Preliminary draft: Do not cite without permission

Discrimination at the intersection of Age, Race, and Gender: Evidence from a lab-in-the-field experiment

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Draft: March 2017

Abstract: Studies exploring race discrimination often focus on youth labor markets. However, this focus neglects how black and white job seekers are treated throughout the lifecycle. This paper combines the new technologies of resume randomization and eye-tracking within a laboratory setting to get a clearer picture of the mechanics of discrimination across the lifecycle. MBA, MPA, HR, and business students viewed and each rated 40 resumes with randomized inputs for hypothetical high school graduate applicants to an entry-level clerical position (a total of 5,960 unique resumes). During this process of rating, their eye movements were tracked, showing where and for how long they looked at relevant portions of each resume, making this experiment the first to determine whether screeners stop looking at a resume when they see a black name. While the ratings of white applicants declined (quadratically) with age, ratings of black applicants showed the reverse pattern. Time spent looking at resumes by race and age follows a similar pattern, implying that while screeners do look at the entire resume, they spend less time on younger black resumes. We find evidence of levels-based statistical discrimination against younger black applicants based on skills and of variance-based statistical discrimination based on overall resume quality, previous work-history, and high school. No evidence is found to support statistical discrimination based on address.

[1] Contact author. Contact information: jlahey@nber.org. We thank the Alfred P. Sloan Foundation for funding this research. We thank Gerianne Alexander for use of her lab and other invaluable help. We also thank all of the undergraduate and graduate assistants who helped make this study successful. It was a joy to work with Molly Beck, Savannah Collins, Luke Franz, Stephanie Leal, Laura Lombardo, Joel Mendez, Megan Mumford, Matt Sanchez, Janet Saenz, and Ashley Yaugher. We especially wish to thank Ryan Beasley for volunteering his time and his technical expertise for several aspects of the study and David Figlio for names. Thanks for feedback from participants at APPAM, ASSA, Auburn University, University of California at Davis, NBER- Cohort Studies, University of North Carolina, Santa Clara University, Syracuse University, University of Toronto, Texas A&M University, and Tulane and from helpful conversations with Lorenzo Casaburi, Kathleen Christensen, Jeff Clemens, Joshua Gottlieb, Damon Jones, Orie Shelef, and John Yinger. All errors and opinions are our own.

I. Introduction

Most of the research done on race discrimination[2] has focused on younger ages or has pooled together all individuals of working age (see Lang and Lehmann 2012 for an extensive literature review). Far less has been written about how labor market differences by race change across the life-cycle.[3] However, people have full working lives; with the average person in the NLSY79 reporting ~12 jobs by age 50 (compared to ~8 by age 30) (author's calculations); it is clear that not all job seekers are young.

Although recent progress has been made on the reasons for differential labor market experiences by race (e.g. Lang and Manove 2011, Lang, Manove and Dickens 2005, Nunley, Romero, and Seals 2015, and many more), there is still much work to be done. In economics, we generally conceptualize discrimination in terms of taste-based discrimination (Becker 1971), levels-based statistical discrimination (Phelps 1972), and variance-based statistical discrimination (Aigner and Cain 1977). Economists generally divide taste-based discrimination into employer-based, employee-based, and customer-based discrimination, and these are conceptualized as employers, employees, or customers gaining disutility from interacting with black workers. Levels-based statistical discrimination can be partitioned into different stereotypes, for example, that black applicants had worse schooling on average or live in neighborhoods with worse transportation options. Variance-based statistical discrimination based on variance is more complicated, but essentially means that employers believe that the signals of quality do not provide as clear a signal for black people than they do for white; for example, employers may know what graduating from a specific high school means for white applicants, but they may not be as clear for black applicants. However, even the theoretical framework of race-based discrimination is still an area of active research with new work (i.e. Bond and Lehmann 2015, Cavounidis and Lang 2015) building on these simpler models.

Audit studies have demonstrated that racial discrimination in hiring occurs for young entry-level applicants (Bertrand and Mullainathan 2004, Nunley et al. 2015, and many more). Much less is known about the mechanics of discrimination. If screeners see a black-sounding name and move onto the next resume, there is not much that potential job seekers can change other than their names. If, instead, screeners view these resumes more intensively for items that could contradict negative stereotypes, then that would indicate that black job seekers could

[2] Note the use of the term "discrimination" in this paper is short-hand for "differential treatment by group status" and does not denote the taste-based discrimination or distaste that the colloquial use of the term implies, nor does it necessarily denote legal definitions of discrimination.

[3] Notable exceptions generally study wage differences over age and cohort and include Blau and Beller (1992), Goldin (1977, 1990), Tomaskovic-Devey, Thomas, and Johnson (2005) among others. Viewing this intersection of race and age from the other direction, significant research (Albert et al. 2011; Bendick et al. 1996, 1999; Lahey 2008; see Finkelstein et al. 1995 for a meta-analysis of laboratory work) demonstrates that in field and laboratory settings, employers and laboratory subjects favor resumes from younger job applicants over those from older job applicants. Less work has been done to determine how age discrimination differs for people of different races or genders; a literature review by Posthuma and Campion (2009) finds calls for such research, but no published papers.

mitigate the effects of those negative stereotypes by including such items on their resumes. Depending on how screeners view minority compared to non-minority resumes, employers who wish to reduce discrimination in hiring could implement structural changes asking all applicants to provide specific information or forcing screeners to view all parts of all resumes.

In addition to potential policy applications for employers and employees, how screeners view resumes can inform economic theory. Information on where screeners look and how they rate resumes containing different information can be used to test theories of statistical discrimination. If increased information indicating positive pre-market characteristics and labor market skills helps black applicants more than it helps white applicants, and if they spend more time looking at these characteristics, then that could indicate levels-based statistical discrimination based on those characteristics. If, on the other hand, positive signals help white applicants more than black (and negative signals hurt white more than black), and screeners do not spent as much time looking at these signals for resumes with black names compared to those with white names, then that would provide evidence of variance-based statistical discrimination.

This paper uses a laboratory experiment to get into the black box of the hiring process. We randomly vary the content of resumes for an entry-level clerical position. We provide resumes with names that signal differences between races, genders, and socioeconomic status, and that vary by date of high school graduation, indicating that the applicant is between the ages of 36 and 76. We then ask MBA, MPA, HR, and undergraduate business students to rate the resumes on a 1-7 "hireability" Likert scale (7 high). While they are viewing the resumes, we track for how long and where on the resumes they are looking.

On average, we find that for resumes of white hypothetical applicants, the rating of the resumes declines with age of the applicant at first, and then flattens out and even increases at older ages. However, when we look at age discrimination by race, resumes with black names show a strikingly different pattern than that for those with white names. Younger black applicants in the sample get much lower ratings on average but as they age, their ratings increase, meeting or surpassing those of the white applicants in middle age, this increase then flattens out and scores turn down again for older black applicants. While this pattern occurs in the Likert ratings for both men and women, the pattern is most pronounced for women. Time spent looking at resumes follows a similar pattern by age and race, indicating that our screeners do look at each resume but that they spend less time on younger black resumes than other resumes.

Simple models of taste-based discrimination assuming a constant distaste for black people vis-à-vis white people across the life-span are not sufficient to explain this differential treatment. However, we find evidence for both levels-based statistical discrimination and variance-based statistical discrimination. Computer training and any training help young black applicant ratings more than white, and screeners spend relatively more time on resumes for younger black applicants with computer training or any training than they do for younger white applicants with similar training, suggesting that these screeners believe that white applicants have higher levels of computer skills and training than do black, providing evidence for levels-based statistical discrimination against younger black applicants.

We also find evidence of variance-based statistical discrimination overall and specifically for work histories and high school quality. Previous work experience seems to be a better signal for white applicants than for black applicants. These results are consistent with findings that previous clerical work experience helps young white applicants more than black, and that screeners spend relatively more time viewing young white resumes with previous clerical experience than they do black. Similarly, quality predicted by high school dummies shows a possibility that the signal given by high school is not as good for young black applicants as it is for young white applicants. Quality predicted by address dummies does not show a pattern consistent with variance-based statistical discrimination.

These results show a pattern of discrimination by age that depends on the race and gender of the applicant that has not been previously examined given our reading of the wider social science literature. Simple taste-based discrimination alone cannot explain these patterns. However, screeners may believe that the computer skills and other training of young black applicants are worse than those of young white applicants and additional training provides relatively higher ratings. The signals given from high school quality or by a having held previous clerical jobs or may not be as strong for young black applicants as they are for young white applicants. Address does not seem to matter for young black applicants compared to young white applicants.

II. Literature Review and Theory

Eye-tracking

Eye-tracking is a technology that allows researchers to track where the eyes are looking and for how long.[4] This technology has improved dramatically in the past decade, and it is now possible for eyes to be tracked over a computer screen using a small box at the base of a monitor (Feng 2011). A more detailed discussion of the eye-tracking methodology in general can be found in Lahey and Oxley (2016).

Using this technology, we divide a resume into boxes called "Areas of interest" (AOI) and we will measure for how long a person fixates at any point within that box. We then determine the order that a screener looks at resumes, for example, where they look immediately after viewing a name.

Existence of Discrimination

[4] Eye-tracking has also been used to study pupil dilation and mental effort, but these uses are outside the scope of our paper. A related technology, Mouse-tracking, in which the computer monitors where the mouse cursor is placed on the computer screen has been used recently to look at questions of discrimination (Bartoš et al. 2016). While mouse-tracking has the advantage of being less expensive and easier to use than eye-tracking, it only tracks where the mouse is placed on a screen and not necessarily where the eyes are looking.

Differential treatment by race has been found using varied methodologies across different contexts (Lang and Lehman 2011 provide a literature review). Early studies used Oaxaca-Blinder decompositions to find “unexplained” bias after controlling for observables which could be coming from racial discrimination. Most recently, audit study evidence has provided compelling evidence of racial discrimination at the hiring margin. With the exception of a few recent studies which look at both genders, most studies on racial discrimination focus on men, particularly young men. Very few studies look at differential labor market outcomes (particularly outcomes other than wage) by race over the lifecycle. While audit studies provide an excellent way to determine hiring differences, they are unable to explore the mechanics of hiring.

Taste-based discrimination

Taste-based discrimination occurs when employers, employees, or customers have a distaste for black workers (Becker 1971). Most tests for taste-based discrimination in hiring rely on comparing positions that rely on interaction with the public (consumer service jobs) to those that do not, comparing patterns of segregation across groups of employees, or match the race of the employer/hiring manager to that of the employee with the assumption that black people are less likely than white people to have taste-based discrimination against black employees. Unfortunately the set-up of our experiment precludes these standard techniques; we are testing for a single position and have limited diversity in our participant sample.

However, if simple taste-based discrimination, in which black people are always disliked compared to white people, were solely driving results, then we would expect a constant difference between ratings of black and white resumes across all ages. Getting older would not result in decreases in the discrimination levels. Either a more complicated model of taste-based discrimination (one in which tastes for discrimination change differentially by age) is needed or there is room for statistical discrimination to be contributing to the results.

Levels-based statistical discrimination

A second type of discrimination is levels-based statistical discrimination (Phelps 1972). With this kind of discrimination, employers believe that there are differences in the average quality of the two groups of applicants, for example black applicants and white applicants. Because screening for applicant quality can be expensive, in the absence of easily accessible information, employers will expedite screening by attributing the average quality of the group to the individual candidate. These short-cuts can be operationalized via stereotypes.[5] Common stereotypes about black workers compared to white workers often focus on pre-labor market differences, such as schooling quality or neighborhood quality. Additional beliefs may concern skills or previous labor market experiences. In simple terms, screeners will assume that white applicants already have these positive attributes if they are not specifically listed, while they will assume that black applicants do not.

[5] Note that depending on the conclusions drawn by the levels-based statistical discrimination model, it may be important whether or not the stereotypes are based on fact or are incorrect. In this experiment we are agnostic about veracity of stereotypes; all that matters is belief in the stereotypes, not their accuracy.

The levels-based statistical discrimination model would have two important predictions in the context of our experiment. First, when information is made easily available and shows that the black candidate is of higher quality than the predicted average or has a specific skill that employers believe are less common in black candidates than in white candidates, then that information should help black candidates more than it helps white candidates. Second, when our hypothetical employers know that this information may be available on resumes, then they should spend more time looking in sections with this information for black resumes than they do for white, because they will assume on average that white applicants already have these skills but black applicants do not.

Literature on variance-based statistical discrimination

Variance-based statistical discrimination is more complicated than level-based (Aigner and Cain 1977). With this type of discrimination, it is not that black applicants necessarily have lower skills than white applicants, but that the signal for these skills is not as strong for black applicants compared to white. Here, a black applicant and a white applicant might show the same signal, for example, a high quality high school, but the signal would be more meaningful for white applicants compared to black applicants. The theory for this type of discrimination predicts that at high levels of signaled quality, the group for whom the signal is better (generally the majority group, in this case white applicants) will be preferred, while at low levels of signaled quality, the group for whom the signal is worse (generally the minority group, in this case black applicants) will be preferred.

The predictions of this model would be first that the graph of ratings vs. predicted ratings by group status would show the pattern described above with the lines for black and white applicants crossing each other. Second, screeners would spend less time looking at black compared to white resumes with positive signals if those signals are stronger for whites. Third, reviewers will spend less time looking for such signals for black resumes compared to white resumes. Note that for variance-based statistical discrimination, unlike levels-based statistical discrimination, additional positive information for specific skills will not help black applicants more than white applicants because the signal will be trusted for white applicants with higher skill signals but not for similar black applicants.

More complicated models of discrimination

More complicated models of race discrimination have been developed and are currently under-development (Lang and Lehmann 2011 provides an excellent review). A recent contribution by Cavounidis and Lang (2015) is of particular interest because of its prediction that as more information is revealed by age, discrimination against blacks compared to whites will decrease.

III. *The Experiment*

Design

The study took place at the Brain and Gender Laboratory at Texas A&M University. Subjects were recruited via flyer and were restricted to MBA and MPA graduate students and human resources and business school students more generally. Subject earnings were $20 for the session. One hundred fifty-two participants participated in the study between January 2013 and January 2014. Two participants were dropped for being non-native English speakers and one participant was dropped because of a diagnosed learning disability.[6] Total time allotted to the study was one hour, but the majority of participants finished in less than 45 minutes.

Participants rated resumes for an open administrative assistant position. The resumes they viewed were created randomly using the program from Lahey and Beasley (2009) and used a database of resume inputs drawn from actual resumes and from previous studies on discrimination. Variation included age, gender, race, high school attended, and work experience. Fictional applicant names indicated race (Aura and Hess 2010, Bertrand and Mullainathan 2004, Figlio 2005, Fryer and Levitt 2004, Levitt and Dubner 2005, Lieberson and Bell 1992, Lieberson and Mikelson 1995), gender (http://www.babynamewizard.com/), and socioeconomic status (Figlio 2005, Levitt and Dubner 2005, Lieberson and Bell 1992, Mehrabian and Piercy 1993).[7] Addresses were drawn from the Houston, Texas metropolitan area. High schools were drawn from the greater Texas area. The perceived race, gender, ethnicity, and socioeconomic status of the names were checked in a separate study using 95 psychology undergraduates, similarly the perceived socioeconomic status of the addresses and high schools were estimated using this separate undergraduate sample.[8]

Using the Lahey and Beasley (2009) program, we generated 40 unique resumes for each participant, for a total of 6,080 unique resumes, 5,960 of which were used after participants were screened for disabilities and English speaking. Some resume line items were repeated across participants; however, each participant only saw each specific line item at most once. 50% of the resumes were given female names, 9% were given black names, and 13% were given Hispanic names. These percentages were chosen to reflect the current composition of clerical workers in Texas according to the CPS and are shown in Table 1.

In post-processing we divided resumes into specific "Areas of Interest" (AOI) in order to measure the amount of time spent on each resume section. These AOI are virtual boxes that surround the fixed parts of the resume and included Name, Address, Employment history, Years associated with employment history, Education, Year associated with high school graduation, Other (which included items such as training, statements of flexibility, and volunteer work), and Outside (which included everything on the page not in another AOI). An example of this partition can be seen in Appendix Figure 1.

[6] Learning disabilities such as dyslexia can affect eye-tracking (see for example, Rayner 1998).

[7] Special thanks to David Figlio who provided additional black and white names by socioeconomic status for us using his database from Figlio (2005). Special care was taken to include low SES white names in our sample. More information on names and their predicted socioeconomic status can be found in companion paper Barlow and Lahey (2017).

[8] Results are consistent when controlling for the SES of the names. A companion paper explores the non-linear effect of perceived SES of addresses and high schools on ratings.

Procedure

Upon entering the laboratory, participants read an informed consent form and provided consent. Participants' eyes were calibrated with eye tracking equipment, a D6 eye tracking system from Applied Science Laboratories (Bedford, MA),[9] to observe where on screen a participant was looking. Participants were told that the purpose of the research was to study how hiring managers make job interview decisions. They were given the description of a clerical position and asked to evaluate applicants for that position. Participants then viewed five sample resumes, and, following that, rated 40 candidates' resumes one at a time for a hypothetical clerical position using a Likert scale regarding the ability of the candidate to fulfill the position. Participants then rank ordered their top two resumes and their top one resume for fulfilling the position from a presentation of their top five most highly rated resumes (with the more recent resume presented in the case of rating ties). However, because not enough black resumes made it into this top five set, we will not be discussing the results of this part of the experiment in this paper. After rating the resumes, participants completed various psychological, political, and demographic questionnaires (Bogardus 1933; Greenwald, Nosek and Banaji 2003; Nosek, Greenwald and Banaji 2007; Henkens 2005). After they completed the survey, participants were debriefed and paid.

The demographics of our sample reflected a variety of people affiliated with the Texas A&M community, with an intended bias towards those from the Mays Business School. As shown in Table 1, 38% of participants were at the Masters level and 1% were PhD students. 38% were upper division undergraduates and 23% were lower division undergraduates. 76% of participants studied business, 13% studied government, 6% studied humanities, and 5% studied other social sciences. The average age was 22 and 56% of the sample was female. The sample was 89% White, 7% Asian, and 5% Black or African American. 15% of participants reported that they identify as Hispanic or Latino.

Empirical Methods and Theoretical predictions

Existence

We first explore how the effect of age varies by race and by gender, both graphically and in a regression framework.

$$Hireability_r = \beta_1 * Age_r + \beta_2 * Age_r^2 + \beta_3 * Black_r + \beta_4 * Black_r * Age_r + \beta_5 * Black_r * Age_r^2 + \gamma_p + \alpha_r + \varepsilon_r \quad (1)$$

Hireability$_r$ is either a Likert (1-7) score with 7 as the highest rating and 1 as the lowest rating. *Age$_r$* is the age of applicant on the resume. *Black$_r$* is an indicator for having a "black" name. The main results are clustered on participant, and some robustness checks include participant fixed effects, γ_p. The equation ends with constant (α_r) and error term ε_r.

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[9] http://www.asleyetracking.com/Site/ASLintheNews/PressReleases/D6Eyetracker/tabid/133/Default.aspx

Another question is whether or not screeners view the entire resume after seeing the name. We use a modified version of (1) with $Time\_spent_r$ on the resume as a whole in place of $Hireability_r$ to explore how long they view each resume based on age and race.

Levels-based statistical discrimination

Recall that with levels-based statistical discrimination, employers believe that on average black applicants lack qualifications that they assume white applicants already have. Thus, support for levels based statistical discrimination would include a positive coefficients on β_1 in:

$$(2) \qquad Y_r = \beta_1 item_r * black_r + \beta_2 item_r + \beta_3 black_r + \boldsymbol{X}\beta_4 + \alpha + \varepsilon_r$$

Here, Y_r will be: $Hireability_r$, $Time\_spent_r$, or $Time\_spent\_AOI_{ar}$. $Time\_spent\_AOI_{ar}$ provides the time spent on a specific area of interest. Additionally, $item_r$ indicates either an item included on the resume, such as computer or other skills, or provides a continuous quality variable such as perceived education quality of the high school or perceived socioeconomic status of the home address. A vector of controls $\boldsymbol{X}$ include age and age^2 and participant fixed effects in some specifications. Other variables are as defined previously.

Equation (1) can combined with equation (2), allowing effects to vary quadratically by age, but the results are difficult to parse given the triple interaction with quadratic age terms. Results for these specifications are available from the authors in regression or graphical form.

Variance-based statistical discrimination

To test for the existence of variance-based statistical discrimination, we first create a predicted quality measure by regressing the $Hireability_r$ measure on a set of controls that covers every resume input except those for race, ethnicity, and age. Each individual resume input (individual job histories, high schools, additional training, volunteering, statements about flexibility, home addresses, email providers) is included as a dummy and additional variables are included that combine job histories, such as having a gap in the job history, length of employment history (and length squared), and length at each job (and length squared).[10] This predicted quality measure is then graphed against the actual ratings of the resumes separately for each race. Variance-based statistical discrimination would predict that the line for white resumes will be higher than that of black resumes at higher levels of resume quality but the line for black resumes will be higher than that of white resumes at lower levels of resume quality.

While the above graph provides a test of the existence of variance-based statistical discrimination, it does not provide information on the specific signals are that employers are using to statistically discriminate. We can test individual items as we did in the section on levels-based statistical discrimination, but with different predictions. Unlike the case of levels-based statistical discrimination, additional positive information for specific skills will not help

[10] Appendix Table 1 shows coefficients for this regression.

black applicants more than white applicants, so we would expect the coefficient of β_1 when Y is *Hireability* in equation (2) to not be significantly positive. Similarly, reviewers will spend less time looking for such signals for black resumes compared to white resumes. Thus, unlike the case of levels-based statistical discrimination, the coefficient of β_1 in equation (2) when Y is $Time\_spent\_AOI_{ar}$ would be negative if the signal was believed to be more meaningful for white applicants than for black.

Finally, we can test for the signal quality of multi-value resume components by using a method similar to our original test of variance-based statistical discrimination. We will do this for two items often mentioned in the literature: high school quality and address quality. We additionally test the quality of individual job history items as the job history is an important component of overall resume quality. It is important to note that we are allowing the resume viewers to determine quality—we are specifically not using an objective measure of quality. For example, to determine high school "quality" we regress our Likert (1-7) scale on all of the high school dummies in our sample and predict the Likert based on that regression. We perform an identical procedure with address dummies. Following that, we graph our predicted "quality" measures against the actual Likert ratings of the resumes by race indicated on the resume. The lines for black and white crossing would again indicate variance-based statistical discrimination while parallel lines or identical lines would not.

IV. *Results*

Existence and patterns of differential treatment by race and age

Resume ratings

Table 1 provides summary statistics for the resume sample and for the participant sample. The average Likert score given to all participants was 4.63, with a standard deviation of 1.39. On average, participants spent 16.24 seconds on each resume with a standard deviation of 10.17 seconds. This is slightly higher than, but comparable with, the estimate of 15 seconds often given by human resource representatives (Lahey 2008).

The majority of experimental papers that find hiring discrimination against black workers (if not all of them, to our knowledge), have focused on younger workers. Although our focus is not on teenagers or applicants in their early 20s, we are interested in differential effects by age. We therefore present a simple t-test in Table 2 to compare outcome for black resumes vs. white for younger applicants and for our entire sample. Using a simple t-test to compare the average scores of black vs. white for the younger portion of our sample, those under the age of 45, we indeed see a significant preference for white resumes over black resumes. On the 7 point Likert scale, white applicants are preferred to black with a significant difference of .28, which is 6% above the average rating for the entire sample of 4.63. However, when we run a t-test on the entire sample from age 36-76, the difference between black resumes and white declines to .03 and is no longer statistically significant.

To visualize these results, we use a local weighted regression (using a lowess smoother) graph to plot how participants rate resumes by age for each race. Figure 1a demonstrates a small quadratic decline and increase in ratings by age for whites. However, the pattern for black resumes is strikingly different. In Figure 1a, black resumes start at a much lower Likert rating than whites and their rating gradually increases with age until the mid-50s. At that point it decreases again to a value slightly above the starting point. Fitting these data to a quadratic in Figure 1b allows us to fit confidence intervals around the outcomes. This fit shows statistically significant differences in the age tails where white resumes are preferred to black as well as in the late 50s and early 60s when black resumes are preferred to white. Figures 1(c)- 1(f) break apart the sample by gender and show similar patterns, though for white men the pattern by age is more linear than quadratic while results for women do not show significant differences in 1(f) given the overlapping confidence intervals.

We further formalize these results in Table 4, which again demonstrates the importance of interacting age and race. Table 4 column 1 provides the results from equation (1) without the age*black interaction. Although the effect of having a black name on the Likert rating has a negative sign in these regressions, it is not significant. However, when race is interacted with the quadratics as in Column (2), the main effects and interacted effects are significant at standard levels. This difference suggests that the different age trends in hireability by race mask the effects of race when this interaction is not taken into account. Similarly, columns (3) and (4) break apart the results by gender and are in line with the pictures shown in figures 1(c)-1(f).

Patterns of Resume Viewing

Screeners do spend time viewing all parts of the resumes, as shown in Table 1. They also spend time viewing all parts of the resumes for both black and white resumes (results not shown). It is not the case that screeners view the name and then stop viewing the remainder of the resume.

Eye-tracking allows us to determine the paths that screeners take when viewing the resumes. Table 3 provides transition matrices showing the movement from one AOI to the next for white resumes and black resumes. For each resume of each participant, we calculated the percentage of movements, known as *saccades*, between all AOIs (dropping any within-AOI saccades), then we averaged those percentages across all white resumes in Table 3a and across all black resumes in Table 3b. Therefore, each cell provides the percentage of between-AOI saccades. Note that if you sum all the cells in a matrix, they will add up to 1. As an example, in Table 3a, 14.17% of all transitions on white resumes were from Employment History to Outside (where outside is outside the defined resume area). Similarly, 2.4% of all transitions were from Name to Outside. Table 3c provides the simple subtraction between the matrix in 3a and the matrix in 3b.

For the most part, screeners follow the same paths when viewing white resumes as they do when viewing black resumes. There does not seem to be any substantive difference by race in where they look immediately after viewing the name on the resume.

There are substantive differences in the number of times the viewer looks "Outside", which we assume to be a measure of time spent thinking, with screeners more likely to look "Outside" for white resumes than for black resumes. Also of potential interest are the saccades between "Other" and "Employment History" AOI—screeners look between the two of these AOI 1.6% (the sum of -.007 and -.009 in Table 3c) more for black resumes than for white resumes.

Time spent on resumes

Figure 2 demonstrates that screeners spend more time viewing resumes that they like than resumes that they do not like, and this pattern is similar for both white resumes and for black resumes.[11] Regression results available from authors show similar (significant) results between time spent and resume rating even when a linear specification is forced on the data.

In Figure 3, we show local weighted regression (lowess) plots for black and white resumes demonstrating how the amount of time spent viewing a resume varies by the age of the applicant. Screeners do not just view a black name on a resume and move on to the next resume; they view all parts of all resumes. However, screeners spend less time looking at young black resumes than they do young white or older black resumes. In fact, the pattern for time spent viewing is similar to that of the pattern for Likert ratings, with the exception of increased time spent viewing resumes in which the applicant is older than age 70 for both black and white applicants (possibly because these resumes may seem particularly unusual). White resumes show a decrease, then uptick with age, while black resumes start at a lower rate but increase with age eventually surpassing that of whites before turning down again at middle ages. (indeed, in a companion paper we show that the pattern of resume viewing is markedly similar, from top to bottom, for most resumes and screeners).

Levels-based statistical discrimination

Table 5, columns (1) and (2) use equation (2) to test whether or not having various types of experience help black applicants more than white. For younger applicants, having computer training on the resume helps black applicants significantly more than white. However, for older applicants, computer training no longer helps black applicants more than white. Similarly, any training is marginally significant for helping young black applicants more than young white applicants but loses significance for the older group. These results provide evidence that employers expect younger black applicants to have worse computer skills than younger white applicants, and that they may expect worse skills overall.

Column (3), however, shows that previous clerical work experience helps young white applicants significantly more than it helps young black applicants by more than one point on the Likert scale, shown in Panel I, column (3). Thus it is not likely that employers view young black applicants as being less likely on average to have clerical experience compared to young white

[11] Note that with 91% of the resumes having "white" names, time outliers are more likely to occur for white resumes than for black resumes.

applicants. No significant effect is found for older black applicants compared to older white applicants.

We also test whether our hypothetical employers spend more time looking at black resumes with computer training or any training compared to white resumes with computer training using equation (3) for these younger applicants. These results are shown in columns (4) and (5) and track Likert ratings results in columns (1) and (2) with screeners spending more additional time on average for young black resumes compared to young white resumes. In terms of magnitude, screeners spend a significant differential of 10 additional seconds for computer training and of 6 additional seconds for any training. These positive and significant findings further bolster the idea that employers are specifically looking for evidence of computer skills and training when looking at resumes for younger black applicants. No significant effects are found for older black applicants compared to older white applicants although signs are the same with smaller magnitudes.

However, clerical experience, in column (6), again shows the opposite effect, with our participants spending 7 seconds longer on young white compared to young black resumes with clerical experience. Again, no significant effects are found for older black resumes compared to older white resumes, although the signs are the same with smaller magnitudes.

Finally, do hypothetical employers specifically look longer at the “other” section for young black vs. white resumes with computer training or any training? Here the answer is no. For younger applicants there is no significant difference to how long the “other” section is looked at in the interaction of computer training or any training and race, although the coefficient for the interaction between computer training and black name is positive.

This lack of a significant relative increase in the time spent on the specific area of interest seems at odds with the finding of relative increased time spent on the resume and relatively higher ratings as a whole. Where are screeners spending more time? Table 6 uses Equation (2) to ask that question for the item computer science with time spent in each potential AOI in a column, that is, conditional on having computer experience, where do people spend longer looking for young black applicants compared to white. Although results are only significant at the 10% level, there is some evidence that once a black applicant shows computer experience, screeners spend comparatively more time looking at the employment history (column 2), about 5.5 seconds, and address (column 4), 1.8 seconds. They also spend comparatively more time looking at the resume outside of any of the AOI (column 1), 4.3 seconds which could indicate time spent thinking. Small negative effects are found for the areas of interest that indicate the years that things happened, specifically the years of employment for different jobs and the high school graduation year. Panel II finds no results for these items for older applicants, though screeners seem to spend more time for white resumes compared to black looking at age (indicated by graduation year in column (6)) and “other” (column (7)). These differences fit more with theories of age discrimination against whites and are out of the scope of this paper. Results for any training are similar and are available from authors.

Taken together, it appears that there is evidence to support levels-based statistical discrimination against young black applicants compared to young white applicants on the basis of computer skills and training. Indicators that black applicants have these skills cause the rest of the resume to be taken more seriously. There does not appear to be evidence to support levels-based statistical discrimination on the basis of previous clerical work experience.

Variance-based statistical discrimination

Figure with quality measures

In Figure 4, we plot predicted quality (described in Section III) against average ratings separately for black and white resumes using an local polynomial command with confidence intervals (lpolyci). The resulting figure mirrors the classical model of variance-based statistical discrimination (Aigner and Cain 1977) which predicts that at higher levels of signaled quality, white applicants will be preferred to black, while at lower levels, black applicants will be preferred to white.

We then look at specific signals that could be driving variance-based statistical discrimination. First we turn to the resume items that we explored in Table 6. Computer training and any training fit with predictions of levels-based statistical discrimination, but do not fit with predictions of variance-based discrimination. However, clerical experience on the resume did not help black applicants more than white. In fact, as shown in Table 6, Panel I, column (3), having clerical experience on the resume helped young white applicants more than it helped young black applicants. Similarly, our participants spent more time viewing young white resumes with clerical experience than they did young black resumes. Finally, although the result is not significant, participants spent less time looking at the work history area of interest for black resumes with clerical experience compared to white resumes with clerical experience. Taken together, these results suggest that our participants believe that clerical experience is a stronger signal of quality for younger white applicants than it is for younger black applicants.

Other commonly suggested reasons for variance-based statistical discrimination against black applicants are those of school quality (does a high school degree mean the same thing for a black graduate as a white graduate?) and address. Figures 5a and 5b explore the effect of high school "quality" on Likert ratings. Graphing "quality" predicted by high school dummies against the actual Likert rating using a local polynomial with confidence intervals, we see what appears to be significant divergence at higher levels of "quality" for young black resumes compared to young white resumes. Although we do not see a cross-over at lower levels of "quality", it may be that our high schools are not of low enough quality to show a crossover. This picture is consistent with variance-based statistical discrimination with high school not being as good an indicator of applicant quality for young black resumes as it is for young white resumes. For older applicants, the black line is actually higher than that of whites although never significantly different and is not consistent with variance-based statistical discrimination.

Figures 6a and 6b repeat this exercise using address dummies in place of high school dummies. Here we see a constant difference (albeit a statistically insignificant one) between young black and white resumes at all points of address "quality" and the lines for older and younger black resumes are very similar. These provide no evidence of variance-based statistical discrimination against black applicants. Note that the reasons posited for address-based discrimination against black applicants are two-fold: first, employers may have worries about the neighborhood quality signaling something about the applicant, or second, employers may be worried about commute time and reliability based on where the job is situated compared to where the applicant lives. Our experience can only test the former, not the latter, as we did not provide an address for our hypothetical job. Address will still be important, possibly in terms of levels-based statistical discrimination, if employers are worried about commute time to work.

Robustness checks

Finally, Table 7 provides some robustness checks for the main results shown in Table 4. Results using participant fixed effects are generally highly similar to those not using these effects, and Column (2) shows the effect of including these effects. Hispanic last names were not found to have any significant effect on the main outcomes in the paper, possibly because this study was done on a population that has a large proportion Hispanic and Hispanic first names were not used. Column (3) shows the main results with resumes with Hispanic last names removed, and as expected the results are close to the original results. There may be some concern that some participants rate resumes higher on average than others and these ratings may be correlated with ratings by age, race, or gender. For that reason, specifications were run with the Likert Rating variable normalized by each participant's average Likert score and standard deviation. This normalization, presented for the main results in column (4) was not found to change any findings, and the non-normalized scores are presented in the main paper for ease of interpretation. Finally, those age 65 and under may be of particular interest as they represent prototypical working ages. Here, as would be predicted by our earlier results, the black main effect is larger at -8.5 (compared to -6.0 in the original), the black interactions are significant and have magnitudes as before, and the age main effects have similar magnitudes to before but are no longer significant.

IV. External Validity and Sub-Group Heterogeneity

This study is a laboratory experiment. As such, there may be concerns that the behavior by study participants does not mimic the behavior of actors in the field. While it is beyond the scope and, in some cases, ability of this paper to check all results, we can make some comparisons with general employment data (such as the Current Population Survey) and with previous audit studies as a first-pass check that our samples are behaving as we might expect given behavior in the field.

The closest test to "hireability" in general labor force statistics is to look specifically at people who are unemployed in month t-1 and measure their probability of employment in time t. Given general equilibrium conditions, we would not necessarily expect to see hiring for the middle-aged black unemployed to meet or outpace that of the white unemployed, but it would be comforting to see quadratic patterns similar to those shown for hireability in this study. Figure XX….

While, to our knowledge, no audit study has been done comparing black and white job applicants over the lifespan, there have been several audit studies looking at the effects of age on job interviews. Lahey (2008) includes several ages in her audit study on women applying to all entry-level jobs in Boston, MA and St. Petersburg, FL and finds quadratic results on probability of being called back similar to those found for "hireability" of white female applicants in this laboratory study.

A common concern in laboratory studies is of the validity of the participant sample. A number of our participants had previous hiring and human resources experience. We found no significant difference between these participants and the rest of our sample.

V. Discussion and conclusion

This paper uses a laboratory experiment on graduate and undergraduate business, human resource and administration and policy students. Participants were asked to rate 40 resumes for an entry-level clerical position on a Likert (1-7) scale while a computer tracked their eye movements. Our results demonstrate that for white applicants, these ratings for resumes decrease with age, then slightly increase. Black resumes show an opposite pattern, starting at a much lower rating, increasing with age, then decreasing. The same pattern on age and race is found for time spent on each resume, although more time is spent overall on resumes for older applicants of both races. We find evidence of levels-based statistical discrimination for computer skills and any training and of variance-based statistical discrimination for relevant work experience and high school quality.

It is important to note that our results only hold for a specific segment of the labor force. The job advertised was that of an entry level administrative assistant position and the applicant pool provided to the participants has less than a year of post high school education. These same patterns, particularly those by race, might not be found for a position requiring more education or experience. Future research should explore these differences by labor market segment.

These results underscore the importance of looking at not only one group characteristic when doing an audit or laboratory discrimination study. Looking only at the labor market experience of black resumes or white resumes provides a limited view of the labor market, and limiting to only inexperienced younger workers only provides a limited snapshot of differential treatment by group characteristic. The labor market facing any one group may vary systematically by another group characteristic.

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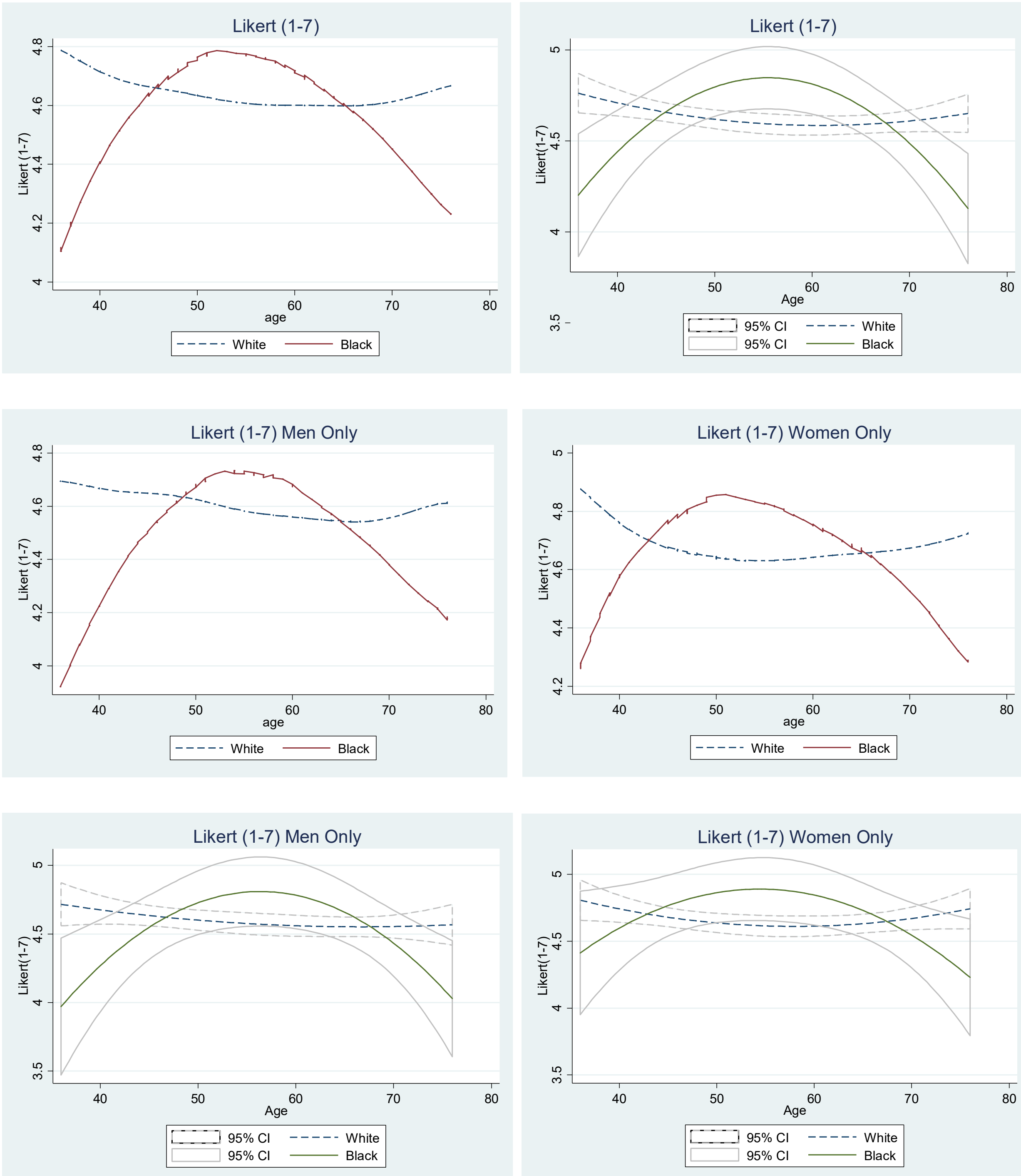


Figures 1a-1f

Notes: Figures 1a, c, d provide the results from a local weighted regression (lowess). Figures 1b, e, f provide the results from a quadratic fit. Age is age on resume as indicated by date of high school graduation.

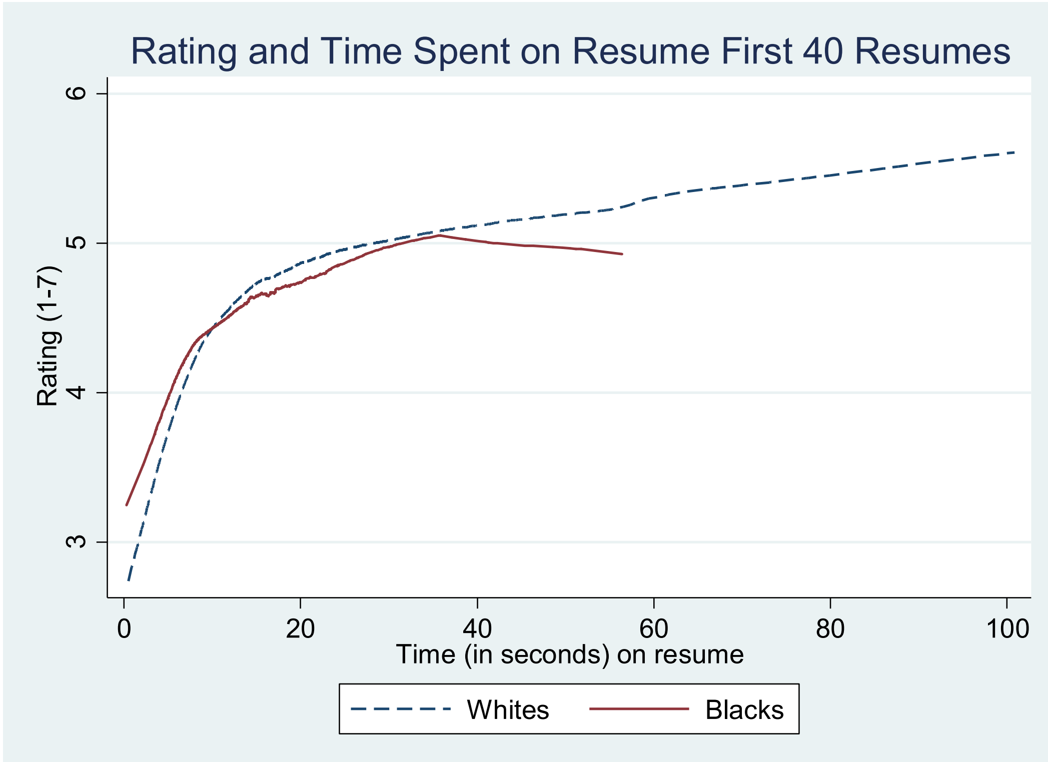


Figure 2

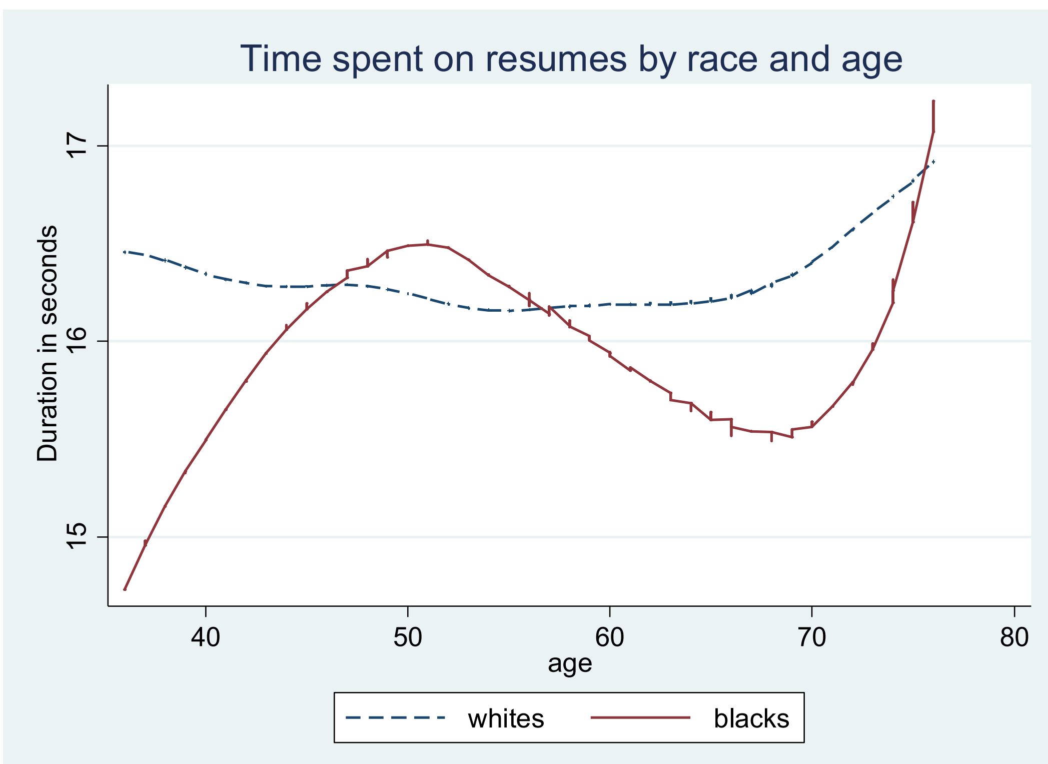


Figure 3

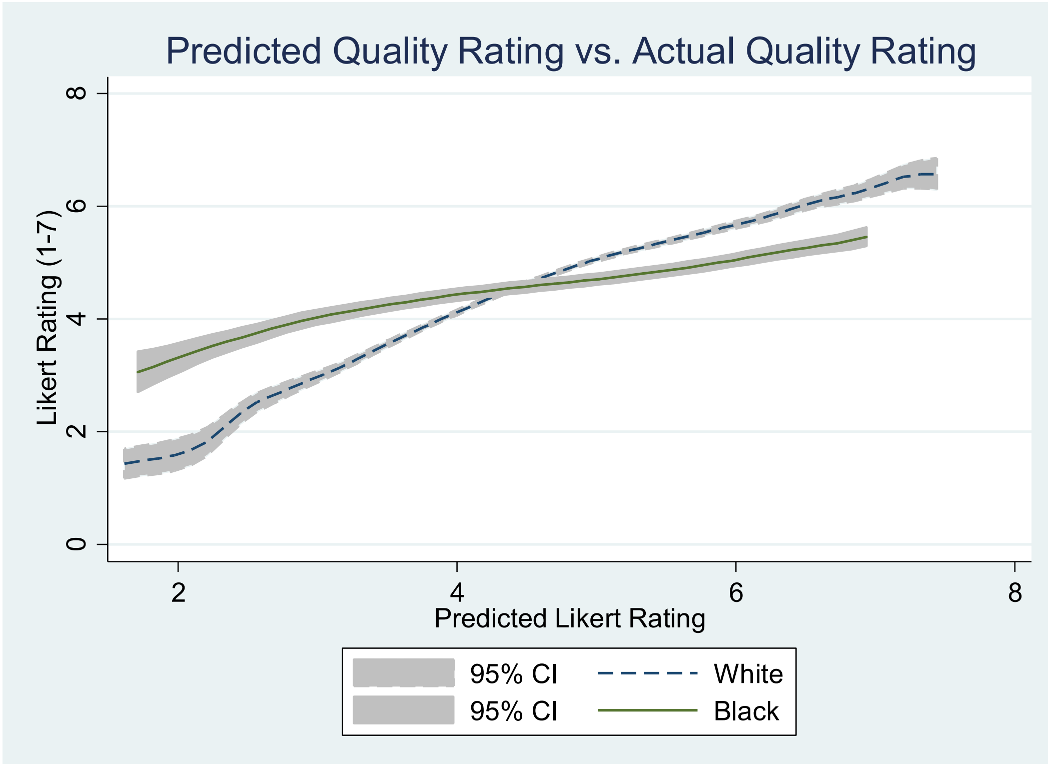


Figure 4

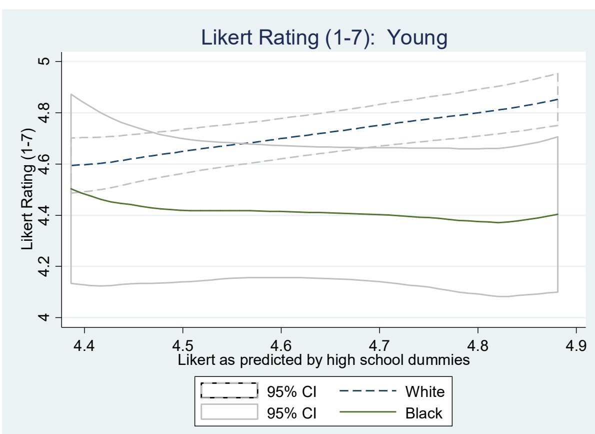


Figure 5a

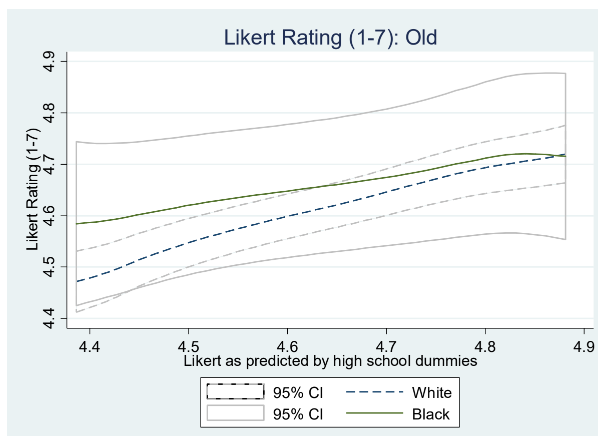


Figure 5b

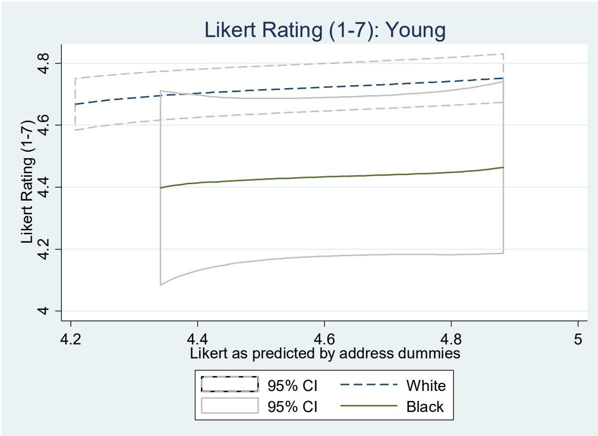


Figure 6a

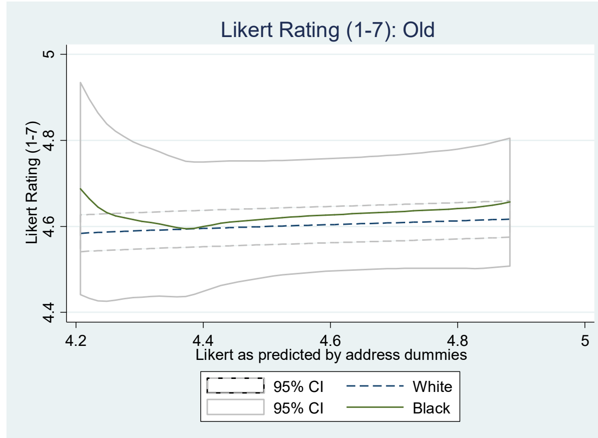
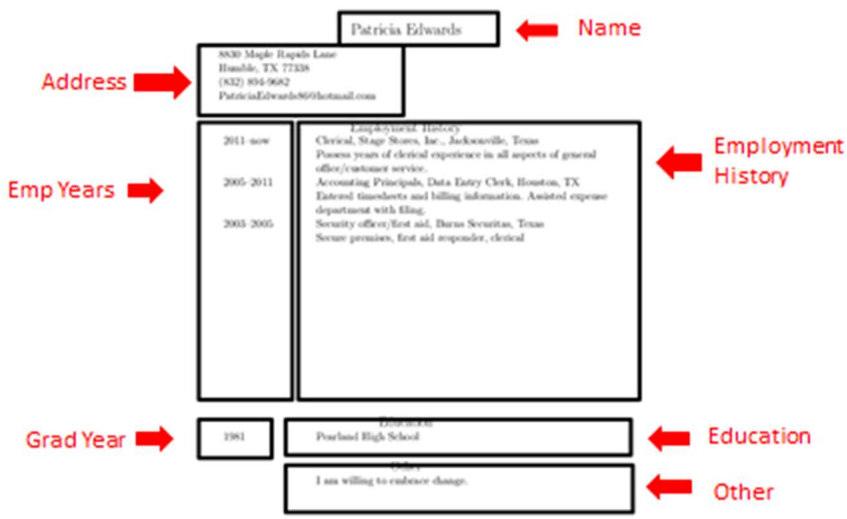


Figure 6b



Appendix Figure 1

Table 1: Summary Statistics

	Mean	SD
Resume Characteristics		
Female	0.50	0.50
Black	0.09	0.29
Hispanic	0.13	0.34
Age	56.20	11.78
Participant Characteristics		
Female	0.56	
White	0.89	
Asian	0.07	
Black	0.05	
Hispanic	0.15	
MA student	0.38	
PhD student	0.01	
Upper division	0.38	
Lower division	0.23	
Business	0.76	
Government	0.13	
Social Science	0.05	
Humanities	0.06	
Age	21.98	2.84
Ratings		
Likert (1-7)	4.63	1.39
Eye-tracking		
Seconds spent: total	16.24	10.17
outside	3.03	3.78
employment history	4.87	5.72
name	0.17	0.52
high school	1.20	1.77
years employed	0.48	1.09
graduation year	0.02	0.14
other	0.22	0.55
education	0.21	0.46

Note: 5,960 resumes for the non-eyetracking statistics. 4,909 resumes for the eyetracking statistics.

TABLE 2: Likert Scale Differences by Race

	Mean (1-7)	N	Difference	p (two-sided)
Age 45 and under				
White	4.72	1293		
Black	4.44	110	0.28	0.042
Ages 36-76				
White	4.63	5425		
Black	4.60	535	0.03	0.616

Table 3a: Transition matrix for white resumes

		Time t							
		Outside	Employment Hist	Name	Personal Info	Years Employed	Graduation Year	Other	Education
Time t-1	Outside	.	0.1397	0.0227	0.0878	0.0212	0.0015	0.0276	0.0197
	Employment History	0.1417	.	0.0039	0.0415	0.0521	0.0006	0.0167	0.0274
	Name	0.0240	0.0035	.	0.0082	0.0004	0.0000	0.0003	0.0004
	Personal Information	0.1072	0.0409	0.0092	.	0.0077	0.0003	0.0016	0.0024
	Years Employed	0.0209	0.0527	0.0005	0.0128	.	0.0005	0.0014	0.0019
	Graduation Year	0.0014	0.0005	0.0000	0.0007	0.0005	.	0.0002	0.0012
	Other	0.0276	0.0078	0.0003	0.0032	0.0008	0.0003	.	0.0052
	Education	0.0193	0.0135	0.0004	0.0039	0.0021	0.0015	0.0090	.

Table 3b: Transition matrix for black resumes

		Time t							
		Outside	Employment Hist	Name	Personal Info	Years Employed	Graduation Year	Other	Education
Time t-1	Outside	.	0.1428	0.0246	0.0948	0.0245	0.0017	0.0193	0.0180
	Employment History	0.1344	.	0.0028	0.0435	0.0482	0.0011	0.0237	0.0228
	Name	0.0259	0.0039	.	0.0057	0.0000	0.0000	0.0000	0.0006
	Personal Information	0.1085	0.0447	0.0074	.	0.0078	0.0005	0.0012	0.0040
	Years Employed	0.0180	0.0540	0.0001	0.0134	.	0.0000	0.0018	0.0007
	Graduation Year	0.0014	0.0004	0.0000	0.0002	0.0001	.	0.0010	0.0019
	Other	0.0229	0.0167	0.0000	0.0050	0.0010	0.0007	.	0.0043
	Education	0.0180	0.0105	0.0000	0.0036	0.0008	0.0010	0.0100	.

Table 3c: White-Black differences for transition matrix

		Time t							
		Outside	Employment Hist	Name	Personal Info	Years Employed	Graduation Year	Other	Education
Time t-1	Outside	.	-0.003	-0.002	-0.007	-0.003	0.000	0.008	0.002
	Employment History	0.007	.	0.001	-0.002	0.004	0.000	-0.007	0.005
	Name	-0.002	0.000	.	0.002	0.000	0.000	0.000	0.000
	Personal Information	-0.001	-0.004	0.002	.	0.000	0.000	0.000	-0.002
	Years Employed	0.003	-0.001	0.000	-0.001	.	0.000	0.000	0.001
	Graduation Year	0.000	0.000	0.000	0.000	0.000	.	-0.001	-0.001
	Other	0.005	-0.009	0.000	-0.002	0.000	0.000	.	0.001
	Education	0.001	0.003	0.000	0.000	0.001	0.001	-0.001	.

Table 4: Effect of black names with and without age interactions

	Likert rating (1-7)			
	All		Female	Male
	(1)	(2)	(3)	(4)
black name	-0.0292	-6.0470***	-5.2600***	-6.9510***
	(0.0591)	(1.3870)	(1.9180)	(2.1610)
black*age		0.224***	0.2010***	0.2520***
		(0.0500)	(0.0694)	(0.0786)
black*age squared		-0.0020***	-0.0018***	-0.0022***
		(0.0004)	(0.0006)	(0.0007)
age	-0.0145	-0.0349**	-0.0471*	-0.0232
	(0.0157)	(0.0170)	(0.0239)	(0.0225)
age squared	0.0001	0.0003*	0.000406*	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Observations	5,960	5,960	2,982	2,978

Note: Standard errors are clustered on participant.

Table 5: Effect of resume items on Likert ratings, total time spent, and time spent on area of interest

	Likert ratings			Time spent viewing resume			Time spent on area of interest		
item =	Computer	Training	Clerical Exp	Computer	Training	Clerical Exp	Computer	Training	Clerical Exp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel I: Younger								
black*item	**1.0363*** **	**0.6338***	**-1.2454*** **	**10.1643*** *	**6.2362*** *	**-7.5121*** *	**0.1457**	**-0.0684**	**-0.7524**
	(0.2629)	**(0.3715)**	**(0.4651)**	**(4.2919)**	**(2.8996)**	**(3.3729)**	**(0.5439)**	**(0.1288)**	**(1.9204)**
blackname	-0.3439***	-0.3698***	0.8353*	-1.6271*	-1.7996*	5.6593*	-0.0112	-0.0089	0.1930
	(0.1318)	(0.1368)	(0.4389)	(0.8882)	(0.9120)	(3.2897)	(0.0320)	(0.0493)	(1.9019)
item	0.3441***	0.2570**	1.5658***	1.5907*	1.0049	5.3575***	0.3109***	0.1180**	1.9601***
	(0.1309)	(0.1067)	(0.1438)	(0.9488)	(0.6650)	(0.9100)	(0.0939)	(0.0539)	(0.5183)
Observations	1,403	1,403	1,403	1,332	1,332	1,332	1,183	1,183	1,183
	Panel II: Older								
black*item	**0.3437**	**0.2062**	**0.1305**	**1.3934**	**2.3768**	**-2.2134**	**-0.3649*** **	**-0.2960*** **	**-1.4892**
	(0.3048)	**(0.1839)**	**(0.3307)**	**(1.9357)**	**(1.6218)**	**(2.0321)**	**(0.1062)**	**(0.0916)**	**(0.9227)**
blackname	0.0235	0.0204	-0.1457	-0.2540	-0.4135	1.6887	-0.0165	0.0004	1.0863
	(0.0721)	(0.0718)	(0.3211)	(0.4077)	(0.4227)	(1.9709)	(0.0231)	(0.0240)	(0.8528)
item	0.0843	0.1615***	1.4748***	1.8610***	1.1417***	5.1299***	0.3453***	0.3459***	2.2486***
	(0.1003)	(0.0574)	(0.0822)	(0.5345)	(0.4091)	(0.4664)	(0.0721)	(0.0582)	(0.2542)
Observations	4,557	4,557	4,557	4,283	4,283	4,283	3,726	3,726	3,726

Notes: Standard errors clustered on participant. Younger includes ages 36-45.

Table 6: Effect of computer training on time spent on areas of interest

	outside	employ. history	name	address	employ. years	grad year	other	education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel I: Younger				
black*computer	**4.3263***	**5.4767***	**-0.0108**	**1.8705***	**-0.3935***	**-0.0479***	**0.1457**	**1.3051**
	(2.3133)	**(3.1080)**	**(0.0528)**	**(1.1028)**	**(0.2041)**	**(0.0266)**	**(0.5439)**	**(1.0257)**
blackname	-0.0916	-0.7603	-0.1000**	-0.2851**	-0.0027	-0.0084	-0.0112	-0.0592
	(0.3753)	(0.4913)	(0.0488)	(0.1425)	(0.1286)	(0.0066)	(0.0320)	(0.0392)
computer training	0.3704	-0.5011	-0.0973**	-0.1062	-0.0226	0.0246	0.3109***	-0.0173
	(0.4815)	(0.5803)	(0.0414)	(0.1481)	(0.0956)	(0.0254)	(0.0939)	(0.0502)
Observations	1,183	1,183	1,183	1,183	1,183	1,183	1,183	1,183
				Panel II: Older				
black*other	**-0.0778**	**0.7981**	**0.0131**	**-0.2304**	**-0.0305**	**-0.0254*****	**-0.3649*****	**-0.0947**
	(0.7797)	**(1.2161)**	**(0.0793)**	**(0.3003)**	**(0.1193)**	**(0.0094)**	**(0.1062)**	**(0.1229)**
blackname	0.2169	-0.3011	-0.0207	0.0589	-0.0615	-0.0005	-0.0165	0.0131
	(0.1861)	(0.2747)	(0.0213)	(0.0862)	(0.0505)	(0.0054)	(0.0231)	(0.0254)
other	0.5252***	-0.3405	0.0340	0.0656	-0.0543	0.0071	0.3453***	0.1121***
	(0.1917)	(0.4072)	(0.0308)	(0.0987)	(0.0586)	(0.0082)	(0.0721)	(0.0349)
Observations	3,726	3,726	3,726	3,726	3,726	3,726	3,726	3,726

Notes: Standard errors clustered on participant. Younger includes ages 36-45. Additional controls include age and age squared.

Table 7: Robustness Checks for Likert Ratings in Table 4

	Original	Participant effects	No Hispanics	Normalized Y	Under 66
	(1)	(2)	(3)	(4)	(5)
age	-0.0349**	-0.0324**	-0.0393**	-0.0262**	-0.0271
	(0.0170)	(0.0164)	(0.0187)	(0.0127)	(0.0348)
age squared	0.0003*	0.000269*	0.0003**	0.000218*	0.0002
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
black name	-6.0470***	-5.038***	-6.703***	-3.870***	-8.4830***
	(1.3870)	(1.3480)	(1.4650)	(0.9970)	(2.7020)
black*age	0.224***	0.187***	0.244***	0.143***	0.3270***
	(0.0500)	(0.0497)	(0.0529)	(0.0359)	(0.1090)
black*age squared	-0.0020***	-0.00167***	-0.0021***	-0.0013***	-0.0030***
	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0011)
Observations	5,960	5,960	5,170	5,960	4,349

Notes: Column 2 includes participant fixed effects. Column 3 removes all Hispanic last names. Column 4 normalizes "respval" variable for each participant's ratings. Column 5 limits universe to ages under 66.