Age and the labor market for Hispanics in the United States

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Abstract: We explore the labor market for Hispanic high school graduates in the United States by age using information from the US Census, American Community Survey, Current Population Survey, and three laboratory experiments. We find, in general, that the differences in outcomes for these two groups do not change across the lifecycle. Moving to a laboratory setting, we provided participants with randomized resumes for a clerical position that are on average equivalent except for name and age (as indicated by date of high school graduation). In all three experiments, hypothetical applicants with Hispanic and non-Hispanic names were generally treated the same across the lifecycle by a student population, a population of human resources managers, and a more general population from mTurk. These results stand in contrast to earlier results that find strong differences by age in how resumes with Black and White names are treated.

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I. Introduction

The population of Hispanics in the United States has been steadily growing over time. In 2015, Hispanics accounted for 17.6% of the total population compared to 6.5% in 1980 (Flores 2017). These increases have occurred among both foreign-born and native-born populations and more than half of adult Hispanics are native-born. Although the median age of Hispanics in the US is still in the 20s, this age has been steadily increasing over time (Flores et al. 2017). The question of what happens to Hispanic workers as they age is an increasingly important one. Despite these increasing demographic pressures, there is not much literature exploring the work outcomes of Hispanics across the lifespan.

By some measures Hispanic workers are doing better than similarly educated whites; lower educated white Hispanics enjoy higher employment and labor market participation than do similarly educated white non-Hispanics (Authors calculations from the CPS). By other measures, however, they are doing worse and these negative gaps between Hispanics and Non-Hispanics increase as these groups age. Earnings trajectories are lower for Hispanic men compared to non-Hispanic white men, particularly among the more educated (Tomaskovic-Devey et al. 2005). Hispanics are more likely than other groups to live in poverty at older ages and experience lower Social Security receipt (Hungerford et al. 2001). They also have a higher risk of being work-disabled at younger ages than white non-Hispanics in the HRS (Brown and Warner 2008).

In addition, the pool of Hispanics in the United States is a non-homogeneous group. Employment opportunities will vary by immigration status, and may also vary by education. Given results on differences in wage trajectories by age and education between Hispanics and non-Hispanics, there is reason to believe that hiring patterns may also be different for different education groups over the lifespan. For this paper, we focus on the outcomes of the largest education groups in the US, that of those with high school education and, in some cases, those with some college but without a completed four-year degree, who make up 26-50% of the White Hispanic population and 28-60% of the White non-Hispanic population depending on how people with some college are categorized (Authors calculations from the 2017 ACS).

We might expect Hispanic job applicants to be discriminated against in the labor market because of potential negative stereotypes. For example, there are beliefs that Hispanics are less likely to be documented workers, have poor communication skills, need more supervision, are lazy, and tend to have many children (Dixon and Rosenbaum 2004, Dong and Murrillo 2007, Jackson 1995, Jones 1991, Market 2004, Ramirez Berg 1990). These stereotypes may vary by age. For example, older job applicants may be more likely to have previously become US citizens under amnesty. Communication skills may be better for younger cohorts, or they may have improved with time spent in the workforce. Having a large number of children may be problematic for workers when the children are in the household, but will be less of a concern as children age out of needing supervision. On the other hand, people with Hispanic ethnicity may be assumed to be bilingual, and knowledge of Spanish is particularly useful in the United States.

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To explore the experiences of Hispanic Americans over the lifecycle, we use three different approaches across four studies. In the first approach, we use publicly available data from the US Census and ACS to explore differences in standard labor market outcomes across time. Unlike previous findings that find stark patterns in the differences in the labor market outcomes for Black and White Americans across age and time (Lahey 2018), differences in these outcomes are much flatter across age for Hispanic and non-Hispanic white Americans. Similarly, point in time data from a recent ACS finds steady differences in outcomes across the lifecycle for many, but not all, of the outcomes tested. In the second approach, we re-analyze data from two previous eye-tracking experiments that asked students (Experiment 1) and human resources (HR) managers (Experiment 2) to rate resumes with randomized inputs for a clerical position while tracking their eyes with an eye-tracking device. Ages listed on resumes (as indicated by date of high school graduation) ranged from mid-30s to mid-70s and 13% of resumes indicated Hispanic status by Hispanic last, but not first, name. Generally, participants did not treat resumes with Hispanic and non-Hispanic resumes differently for the different age groups. Finally, our third approach (Experiment 3) used a large sample of mTurk managers, clerical workers, and the general population as our participant population and again asked participants to rate resumes for a clerical position. In this study, we expanded indicators of Hispanic status to include Hispanic first names in addition to last names, we added indicators on resumes to contradict or reinforce Hispanic stereotypes, and we asked questions about specific aspects of each worker such as need for supervision and communication skills. As with the previous approaches, we find little evidence that Hispanic applicants are treated differently than non-Hispanics across these age groups. Although each of these four approaches may be flawed, they are generally flawed in different ways. Together, they suggest that, unlike the case for Black Americans (Lahey and Oxley *forthcoming*), Hispanic Americans with high school education but without a college degree are treated similarly in the first stage of hiring across middle and older ages.

II.   Results from Survey Data

We might expect differences in labor force outcomes for similarly educated Hispanic and non-Hispanic workers in the US because there are differences in these data for Black vs. White people (Lahey 2018). Figure 1a shows the difference in the probability of being employed in the US Census/ACS by age for birth cohorts from 1933 to 1973 for Hispanic women compared to non-Hispanic women, while Figure 1b shows the same comparison for men. Unlike similar graphs comparing Black vs. White women (Lahey 2018), there are no discernable patterns for women by age or by cohort. The difference in probability of employment ranges generally ranges between -0.04 and 0.02 points with a few outliers, indicating on average that Hispanic women are less likely to be employed. The difference in probability of employment for men is generally negative, indicating that Hispanic men are less likely to be employed than are non-Hispanic Men.

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Figure 1 Census/ACS Trends

(a)

(b)

(c)

(d)

(e)

(f)

For men, differences tend to be smaller and flatter for newer cohorts, and for older members of earlier cohorts. Figure 1c and 1d repeat this exercise for wage differences and find little difference in wages at younger ages, and generally negative differences at older ages for women, suggesting that older Hispanic women make less on average than do older non-Hispanic women. Figure 1e and 1f again repeat this exercise for differences in the probability of unemployment for women and men respectively. For the most part, at older ages Hispanic men and women are somewhat more likely to be unemployed than are non-Hispanic. At younger ages, differences are mixed with no discernable patten by cohort. In general, differences in employment outcomes for Hispanic compared to non-Hispanic people by age and cohort are neither as stark as those for Black vs. White people (Lahey 2018), nor do they follow any obvious patterns.

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Figure 2 Employment Outcomes ACS 2019

(a)

(b)

(c)
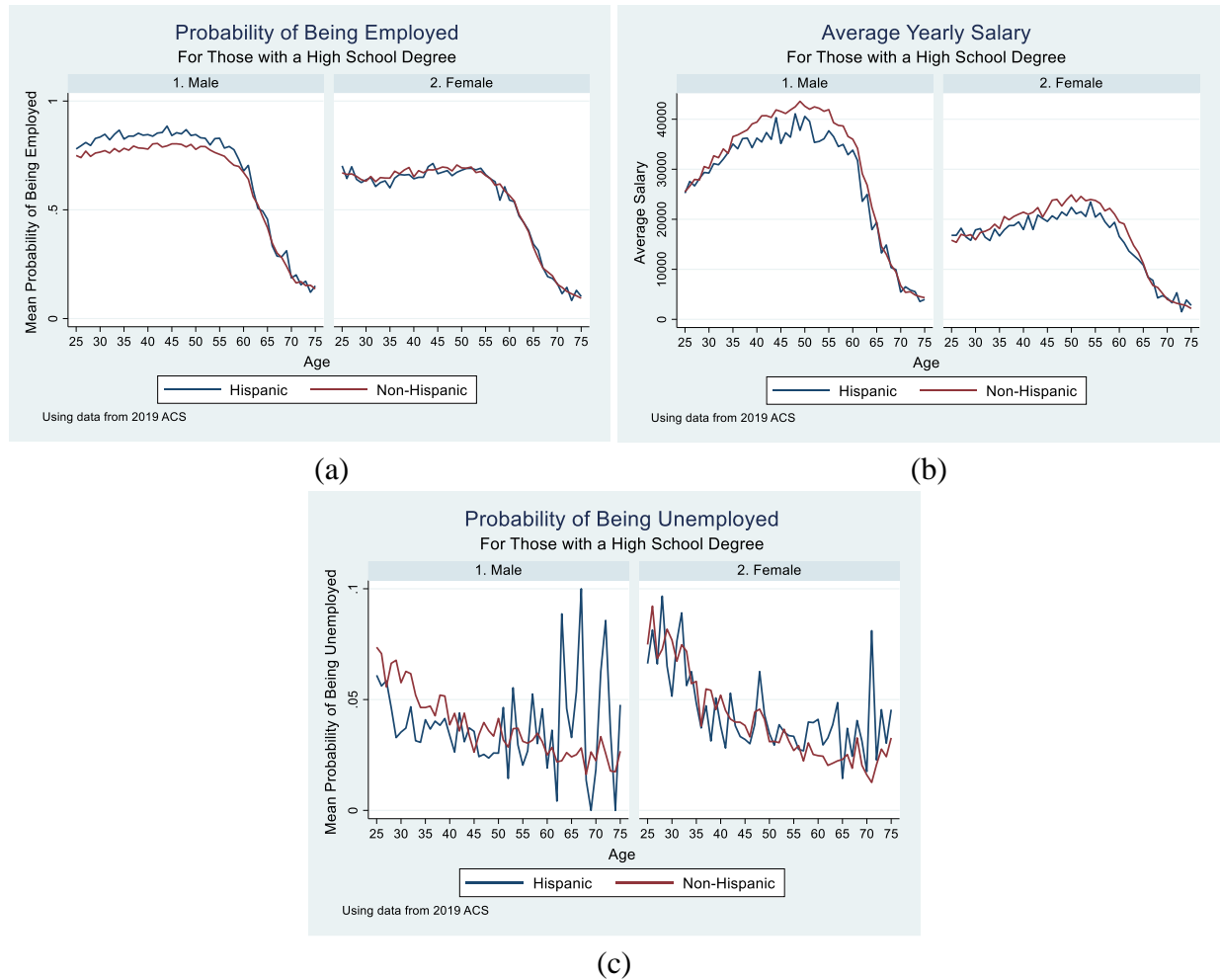
A second way to look at differences in outcomes for Hispanic compared to non-Hispanic people by age is to use a point in time estimate using a dataset such as the 2019 American Community Survey. Figure 2 (a-c) shows employment outcomes separately by age comparing Hispanic and non-Hispanic men and women. In general, Hispanic men are slightly more likely to be employed than are non-Hispanic men, though this difference decreases as men reach standard retirement ages. There seems to be no difference in employment outcomes between Hispanic and non-Hispanic women. Non-Hispanic men and women both have higher annual wages on average than do their Hispanic counterparts, though again, this difference decreases at standard retirement ages. Younger Hispanic men may be less likely to be unemployed than their non-Hispanic counterparts, but there do not appear to be any differences in unemployment rates between the two ethnicities starting around age 50, although these data are highly noisy for older Hispanic adults. Women appear to have smaller differences in unemployment rates overall and across age.

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A third way to look at differences in outcomes for Hispanic compared to non-Hispanic people by age is to use the rotating panel aspects of the Current Population Survey (CPS) to study how job flows into and out of employment vary by Hispanic status. Here we use the methodology from (Bleakley et al 1999) on the Ipums CPS (Flood et al. 2020) to create measures of job accessions, defined as being not employed in month t and employed in month t+1 and job losses, defined as being employed in month t and not employed in month t+1. This rough measure of job flows does not capture many short spells of unemployment, nor does it capture moving jobs without a break in between. However, it provides a consistent measure of movements into and out of longer spells non-employment. Figures 3a-d present probabilities by age using a lowess smoother.

Figure 3 Job Flows CPS 2019

(a)   (b)

(c)   (d)
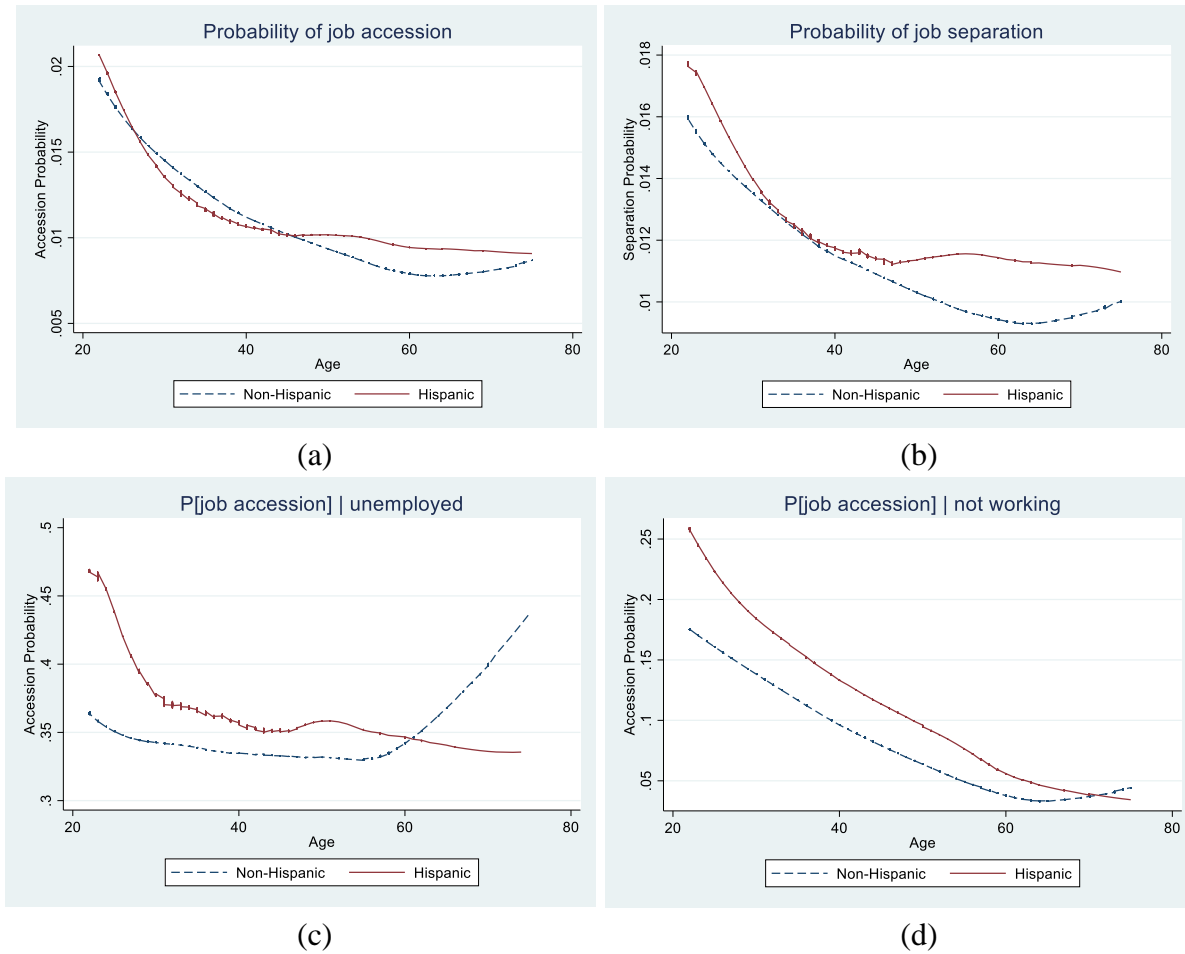
Although there are slight differences in the probability of a job accession between the two groups that vary with age of the worker shown in Figure 3a, it is not large. Hispanic workers are more likely to see a job separation than are non-Hispanic workers, particularly after age 50, shown in Figure 3b. Once we condition on people who are unemployed as in Figure 3c or not working, as in Figure 3d, it appears that Hispanic job seekers are more likely to have a job accession, though this difference decreases by age 60 and reverses for unemployed job seekers.

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Figure 4 Characteristics and Items that could affect Employment Outcomes

(a)

(b)

(c)

(d)

(e)
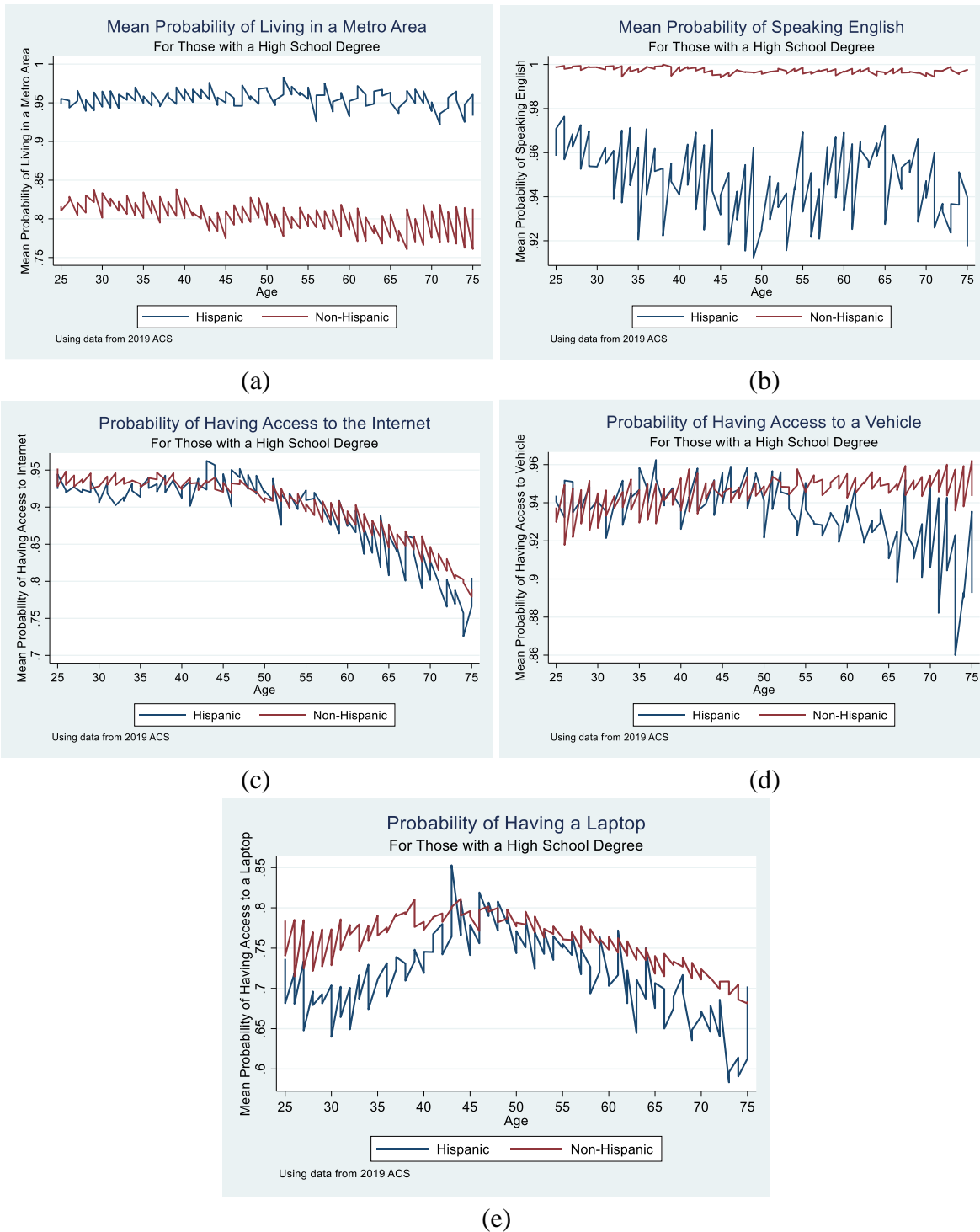
We next return to the 2019 ACS to look at differences in characteristics and items that could affect employment outcomes. With a few exceptions, this access for Hispanic and non-Hispanic people does not differ across the lifecycle. Figures 4a-e plot different outcomes by age. Although

Hispanics are more likely, on average, to live in a metropolitan area than are non-Hispanics, this difference remains relatively constant across the adult lifecycle with about 95% of Hispanics reporting living in a metropolitan area compared to 80% of non-Hispanics. Similarly, although nearly 100% of non-Hispanics report speaking English, there is very little difference in the probability of Hispanics speaking English with probabilities ranging from 92% to 96%. Although access to internet decreases with age, this access is nearly identical for Hispanics and non-Hispanics. Access to a vehicle is nearly the same for younger Hispanics and non-Hispanics, but while it remains around 94% for non-Hispanics between ages 55 and 75, it gradually decreases to around 86% for non-Hispanics during this time period. Access to a laptop is generally lower for Hispanics compared to non-Hispanics, though this difference reaches its lowest point around ages 45-50, when both groups report 75% having access to a laptop, before increasing again.

There are several problems with using data from national surveys to compare Hispanic to non-Hispanic outcomes, particularly over time as with the cohort graphs. First, the Census and ACS data were affected by several question changes in 1980, 2000, and 2008 that increased the number of people responding that they were Hispanic which could also change the composition of people who report being Hispanic and non-Hispanic. Second, these surveys do not fully capture all Hispanic people in the US, particularly those who are not native born (O'Hare 2019), and the extent of this problem will vary with changes to citizenship status, xenophobia, and the legal status of immigrants (O'Hare 2019). Additionally, survey data can only provide information about point-in-time general equilibrium, which includes both supply and demand sides of markets. Resume experiments like the three discussed below can instead look at the first step of the hiring process to determine how hypothetical job applicants are treated by Hispanic status, ceteris paribus.

III.   Experiment 1—Student sample

The first two experiments discussed in this paper have a similar methodology. In both studies, participants were asked to rate 40 resumes for an entry-level clerical position for which the items in the resume had been randomized. While doing the rating, their eyes were tracked with an eye-tracking device. In both experiments about 13% of the resumes had Hispanic last names. Thus, these experiments will only be able to say something about Hispanic applicants with Hispanic last-names and non-Hispanic first names.

III.A. Design

The study took place between January 2013 and January 2014. We recruited participants using flyers at a large southwestern university. The sample was restricted to professional students, particularly MBA, MPA, and HR graduate students as well as business undergraduates. We dropped two non-native English speakers and one participant with a diagnosed learning disability because these could affect eye-tracking (Holmqvist et al., 2011). The final sample has 152

participants who were paid $20 for the session. As shown in Table 1, thirty-eight percent of participants were Master students, one percent were Ph.D. students, 38 percent were upper-division undergraduates, and 23 percent were lower-division undergraduates. The average age was 22, and 56 percent of the sample was female. Eighty-nine percent of the participants identified as White, 7 percent as Asian, and 5 percent as Black or African American. Fifteen percent of participants identified as Hispanic or Latino.

Because of constraints of the eye-tracking system, the sessions were run individually for each participant. Most people finished in less than 45 minutes. The task consisted of rating resumes for an administrative level one position. We created the resumes using Lahey and Beasley's (2009) resume randomizer program and used a database of resume inputs drawn from actual resumes. The program randomly chooses from the database high school graduation date (to signal age), first name (to signal gender and race), home address, email address, high school attended, previous work experience texts, additional training, volunteer experience, and a statement about flexibility. Addresses were selected randomly from the Houston metropolitan area, and we took high school names randomly from across Texas. In another study, we checked the perceived race, gender, ethnicity, and socioeconomic status of the names using a sample of 95 psychology students (Barlow and Lahey, 2018).

Each participant rated 40 unique resumes. Resume characteristics repeated across participants, but each participant saw each specific line at most once. Graduation dates followed a uniform distribution, 50 percent of the resumes had a female name, 9 percent had black names, and 13 percent had Hispanic last names and non-Hispanic first names. After the sessions, we divided the resumes into "Areas of Interest" (AOI) to measure the time spend in each section. For the purposes of this study, we removed the resumes with Black first names prior to data analysis because there may be interactions between Black and Hispanic names but we do not have a large enough sample size to investigate those interactions.

At the start of the session, participants read an information sheet and consented to participate. We told participants that the purpose of the study was understanding how hiring managers decide whom to interview. We calibrated the eye-tracking equipment, a D6 eye tracking system from Applied Science Laboratories (Bedford, MA), to capture where the participant was looking on the computer screen. Participants read a description of the administrative position and were asked to rate the ability of the candidate to fulfill the position, using a 7-point Likert scale, with 7 as most "hireable". Participants rated 40 resumes, one at a time. After rating the resumes, participants completed a series of psychological, political, and demographic questions. After finishing the survey, participants were debriefed and paid.

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III.B. Results

In Figure 5 we plot separately for Hispanic and non-Hispanic hypothetical applicants, age, as indicated by date of high school graduation, against the participant's Likert (1-7) rating, with 7 indicating most hireable, using an lpoly smoother with 95% confidence intervals. Here we see a general, but not necessarily statistically significant, decline of resume rating with age for both groups. The lines for the two groups are overlapping until around age 60 when the non-Hispanic group increases in ratings while the Hispanic group continues on its downward trend. Even with the trends diverging, the non-Hispanic line is still within the confidence intervals of the Hispanic line.

Figure 5 Ratings across Ethnicity and Age – Experiment 1
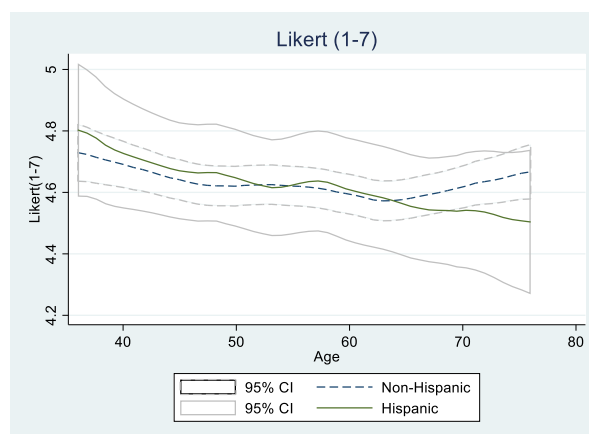
Figures 6a and b repeat this exercise for male and female hypothetical applicants respectively. We see in general that for men, Hispanic applicants are generally preferred to non-Hispanic applicants, but that their confidence intervals are generally overlapping and trends overall seem similar: mostly flat with a slight downward trend. For women, the order of the lines is reversed, with non-Hispanic women preferred over Hispanic women. Here, the line for Hispanic women is a straight downward trend while that for non-Hispanic women shows an initial decline followed by a bump up around age 50. Even so, the confidence intervals for these two groups have substantial overlap. While there may be concerns about sample size, it is important to note that using the same experiment, Lahey and Oxley (*forthcoming*) found significant differences in the patterns of hypothetical applicants with black names and those without, even though the proportion of resumes with black first names (9%) is smaller than those with Hispanic last names (13%). Regression analysis in Table 2 finds no significant interaction with Hispanic last names and a quadratic age term.

Figure 6 Ratings across Ethnicity and Age by Gender – Experiment 1

(a)   (b)
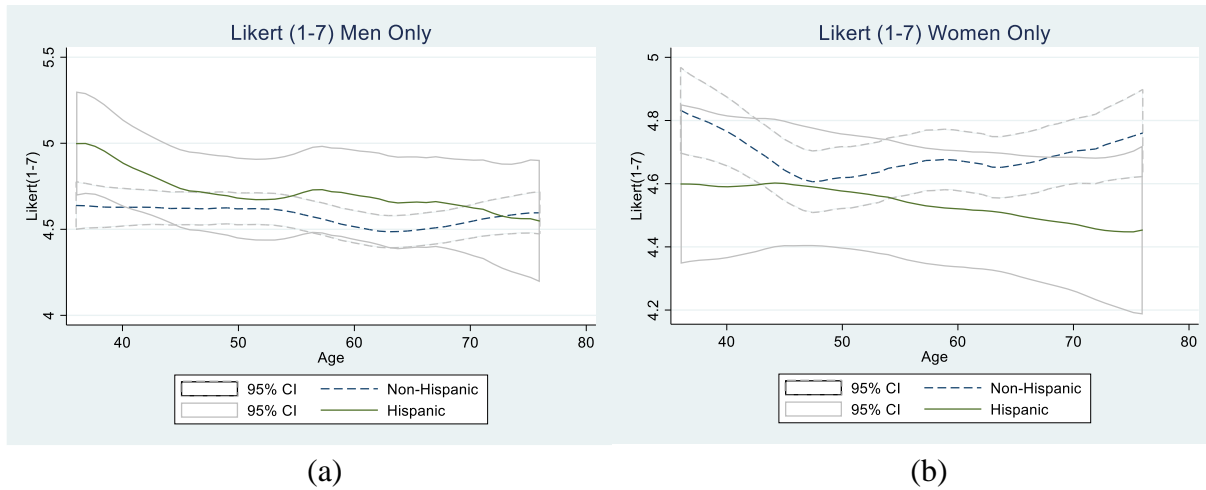
We have also repeated the previous charts using time spent on the resume as the outcome variable, as demonstrated in Figures 7a-c. There are no consistent differences in time spent by Hispanics compared to non-Hispanics and the confidence intervals overlap.

There may be concern that the student sample, while made up of masters and undergraduate students likely to be hiring in the future, is too young to provide an externally valid group for this study. Therefore experiment 2 repeats this study with a sample of human resource managers recruited from career fairs and businesses.

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Figure 7 Time Spent on the Resume by Ethnicity and Age – Experiment 1
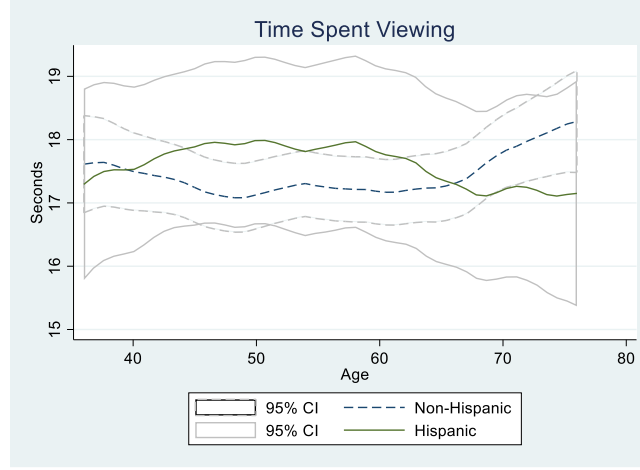
(a)
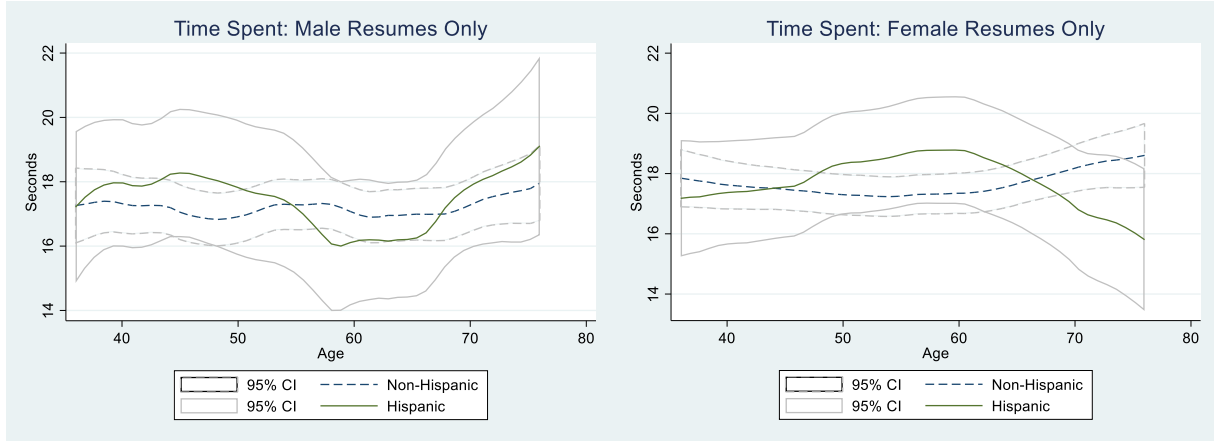
(b)

(c)

IV.   Experiment 2—Human resources sample

IV.A. Methods

The design and methodology to Experiment 2 were identical to that of Experiment 1 with the following changes: First, and importantly, the participants of this study were 67 human resource professionals who were recruited with the help of a regional human resources association. Instead of bringing participants into the laboratory, we brought a portable Tobii X2-50 eye-tracker to human resources conferences and to participants' places of work. Finally, participants were paid $50 to compensate them for their time rather than $20 in acknowledgement of the increased value of their time.

The demographics of this new sample differ considerably from the student sample, as demonstrated in Table 1. They are more likely to be female (81%), somewhat less likely to be

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White (85%), less likely to be Asian (1%), more likely to be Black (15%), slightly more likely to be Hispanic (19%) and about 20 years older on average (average age is 44).

IV.B. Results

Figures 8a-c repeat the exercise in Figures 5 and 6 for the population of HR manager participants. Again, we see evidence of a slight downward trend and the non-Hispanic line being entirely within the confidence intervals for the Hispanic line. As with the student sample, if anything, there is a divergence at older ages with the Hispanic sample less preferred than the non-Hispanic sample. Given the smaller sample size, the lines, particularly for Hispanic applicants, are not as smooth as they are for the larger student sample, which could account for the odd bumps in the middle of the HR sample. Alternatively, these bumps could be representative of differences in beliefs between the two samples.

Figure 8 Ratings across Ethnicity and Age – Experiment 2

(a)

(b)

(c)

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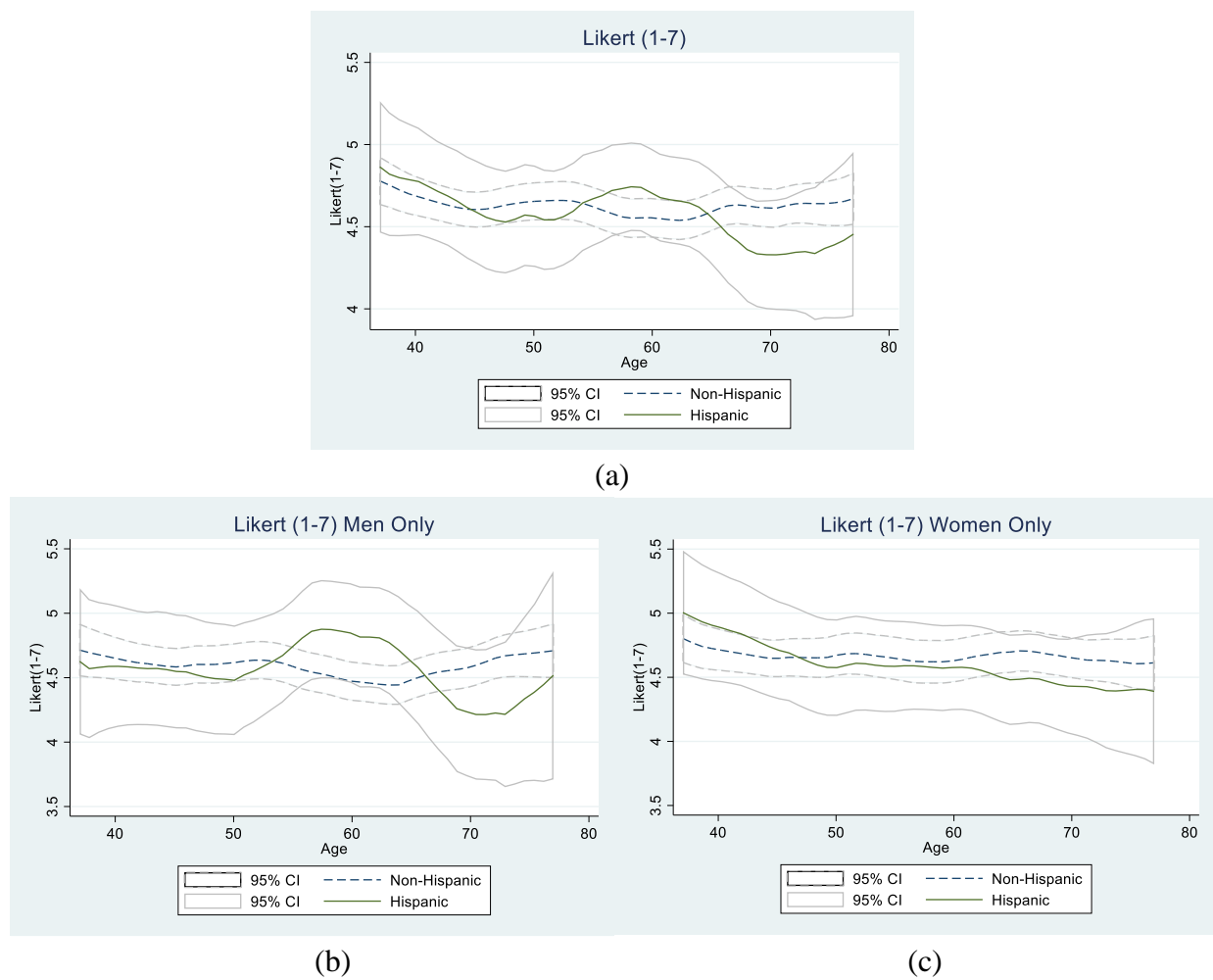
Figures 8b and c again repeat these exercises for male and female hypothetical resumes, respectively. In Figure 8b, we see that the male resumes account for the odd bumps in the entire sample. Unlike the student sample, there is no dominating pattern of Hispanic male resumes being preferred over non-Hispanic male resumes. Instead, the lines are generally overlapping. Similarly, there is no dominating pattern of non-Hispanic female resumes being preferred over female Hispanic resumes with the HR sample. Again, the lines are generally overlapping, although there may be some divergence at older ages as Hispanic female resumes earn lower hireability ratings at older ages. Regression analysis in Table 2 finds no significant interaction with Hispanic last names and a quadratic age term. In general, it appears that Hispanic and non-Hispanic resumes are not treated very differently by the HR sample. Again, this is in contrast to findings for black and white resumes, which show different patterns (see Lahey and Oxley *forthcoming*), although statistical significance is too small to say anything definitive.

We again repeat these charts using time spent on resumes as the Y variable in Figures 9a-c. HR managers may spend slightly less time on non-Hispanic slightly more time on Hispanic resumes as the applicants get older, but if so, the differences are less than a second per resume. Time spent on male Hispanic resumes may increase with age while remaining flat or downward shaped for male non-Hispanic resumes, while HR professionals spend more time on female Hispanic compared to female non-Hispanic resumes throughout the ages in our sample. However, these differences, if they exist, remain small.

V.   Experiment 3—New experiment with mTurk sample

One limitation of the first and second experiments is that ethnicity is signaled using only Hispanic last names. It is plausible that either the signal is too weak to convey ethnicity or that participants perceive a non-Hispanic first name with a Hispanic last name as a second- or later-generation person who is no different from a non-Hispanic person. Both reasons could explain the absence of significant differences in ratings between Hispanic and non-Hispanic resumes in these experiments. Thus, in the third experiment, we widen the signal of Hispanic names to include combinations with Hispanic first names. We also take the study to mTurk to expand the sample to cover a broader part of the US population and recruit a larger sample to increase statistical power. One disadvantage of this sample is that we cannot use eye-tracking technology to validate if the participants are paying attention to the different sections of the resumes.

In addition to widening the Hispanic signal, we test if stereotypes against Hispanics affect ratings. Potential stereotypes include the beliefs that Hispanics have poor communication skills, need more supervision, are lazy, tend to have many children, and are more suited to manual labor (Dixon and Rosenbaum 2004, Dong and Murrillo 2007, Jackson 1995, Jones 1991, Market 2004, Ramierez Berg 1990). These stereotypes may affect resume ratings and point towards discrimination. We introduce questions and resume elements to test if specific stereotypes against Hispanics may explain potential differences in resume ratings.

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Figure 9 Time Spent on the Resume by Ethnicity and Age – Experiment 2
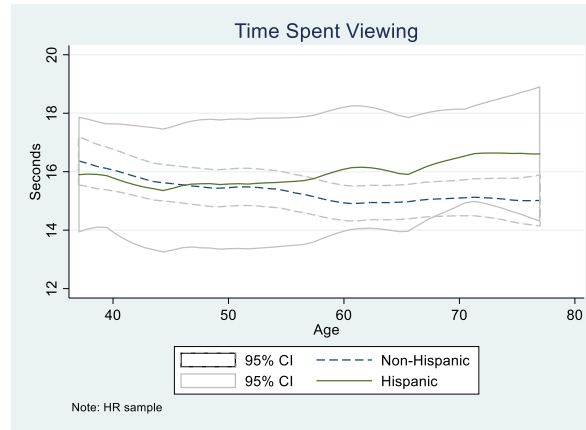
(a)
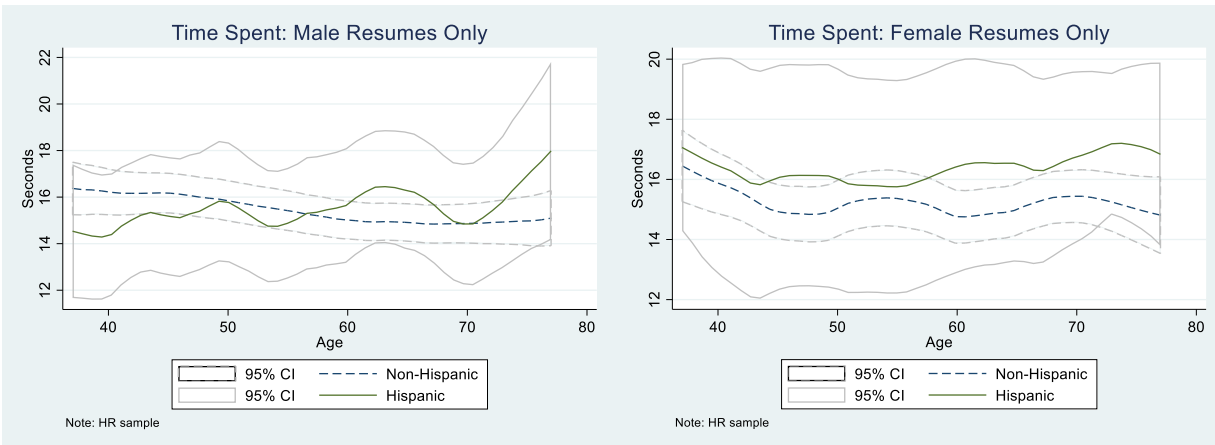
(b)

(c)

V.A. Design

We recruited 1,068 participants from Amazon's mTurk in five waves between September 2019 and July 2020. We recruited participants with verified managerial experience in the first two rounds, participants with clerical experience in waves three and four, and the general population in waves four and five.[2] We created a task in mTurk asking mTurk workers to rate 30 resumes of applicants to the same administrative position as in experiments 1 and 2 (for a total of 32,040 unique resumes). If the worker accepted the task, they were directed to a survey hosted in Qualtrics. To prevent biasing participants, we did not disclose that the survey was part of a research project until they completed the survey. The survey described first the characteristics of the position, then displayed the resumes one by one, asking participants to rate them on a 7-point Likert scale for

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[2] mTurk allows for tasks to be sent to participants with particular traits previously identified by mTurk.

"hireability" as in the prior studies. Then, in a second round, we redisplayed the resumes in the same order asking participants to rate if the applicant had necessary skills, the applicant's communication skills, and their need for supervision. We followed with a series of demographic questions, and unincentivized trust, reciprocity, and altruism questions (Appendix B). After completing the surveys, the participants received a code to enter in mTurk to receive their payment. We debriefed participants, revealing that they had participated in academic research, and gave them the option to drop out of the study without affecting their payment. Nobody dropped out of the study. We paid participants $4 for a half an hour task.[3]

We created fictitious resumes using the same procedure described in experiments 1 and 2. As mentioned above, we enhanced the Hispanic signal introducing Hispanic first names to the resumes. The resumes were randomized such that the proportion of Hispanics and non-Hispanics is representative of the population in Texas. Specifically, 80 percent of the resumes have non-Hispanics first and last name, 10 percent have Hispanic first and last name, 5 percent have a non-Hispanic first name and Hispanic last name, and 5 percent have a Hispanic first name and non-Hispanic last name. Fifty percent of the resumes have female names, and age ranges between 35 and 75 years. To test some of the stereotypes affecting Hispanics, we introduced volunteer experiences that randomly combine Catholic and non-Catholic volunteering and PTA volunteering to signal religiosity and having children.

V.B. Data Quality and Participants

While recent research shows that experimenter demand effects are not likely to be a concern in survey experiments in general and mTurk survey experiments in particular (Mummolo and Peterson, 2019; de Quidt et al., 2018), we took several steps to ensure the best possible data quality. First, as mentioned above, participants did not know the rating process was part of academic research until they finished the survey. Small companies use mTurk to rate applicants, so this task is not unusual for mTurk workers. Second, after the participants finished rating the resumes, we introduced an attention check question asking for a specific answer to stimulate respondents to pay extra attention to the subsequent rating questions (Appendix B). We introduced a second attention check question after the demographics questions. Finally, there may be some concerns about lack of effort, lack of attention, and deception in MTurk that could affect the quality of the data collected (Hauser et al., 2018; Kennedy et al., 2018; Dennis et al., 2019). To address this concern, we restrict the sample to participants who passed attention checks, took more than 20 minutes to complete the survey, and have a unique IP address. We also checked three open-ended questions that asked participants in which state they were born, grew up, and where they currently reside. We excluded participants who did not write a valid US state name in these questions. As a last check, Qualtrics reports GPS coordinates associated with IP addresses at the city level. We deleted

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[3] The first wave was a pilot with 79 participants to obtain data to calculate power and calibrate payment according to mTurk's ongoing rates. In this wave, we paid participants $3 for completing the task.

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any participants whose coordinates do not belong to the United States. The final sample has 739 participants (22,170 resumes).

Table 3 presents summary statistics for the mTurk participants. Fifty-five percent of the participants in the third experiment are women. The average age of the participants is 41.7 years. Eighty-two percent of the sample identifies as White, and 10 percent as Hispanics. These proportions are close to the general U.S. population. Sixty-three percent of the sample has a college education or more, which is a larger proportion than in the general US population. Almost 55% of the sample has worked for more than 15 years. Ninety-two percent report having worked for payment during the last week, and 44% report having an annual income above $50,000. Almost 30 percent of the sample has human resources experience, 62 percent has some hiring experience, and 68 percent of the participants report having some managerial experience, which is consistent with our targeting of managers.

We used data from the first wave (79 participants) to calculate the sample size needed to detect effect sizes larger than 0.1 with 80 percent power. This way, we can detect anything but small effect sizes. Given our design, to detect differences among the four ethnicity signals (non-Hispanics, Hispanic first and last name, non-Hispanic first name and Hispanic last name, and Hispanic first name and non-Hispanic last name), we required a sample of 271 participants. To detect differences across the age range, we required a sample with 276 participants. To detect differences among the ethnicity signals as they age, we required a sample with 394 participants. Hence, the final sample of 739 participants has enough power to detect anything but small effect sizes.

VI. Results

VI.A. mTurk Participants Pay Attention to the Resumes

Moving the study to mTurk has the disadvantage that we are not able to track what participants are looking in the resumes. We address this issue in four ways. First, we restricted the sample to ensure high quality data as we discussed in the previous section so that people who were not engaging with the survey as a whole were removed.

Second, in the pilot wave, we designed questions similar to Equal Employment Opportunity items and asked participants if they believed that the candidate was over 40 years, if the candidate was part of an underrepresented minority group, and whether or not the candidate was a veteran (although we do not use answers to the latter). Table 4 shows that for resumes with age less than 40, almost 90 percent of the participants correctly indicate that the candidate is younger 40 years old. For resumes signaling age 40 or more, 69 percent of the participants correctly indicate that the candidate is age 40 or older. Similarly, Table 5 shows that for non-Hispanic resumes, 92.6 percent of the participants correctly indicate that the candidate is not from a minority group. For resumes with both a Hispanic first and last name, 67.1 percent of the participants correctly indicate the candidate is from a minority group. Results are not as clear for resumes with a Hispanic and non-

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Hispanic mix in the name. Participants believe that 57 percent of the resumes with a non-Hispanic first name and a Hispanic last name belong to a minority group. In comparison, they indicate that 44 percent of the resumes with a Hispanic first name and a non-Hispanic last name are part of a minority group. We can conclude that, in general, participants can get age and ethnicity from the resumes.

Third, there is a concern that participants who answered the survey on a cellphone or tablet might not be able to read the resumes clearly because of a smaller screen. Qualtrics reports the device's operating system where the participant completed the survey, and we use this information to identify the type of device. Of the participants who pass all the data quality checks, only 34 answered the survey on a cellphone or tablet. These participants do not exhibit significant differences in ratings compared to participants who completed the survey on a computer.

Finally, to check if participants pay attention to resumes, we estimated three machine learning models that use resume characteristics, excluding age and ethnicity, to predict resume ratings. Specifically, we included as predictors indicators for every job history, skill, email provider, high school name, and volunteering experience included in the resumes. We estimated a linear LASSO, a two-step adaptative LASSO, and a Random Forest. For comparison, we also estimated a linear regression, including the same resume characteristics we used to train the machine learning models. Table 6 presents the predictive power of these models. The LASSO models' R^2 fluctuates between 0.218 and 0.229 in the training and validation sets. For comparison, the linear regression with the same controls has an R^2 of 0.2. The Random Forest model has an R^2 of 0.793. This model has a higher predictive power because it tests arbitrarily for more interactions than the LASSO. Table A 1 shows that all these specifications are highly correlated. We can conclude that resume characteristics have high predictive power for resume ratings.

We also take advantage of the fact that all of the resume controls (other than age, which we do not include in our machine learning) are dummy variables to rank the variables LASSO keeps as predictors by the magnitude of their coefficients and check which characteristics of the resume contribute more to the prediction. We find that detailed job histories related to clerical experience and skills related to clerical work have the highest weights in LASSO. On the other hand, job histories not related to clerical work like babysitting, waiter or cook, high school name, and email provider have the lowest weights or are not chosen as predictors by LASSO. The same is true for OLS estimates that use the same variables as LASSO as predictors (Appendix Table A 2). For example, values in bold in the table correspond to jobs that explicitly use the words "clerical" or "clerk," highlighting their relevance for the rating. These estimates are positive, highly significant and have large magnitudes. Similarly, volunteer experience generally has a positive effect on resume ratings, unemployment spells have a negative effect, and listed skills have positive effects. Overall, these results suggest that participants read the resumes and used their information to rate the candidates.

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VI. B. Baseline Results on Age and Hispanic Status

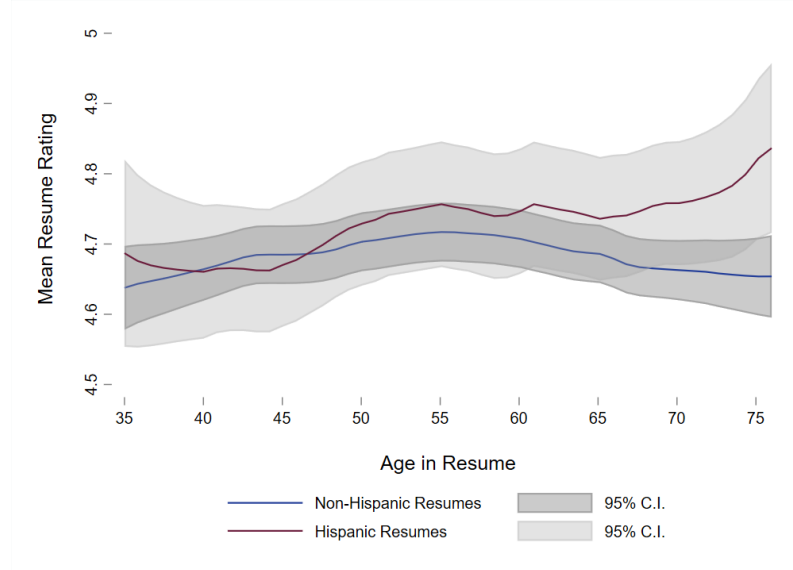### Figure 10 Resume Ratings by Ethnicity and Age – mTurk Sample

Figure 10 replicates the same exercise as in Figures 5 and 8a. In contrast with the results of the previous experiments, we only observe a decline of resume ratings for non-Hispanics starting around age 55. However, the trends in ratings across age are not necessarily statistically significant. For Hispanic applicants, we can see a decline in ratings until age 45. After that point, ratings increase with age. There is no statistically significant difference between Hispanic and non-Hispanic ratings. The non-Hispanic line is within the confidence intervals of the Hispanic line except for the oldest hypothetical applicants.[4] Table 7, Panel A, provides regression estimates for Figure 10 and shows no meaningful difference in resume ratings between Hispanic and non-Hispanic resumes. Similarly, in Table 8, we present the results of a regression of a quadratic trend in age interacted with a Hispanic indicator. For non-Hispanics, we cannot reject that ratings are not affected by age. The point estimates are small and statistically insignificant. For Hispanics, the results support that ratings have an inverse-U shaped pattern across age. To visualize this effect of age on ratings, Figure 11 plots the marginal effect of age for Hispanics and non-Hispanics at different age thresholds. For non-Hispanics, the marginal effect of age has a negative trend, but the coefficients are small and statistically insignificant. For Hispanics, the marginal effect of age has a positive trend, and the marginal effects become statistically significant at age 60.

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[4] In addition to asking about the "Hireability" rating in the first round of resume rating, we also asked participants whether or not each candidate had the necessary skills to fulfill the position in the second round of rating (Appendix Figure A 1). Again, we find no significant difference between Hispanic and non-Hispanic resumes. The patterns are similar to the results in Figure 10. For non-Hispanics, ratings are flat, with a slight decline starting at age 55. For Hispanics, ratings increase with age.

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Figure 11 Marginal Effect of Age for Hispanics and non-Hispanics – mTurk Sample
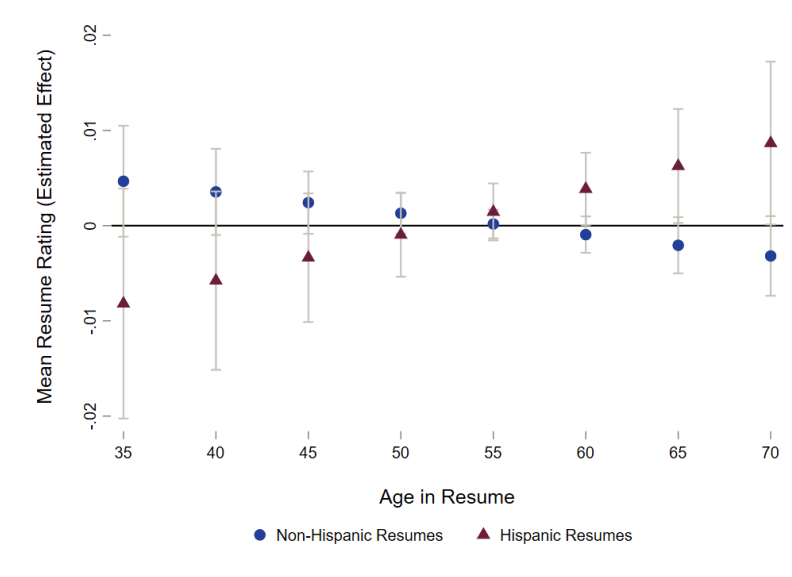
In Figures 12a-c, we split Hispanic resumes by the three different types of Hispanic names. We find that resume ratings for resumes with a full Hispanic name follow the ratings for non-Hispanic resumes closely. The increasing trend in ratings with age is present only for resumes with a mixed name (either a Hispanic first name or last name, but not both). However, there is no significant difference with non-Hispanic resumes. Regressions to verify the patterns in Figure 12 in Table 7, Panel B, indicate that, on average, there is no meaningful difference in resume ratings between Hispanic and non-Hispanic resumes. In every case, that point estimates are smaller than 1.5 percent of the average rating for non-Hispanics and statistically insignificant.[5]

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[5] We also check if the most common Hispanic names according to Census data elicit a different response. Again, the point estimates are small and there is no significant difference in the response to these names compred to other, less common, Hispanic names.

Figure 12 Resume Ratings by Type of Hispanic Signal
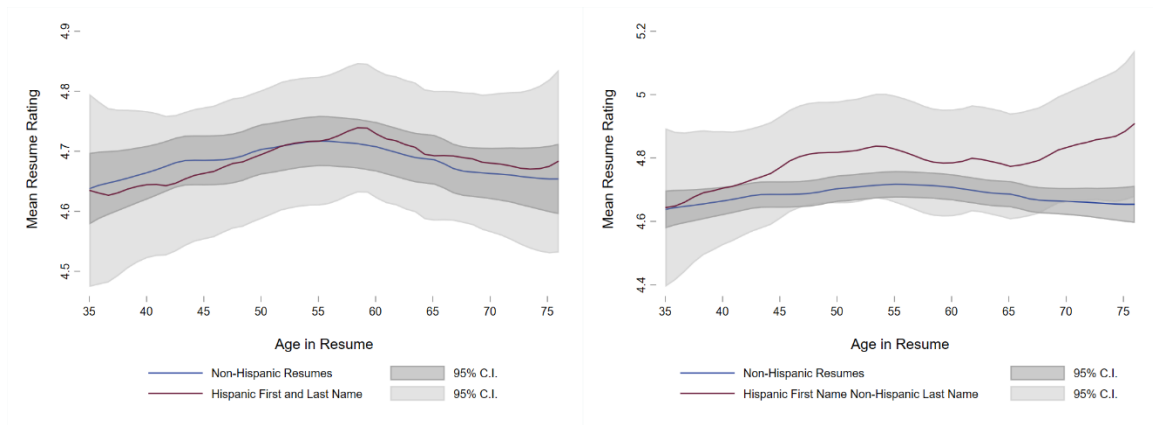
(a) Hispanic first and last name

(b) Hispanic first name, non-Hispanic last name
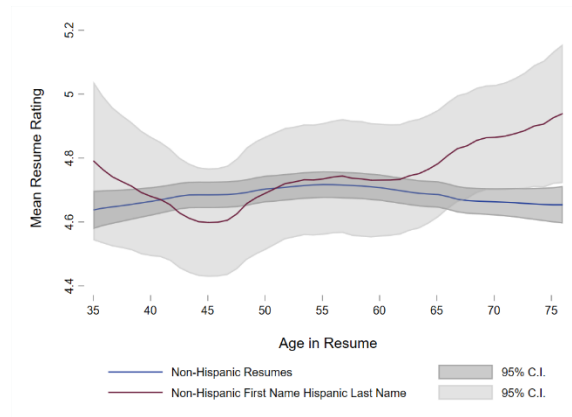
(c) Non-Hispanic first name, Hispanic last name

Figure 13 splits Figure 10 by gender, comparable to Figures 6a-b and 8b-c. Again, there is no significant difference between Hispanics and non-Hispanics across different ages. For men, both Hispanic and non-Hispanics display an inverse-U trend, and the ratings are close to each other. For non-Hispanic women, there is a slight negative trend, while Hispanic women display an increasing trend. For both genders, for almost every age, the non-Hispanic line lies within the Hispanic line's confidence interval.

Figure 13 Resume Ratings by Ethnicity, Age, and Gender – mTurk Sample

To test the robustness of these results, we apply several restrictions to the sample to try to match it to the HR sample from Experiment 2. First, we restrict the sample to participants with at least a college education (Figure A 2). We then select participants with a college education, HR experience, and hiring experience (Figure A 3). We also matched participants to the HR sample using propensity score matching on all observable demographics (Figure A 4). Finally, we restrict the sample to waves one and two, where we contacted mTurk workers with manager qualifications registered in mTurk (Figure A 5). We find similar patterns as the results in Experiments 1 and 2, and we cannot reject that Hispanics have the same pattern as non-Hispanics.

V.F.1. Heterogeneity by Participant Characteristics

We now explore if there are different patterns in resume ratings among participants with different characteristics. Figures 14a-f present these results. In general, we find no significant differences in ratings between Hispanic and non-Hispanic resumes, and the patterns are consistent with the main results. Figure 14a shows that men and women give similar ratings to Hispanic and non-Hispanic resumes. Patterns across age are similar, and there is no significant difference in ratings. Splitting participants by age, we find that participants older than 45 years give lower ratings than younger participants, give lower ratings for older non-Hispanic candidates, and prefer an older Hispanic applicant to an older non-Hispanic applicant (Figure 14b). Participants younger than 45 years give flatter ratings for both Hispanics and non-Hispanics, with no meaningful differences between both groups.

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Figure 14 Heterogeneity in Resume Ratings by Participant Characteristics

(a) Gender

(b) Age

(c) Race

(d) Ethnicity
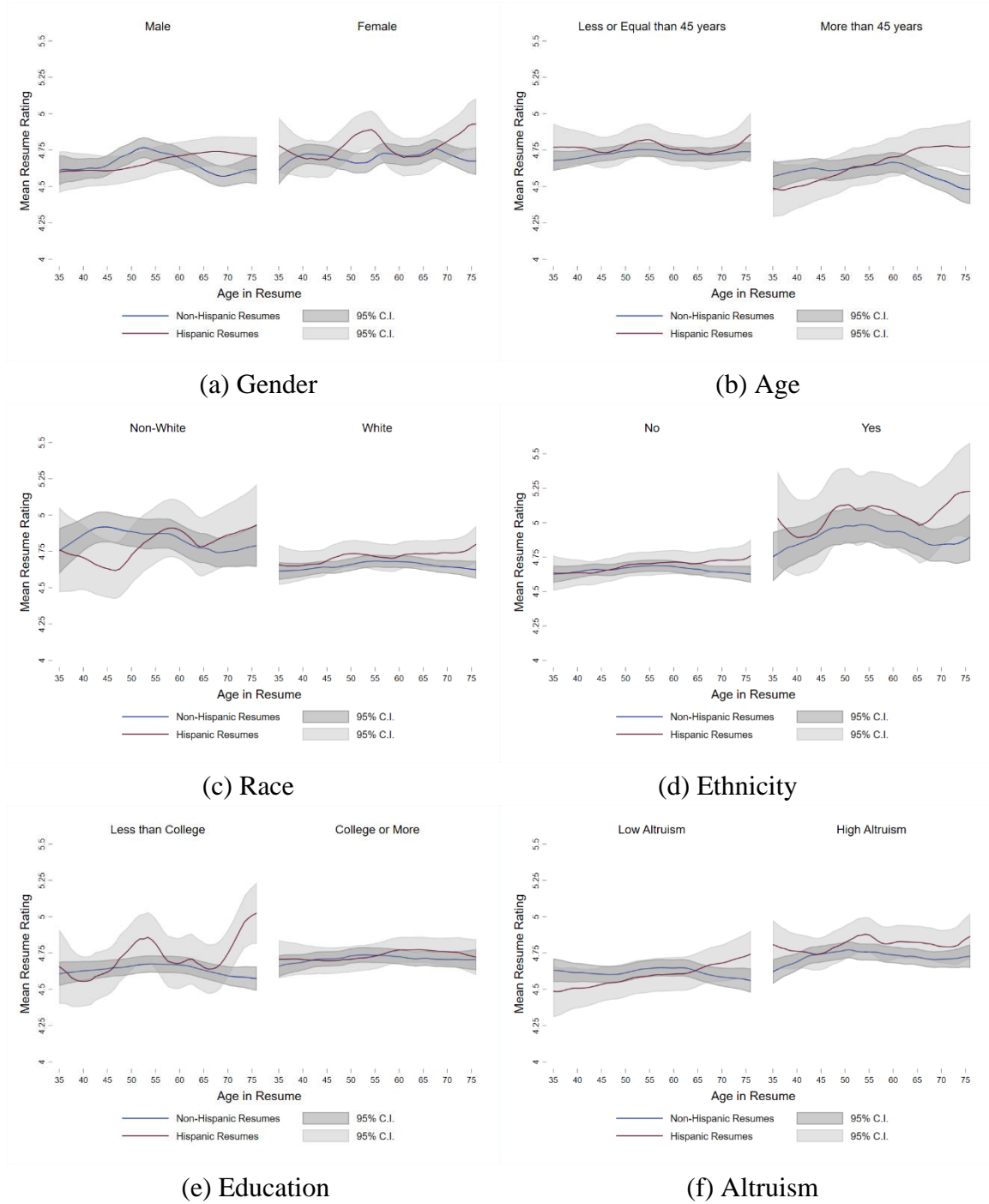

(e) Education

(f) Altruism

Figure 14c displays ratings splitting participants by race. White participants give lower ratings than non-White participants in general, and there are no significant differences between Hispanics and non-Hispanic resumes. The estimates for non-White participants are noisier than the ones for

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White participants due to a smaller sample size, but again there are no differences between Hispanics and non-Hispanic resumes. Regarding ethnicity, participants who identify as Hispanic give higher ratings than participants who do not identify as Hispanic and slightly higher ratings for Hispanic resumes (Figure 14d).

Figure 14e explores differences by participant's education. Participants with a college education or more give flat ratings across age for both Hispanic and non-Hispanic applicants, with no significant difference between both groups. Less-educated participants give higher ratings to older Hispanic candidates.

Finally, we also included a question to elicit altruism from participants and check if differences in altruism lead to differences in ratings between Hispanic and non-Hispanic resumes. Figure 14f presents these results. High-altruism participants give Hispanics higher ratings, and the difference to low-altruism participants is statistically significant. However, these results are only suggestive since we did not incentivize the question that elicits altruism.

V.F.2. Regional Heterogeneity in Resume Ratings

Now, we check if resume ratings for Hispanics and non-Hispanics vary across the United States. We asked participants in which state they currently reside, and Qualtrics reports the geographic coordinates associated with the participant's internet provider's IP address. With these inputs, we distribute participants into five regions: Northeast, Southeast, Midwest, Southwest, and Northwest. It is important to note that in this classification, the Southwest includes all territories that were once part of Mexico, including California.

Figure 15 presents how resume ratings vary across regions. Participants in the Northeast and Southeast rate non-Hispanic applicants similarly, with a flat trend across age. In contrast, non-Hispanic resume ratings display a negative trend across age in the Midwest, Southwest, and Northwest. In the first two regions, this negative trend starts around age 55, while it is present in the Northwest's entire age range. We cannot find statistically significant differences in ratings for Hispanic applicants than non-Hispanics in any region, but we find different patterns across regions. In the Midwest and Southwest, which have large Hispanic populations, resume ratings for Hispanics display an increasing trend across the entire age range. This increasing trend is also present in the Northeast, which also has a significant Hispanic population, particularly in New York, but it only affects older Hispanics, starting around age 60. In the Southeast, ratings for Hispanic resumes are flatter, more similar to ratings of non-Hispanics. Finally, in the Northwest, ratings for Hispanic resumes exhibit a negative trend, similar to the one for non-Hispanic resumes.

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Figure 15 Regional Heterogeneity in Resume Ratings
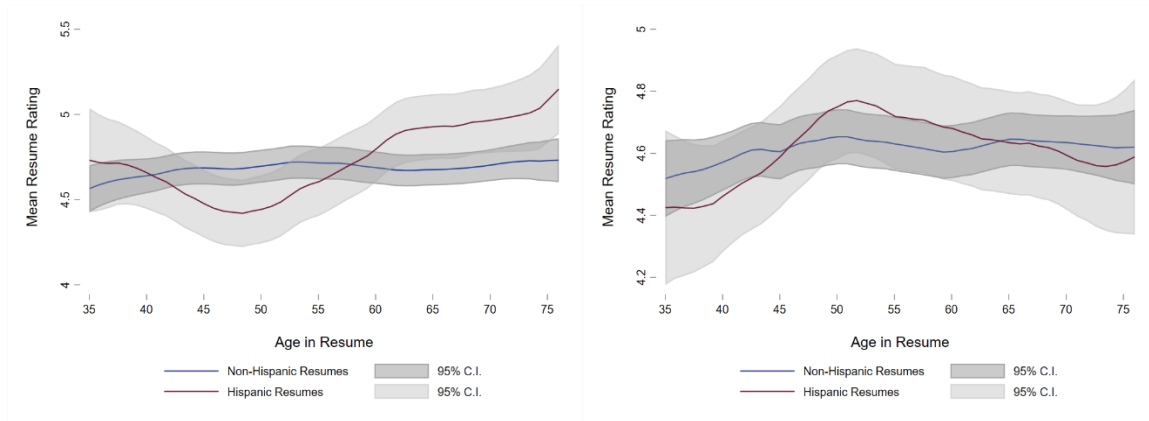
(a) Northeast

(b) Southeast
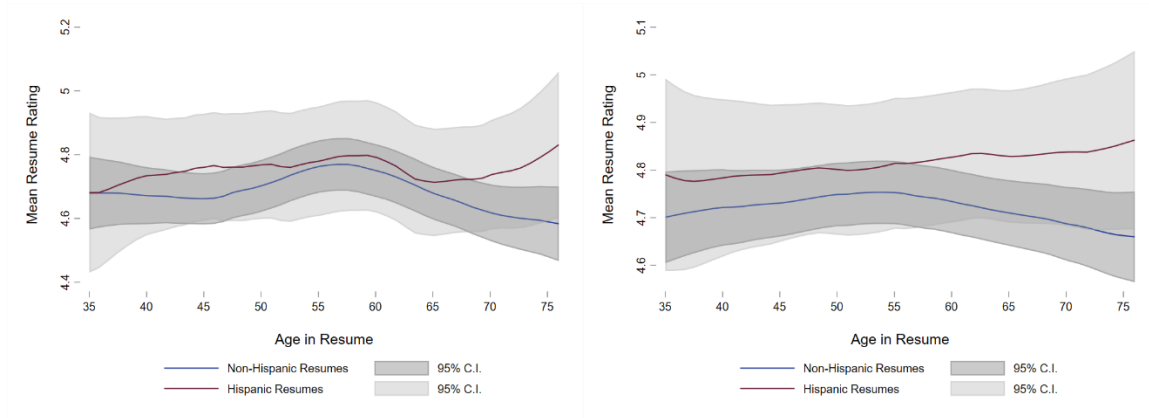
(c) Midwest

(d) Southwest
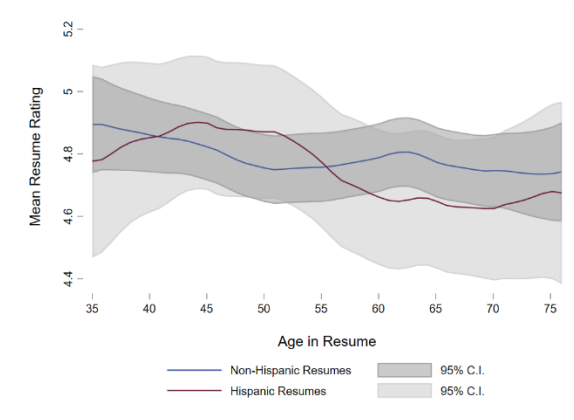
(e) Northwest

Figure 16 Differences between Red vs Blue States
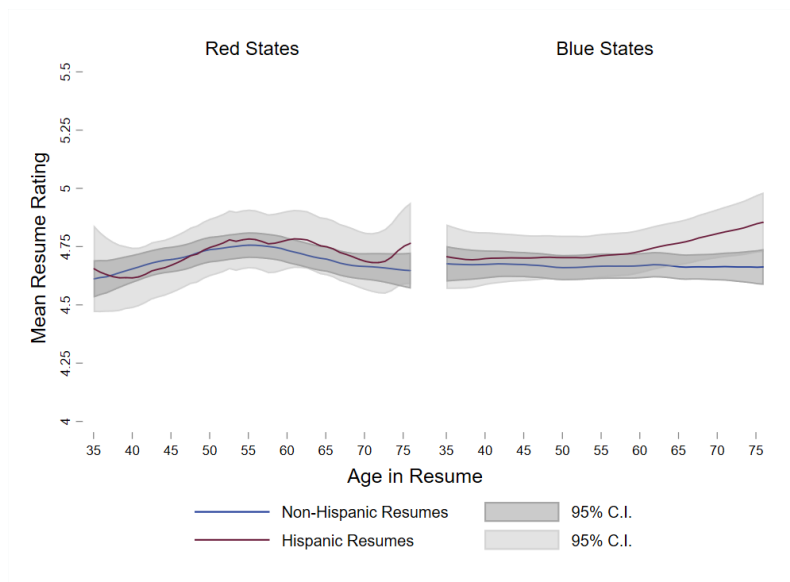
We also split participants into living in "Red" or "Blue" states using the 2016 Presidential Election results (Figure 16). In "Red" states, resume ratings for Hispanic and non-Hispanic applicants are similar, following the same trends across age. In "Blue" states, resume ratings for Hispanic candidates display an increasing trend starting at age 55. In both cases, there are no statistically significant differences in ratings between Hispanic and non-Hispanic resumes.

V.F.3. Checking Hispanic Stereotypes

The literature on psychology and film and television identify several stereotypes of Hispanics that could also be present in labor markets. These stereotypes include being lazy and needing more supervision, having poor communication skills, having many children and taking time off work, and being suited to manual labor (Ramirez Berg, 1990; Jones, 1991; Jackson, 1995). We introduced two approaches in the survey to analyze the potential effects of these stereotypes on resume ratings. First, when we brought back the resumes after the first rating, we asked participants questions to assess potential stereotypes as outcome variables. We asked participants how much supervision they think the candidate needs and rate the candidates' communication skills.[6]

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[6] We also asked whether or not they had the skills for the position, as noted in footnote 4.

Figure 17 Need for Supervision and Communication Skills

(a) Supervision   (b) Communication Skills
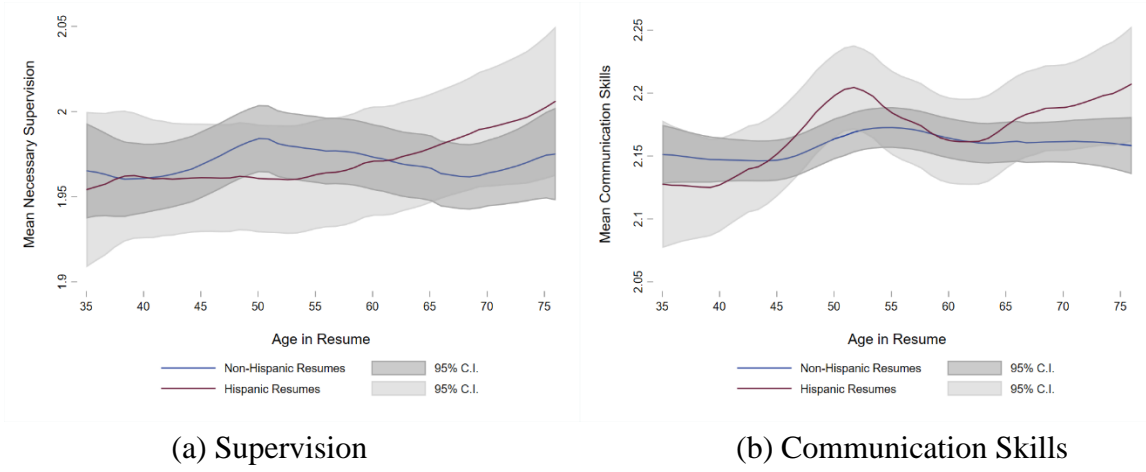
Figure 17 presents these results. Note that in Figure 17a, we inverted the measure, so a higher number means less need for supervision. While younger Hispanics have slightly lower ratings, we do not find statistically significant differences between Hispanic and non-Hispanic candidates. The patterns across age are consistent with the ones for resume ratings, with Hispanics experiencing an increasing trend starting at age 55. Figure 17b shows the ratings for communication skills. Again, we do not find statistically significant differences between Hispanic and non-Hispanic candidates, and the patterns across age are consistent with the ones for resume ratings. If anything, communication skills for Hispanics increase with age.

As a second approach to study the effect of stereotypes of Hispanics, we randomly changed resume characteristics to highlight traits related to stereotypes, then used an interaction term in a regression to determine whether the characteristic differentially affected Hispanics compared to non-Hispanics. Specifically, for resume i rated by participant j, we run the following regression:

(1) $Rating_{ij} = \alpha_j + \delta Characteristic_i + \beta Hispanic_i + \theta Characteristic_i \times Hispanic_i + u_{ij}$

Where θ is the coefficient of interest. We use this approach to test the effect of having many children and being suited for manual labor on ratings.

We use two signals of having children: volunteering at a Parent Teacher Association (PTA) and volunteering at a Catholic food bank compared to volunteering at a secular food bank. The latter's intuition is that volunteering at a Catholic food bank signals religiosity, and Catholics tend to have many children. Table 9 presents these results. The PTA signal has a positive effect on ratings (Column1). On average, resume ratings increase by 0.13 Likert points (2.7 percent of the baseline) for candidates with this signal. The interaction term between the PTA signal and Hispanic is positive and small (0.8 percent of the baseline) and statistically insignificant. These results hold if we restrict the sample to resumes with a female name (Column 3). The Catholic signal positively affects ratings with a similar magnitude as the PTA signal (Column 2). On average, resume ratings

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increase by 0.12 Likert points (2.6 percent of the baseline) for candidates with the Catholic signal. The interaction between the Catholic signal and Hispanic is negative, insignificant, but its magnitude is twice as large (1.9 percent of the baseline) as the magnitude of the interaction between the PTA and the Hispanic signals. For women, the Catholic signal also has a positive effect, but the interaction term almost completely counters this premium for Hispanic women (Column 4). Overall, these results suggest that having children may negatively affect Hispanic women's job prospects, but the evidence is not conclusive.

To test if the stereotype that Hispanics are suited for manual work affects ratings, we first exploit the notion that this stereotype is also associated with the idea that Hispanics often work as cooks. We check if previous job experience related to cooking and working in a restaurant affects ratings. Column 1 in Table 10 shows that having cooking or restaurant-related work experience in the resume decreases ratings by 0.35 Likert points (7.4 percent of the baseline). However, there is no differential effect on Hispanics. The interaction term is small (0.4 percent of the baseline) and insignificant.

Next, we enhance the low-skill, manual labor signal by including previous job experience related to sales, being a cashier, and babysitting to the restaurant signal. The estimates in Column 2 show that the new low-skill signal has a negative effect on ratings of 0.24 Likert points (5.1 percent of the baseline). However, this effect is attenuated for Hispanics by 8.7 Likert points (1.8 percent of the baseline), significant at the ten percent level. This result is consistent with a setting where participants believe that it is more likely for Hispanics to work in low-skill jobs, thus penalizing them less for having these jobs on their resumes.

To further explore the previous result, we estimate the effect of having relevant job experience on ratings. We perform this test in two ways. First, we estimate the effect of having previous jobs on the resume that explicitly have the words "clerical" or "clerk" in their description. Column 3 in Table 10 presents these results. The words "clerical" or "clerk" on the job descriptions increase resume ratings by 0.46 Likert points (10.2 percent of the baseline). Hispanics benefit from an additional increase of 0.08 Likert points (1.7 percent of the baseline), although this result is imprecise. Second, we estimate the effect of having detailed job descriptions on the resume. We count the number of characters in the job description section and define detailed job experience as having more characters in the section than the median (1134 characters). Column 3 in Table 10shows that having detailed job experience on the resume increases ratings by 0.55 Likert points (12.5 percent of the baseline). Hispanics benefit from an extra increase of 0.09 Likert points (2.1 percent of the baseline), significant at the 5 percent level. These results are also consistent with participants believing that Hispanics are more likely to have low-skill jobs, as having relevant job experience grants them a premium in ratings.

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VI.   Discussion and Conclusion

We have combined public-use survey data from the Census/ACS with three different laboratory experiments to demonstrate that, unlike the case for Black and White high school graduates, Hispanic and non-Hispanic high school graduates are treated similarly across the lifecycle. Although general equilibrium survey results suggest gaps in labor market outcomes in favor of non-Hispanics, these gaps tend to be steady or to have no apparent patterns across the lifecycle. Results from two laboratory resume experiments using a student sample and an HR sample suggest no differences in how resumes with Hispanic last names compared to those with non-Hispanic last names are treated overall and few differences when the sample is split by gender of the resume. The mTurk results from the third laboratory experiment similarly do not show differences in how resumes are rated across the lifecycle, except perhaps for a slight preference for Hispanic compared to non-Hispanic applicants at much older ages.

The next question is why do we find no differences in the general equilibrium results across age and in how hypothetical applicants are rated by ethnicity when previous studies show differences by applicant race and immigrant status. First and most obviously, there is likely measurement error in the surveys—the means of the results are suggestive that we miss the worst-off of the Hispanic population in the United States, though given our limiting to those with a high school degree, this problem may be less prevalent than it would be had we looked at the Hispanic vs. non-Hispanic population as a whole. However, measurement error in the general equilibrium survey does not explain the lack of differences by ethnicity across the lifespan in our three experiments.

The first, most worrisome, suggestion is that our participants, unlike hiring managers going through the actual hiring process, simply do not pay attention to signals of name and age as they would were they not in an experiment. However, we show that participants in all three experiments do look at the names and have a sense of the hypothetical applicants' general age. In Experiments 1 and 2, we show directly in Table 1 that the participants view the areas of interest for name and for date of high school graduation. In Experiment 3, participants report, on average, that Hispanic applicants are minority applicants and applicants over 40 are over the age of 40. Also, resume characteristics that should be useful for rating resumes (relevant job experience and skills) are highly significant and contribute to predict ratings. Because of these results, and after eliminating mTurk participants for standard quality checks (out of US IP addresses, taking too little time to complete the survey, failing quality checks, etc.), we are confident that participants are seeing the signals of ethnicity and age.

A less worrisome possibility is that participants do not consider people with non-Hispanic first names to truly be "Hispanic," that is they consider people with Hispanic heritage and US first names to be equivalent to white people, particularly in the Southwest where the first two experiments take place. Indeed, results from the mTurk checks mentioned in the previous

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paragraph suggest a stronger identification of minority group status when both the first and last name of the applicant are Hispanic, although even with these groups the majority of participants identify people with Hispanic last names and non-Hispanic first names as minorities on average. There is some evidence that mTurk participants in parts of the country that once belonged to Mexico have a preference for applicants with Hispanic names over those with non-Hispanic first and last names, especially for ages older than 50. These results are consistent with the results broken apart by gender in Experiments 1 and 2. If there is no difference across Hispanic status at all, then there will also be no difference across ages.

A final possibility is that positive and negative stereotypes about Hispanic workers balance out on average in our samples, leading to overall null results by ethnicity and by age. In the mTurk experiment, we included signals that reinforce or contradict different stereotypes that people have about Hispanic workers compared to non-Hispanic workers. We find suggestive evidence that Hispanic women may be negatively affected by the belief that they have many children. We also find evidence consistent with participants believing that it is more likely for Hispanics to work in low-skill jobs, thus penalizing them less for having these jobs on their resumes and granting them a premium for relevant job experience.

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Table 1 Summary Statistics Experiments 1 and 2

	Experiment 1		Experiment 2	
	Mean	SD	Mean	SD
Resume Characteristics				
Female	0.50	0.50	0.50	0.50
Hispanic	0.13	0.34	0.12	0.33
Age	56.10	11.7	56.69	11.95
Participant Characteristics				
Female	0.56		0.81	
White	0.89		0.85	
Asian	0.07		0.01	
Black	0.05		0.15	
Hispanic	0.15		0.19	
Age	21.97	2.83	44.15	11.43
Ratings				
Likert (1-7)	4.63	1.40	4.63	1.44
Eye-tracking				
Seconds spent: total	16.28	10.2	15.45	9.35
outside	3.01	3.77	0.37	0.69
employment history	4.90	5.75	5.82	4.74
name	0.18	0.53	0.09	0.20
high school	1.20	1.78	0.43	0.67
years employed	0.49	1.10	0.76	1.01
graduation year	0.02	0.14	0.05	0.14
other	0.22	0.56	0.20	0.51
education	0.21	0.46	0.27	0.37

Notes: In the student sample, there are 5,425 resumes for the non-eyetracking statistics and 4,475 resumes for the eyetracking statistics, other than seconds spent total which has 5,109 resumes. In the HR sample, there are 2,680 resumes for the non-eyetracking statistics and 2,624 resumes for the eye-tracking statistics, except seconds spent total which has 2,637 resumes.

Table 2 Regression Results Experiments 1 and 2

Likert (1-7) Hireability Rating

	(1)	(2)
Sample:	Student	HR.
Hispanic name	-0.7369	-1.4657
	(1.4153)	(2.4916)
Age in Resume	-0.0393**	-0.0515
	(0.0187)	(0.0312)
Hispanic × Age in Resume	0.0325	0.0676
	(0.0518)	(0.0921)
Age in Resume Squared	0.0003**	0.0004
	(0.0002)	(0.0003)
Hispanic × Age in Resume Squared	-0.0003	-0.0007
	(0.0005)	(0.0008)
Observations	5,425	2,416

Note: These are results from Experiments 1 and 2 interacting Hispanic status of names on resumes with ages on resume as indicated by date of high school graduation. Robust standard errors clustered on participant are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3 Summary Statistics of mTurk Participants

Proportion of women	0.555	Hiring experience	0.621
	(0.497)		(0.485)
Age	41.697	Managerial experience	0.675
	(12.127)		(0.469)
Proportion of White	0.825	Number of children	0.790
	(0.380)		(1.195)
Proportion Hispanics	0.104	Worked last week	0.919
	(0.306)		(0.273)
Less than college	0.367	Income above $50,000	0.444
	(0.482)		(0.497)
College	0.445	Up to 5 years of work experience	0.126
	(0.497)		(0.332)
More than college	0.188	6-15 years of work experience	0.326
	(0.391)		(0.469)
Human resources experience	0.298	More than 15 years of work experience	0.548
	(0.458)		(0.498)

Notes: This table presents summary statistics for the final sample of 739 mTurk workers. Standard deviations in parentheses.

Table 4 Participants Assessing Age from Resumes

	Participant believes the candidate has less than 40 years	Participant believes the candidate has 40 years or more
Less Than 40	0.895	0.105
40 or More	0.312	0.688

Notes: This table presents how the participants in the pilot wave infer age from the resumes. The sample is 739 participants, 22,170 resumes.

Table 5 Participants Assessing Ethnicity from Resumes

	No Minority	Minority
Non-Hispanic	0.926	0.074
Hispanic First and Last Name	0.329	0.671
Non-Hispanic First Name Hispanic Last Name	0.431	0.569
Hispanic First Name Non-Hispanic Last Name	0.563	0.437
Any Hispanic Signal	0.420	0.580

Notes: This table presents how the participants in the pilot wave infer ethnicity from the resumes. The sample is 739 participants, 22,170 resumes.

Table 6 Machine Learning Models Predictive Power

		MSE	R2	N
Linear LASSO	Training set	1.9619	0.2289	15840
	Validation set	2.0256	0.2187	6780
Adaptive LASSO	Training set	1.9647	0.2278	15840
	Validation set	2.0260	0.2185	6780
Random Forest	Full Sample	0.536	0.793	22620

Notes: This table presents the predictive power of three machine learning models estimated to predict resume ratings using resume characteristics as inputs.

Table 7 Estimated Differences for Likert (1-7) Rating – mTurk Sample

	(1)	(2)
	a. Any Hispanic Type	
Any Hispanic Type	0.0322	0.0268
	(0.0247)	(0.0203)
	[0.0069]	[0.0057]
	b. By Hispanic Type	
Hispanic First and Last Name	-0.0033	0.0050
	(0.0341)	(0.0289)
	[-0.0006]	[0.0011]
Non-Hispanic First Name Hispanic Last Name	0.0549	0.0476
	(0.0443)	(0.0353)
	[0.0117]	[0.0102]
Hispanic First Name Non-Hispanic Last Name	0.0789*	0.0487
	(0.0452)	(0.0378)
	[0.0169]	[0.0104]
Baseline Rating	4.6809	
Control for resume quality		X

Notes: Standard errors clustered by participants are in parentheses. Percent change from the baseline is in brackets. The Likert resume rating ranges from 1 (least hireable) to 7 (most hireable). Each Panel and column presents results for a separate OLS regression. The baseline in Panel b is the average rating for non-Hispanic resumes. Estimates control for participant fixed effects. The sample size is 22,170 resumes.
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Effect of Age on Ratings – mTurk Sample

Any Hispanic Type	0.9744**
	(0.4756)
Age in Resume	0.0125
	(0.0078)
Any Hispanic Type × Age in Resume	-0.0375**
	(0.0176)
Age in Resume Squared	-0.0001
	(0.0001)
Any Hispanic Type × Age in Resume Squared	0.0004**
	(0.0002)

Notes: Standard errors clustered by participants are in parentheses. The baseline is the average rating for non-Hispanic resumes. Estimates control for resume quality and participant fixed effects. The sample size is 739 participants.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9 Testing the Stereotype that Hispanics have many Children Requiring to take Time off Work

	Full Sample		Female Resumes	
Any Hispanic Type	0.0288	0.0365	0.0413	0.0524
	(0.0264)	(0.0255)	(0.0371)	(0.0361)
	[0.0062]	[0.0078]	[0.0088]	[0.0111]
PTA Signal	0.1249***		0.1053**	
	(0.0369)		(0.0508)	
	[0.0267]		[0.0224]	
Any Hispanic Type × PTA Signal	0.0380		0.0439	
	(0.0804)		(0.1171)	
	[0.0081]		[0.0093]	
Catholic Signal		0.1215**		0.1610**
		(0.0487)		(0.0686)
		[0.0260]		[0.0342]
Any Hispanic Type × Catholic Signal		-0.0891		-0.1591
		(0.1092)		(0.1505)
		[-0.0191]		[-0.0338]
Baseline	4.6717	4.6783	4.7019	4.7047

Notes: Standard errors clustered by participant are in parentheses. Percent with respect to baseline is in brackets. Estimates control for participant fixed effects. The sample size is 22,170 resumes. *** p<0.01, ** p<0.05, * p<0.1

Table 10 Heterogeneity in Ratings to Job History Content

	Cooking/ Restaurant Experience	Low-Skill Job Experience	Clerical/ Clerk in Job Description	Detailed Job Experience
Any Hispanic Type	0.0315	0.0023	-0.0048	-0.0049
	(0.0267)	(0.0310)	(0.0348)	(0.0341)
	[0.0067]	[0.0005]	[-0.0011]	[-0.0011]
Cooking/Restaurant Signal	-0.3466***			
	(0.0358)			
	[-0.0735]			
Any Hispanic Type × Cooking/Restaurant	-0.0198			
	(0.0850)			
	[-0.0042]			
Low-Skill Job		-0.2425***		
		(0.0237)		
		[-0.0509]		
Any Hispanic Type × Low-Skill Job		0.0868*		
		(0.0483)		
		[0.0182]		
Clerical/Clerk in Job Description			0.4581***	
			(0.0232)	
			[0.1024]	
Any Hispanic Type × Clerical/Clerk			0.0778	
			(0.0476)	
			[0.0174]	
Detailed Job Experience				0.5511***
				(0.0238)
				[0.1251]
Any Hispanic Type × Detailed Job Experience				0.0940**
				(0.0467)
				[0.0213]
Baseline	4.7185	4.7682	4.4725	4.4064

Notes: Standard errors clustered by participant in parentheses. Percent with respect to baseline in brackets. Estimates control for participant fixed effects. The sample size is 22,170 resumes.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A 1 Having the Necessary Skills by Ethnicity and Age

Figure A 2 Resume Ratings by Ethnicity and Age – mTurk Sample Restricted to Participants with a College Education
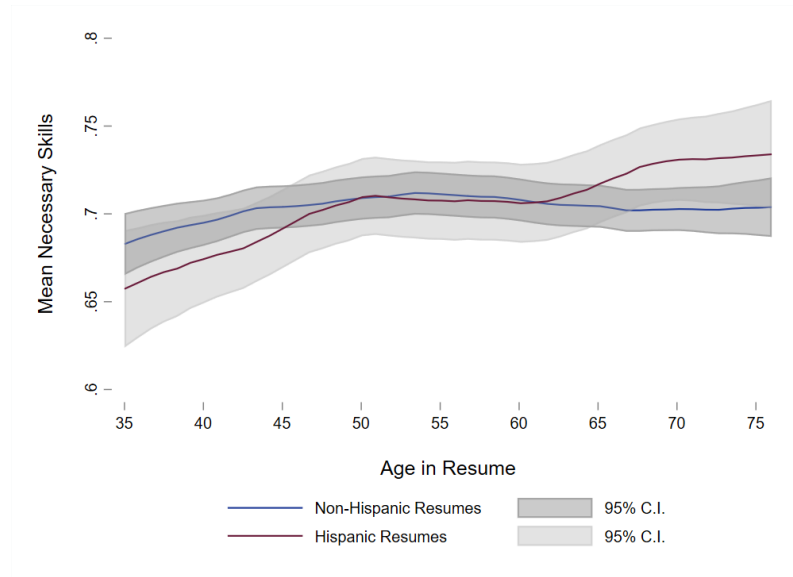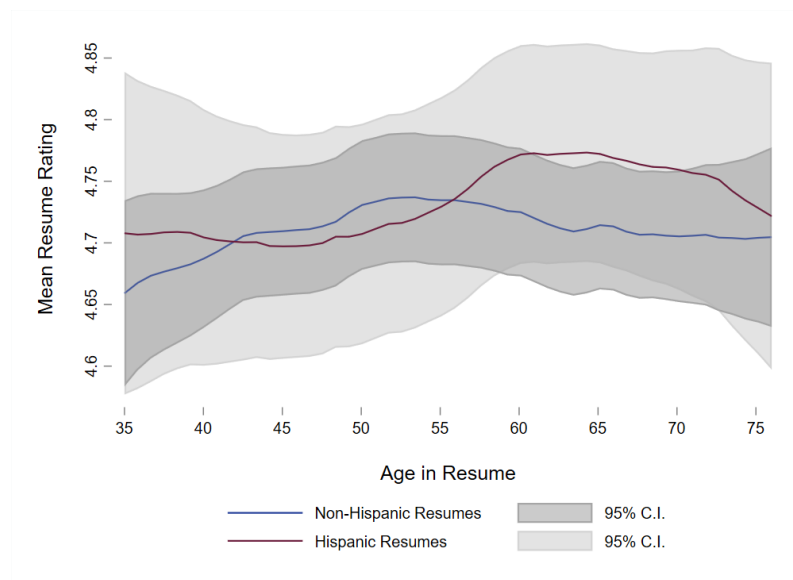
Figure A 3 Resume Ratings by Ethnicity and Age – mTurk Sample Restricted to Participants
with Hiring and HR Experience
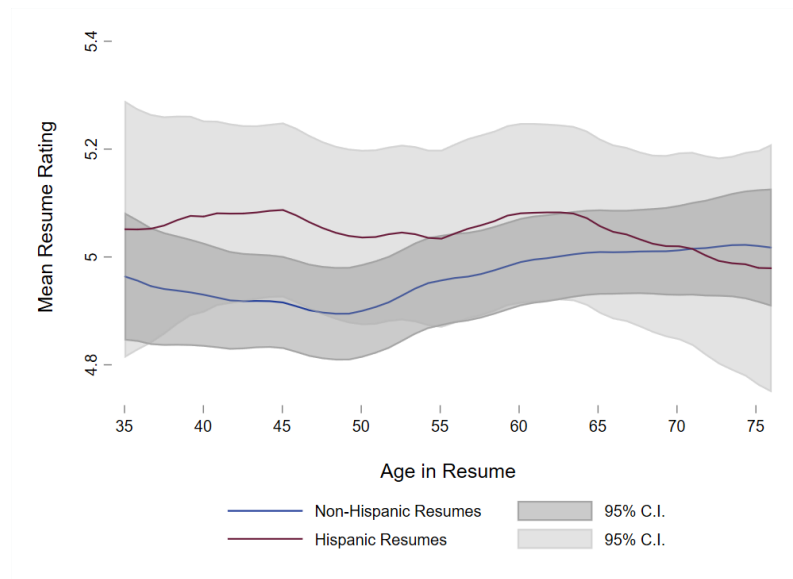
Figure A 4 Resume Ratings by Ethnicity and Age – mTurk Sample Restricted to Participants matched with HR Sample using Propensity Score Matching

Figure A 5 Resume Ratings by Ethnicity and Age – mTurk Sample Restricted to Waves 1 and 2

Table A 1Correlation between Machine Learning Models
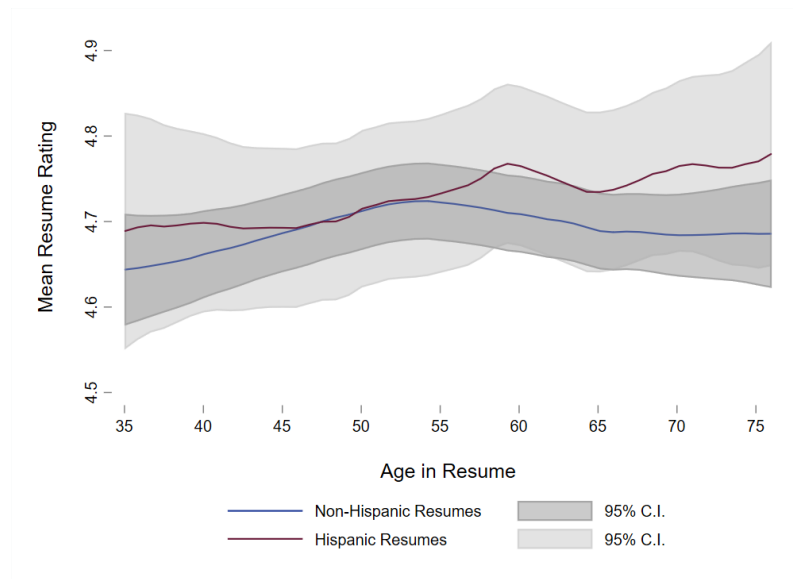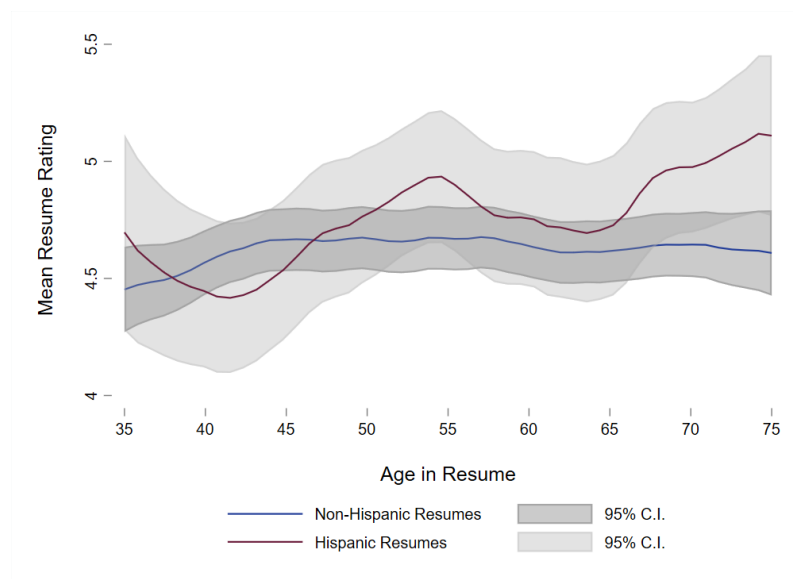
	Adaptative LASSO	OLS
Causal Forest	0.550	0.551
Adaptative LASSO		0.999

Notes: This table presents the correlation coefficient for the forecasts of the machine learning models.

Table A 2 OLS Coefficients Predicting Ratings

Variable	Coefficient	Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Years Employed	0.3151***	Job72	0.5964***	Job146	0.5716***	2.Email provider	0.0143
YearsEmployed Squared	-0.0216***	**Job73**	**0.3983***	Job147	0.9259***	3.Email provider	-0.0166
Unemployment Spells	-0.0794**	Job74	0.8357***	**Job148**	**0.5514***	2.HighSchool name	-0.1484
Job1	**0.3704***	**Job75**	**0.6659***	**Job149**	**0.2318***	3.HighSchool name	-0.1558
Job2	**0.5122***	Job76	0.6744***	Job150	0.9708***	4.HighSchool name	-0.1697*
Job3	**0.3571***	**Job77**	**0.1649**	Job151	0.4205***	5.HighSchool name	-0.1324
Job4	**0.3887***	Job78	0.1922***	Job152	0.0795	6.HighSchool name	-0.1099
Job5	**0.7661***	Job79	-0.0966	**Job153**	**0.3877***	7.HighSchool name	0.0021
Job6	**0.5138***	Job80	-0.1786***	Job154	0.9234***	8.HighSchool name	-0.1141
Job7	**0.4210***	Job81	-0.0927	**Job155**	**0.8497***	9.HighSchool name	0.0573
Job8	**0.3843***	**Job82**	**0.4774***	Job156	0.7826***	10.HighSchool name	-0.0599
Job9	0.7847***	Job83	0.4854***	Job157	-0.1028	11.HighSchool name	-0.0230
Job10	**0.4499***	Job84	0.3138***	Job158	-0.1694**	12.HighSchool name	-0.2852***
Job11	0.3507***	**Job85**	**0.2577***	Job159	-0.0224	13.HighSchool name	-0.0549
Job12	**0.2664***	**Job86**	**0.6013***	Job160	-0.0668	14.HighSchool name	-0.1963**
Job13	0.2441***	**Job87**	**0.4288***	Job161	1.0188***	15.HighSchool name	-0.0461
Job14	**0.4873***	Job88	0.5635***	Job162	0.8634***	16.HighSchool name	-0.0328
Job15	**0.7347***	Job89	0.5034***	Job163	0.2953***	17.HighSchool name	-0.1743*
Job16	**0.5835***	Job90	0.3169***	Job164	0.4547***	18.HighSchool name	-0.2151**
Job17	**0.3768***	**Job91**	**0.2321***	Job165	-0.0942	19.HighSchool name	-0.1664*
Job18	-0.0019	Job92	0.3021***	Job166	0.3195***	20.HighSchool name	-0.1244
Job19	0.5279***	Job93	0.0361	Job167	0.0661	21.HighSchool name	-0.1421
Job20	**0.2016***	Job94	0.2931***	Job168	-0.0412	22.HighSchool name	-0.1566
Job21	0.6532***	Job95	0.6856***	Job169	0.5437***	23.HighSchool name	-0.0726
Job22	**0.3379***	Job96	0.6686***	Job170	0.4302***	24.HighSchool name	-0.1676*
Job23	0.4886***	Job97	0.9246***	Job171	0.5986***	25.HighSchool name	-0.0328
Job24	0.5358***	Job98	0.5720***	Job172	0.4874***	26.HighSchool name	-0.2315**
Job25	0.1369**	Job99	0.2528***	Job173	0.1082	27.HighSchool name	-0.1716*
Job26	0.0282	Job100	0.9247***	Job174	0.0490	28.HighSchool name	-0.2508***
Job27	**0.7299***	Job101	0.4218***	Job175	-0.2262***	29.HighSchool name	-0.2576***
Job28	0.3399***	**Job102**	**0.4191***	Job176	-0.1090	30.HighSchool name	-0.1211
Job29	0.2802***	Job103	0.0266	Job177	0.0015	31.HighSchool name	-0.1850*
Job30	**0.2545***	Job104	0.0580	Job178	-0.0480	32.HighSchool name	-0.2967***
Job31	**0.1408**	Job105	0.3106***	Job179	-0.1156*	33.HighSchool name	-0.1753*
Job32	0.0775	Job106	-0.0546	Job180	-0.0418	34.HighSchool name	-0.1454
Job33	**0.6563***	Job107	0.8582***	Job181	-0.0442	35.HighSchool name	-0.1989**
Job34	0.2958***	Job108	-0.1537**	Job182	0.2431***	36.HighSchool name	-0.0153
Job35	**0.2605***	**Job109**	**0.4772***	Job183	0.2555***	37.HighSchool name	-0.0853
Job36	-0.0929	Job110	1.1405***	Job184	-0.2398***	38.HighSchool name	-0.1608*
Job37	0.2183***	**Job111**	**0.5960***	Job185	-0.1812***	39.HighSchool name	-0.0563
Job38	**0.3470***	Job112	0.4070***	**Job186**	**0.3847***	40.HighSchool name	-0.1582

Variable	Coefficient	Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Job39	0.0438	Job113	0.7495***	**Job187**	**0.6690***	41.HighSchool name	-0.2219**
Job40	0.2724***	**Job114**	**0.4443***	Job188	-0.1467**	42.HighSchool name	-0.1179
Job41	0.1643**	Job115	0.1694**	Job189	-0.0219	43.HighSchool name	0.0006
Job42	0.2928***	Job116	0.2538***	Job190	-0.0095	44.HighSchool name	0.0248
Job43	0.2717***	**Job117**	**0.5741***	Job191	0.0875	45.HighSchool name	0.0277
Job44	**0.6954***	Job118	0.0457	Job192	-0.1362**	46.HighSchool name	-0.1265
Job45	**0.8696***	Job119	-0.0730	Job193	-0.2580***	47.HighSchool name	-0.1068
Job46	**0.5456***	**Job120**	**0.8671***	Job194	0.0604	48.HighSchool name	-0.0790
Job47	**0.6934***	Job121	0.3304***	Job195	-0.3305***	49.HighSchool name	-0.0847
Job48	0.3324***	Job122	0.5850***	Skill1	0.1925***	50.HighSchool name	-0.1518
Job49	**0.3993***	Job123	0.6577***	Skill2	0.1365***	51.HighSchool name	-0.0805
Job50	**0.2746***	**Job124**	**0.3437***	Skill3	0.0765***	52.HighSchool name	-0.1312
Job51	-0.2015***	**Job125**	**0.3110***	Skill4	0.0780***	53.HighSchool name	-0.0755
Job52	**0.3281***	Job126	0.0216	Skill5	0.0582**	54.HighSchool name	-0.0550
Job53	0.1575**	Job127	0.2362***	Skill6	0.0900***	55.HighSchool name	-0.1259
Job54	**0.4084***	Job128	0.6202***	Skill7	0.1248***	56.HighSchool name	-0.1083
Job55	-0.0802	Job129	0.3479***	Skill8	0.0793***	57.HighSchool name	-0.0160
Job56	0.2568***	**Job130**	**0.1543**	Skill9	0.0791***	58.HighSchool name	-0.0799
Job57	0.9682***	**Job131**	**0.3557***	Skill10	0.0431	59.HighSchool name	-0.0684
Job58	0.4783***	Job132	0.4040***	Skill11	0.1089***	60.HighSchool name	-0.0133
Job59	**0.7337***	Job133	-0.2855***	Skill12	0.0758***	61.HighSchool name	-0.1108
Job60	0.6558***	Job134	0.2907***	Skill13	0.0656**	62.HighSchool name	-0.1180
Job61	**0.5679***	**Job135**	**0.7346***	Skill14	0.2542***	63.HighSchool name	-0.1739*
Job62	**0.6097***	**Job136**	**0.6472***	Skill15	0.1156***	64.HighSchool name	0.0431
Job63	**0.7721***	Job137	0.9693***	Skill16	0.1373***	65.HighSchool name	-0.1633
Job64	**0.5142***	Job138	0.7288***	Skill17	0.1166***	66.HighSchool name	-0.1334
Job65	0.1300*	**Job139**	**0.6753***	Skill18	0.0449	67.HighSchool name	-0.2121**
Job66	**0.3753***	Job140	-0.0447	Skill19	0.1645***	68.HighSchool name	0.0808
Job67	0.6549***	Job141	0.0579	Skill20	0.0759***	69.HighSchool name	-0.0898
Job68	0.2033***	**Job142**	**0.5689***	Skill21	0.1056***	70.HighSchool name	-0.1202
Job69	0.7533***	**Job143**	**0.5575***	Skill22	0.0648**	71.HighSchool name	-0.0857
Job70	0.6797***	Job144	0.0752	Skill23	0.1184***	72.HighSchool name	-0.1188
Job71	0.5737***	Job145	-0.0747	Skill24	0.1279***	73.HighSchool name	0.0122
						74.HighSchool name	-0.1994**
						75.HighSchool name	-0.1143
						76.HighSchool name	-0.1537
						77.HighSchool name	-0.1303
						2.Volunteering	0.0477
						3.Volunteering	0.1510***
						4.Volunteering	-0.0082
						5.Volunteering	0.0982*
						6.Volunteering	0.1583***
						Constant	2.4098***

Variable	Coefficient	Variable	Coefficient	Variable	Coefficient	Variable	Coefficient

Notes: Values in bold correspond to jobs where the words "clerical" or "clerk" are present. Sample is 22,170 resumes.

*** p<0.01, ** p<0.05, * p<0.1

Appendix B mTurk Survey

Instructions

This task has three parts. In the first part, we will show you 30 resumes from applicants to a clerical position. Please rate each candidate's ability to fulfill the position. The job description for the position is as follows:

Administrative Assistant I

To provide administrative support in an office environment.

Main Job Tasks and Responsibilities

- Answering and directing phone calls
- Taking phone calls
- Taking and distributing messages
- Handling inquiries and incoming work requests
- Reviewing files and records to answer requests for information
- Checking and distributing documents and correspondence
- Receiving, sorting and distributing incoming mail
- Maintaining filing systems
- Compiling records of office activities
- Photocopying   Preparing outgoing mail
- Typing documents
- Organizing meetings and appointments
- Coordinating workflow

Education Requirements

High school diploma or equivalent

In the second part, we will show the same 30 resumes and ask you more detailed questions about each candidate.

In the third part, we will ask you to complete a short survey. Once you complete these questions you will receive a code that you should enter in Amazon Mechanical Turk to complete the task and receive your payment.

Your payment will be credited to your Worker account up to three days after you complete the task.

The entire task should take up to 30 minutes to complete.

X→

Please rate the candidate's ability to fulfill the position (1 - Most Unable, 7 - Most Able) (For 30 resumes)

○ 1 (1)

○ 2 (2)

○ 3 (3)

○ 4 (4)

○ 5 (5)

○ 6 (6)

○ 7 (7)

Attention Check 1

We want to know your opinion on the potential candidates. We also want to know whether people read resumes carefully. To show you've read this much, please ignore the question and select both "List skills" and "Volunteering experience". Yes, ignore the question and select both of these options

Which of the following do you think are the most important characteristics of a successful candidate?

Complete work history (1)

☐　　　Professional-looking resume (2)

☐　　　Lists skills (3)

☐　　　Volunteering experience (4)

Second view of resumes (for the same 30 resumes)
Does this candidate have the necessary skillset for an administrative assistant position?

○ Yes (1)

○ No (2)

How much supervision do you think this candidate will need to perform his or her duties?

○ High supervision (1)

○ Average supervision (2)

○ Low supervision (3)

How would you rate this candidate's communication skills?

○ Deficient communication skills (1)

○ Average communication skills (2)

○ Excellent communication skills (3)

Demographic questions

Compared to 6 months ago, how important do you think are the following technology skills for a person working in a clerical position now. Please select one for each option. (only in waves 4-5)

	(1)	(2)	(3)	(4)	(5)
Analyze data and create graphs in Microsoft Excel or a similar software (1)	○	○	○	○	○
Save files so they can be opened in different software versions (i.e., Word 97 vs. Word 2000) (2)	○	○	○	○	○
Take digital video and transfer it to my computer (3)	○	○	○	○	○
Take digital pictures and transfer them to my computer (4)	○	○	○	○	○
Create presentations in Microsoft PowerPoint or a similar software (5)	○	○	○	○	○
Use videoconference applications like Skype or Zoom (6)	○	○	○	○	○
Use applications for remote collaboration like Microsoft Teams (7)	○	○	○	○	○
Plan and integrate technology-based learning in the workplace (8)	○	○	○	○	○

What is the highest level of education you have completed?

○ Elementary or some high school (1)

○ High school graduate/GED (2)

○ Trade or vocational certification (3)

○ Some college/Associates degree (4)

○ College graduate (5)

○ Some post-graduate work (6)

○ Post-grad degree (7)

Last week did you do any work for either pay or profit?

○ Yes, full-time employment (1)

○ Yes, part-time employment (2)

○ No (3)

○ Retired (4)

○ Disabled (5)

○ Unable to work (6)

How many years of paid work experience have you had over the course of your life?

○ Less than 1 year (1)

○ Between 1 and 5 years (2)

○ Between 6 and 10 years (3)

○ Between 11 and 15 years (4)

○ Between 16 and 20 years (5)

○ More than 20 years (6)

How much has your income changed in the past three months? (only in waves 4-5)

○ Decreased a lot (1)

○ Some decrease (2)

○ Decreased a little (3)

○ No change (4)

○ Increased a little (5)

○ Some increase (6)

○ Increased a lot (7)

Have you ever worked in a human resources role as your primary occupation?

○ I have worked in that capacity (1)

○ I have not worked in that capacity (2)

X→

How many years of experience do you have working in human resources?

        Less than 1 year (1)
        Between 1 and 5 years (2)
        Between 6 and 10 years (3)
        Between 11 and 15 years (4)
        Between 16 and 20 years (5)
        More than 20 years (6)

Do you have any experience in hiring employees even if it was not your primary occupation?

○ Yes (1)

○ No (2)

Have you ever worked in a managerial role as your primary occupation?

○ I have worked in that capacity (1)

○ I have not worked in that capacity (2)

X→

How many years of experience do you have working in a managerial role?

○ Less than 1 year (1)

○ Between 1 and 5 years (2)

○ Between 6 and 10 years (3)

○ Between 11 and 15 years (4)

○ Between 16 and 20 years (5)

○ More than 20 years (6)

Have you ever worked in a clerical/administrative position? (only in wave 5)

○ I have worked in that capacity (1)

○ I have not worked in that capacity (2)

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How many years of experience do you have working in a clerical/administrative position? (only in wave 5)

○ Less than 1 year (1)

○ Between 1 and 5 years (2)

○ Between 6 and 10 years (3)

○ Between 11 and 15 years (4)

○ Between 16 and 20 years (5)

○ More than 20 years (6)

In what year were you born?
From the following options, do you consider yourself to be (select all that apply):

☐ Black, or African American (1)

☐ White (2)

☐ Asian (3)

☐ American Indian (4)

☐ Native Hawaiian or other Pacific Islander (5)

☐ I prefer not to answer (6)

Do you identify yourself as Hispanic or Latino?

○ Yes (1)

○ No (2)

Are you

○ Single (1)

○ Married (living together) (2)

○ Married (living apart) (3)

○ Separated (4)

○ Divorced (5)

○ Widowed (6)

○ Cohabiting (7)

○ Other (8) _____

How many children under the age of 18 live in your household?

_____

What was the estimated annual income for your household for 2018?

○ Less than $10,000 (1)

○ $10,000 to $20,000 (2)

○ $21,000 to $30,000 (3)

○ $31,000 to $40,000 (4)

○ $41,000 to $50,000 (5)

○ $51,000 to $60,000 (6)

○ $61,000 to $70,000 (7)

○ $71,000 to $80,000 (8)

○ $81,000 to $90,000 (9)

○ $91,000 to $100,000 (10)

○ More than $100,000 (11)

Are you male or female?

○ Male (1)

○ Female (2)

In what state were you born?

_____

In what state did you primarily grow up?

_____

In what state do you currently reside?

_____

Assuming that money is not an issue, rank the following destinations for vacation (1 is the most preferred and 10 is your least preferred)

_____ Outer Banks, North Carolina (1)
_____ Honolulu, Hawaii (2)
_____ Boca Raton, Florida (3)
_____ Galveston, Texas (4)
_____ Santa Barbara, California (5)
_____ Cancun, Mexico (6)
_____ Playa del Carmen, Mexico (7)
_____ San Andres, Colombia (8)
_____ Bocas del Toro, Panama (9)
_____ Punta del Este, Uruguay (10)

Which of the following reasons make ${Q1383/ChoiceGroup/ChoiceWithHighestValue} the least preferred? Select all that apply.

☐ Not my type of vacation (1)

☐ Never heard about this place (2)

☐ I already visited this place (3)

☐ Concerned about safety (4)

☐ I don't speak the language (5)

☐ Worried about the food (6)

☐ Health concerns (7)

As you have seen in this survey, we want to know your opinion on the potential candidates. We also want to know whether people read questions carefully. To show you've read this much, please ignore the question below, select other and write "none" as your answer.

Which of these facilities are available at your workplace?

☐   Vending machine (1)

☐   Lounge (2)

☐   Coffee maker (3)

☐   Windows (4)

☐   Parking (5)

☐   Childcare facilities (6)

☐   Store room (7)

☐   Other (8) _____

To what degree do you agree with the following statements? Please use a scale from 0 to 10, where 0 means you "completely disagree" and 10 means you "completely agree" with the statement. You can also use any numbers between 0 and 10 to indicate where you fall on the scale, like 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
If someone does me a favor, I am prepared to return it (1)	C	C	C	C	C	C	C	C	C	C	O
I go out of my way to help somebody who has been kind to me before (4)	C	C	C	C	C	C	C	C	C	C	O
I am willing to undergo personal costs to help somebody who helped me before (5)	C	C	C	C	C	C	C	C	C	C	O
If I suffer a serious wrong, I will take revenge as soon as possible, no matter what the cost (6)	C	C	C	C	C	C	C	C	C	C	O
If somebody puts me in a difficult position, I will do the same to him/her (7)	C	C	C	C	C	C	C	C	C	C	O
If somebody offends me, I will offend him/her back (8)	C	C	C	C	C	C	C	C	C	C	O
On the whole one can trust people (9)	C	C	C	C	C	C	C	C	C	C	O
Nowadays one can't rely on anyone (10)	C	C	C	C	C	C	C	C	C	C	O

If one is dealing with strangers, it is better to be careful before one can trust them (11)	C	C	C	C	C	C	C	C	C	C	O

*

Imagine the following situation: Today you unexpectedly received 100000 dollars. How much of this amount would you donate to a good cause? (Values between 0 and 100000 are allowed, do not use commas)

_____

Thank you for completing the survey!

Please copy the following code that you will enter on MTURK in order to receive payment. CODE: ${e://Field/Code}

Please select "Next" to continue.

Thank you for your participation!

Purpose of the Study:

This task was part of a research study whose purpose is examining what characteristics of resumes are important in decision making.

Confidentiality:

You may view the survey host's confidentiality policy at https://www.qualtrics.com/privacystatement/

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mTurk will **not** provide the researchers with your identifying information. All information you provided in this task will be kept on a password protected computer and is only accessible by the research team.

The results of this study may be published but no one will be able to identify you.

You may decide that you do not want your data used in this research. If you would like your data removed from the study and permanently deleted please contact ████████████@gmail.com and provide your unique identification number **${e://Field/Code}**.

Whether you agree or do not agree to have your data used for this study, you will still receive **$4** for your participation.

Please do not disclose that this is a research study to anyone who might participate in this study in the future as this could affect the results of the study.

Final Report:

If you would like to receive a copy of the final report of this study (or a summary of the findings) when it is completed, please feel free to contact us.

Useful Contact Information:

If you have any questions or concerns regarding this study, its purpose or procedures, or if you have a research-related problem, please contact the principal investigator, Joanna N. Lahey at 979 458 3463 or jlahey@tamu.edu.

If you have any questions concerning your rights as a research subject, you may contact the ████ ██ ██ ████████████

Once again, thank you for your participation in this study!