 1.047 |
| Test: homoscedastic vs. heteroskedastic probit (p-value, Wald test for equal variances) | 0.282 | 0.986 | 0.824 | 0.181 | 0.960 | 0.880 |
| Indigenous-level (marginal) | 0.024(0.021) | 0.008(0.036) | -0.005(0.041) | 0.030 (0.029) | 0.011(0.058) | -0.009(0.073) |
| Indigenous -variance (marginal) | -0.022(0.021) | -0.001(0.035) | 0.009(0.040) | -0.036 (0.027) | 0.003(0.059) | 0.011(0.074) |
| N  | 13,516 | 2,926 | 2,774 | 4,858 | 1,306 | 1,652 |

Notes: See Neumark (2012) and Neumark, Burn, and Button (forthcoming) for a discussion of this methodology. See also the notes in Table 6. Different from zero at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*). Regressions use the “Regular Controls” from Table 6. All higher-quality resumes randomly receive all but one of the following quality features: fluency in Spanish as a second language, a more detailed cover letter, the lack of typos in the cover letter, and two occupation-specific skills. The occupation-specific skills for retail included knowledge of programs used to monitor inventory (VendPOS, AmberPOS, and Lightspeed) and experience with Microsoft Office applications; janitor included a certificate in using particular machines and a certification in janitorial and cleaning sciences; security included CPR and First Aid and stating that they are licensed in their state; server included CPR and First Aid and experience with point-of-service (POS) software used in food service; kitchen staff included CPR and First Aid and a certificate or training in food safety.

**Online Appendix D: Additional Robustness Checks**

**Probit vs. Linear Probability Model**

 As noted, we originally committed to using a probit model in our pre-analysis plan. However, we became aware that it was more common to use a linear probability model due to issues with coefficients in probit models (Ai and Norton 2003; Greene 2010). Our main results (Table 6) are nearly identical regardless of if we use a linear probability model or a probit model (either with average marginal effects or marginal effects at the means.) We present these results in Online Appendix Table D1.

**Clustering**

In resume-correspondence studies, there are two levels of clustering. First, there is clustering on the resume. This occurs because we do not control for every detail on the resume or in the application, given all the randomized inputs into each resume. Resumes are also sent out more than once. Each day, a particular pair of resumes is sent out to all job openings in that city and occupation. For this reason, it is essential to cluster on the resume so as to not understate the standard errors. Second, there is clustering on the employer, who is likely to treat both applicants somewhat similarly given the particulars of their position and candidate search.

Dealing with these two possible levels of clustering is not straightforward. Our main results cluster our standard errors on the resume. The difficulty with clustering on the job, however, is that we cannot match all responses perfectly to job ads.[[8]](#footnote-8) However, for the pairs of applications that we can match to jobs, our standard errors are nearly identical regardless of if we cluster on the resume, job, or multi-way cluster on both. We present these results in Online Appendix Table D2.

**Estimates by Signal Type and Saliency of Signals**

In Online Appendix Tables D3 and D4, we re-estimate our main results in two different ways to deal with the issue that our Navajo names signal may not have been salient. In Online Appendix Table D3 we present in column (1) the main results for comparison from Table 6 column (2). In column (2) we re-code resumes with the Navajo last name signal as no longer Native American (*NA = 0*). In column (3) we instead create a separate control variable for resumes that have only the Navajo last name signal, such that *NA* identifies only those resumes with at least one other signal. The results are unchanged in all cases.

Online Appendix Table D4 presents the results by signal type from Table 10, but with the Navajo name signal re-coded as not being a signal. So, a resume with a Navajo name signal and a language signal, for example, is re-coded as only having a language signal. This re-coding also does not affect the results. Across both these tables, there is no evidence of our results changing when we drop or otherwise separately control for the Navajo last name signal.

**The “Heckman-Siegelman” Critique and the Neumark (2012) Correction**

 See Online Appendix C for a detailed discussion of this issue, with a model and full results.

**Do Callbacks Capture Hiring Discrimination?**

We coded two forms of employer responses: (1) callbacks, and (2) explicit interview offers only. The former is used as the default in many other resume correspondence studies. Callbacks include explicit interview offers but also more ambiguous positive responses (e.g., “I have reviewed your application and have some additional questions for you.”). Online Appendix Table D5 compares how our main results from Table 6 change when we use explicit interview offers instead of callbacks. Our results do not vary.

**Population and Occupation Weighting**

We attempted to apply for all eligible job openings that met our criteria in each city and occupation. Since our main estimates are unweighted, this means that we oversampled populous cities. What would be more realistic would be to weight the estimates by city so that they reflect the population distribution of Indigenous Peoples across these cities. Similarly, we can weight by the frequency of occupations according to the CPS data. This helps us balance the sample if we over- or under-sampled certain occupations. For example, some research assistants may have been more consistent about finding jobs to apply to or the proportions of job ads by occupation on the job website we use may not match the national distribution. This is indeed possible, although we expect the number of jobs that we applied to in each occupation to be highly correlated with the actual frequencies of those jobs. Neumark, Burn, Button, and Chehras (2018) grappled with this issue at around the same time as us, and we direct the reader there for a more detailed discussion about weighting.

Online Appendix Table D6 describes how we created population weights. We first used population counts for AIANs and NHPIs from Norris, Vines, and Hoeffel (2012) and Hixson, Hepler, and Kim (2012), respectively. We used two different population estimates: AIAN (NHPI) alone or AIAN (NHPI) alone or in combination (“in comb”). We constructed population weights by dividing the number of jobs applied to, by city, and by the AIAN or NHPI population in each city, and then normalizing such that a value of one meant no relative weight (neither up nor down) is applied to that city.[[9]](#footnote-9) Weights greater than (less than) one meant that our number of observations for that city was lower (higher) relative to the Indigenous population compared to other cities, and thus the observations for that city needed to be up-weighted (down-weighted). This table indicates that, as expected, we over-sampled Chicago and Houston, large cities with a small proportion of Indigenous Peoples, and under-sampled Honolulu, Anchorage, and other cities with a larger proportion of Indigenous Peoples.

Online Appendix Table D7 presents our construction of occupation weights. To construct these weights, we used all months of the 2015 Current Population Survey (CPS) to estimate the proportion of those aged 25 to 35 who were employed in each occupation. To match the narrower occupational coding in the CPS to our broader occupations (retail, kitchen, server, janitor, and security), we add up occupation counts for each CPS occupation that matched our broader occupations.[[10]](#footnote-10) Online Appendix Tables A3 and A4 present most of the occupation frequencies for these narrower occupations. These occupation weights suggest that relative to the nationally-representative employment estimates in the CPS, we oversampled server and security and under-sampled retail.

Online Appendix Table D8 presents our occupation-by-population weights. We calculated these by multiplying the occupation and population weights together. These weights have a high range, from 0.11 (Chicago, servers, using “in combination”) to 5.20 (Honolulu, retail, “in combination”).

Finally, in Online Appendix Table D9, we present our main results (replicating Table 6, column (2)) under different types of weighting (Indigenous population in the city, occupational popularity, and both). Our results are unchanged regardless of how we weight (or do not weight) the results.[[11]](#footnote-11)

**Robustness to the Proportion Hispanic in each Occupation and City.**

Related to the concern about whether jobs are “typed” to be more appropriate for certain racial groups is that typing could vary by city, especially by the size of the Hispanic population. Thoughtful discussions with Randall Akee and others made it clear that we need to explore if discrimination varies by how often Hispanics take certain jobs in our occupation and city combinations.

We re-analyzed our data, dropping some occupation-city-gender combinations where Hispanics outnumber whites, finding similar results (results are available upon request). While our analysis of occupations in Tables 2 and 3 showed that all our occupations are common for whites, this analysis used national data. We re-did this analysis to present the proportion of individuals, by sex, in each occupation and city who are white (defined as white only and non-Hispanic), AIAN (alone or in combination, independent of Hispanic ancestry), or Hispanic (independent of race).

This more detailed analysis shows that, while whites are common in all occupation-city-sex combinations, they are outnumbered by Hispanics in some cases. This is especially the case in kitchen staff and janitor occupations, where Hispanics outnumber whites everywhere except in Oklahoma City (women and men) and Chicago (women only). This is also especially the case for Los Angeles, where Hispanics outnumber whites in all cases. Outside of kitchen staff, janitor, and Los Angeles, Hispanics outnumber whites in only a few cases: retail sales for women in Albuquerque and Houston and servers for men in Albuquerque.

To investigate whether our results are robust to the proportion of Hispanics in each occupation by city, we re-estimated the results in Tables 6 to 9 dropping any occupation-city-gender combination where Hispanics outnumber whites. These results, available upon request, do not show any different results. We also re-estimate the regression in Table 6, column (2) (based off Equation [1]), but we add an interaction between the Native American (*NA*) indicator variable and a variable equal to the ratio of whites to Hispanics in each occupation-city-gender cell. The coefficient on this interaction variable is not statistically significant and is not of a meaningful magnitude (it is 0.005, with a standard error of 0.005 in the preferred specification). Thus, it does not appear that our discrimination estimates vary with the proportion of people in the occupation who are Hispanic.

Online Appendix Table D1 – Main Results Under Linear Probability and Probit Models

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  | Probit, Marginal Effects at Means (1) | Probit, Average Marginal Effects(2) | Linear Probability Model(3) |
| Native American | -0.004 | -0.004 | -0.004 |
|  | (0.010) | (0.009) | (0.009) |
| … x Reservation | 0.000 | 0.000 | -0.000 |
|  | (0.012) | (0.012) | (0.012) |
| … x Reservation x Reservation Job | 0.008 | 0.008 | 0.006 |
|  | (0.017) | (0.016) | (0.017) |
| Alaska Native | 0.004 | 0.004 | 0.005 |
|  | (0.030) | (0.030) | (0.035) |
| Native Hawaiian | -0.004 | -0.004 | -0.003 |
|  | (0.012) | (0.012) | (0.013) |
| Rural | -0.016 | -0.016 | -0.016 |
|  | (0.014) | (0.014) | (0.013) |
| … x Rural Job | 0.002(0.020) | 0.002(0.020) | 0.002(0.018) |
| Callback Rate for White: | 19.8% |

Notes: N = 13,516. See the notes to Table 6. Column (3) presents the main results from Table 6 (Column (2).)

Online Appendix Table D2 – Robustness of the Estimates in Table 6 to Alternative Standard Error Clustering

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  | Cluster on Resume(1) | Cluster on Job(2) | Multi-way Cluster, Resume and Job(3) |
| Native American | -0.002(0.006) | -0.002(0.008) | -0.002(0.008) |
| … x Reservation | -0.003(0.009) | -0.003(0.009) | -0.003(0.009) |
| … x Reservation x Reservation Job | -0.005(0.012) | -0.005(0.012) | -0.005(0.012) |
| Alaska Native | -0.004(0.014) | -0.004(0.024) | -0.004(0.024) |
| Native Hawaiian | -0.007(0.007) | -0.007(0.012) | -0.007(0.012) |
| Rural | -0.019(0.010)  | -0.019(0.010)  | -0.019(0.010)  |
| … x Rural Job | 0.004(0.014) | 0.004(0.014) | 0.004(0.014) |
| Callback Rate for White: | 19.8% |

Notes: See the notes to Table 6. N=11,759 since we dropped 1,757 applications that could not be matched to a specific job.

Online Appendix Table D3 – Replicating Table 6, Column (2), Ignoring Navajo Last Name Signals

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  | All Signals(1) | Navajo Last Name Signals Dropped(2) | Navajo Name Signal as a Control(3) |
| Native American | -0.004(0.009) | -0.003(0.009) | -0.004(0.009) |
| … x Reservation | -0.000(0.012) | -0.001(0.012) | 0.000(0.012) |
| … x Reservation x Reservation Job | 0.006(0.016) | 0.006(0.016) | 0.006(0.016) |
| Alaska Native | 0.005(0.035) | 0.005(0.035) | 0.005(0.035) |
| Native Hawaiian | -0.003(0.013) | -0.003(0.013) | -0.003(0.013) |
| Rural | -0.016(0.013) | -0.015(0.013) | -0.016(0.013) |
| … x Rural Job | 0.002(0.018) | 0.002(0.018) | 0.002(0.018) |
| Navajo Last Name Signal | … | … | -0.007(0.026) |
| Callback Rate for White: | 19.8% |

Notes: N=13,516. Column (1) is Column (2) from Table 6. For column (2), any Indigenous resume with the only signal being a Navajo last name signal was recoded as being a non-Indigenous resume. For column (3), Navajo last name signals were added as a separate control variable to the regression in Column (1).

Online Appendix Table D4 – Replicating Table 10, Ignoring Navajo Last Name Signals

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Default(1) | N | Ignore Navajo Name(2) | N |
| Indigenous |  |  |  |  |
| … x Volunteer Only | -0.006 | 3,029 | -0.007 | 3,118 |
|  | (0.010) |  | (0.010) |  |
| … x Language Only | 0.006 | 1,723 | 0.006 | 1,801 |
|  | (0.010) |  | (0.010) |  |
| … x First Name (Native Hawaiian) Only | -0.017 | 475 | -0.016 | 475 |
|  | (0.018) |  | (0.018) |  |
| … x Last Name (Navajo) Only | -0.007 | 222 | N/A | 0 |
|  | (0.026) |  |  |
| … x Two Signals | 0.003 | 823 | 0.013 | 802 |
|  | (0.015) |  | (0.016) |  |
| … x Three Signals | 0.038 | 92 | 0.028 | 65 |
|  | (0.037) |  | (0.044) |  |
| Boys & Girls Club (Volunteer Control) | -0.007 | 3,298 | -0.006 | 3,298 |
|  | (0.009) |  | (0.009) |  |
| Food Bank (Volunteer Control) | -0.006 | 3,460 | -0.005 | 3,460 |
|  | (0.009) |  | (0.009) |  |
| Irish Gaelic (Language Control) | -0.017 | 831 | -0.016 | 831 |
|  | (0.013) |  | (0.013) |  |
| Callback Rate for White: | 19.8% |

Notes: N=13,516. See the notes to Tables 6 and 10. Regressions use the “Regular Controls” from Table 6 (column (2)). Column (1) presents the results from Table 10 for comparison. Column (2) repeats this analysis, pretending that there is no Navajo last name signal. This re-codes some resume with a last name signal and one other signal as just having that one other signal, and re-codes resumes with the last name signal, volunteer signal, and language signal as “Two Signals.” Different from zero at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*).

Online Appendix Table D5 – Estimates from Tables 6, 8, 9, and 10, Comparing Results Using Interview Rates Instead of Callback Rates

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  | Callback(1) | Interview(2) |
| Panel (a) (Corresponding to Table 6) |
| Native American | -0.004 (0.009) | -0.002 (0.008) |
| … x Reservation | -0.000 (0.012) | 0.007 (0.010) |
| … x Reservation x Reservation Job | 0.006 (0.016) | 0.001 (0.014) |
| Alaska Native | 0.005 (0.035) | 0.010 (0.030) |
| Native Hawaiian | -0.003 (0.013) | -0.001 (0.011) |
| Panel (b) (Corresponding to Table 8) |
| Indigenous |  |  |
| … x Retail | 0.006 (0.017) | 0.013 (0.015) |
| … x Server | -0.002 (0.016) | 0.008 (0.015) |
| … x Kitchen | -0.007 (0.014) | 0.007 (0.013) |
| … x Janitor | 0.003 (0.021) | 0.009 (0.018) |
| … x Security | 0.011 (0.022) | -0.005 (0.018) |
| … x Female x Retail | -0.003 (0.025) | -0.018 (0.022) |
| … x Female x Server | 0.002 (0.024) | -0.007 (0.022) |
| … x Female x Kitchen | 0.001 (0.021) | -0.011 (0.018) |
| … x Female x Janitor | -0.008 (0.031) | -0.023 (0.024) |
| Panel (c) (Corresponding to Table 9)  |
| Indigenous |  |  |
| … x Phoenix | 0.041 (0.023) | 0.032 (0.019) |
| … x Chicago | -0.009 (0.018) | -0.013 (0.014) |
| … x Los Angeles (NA) | -0.001 (0.014) | 0.006 (0.011) |
| … x Los Angeles (NH) | -0.014 (0.019) | -0.016 (0.015) |
| … x Alaska (AN) | 0.005 (0.035) | 0.010 (0.030) |
| … x Honolulu (NH) | 0.002 (0.019) | 0.005 (0.015) |
| … x Billings | 0.012 (0.062) | -0.024 (0.054) |
| … x Albuquerque | -0.037 (0.029) | -0.036 (0.027) |
| … x New York City | -0.011 (0.011) | -0.002 (0.010) |
| … x Oklahoma City | 0.018 (0.033) | 0.001 (0.028) |
| … x Sioux Falls | -0.004 (0.078) | 0.023 (0.073) |
| … x Houston | -0.002 (0.024) | 0.005 (0.020) |
| Panel (d) (Corresponding to Table 10) |
| Indigenous |  |  |
| … x Volunteer | -0.006 (0.010) | 0.000 (0.008) |
| … x Language | 0.006 (0.010) | 0.009 (0.009) |
| … x First Name (Native Hawaiian) | -0.017 (0.018) | -0.023 (0.015) |
| … x Last Name (Navajo) | -0.007 (0.026) | -0.011 (0.025) |
| Two Signals | 0.003 (0.015) | 0.004 (0.013) |
| Three Signals | 0.038 (0.037) | 0.033 (0.034) |

Notes: N=13,516. See the notes to Tables 6, 8, 9, and 10. Column (1) repeats the results from these tables. Different from zero at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*).

Online Appendix Table D6 – Construction of Population Regression Weights

|  |
| --- |
| Panel (a): Cities with Native American and Alaska Native Applicants |
|  | Total | AIAN alone or in combination | AIAN alone | Jobs Applied | Population Weight |
| City | Population | % | Count | % | Count | In Comb. | Alone |
| New York | 8,175,133 | 1.4% | 111,749 | 0.7% | 57,512 | 2,756 | 0.85 | 0.85 |
| Los Angeles | 3,792,621 | 1.4% | 54,236 | 0.7% | 28,215 | 1,866 | 0.61 | 0.62 |
| Phoenix | 1,445,632 | 3.0% | 43,724 | 2.2% | 32,366 | 1,530 | 0.60 | 0.86 |
| Oklahoma City | 579,999 | 6.3% | 36,572 | 3.5% | 20,533 | 614 | 1.25 | 1.36 |
| Anchorage | 291,826 | 12.4% | 36,062 | 7.9% | 23,130 | 564 | 1.34 | 1.67 |
| Albuquerque | 545,852 | 6.0% | 32,571 | 4.6% | 25,087 | 700 | 0.97 | 1.46 |
| Chicago | 2,695,598 | 1.0% | 26,933 | 0.5% | 13,337 | 1,466 | 0.38 | 0.37 |
| Houston | 2,099,451 | 1.2% | 25,521 | 0.7% | 14,997 | 1,106 | 0.48 | 0.55 |
| Sioux Falls | 153,888 | 3.6% | 5,540 | 2.7% | 4,155 | 154 | 0.75 | 1.10 |
| Billings | 104,170 | 6.0% | 6,251 | 4.4% | 4,584 | 212 | 0.62 | 0.88 |
| National | 308,745,538 | 1.7% | 5,220,579 | 0.9% | 2,932,248 | 10,968 |  |   |
| Panel (b): Cities with Native Hawaiian Applicants |
|  | Total | NHPI alone or in combination | NHPI alone |   | Population Weight |
| City | Population | % | Count | % | Count | Jobs Applied | In Comb. | Alone |
| Honolulu | 953,207 | 24.5% | 233,637 | 9.5% | 90,878 | 2,020 | 2.42 | 1.84 |
| Los Angeles | 3,792,621 | 0.6% | 20,924 | 0.3% | 10,079 | 508 | 0.86 | 0.81 |
| National | 308,745,538 | 0.4% | 1,225,195 | 0.2% | 540,013 | 2,290 |   |   |

Notes: We split Los Angeles into two samples since we sent either Native American/white pairs (NA) or Native Hawaiian/white pairs (NH) to each job opening. We construct population weights using 2010 Census population counts for AIANs and NHPIs from Norris, Vines, and Hoeffel (2012) and Hixson, Hepler, and Kim (2012), respectively. The percents for Los Angeles in Panel (b) are based on county-level rather than city-level data, from Hixson, Hepler, and Kim (2012). Weights are constructed by dividing the number of observations, by city, by the Indigenous population in each city, and then normalizing such that a value of one means no weight is applied to that city. Weights greater than (less than) one mean that our number of observations for that city is lower (higher) relative to the Indigenous population, compared to for other cities, and thus the observations for that city need to be up-weighted (down-weighted.)

Online Appendix Table D7 – Construction of Occupation Regression Weights

|  |  |  |  |
| --- | --- | --- | --- |
|  | Jobs Applied(1) | Employment Share(2) | Occupation Weight(3) |
| Retail | 2,926 | 3.81% | 2.15 |
| Kitchen | 4,858 | 2.18% | 1.23 |
| Server | 2,774 | 0.49% | 0.28 |
| Janitor | 1,652 | 1.84% | 1.04 |
| Security | 1,306 | 0.53% | 0.30 |

Notes: See the notes to Online Appendix Table D6. Estimates from Column (2) are the proportion of those aged 25 to 35 who are employed and report that occupation (instead of another occupation), using all months of the 2015 Current Population Survey.

Online Appendix Table D8 – Construction of Occupation-by-Population Regression Weights

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Occupation (weight) | Retail (2.15) | Kitchen (1.23) | Server (0.28) | Janitor (1.04) | Security (0.30) |
| City | In Comb.(3) | Alone(4) | In Comb.(5) | Alone(6) | In Comb.(7) | Alone(8) | In Comb.(9) | Alone(10) | In Comb.(11) | Alone(12) |
| New York | 1.82 | 1.55 | 1.04 | 0.89 | 0.24 | 0.20 | 0.88 | 0.75 | 0.25 | 0.22 |
| Los Angeles (NA) | 1.31 | 0.81 | 0.75 | 0.46 | 0.17 | 0.10 | 0.63 | 0.39 | 0.18 | 0.11 |
| Phoenix | 1.29 | 1.11 | 0.74 | 0.64 | 0.17 | 0.14 | 0.62 | 0.54 | 0.18 | 0.15 |
| Oklahoma City | 2.68 | 3.66 | 1.53 | 2.09 | 0.35 | 0.47 | 1.30 | 1.77 | 0.37 | 0.51 |
| Anchorage | 2.88 | 4.82 | 1.65 | 2.75 | 0.37 | 0.62 | 1.39 | 2.33 | 0.40 | 0.67 |
| Albuquerque | 2.09 | 3.06 | 1.20 | 1.75 | 0.27 | 0.40 | 1.01 | 1.48 | 0.29 | 0.43 |
| Chicago | 0.83 | 0.31 | 0.47 | 0.18 | 0.11 | 0.04 | 0.40 | 0.15 | 0.12 | 0.04 |
| Houston | 1.04 | 0.57 | 0.59 | 0.33 | 0.13 | 0.07 | 0.50 | 0.28 | 0.14 | 0.08 |
| Sioux Falls | 1.62 | 1.78 | 0.93 | 1.02 | 0.21 | 0.23 | 0.78 | 0.86 | 0.23 | 0.25 |
| Billings | 1.33 | 1.17 | 0.76 | 0.67 | 0.17 | 0.15 | 0.64 | 0.57 | 0.18 | 0.16 |
| Honolulu | 5.20 | 9.56 | 2.98 | 5.47 | 0.67 | 1.24 | 2.52 | 4.62 | 0.72 | 1.33 |
| Los Angeles (NH) | 1.85 | 1.50 | 1.06 | 0.86 | 0.24 | 0.19 | 0.90 | 0.73 | 0.26 | 0.21 |

Notes: See the notes to Online Appendix Tables D6 and D7. The combined occupation and population weights are created by multiplying the occupation and population weights together.

Online Appendix Table D9 – Robustness of the Estimates in Table 6 to Different Weights

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  | Un-Weighted (1) | Pop. Weights (Alone)(2) | Pop. Weights(+ in Comb.)(3) | Occ. Weights(4) | Occ. + Pop. Weights (Alone)(5) | Occ. + Pop. Weights(+ in Comb.)(6) |
| Native American | -0.002(0.006) | -0.005(0.011) | -0.004(0.010) | -0.006(0.011) | 0.015(0.023) | 0.009(0.018) |
| … x Reservation | -0.003(0.009) | -0.000(0.013) | -0.003(0.013) | 0.004(0.014) | -0.050\*(0.030) | -0.039\*(0.023) |
| … x Reservation x Reservation Job | -0.005(0.012) | 0.003(0.018) | 0.005(0.017) | 0.007(0.018) | 0.036(0.033) | 0.031(0.028) |
| Alaska Native | -0.004(0.014) | 0.005(0.035) | 0.005(0.035) | -0.005(0.040) | -0.013(0.041) | -0.013(0.041) |
| Native Hawaiian | -0.007(0.007) | -0.001(0.014) | 0.000(0.014) | -0.002(0.016) | -0.006(0.015) | -0.008(0.014) |
| Rural | -0.019(0.010)  | -0.021(0.014) | -0.019(0.013) | -0.019(0.014) | -0.026(0.033) | -0.020(0.026) |
| … x Rural Job | 0.004(0.014) | 0.007(0.021) | 0.011(0.020) | 0.019(0.014) | 0.045(0.047) | 0.026(0.036) |
| Callback Rate for White: | 19.8% |

Notes: See the notes to Table 6. N=13,516. Different from zero at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*).

Online Appendix Table D10 – Demographics of Each Occupational Grouping, by City and Gender

|  |  |  |
| --- | --- | --- |
|  | % of Men in the Occupation that are: | % of Women in the Occupation that are: |
|  | White Only | Hispanic | AIAN | White Only | Hispanic | AIAN |
|  | Retail |
| Albuquerque | 48.8 | 37.2 | 8.3 | 34.6 | **43.8** | 13.8 |
| Chicago | 64.5 | 14.8 | 0.5 | 51.2 | 22.7 | 0.9 |
| Houston | 37.7 | 33.6 | 1.9 | 31.6 | **39.0** | 0.9 |
| Los Angeles | 30.2 | **47.5** | 1.8 | 25.3 | **52.4** | 3.9 |
| New York | 46.5 | 21.2 | 0.7 | 42.1 | 25.5 | 0.5 |
| Oklahoma City | 74.4 | 7.3 | 5.9 | 65.8 | 7.9 | 14.4 |
| Phoenix | 67.5 | 24.0 | 0.6 | 58.9 | 28.3 | 2.1 |
|  | Server |
| Albuquerque | 39.6 | **44.6** | 10.0 | 45.5 | 38.4 | 7.2 |
| Chicago | 59.9 | 28.4 | 0.7 | 64.0 | 20.0 | 0.5 |
| Houston | 39.8 | 35.6 | 1.7 | 40.8 | 42.1 | 0.6 |
| Los Angeles | 31.4 | **46.7** | 2.1 | 35.2 | **36.2** | 1.8 |
| New York | 41.8 | 25.1 | 1.5 | 41.8 | 25.1 | 1.5 |
| Oklahoma City | 70.8 | 11.2 | 1.7 | 61.6 | 16.0 | 7.1 |
| Phoenix | 54.2 | 35.7 | 2.4 | 64.8 | 22.8 | 4.2 |
|  | Kitchen |
| Albuquerque | 24.8 | **55.9** | 14.4 | 21.6 | **59.6** | 10.3 |
| Chicago | 25.8 | **54.8** | 1.2 | 40.9 | 38.2 | 0.7 |
| Houston | 14.1 | **57.3** | 4.9 | 14.7 | **66.8** | 1.2 |
| Los Angeles | 12.8 | **71.7** | 1.6 | 13.9 | **68.8** | 2.1 |
| New York | 22.1 | **51.5** | 2.1 | 33.8 | **34.1** | 2.9 |
| Oklahoma City | 50.5 | 19.5 | 10.7 | 55.7 | 21.4 | 8.8 |
| Phoenix | 37.6 | **49.0** | 2.2 | 39.9 | **45.8** | 2.3 |
|  | Janitor |
| Albuquerque | 20.0 | **69.5** | 9.7 | 20.5 | **76.0** | 3.5 |
| Chicago | 37.8 | **45.3** | 0.7 | 45.5 | 32.9 | 1.9 |
| Houston | 12.7 | **69.5** | 1.3 | 9.7 | **72.8** | 3.9 |
| Los Angeles | 8.1 | **81.6** | 3.0 | 5.1 | **84.5** | 2.9 |
| New York | 29.9 | **49.1** | 1.4 | 24.6 | **59.6** | 1.0 |
| Oklahoma City | 50.7 | 23.0 | 13.3 | 54.9 | 26.9 | 9.0 |
| Phoenix | 22.9 | **69.3** | 2.8 | 15.6 | **67.8** | 8.0 |
|  | Security |
| Albuquerque | 45.7 | 41.1 | 11.4 | N/A | N/A | N/A |
| Chicago | 38.8 | 18.1 | 1.0 | N/A | N/A | N/A |
| Houston | 33.4 | 17.6 | 4.5 | N/A | N/A | N/A |
| Los Angeles | 22.9 | **41.3** | 2.9 | N/A | N/A | N/A |
| New York | 25.1 | 20.9 | 2.3 | N/A | N/A | N/A |
| Oklahoma City | 59.2 | 8.2 | 12.1 | N/A | N/A | N/A |
| Phoenix | 62.7 | 17.4 | 7.3 | N/A | N/A | N/A |

Notes: Bolded number indicate when the % Hispanic > % white. Calculated from Current Population Survey data from IPUMS-CPS (Flood et al., 2015). White only includes those who only report white as a race and do not report being Hispanic. Hispanic includes those who reporting being Hispanic, regardless of race. AIAN includes those who report being AIAN alone or in part, regardless of if they report being Hispanic or report another race as well. The occupational groupings correspond to the following occupational codes: retail sales (retail salespersons; cashiers; counter and rental clerks; sales representatives, services, all other; and sales and related workers, all others, in the Census occupational classification), kitchen staff (cooks; food preparation workers; dishwashers; combined food preparation and serving workers, including fast food; counter attendants, cafeteria, food concession, and coffee shops; food servers, non-restaurant; and dining room and cafeteria attendants and bartender helpers), server (waiters and waitresses; bartenders; and hosts and hostesses, restaurant, lounge, and coffee shop), janitors (janitors and building cleaners and grounds maintenance workers), and security guards (security guards and gaming surveillance officers).

Online Appendix Table D11 – Comparison of the Timing of Our Study with Others in the US

|  |  |  |  |
| --- | --- | --- | --- |
| Study | Timing | Unemployment Rates During Timing | Percentile Range |
| *This Paper* | March to December 2017 | 4.1-4.5 | 16th-24th |
| Agan and Starr (2018) | Jan, Feb, May, June 2015 | 5.3-5.7 | 42nd-55th |
| Ameri et al. (2015) | June to August 2013 | 7.2-7.5 | 80th-85th |
| Bailey et al. (2013) | March to May 2010 | 9.6-9.9 | **97th-99th** |
| Bendick et al. (1997) | March to June 1993 | 7.0-7.1 | 77th-79th |
| Bendick et al. 1999 | March 1995 to March 1996 | 5.4-5.8 | 44th-59th |
| Bertrand and Mullainathan (2004) | July 2001 to May 2002 | 4.6-5.8 | 25th-59th |
| Darolia et al. (2016) | May 2013 to May 2014 | 6.3-7.5 | 69th-86th |
| Decker et al. (2015) | June to August 2011, June to August 2012\* | 8.1-9.1 | **90th-96th** |
| Farber et al. (2017) | March to May 2012, July to September 2012 | 7.8-8.2 | **89th-91st** |
| Gaddis (2015) | March to August 2011 | 9.0-9.1 | **95th-96th** |
| Hipes et al. (2016) | June 2011 to May 2012 | 8.2-9.1 | **91st-96th** |
| Jacquement and Yannelis (2012) | August 2009 to February 2010 | 9.6-10.0 | **97th-99th** |
| Kleykamp (2009) | Year of 2007\* | 4.4-5.0 | 21st-35th |
| Lahey (2008) | February 2002 to February 2003 | 5.7-6.0 | 55th-65th |
| Mishel (2016) | March, April, May 2014\* | 6.3-6.7 | 69th-74th |
| Neumark et al. (forthcoming) | January to June 2015 | 5.3-5.7 | 41st-56th |
| Nunley et al. (2015) | January to July 2013 | 7.3-8.0 | **82nd-91st** |
| Pager (2003) | June to December 2001 | 4.5-5.7 | 23rd-56th |
| Tilcsik (2011) | Year of 2005\* | 4.9-5.4 | 30th-45th |
| Widner and Chicoine (2011) | February and March 2008\* | 4.9-5.1 | 30th-37th |
| Wright et al. (2013) | July to October 2009 | 9.5-10.0 | **96th-99th** |

Notes: This table includes resume or audit studies listed in the tables in Neumark (2018) and Baert (2018) that were done in the United States. Unemployment rates are national and seasonally adjusted and come from series LNS14000000 (accessed November 25, 2018 from <https://data.bls.gov/timeseries/LNS14000000>) using January 1948 to October 2018. The percentile rank is calculated as the percentile for the unemployment range, given all unemployment rate estimates since 1948. Bolding of the percentile rank indicates studies where the percentile range includes at least the 90th percentile. For those timing allocations with a \*, we estimated the timings as follows, based on vague descriptions from the paper: Decker et al. (2015) “two 16-week periods during the summer of 2011 and during the same timeframe in 2012”, Kleykamp (2009) “six-month period” (no year specified), Mishel (2016) “spring of 2014”, Tilcsik (2011) “six-month period in 2005”, Widner and Chicoine (2011) “In February 2008, we began sending…”

Online Appendix Table D12 – Discrimination Estimates by City with Reservation Signal Interactions

|  |  |  |
| --- | --- | --- |
|  |  |  |
| Indigenous x Reservation | Estimate | N Applicants |
| … x Albuquerque | 0.0116(0.0397) | 163 |
| … x Billings | 0.0457(0.0897) | 45 |
| … x Chicago | 0.0166(0.0251) | 290 |
| … x Houston | -0.0026(0.0359) | 276 |
| … x Los Angeles (Native Am.) | -0.0224(0.0214) | 423 |
| … x New York | -0.0099(0.0149) | 588 |
| … x Oklahoma City | -0.0693(0.0471) | 177 |
| … x Phoenix | 0.0238(0.0335) | 385 |
| … x Sioux Falls | 0.0079(0.1190) | 32 |

Notes: N=13,516. See the notes to Table 6. Regressions use the “Regular Controls” from Table 6. Different from zero at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*).

**Online Appendix E: Additional Details and Results from the Resume Survey**

We fielded two surveys on Amazon Mechanical Turk to test the saliency of our signals of Indigenous status. The first survey (“resume survey”) was similar to Kroft, Notowidigdo, and Lange (2013), where we asked individuals what they remember about applicants after reading our resumes. We present the questions from this survey at the end of this appendix.

**More Details on the Resume Survey**

First, we asked surveyed individuals to read one of the resumes from our study and consider the candidate for a job position in the relevant occupation. Specifically, the survey prompted the subjects with the following right above the resume that appeared on screen: “Suppose you were a hiring manager in a firm who is hiring for an entry-level (retail/cook/server/janitor/security guard) position. Please spend up to a minute reading the resume.”

The specific resumes we tested had the following signals of Indigenous status (or no signal):[[12]](#footnote-12)

1. Language signal only (N = 323)
2. Volunteer signal only (N = 173)
3. Volunteer + language (N = 170)
4. Navajo last names only (N = 281; Begay, Tsosie, Benally, or Yazzie)
5. Navajo last names + language (N = 255)
6. Navajo last names + volunteer (N = 176)
7. Navajo last names + language + volunteer (N = 161)
8. Hawaiian first names (N = 201; Keoni, Kekoa, Ikaika, or Maile)
9. White (N = 205; no signals, three versions)

We then asked the subjects to recall or guess the socioeconomic and demographic characteristics of the applicant to see what was detected and remembered from the resume (see below for the entire list of questions). We asked individuals what they thought about the job applicant’s race or ethnicity, likelihood of being born in the US, age, and gender. We also asked individuals to recall aspects featured on the resume, such as employment status, duration of the last job, if they spoke a second language spoken, and their highest educational attainment. We asked these additional questions to determine how often these aspects were detected and recalled, compared to our signals of Indigenous status.

**Resume Survey Questions**

1. What is the race or ethnicity of this applicant?
2. How likely is it that this person was born in the US?
3. How old, in years, do you think the applicant is? Please enter a number (e.g., 35)
4. What’s the gender of the applicant?
5. Was the applicant currently employed?
6. How long, in years, did the applicant hold their last job? Please enter as a number (e.g., 2.5)
7. Does the applicant speak a second language?
8. If you answered yes to Q7, which language is it?
9. What is the highest degree this applicant earned?
10. Please guess the total combined family income for the applicant’s household for the past 12 months. This should include income (before taxes) from all sources, wages, rent from properties, social security, disability and/or veteran’s benefits, unemployment benefits, workman’s compensation, help from relatives (including child payments and alimony), and so on.
11. Do you think that the applicant grew up in a rural, suburban, or urban environment?
12. What is your State of residence?
13. What is your age?
14. Which category(s) best describe(s) your race?
15. Are you Spanish, Hispanic, or Latino/Latina?
16. What is the highest degree or level of school you have completed? If currently enrolled, highest degree received.
17. What is your current employment status?
18. What is your gender?

**More Detailed Resume Survey Results**

Online Appendix Table E1 – Responses to “What is the race or ethnicity of this applicant?” from the Resume Survey, Full Sample

|  |  |
| --- | --- |
| Resume Type | Distribution of Responses (by Resume Type) |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| No Signals (White) | x |  |  |  |  |  |  |  |  |  |  |
| Native HawaiianFirst Name |  | x |  |  |  |  |  |  |  |  |  |
| Navajo Last Name |  |  | x |  |  | x | x |  | x |  |  |
| Language (Navajo) |  |  |  | x |  | x |  | x | x |  |  |
| Volunteer(Native American) |  |  |  |  | x |  | x | x | x |  |  |
| Language (Hawaiian) |  |  |  |  |  |  |  |  |  | x |  |
| Volunteer + Language(Hawaiian) |  |  |  |  |  |  |  |  |  |  | x |
| Response |  |  |  |  |  |  |  |  |  |  |  |
| White | **86.8%** | 35.8% | 58.9% | 46.8% | 32.2% | 17.0% | 23.9% | 21.8% | 20.5% | 10.0% | 20.1% |
| American Indian orAlaska Native | 1.5% | 1.5% | **18.8%** | **32.4%** | **37.2%** | **74.2%** | **58.0%** | **59.4%** | **62.1%** | 0% | 0% |
| Native Hawaiian orPacific Islander | 0% | **26.4%** | 2.1% | 14.5% | 15.8% | 3.8% | 4.0% | 12.9% | 6.8% | **82.0%** | **75.0%** |
| Hispanic | 1.5% | 6.5% | 8.5% | 2.3% | 4.3% | 2.1% | 5.1% | 1.2% | 3.7% | 0% | 4.2% |
| Black | 4.4% | 19.9% | 4.6% | 2.3% | 3.4% | 1.7% | 2.8% | 0.6% | 3.1% | 2.0% | 0% |
| Asian | 0% | 1.5% | 1.1% | 0% | 0.9% | 0% | 1.1% | 1.2% | 0% | 2.0% | 0% |
| Other | 5.9% | 8.5% | 6.0% | 1.7% | 6.2% | 1.3% | 5.1% | 2.9% | 3.7% | 4.0% | 0% |
| N | 205 | 201 | 282 | 173 | 323 | 236 | 176 | 170 | 161 | 50 | 24 |

Notes: The sample includes both a national sample (no restriction based on state of residence) and an oversample of Arizona and New Mexico. Estimates are bolded to highlight the race that is intended to be signaled in each case. Row totals are non-exclusive, with values in the lower half of the table being nested within those values from the upper half of the table.

Online Appendix Table E2 – Responses to “What is the race or ethnicity of this applicant?” from the Resume Survey, Arizona and New Mexico Only

|  |  |
| --- | --- |
| Resume Type | Distribution of Responses (by Resume Type) |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Navajo Last Name | x |   |   | x | x |   | x |
| Language (Navajo) |   | x |   | x |   | x | x |
| Volunteer (Native American) |   |   | x |   | x | x | x |
| Response |  |  |  |  |  |  |  |
| White |  23.6% |  0% |  17.1% |  17.5% |  21.1% |  16.9% |  18.0% |
| American Indian or Alaska Native | **58.3%** | **71.1%** | **73.2%** | **76.7%** | **70.7%** | **78.3%** | **68.5%** |
| Native Hawaiian or Pacific Islander | 5.5% |  3.6% |  4.9% |  2.9% |  3.3% |  2.4% |  6.3% |
| Hispanic |   4.7% |   2.4% |  3.7% |  1.9% |  1.6% |  2.4% |  5.4% |
| Black |  0.8% |  0% |  1.2% |  0% |  0% |  0% |  0% |
| Other |  7.1% |  22.9% |  0% |  1.0% |  3.3% |  0% |  1.8% |
| N | 127 | 83 | 82 | 103 | 123 | 83 | 111 |

Notes: See the notes to Online Appendix Table F1. Results include only the oversample of Arizona and New Mexico. Row totals are non-exclusive, with values in the lower half of the table being nested within those values from the upper half of the table.

**Online Appendix F: Additional Details and Results from the Names Survey**

In addition to fielding the resume survey on Amazon Mechanical Turk, we also fielded a second survey (“names survey”), which was a simpler version of the resume survey. It showed individuals one of the full names from our study and asked them questions about their perceptions of that name, most importantly the perceived race. This allowed us to focus more data collection on the saliency of our name signals. Below we list all the questions from this survey and summarize the results from questions about race and national original in more depth.

**Names Survey Questions**

1. Consider the name [e.g., Emily Adams]. What comes to mind when you think of a person with this name? What characteristics do you think this person might have?
2. What race or ethnicity do you associate with the name [e.g., Emily Adams]? Choose one answer.
	1. American Indian or Alaska Native
	2. Asian
	3. Black or African American
	4. Hispanic/Latino(a)
	5. Native Hawaiian or Pacific Islander
	6. Other
	7. White
3. How confident are you in your answer to Question 2?
4. How likely do you think it is that [e.g., Emily Adams] was born and raised in the United States?
	1. Extremely likely
	2. Somewhat likely
	3. Neither likely nor unlikely
	4. Somewhat unlikely
	5. Extremely unlikely
5. Consider the name [e.g., Daniel Begay]. What comes to mind when you think of a person with this name? What characteristics do you think this person might have?
6. What race or ethnicity do you associate with the name [e.g., Daniel Begay]? Choose one answer.
	1. American Indian or Alaska Native
	2. Asian
	3. Black or African American
	4. Hispanic/Latino(a)
	5. Native Hawaiian or Pacific Islander
	6. Other
	7. White
7. How confident are you in your answer to Question 6?
8. How likely do you think it is that [e.g., Daniel Begay] was born and raised in the United States?
	1. Extremely likely
	2. Somewhat likely
	3. Neither likely nor unlikely
	4. Somewhat unlikely
	5. Extremely unlikely
9. What is your current age?
10. What is your race? (Mark one or more)
11. Are you Spanish, Hispanic, or Latino/a?
12. Which best describes your gender?
13. What is the highest level of education you've completed?
14. Which best describes your annual household income before taxes in 2016?

**More Detailed Name Survey Results**

Online Appendix Table F1 presents a summary of the survey results for what race individuals think those with white names and Navajo last names are in terms of race. Unsurprisingly, the white names are almost always perceived as white, regardless of which sample is used (92.8% white in the Arizona and New Mexico sample, 91.0% white in the national sample). Perceptions of the Navajo names differ geographically and by the specific name used. The signal ranges from moderately salient (52.4% AIAN, Daniel Begay) to not salient (5.4% AIAN, Sarah Benally) in the Arizona and New Mexico sample, with the average perception across all four Navajo names being 47.5% white and 27.8% AIAN. For the national sample, this was 60.2% white and 9.4% AIAN. Thus, the last name signal of Navajo status was weak, especially in the national sample. These results were similar in the resume survey for resumes where only Navajo last name signals were used.

Online Appendix Table F1 – Racial Perceptions from the Names Survey for White and Navajo Names

|  |  |
| --- | --- |
| Name | Sample |
| AZ + NM (N) | National (N) |
| Zachary White | 92.1% White, 0.0% AIAN (36) | 90.8% White, 0.7% AIAN (100) |
| Emily Adams | 100% White, 0.0% AIAN (42) | 97.1% White, 0.0% AIAN (104) |
| Benjamin Miller | 94.3% White, 0.0% AIAN (35) | 90.0% White, 2.0% AIAN (100) |
| Grace Baker | 84.2% White, 0.0% AIAN (38) | 85.9% White, 1.0% AIAN (99) |
| All White Names | 92.8% White, 0.0% AIAN (151) | 91.0% White, 0.9% AIAN (403) |
| Grace Tsosie | 41.3% White, 26.7% AIAN (36) | 54.1% White, 10.2% AIAN (99) |
| Daniel Begay | 28.6% White, 52.4% AIAN (42) | 58.7% White, 11.5% AIAN (104) |
| Zachary Yazzie | 40.0% White, 22.9% AIAN (35) | 47.0% White, 12.0% AIAN (100) |
| Sarah Benally | 81.1% White, 5.4% AIAN (37) | 81.0% White, 4.0% AIAN (100) |
| All Navajo Names | 47.5% White, 27.8% AIAN (150) | 60.2% White, 9.4% AIAN (403) |

Notes: Sample sizes are in parentheses. AZ + NM is a separate sample of Arizona and New Mexico residents, only, while the national sample includes no restriction on state of residence. The national sample does not include those from the AZ + NM sample but does include some other individuals from those states.

Online Appendix Table F2 – Nationality Perceptions from the Names Survey: Percent Who Said Individual with Name was “Extremely Likely” or “Very Likely” Born in the United States

|  |  |
| --- | --- |
| Name | Sample |
| AZ + NM (N) | National (N) |
| Zachary White | 100% (36) | 96.0% (100) |
| Emily Adams | 100% (42) | 95.2% (104) |
| Benjamin Miller | 94.3% (35) | 89.0% (100) |
| Grace Baker | 89.5% (38) | 88.0% (99) |
| All White Names | 96.0% (151) | 92.1% (403) |
| Grace Tsosie | 63.9% (36) | 57.0% (99) |
| Daniel Begay | 86.0% (42) | 63.5% (104) |
| Zachary Yazzie | 62.9% (35) | 59.0% (100) |
| Sarah Benally | 73.7% (37) | 80% (100) |
| All Navajo Names | 72.3% (150) | 64.8% (403) |

Notes: Sample sizes in parenthesis.

Online Appendix Table F3 – Detailed Racial Perception Results from the Names Survey – White Names

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
| Question | All | AZ | NM | AZ + NM | National |
| What race or ethnicity do you associate with the name Zachary White? |
| American Indian or Alaska Native | 0.5% | 0.0% | 0.0% | 0.0% | 0.7% |
| Asian | 0.4% | 0.0% | 0.0% | 0.0% | 0.5% |
| Black or African American  | 6.9% | 7.2% | 5.6% | 6.6% | 7.0% |
| Hispanic/Latino(a)  | 0.5% | 1.0% | 0.0% | 0.7% | 0.5% |
| Native Hawaiian or Pacific Islander  | 0.2% | 0.0% | 0.0% | 0.0% | 0.3% |
| Other | 0.4% | 0.0% | 1.9% | 0.7% | 0.3% |
| White | 91.2% | 91.8% | 92.1% | 92.1% | 90.8% |
| N | 136 | 24 | 12 | 36 | 100 |
| What race or ethnicity do you associate with the name Benjamin Miller? |
| American Indian or Alaska Native | 1.5% | 0.0% | 0.0% | 0.0% | 2.0% |
| Asian | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Black or African American  | 5.9% | 8.3% | 0.0% | 5.7% | 6.0% |
| Hispanic/Latino(a)  | 0.7% | 0.0% | 0.0% | 0.0% | 1.0% |
| Native Hawaiian or Pacific Islander  | 0.7% | 0.0% | 0.0% | 0.0% | 1.0% |
| Other | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| White | 91.1% | 91.7% | 100.0% | 94.3% | 90.0% |
| N | 135 | 24 | 11 | 35 | 100 |
| What race or ethnicity do you associate with the name Grace Baker? |
| American Indian or Alaska Native | 0.7% | 0.0% | 0.0% | 0.0% | 1.0% |
| Asian | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Black or African American  | 13.1% | 16.0% | 7.7% | 13.2% | 13.1% |
| Hispanic/Latino(a)  | 0.7% | 4.0% | 0.0% | 2.6% | 0.0% |
| Native Hawaiian or Pacific Islander  | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Other | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| White | 85.4% | 80.0% | 92.3% | 84.2% | 85.9% |
| N | 137 | 25 | 13 | 38 | 99 |
| What race or ethnicity do you associate with the name Emily Adams? |
| American Indian or Alaska Native | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Asian | 0.7% | 0.0% | 0.0% | 0.0% | 1.0% |
| Black or African American  | 1.4% | 0.0% | 0.0% | 0.0% | 1.9% |
| Hispanic/Latino(a)  | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Native Hawaiian or Pacific Islander  | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Other | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| White | 98.0% | 100.0% | 100.0% | 100.0% | 97.1% |
| N | 146 | 24 | 18 | 42 | 104 |

Notes: Survey was implemented via Amazon Mechanical Turk in the spring of 2018. See description in Online Appendix F for more details.

Online Appendix Table F4 – Detailed Racial Perception Results from the Names Survey – Navajo Names

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Question | All | AZ | NM | AZ + NM | National |
| What race or ethnicity do you associate with the name Daniel Begay? |
| American Indian or Alaska Native | 23.3% | 33.3% | 77.8% | 52.4% | 11.5% |
| Asian | 4.8% | 8.3% | 0.0% | 4.8% | 4.8% |
| Black or African American  | 7.5% | 0.0% | 0.0% | 0.0% | 10.6% |
| Hispanic/Latino(a)  | 6.9% | 4.2% | 5.6% | 4.8% | 7.7% |
| Native Hawaiian or Pacific Islander  | 1.4% | 0.0% | 5.6% | 2.4% | 1.0% |
| Other | 6.2% | 12.5% | 0.0% | 7.1% | 5.8% |
| White | 50.0% | 41.7% | 11.1% | 28.6% | 58.7% |
| N | 146 | 24 | 18 | 42 | 104 |
| What race or ethnicity do you associate with the name Zachary Yazzie? |
| American Indian or Alaska Native | 14.8% | 8.3% | 54.6% | 22.9% | 12.0% |
| Asian | 3.7% | 8.3% | 0.0% | 5.7% | 3.0% |
| Black or African American  | 10.4% | 4.2% | 0.0% | 2.9% | 13.0% |
| Hispanic/Latino(a)  | 4.4% | 4.2% | 0.0% | 2.9% | 5.0% |
| Native Hawaiian or Pacific Islander  | 5.2% | 0.0% | 9.1% | 2.9% | 6.0% |
| Other | 16.3% | 25.0% | 18.2% | 22.9% | 14.0% |
| White | 45.2% | 50.0% | 18.2% | 40.0% | 47.0% |
| N | 135 | 24 | 11 | 35 | 100 |
| What race or ethnicity do you associate with the name Grace Tsosie? |
| American Indian or Alaska Native | 14.7% | 16.7% | 44.4% | 26.7% | 10.2% |
| Asian | 8.0% | 10.4% | 3.7% | 8.0% | 7.9% |
| Black or African American  | 8.5% | 4.2% | 3.7% | 4.0% | 10.2% |
| Hispanic/Latino(a)  | 4.5% | 3.1% | 1.9% | 2.7% | 5.2% |
| Native Hawaiian or Pacific Islander  | 3.6% | 2.1% | 5.6% | 3.3% | 3.7% |
| Other | 10.1% | 14.6% | 13.0% | 14.0% | 8.7% |
| White | 50.6% | 49.0% | 27.8% | 41.3% | 54.1% |
| N | 135 | 24 | 12 | 36 | 99 |
| What race or ethnicity do you associate with the name Sarah Benally? |
| American Indian or Alaska Native | 4.4% | 4.2% | 7.7% | 5.4% | 4.0% |
| Asian | 2.2% | 8.3% | 0.0% | 5.4% | 1.0% |
| Black or African American  | 2.9% | 0.0% | 0.0% | 0.0% | 4.0% |
| Hispanic/Latino(a)  | 1.5% | 0.0% | 0.0% | 0.0% | 2.0% |
| Native Hawaiian or Pacific Islander  | 0.7% | 0.0% | 0.0% | 0.0% | 1.0% |
| Other | 7.3% | 4.2% | 15.4% | 8.1% | 7.0% |
| White | 81.0% | 83.3% | 76.9% | 81.1% | 81.0% |
| N | 137 | 24 | 13 | 37 | 100 |

Notes: See the notes to Online Appendix Table F1.

Online Appendix Table F5 – Detailed Nationality Perception Results from the Names Survey – White Names

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Question | All | AZ | NM | AZ + NM | National |
| How likely do you think it is that Zachary White was born and raised in the United States? |
| Extremely likely | 69.1% | 62.5% | 83.3% | 69.4% | 69.0% |
| Somewhat likely | 27.9% | 37.5% | 16.7% | 30.6% | 27.0% |
| Neither likely nor unlikely | 2.9% | 0.0% | 0.0% | 0.0% | 4.0% |
| Somewhat unlikely | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| Extremely unlikely | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| N | 136 | 24 | 12 | 36 | 100 |
| How likely do you think it is that Emily Adams was born and raised in the United States? |
| Extremely likely | 66.0% | 56.0% | 61.1% | 58.1% | 69.2% |
| Somewhat likely | 30.6% | 44.0% | 38.9% | 41.9% | 26.0% |
| Neither likely nor unlikely | 2.0% | 0.0% | 0.0% | 0.0% | 2.9% |
| Somewhat unlikely | 1.4% | 0.0% | 0.0% | 0.0% | 1.9% |
| Extremely unlikely | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| N | 147 | 25 | 18 | 43 | 104 |
| How likely do you think it is that Grace Baker was born and raised in the United States? |
| Extremely likely | 63.0% | 64.0% | 61.5% | 63.2% | 63.0% |
| Somewhat likely | 25.4% | 24.0% | 30.8% | 26.3% | 25.0% |
| Neither likely nor unlikely | 9.4% | 12.0% | 7.7% | 10.5% | 9.0% |
| Somewhat unlikely | 2.2% | 0.0% | 0.0% | 0.0% | 3.0% |
| Extremely unlikely | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| N | 138 | 25 | 13 | 38 | 100 |
| How likely do you think it is that Benjamin Miller was born and raised in the United States? |
| Extremely likely | 57.0% | 66.7% | 54.6% | 62.9% | 55.0% |
| Somewhat likely | 33.3% | 29.2% | 36.4% | 31.4% | 34.0% |
| Neither likely nor unlikely | 5.2% | 4.2% | 9.1% | 5.7% | 5.0% |
| Somewhat unlikely | 4.4% | 0.0% | 0.0% | 0.0% | 6.0% |
| Extremely unlikely | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| N | 135 | 24 | 11 | 35 | 100 |

Notes: See the notes to Online Appendix Table F1.

Online Appendix Table F6 – Detailed Nationality Perception Results from the Names Survey – Navajo Names

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Question | All | AZ | NM | AZ + NM | National |
| How likely do you think it is that Grace Tsosie was born and raised in the United States? |
| Extremely likely | 16.9% | 16.7% | 41.7% | 25.0% | 14.0% |
| Somewhat likely | 41.9% | 45.8% | 25.0% | 38.9% | 43.0% |
| Neither likely nor unlikely | 17.7% | 8.3% | 16.7% | 11.1% | 20.0% |
| Somewhat unlikely | 16.9% | 20.8% | 16.7% | 19.4% | 16.0% |
| Extremely unlikely | 6.6% | 8.3% | 0.0% | 5.6% | 7.0% |
| N | 136 | 24 | 12 | 36 | 100 |
| How likely do you think it is that Daniel Begay was born and raised in the United States? |
| Extremely likely | 32.0% | 32.0% | 66.7% | 46.5% | 26.0% |
| Somewhat likely | 38.1% | 48.0% | 27.8% | 39.5% | 37.5% |
| Neither likely nor unlikely | 15.7% | 20.0% | 5.6% | 14.0% | 16.4% |
| Somewhat unlikely | 12.9% | 0.0% | 0.0% | 0.0% | 18.3% |
| Extremely unlikely | 1.4% | 0.0% | 0.0% | 0.0% | 1.9% |
| N | 147 | 25 | 18 | 43 | 104 |
| How likely do you think it is that Zachary Yazzie was born and raised in the United States? |
| Extremely likely | 17.8% | 8.3% | 63.6% | 25.7% | 15.0% |
| Somewhat likely | 42.2% | 41.7% | 27.3% | 37.1% | 44.0% |
| Neither likely nor unlikely | 17.0% | 20.8% | 9.1% | 17.1% | 17.0% |
| Somewhat unlikely | 19.3% | 29.2% | 0.0% | 20.0% | 19.0% |
| Extremely unlikely | 3.7% | 0.0% | 0.0% | 0.0% | 5.0% |
| N | 135 | 24 | 11 | 35 | 100 |
| How likely do you think it is that Sarah Benally was born and raised in the United States? |
| Extremely likely | 36.2% | 36.0% | 46.2% | 39.5% | 35.0% |
| Somewhat likely | 42.0% | 40.0% | 23.1% | 34.2% | 45.0% |
| Neither likely nor unlikely | 17.4% | 16.0% | 30.8% | 21.1% | 16.0% |
| Somewhat unlikely | 4.4% | 8.0% | 0.0% | 5.3% | 4.0% |
| Extremely unlikely | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| N | 138 | 25 | 13 | 38 | 100 |

Notes: See the notes to Online Appendix Table F1.

**Online Appendix G: Secondary Data Analysis of Discrimination**

**Data Source and Sample Composition**

We used data from the Current Population Survey (CPS) (Flood et al., 2015) to measure the unconditional and conditional gaps in economic outcomes between AIAN, NHPI, and white populations. We study disparities in log hourly wages, unemployment rates, and unemployment duration in weeks. We pooled data for the years 2010 to 2017 and we restricted the sample to individuals of age 25 to 64 of any gender. We also estimated results using some restricted samples that more closely match our experiment. These results were similar and are available upon request.

**Coding Race**

We code individuals as either (1) AIAN alone (NHPI alone), meaning they only report being AIAN (NHIP), or (2) AIAN alone and in combination (NHPI alone or in combination) which is a broader group that includes anyone who reports being AIAN (NHPI) in combination with other races. The main paper presents results for AIAN alone (NHPI alone). We present the full results below, which includes using AIAN (NHPI) alone and in combination. These results are similar. In all cases, we compare these Indigenous groups to non-Hispanic whites, who report being white only.

**Measuring Economic Outcomes**

To measure gaps in wages and earnings, we calculated the hourly wage for each individual. We calculated the hourly wage by setting it equal to the reported hourly wage if the individual was paid on an hourly basis or equal to weekly earnings divided by usual hours worked per week, if the individual was not paid on an hourly basis. We also measured differences in unemployment rates and unemployment duration, in weeks. Individuals were coded as unemployed if they were designated as “Unemployed,” “Unemployed, experienced worker,” or “Unemployed, new worker,” and as not unemployed if they were designated as “At work” or “Has job, not at work last week.” Duration of unemployment is measured as consecutive weeks unemployed or without a job and seeking work.

**Oaxaca-Blinder Decomposition**

We decomposed our outcome variables following an Oaxaca-Blinder decomposition (Oaxaca and Ransom 1994). Our description of this strategy mirrors (Feir 2013). Our estimating equation is:

|  |  |
| --- | --- |
| Ln(Wage0) - Ln(Wage1) = β0 (X0 – X1)’ + (β0 - β1)X’0, | [G1] |

where the superscript and subscript 0 signifies Indigenous workers while the superscript and subscript 1 signifies white workers, the X’s represent productive characteristics for each respective group, and the βs represent the rates of return to the productive characteristics for each group. This equation comes from taking the difference between the expectation of log wages for each group:

|  |  |
| --- | --- |
| E[Ln(Wagei0) = β0 X’0i + ε0i] – E[Ln(Wagei1) = β1 X’1i + ε1i], | [G2] |

where variables and estimators are the same as above with i additionally indexing the individual. The term β0X1 is subtracted and added, and the entire equation is rearranged to obtain Equation G1.

 The term β0(X0 – X1)’ is the explained part of the wage differential while the term (β0 - β1)X’0 is the unexplained part of the wage differential. The variables in X0 and X1 include: location (indicator variables for each state), marital status (indicator variables for each type of status including married with or without spouse present, separated, divorced, never married, widowed), occupation (indicator variables for each category, harmonized to 2010 variables), education (indicator variables for each highest grade, or range of grades, attained), whether the individual is Hispanic, age and age squared terms, indicators for the number of children, whether the individual is female, experience (indicator variables for minimum expected years of experience), indicators for month and year combinations, and whether the individual lives in metro or non-metro location.

**Results**

We present the more detailed results in Online Appendix Tables G1 through G4, with a summary of these results in the main paper (Tables 11 and 12).

Online Appendix Table G1 – Summary Statistics for Highest Educational Attainment, by Race

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Outcome Variable | AIAN Alone | AIAN Alone or In Part | NHPI Alone | NHPI Alone or in Part | Non-Hispanic White Alone |
| Less Than High School Graduate | 17.3% | 15.1% | 9.7% | 8.3% | 5.2% |
| High School Graduate | 35.8% | 33.3% | 37.8% | 38.4% | 27.5% |
| Attended Some College | 31.5% | 33.3% | 30.2% | 30.6% | 29.0% |
| College Graduate | 10.4% | 12.4% | 16.0% | 16.1% | 24.5% |
| Masters Graduate | 3.8% | 4.6% | 5.1% | 5.2% | 10.2% |
| Doctoral Graduate | 1.2% | 1.4% | 1.2% | 1.4% | 3.6% |
| N | 49,187 | 79,678 | 19,121 | 26,892 | 2,762,286 |

Notes: Calculated using IPUMS-CPS data from 2010 to 2017 (Flood et al., 2015). Categories were calculated using the “educ” variable, which encodes multiple levels of highest educational attainment. Those with anything less than a high school diploma or equivalent (which itself was coded as *High School Graduate*) was coded as *Less Than High School Graduate*. Those with any amount of college study short of a bachelor’s degree (itself coded as *College Graduate*), including an Associate’s degree, was coded as *Attended Some College*. For graduate degrees only completed degrees are coded, and professional school degree (which could include doctoral degrees like JD or MD or professional masters) were coded as *Doctoral Graduate*.

Online Appendix Table G2 – Oaxaca-Blinder Decomposition Estimates – Log Hourly Wage

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | AIAN Alone | AIAN Aloneor In Part | NHPI Alone | NHPI Aloneor in Part |
| Total Difference | -0.145\*\*\* (0.006) | -0.128\*\*\* (0.004) | -0.087\*\*\* (0.012) | -0.068\*\*\* (0.011) |
| *Explained* | -0.133\*\*\* (0.006) | -0.113\*\*\* (0.004) | -0.046\*\*\* (0.011) | -0.039\*\*\* (0.010) |
| Occupation | -0.072\*\*\* (0.004) | -0.068\*\*\* (0.004) | -0.053\*\*\* (0.007) | -0.050\*\*\* (0.006) |
| Education | -0.053\*\*\* (0.002) | -0.042\*\*\* (0.002) | -0.026\*\*\* (0.003) | -0.021\*\*\* (0.003) |
| State | 0.017\*\*\* (0.001) | 0.018\*\*\* (0.001) | 0.049\*\*\* (0.003) | 0.052\*\*\* (0.003) |
| Hispanic | -0.014\*\*\* (0.001) | -0.013\*\*\* (0.000) | -0.010\* (0.006) | -0.009\* (0.005) |
| Age | -0.010\*\*\* (0.001) | -0.010\*\*\* (0.001) | -0.018\*\*\* (0.004) | -0.020\*\*\* (0.005) |
| Married | -0.006\*\*\* (0.000) | -0.006\*\*\* (0.000) | -0.002\*\*\* (0.001) | -0.004\*\*\* (0.001) |
| Gender | 0.005\*\*\* (0.001) | 0.005\*\*\* (0.001) | 0.005\*\*\* (0.002) | 0.004\*\* (0.002) |
| Metro Status | -0.003\*\*\* (0.000) | -0.001\*\*\* (0.000) | 0.008\*\*\* (0.001) | 0.007\*\*\* (0.001) |
| Experience | 0.003\*\* (0.001) | 0.003\*\* (0.001) | 0.000 (0.003) | -0.000 (0.004) |
| Survey Timing | 0.001\*\* (0.001) | 0.001\*\* (0.000) | 0.003\*\*\* (0.001) | 0.002\*\*\* (0.001) |
| Children | -0.000\*\* (0.000) | -0.000\*\*\* (0.000) | -0.000 (0.000) | -0.000 (0.000) |
| *Unexplained* | -0.012\*\*\* (0.003) | -0.015\*\*\* (0.002) | -0.041\*\*\* (0.012) | -0.029\*\*\* (0.011) |
| Observations | 239,981 | 242,856 | 237,105 | 237,895 |

Notes: These estimates use data from the outgoing rotation group (ORG) of the IPUMS-CPS monthly data from 2010-2017 (Flood et al., 2015). Statistically significantly different from at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*). The mean hourly wage for non-Hispanic whites (the comparison group) is $19.13. Hourly wage was generated using the reported hourly wage for those who are paid hourly and are below the censored limit or the calculated hourly wage from weekly earnings divided by the usual working hours. Controls include indicator variables for state, marital status, occupation, education, number of children, sex, metro status, years of experience, month by year, whether the individual is Hispanic, and age and age squared terms, indicators for month and year combinations.

Online Appendix Table G3 – Oaxaca-Blinder Decomposition Estimates – Unemployment

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | AIAN Alone | AIAN Aloneor In Part | NHPI Alone | NHPI Aloneor in Part |
| Total Difference | 0.045\*\*\* (0.001) | 0.042\*\*\* (0.000) | 0.017\*\*\* (0.001) | 0.015\*\*\* (0.001) |
| *Explained* | 0.003\*\*\* (0.000) | 0.004\*\*\* (0.000) | 0.010\*\*\* (0.001) | 0.009\*\*\* (0.001) |
| Hispanic | -0.019\*\*\* (0.000) | -0.015\*\*\* (0.000) | -0.005\*\*\* (0.000) | -0.004\*\*\* (0.000) |
| Occupation | 0.013\*\*\* (0.000) | 0.010\*\*\* (0.000) | 0.009\*\*\* (0.001) | 0.008\*\*\* (0.001) |
| Education | 0.007\*\*\* (0.000) | 0.006\*\*\* (0.000) | 0.004\*\*\* (0.000) | 0.003\*\*\* (0.000) |
| Married | 0.003\*\*\* (0.000) | 0.003\*\*\* (0.000) | 0.002\*\*\* (0.000) | 0.002\*\*\* (0.000) |
| Experience | -0.001\*\*\* (0.000) | -0.001\*\*\* (0.000) | -0.001\*\*\* (0.000) | -0.001\*\*\* (0.000) |
| State | 0.001\*\*\* (0.000) | 0.001\*\*\* (0.000) | 0.002\*\*\* (0.000) | 0.000\*\*\* (0.000) |
| Age | -0.000\*\*\* (0.000) | -0.000\*\*\* (0.000) | 0.000\*\*\* (0.000) | 0.000\*\*\* (0.000) |
| Survey Timing | -0.000\*\*\* (0.000) | -0.000\*\*\* (0.000) | -0.000 (0.000) | 0.000\* (0.000) |
| Children | 0.000\*\*\* (0.000) | 0.000\*\*\* (0.000)  | 0.000\*\*\* (0.000) | 0.000\*\*\* (0.000) |
| Metro Status | 0.000\*\*\* (0.000) | 0.000\*\*\* (0.000) | -0.000\*\*\* (0.000) | -0.000\*\*\* (0.000) |
| Gender | -0.000\*\* (0.000) | 0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) |
| *Unexplained* | 0.043\*\*\* (0.000) | 0.038\*\*\* (0.000) | 0.007\*\*\* (0.001) | 0.006\*\*\* (0.001) |
| Observations | 2,186,764 | 2,208,140 | 2,167,445 | 2,173,346 |

Notes: These estimates use data from the IPUMS-CPS monthly data from 2010-2017 (Flood et al., 2015). Statistically significantly different from at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*). The unemployment rate for non-Hispanic whites (the comparison group) is 0.037. Controls include indicator variables for state, marital status, occupation, education, number of children, sex, metro status, years of experience, month by year, whether the individual is Hispanic, and age and age squared terms, indicators for month and year combinations. The Unemployment outcome is an indicator variable and the Oaxaca model used is a linear probability model.

Online Appendix Table G4 – Oaxaca-Blinder Decomposition Estimates – Unemployment Duration in Weeks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | AIAN Alone | AIAN Aloneor In Part | NHPI Alone | NHPI Aloneor in Part |
| Total Difference | -1.705\*\*\* (0.502) | 0.004 (0.360) | -2.876\*\* (1.383) | -2.315\* (1.218) |
| *Explained* | -3.313\*\*\* (0.263) | -3.573\*\*\* (0.201) | 0.010 (0.646) | -0.168 (0.563) |
| Age | -2.744\*\*\* (0.173) | -2.483\*\*\* (0.138) | -3.461\*\*\* (0.344) | -3.361\*\*\* (0.298) |
| Hispanic | -2.466\*\*\* (0.120) | -2.490\*\*\* (0.093) | 0.731\* (0.396) | 0.181 (0.352) |
| Education | 1.330\*\*\* (0.081) | 0.958\*\*\* (0.064) | 0.858\*\*\* (0.165) | 0.867\*\*\* (0.147) |
| Experience | 1.226\*\*\* (0.114) | 1.065\*\*\* (0.088) | 1.647\*\*\* (0.228) | 1.493\*\*\* (0.197) |
| State | -1.086\*\*\* (0.081) | -1.064\*\*\* (0.066) | 0.694\*\*\* (0.138) | 0.613\*\*\* (0.129) |
| Married | 0.503\*\*\* (0.080) | 0.601\*\*\* (0.063) | -0.434\*\*\* (0.151) | -0.246\* (0.14) |
| Occupation | 0.495\*\*\* (0.156) | 0.392\*\*\* (0.119) | 0.068 (0.308) | 0.306 (0.280) |
| Survey Timing | -0.304\*\*\* (0.100) | -0.299\*\*\* (0.080) | 0.151 (0.215) | 0.187 (0.189) |
| Children | -0.282\*\*\* (0.035) | -0.235\*\*\* (0.025) | -0.295\*\*\* (0.058) | -0.292\*\*\* (0.051) |
| Gender | 0.088\*\* (0.041) | 0.038 (0.034) | -0.209\*\* (0.082) | -0.183\*\* (0.073) |
| Metro Status | -0.074\*\*\* (0.025) | 0.038\*\*\* (0.034) | 0.260\*\*\* (0.035) | 0.268\*\*\* (0.031) |
| *Unexplained* | 1.609\*\*\* (0.410) | 3.577\*\*\* (0.294) | -2.887\*\* (1.219) | -2.147\*\* (1.070) |
| Observations | 81,543 | 83,125 | 79,036 | 79,263 |

Notes: See the notes to Online Appendix Table G3. Statistically significantly different from at 1-percent level (\*\*\*), 5-percent level (\*\*) or 10-percent level (\*). The average unemployment duration for non-Hispanic whites (the comparison group) is 30.11.

**Online Appendix H: Sample Resumes and Cover Letters**

**Sample Resume #1 – Type A (Non-Indigenous), Retail Sales**

|  |
| --- |
| **Christopher Johnson****4320 E Pearce Rd****Phoenix, AZ 85044****\*Phone\*****\*Email\*** |
| Objective | To obtain a position as a sales associate. |
| Work Experience | Sales AssociateCostco, Phoenix, AZ*Oct. 2009 - Present*Assist customers as they shop, answering questions and trying to find the merchandise that fits their needs the best. Straighten up merchandise to ensure a professional appearance. Ring up customers at check out. |
|  | CashierWalmart, Phoenix, AZ*July 2008 - Sept. 2009*Worked as a cashier and in customer service Primary responsibilities were related to working the cash register, but also assisted with stocking shelves. Occasionally, I checked merchandise for damage and incorrect tags. |
|  | Sales AssociateTarget, Phoenix, AZ*Nov. 2004 - June 2008*Answer customers’ questions. Ring up customers at checkout. Handle returns and other customer service responsibilities. Straighten up merchandise to insure a professional appearance at all times.  |
| **Volunteering**  | VolunteerWarner A. Gabel Boys & Girls Club, Phoenix, AZ*Mar. 2014 - Present*I assisted kids with homework, played sports with them, and assisted staff in caring for the kids. |
| Education | High School DiplomaChandler High School, 2004Chandler, AZ |
| References | References available upon request. |

**Sample** **Cover Letter #1 – Type A (Non-Indigenous), Retail Sales**

From: “Christopher Johnson” \*Email\*

To: \*Employer Email\*

Subject: Application for \*Position\*

Attachment: ResumeChristopherJohnson.pdf

Dear Hiring Manager,

My name is Christopher Johnson and I am very interested in your posted job application and I would like to formally apply.

Please see my attached resume

I have significant experience in retail sales through positions at Costco and Walmart. In these positions, I gained significant experience serving customers, promoting products, and resolving customer issues and concerns.

Thank you for your time and considaration. I look forward to hearing from you.

Christopher Johnson

\*Email\*

\*Phone\*

*[Note: This applicant got the randomly-assigned quality feature of a more detailed cover letter (the added paragraph “I have significant experience”) but did not get the correction of typos quality feature. The typos, highlighted above, are intentionally added to this resume. All cover letters for applicants that were not given the “no typos” quality feature had one minor typo and one missing period at the end of a sentence.]*

**Sample Resume #2 – Type B (Native Hawaiian), Language Signal, Server**

|  |
| --- |
| Emma Lewis1607 Makiki St., Unit 9Honolulu, HI 96822\*Phone\* \*Email\* |
| Experience |  |
| *Server*P. F. Chang’s, Honolulu, HIMar. 2016 - Mar. 2017 Took orders, served food and drinks, managed and cleaned tables, and created a positive atmosphere for guests. |
| *Server*Cheesecake Factory, Honolulu, HIFeb. 2011 - Dec. 2015Responsible for ensuring a great guest experience by greeting guests, taking their orders, answering questions, and keeping tables clean.*Server*Benihana, Honolulu, HISept. 2005 - Dec. 2010Communicated with guests, answered customer menu questions, handled food and drinks, and cleaned tables. |
| Education |
| *High School Diploma*McKinley High School, Honolulu, HI, 2005 |
| Skills |  |
| I speak English and Hawaiian (mother tongues). |
| Volunteering |
| *Youth Mentor*Big Brothers Big Sisters of Honolulu, Honolulu, HISept. 2013 - Dec. 2016 Mentored kids in my community. Helped them develop social and study skills and community involvement. |
| References are available on request. |

**Sample Cover Letter #2 - Type B (Native Hawaiian), Language Signal, Server**

From: “Emma Lewis” \*Email\*

To: \*Employer Email\*

Subject: Application for \*Position\*

Attachment: EmmaLewisResume.pdf

Dear Hiring Manager,

My name is Emma Lewis and I am contracting you to respond to your recently posted job ad

I have enclosed my resume.

I am looking forward to hearing from you soon.

Sincerely,

Emma Lewis

\*Email\*

\*Phone\*

*[Note: This applicant did not get the randomly-assigned quality features of a more detailed cover letter or a correction of typos. The typos, highlighted above, are intentionally added to this resume. All cover letters for applicants that were not given the “no typos” quality feature had one minor typo and one missing period at the end of a sentence.]*

|  |
| --- |
| Sample Resume #3 – Type C (Native American Applicant, Reservation Upbringing) -Plus Language Signal and Occupation-Specific Skills, CookTyler King2415 Northwest Circle NWAlbuquerque, NM 87104\*Phone\*, \*Email\* |
| Experience |
| CookP.F. Chang’s, Albuquerque, NMApr. 2012 - Mar. 2017 * Cooked and prepared food, followed safety training, and mastered the use of multiple types of kitchen tools.
 |
| CookTexas Roadhouse, Albuquerque, NMFeb. 2009 - Feb. 2012* Cooked food, prepped food, and completed tasks on time and with high quality.
 |
| CashierSmith’s, Albuquerque, NMJuly 2005 - Jan. 2009* I worked at the check out. I scanned items, collected payment, and gave change as appropriate.
 |
| Education |
| High School Diploma, 2005Navajo Preparatory SchoolFarmington, Navajo Reservation, NM |
| **Skills** |
| Fluent in English and Navajo (both native languages). I have received training in food safety.I have received CPR/AED and First Aid training. |
| **Volunteer Experience** |
| Food Bank VolunteerRoadrunner Food Bank, Albuquerque, NMMar. 2013 - Nov. 2016I organized food donations and checked for damages and expiration dates. |
| References available upon request. |

**Sample Cover Letter #3 - Type C (Native American Applicant, Reservation Upbringing) -Plus Language Signal and Occupation-Specific Skills, Cook**

From: “Tyler King” \*Email\*

To: \*Employer Email\*

Subject: \*Position\* - Tyler King

Attachment: TylerKingResume.pdf

To Whom it May Concern,

My name is Tyler King and I contacting you to respond to your recently posted job ad.

I have enclosed my resume.

To briefly summarize my work history, I gained significant experience as a cook through positions at P.F. Chang’s and Texas Roadhouse. In these positions, I learned how to properly prepare a wide variety of foods.

I am looking forward to hearing from you soon.

Sincerely,

Tyler King

\*Phone\*

\*Email\*

*[Note: This applicant got both the randomly-assigned quality feature of a more detailed cover letter (the added paragraph “To briefly summarize…”) and the correction of typos quality feature.]*

**Online Appendix I: Additional Socioeconomic Status Statistics by Native American Tribal Group**

Online Appendix Table I1 – Basic Socioeconomic Means by Native American Tribal Group

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Indigenous Group | N | % High School Attainment | % Employed | Mean Income | % in a PUMA that includes an Indian Reservation |
| White | 10,088,366 | 92.4% | 94.6% | $47,553 | 16.5% |
| AIAN | 137,632 | 83.3% | 87.2% | $26,652 | 65.5% |
| Navajo | 22,132 | 81.3% | 83.8% | $20,024 | 89.1% |
| Apache | 3,567 | 81.2% | 80.8% | $22,280 | 58.8% |
| Blackfeet | 1,380 | 87.9% | 84.1% | $23,753 | 53.6% |
| Tohono O’odham | 1,100 | 76.6% | 80.3% | $18,677 | 78.5% |

Notes: Data is from the American Community Survey data from 2010-2017. Population was inclusive of individuals between age 26 to 65. Data for Oglala Lakota and Osage were not available. Income means include observations that are negative. The % in a PUMA [Public Use Microdata Area] variable comes from the HOMELAND variable in IPUMS-USA, which “indicates whether the household is in a PUMA [Public Use Microdata Area] that includes any Census block that was designated as an American Indian, Alaska Native, or Native Hawaiian homeland area.”

**Online Appendix J: References Not Included in the Main Paper**

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McGinnity, Frances, and Peter D Lunn. 2011. “Measuring Discrimination Facing Ethnic Minority Job Applicants: An Irish Experiment.” *Work, Employment & Society* 25 (4): 693–708. https://doi.org/10.1177/0950017011419722.

Neumark, David. 2001. “The Employment Effects of Minimum Wages: Evidence from a Prespecified Research Design The Employment Effects of MinimumWages.” *Industrial Relations: A Journal of Economy and Society* 40 (1): 121–44. https://doi.org/10.1111/0019-8676.00199.

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1. We calculated this by taking the number of people with that name per 100,000 people and multiplying it by the share that identified as AIAN only to create an estimate of the number of people per 100,000 with that last name that identified as AIAN. Using the 80% criteria for AIAN-specific names, 3,326 people per 100,000 identified as AIAN only and have an AIAN-specific last name, compared to 56,790 people per 100,000 who identified as AIAN only and do not have an AIAN-specific last name. [↑](#footnote-ref-1)
2. Our primary sources were Ancestry.com (e.g., http://www.ancestry.com/name-origin?surname=begay (accessed October 30, 2016)) and http://tribalemployee.blogspot.com/2013/03/navajo-last-names.html (accessed June 25, 2016). While these sources identified other names on our list of 12 as being Navajo, we could not sufficiently corroborate this with other sources. We also found many other sources through a web search that confirmed that Begay, Yazzie, Benally, and Tsosie were Navajo. [↑](#footnote-ref-2)
3. A few email addresses were randomly repeated based on the randomization process to generates names and email address. So, there may be more than one unique applicant with the same or similar name that uses the same email address, but this only occurs a few times. Also, since we assign each day to be a different pair of applicants, an applicant with a particular email may apply to multiple jobs in one day. [↑](#footnote-ref-3)
4. For only a handful of voicemail responses, we did not have enough information even to match it to the applicant. [↑](#footnote-ref-4)
5. See <https://www.socialscienceregistry.org/trials/2299> (accessed January 20, 2019). [↑](#footnote-ref-5)
6. For reference, the regular controls, which are the default for all tables, are indicator variables for employment status, added resumes quality features (Spanish, no typos in the cover letter, better cover letter, and two occupation-specific skills), occupation, gender, resume sending order, volunteer experience, and city. The full controls include the regular controls and graduation year, resume naming style, e-mail script version, e-mail format, e-mail subject, e-mail opening line, e-mail body, e-mail signature format, e-mail domain, voicemail greeting, oldest job (Job 3) start month, gap (in months) between Job 3 and Job 2, gap between Job 2 and 1, and the duration of volunteer experience (in months). [↑](#footnote-ref-6)
7. For example, Spanish, a college degree, and the occupation-specific skills often boosted interview rates in Neumark, Burn, and Button (forthcoming), while adding typos to the resume (missing periods or commas), volunteer experience, and employee of the month awards did not have positive effects, sometimes having negative ones. Lahey and Beasley (2018) also discuss a similar issue for typos. These differential results by quality element prompted us to choose some different quality elements. We also noticed that typos are less common on resumes themselves but are more common in the emails that job applicants send to submit their resumes, which prompted us to try using typos in the cover letter rather than on the resume. [↑](#footnote-ref-7)
8. This occurs because we do not have a unique phone number for each applicant. Since we assign multiple applicants the same number, we are sometimes not able to match a voicemail response to a specific job even if we can match it to a specific resume. More details on how this is addressed generally can be found in Online Appendix A. [↑](#footnote-ref-8)
9. We split our applications to jobs in Los Angeles into two groups and weighted them differently since we sent either Native American/white pairs or Native Hawaiian/white pairs to each job opening, and these are weighted differently. [↑](#footnote-ref-9)
10. Our broader occupation of retail corresponds to retail salespersons, cashiers, counter and rental clerks, sales representatives (services, all other), and sales and related workers (all others); kitchen, our broadest occupational category, corresponds to cooks, food preparation workers, dishwashers, combined food preparation and serving workers (including fast food), counter attendants (cafeteria, food concession, and coffee shops), food servers (non-restaurant), and dining room and cafeteria attendants and bartender helpers; server corresponds to waiters and waitresses, bartenders, and hosts and hostesses (restaurant, lounge, and coffee shop); janitor corresponds to janitors and building cleaners and grounds maintenance workers; and security corresponds only to security guards and gaming surveillance officers. [↑](#footnote-ref-10)
11. Our other results, replicating other tables, are also fundamentally the same, regardless of which type of weighting we use. These results are available upon request. [↑](#footnote-ref-11)
12. The actual resumes are available upon request. [↑](#footnote-ref-12)