Racial Discrimination in the Labor Market for Recent College Graduates: Evidence from a Field Experiment

John M. Nunley,* Adam Pugh,† Nicholas Romero,‡and R. Alan Seals§

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Abstract

We present experimental evidence from a correspondence test of racial discrimination in the labor market for recent college graduates. We find strong evidence of differential treatment by race: black applicants receive approximately 14 percent fewer interview requests than their otherwise identical white counterparts. The racial gap in employment opportunities is larger when comparisons are made between job seekers with credentials that are proxies for expected productivity and/or match quality. Indirect tests suggest that either taste-based discrimination, particularly at the race-skill level, or risk aversion on the part of employers are the most likely explanations. In addition, the racial differences identified are driven primarily by greater discrimination for jobs that require substantial customer interaction.

JEL categories: J23, J24, J71

Key words: racial discrimination, employment, productivity, field experiments, correspondence studies

*John M. Nunley, Department of Economics, University of Wisconsin—La Crosse, La Crosse, WI 54601, phone: 608-785-5145, email: jnunley@uwlax.edu, webpage: http://johnnunley.org/.

†Adam Pugh, CUNA Mutual Group, Madison, WI 53705, phone: 920-229-6778, fax: 608-785-8549, email: adam.pugh@cunamutual.com.

‡Nicholas B. Romero, Department of Economics, University of Pennsylvania, Philadelphia, PA 19104, phone: 334-233-2664, email: romeron@sas.upenn.edu, webpage: http://economics.sas.upenn.edu/graduate-program/current-students/nicholas-romero.

§Richard Alan Seals Jr., Department of Economics, Auburn University, Auburn, AL 36849-5049, phone: 615-943-3911, email: alan.seals@auburn.edu, webpage: www.auburn.edu/ras0029.

1 Introduction

College graduates who entered the labor market during and following the Great Recession experienced high rates of unemployment and underemployment (Abel, Deitz, and Su 2014; Spreen 2013). The labor-market opportunities, while grim for those who completed their degrees during this time period, were worse for blacks. Spreen (2013, Table 7) reports unemployment rates for recent college graduates that differ substantially between whites and blacks (10.6 percent for whites and 20.2 percent for blacks). In addition, research on the impact of recessions on demographic groups indicates that blacks are disproportionately affected (Hoynes et al. 2012).[1] Anecdotal evidence suggests a higher degree of selectivity on the part of employers with respect to their hiring during and following the Great Recession.[2] Given the higher rates of unemployment for blacks relative to whites, it could be the case that employers were selective on the basis of race. We use data from a randomized résumé-audit study to examine racial discrimination in the labor market for college graduates who completed their degrees during the worst employment crisis since the Great Depression.

Discrimination against minority job seekers is a worldwide phenomenon that has been documented in experimental studies of the labor market (Baert et al. 2013; Bertrand and Mullainathan 2004; Booth, Leigh and Varganova 2012; Carlsson and Rooth 2007; Oreopoulos 2011). The most common experimental design in this literature combines random assignment of perceived productivity and other résumé characteristics with popular first and last/family names that signal race to estimate the discrimination coefficient (e.g., Bertrand and Mullainathan 2004). However, it has proven conceptually difficult to determine whether discrimination is taste-based (i.e. employers have racist preferences) or statistical (i.e. imperfect information causes employers to update their beliefs about future productivity, which

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[1]Hoynes et al. (2012) show that men, blacks, hispanics and uneducated workers have suffered more than other demographic groups from recessions. It is also noteworthy that the groups who suffered the most from the Great Recession are the same groups who suffered the most from the recession of the early 1980s.

[2]As a an example, see the following *New York Times* article: http://www.nytimes.com/2013/03/07/business/economy/despite-job-vacancies-employers-shy-away-from-hiring.html?pagewanted=all&_r=0.

may be correlated with race, when confronted with racial-sounding names). Our primary objective is to determine the extent to which discrimination can explain the (un)employment gap between white and black college graduates. If discrimination cannot be ruled out, a secondary objective is to determine whether the source of the discrimination is based on tastes or imperfect information.

If the (un)employment differentials between blacks and whites are large early in their careers, employers may have different beliefs about the quality of experience of white and black workers later in their careers, which could complicate an analysis of racial discrimination. For this reason, we focus on the employment prospects facing recent college graduates within the context of a résumé-audit experiment in which the job applicant's race is signaled with a white- and black-sounding name. Over 9000 randomly-generated résumés from fictitious, recently-graduated job seekers were submitted to online job advertisements from January 2013 through the end of August 2013. All applicants were assigned a college graduation date of May 2010.[3] By randomizing the timing of gaps in the work history, we indicate both current and past unemployment spells. Because recent college graduates have also suffered from high rates of underemployment (Abel, Deitz and Su 2014), we also include two types of work experience: (i) in-field experience that requires a college degree and (ii) out-of-field experience that does not require a college degree. The latter is indicative of underemployment.

In order to further differentiate between statistical and taste-based discrimination, which could arise from perceived differences in the the quality of training and/or job-skill match, approximately half of the applicants were assigned traditional business degrees (i.e. accounting, economics, finance, marketing, and management), while the other applicants were assigned degrees from the arts and sciences (i.e. biology, English, history, and psychology).

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[3]The national unemployment rate was 9.6 percent in May 2010, but the unemployment rate among college graduates was only 4.6 percent at the time of graduation (http://data.bls.gov/timeseries/LNS14000000). Spreen (2013) reports that the unemployment rates of college graduates who completed their degrees in the wake of the Great Recession were over 10 percent (approximately 13 percent in 2010), and that there were differences between blacks and whites.

Additionally, we randomly assigned in-field internships to provide another source of experience that is gained before the applicant enters the job market. We then responded to job advertisements exclusively from the business sector (i.e. banking, finance, insurance, management, marketing, and sales) so that we are able to study how mismatches in qualifications might affect the racial gap in employment opportunities.

Our experimental data indicate that black-named job seekers are approximately 14 percent less likely to receive interview requests than applicants with white-sounding names. We find no evidence that the uniqueness of the racially-identifying names, socioeconomic status or gaps in work history are the driving forces behind the black-white differentials in interview rates. However, we find strong evidence that the racial gap in interview rates increases substantially with perceived productivity characteristics, including business degrees, internship experience and in-field work experience. While we are unable to narrow the interpretation of the data to one explanation, our findings could be explained by the taste-based model, particularly at the race-skill level, or risk aversion on the part of employers. Our data also indicate that the racial gap in employment opportunities is driven by differential treatment by race in jobs that require substantial customer interaction.

2   Empirical Evidence on Racial Discrimination

Earlier studies in the discrimination literature primarily rely on regression analysis of survey data to test for the presence and type of discrimination. For the most part, these studies find lower wages and poorer job opportunities for blacks (Altonji and Blank 1999). Regression-based studies on racial discrimination have been criticized, as the estimates are sensitive to the data set used and choice of control variables (Riach and Rich 2002). The inability to control for unobserved differences between blacks and whites make it difficult to test reliably for the presence of racial discrimination as well as the channel through which discrimination operates.[4]

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[4]Charles and Guryan (2008) provide a test of Becker's (1971) model of taste-based discrimination using a variety of different data sets based on surveys, but their purpose is not to determine whether the data

Experimental design can circumvent many of the estimation problems associated with survey data. Laboratory experiments have successfully isolated particular channels through which discrimination occurs. Ball et al. (2001) find evidence of in-group preferences; Glaeser et al. (2000) find that trust and trustworthiness are important determinants of discrimination; and Fershtman and Gneezy (2001) find evidence of statistical discrimination.[5] However, the ability of researchers to extrapolate the results of laboratory experiments to "real-world" situations has been questioned (Levitt and List 2007). Field experiments provide a useful alternative to laboratory experiments because they take place in naturally-occurring environments and, much like laboratory experiments, provide substantial control over the variables of interest.[6]

There are two types of field experiments primarily used to study racial discrimination in the labor market: in-person audits and correspondence studies. For the in-person audits, white and black "actors" are recruited and trained to navigate the interview process as if they are perfect substitutes. Such studies have been criticized because of the fragility of the estimates to different assumptions regarding unobservables (Heckman 1998; Heckman and Siegelman 1993). In addition, the "actors" in the experiments are aware of the goals of the experiment, which has the potential to influence their behavior and produce misleading results. Correspondence studies, which send résumés instead of actual people to apply for jobs, offer advantages over audit studies because researchers can make members of particular groups appear identical to employers in every respect other than the variable(s) of interest (e.g., race) via careful matching of applicant characteristics or randomization (Bertrand and Mullainathan 2004; Lahey 2008).[7] Correspondence studies are void of so-called "experimenter

support a particularly theory but to test certain predictions made by Becker (1971). Fryer, Pager and Spenkuch (2011) use a unique data set to examine racial differences in job finding and wage offers. Their findings are supportive of statistical discrimination, but they are unable to rule out other interpretations.

[5]Anderson, Fryer and Holt (2006) provide a detailed review of these studies as well as others that rely on laboratory experiments to study discrimination.

[6]The most studied markets include labor markets (Bertrand and Mullainathan 2004; Carlsson and Rooth 2007; Lahey 2008; Neumark et al. 1996; Oreopoulos 2011), housing markets (Ahmed and Hammarstedt 2008; Bosch et al. 2010; Yinger 1986), and product markets (Ayres and Siegelman 1995; Doleac and Stein 2013; List 2004; Nunley, Owens and Howard 2011).

[7]There is a lengthy history of correspondence tests in the literature. Riach and Rich (2002) provide an

effects," as the subjects (i.e. employers) are unaware that they are part of an experiment and the job seekers are fictitious. Because employers are unaware that they are the subjects of an experiment, correspondence tests likely elicit the behavior that employers would exhibit in actual hiring decisions.

Neumark (2012) contends that correspondence studies are likely to address complications associated with mean differences in unobservables between blacks and whites. However, both the in-person audit and correspondence methodologies share the common limitation that the variance of unobserved characteristics may differ between members of particular groups. Unequal variances of the unobserved determinants of the outcome variable can lead to spurious evidence in favor or against discrimination (Heckman 1998; Heckman and Siegelman 1993). As a result, differentiating between theories based on tastes (Becker 1971) or imperfect information (Aigner and Cain 1977; Arrow 1973; Cornell and Welch 1996; Lundberg and Startz 1983; Phelps 1972) is equally difficult in both the audit- and correspondence-study frameworks. We use two different approaches to test for different types of discrimination: one used by Bertrand and Mullainathan (2004) and Lahey (2009), which relies on race-credential interactions, and another advanced by Neumark (2012), which decomposes discrimination into "level" and "variance" components.[8] However, correspondence studies are likely to identify what the law considers discrimination, which is effectively the sum of taste-based and statistical discrimination (Neumark 2012).

The most relevant study for our purpose is Bertrand and Mullainathan (2004), who examine racial discrimination in the U.S. with a correspondence methodology that incorporates racially-distinct names to signal race to prospective employers. They find that black applicants receive about 50 percent fewer callbacks/interviews than their white counterparts. As in most studies of discrimination, Bertand and Mullainathan (2004) relate their findings

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excellent overview of field experiments aimed at testing for discrimination in various market settings.

[8]The methodology proposed by Neumark (2012) is discussed in more detail in Section 4.2. It is sufficient, at this point, to note that the level component is the structural parameter, which measures taste-based discrimination, and the variance component measures statistical discrimination in the context of Aigner and Cain (1973).

to existing theories. Neither taste-based nor statistical discrimination models convincingly explain their results. They argue that lexicographic search by employers, in which employers examine an applicant's name and look no further, could explain the lower return to credentials that are detected for black applicants.

3   Experimental Design

Approximately 9400 randomly-created résumés were submitted to online advertisements for job openings across multiple job categories in seven large cities across the U.S.[9] The job categories were banking, finance, management, marketing, insurance and sales, while the cities in which applications were submitted include Atlanta, GA, Baltimore, MD, Boston, MA, Dallas, TX, Los Angeles, CA, Minneapolis, MN and Portland, OR. The résumés were submitted from January 2013 through the end of July 2013.

For each job advertisement, four résumés were submitted. The four résumés were randomly assigned a number of different characteristics, which were generated using the computer program developed by Lahey and Beasley (2009). We chose eight applicant names for our study. Four of the names are distinctively female, while the remaining four names are distinctively male. In both the male and female categories, two of the names are "distinctively white," while the other two names are "distinctively black." The distinctively white female names are Claire Kruger and Amy Rasmussen, and the distinctively black female names are Ebony Booker and Aaliyah Jackson. The distinctively white male names are Cody Baker and Jake Kelly, and the distinctively black male names are DeShawn Jefferson and DeAndre Washington. Each of the first and family names rank at or near the top of the "whitest" and "blackest" names in the U.S. We use the racial distinctiveness of the applicants' names to signal race to prospective employers.[10]

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[9]We applied to job openings through two well-known online-job-search websites. Per our Institutional Review Board (IRB) agreements, we are unable to disclose the names of these websites.

[10]Racially- or ethnically-distinct names are commonly used in studies like ours. Examples include Ahmed and Hammarstedt (2008), Bertrand and Mullainathan (2004), Bosch et al. (2010), Carlsson and Rooth (2007) and Nunley, Owens and Howard (2011). The reliability of the racially-distinct names as signals for race is discussed in more detail in Section 4.1.

Our fictitious applicants graduated with a Bachelor's degree in May 2010. We randomly assign each applicant a name (one of the eight listed above), a street address, a university where their Bachelor's degree was completed, academic major, (un)employment statuses,[11] whether they report their grade point average (GPA) on their résumé, whether the applicant completed their Bachelor's degree with an Honor's distinction, whether the applicant has work experience specific to the job category for which they are applying, and whether the applicant worked as an intern while completing their Bachelor's degree. Each of these randomized résumé characteristics are coded as zero-one indicator variables.[12]

While much of the experimental design is produced via randomization, there are some features of the experiment that are held constant. First, we assigned a Bachelor's degree to each of our fictitious résumés. The assignment of only Bachelor's degrees is driven by our interest in the labor-market opportunities facing college graduates, particularly those that graduated during the worst employment crisis since the Great Depression. Secondly, we only applied to jobs in business-related fields: banking, finance, insurance, marketing, management and sales. We submit applications to job categories which are associated with business degrees in order to examine mismatch in qualifications between black and white applicants. Thirdly, we applied to jobs that met the following criteria: (i) no certificate or specific training was required for the job; (ii) the prospective employer did not require a detailed application be submitted; (iii) and the prospective employer only required the submission of a résumé to be considered for the job. The decision to apply for jobs that did not require detailed application procedures is driven by the need to (a) avoid introducing unwanted variation into the experimental design and (b) maximize the number of résumés

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[11]Eriksson and Rooth (2014) and Kroft, Lange and Notowidigdo (2013) use the correspondence methodology to examine how different length unemployment spells affect job opportunities.

[12]Because of the extensive detail associated with each of the résumé characteristics mentioned in this paragraph, we relegate this information to Appendix Section A1.1, which provides the details on each of the résumé characteristics. However, we use a number of these résumé characteristics to conduct indirect tests that shed light on which theory of discrimination best fits the data. When we use a particular résumé attribute, we discuss the important aspects of that attribute at that point in the paper. Appendix Section A1.2 provides some examples of the résumés that were submitted, and Appendix Section A1.3 provides information on the application process.

submitted at the lowest possible cost. The only decision that was made on our part that could affect the estimates is the selection of the jobs for which applications were submitted. That is, there may be unobserved heterogeneity at the job level. Because we sent four résumés to each job opening, this potential source of bias is mitigated by including job-advertisement dummy variables, which holds constant unobservables specific to all four résumés. In addition, we cluster standard errors at the job-advertisement level, which follows other correspondence studies (e.g., Lahey 2008; Neumark 2012).

Because we use randomization to examine the effects of race on employment prospects, it is important to ensure that our randomization process distributed the résumé attributes to black and white applicants in similar ways. Table 1 presents the means for a subset of the résumé characteristics for all applicants (column 1), black applicants (column 2) and white applicants (column 3).[13] In column 4, the p-values for the difference-in-means tests between black and white applicants for each résumé attributed are presented.[14] It is apparent from the means of the résumé attributes and the difference-in-means tests that black and white applicants were assigned each of the résumé characteristics similarly. In addition, the sample means for the résumé characteristics overall and by race are consistent with the probabilities that we chose for the random assignment of the résumé characteristics.

We proxy employment opportunities with interview requests from prospective employers. A response is treated as an interview request when an employer calls or emails to set up an interview or requests to speak in more detail about the opening with the applicant. Our measure of employment prospects, i.e. the interview rate, is similar to the measures commonly used in other correspondence studies (e.g, Bertrand and Mullainathan 2004). It

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[13]We omit a few of the résumé credentials from Table 1, as they are not central to our empirical models. These remaining attributes include the university where the applicant graduated from, whether the applicant reports their grade point average on their résumé, whether the applicants completed their degree with an Honor's distinction, and the type of job the applicant had while they were completing their degree. However, the means of these characteristics are consistent with the probabilities assigned to such attributes, and the difference-in-means tests between black and white applicants are not statistically significant. These estimates are available upon request.

[14]The differences-in-means tests are conducted by estimating a linear regression of the résumé credential on a constant and a dummy variable that equals one when an applicant is assigned a black-sounding name and zero otherwise.

is possible for us to consider "positive" responses (e.g., Lahey 2008), but the results are not sensitive to this alternative coding of the dependent variable because the majority of "callbacks" were interview requests.[15] As a result, we omit these results from the paper.

Table 2 presents summary statistics for the interview-request rates overall and by race. The baseline interview rate in the sample is slightly over 16 percent, with white applicants having a higher-than-average interview rate and black applicants having a lower-than-average interview rate. The unconditional difference in the interview rates between black and white applicants is approximately 2.7 percentage points, which is statistically significant at the 0.1 percent level. The overall interview rates vary somewhat across cities. Atlanta and Boston have the lowest overall interview rates at about 13 percent, while Baltimore has the highest interview rate at about 25 percent. When the interview rates are separated by race, we observe lower interview rates for blacks relative to whites. The majority of the unconditional differences in the interview rates between black and white applicants are statistically significant at conventional levels. There is also variation in the interview rates by job category. Insurance, marketing and sales have the highest interview rates, which are each in excess of 20 percent. Banking, finance and management have the lowest interview rates, which are around 10 percent or slightly less. The interview rates for black applicants are lower, in some cases substantially, than their white counterparts for each of the job categories. The unconditional differences in the interview rates between black and white applicants are statistically significant at conventional levels for most of the job categories. While the racial differences

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[15]There were five types of "callbacks" for which coding the dependent variable is unclear. First, we received six callbacks from firms that asked if the applicant was interested in other positions. Second, we received one callback from a firm that requested information from the applicant regarding salary requirements. Third, we received two callbacks from firms that asked whether the applicant was interested in full- or part-time work. Fourth, we received eight callbacks from firms that asked if the applicants had a location preference. Fifth, we received 108 callbacks from firms requesting applicants to to complete another step in the interview process (i.e. filling out a detailed application). However, when this happened, all four applicants that applied to the job received the same email or phone call, suggesting that the response from the prospective employers might have been automated. Alternatively, these situations might indicate no discrimination on the part of these firms. However, the inclusion of job-specific dummy variables removes the influence of these types of callbacks. In total, there were 125 callbacks for which coding of the dependent variable is unclear. The estimates presented in Section 4 treat these callbacks as interview requests. However, we checked the robustness of our estimates to these callbacks by treating them as non-interview requests and by including observation-specific dummy variables, finding similar results to those presented in Section 4.

in interview rates presented in Table 2 are suggestive of differential treatment by race, a formal analysis is required to determine whether these differences reflect discrimination and, if so, the type of discrimination that is observed.

4   Results

4.1   The Effects of Race on Employment Prospects

We begin by estimating the following regression equation:

$$interview_{imcfj} = \beta_0 + \beta_1 black_i + \gamma \mathbf{X}_i$$
$$+ \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \tag{1}$$

The subscripts i, m, c, f and j index applicants, the month the application was submitted, the city in which the application was submitted, the category of the job (i.e. banking, finance, management, marketing, insurance and sales), and job advertisements, respectively. The variable *interview* is a zero-one indicator variable that equals one when an applicant receives a request for an interview and zero otherwise; *black* is a zero-one indicator variable that equals one when the name of the applicant is distinctively black and zero when the name of the applicant is distinctively white; $\mathbf{X}$ is a vector of résumé-specific controls, which includes all of the résumé characteristics that are randomly assigned to applicants (briefly discussed in Section 3 and discussed in-depth in Appendix A1); ϕ_m, ϕ_c, ϕ_f, and ϕ_j represent sets of dummy variables for the month that the applications were submitted, the city where the applications were submitted, the category that describes the job opening and the job advertisement, respectively; u represents other factors that are not held constant that affect interview rates; and β_0, β_1 and γ are parameters. We are primarily interested in the parameter β_1, which gives the average difference in the interview rate between black and white applicants.

The use of randomization ensures that the race identifier (*black*) in equation 1 is orthogonal to the error term (u), allowing us to interpret the parameter attached to the race

identifier as the *causal* difference in the interview rate between black and white applicants. While our regression models are likely to capture the legal definition of racial discrimination, they do not provide an explicit test for the type of discrimination observed. As pointed out by Heckman and Siegelman (1993), Heckman (1998) and Neumark (2012), mean differences in unobservables and differences in the variances of unobservables between blacks and whites confound attempts to identify discrimination as well as separately identifying taste-based and statistical discrimination. Neumark (2012) contends that correspondence studies, like the one that we use, are likely to circumvent the critique regarding mean differences in unobservables between groups, given that such studies are better at controlling what employers observe.[16] However, Neumark (2012) argues that the correspondence methodology (as well as in-person audits) do not circumvent the critique regarding the possibility that the variances of unobservables between blacks and whites may differ. As a result, the estimates that we present in what follows likely capture what the law considers discrimination, which is effectively the sum of taste-based and statistical discrimination. We return to the issue of unequal variances of unobservables between blacks and whites in Section 4.2.

Table 3 presents estimates for the parameter β_1 from equation 1. The columns in Table 3 differ based on the explanatory variables included in the regression models. Column (1) includes no controls; column (2) includes controls for the randomly-assigned résumé characteristics ($\mathbf{X}$); column (3) adds the set of month-of-application dummy variables (ϕ_m); column (4) adds the city-of-application dummy variables (ϕ_c); column (5) adds the job-category dummy variables (ϕ_f); and column (6) adds the job-advertisement dummy variables (ϕ_j). As is apparent from the Table 3, the estimated differences in the interview rates between black and white applicants are remarkably stable as control variables are successively added, although there is a slight decline in the estimated racial gap when the job-advertisement dummy variables are included.[17]

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[16]To be clear, we are not able to control all of the résumés that an employer observes. However, we are able to control what employers observe regarding the four résumés that we submit for consideration.

[17]We also tested for different interview rates between men and women, finding no economically or statistically significant difference in their interview rates (See Table A1). Furthermore, we tested for different

For the comparisons between black and white applicants, the estimated differentials range from -0.022 to -0.028. The most reliable estimate is likely the one shown in column (6), which includes the complete set of control variables (i.e. $\mathbf{X}$, ϕ_m, ϕ_c, ϕ_f, ϕ_j from equation 1). In that specification, black applicants have a 2.2 percentage point lower interview rate than otherwise identical white applicants. Because the average interview rate in the sample is about 16 percent, the interview rate for black applicants is approximately 14 percent lower than that for white applicants. Each of the estimated differentials in Table 3 is statistically significant at the 0.1 percent level.

Although racially-distinct names, as a signal of race, may not be a perfect substitute for the random assignment of race, it is perhaps the best approach advanced in the literature in recent years. However, the use of racially-distinct names does introduce potential confounds. For example, Charles and Guryan (2011) argue that employers could view distinctively-black names as unique or odd, and discriminate based on those perceptions. Such differential treatment would be discrimination, but it would not be racial in nature. While we cannot rule out this possibility, we contend that the first and last/family names chosen are quite common. Based on data from the U.S. Census, the last names chosen for our black applicants are the most common last/family names for blacks.[18] Furthermore, we are able to use the Social Security Administration's data on baby names to justify the popularity of our first names for the black and white applicants.[19] While the rankings change from year to year, we examine the rankings (in terms of popularity) of the chosen first names to obtain a sense of how common or uncommon the first names are for babies born in the late-1980s and

interview rates between race and gender. We find that black men and black women experience similar treatment in the labor market in terms of interview rates, as both have lower interview rates than their white counterparts. The magnitudes of estimated differences vary somewhat, but statistical tests indicate that the difference, for example, between the black-white male differential is not statistically different from the black-white female differential. We discuss these results in the Appendix Section A2.1 and present the estimates in Appendix Table A2.

[18]Washington is the most common; Jefferson is second from the top; Booker is third from the top; and Jackson is 5th from the top. For information on last/family/surnames that are distinct in a racial and/or ethnic sense, visit the following webpage: http://www.census.gov/genealogy/www/data/2000surnames/surnames.pdf.

[19]The database can be found at http://www.ssa.gov/OACT/babynames/#ht=0.

early-1990s, which is approximately when our applicants would have been born. For the white names, Amy is ranked about 50th; Claire is ranked about 150th; Cody is ranked about 40th; and Jake is ranked about 140th. For the black names, Ebony is ranked about 160th; Aaliyah is ranked about 200th; DeAndre is ranked about 250th; and DeShawn is ranked about 450th. While the distinctively-black names are less frequent, it is important to point that these rankings are based on popular male and female names overall, not by race.

A second criticism of using racially-distinct names is that they may signal socioeconomic status instead of race. We incorporate socioeconomic status into our experimental design by randomly assigning street addresses in neighborhoods that have high and low house prices. The indicator for high socioeconomic status is a street address with house prices that exceed $750,000, while the indicator for low socioeconomic status is a street address with house prices that are less than $120,000.

While there is no clear-cut way to deflect concerns that the racially-distinct names reflect race in lieu of uniqueness or socioeconomic status, we use two approaches to address these concerns. First, we examine a subset of the full sample that excludes the most popular and least popular first names from the sample. The names with the highest rankings are Amy and Cody, and the name with the lowest ranking is DeShawn. Excluding observations from applicants with these names effectively results in a sample of applicants with names that have similar frequency in the population. We address the socioeconomic-status concern by estimating racial differences in interview rates for applicants with street addresses in high- and low-socioeconomic-status neighborhoods, which is similar to the strategy used by Bertrand and Mullainathan (2004).[20]

The sensitivity checks for the uniqueness and socioeconomic status of the racially-distinct names are presented in Table 4. Column (1) shows the estimated difference in the interview rate between black and white applicants with common names; columns (2) and (3) present the estimated differences in the interview rates between black and white applicants with low-

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[20]Bertrand and Mullainathan (2004) use characteristics at the zip-code level to signal more affluent neighborhoods, such as the racial make-up, education level and income level.

socioeconomic-status addresses; and columns (4) and (5) present the estimated differences in the interview rates between black and white applicants with high-socioeconomic-status addresses. Columns (2) and (3) and columns (4) and (5) differ based on the sample that is used, as columns (2) and (4) use the full sample and columns (3) and (5) use the subsample based on applicants with common names.[21] In column (1), the estimate indicates that black applicants have a 2.7 percentage point lower interview rate than otherwise identical white applicants, and this estimated differential is statistically significant at the one-percent level. The estimates for applicants with low-socioeconomic-status street addresses range from -0.022 to -0.029, which varies depending on the sample used. Each of these estimates is statistically significant at the five-percent level. The estimates for applicants with high-socioeconomic-status street addresses range from -0.021 to -0.023. The former estimate is statistically significant at the five-percent level, while the latter estimate is statistically significant at the 10-percent level. To the extent the subset of names analyzed are truly common, which is supported by name data, and the measure that we use indicates socioeconomic status reliably, our results in Table 3 do not appear to reflect differential treatment based on the uniqueness of the applicant's first and last names or socioeconomic status, which increases the likelihood that our estimates reflect differential treatment by race.[22]

Because we randomized gaps in the work histories of applicants, it is possible that the black-white differential detected previously could be driven by lower interview rates for blacks with unemployment spells. To investigate this possibility, we estimate a variant of equation

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[21]To produce the estimates shown in columns (2)-(5), we estimate the following regression equation:

$$interview_{imcfj} = \beta_0 + \beta_1 black_i + \beta_2 highses_i + \beta_3 black_i \times highses_i + \ldots$$

The regression model above includes the full set of controls described in equation 1. The estimates for β_1, which give the estimated racial gap in interview rates between job seekers with low-socioeconomic-status addresses, are shown in columns (2) and (3), while the estimates for $\beta_1 + \beta_3$, which give the estimated racial gap in interview rates between job seekers with high-socioeconomic-status addresses, are shown in columns (4) and (5).

[22]It is also important to point out that the applicants with particular black names are discriminated against similarly. That is, the interview rates for DeShawn, DeAndre, Ebony and Aaliyah are not statistically different from each other, and they are lower by similar magnitude when separately compared to each of the white names (i.e. Amy, Claire, Cody and Jake).

[1](#) that includes interactions between the race identifier and unemployment-spell identifiers. Formally, we estimate the following regression model:

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\begin{aligned}
interview_{imcfj} = {} & \beta_0 + \beta_1 black_i + \beta_2 unemp_i^{3mo} + \beta_3 unemp_i^{6mo} + \beta_4 unemp_i^{12mo} \\
& + \lambda_1 black_i \times unemp_i^{3mo} + \lambda_2 black_i \times unemp_i^{6mo} \\
& + \lambda_3 black_i \times unemp_i^{12mo} + \gamma \mathbf{X}_i + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}.
\end{aligned} \tag{2}
$$

The subscripts i, m, c, f and j and the variables $black$, $\mathbf{X}$, ϕ_m, ϕ_c, ϕ_f, ϕ_j and u are defined above. The variable $unemp^{3mo}$ is a zero-one indicator that equals one when an applicant is randomly assigned a three-month current unemployment spell and zero otherwise; $unemp^{6mo}$ is a zero-one indicator that equals one when an applicant is randomly assigned a six-month current unemployment spell and zero otherwise; and $unemp^{12mo}$ is a zero-one indicator that equals one when an applicant is randomly assigned a 12-month current unemployment spell and zero otherwise.

From equation [2](#), the parameters and combinations of parameters of interest are λ_1, λ_2, λ_3, $\lambda_2 - \lambda_1$, $\lambda_3 - \lambda_1$ and $\lambda_3 - \lambda_2$, which are difference-in-differences estimators. Relative to being currently employed, the parameter λ_1 indicates whether an three-month current unemployment spell affects black applicants more or less adversely than it does white applicants; λ_2 indicates whether a six-month current unemployment spell affects black applicants more or less adversely than it does white applicants; and λ_3 indicates whether a 12-month current unemployment spell affects black applicants more or less adversely than it does white applicants. Relative to being currently unemployed for three months, the parameter combinations of $\lambda_2 - \lambda_1$ and $\lambda_3 - \lambda_1$ indicate whether black applicants are affected more or less adversely than white applicants when they both have six- and 12-month current unemployment spells, respectively. Relative to being currently unemployed for six months, the parameter combination of $\lambda_3 - \lambda_2$ indicates whether black applicants are affected more or less adversely than white applicants when both have 12-month current unemployment spells.

Each of the estimated difference-in-differences parameters or parameter combinations are

presented in Table 5. Columns (1), (2) and (3) use "currently employed" as the base category; columns (4) and (5) use "currently unemployed for three months" as the base category; and column 6 uses "currently unemployed for six months as the base category. The estimates shown in Table 5 show that race-unemployment interactions are not responsible for the estimated differentials in interview rates detected in Table 3. None of the estimates are statistically significant at any reasonable level, nor is it likely that the estimated differentials would be considered economically significant.[23]

4.2   Empirical Tests for Different Types of Discrimination

In general, there are two economic models of discrimination: the taste-based model (Becker 1971) and models of statistical discrimination (Aigner and Cain 1977; Arrow 1973; Cornell and Welch 1996; Lundberg and Startz 1983; Phelps 1972).[24] The key difference between these different models is that the taste-based model emphasizes animosity as the source of differential treatment by race, and models of statistical discrimination are based on incomplete information. Becker's (1971) model predicts that racist employers would interview fewer black applicants than white applicants, despite both having the same productivity characteristics.[25] Models of statistical discrimination can be separated into three classes: (i) differences in the means of unobservables between blacks and whites;[26] (ii) differences

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[23]It is also possible for the black and white job seekers to be randomly assigned a work-history gap immediately after completing their degrees. We examined whether "front-end" gaps in work history are responsible for the racial gap in interview requests, but we find no evidence that "front-end" gaps in work history explain the estimates presented in Table 3.

[24]Another theory of discrimination is implicit discrimination, which originated in the field of psychology. It is a form of discrimination that can be taste based or statistical, but the differential treatment by race occurs unconsciously rather than consciously (Bertrand et al. 2005). In our context, implicit discrimination occurs when employers choose to interview otherwise identical white and black applicants at different rates without being aware that they are treating the two applicants differently on the basis of race. Such a situation might occur if employers make quick decisions concerning which job applicants to interview. Implicit discrimination is difficult to investigate empirically, but Price and Wolfers (2010) and Rooth (2010) are notable exceptions. Admittedly, our data are not well-suited to determine whether discrimination occurs consciously or unconsciously.

[25]The discussion concerning Becker's (1971) model is not meant to be exhaustive, as there are many aspects of Becker's model that we are unable to examine (e.g., market power, competition). See Charles and Guryan (2008) for an examination of other predictions made by Becker (1971).

[26]Recall that correspondence studies are generally thought to circumvent the identification issues associated with mean differences in unobservables between blacks and whites (See Neumark 2012).

in the variances of unobservables between blacks and whites; and (*iii*) risk aversion on the part of employers. While there are no definitive tests to isolate the type of discrimination observed, we rely on two approaches to help sort out the competing explanations for the observed patterns in the data: race-credential interactions (See Bertrand and Mullainathan 2004; Lahey 2008) and the decomposition of racial discrimination into "level" and "variance" components (See Neumark 2012).

The first set of empirical tests uses the following regression equation to examine how race interacts with different productivity/match-quality indicators:

$$interview_{imcfj} = \beta_0 + \beta_1 black_i + \beta_2 signal_i + \beta_3 black_i \times signal_i$$
$$+ \gamma \mathbf{X}_i + \phi_m + \phi_c + \phi_f + \phi_j + u_{icmfj}. \tag{3}$$

The subscripts i, m, c, f and j and the variables $black$, $\mathbf{X}$, ϕ_m, ϕ_c, ϕ_f, ϕ_j, and u are defined above. The variable *signal* is a indicator variable that equals one when an applicant is assigned a résumé attribute that indicates high expected productivity and/or a high degree of match quality between the applicant and the job opening. The parameter β_1 gives the average difference in the interview rate between black and white applicants with no signal assigned to them; the parameter combination $\beta_1 + \beta_3$ gives the average difference in the interview rate between black and white applicants with a signal assigned to them; and the parameter β_3 indicates whether the racial gap in employment opportunities in smaller, larger, or similar between applicants with and without the productivity/match-quality signals assigned to them.[27] We use three separate signals for expected productivity and/or match quality when estimating equation 3: business degrees, internship experience and in-field work experience. Each of these résumé attributes has a positive effect on the interview rate, but internship and in-field work experience have much larger effects than business degrees.

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[27]The parameter β_3 is a difference-in-differences estimator, as it is the difference between two differences. The first difference is between black and white applicants with a signal assigned to them, which is $\beta_1 + \beta_3$. The second difference is between black and white applicants without a signal assigned to them, which is β_1. Taking the difference between these two differences leaves β_3—the difference-in-differences estimator.

Table 6 presents the estimates for equation 3 when different expected-productivity/match-quality signals are used. Panel A presents the estimates for the racial gap in employment opportunities for non-business and business majors. In particular, we compare the interview rates of black and white applicants with and without business degrees. In addition, we examine whether the racial gap in interview rates is larger, smaller or similar between applicants with and without business degrees. We consider accounting, economics, finance, management and marketing as business degrees, while psychology, biology, history and English are considered non-business degrees.[28] For non-business majors, black applicants have a one percentage point lower interview rate than white applicants (column 1). The analogous differential is over twice as large for business majors (column 2). The racial gap in interview rates is two percentage points larger for business majors than for non-business majors (column 3). The estimate presented in column (1) is not statistically significant at convention levels; column (2) is statistically significant at the 0.1 percent level; and column (3), which gives the relative racial difference between business majors and non-business majors, is statistically significant at the 10-percent level.[29]

Panel B presents the estimates for the racial gap in employment opportunities for applicants with and without internship experience. In our case, internship experience is a type of in-field work experience, as the applicants were assigned an internship within the job category for which they are applying.[30] Internship experience is working as a(n) "Equity

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[28]It is likely that the employers in the job categories in which we apply consider economics a business-related degree. However, we also included economics in the "non-business-degree" category due to a nontrivial portion of economics departments being housed outside of business schools. With this reclassification, the results are slightly different. In particular, when economics is included in the non-business-degree category, we find a negative and statistically significant differential between black and white applicants with non-business degrees. We continue to find an economically and statistically significant racial differential for applicants with business degrees. However, the difference-in-differences estimator, i.e. β_3, is not statistically different from zero. However, it is potentially significant in an economic sense, as the estimated differential is over two percentage points. While the results differ slightly, the overall message is the same: the extent of racial discrimination is greater in the business-degree category than in the non-business-degree category.

[29]We also tried an alternative specification that grouped the degrees into the following categories: business, social sciences, sciences and humanities. These estimates are presented in Appendix Table A3. Ultimately, our findings with respect to the interaction between race and business degrees are corroborated by this alternative specification: the extent of racial discrimination is economically and statistically more important in the business-degree category than the other degree categories.

[30]The internship experience was acquired in Summer 2009, the year before the applicants completed their

Capital Markets Intern" in banking; "Financial Analyst Intern" in finance; "Insurance Intern" in insurance; "Project Management Intern" or "Management Intern" in management; "Marketing Business Analyst" in marketing; and "Sales Intern" or "Sales Future Leader Intern" in sales. For applicants without internship experience, black applicants have a 1.6 percentage point lower interview rate than white applicants (column 1). The analogous differential is more than twice as large for applicants with internship experience (column 2). The larger racial gap detected for applicants with internship experience is economically larger than the analogous estimated differential for applicants without internship experience. In particular, the racial gap between applicants with internship experience is 2.4 percentage points larger than that for applicants without internship experience (column 3). The estimates presented in columns (1), (2) and (3) are statistically significant at the five-, 0.1- and 10-percent levels, respectively.

Panel C presents the estimates for the racial gap in employment opportunities for applicants with and without in-field work experience. In-field work experience varies by the job category: it is working as a "Bank Branch Assistant Manager" in banking; "Accounts Payable" or "Financial Advisor" in finance; "Insurance Sales Agent" in insurance; "Distribution Assistant Manager" or "Administrative Assistant" in management; "Marketing Specialist" in marketing; and "Sales Representative" or "Sales Consultant" in sales. Out-of-field experience is employment at well-known retail stores with either a "Retail Associate" or "Sales Associate" job title.[31] The "out-of-field" experience that is randomly assigned to applicants is effectively "underemployment," as a college degree would not be required for these types of jobs. For applicants with out-of-field experience, we find no statistical evidence of a differential in the interview rates between black and white applicants (column 1). However, we find economically and statistically significant interview differentials between black and white applicants with in-field work experience. In particular, the interview rate for black

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college degrees in May 2010. The internships lasted only for three months.

[31]For the sales job category, we exclusively use "Retail Associate" as the relevant type of out-of-field experience.

applicants with in-field work experience is 3.5 percentage points lower than that for white applicants with in-field work experience (column 2). In addition, the difference-in-differences estimator is negative and statistically significant at conventional levels, an indication that the estimated difference in the interview rate between black and white applicants with in-field work experience is larger both economically and statistically than the analogous differential for applicants with out-of-field experience (column 3).[32]

In Table 7, we examine the racial gap in employment opportunities between job seekers with none, some or all of the three aforementioned productivity signals. In particular, column (1) presents the estimated differential between black and white job applicants with non-business degrees, no internship experience and out-of-field work experience; column (2) presents the estimated interview differential between black and white applicants with business degrees (also presented in column (2) of Table 6); column (3) presents the estimated interview differential between black and white applicants with business degrees and internship experience; and column (4) shows the estimated interview differential between black and white applicants with business degrees, internship experience and in-field work experience.[33] We find no evidence of a racial gap in employment opportunities for applicants with non-business degrees, no internship experience and out-of-field work experience (column 1). However, black applicants have a 3.1 percentage point (19 percent) lower interview rate than white applicants when both have business degrees (column 2). The racial gap in employment opportunities is even larger when job seekers have business degrees and internship experience (column 3). In particular, black applicants have a 5.2 percentage point (31 percent) lower interview rate than their white counterparts. When applicants have business degrees,

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[32]Because the random assignment of gaps in work history created random variation in experience levels, we examine whether race interacts with the amount of experience in general, the amount of out-of-field work experience and the amount of in-field work experience. This specification and the results from it are discussed in Appendix Section A2.2, and the estimates are presented in Appendix Table A4. Overall, we find that racial gap in interview rates declines with the amount of work experience. However, these findings mask some interesting patterns in the data: the effects of work experience on the racial gap in interview rates differs markedly based on the type of work experience. For out-of-field experience, the racial gap in interview rates declines with work experience, but the racial gap in interview rates *increases* with the amount of in-field work experience.

[33]Appendix Section A2.3 provides details on how the estimates in Table 7 are generated.

internship experience and in-field work experience, black applicants face a 6.7 percentage point (33 percent) lower interview rate than otherwise identical white applicants (column 4).[34]

Our final attempt to shed light on the channel through which discrimination operates is the methodology developed by Neumark (2012).[35] Using a heteroskedastic probit model that allows the variance of unobservables to depend on race, we decompose the marginal effect of race into two components: an effect than operates through the "level" and an effect that operates through the "variance". The level component measures taste-based discrimination, while the variance component measures statistical discrimination. We find that the partial effect, which is the sum of the level and variance components, is -0.025,[36] which is consistent with what we find via the linear probability models presented in Section 4.1. The marginal effect through the level is -0.038 and the marginal effect through the variance is 0.013. The marginal effect through the level and the marginal effect through the variance are not statistically significant at conventional levels. However, the marginal effect that operates through the level is very close to being statistically significant at the 10-percent level (p-value $= 0.12$), while the marginal effect that operates through the variance is nowhere near statistically significant (p-value $= 0.63$). When applied to our data, the empirical strategy proposed by Neumark (2012) suggests that the linear probability models used in Section 4.1 tend to un-

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[34]It may appear that black applicants are worse off (in terms of job opportunities) when they acquire business degrees, internship experience and in-field work experience, but this is not the case. In fact, the discrimination against black job seekers is much worse when white applicants have these credentials and black applicants do not have these credentials. However, when black applicants have these credential and white applicants do not, there is generally no economically or statistically significant differences in interview rates between black and white job seekers. The estimates that generate these conclusions are discussed in Appendix Section A2.4 and presented in Appendix Tables A5 and A6.

[35]A requirement of Neumark's decomposition is the incorporation of multiple productivity-related characteristics into the experimental design. We randomize the characteristics displayed on the applicants' résumés that affect interview rates (e.g., in-field and internship experience).The incorporation of such characteristics can be used to obtain an estimate for the ratio of standard deviations of unobservables, which allows one to test whether they are statistically different from one another between groups (e.g., blacks versus whites). We find that the effects of the observable characteristics are not statistically different for black and white applicants, which is necessary for identification in Neumark's proposed methodology.

[36]We were unable to estimate the full model that is depicted in equation 1. In particular, it was not possible to estimate equation 1 via the heteroskedastic probit model with the job-advertisement dummy variables (ϕ_j) included. However, we were able to estimate the heteroskedastic probit model with all of the other controls included.

derstate the extent of taste-based discrimination against black applicants (i.e. -0.038 versus -0.022). Overall, these findings suggest that the structural parameter, i.e. the marginal effect of race through the level, is indeed negative and economically large, which could be interpreted as evidence of taste-based discrimination. Using Neumark's (2012) decomposition, we find no evidence, either in an economic or statistical sense, that the variance of unobservables are important determinants of racial differences in job opportunities. These findings cast some doubt on interpretations that rely on differences in the variance of unobservables between blacks and whites as the driving force behind the patterns in the data.

Our experiment provides an opportunity to narrow the interpretation of the patterns in the data. Firstly, our findings are largely consistent with the taste-based model, as we generally detect racial differences in interview-request rates for given levels of productivity (proxied by the expected-productivity/match-quality indicators). However, the fact that we sometimes do not observe economically or statistically significant racial differences in interview rates at "low-skill" levels is somewhat at odds with a taste-based interpretation. It is possible, however, that our findings fit an augmented version of the taste-based model that emphasizes discrimination at the race-skill level. Secondly, randomization, in the context of a correspondence audit, addresses the critique regarding mean differences in unobservables between blacks and whites (See Neumark 2012). As such, we can reasonably conclude that statistical discrimination that operates through mean differences is not a viable explanation for our findings. Lastly, the decomposition approach developed by Neumark (2012), which is designed to separate out taste-based discrimination and variance-based statistical discrimination, suggests that differences in the variances of unobservables between blacks and white is an unlikely explanation for our findings. In fact, the use of Neumark's methodology suggests that our baseline model tends to understate the extent of taste-based discrimination.

While we are unable to isolate only one explanation for the patterns in our data, we are able to narrow the interpretation down to two possible explanations: taste-based discrimination, particularly at the race-skill level, or risk aversion on the part of employers. The

substantial slack in the labor market during the time at which applications were submitted to prospective employers would make taste-based discrimination less costly. As such, one might expect to observe more animus-based discrimination. Risk aversion on the part of employers could also explain some of the patterns in the data. Given that we applied to higher-skill jobs (i.e. those that require a college degree), it is likely that employers would expect to invest in the human capital of their new hires. Moreover, there is uncertainty regarding applicant quality. If the signal-to-noise ratio is lower for blacks than it is for whites, employers would interview relatively fewer black applicants because of their aversion to risk, which could explain the larger racial gap in employment opportunities at the high-skill level. Unfortunately, there is no credible strategy to differentiate between these possible explanations.

4.3 Discrimination in Jobs with Customer and Employee Interactions

Becker (1971) contends that discrimination in hiring need not operate through employer preferences. Instead, discrimination can also occur via customer and/or employee discrimination.[37] In this subsection, we examine whether the differential treatment by race is robust across jobs that require significant customer and employee interaction. While our data do not provide a clear test of the customer and employee channels, the submission of applications to many different types of jobs provides an indirect way of examining the possibility that discrimination could occur because of an employer's beliefs about its customer base or the employers' existing workforce. Our approach is similar to that of Holzer and Ihlanfeldt (1998), who consider evidence of greater discrimination in jobs that require contact with customers, such as sales and service occupations, as evidence of customer discrimination. In our case, we compare the employment opportunities facing black and white applicants for jobs that require contact with customers, and we compare the differentials in the employment opportunities facing black and white applicants for jobs that require collaboration

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[37]It is also possible for customer and employee discrimination to be a type of statistical discrimination.

among colleagues. To classify the job openings, we use the information conveyed in the job titles as a way to classify jobs into those that require interaction with customers and co-workers. In particular, we treat job titles that include the words "Customer", "Sales", "Advisor", "Representative", "Agent" and "Loan Officer" as jobs that require interaction with the firm's customers. By contrast, we treat job titles that include the words "Manager", "Director", "Supervisor", "Administration", "Coordinator", "Operations" and "Leader" as jobs that require interaction between co-workers.[38] We estimate the following regression model:

$$
\begin{aligned}
interview_{imcfj} = {} & \beta_0 + \beta_1 black_i + \beta_2 customer_j + \beta_3 employee_j \\
& + \lambda_1 black_i \times customer_j + \lambda_2 black_i \times employee_j \\
& + \gamma \mathbf{X}_i + \phi_m + \phi_c + \phi_f + \phi_j + u_{icmfj}.
\end{aligned}
\tag{4}
$$

The subscripts i, m, c, f and j and the variables $black$, $\mathbf{X}$, ϕ_m, ϕ_c, ϕ_f, ϕ_j and u are defined above. The variable $customer$ is a zero-one indicator that equals one when the job requires interaction between the applicant and the firm's customers and zero otherwise, while the variable $employee$ is a zero-one indicator that equals one when the job requires interaction between the applicant and the firm's employees. We are interested in two linear combinations of parameters from equation 4. In particular, $\beta_1 + \lambda_1$ gives the average difference in the interview rate between black and white applicants who applied to jobs that require interaction with customers, and $\beta_1 + \lambda_2$ gives the average difference in the interview rate between black and white applicants who applied to jobs that require interaction between co-workers.

The estimates for these linear combinations of parameters are presented in Table 8. The columns in Table 8 differ based on the words in the job titles that are used to create the $customer$ and $employee$ variables. The words in the job titles used to classify jobs as

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[38]One might be concerned that the "employee" jobs are higher-level jobs than those in the "customer" category. While this may be true, it is important to point out that we only applied to jobs that our applicants were qualified to get. In fact, many of our applicants have, for example, managerial experience, as a portion of them became employed in such jobs after completing their degrees in May 2010.

being customer- or employee-focused are listed below the estimates in Table 8. In column (1), we begin with job titles that have a high likelihood of having significant customer and employee interaction. In columns (2)-(5), we successively add jobs that are also likely to have significant customer and employee interaction. The purpose of successively adding job titles to the customer/employee categorizations stems from the need to gauge the sensitivity of the estimates to broader definitions of the *customer* and *employee* identifiers. The estimates presented in Table 8 indicate that the racial discrimination detected in previous specifications operates primarily through a higher degree of discrimination in jobs that require customer interaction. As a way to further investigate whether discrimination operates through a customer channel, we examine whether there is more/less discrimination in jobs that require customer interaction in cities with relatively lower and relatively higher shares of blacks in the population. For customer-related jobs, we find an even larger black-white interview differential in cities where blacks make up a relatively smaller share of the total population (Los Angeles and Portland) than in cities where blacks make up a relatively larger share of the total population (Atlanta and Baltimore).[39] We find no empirical evidence of racial discrimination in jobs that require interaction among colleagues, as the the estimates are economically small and not statistically different from zero. While inconclusive, these findings could indicate that employers attempt to appease their customer base, which may have racial preferences, by interviewing fewer blacks relative to whites. Alternatively, these findings could be explained, again, by employer risk aversion. Assume that there are diminishing returns to ability, and that employers are searching for job candidates that meet a particular threshold level of ability. If the signal-to-noise ratio is lower for blacks, then risk aversion could explain the greater discrimination in jobs that require customer interaction.

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[39]The black-white interview differentials in customer-related jobs in cities with a relatively smaller share of blacks in the population is 4.9 percentage points, while the analogous estimate is 2.7 percentage points in cities with a relatively larger share of blacks in the population.

5 Conclusions

We present experimental evidence from a correspondence test of racial discrimination in the labor market for recent college graduates. The race of potential employees is signaled with black-sounding and white-sounding names, which follows Bertrand and Mullainathan (2004). The timing of our study allows us to test whether differential treatment by race is present but also to investigate the impact of the last recession on employment prospects facing white and black job seekers. Given the severity of the employment crisis associated with the Great Recession, the scarring effect on the cohort of recent black college graduates could also be much larger than past recessions.

The correspondence framework, which incorporates a detailed set of randomly assigned productivity characteristics for a large number of résumés from white- and black-named job candidates, provides a powerful method to detect racial discrimination among the college-educated. The analysis of survey data is unlikely to yield convincing evidence of discrimination among the college educated because of selection bias. The coarseness of the education variables (e.g., highest grade completed, school quality, and school inputs) and other productivity characteristics contained in prominent employment data series could also mask important premarket factors that predict differences in the skill distributions between black and white college graduates.

Our results indicate that black-named candidates are approximately 14 percent less likely than white-named candidates to receive interview requests. We demonstrate that the results are unlikely to be driven by the uniqueness of the racially-distinct names, socioeconomic status, or greater discrimination against blacks with unemployment spells. We find strong evidence that the racial gap in employment opportunities *widens* with perceived productivity characteristics. While it is difficult to determine the channel through which discrimination operates, taste-based discrimination, particularly at the race-skill level, or risk aversion on the part of employers are the most likely explanations. In addition, the differential treatment by race detected appears to operate primarily through greater discrimination in jobs that require

significant customer interaction, as we find much larger black-white interview differentials (about 28 percent) when applying to such jobs. In addition, we find that the extent of racial discrimination for customer-related jobs is even larger in cities where the share of blacks in the population is relatively smaller than in other cities.

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Table 1: Covariate Balance Between Black and White Applicants

Covariate	All Applicants	Black Applicants	White Applicants	p-values for Black-White Differences
Female	0.499	0.494	0.504	0.331
High Socioeconomic Status	0.499	0.498	0.501	0.804
No Gap in Work History	0.254	0.254	0.256	0.782
3 Month Front End Gap	0.125	0.120	0.129	0.180
6 Month Front End Gap	0.121	0.121	0.121	0.918
12 Month Front End Gap	0.125	0.128	0.122	0.383
3 Month Back End Gap	0.124	0.124	0.124	0.949
6 Month Back End Gap	0.123	0.124	0.122	0.756
12 Month Back End Gap	0.127	0.129	0.125	0.493
Business Degree	0.552	0.551	0.553	0.907
Internship Experience	0.248	0.248	0.249	0.866
In-Field Work Experience	0.501	0.498	0.502	0.696

Notes: The covariates listed are zero-one dummy variables. 'Female' equals one when an applicant is assigned a female name; 'High Socioeconomic Status' equals one when an applicant is assigned a high socioeconomic status street address; 'No Gap in Work History' equals one when an applicant is assigned no gap in their work history; '3 Month Front End Gap' equals one when an applicant is assigned a three month unemployment spell immediately after graduation; '6 Month Front End Gap' equals one when an applicant is assigned a six month unemployment spell immediately after graduation; '12 Month Front End Gap' equals one when an applicant is assigned a 12 month unemployment spell immediately after graduation; '3 Month Back End Gap' equals one when an applicant is assigned a three month unemployment spell at the time of application; '6 Month Back End Gap' equals one when an applicant is assigned a six month unemployment spell at the time of application; '12 Month Back End Gap' equals one when an applicant is assigned a 12 month unemployment spell at the time of application; 'Business Degree' equals one when applicant is assigned a business degree; 'Internship Experience' equals one when an applicant is assigned internship experience while completing their degree; and 'In-Field Work Experience' equals one when an applicant is assigned in-field work experience following graduation. Each of these résumé characteristics as well as those not listed in the table are described in Appendix Section A1.

Table 2: Average Interview Rates

	All	White	Black	Difference in Means	
	(1)	(2)	(3)	(4)	
Overall	0.166	0.180	0.152	-0.028	***
By City:					
Atlanta	0.131	0.148	0.114	-0.034	*
Baltimore	0.257	0.254	0.248	-0.006	
Boston	0.130	0.144	0.116	-0.028	
Dallas	0.180	0.199	0.161	-0.038	*
Los Angeles	0.138	0.157	0.119	-0.037	*
Minneapolis	0.181	0.200	0.163	-0.037	*
Portland	0.160	0.169	0.152	-0.017	
By Job Category:					
Banking	0.090	0.112	0.070	-0.042	*
Finance	0.102	0.110	0.094	-0.015	
Insurance	0.243	0.276	0.210	-0.065	**
Management	0.103	0.107	0.099	-0.007	
Marketing	0.214	0.218	0.209	-0.008	
Sales	0.215	0.233	0.195	-0.038	*

Notes: There are 1385 observations from Atlanta; 1146 observations from Baltimore; 1339 observations from Boston; 1415 observations from Dallas; 1375 observations from Los Angeles; 1386 observations from Minneapolis; and 1377 observations from Portland. For the job categories, there are 929 observations from banking; 1636 observations from finance; 1067 observations from management; 1046 observations from marketing; and 2326 observations from sales. *, ** and *** indicate statistical significance at the 5, 1 and 0.1 percent levels, respectively.

Table 3: Race and Job Opportunities

	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.028***	-0.027***	-0.027***	-0.027***	-0.026***	-0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Résumé	No	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes
Category	No	No	No	No	Yes	Yes
Advertisement	No	No	No	No	No	Yes
R^2	0.002	0.008	0.010	0.018	0.044	0.724
Observations	9396	9396	9396	9396	9396	9396

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. *** indicates statistical significance at the 0.1 percent level. 'Résumé' represents controls for the randomized résumé characteristics other than race; 'Month' represents month-of-application dummy variables; 'City' represents city-of-application dummy variables; 'Category' represents job-category (i.e. banking, finance, management, marketing, insurance and sales) dummy variables; and 'Advertisement' represents dummy variables for the job for which applications were submitted.

Table 4: Race, Uniqueness, and Socioeconomic Status

| | Common Names | Low Socioeconomic Status | | High Socioeconomic Status | |
| | | Full Sample | Common Names | Full Sample | Common Names |
	(1)	(2)	(3)	(4)	(5)
Black	-0.027**	-0.022*	-0.029*	-0.021*	-0.023+
	(0.009)	(0.009)	(0.014)	(0.008)	(0.014)
R^2	0.776	0.724	0.777	0.724	0.777
Observations	5811	9396	5811	9396	5811

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. +, * and ** indicate statistical significance at the 10, 5 and 1 percent levels, respectively. Columns (2)-(5) are estimated by including an interaction term between the race identifier and the high-socioeconomic-status-address identifier. We compute linear combinations or the parameters of interest to obtain the marginal differences between black and white applicants with low-socioeconomic-status and high-socioeconomic-status addresses. Each regression model includes the full set of control variables. The samples used in columns (1), (3) and (5) inlcude only observations from applicants with 'common' names, while columns (2) and (4) present results using the full sample of applicants.

Table 5: Race, Unemployment Spells, and Job Opportunities

	$unemp^{3mo}$ relative to $employed$	$unemp^{6mo}$ relative to $employed$	$unemp^{12mo}$ relative to $employed$	$unemp^{6mo}$ relative to $unemp^{3mo}$	$unemp^{12mo}$ relative to $unemp^{3mo}$	$unemp^{12mo}$ relative to $unemp^{6mo}$
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.008 (0.019)	-0.011 (0.021)	-0.002 (0.020)	0.019 (0.026)	0.006 (0.024)	-0.013 (0.026)
Parameters or Combinations of Parameters	λ_1	λ_2	λ_3	$\lambda_2 - \lambda_1$	$\lambda_3 - \lambda_1$	$\lambda_3 - \lambda_2$

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. The full sample of 9396 observations and Equation 2, which holds constant the full set of control variables, is used to produce the estimates.

Table 6: Race, Productivity Signals and Job Opportunities

	No Productivity Signal	Productivity Signal	Productivity Signal Relative to No Productivity Signal
	(1)	(2)	(3)
Panel A: Business Degrees			
Black	-0.010 (0.009)	-0.031*** (0.008)	-0.021+ (0.012)
Panel B: Internships			
Black	-0.016* (0.008)	-0.040*** (0.013)	-0.024+ (0.015)
Panel C: In-Field Experience			
Black	-0.008 (0.008)	-0.035*** (0.009)	-0.027* (0.013)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. +, * and *** indicate statistical significance at the 10, 5 and 0.1 percent levels, respectively. The estimates shown in each panel are based on separate regression models. In particular, equation 3 is used for each specifiation. The full sample of 9396 observations is used for each regression model. The regression models rely on the full set of control variables. Panel A presents the estimated racial differences for business and non-business degree holders; Panel B presents the estimated racial differences for applicants with and without internship experience; and Panel C presents the estimated racial differences when applicants have in-field and out-of-field work experience.

Table 7: Racial Gap in Job Opportunities with None, Some or All Productivity Signals

	(1)	(2)	(3)	(4)
Black	0.008	-0.031***	-0.052**	-0.067**
	(0.014)	(0.008)	(0.017)	(0.024)
Productivity Signals				
College Degree	No	Yes	Yes	Yes
Internship Experience	No	No	Yes	Yes
In-Field Experience	No	No	No	Yes
Observations in Cells	1610	1941	643	671

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-opening level are in parentheses. ** and *** indicate statistical significance at the 1 and 0.1 percent levels, respectively. The estimates presented in columns (1), (2), (3) and (4) are conditioned the full set of control variables. The estimated differences between black and white applicants are based on the computation of linear combinations of parameters. Appendix Section A2.3 provides details on how the estimates for the linear combinations of parameters presented above are produced.

Table 8: Discrimination in Jobs with Customer and Employee Interaction

	(1)	(2)	(3)	(4)	(5)
Customer-Related Jobs					
Black	-0.037**	-0.039**	-0.043***	-0.043***	-0.045***
	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)
Words in Job Title:					
Customer	Yes	Yes	Yes	Yes	Yes
Sales	Yes	Yes	Yes	Yes	Yes
Advisor	No	Yes	Yes	Yes	Yes
Representative	No	No	Yes	Yes	Yes
Agent	No	No	No	Yes	Yes
Loan Officer	No	No	No	No	Yes
Observations in Cells	2701	2797	3128	3255	3377
Employee-Related Jobs					
Black	-0.003	-0.003	-0.003	-0.002	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Words in Job Title:					
Manager	Yes	Yes	Yes	Yes	Yes
Director	Yes	Yes	Yes	Yes	Yes
Supervisor	Yes	Yes	Yes	Yes	Yes
Administration	No	Yes	Yes	Yes	Yes
Coordinator	No	No	Yes	Yes	Yes
Operations	No	No	No	Yes	Yes
Leader	No	No	No	No	Yes
Observations in Cells	1965	2042	2459	2527	2547

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. The full sample is used to produce the estimates in each column. ** and *** indicate statistical significance at the 1 and 0.1 percent levels, respectively. The estimates presented in columns (1), (2), (3), (4) and (5) use the full set of control variables and the full sample of 9396 observations.

For Review Purposes Only

Appendix

A1 Data

A1.1 Résumé Characteristics

Applicant Names

Following the work of other correspondence studies (e.g., Bertrand and Mullainathan 2004; Carlsson and Rooth 2007; Nunley et al. 2011), we randomly assign names to applicants that are distinct to a particular racial group. For our purposes, we chose eight names: Claire Kruger, Amy Rasumussen, Ebony Booker, Aaliyah Jackson, Cody Baker, Jake Kelly, DeShawn Jefferson, and DeAndre Washington. Claire Kruger and Amy Rasmussen are distinctively white female names; Ebony Booker and Aaliyah Jackson are distinctively black female names; Cody Baker and Jake Kelly are distinctively white male names; and DeShawn Jefferson and DeAndre Washington are distinctively black male names. The first names and surnames were taken from various websites that list the most female/male and the blackest/whitest names. The Census breaks down the most common surnames by race, and we chose our surnames based on these rankings.[40] The whitest and blackest first names, which are also broken down by gender come from the following website: http://abcnews.go.com/2020/story?id=2470131&page=1. The whitest and blackest first names for males and females are corroborated by numerous other websites and the baby name data from the Social Security Administration.

The names listed above are randomly assigned with equal probability. Once a name has been randomly assigned within a four-applicant group (i.e. the number of résumés we submit per job advertisement), that name can no longer be assigned to the other applicants in the

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[40]Here is the link to the most common surnames in the U.S.: http://www.census.gov/genealogy/www/data/2000surnames/index.html

four-applicant pool. That is, there can be no duplicate names within a four-applicant pool.

We created an email address and a phone number for each name, which were all created through http://gmail.com. Each applicant name had an email address and phone number that is specific to each city where we applied for jobs. As an example, DeAndre Washington had seven different phone numbers and seven different email addresses. For each city, we had the emails and phone calls to applicants within a particular city routed to an aggregated Google account, which was used to code the interview requests.

Street Address

Four street addresses were created for each city. The addresses are created by examining house prices in and around the city in which the applications are submitted. Two of these addresses are in high-socioeconomic-status areas, while the other two are in low-socioeconomic-status areas. High-socioeconomic-status addresses are in areas where house prices on the street are in excess of \$750,000, while those in low-socioeconomic-status addresses are in areas where house prices on the street are less than \$120,000. We obtained house price information from http://trulia.com. Each applicant is assigned one of the four possible street addresses within each city. Applicants are assigned high- and low-socioeconomic-status addresses with equal probability, i.e. 50 percent. The table below shows the high- and low-socioeconomic street addresses used for each city.

Addresses				
	High Socio-Economic 1	High Socio-Economic 2	Low Socio-Economic 1	Low Socio-Economic 2
Atlanta	4164 Paran Pines Dr Nw Atlanta, GA 30327	908 Kings Ct Ne Atlanta, GA 30306	698 Moreland Ave Se Atlanta, GA 30316	4300 Rosewell Rd Atlanta, GA 30342
Baltimore	207 Club Rd Baltimore, MD 21210	2303 Essex St Baltimore, MD 21224	2998 Sollers Point Rd Baltimore, MD 21222	2803 Roselawn Ave Baltimore, MD 21214
Boston	590 E 8Th St Boston, MA 02127	71 School St Boston, MA 02129	38 Messinger St Boston, MA 02126	1409 River St Apt 37 Boston, Ma 02136
Dallas	3443 Normandy Ave Dallas, TX 75205	7360 Paldao Dr Dallas, TX 75240	3906 Antigua Dr Dallas, TX 75244	18211 Muir Cir Dallas, TX 75287
Los Angeles	6970 La Presa Dr Los Angeles, CA 90068	181 S Gardner St Los Angeles, CA 90036	10738 Gorman Ave Los Angeles, CA 90059	5608 Fortuna St Los Angeles, CA 90011
Minneapolis	1832 Kenwood Pkwy Minneapolis, MN 55405	4628 W Lake Harriet Pkwy Minneapolis, MN 55410	2526 Ulysses Ne St Minneapolis, MN 55418	4301 14th S Ave Minneapolis, MN 55407
Portland	5472 Sw Champion Pl Portland, OR 97225	3239 Sw 55Th Dr Portland, OR 97221	5715 Se 83Rd Ave Portland, OR 97266	309 N Bridgeton Rd Portland, OR 97217

Universities

The fictitious applicants were randomly assigned one of four possible universities. The universities are likely recognizable by prospective employers, but they are unlikely to be regarded as prestigious; thus, we can reasonably conclude that "name recognition" of the school plays little role as a determinant of receiving a interview from a prospective employer. In addition, each of the applicants is randomly assigned each of these four universities at some point during the collection of the data. While the university one attends likely matters, our data suggest that the universities that we randomly assigned to applicants do not give an advantage to our fictitious applicants. That is, there is no difference in the interview rates between the four possible universities.

Academic Major

The following majors were randomly assigned to our fictitious job applicants with equal probability: accounting, biology, economics, english, finance, history, management, marketing, and psychology. We chose these majors because they are commonly selected majors by college students. In fact, the Princeton Review[41] rates business-related majors as the most selected by college students; psychology is ranked second; biology is ranked fourth; english is ranked sixth; and economics is ranked seventh.

Grade Point Average and Honor's Distinction

Twenty-five percent of our fictitious applicants are randomly assigned an résumé attribute that lists their GPA. When an applicant is randomly assigned this résumé attribute, a GPA of 3.9 is listed. Twenty-five percent of the our fictitious applicants were randomly assigned an Honor's distinction for their academic major. Note that applicants were not randomly assigned both of these attributes; that is, applicants receive one of the two or neither. Below

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[41]Visit the following webpage: http://www.princetonreview.com/college/top-ten-majors.aspx.

is an example of how the "Honor's" (left) and "GPA" (right) traits were signaled on the résumés.[42]

Education

Bachelor of Science, May 2010
University of XYZ
English (Honors)

Education

University of XYZ
Bachelor of Science, May 2010
English
GPA 3.9

(Un)Employment Status

Applicants were randomly assigned one of the following (un)employment statuses: employed at the date of application with no gap in work history, unemployed for three months at the date of application, unemployed for six months at the date of application, unemployed for 12 months at the date of application, unemployed for three months immediately following their graduation date but currently employed, unemployed for six months immediately following their graduation date but currently employed, and unemployed for 12 months immediately following their graduation date but currently employed. Applicants receive no gap in their work history at a 25 percent rate, while the different unemployment spells are randomly assigned with equal probability (12.5 percent). The (un)employment statuses are not mutually exclusive. It is possible for two workers in a four-applicant pool to be randomly assigned, for example, a three-month current unemployment spell. The unemployment spells were signaled on the résumés via gaps in work history, either in the past or currently.

In-Field, Out-of-Field, Internship and College Work Experience

For each job category (i.e. banking, finance, management, marketing, insurance and sales), applicants were randomly assigned "in-field" or "out-of-field" work experience. "In-field" work experience is specific to the job category that the applicant is applying. "Out-of-field" experience is either currently working or having previously worked as a sales person

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[42]The university name was replaced with XYZ to conform to the terms of the agreement with our institutional review boards.

in retail sales. Ultimately, out-of-field experience represents a form of "underemployment," as a college degree is not a requirement for these types of jobs. Fifty percent of applicants are randomly assigned "in-field" experience, and the remaining 50 percent of applicants are randomly assigned "out-of-field" experience. Twenty-five percent of the applicants were randomly assigned internship experience during the summer 2009, which is the summer before they complete their Bachelor's degree. The internship experience is specific to the job category. All of the applicants were assigned work experience while completing their college degree, which consisted of working as a barista, tutor, customer service representative and sales associate. The following series of tables provide detailed information on each type of work experience by job category:

	Banking	
	Job Title	Resume Description
Infield 1	Bank Branch Assistant Manager	•Evaluate present market conditions to decide resource allocation to different products and services •Design employee schedules, appointed temporary workforce for a busy seasons, and interview and hire all new employees •Kept in depth records of all industry activities to attain the regulatory needs •Focus on process flow improvement by examining sales relationships and visit several company locations frequently to ensure smooth processes •Produce thorough budgets for the number of operations, tracked the actual expenditures and reviews exceptions •Train and handle a number of employees and build operational principles •Manage branch employees with a focus on branch compliance
Infield 2	Bank Branch Assistant Manager	•Trained 30 new employees and attained significant improvements in their productivity over time •Visited several company locations frequently to ensure smooth processes •Maintain records of cash limits, checks, deposits, fund transfer, money orders, debit cards issued and other banking activities •Suggested new methods for business, developing services for business clients and reducing wait for the personal account clients •Overhauled accounting systems, bookkeeping operations, and interview processes •Provide support in all clerical responsibilities and other daily tasks within the bank
Internship 1	Equity Capital Markets Intern	•Created analytical models and spreadsheets •Assessed market capacity for equity products •Analyzing cost of capital of various financing options
Internship 2	Capital Markets Intern	•Created statistical models to capture and present quantitative data •Generated reports and prepared presentations to assist senior managers •Used Excel and Access to perform analysis and conduct research

Finance		
	Job Title	Resume Description
Infield 1	Accounts Payable	•Prepare and analyze fund statements, balance sheets and salary schedules for firm and her subsidiaries •Responsible for supporting program managers in the development and analysis of financial reports, and spending plans •Review all invoices for appropriate documentation and approval prior to payment •Responds to questions and makes calls regarding billing problems; acts as a liaison between department and vendors
Infield 2	Financial Advisor	•Conduct in-depth reviews of clients' financial circumstances and prepared plans best suited to their requirements •Design detailed financial strategies and explained reports to cliental •Contact clients with news of new financial products or changes to legislation that may affect their savings and investments •Meet all regulatory aspects of the role, e.g. requirements for disclosure, and costs of services provided •Responsible for preparing and maintaining financial statements and invoices in an accurate manner
Internship 1	Financial Analyst Intern	•Conducted financial and business analysis to generate insights that influenced cross-functional decision-making •Led process innovation to drive efficiency and deliver insightful perspective on key business drivers •Leveraged data and information systems to forecast performance and articulate key drivers of change
Internship 2	Financial Analyst Intern	•Conducted financial and business analysis to generate insights that influenced cross-functional decision-making •Led process innovation to drive efficiency and deliver insightful perspective on key business drivers •Leveraged data and information systems to forecast performance and articulate key drivers of change

	Job Title	Resume Description
		Insurance
Infield 1	Insurance Sales Agent	•Customize insurance programs to suit individual customers, often covering a variety of risks •Develop marketing strategies to compete with other individuals or companies who sell insurance •Seek out new clients and develop clientele by networking to find new customers and generate lists of prospective clients •Prepared activity reports with the interpretation, implementation and enforce company policies, strategies and procedures •Monitor insurance claims to ensure they are settled equitably for both the client and the insurer •Inspect property, examining its general condition, type of construction, age, and other characteristics, to decide if it is a good insurance risk •Resolved clients' claim issues in assistance of manager
Infield 2	Insurance Sales Agent	•Sell various types of insurance policies to businesses and individuals on behalf of insurance companies, including automobile, fire, life, property, medical and dental insurance or specialized policies such as marine, farm/crop, and medical malpractice •Strive to achieve optimum customer satisfaction and access coverage, liability and damage •Responsible for appointing a legal representative for the court cases and communicating with the agents to resolve the issues •Ensure that policy requirements are fulfilled, including any necessary medical examinations and the completion of appropriate forms •Calculate premiums and establish payment method
Internship 1	Intern	•Asked probing and challenging questions to uncover a prospective clients needs •Identified and understood a prospect's needs to help create solutions •Handled objections and effectively built relationships
Internship 2	Intern	•Asked probing and challenging questions to uncover a prospective clients needs •Identified and understood a prospect's needs to help create solutions •Handled objections and effectively built relationships

		Marketing
	Job Title	Resume Description
Infield 1	Marketing Specialist	•Conducted qualitative and quantitative research to help guide new creative efforts •Evaluated all potential sponsorship/partnership opportunities •Researched multi-channel marketing efforts of five key advertisers to prepare comprehensive report on how to target consumers for agency-wide project •Directed and manage 4 internal staff and network of 3 external local-market agencies/consultants •Developed, sold, moderated, and interpreted results for more than 100 qualitative focus groups and one-on-one sessions for firm •Evaluated target markets and proposed marketing strategies •Turned 17% sales decline into 20% increase in two years by overhauling entire marketing effort and launching company's first-ever national advertising campaign
Infield 2	Marketing Specialist	•Analyzed regular corporate retail sales reports and tailor each local marketing profit-plan with retail leadership •Programs increased average store traffic 21% and sales averaging 12%, contributing to unprecedented growth •Explored multi-cultural trends and developed volumetric sales analysis to convince firm to address diverse '"non-traditional" audiences across all brands •Created 5 integrated and multi-tiered new store opening programs in domestic & international locations •Designed, developed and implemented marketing and sales campaigns, fundraisers, employee incentive programs and contests •Introduced planning discipline and mass advertising techniques to entertainment retailer with more than ten million in sales •Managed all phases of direct mail projects; monitored production teams; recruited and guided vendors; oversaw print operations and coordinated mailing process
Internship 1	Marketing Business Analyst Intern	•Analyzed the divisional business to identify problems, opportunities, and trends •Executed elements of the marketing plan, including price promotions •Managed multiple projects
Internship 2	Marketing Business Analyst Intern	•Analyzed the divisional business to identify problems, opportunities, and trends •Executed elements of the marketing plan, including price promotions •Managed multiple projects

Sales		
	Job Title	Resume Description
Infield 1	Sales Representative	•Sold and marketed packaging products to manufacturers in a two-state territory •Managed account base of 70 which is an increase of 14 accounts over from previous year •Assigned responsibility to mentor/develop three inside salespeople for promotion to outside sales positions •Recaptured 4 lost accounts during first year of employment •Developed strong referral system which provides continuous leads for new business development •Exceptional leadership, organizational, oral/written communication, interpersonal, analytical, and problem resolution skills •Named "Salesman of the Month" four times during work tenure
Infield 2	Sales Consultant	•Proactive leader with refined business acumen and exemplary people skills. Facilitate a team approach to achieve organizational objectives, increase productivity and enhance employee morale •Helped develop an expansive plan to increase sales by over 30% over the next five years •Conduct new product training for the sales force and dealer network including providing test units to region managers and key dealers for use in demonstrations. •Quick study, with an ability to easily grasp and put into application new ideas, concepts, methods and technologies •Dedicated, innovative and self-motivated team player/builder •Thrive in both independent and collaborative work environments •Review product pricing and gross margin goals for existing products annually
Internship 1	Sales Intern	•Assisted sales representatives, who sold Auto, Home, Life, and other insurance products •Spent time out of the office observing and assisting with sales events •Worked with Sales Reps to identify prospective customers using established lead methods
Internship 2	Sales Future Leader Intern	•Utilized analytical and fact-based selling skills to grow volume, revenue, and profitability goals for the assigned territory •Activated local and national marketplace initiatives and promotions through merchandising products and building creative displays •Performed at a fast pace in a self-motivated position

Out-of-Field & College		
	Job Title	Resume Description
Outfield 1	Sales Associate[1]	•Team leader in sales for two consecutive months •Greet patrons at door and assisted them in locating their desired purchases •Manage sales desk while assisting customers with purchase •Promote company brands whenever possible •Communicate to manager any possible areas of improving the customer service experience •Restock items on sales floor as needed •Handle customer complaints and problems in the most efficient way possible
Outfield 2	Retail Associate	•Open and close cash registers, performing tasks such as counting money, separating charge slips, coupons, and vouchers, balancing cash drawers, and making deposits •Recommend, select, and help locate or obtain merchandise based on customer needs and desires •Describe merchandise and explain use, operation, and care of merchandise to customers •Place special orders or call other stores to find desired items
College 1	Barista	•Ensured counters, customer areas are neat, clean and presentable •Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment •Served food, beverages, or desserts to customers in a fast paced environment •Followed cash handling procedures and cash register policies
College 2	Tutor[2]	•Worked with students to help them better understand _____ [3] concepts •Identified the preferred communication style of the students and adjusted tutorial sessions accordingly •Taught tailored large-group review sessions before exams
College 3	Customer Service Representative	•Served as a resource by providing accurate and current information regarding recreation and university-related programs and facilities •Maintained current certifications in first aid, CPR, and AED. •Counseled peers on personal, academic, and career concerns •Assist with data entry of fitness and intramural participants into Access database and IMTrack
College 4	Sales Associate	•Asked lifestyle questions to thoroughly understand customer needs, offers relevant services, solutions, and accessories so customer can make informed decision to complete their purchase •Leveraged on-line resources, tools, and peer knowledge to self-train •Utilized all relevant sales tools to drive profitable growth

Notes:
1. For jobs within the 'Sales' field, this job title was changed to Retail Associate.
2. The candidate was a tutor for their specific major. For example, if candidate A was a finance major, he/she would be a finance tutor)
3. The first bullet point within the resume description had a tailored line for each major but followed the same outline (e.g., Economics tutor - •Worked with students to help them better understand **economic** concepts)

A1.2 Sample Résumés

In this section, we present a few résumés that capture the essence of our résumé-audit study. The names of schools and companies where the applicants attended and worked have been removed per our agreement with our respective institutional review boards.

Ebony Booker

ebonybooker231@gmail.com
(678) 753-5139
908 Kings Ct Ne
Atlanta, GA 30306

Education

ABC University
Bachelor of Science, May 2010
Management

Work Experience

May 2010 - July 2012
Administrative Assistant
XYZ Company

•Communicated with managers and coordinated the financial reporting of five locations to consolidate financial data
•Decentralized accounts payable to facilitate transition from cost centers to profit centers, and trained employees in the new system
•Recognized for efforts to identify new processes to improve quality, reduce costs, and increase margin
•Coordinated the administration of product orders, understood customer needs and guaranteed delivery of company's commitment
•Accustomed to working in fast-paced environments with the ability to think quickly and successfully handle difficult clients
•Excellent interpersonal skills, ability to work well with others, in both supervisory and support staff roles
•Developed strong relationships with established accounts while acquiring new accounts

September 2006 - May 2010
Sales Associate
DEF Company

•Asked lifestyle questions to thoroughly understand customer needs, offers relevant services, solutions, and accessories so customer can make informed decision to complete their purchase
•Leveraged on-line resources, tools, and peer knowledge to self-train
•Utilized all relevant sales tools to drive profitable growth

Cody Baker

codybaker589@gmail.com
(404) 913-4459
4300 Rosewell Rd
Atlanta, GA 30342

Education

University of ABC
Bachelor of Science, May 2010
Psychology
GPA 3.9

Work Experience

Sales Associate
May 2010 - Present
XYZ Company

- Team leader in sales for two consecutive months
- Greet patrons at door and assisted them in locating their desired purchases
- Manage sales desk while assisting customers with purchase
- Promote company brands whenever possible
- Communicate to manager any possible areas of improving the customer service experience
- Restock items on sales floor as needed
- Handle customer complaints and problems in the most efficient way possible

Customer Service Representative
September 2006 - May 2010
University of ABC Recreation Center

- Served as a resource by providing accurate and current information regarding recreation and university-related programs and facilities
- Maintained current certifications in first aid, CPR, and AED.
- Counseled peers on personal, academic, and career concerns
- Assist with data entry of fitness and intramural participants into Access database and IMTrack

DeShawn Jefferson

d2jefferson@gmail.com
(678) 653-0550
698 Moreland Ave Se
Atlanta, GA 30316

Education

Bachelor of Science, May 2010
University of ABC
Management

Work Experience

XYZ Company
May 2010 - Present
Distribution Assistant Manager

• Responsible and accountable for the coordinated management of multiple related projects directed toward strategic business and other organizational objectives
• Build credibility, establish rapport, and maintain communication with stakeholders at multiple levels, including those external to the organization
• Maintain continuous alignment of program scope with strategic business objectives, and make recommendations to modify the program to enhance effectiveness toward the business result or strategic intent
• Fostered customer loyalty by ensuring that our customers fully utilize the value of our solutions and services
• Direct the coordination of all implementation tasks involving third party vendors as well as provide consultation to clients on system implementation
• Coach, mentor and lead personnel within a fast paced environment

DEF Company
May 2009 – September 2009
Project Management Intern

• Implemented a program to reduce operation costs
• Designed a new program to increase employee moral
• Handled multiple projects simultaneously and effectively built relationships

GHI Company
September 2006 - May 2010
Barista

• Ensured counters, customer areas are neat, clean and presentable
• Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment
• Served food, beverages, or desserts to customers in a fast paced environment
• Followed cash handling procedures and cash register policies

DeAndre Washington
deandre.washington129@gmail.com
(971) 225-0374

309 N Bridgeton Rd Slipb
Portland, OR 97217

Education

Bachelor of Science, May 2010
University of Colorado at ABC
Accounting

Work Experience

May 2010 - Present
Sales Representative
XYZ Company

•Sold and marketed packaging products to manufacturers in a two-state territory
•Managed account base of 70 which is an increase of 14 accounts over from previous year
•Assigned responsibility to mentor/develop three inside salespeople for promotion to outside sales positions
•Recaptured 4 lost accounts during first year of employment
•Developed strong referral system which provides continuous leads for new business development
•Exceptional leadership, organizational, oral/written communication, interpersonal, analytical, and problem resolution skills
•Named "Salesman of the Month" four times during work tenure

Sales Future Leader Intern, May 2009 – September 2009
DEF Company

•Utilized analytical and fact-based selling skills to grow volume, revenue, and profitability goals for the assigned territory
•Activated local and national marketplace initiatives and promotions through merchandising products and building creative displays
•Performed at a fast pace in a self-motivated position

GHI Company, September 2006 - May 2010
Barista

•Ensured counters, customer areas are neat, clean and presentable
•Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment
•Served food, beverages, or desserts to customers in a fast paced environment
•Followed cash handling procedures and cash register policies

Aaliyah Jackson

Aaliyah.Jackson321@gmail.com
(971) 225-0726
309 N Bridgeton Rd Slipb
Portland, OR 97217

Education

Bachelor of Science, May 2010
University of ABC
Finance (Honors)

Work Experience

XYZ Company (May 2010 - December 2012)
Retail Associate

• Open and close cash registers, performing tasks such as counting money, separating charge slips, coupons, and vouchers, balancing cash drawers, and making deposits
• Recommend, select, and help locate or obtain merchandise based on customer needs and desires
• Describe merchandise and explain use, operation, and care of merchandise to customers
• Place special orders or call other stores to find desired items.

DEF Company (September 2006 - May 2010)
Barista

• Ensured counters, customer areas are neat, clean and presentable
• Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment
• Served food, beverages, or desserts to customers in a fast paced environment
• Followed cash handling procedures and cash register policies

A1.3 The Application Process

We applied to online postings for job openings in six categories: banking, finance, insurance, management, marketing and sales. To obtain an list of openings, we chose specific search criteria through the online job posting websites to find the appropriate jobs within each of the aforementioned job categories. We further constrained the search by applying only to jobs that had been posted in the last seven days within 30 miles of the city center.

Job openings would be applied to if they had a "simple" application process. An application process was deemed "simple" if it only required a résumé to be submitted or if the information to populate the mandatory fields could be obtained from the résumé (e.g., a candidate's name or phone number). Jobs that required a detailed application were discarded for two reasons. First and foremost, we wanted to avoid introducing variation in the application process that could affect the reliability of our results. A detailed application specific to a particular firm might include variation that is difficult to hold constant across applicants and firms. Second, detailed applications take significant time, and our goal was to submit a large number of résumés to increase the power of our statistical tests. Job openings were discarded from our sample if any of the following were specified as minimum qualifications: five or more years of experience, an education level greater than a bachelor's degree, unpaid or internship positions, or specific certifications (e.g. CPA or CFA).

We used the résumé-randomizer from Lahey and Beasely (2009) to generate four résumés to submit to each job advertisement. Templates were created for each job category (i.e. banking, finance, insurance, management, marketing and sales) to incorporate in-field experience. After the résumés were generated, we then formatted the résumés to look presentable to prospective employers (e.g., convert Courier to Times New Roman font; make the applicant's name appear in boldface font, etc.). We then uploaded the résumés and filled out required personal information, which included the applicant's name, the applicant's location, the applicant's desire to obtain an entry-level position, the applicant's educational attainment (i.e. Bachelor's), and whether the applicant is authorized to work in the U.S. All job advertisement identifiers and candidate information was recorded. Upon receiving a interview request, we promptly notified the firm that the applicant was no longer seeking employment to minimize the cost incurred by firms.

A2 Supplementary Estimates

A2.1 Race-Gender Interactions

We check our baseline estimates by examining whether the interview rates differ by race and gender. Formally, we estimate the following regression equation:

$$interview_{imcfj} = \beta_0 + \beta_1 black_i + \beta_2 female_i + \beta_3 black_i \times female_i$$
$$\gamma \mathbf{X}_i + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \tag{5}$$

Equation 5 is identical to equation 1 except for the inclusion of the interaction term $black \times female$. The variable $female$ is a zero-one indicator that equals one when an applicant is assigned a distinctively female name. The interaction term, i.e. $black \times female$, equals one when the applicants is randomly assigned a name that is distinctively black *and* female. Using equation 5, we are able to test for differences in interview rates between whites and blacks of the same gender, males and females of the same race, and males and females of different races. For example, the difference in the interview rate between black males and white males is β_1, while the difference in the interview rate between black females and white females is $\beta_1 + \beta_3$. The difference in the interview rate between black females and black males is $\beta_2 + \beta_3$, while the difference in the interview rate between white females and white males is β_2. The difference in the interview rate between black males and white females is $\beta_1 - \beta_2$, while the difference in the interview rate between black females and white males is $\beta_1 + \beta_2 + \beta_3$.

Table A2 presents the results from equation 5. Relative to white males, the interview rate for black males is 1.9 percentage points lower, and this estimated differential is statistically significant at the five-percent level. The interview rate for black females is about 2.5 percentage points lower than otherwise identical white females, with the estimated difference being statistically significant at the one-percent level. White females receive higher interview rates

than black males: the interview rate is 2.7 percentage points lower for black males, and this estimated differential is significant statistically and economically. White males also experience a higher interview rate than black females. The differential is statistically significant at the five-percent level, indicating that black females receive a 1.6 percentage point lower callback rate than white men. Within races, there is no economically or statistically significant difference in interview rates between black males and black females and white males and white females.

A2.2 Race and Work Experience

We are also able to examine how discrimination varies with the amount of work experience, as the random assignment of gaps in the work histories of applicants creates random variation in work experience; our applicants have between 20 and 38 months of work experience. In addition, we have applicants with in-field and out-of-field experience. As a result, we are able to examine whether there are interaction effects between race and work experience and race and particular types of work experience (i.e. in-field and out-of-field). The data would support the taste-based model if black applicants receive lower interview rates when compared with white applicants with identical productivity characteristics, while models of statistical discrimination would predict a narrowing of the racial gap as work experience increases. To examine whether there is an interaction effect between race and work experience, we estimate a variant of equation 1 that includes an interaction term between race and months of work experience. Formally, we estimate the following regression model:

$$
\begin{aligned}
interview_{imcfj} = \beta_0 + \beta_1 black_i + \beta_2 exp_i + \beta_3 black_i \times exp_i \\
+ \gamma \mathbf{X}_i + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}.
\end{aligned}
\tag{6}
$$

All variables included in equation 6 are defined in the main text, except exp. The variable exp measures work experience in months, and $black \times exp$ is an interaction term. We estimate

equation 6 for the full sample and for subsamples based on the type of work experience (i.e. in field and out of field). In all specifications, our estimate for β_3 is not statistically significant. Despite the insignificance of the interaction term, we evaluate the difference in the interview rate between black and white applicants at different points in the work-experience distribution (i.e. $\beta_1 + \beta_3 exp$). In Table A4, we evaluate the difference in interview rates between black and white applicants at the 10th (23 months), 25th (26 months), 50th (31 months), 75th (33 months) and 90th (36 months) percentiles of the exp variable. We examine overall work experience in Panel A; out-of-field work experience in Panel B; and in-field work experience in Panel C. For the estimated differences in Panel A, the estimates are negative and statistically significant, an indication that black applicants experience lower interview rates regardless of the level of work experience. However, the magnitudes of the differentials fall slightly as the work experience increases. Relative to their white counterparts, black applicants have a 2.7 percentage point lower interview rate at the 10th percentile of the experience variable; a 2.5 percentage point lower interview rate at the 25th percentile of the experience variable; a 2.1 percentage point lower interview rate at the median of the experience variable; a 1.9 percentage point lower interview rate at the 75th percentile of the experience variable; and a 1.8 percentage point lower interview rate at the 90th percentile of the experience variable. These findings suggest that increases in work experience reduce the extent of discrimination, but increases in work experience does not eliminate the differential treatment by race.

The results from Panel A mask some interesting patterns in the data. The estimates presented in Panel B, which examines applicants with out-of-field experience, have the same pattern, except none of the estimated differences between black and white applicants are statistically significant. The results from Panel C, which examine applicants with in-field experience, have the opposite pattern. Interestingly, the differences in the interview rates between black and white applicants become larger as the work experience that is "in field" increases. Some of the estimated differences are statistically significant, but all of the estimates

appear to be economically significant (more than two percentage points).

A2.3 Details on the Estimates Presented in Table 7

To produce the estimates presented in Table 7, we use three different regression models. The first regression equation of interest is

$$
\begin{aligned}
interview_{imcfj} = {} & \beta_0 + \beta_1 black_i + \beta_2 bus_i + \beta_3 black_i \times bus_i \\
& + \lambda \mathbf{X}_i + \phi_m + \phi_c + \phi_f + \phi_j + u_{icmfj}.
\end{aligned}
\tag{7}
$$

The subscripts i, m, c, f and j and the variables $interview$, $black$, $\mathbf{X}$, ϕ and u are defined in the main part of the manuscript. The variable bus is a zero-one indicator variable that equals one when an applicant is assigned a business degree and zero otherwise. The second regression equation of interest is

$$
\begin{aligned}
interview_{imcfj} = {} & \beta_0 + \beta_1 black_i + \beta_2 bus_i + \beta_3 intern_i + \beta_4 bus_i \times intern_i \\
& + \gamma_1 black_i \times bus_i + \gamma_2 black_i \times intern_i \\
& + \gamma_3 black_i \times bus_i \times intern_i + \lambda \mathbf{X}_i \\
& + \phi_m + \phi_c + \phi_f + \phi_j + u_{icmfj}.
\end{aligned}
\tag{8}
$$

The subscripts i, m, c, f and j and the variables $interview$, $black$, bus, $\mathbf{X}$, ϕ, and u are either defined in the main part of the manuscript or above. The only variable not previously defined is $intern$, which is a zero-one indicator variable that equals one when an applicant is assigned internship experience and zero otherwise. The third and last regression equation of interest is

$$
\begin{aligned}
interview_{imcfj} = {} & \beta_0 + \beta_1 black_i + \beta_2 bus_i + \beta_3 intern_i + \beta_4 infield_i \\
& + \gamma_1 black_i \times bus_i + \gamma_2 black_i \times intern_i \\
& + \gamma_3 black_i \times infield_i + \gamma_4 black_i \times bus_i \times intern_i \\
& + \gamma_5 black_i \times bus_i \times infield_i + \gamma_6 black_i \times intern_i \times infield_i \\
& + \gamma_7 black_i \times bus_i \times intern_i \times infield_i \\
& + \theta_1 bus_i \times intern_i + \theta_2 bus_i \times infield_i \\
& + \theta_3 intern_i \times infield_i + \theta_4 bus_i \times intern_i \times infield_i \\
& + \lambda \mathbf{X}_i + \phi_m + \phi_c + \phi_f + \phi_j + u_{icmfj}.
\end{aligned}
\tag{9}
$$

The subscripts i, m, c, f and j and the variables $black$, bus, $intern$, $\mathbf{X}$, ϕ, and u are either defined in the main part of the manuscript or above. The only variable not previously defined is $infield$, which is a zero-one indicator variable that equals one when an applicant is assigned in-field work experience and zero otherwise.

The estimated difference in column (1) is β_1 from equation 9, which gives the estimated differential in employment opportunities between black and white job seekers with non-business degrees, no internship experience and out-of-field work experience. The estimated difference in column (2) is $\beta_1 + \beta_3$ from equation 7, which gives the estimated differential in employment opportunities between black and white job seekers with business degrees. The estimated difference in column (3) is $\beta_1 + \gamma_1 + \gamma_2 + \gamma_3$, which gives the estimated differential in employment opportunities between black and white job seekers with business degrees and internship experience. The estimated difference in column (4) is $\beta_1 + \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 + \gamma_5 + \gamma_6 + \gamma_7$, which gives the estimated differential in employment opportunities between black and white job seekers with business degrees, internship experience and in-field experience.

A2.4 Black and White Applicants With and Without Productivity Signals

In Table A5, we compare white applicants *with* the productivity signals to black applicants *without* the productivity signals. Column (1) presents the estimated difference in the interview rate between black applicants with non-business degrees relative to white applicants with business degrees; column (2) presents the estimated difference in the interview rate between black applicants with non-business degrees and no internship experience to white applicants with business degrees and internship experience; and column (3) presents the estimated difference in the interview rate between black applicants with non-business degrees, no internship experience and out-of-field work experience to white applicants with business degrees, internship experience and in-field work experience. From column (1), the interview rate of black applicants with non-business degrees is 1.4 percentage points lower than white applicants with business degrees. From column (2), the interview rate of black applicants with non-business degrees and no internship experience is 5.6 percentage points lower than white applicants with business degrees and internship experience. From column (3), the interview rate of black applicants with non-business degrees, no internship experience and out-of-field work experience is 10.3 percentage points lower than white applicants with business degrees, internship experience and in-field work experience.

In Table A6, we compare white applicants *without* the productivity signals to black applicants *with* the productivity signals. Column (1) presents the estimated difference in the interview rate between black applicants with business degrees relative to white applicants with non-business degrees; column (2) presents the estimated difference in the interview rate between black applicants with business degrees and internship experience to white applicants with non-business degrees and no internship experience; and column (3) presents the estimated difference in the interview rate between black applicants with business degrees, internship experience and in-field work experience to white applicants with non-business degrees, no internship experience and out-of-field work experience. From columns (1), (2)

and (3), we find no economically or statistically significant differences in the interview rates between black applicants with the productivity signals and white applicants without the productivity signals.

Taken together, the results from Tables A5 and A6 indicate the experience/productivity signals do not help black applicants as much as they do white applicants. To be clear, black applicants have better job opportunities if they have these attributes than they would without them, but these credentials do not reduce the racial gap in the interview rates in any economically important way.

Table A1: Gender and Interview Rates

	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.009	0.008	0.007	0.008	0.007	0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Résumé	No	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes
Category	No	No	No	No	Yes	Yes
Advertisement	No	No	No	No	No	Yes
R^2	0.002	0.008	0.010	0.018	0.044	0.724
Observations	9396	9396	9396	9396	9396	9396

Table A2: Race-Gender Interactions and Interview Rates

	(1)	(2)	(3)	(4)	(5)	(6)
Regression Estimates						
Black	-0.021*	-0.021*	-0.020*	-0.020*	-0.019*	-0.019*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Female	0.015	0.014	0.014	0.015	0.014	0.008
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Black*Female	-0.013	-0.013	-0.014	-0.015	-0.015	-0.006
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.011)
Linear Combinations						
Black Males	-0.021*	-0.021*	-0.020*	-0.020*	-0.019*	-0.019*
versus White Males	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Black Females	-0.034***	-0.034***	-0.034***	-0.035***	-0.034***	-0.025**
versus White Females	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Black Males	-0.036***	-0.034***	-0.034***	-0.035***	-0.033***	-0.027**
versus White Females	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Black Females	-0.019*	-0.020*	-0.020*	-0.019*	-0.020*	-0.016*
versus White Males	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Black males	-0.002	-0.001	0.000	-0.000	0.001	-0.002
versus Black Females	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
White Males	-0.015	-0.014	-0.014	-0.015	-0.014	-0.008
versus White Females	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Résumé	No	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes
Category	No	No	No	No	Yes	Yes
Advertisement	No	No	No	No	No	Yes
R^2	0.002	0.008	0.010	0.018	0.044	0.724
Adjusted R^2	0.001	0.005	0.006	0.014	0.040	0.630
Observations	9396	9396	9396	9396	9396	9396

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. *, **, and *** indicate statistical significance at the 5, 1 and 0.1 percent levels, respectively. 'Résumé' represents controls for the randomized résumé characteristics other than race; 'Month' represents month-of-application dummy variables; 'City' represents city-of-application dummy variables; 'Category' represents job-category (i.e. banking, finance, management, marketing, insurance and sales) dummy variables; and 'Advertisement' represents dummy variables for the job for which applications were submitted.

Table A3: Race, Degree Categories, and Job Opportunities

	Degree Category			
	Business	Social Sciences	Sciences	Humanities
	(1)	(2)	(3)	(4)
Specification 1:				
Black	-0.031***	-0.018	-0.011	0.008
	(0.008)	(0.013)	(0.014)	(0.017)
Specification 2:				
Black	-0.032***	-0.021*	-0.011	0.008
	(0.009)	(0.009)	(0.014)	(0.017)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-opening level are in parentheses. * and *** indicate statistical significance at the 5 and 0.1 percent levels, respectively. Specification 1 includes economics in the business-degree category, while specification 2 includes economics in the social-sciences-degree category. Both specifications include the ful set of control variables.

Table A4: Race, Work Experience, and Interview Rates

| | Experience Level by Percentile | | | | |
	10th	25th	50th	75th	90th
Panel A: Overall					
Black	-0.027*	-0.025**	-0.021***	-0.019*	-0.017+
	(0.011)	(0.008)	(0.006)	(0.008)	(0.10)
Observations	9396	9396	9396	9396	9396
Panel B: Out-of-Field Experience					
Black	-0.022	-0.017	-0.007	-0.000	0.004
	(0.021)	(0.015)	(0.011)	(0.014)	(0.017)
Observations	4693	4693	4693	4693	4693
Panel C: In-Field Experience					
Black	-0.021	-0.023	-0.027*	-0.029+	-0.031
	(0.023)	(0.017)	(0.014)	(0.017)	(0.021)
Observations	4703	4703	4703	4703	4703

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-opening level are in parentheses. +, *, ** and *** indicate statistical significance at the 10, 5, 1 and 0.1 percent levels, respectively. The results in Panel A, B and C are based on equation 6. The results in Panel A are based on the full sample; those in Panel B are based on a subsample of applicants who were randomly assigned out-of-field experience; and those in Panel C are based on a subsample of applicants who were randomly assigned in-field experience. The experience level is 23 months at the 10th percentile; 26 months at the 25th percentile; 31 months at the 50th percentile; 33 months at the 75th percentile; and 36 months at the 90th percentile. Each specification includes the full set of control variables.

Table A5: Comparison of Whites with to Blacks without Productivity Signals

	(1)	(2)	(3)
Black	-0.014	-0.056***	-0.103***
	(0.009)	(0.014)	(0.020)
Productivity Signals			
Business Degree	Yes	Yes	Yes
Internship Experience	No	Yes	Yes
In-Field Experience	No	No	Yes

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-opening level are in parentheses. *** indicates statistical significance at the 0.1 percent level. Each model uses the full set of control variables. From Appendix Section A2.3, column (1) is based on equation 7; column (2) is based on equation 8; and column (3) is based on equation 9.

Table A6: Comparison of Whites without to Blacks with Productivity Signals

	(1)	(2)	(3)
Black	-0.017+	-0.006	-0.002
	(0.009)	(0.013)	(0.033)
Productivity Signals			
Business Degree	Yes	Yes	Yes
Internship Experience	No	Yes	Yes
In-Field Experience	No	No	Yes

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-opening level are in parentheses. + indicates statistical significance at the 10-percent level. Each model uses the full set of control variables. From Appendix Section A2.3, column (1) is based on equation 7; column (2) is based on equation 8; and column (3) is based on equation 9.