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# An Examination of Racial Discrimination in the Labor Market for Recent College Graduates: Estimates from the Field

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## Abstract

We present experimental evidence from a correspondence test of racial discrimination in the labor market for recent college graduates. Online job advertisements were answered with over 9,000 résumés from fictitious, recently-graduated job seekers. 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 increases as perceived productivity characteristics are added, which is difficult to reconcile with models of statistical discrimination. We investigate different channels through which the observed racial differences might occur and conclude that taste-based discrimination at the race-skill level is the most likely explanation. The racial differences identified operate primarily through customer-level discrimination.

**JEL categories:** J23, J24, J71

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

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# 1 Introduction

Recessions disproportionately affect young black workers in the United States.<sup>1</sup> Although the unemployment rates of both black and white college graduates are significantly lower than non-graduates, Figure 1 shows that the unemployment differential between black and white college graduates becomes exacerbated during and following economic downturns. While the employment disparity between blacks and whites with college degrees could be explained by market discrimination, identifying racial discrimination from regression analysis of observational data is problematic.

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; 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 may be correlated with race, when confronted with racial-sounding names). The primary objective of this study 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 discrimi-

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<sup>1</sup>The national unemployment rate for this group remains over 25 percent almost four years after the official end of the last recession. The March 2007 unemployment rate for blacks aged 18-24 was 16.4 percent, while the March 2013 unemployment rate was 25.3 percent.

nation. For this reason, we focus on the employment prospects of 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, which follows Bertrand and Mullainathan (2004). 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.<sup>2</sup> By randomizing the timing of gaps in the work history, we indicate both unemployment spells and different levels of experience. The timing of work history gaps is randomized such that roughly 40 percent of the applicants are currently unemployed. 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.

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). We then responded to job advertisements exclusively from the business sector: banking, finance, insurance, management, marketing, and sales. Additionally, we randomly assigned in-field internships to provide another source of experience that is gained before the applicant enters the job market.

Our results 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

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<sup>2</sup>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.

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 there is no definitive test that would identify the type of discrimination observed, we implement a variety of indirect tests, which suggest that preferences for white candidates provide the underlying motivation for discrimination rather than beliefs about unobserved differences in the skill distribution between white and black job seekers. First, taste-based discrimination is less costly when there is slack in the labor market, which could explain the large (un)employment differentials from Figure 1 observed during and following recessions. Second, the return (as measured by interview requests) to observable productivity characteristics for black-named applicants is substantially lower than that for white-named applicants. Models of statistical discrimination predict that the racial gap in interview rates would close as employers are provided with more information about the applicant’s expected productivity. Third, the implementation of the methodology proposed by Neumark (2012), which decomposes discrimination into “level” and “variance” components, support taste-based discrimination as the most likely explanation for our findings. Because we often either do not detect or identify smaller differences at low-skill levels, our findings tend to support an augmented version of the taste-based model in which discrimination occurs at the race-skill level. The racial gap in employment opportunities that we detect seems to operate primarily through customer-level discrimination, as we find substantially larger interview rate differentials between black and white applicants for jobs that require 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. Altonji and Blank (1999) present a comprehensive review of such studies. For the most part, these studies find lower wages and

poorer job opportunities for blacks. Regression-based studies on racial discrimination have been criticized, as 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.<sup>3</sup>

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.<sup>4</sup> 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.<sup>5</sup>

There are two types of field experiments primarily used to study racial discrimination in the labor market: in-person audit and correspondence studies.<sup>6</sup> For the in-person audit framework, white and black “actors” are recruited and trained to navigate the interview process as if they are perfect substitutes. In-person audit studies have been criticized because

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<sup>3</sup>As a result, it is difficult to differentiate between the competing models of discrimination. Charles and Guryan (2008) and Fryer, Pager and Spenkuch (2011) are notable exceptions. 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 support a particular theory but to test certain predictions made by Becker’s (1971) theory. 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.

<sup>4</sup>Ball et al. (2001) focus on membership in low and high status groups, not racial discrimination; Glaeser et al. (2000) focus on trust and trustworthiness between members of several different demographic groups; and Fershtman and Gneezy (2001) examine ethnic discrimination in Israel. For more details on these studies as well as others that are related, see Anderson et al. (2006), who provide a thorough review of studies that use laboratory experiments to study discrimination.

<sup>5</sup>In the context of field experiments, 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 Siegleman 1995; Doleac and Stein forthcoming; List 2004; Nunley, Owens and Howard 2011).

<sup>6</sup>Correspondence studies, like the one that we use, are sometimes referred to as correspondence audits.

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 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). Correspondence studies are void of so-called “experimenter 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.

Both the 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; 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.<sup>7</sup> 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

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<sup>7</sup>The methodology proposed by Neumark (2012) is discussed in more detail in Section 4.3. 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).

racially-distinct names to signal race to prospective employers.<sup>8</sup> They find that black applicants receive about 50 percent fewer callbacks/interviews than their white counterparts. As in most studies of discrimination, Bertrand and Mullainathan (2004) relate their findings to existing theories. Neither taste-based nor statistical discrimination models convincingly explain their results. They argue that lexicographic search by employers, in which examination of an applicant’s résumé stops after the name is read, may explain the lower return to credentials that are detected for black applicants. Thus, the lower return to credentials could be due to employers never examining those résumé characteristics.

Our study differs from the study by Bertrand and Mullainathan (2004) in that we are interested in the labor-market opportunities facing recent college graduates. There are three reasons we focus on this group. First, understanding how discrimination might inhibit skilled workers (i.e. the college-educated) early in their careers has important policy implications. Secondly, unemployment differentials between black and white job seekers with college degrees are generally present but become surprisingly large during and after recessions (Figure 1). While numerous studies examine racial wage gaps, few studies examine the source of black-white unemployment differentials. Ritter and Taylor (2011) show that the same factors that account for the black-white wage gap cannot explain unemployment differentials between blacks and whites.<sup>9</sup> We are able to examine whether race-based discrimination is a source of the differentials in unemployment rates between black and white job seekers with college degrees. Thirdly, the use of applicants with lengthy work histories complicates tests for the type of discrimination. A sample of job seekers with short work histories and randomly assigned “hard” skills (i.e. in-field and internship experience) provides a cleaner test for the type of discrimination newly graduated job seekers might face.

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<sup>8</sup>There is a lengthy history of correspondence tests in the literature. Riach and Rich (2002) provide an excellent overview of field experiments aimed at testing for discrimination in various market settings.

<sup>9</sup>Couth and Fairlie (2010) examine whether “last hired, first fired” hypothesis can explain the black-white unemployment differentials, finding that narrowing of the unemployment gap between blacks and whites at the peak of business cycle is due to lower relative rates of job loss for blacks instead of increased hiring of blacks.

### 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.<sup>10</sup> 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.<sup>11</sup>

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,<sup>12</sup> whether they report their grade point average (GPA) on their résumé, whether the applicant

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<sup>10</sup>We applied to job openings through two well-known online-job-search websites.

<sup>11</sup>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 et al. (2011). The reliability of the racially-distinct names as signals for race is discussed in more detail in Section 4.2.

<sup>12</sup>Baert et al. (2013), Eriksson and Rooth (2014) and Kroft, Lange and Notowidigdo (2013) also examine how different length unemployment spells affect job opportunities.

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.<sup>13</sup> Each of these randomized résumé characteristics are coded as zero-one indicator variables.<sup>14</sup>

While much of the experimental design is produced via randomization, there are some features that we 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 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-specific dummy variables, which

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<sup>13</sup>Appendix Table A1 lists the variable names of the résumé characteristics, how the variables are defined and the sample means of the variables. The sample means are consistent with the probabilities that we chose for the random assignment of the résumé characteristics.

<sup>14</sup>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 are using 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.

holds constant unobservables specific to all four résumés. In addition, we cluster standard errors at the job-advertisement level.

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 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.<sup>15</sup> As a result, we omit these results from the paper.

Table 1 presents summary statistics for the interview 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 signif-

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<sup>15</sup>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 complete another step in the interview process (e.g., 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. As a result, there is a total of 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 results to these 17 callbacks by treating them as non-interview requests and by including observation-specific dummy variables, finding similar results to those presented in Section 4.

icant 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 in interview rates presented in Table 1 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 our analysis by estimating the following regression equation:

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

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* takes on a value of one when an applicant receives a request for an interview and zero otherwise; *black* is a zero-one indicator variable that takes on a value of 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);  $\phi_m$ ,  $\phi_c$ ,  $\phi_f$ , and  $\phi_j$  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  $\beta_0$ ,  $\beta_1$  and  $\gamma$  are parameters. We are primarily interested in the parameter  $\beta_1$ , which gives the average difference in the interview rate between black and white applicants.

Table 2 presents estimates for the parameter  $\beta_1$  from equation 1. The columns in Table 2 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; column (3) adds the set of month-of-application dummy variables; column (4) adds the city-of-application dummy variables; column (5) adds the job-category dummy variables; and column (6) adds the job-advertisement dummy variables. As is apparent from the Table 2, 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.<sup>16</sup>

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.  $\mathbf{X}$ ,  $\phi_m$ ,  $\phi_c$ ,  $\phi_f$ ,  $\phi_j$  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 2 is statistically significant at the 0.1 percent level.

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<sup>16</sup>We also tested for different interview rates between men and women, finding no economically or statistically significant difference in their interview rates. Furthermore, we tested for different 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.

## 4.2 Sensitivity Checks

While the use of racially-distinct names to signal race is not 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 uniqueness or oddity. 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.<sup>17</sup> 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.<sup>18</sup> 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 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

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<sup>17</sup>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>.

<sup>18</sup>The database can be found at <http://www.ssa.gov/OACT/babynames/#ht=0>.

\$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. In particular, we exclude names that have the highest and lowest rankings. 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).<sup>19</sup>

The sensitivity checks for the uniqueness and socioeconomic status of the racially-distinct names are presented in Table 3. 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-socioeconomic-status addresses randomly assigned to them; and columns (4) and (5) present the estimated differences in the interview rates between black and white applicants with high-socioeconomic-status addresses randomly assigned to them. 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.<sup>20</sup> In column (1), the estimate indicates that black applicants have

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<sup>19</sup>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.

<sup>20</sup>To produce the estimates shown in columns (2)-(5), we estimate the following regression equation:

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

The regression model above includes the full set of controls described in equation 1. The estimates for  $\beta_1$ , which give the estimated racial gap in interview rates between job seekers with low-socioeconomic-status

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 2 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.<sup>21</sup>

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

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

The subscripts  $i$ ,  $m$ ,  $c$ ,  $f$  and  $j$  and the variables  $black$ ,  $\mathbf{X}$ ,  $\phi_m$ ,  $\phi_c$ ,  $\phi_f$ ,  $\phi_j$  and  $u$  are defined above. The variable  $unemp_i^{3mo}$  is a zero-one indicator that equals one when an applicant is  


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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).

<sup>21</sup>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).

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  $\lambda_1$ ,  $\lambda_2$ ,  $\lambda_3$ ,  $\lambda_2 - \lambda_1$ ,  $\lambda_3 - \lambda_1$  and  $\lambda_3 - \lambda_2$ , which are difference-in-differences estimators. Relative to being currently employed, the parameter  $\lambda_1$  indicates whether a three-month current unemployment spell affects black applicants more or less adversely than it does white applicants;  $\lambda_2$  indicates whether a six-month current unemployment spell affects black applicants more or less adversely than it does white applicants; and  $\lambda_3$  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 with a 12-month current unemployment spell.

Each of the estimated difference-in-differences parameters or parameter combinations are presented in Table 4. 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 4 show that race-unemployment interactions are not responsible for the estimated differentials in interview rates detected in Table 2. None of the estimates are statistically significant at any reasonable level, nor are the estimated differentials economically significant.<sup>22</sup>

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<sup>22</sup>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

### 4.3 Empirical Tests for Different Types of Discrimination

There are two primary economic theories of discrimination, one based on tastes (Becker 1971) and the other based on incomplete information (Aigner and Cain 1977; Arrow 1973; Cornwell and Welch 1996; Lundberg and Startz 1983; Phelps 1972).<sup>23</sup> In the taste-based framework, members of minority groups are treated differently than members of majority groups because of prejudice or animosity (Becker 1971).<sup>24</sup> If employers have racist preferences, Becker’s (1971) model predicts that employers hire fewer black applicants than white applicants, despite both having the same productivity characteristics.<sup>25</sup>

Another class of discrimination models emphasizes the role of incomplete information as the source of differential treatment by race, which is often referred to as statistical discrimination. Such discrimination is not based on animus but instead on incomplete information. First, employers may use observable characteristics, such as race, to proxy for unobservables (e.g., productivity) (Arrow 1973; Phelps 1972). This type of discrimination in hiring should be mitigated or possibly eliminated when observables signal high productivity, which business degrees, internship experience and in-field work experience proxy. Secondly, the precision of information that employers have concerning productivity may vary by race; that is, employers may place less weight on the observables skills of black job seekers, which implies a lower “return” for black applicants who possess such skills (Cain and Aigner 1977;

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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 2.

<sup>23</sup>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 otherwise identical 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.

<sup>24</sup>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, etc.). See Charles and Guryan (2008) for an examination of other predictions made by Becker (1971).

<sup>25</sup>In the context of Becker (1971), discrimination in hiring need not operate only through employer preferences, it can also occur via customer and/or employee discrimination. Later in this section, we examine and discuss the possibility that the discrimination that we identify operates through the customer and/or employee channels.

Cornwell and Welch 1996; Lundberg and Startz 1983). Our experimental design randomly assigns the same sets of skills to black and white applicants, making it unlikely that the precision of information is driving the interview differentials between black and white applicants. Third, there may be bias associated with the observed signal, which may be the result of employers discounting the skills of black applicants because of affirmative action or related policies that may make it easier for black applicants to obtain such credentials. As Bertrand and Mullainathan (2004) argue, such differential treatment by race may result from certain credentials (e.g., employee of the month), but it should be less likely to result from attributes that are easily verifiable (e.g., internship or in-field work experience). Because of the reasoning presented above, we discount the possibility that the precision of information or bias associated with the observable signal is driving the differential treatment by race. Instead, we focus on the type of statistical discrimination that emphasizes the use of race by employers to proxy for unobservables, such as expected productivity.

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 potentially confound attempts to identify discrimination as well as parsing taste-based from 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 correspondence studies are better at controlling what employers observe.<sup>26</sup> However, Neumark (2012) argues that the correspondence methodology and in-person audits share the common limitation that the variance of unobservables

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<sup>26</sup>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.

between blacks and whites may be different. In the context of Aigner and Cain’s (1977) model of statistical discrimination, the differential treatment between black and white applicants is based on differences in the variances of unobservables between black and white applicants. In what follows, we conduct a variety of indirect tests of the predictions made by discriminatory models based on tastes and incomplete information.

The first set of empirical tests uses the following regression equation to examine how race interacts with different productivity signals:

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

The subscripts  $i$ ,  $m$ ,  $c$ ,  $f$  and  $j$  and the variables  $black$ ,  $\mathbf{X}$ ,  $\phi$ , and  $u$  are defined above. The variable  $signal$  is a indicator variable that equals one when an applicant is assigned a resume attribute that signals high productivity. The parameter  $\beta_1$  gives the average difference in the interview rate between black and white applicants with no productivity 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 high productivity signal assigned to them; and the parameter  $\beta_3$  indicates whether the racial gap in employment opportunities is smaller, larger, or similar between applicants with and without the productivity signals assigned to them.<sup>27</sup> We use three separate productivity signals when estimating equation 3: business degrees, internship experience and in-field work experience. The first two productivity signals are accumulated while the applicants are completing their college degrees, while the latter productivity signal is accumulated after the applicants complete their college degrees.

We begin our indirect tests by examining whether the racial gap in employment opportunities varies with the type of degree applicants possess. Because we apply exclusively to

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<sup>27</sup>The parameter  $\beta_3$  is a difference-in-differences estimator, as it is the difference between two differences. The first difference is between black and white applicants with the productivity signal, which is  $\beta_1 + \beta_3$ . The second difference is between black and white applicants without the productivity signal, which is  $\beta_1$ . Taking the difference between these two differences leaves  $\beta_3$ —the difference-in-differences estimator.

jobs in business-related categories, it is possible that the black-white differentials in interview rates vary by the type of college major, as business majors may be more suitable for such jobs than non-business majors. For this purpose, we compare the difference in interview rates between black and white applicants with and without business degrees and also examine whether the racial gap in interview rates is larger, smaller or similar between applicants with and without business degrees. We treat accounting, economics, finance, management and marketing as business degrees, while psychology, biology, history and English are considered non-business degrees.<sup>28</sup> These estimates are presented in Table 5. 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; the estimate presented in column (2) is statistically significant at the 0.1 percent level; and the relative difference between racial difference in interview rates for business majors and that for non-business majors is statistically significant at the 10-percent level.<sup>29</sup>

Our second indirect test examines whether the racial gap in employment opportunities varies between 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

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<sup>28</sup>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.  $\beta_3$ , is not statistically different from zero. However, it is likely economically significant with a estimated differential of 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.

<sup>29</sup>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.

within the job category for which they are applying.<sup>30</sup> Internship experience is working as a(n) “Equity 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. These estimates are presented in Table 6. 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.

Next, we examine whether racial discrimination varies with the type of work experience that applicants accumulate after they complete their degrees. As a part of our experimental design, we randomly assign “in-field” and “out-of-field” work experience to our applicants. 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.<sup>31</sup> 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. Table 7 presents these estimates. For applicants with out-of-field experience, we find no statistical evidence of a differential in the interview rates

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<sup>30</sup>The internship experience was acquired in Summer 2009, the year before the applicants completed their college degrees in May 2010. The internships lasted only for the summer (i.e. three months).

<sup>31</sup>For the sales job category, we exclusively use “Retail Associate” as the relevant type of out-of-field experience.

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 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).<sup>32</sup>

In Table 8, we examine the racial gap in employment opportunities between job seekers with none, some and all of the three aforementioned productivity signals. Column (1) presents the estimated differential between black and white job applicants with none of the productivity signals; column (2) shows the estimated interview differential between black and white applicants with business degrees (also presented in column (2) of Table 5); column (3) shows 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.<sup>33</sup>

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

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<sup>32</sup>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 in-field work experience.

<sup>33</sup>Appendix Section A2.3 provides details on how the estimates in Table 8 are generated.

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, 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).<sup>34</sup>

Our final attempt to separate taste-based (in general) from statistical discrimination relies on the methodology proposed by Neumark (2012). A requirement of Neumark’s identification strategy 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).<sup>35</sup> 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. 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 that 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. Computing these marginal effects, we find that the partial effect, which is the sum of the level and variance components, is  $-0.025$ ,<sup>36</sup> which is consistent with what we find via the linear prob-

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<sup>34</sup>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.

<sup>35</sup>In our data, internship experience and in-field work experience both raise the probability of receiving an interview request in economically and statistically significant ways.

<sup>36</sup>We were unable to estimate the full model that is depicted in equation 1. In particular, it was not

ability models presented in Section 4.1. The marginal effect through the level is  $-0.038$  and the marginal effect through the variance is  $0.013$ . Neither the marginal effect through the level or the marginal effect through the variance is 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 understate the extent of taste-based discrimination against black applicants. These results suggest that the structural parameter, i.e. the marginal effect of race through the level, is indeed negative and economically large, an indication that there is some evidence of taste-based discrimination.

The random assignment of business degrees, internship experience and in-field work experience allows us to conduct a simultaneous indirect test of taste-based discrimination on the part of employers and statistical discrimination. If employers have a preference for white applicants over black applicants, Becker’s (1971) model posits that employers will hire black applicants at lower rates than white applicants with the same productivity characteristics. Models emphasizing statistical discrimination predict that discrimination declines with positive productivity signals (e.g., Arrow 1973; Phelps 1972), which business degrees, internship experience and in-field work experience proxy. Taken together, our findings presented in Tables 5, 6, 7 and 8 indicate that the differential treatment by race *increases* with perceived productivity characteristics. These findings as well as those using the approach developed by Neumark (2012) are difficult to reconcile with theories of statistical discrimination. Our findings are largely consistent with the taste-based model. However, the fact that we sometimes do not observe economically or statistically significant racial differences in interview rates at low-skill levels is at odds with a taste-based interpretation. Alternatively, our results

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possible to estimate equation 1 via the heteroskedastic probit model with the job-advertisement dummy variables ( $\phi_j$ ) included. However, we were able to estimate the heteroskedastic probit model with all of the other controls included.

seemingly fit an augmented version of the taste-based model that emphasizes discrimination at the race-skill level.

Because our data tend to support a form of taste-based discrimination, we examine whether the differential treatment by race operates through customer- and/or employee-level discrimination. An empirical test of customer discrimination is to compare the employment opportunities facing black and white applicants for jobs that require contact with customers.<sup>37</sup> Similarly, an empirical test of employee discrimination is to compare the differentials in the employment opportunities facing black and white applicants for jobs that require collaboration among colleagues. In order to conduct indirect tests for customer and employee discrimination, 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.<sup>38</sup> We estimate the following regression equation:

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

The subscripts  $i$ ,  $m$ ,  $c$ ,  $f$  and  $j$  and the variables  $black$ ,  $\mathbf{X}$ ,  $\phi$  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

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<sup>37</sup>Holzer and Ihlanfeldt (1998) present evidence of customer discrimination, finding that differential treatment of minorities is particularly present in jobs that require contact with customers, such as sales and service occupations.

<sup>38</sup>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.

*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.<sup>39</sup> The estimates for these linear combinations of parameters are presented in Table 9. The columns in Table 9 differ based on the words used to create the *customer* and *employee* variables. 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 9 indicate that the racial discrimination detected in previous specifications operates primarily through discrimination on the part of customers; that is, it appears that employers attempt to appease their customer base by interviewing fewer blacks (relative to whites) in jobs that require contact with customers. As a way to further investigate whether discrimination operates through customers, 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).<sup>40</sup>

We find no empirical support for employee discrimination, as the estimates are economically

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<sup>39</sup>The estimate for  $\beta_1$  gives the average difference in the interview rate between black and white applicants for jobs that are difficult to classify as requiring significant customer and/or employee interaction.

<sup>40</sup>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.

small and none of the estimates are statistically different from zero.

## 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, which is difficult to reconcile with models of statistical discrimination.

However, our findings are not entirely consistent with the taste-based model (Becker 1971), as we sometimes detect no difference in the employment opportunities facing black and white job seekers with low productivity signals. As a result, our results support a variant of the taste-based model that emphasizes discrimination at the race-skill level. The differential treatment by race detected appears to operate primarily through customer-level discrimination, as we find substantial black-white interview differentials in jobs that require interaction with customers. 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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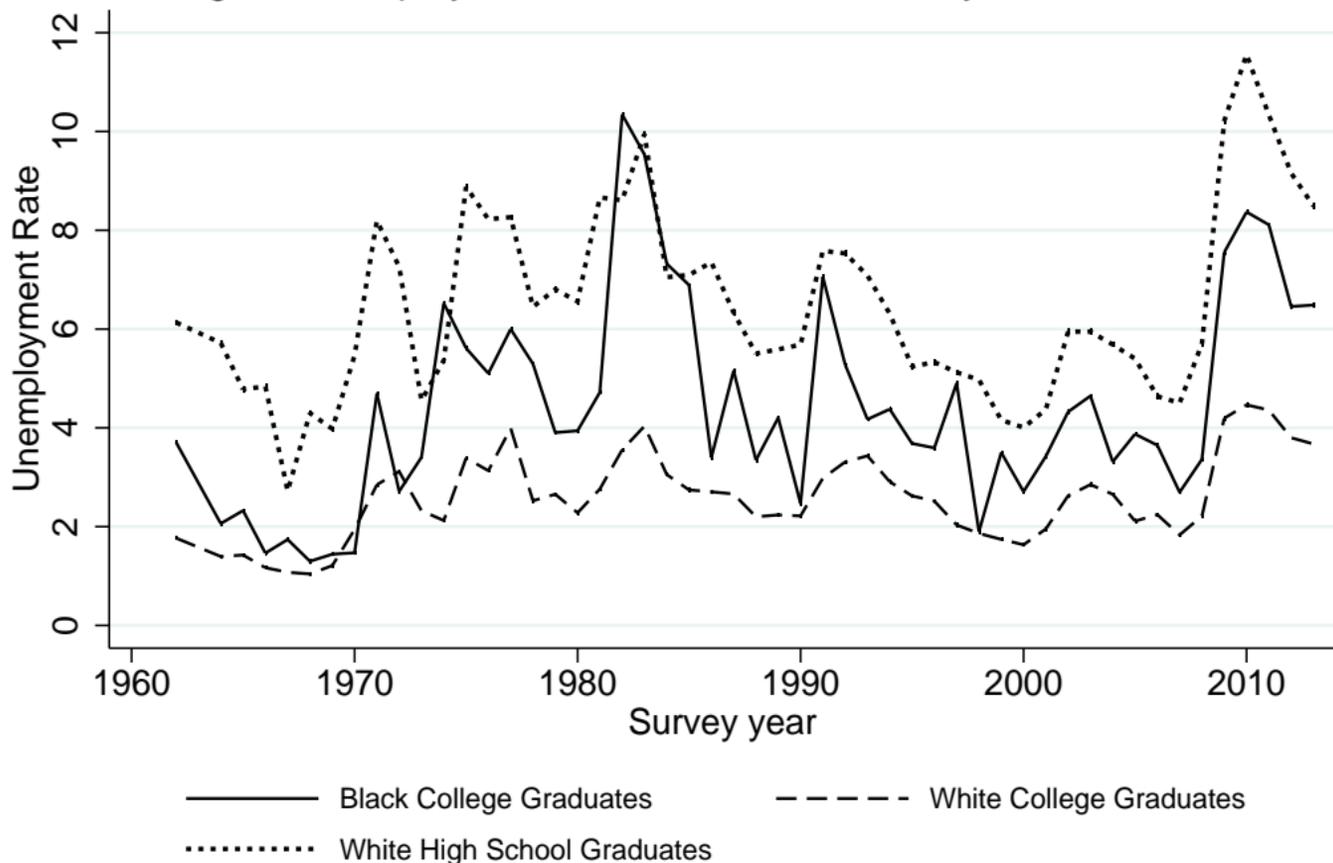
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Fig. 1: Unemployment of Blacks and Whites by Education Level



Notes: Each series was constructed of all black and white individuals of working age in the labor force from the March CPS for the years 1962-2013.

Table 1: Average Interview Rates

	All	White	Black	Difference in Means	
	(1)	(2)	(3)	(4)	
Overall	0.166	0.180	0.152	-0.028	***
<i>By City:</i>					
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	
<i>By Job Category:</i>					
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 2: Race and Job Opportunities

	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.028*** (0.007)	-0.027*** (0.007)	-0.027*** (0.007)	-0.027*** (0.007)	-0.026*** (0.007)	-0.022*** (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. ‘Resume’ represents controls for the randomized resume 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 3: Race, Uniqueness, and Socioeconomic Status

	Low Socioeconomic Status		High Socioeconomic Status		
	Common Names	Full Sample	Common Names	Full Sample	Common Names
	(1)	(2)	(3)	(4)	(5)
Black	-0.027** (0.009)	-0.022* (0.009)	-0.029* (0.014)	-0.021* (0.008)	-0.023+ (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 (See footnote 20). Each regression model includes the full set of control variables. The samples used in columns (1), (3) and (5) include only observations from applicants with ‘common’ names, while columns (2) and (4) present results using the full sample of applicants.

Table 4: Race, Unemployment Spells, and Job Opportunities

	<i>unemp</i> <sup>3mo</sup> relative to <i>employed</i>	<i>unemp</i> <sup>6mo</sup> relative to <i>employed</i>	<i>unemp</i> <sup>12mo</sup> relative to <i>employed</i>	<i>unemp</i> <sup>6mo</sup> relative to <i>unemp</i> <sup>3mo</sup>	<i>unemp</i> <sup>12mo</sup> relative to <i>unemp</i> <sup>3mo</sup>	<i>unemp</i> <sup>12mo</sup> relative to <i>unemp</i> <sup>6mo</sup>
	(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	$\lambda_1$	$\lambda_2$	$\lambda_3$	$\lambda_2 - \lambda_1$	$\lambda_3 - \lambda_1$	$\lambda_3 - \lambda_2$
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. Each specification uses the full set of control variables.

Table 5: Race, Type of Degree, and Job Opportunities

	Non- Business	Business	Business Relative to Non- Business
	(1)	(2)	(3)
Black	-0.010 (0.009)	-0.031*** (0.008)	-0.021+ (0.012)
$R^2$	0.724	0.724	0.724
Observations	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 10 and 0.1 percent levels, respectively. The regression model used to produce the estimates relies on the full set of control variables.

Table 6: Race, Internship Experience, and Job Opportunities

	No Internship	Internship	Internship Relative to No Internship
	(1)	(2)	(3)
Black	-0.016* (0.008)	-0.040*** (0.013)	-0.024+ (0.015)
$R^2$	0.724	0.724	0.724
Observations	9396	9396	9396

*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 and 0.1 percent levels, respectively. The regression model used to produce the estimates relies on the full set of control variables.

Table 7: Race, Type of Work Experience, and Job Opportunities

	Out-of-Field Experience	In-Field Experience	In-Field Experience Relative to Out-of-Field Experience
	(1)	(2)	(3)
Black	-0.008 (0.008)	-0.035*** (0.009)	-0.027* (0.013)
$R^2$	0.725	0.725	0.725
Observations	9396	9396	9396

*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. The regression model used to produce the estimates relies on the full set of control variables.

Table 8: Race, Productivity Signals and Job Opportunities

	(1)	(2)	(3)	(4)
Black	0.008 (0.014)	-0.031*** (0.008)	-0.052** (0.017)	-0.067** (0.024)
<i>Productivity Signals</i>				
College Degree	No	Yes	Yes	Yes
Internship Experience	No	No	Yes	Yes
In-Field Experience	No	No	No	Yes

*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) use 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 9: Indirect Tests for Customer and Employee Discrimination

	(1)	(2)	(3)	(4)	(5)
<i>Customer Discrimination</i>					
Black	-0.037** (0.013)	-0.039** (0.014)	-0.043*** (0.013)	-0.043*** (0.013)	-0.045*** (0.013)
<i>Words in Job Title:</i>					
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
<i>Employee Discrimination</i>					
Black	-0.003 (0.009)	-0.003 (0.009)	-0.003 (0.009)	-0.002 (0.009)	-0.001 (0.008)
<i>Words in Job Title:</i>					
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

*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. For the customer categorization, there are 2701, 2797, 3128, 3255 and 3377 observations in columns (1), (2), (3), (4) and (5), respectively, that have the words listed in the table within the job titles. For the employee categorization, there are 1965, 2042, 2459, 2527 and 2547 observations in columns (1), (2), (3), (4) and (5), respectively, that have the words listed in the table within the job titles.

# For Review Purposes Only

## Appendix

### A1 Data

#### A1.1 Résumé Characteristics

While details on the résumé characteristics are provided in what follows, Table A1 summarizes the variable names, definitions and provides the means of the variables. Some of the variables are omitted from Table A1 (e.g., university that the applicant graduated from) per our agreement with our respective institution review boards.

##### *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.<sup>41</sup> 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

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<sup>41</sup>Here is the link to the most common surnames in the U.S.: <http://www.census.gov/genealogy/www/data/2000surnames/index.html>

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 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<sup>42</sup> 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.

<sup>42</sup>Visit the following webpage: <http://www.princetonreview.com/college/top-ten-majors.aspx>.

*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 is an example of how the “Honor’s” (left) and “GPA” (right) traits were signaled on the *résumés*.<sup>43</sup>

<b>Education</b>	<b><u>Education</u></b>
<b>Bachelor of Science, May 2010</b>	University of XYZ <sup>43</sup>
<b>University of XYZ</b>	Bachelor of Science, May 2010
<b>English (Honors)</b>	English
	<b>GPA 3.9</b>

*(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

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<sup>43</sup>The university name was replaced with XYZ to conform to the terms of the agreement with our institutional review boards.

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 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	<ul style="list-style-type: none"> <li>•Evaluate present market conditions to decide resource allocation to different products and services</li> <li>•Design employee schedules, appointed temporary workforce for a busy seasons, and interview and hire all new employees</li> <li>•Kept in depth records of all industry activities to attain the regulatory needs</li> <li>•Focus on process flow improvement by examining sales relationships and visit several company locations frequently to ensure smooth processes</li> <li>•Produce thorough budgets for the number of operations, tracked the actual expenditures and reviews exceptions</li> <li>•Train and handle a number of employees and build operational principles</li> <li>•Manage branch employees with a focus on branch compliance</li> </ul>
Infield 2	Bank Branch Assistant Manager	<ul style="list-style-type: none"> <li>•Trained 30 new employees and attained significant improvements in their productivity over time</li> <li>•Visited several company locations frequently to ensure smooth processes</li> <li>•Maintain records of cash limits, checks, deposits, fund transfer, money orders, debit cards issued and other banking activities</li> <li>•Suggested new methods for business, developing services for business clients and reducing wait for the personal account clients</li> <li>•Overhauled accounting systems, bookkeeping operations, and interview processes</li> <li>•Provide support in all clerical responsibilities and other daily tasks within the bank</li> </ul>
Internship 1	Equity Capital Markets Intern	<ul style="list-style-type: none"> <li>•Created analytical models and spreadsheets</li> <li>•Assessed market capacity for equity products</li> <li>•Analyzing cost of capital of various financing options</li> </ul>
Internship 2	Capital Markets Intern	<ul style="list-style-type: none"> <li>•Created statistical models to capture and present quantitative data</li> <li>•Generated reports and prepared presentations to assist senior managers</li> <li>•Used Excel and Access to perform analysis and conduct research</li> </ul>

Finance		
	Job Title	Resume Description
Infield 1	Accounts Payable	<ul style="list-style-type: none"> <li>•Prepare and analyze fund statements, balance sheets and salary schedules for firm and her subsidiaries</li> <li>•Responsible for supporting program managers in the development and analysis of financial reports, and spending plans</li> <li>•Review all invoices for appropriate documentation and approval prior to payment</li> <li>•Responds to questions and makes calls regarding billing problems; acts as a liaison between department and vendors</li> </ul>
Infield 2	Financial Advisor	<ul style="list-style-type: none"> <li>•Conduct in-depth reviews of clients' financial circumstances and prepared plans best suited to their requirements</li> <li>•Design detailed financial strategies and explained reports to cliental</li> <li>•Contact clients with news of new financial products or changes to legislation that may affect their savings and investments</li> <li>•Meet all regulatory aspects of the role, e.g. requirements for disclosure, and costs of services provided</li> <li>•Responsible for preparing and maintaining financial statements and invoices in an accurate manner</li> </ul>
Internship 1	Financial Analyst Intern	<ul style="list-style-type: none"> <li>•Conducted financial and business analysis to generate insights that influenced cross-functional decision-making</li> <li>•Led process innovation to drive efficiency and deliver insightful perspective on key business drivers</li> <li>•Leveraged data and information systems to forecast performance and articulate key drivers of change</li> </ul>
Internship 2	Financial Analyst Intern	<ul style="list-style-type: none"> <li>•Conducted financial and business analysis to generate insights that influenced cross-functional decision-making</li> <li>•Led process innovation to drive efficiency and deliver insightful perspective on key business drivers</li> <li>•Leveraged data and information systems to forecast performance and articulate key drivers of change</li> </ul>

Insurance		
	Job Title	Resume Description
Infield 1	Insurance Sales Agent	<ul style="list-style-type: none"> <li>•Customize insurance programs to suit individual customers, often covering a variety of risks</li> <li>•Develop marketing strategies to compete with other individuals or companies who sell insurance</li> <li>•Seek out new clients and develop clientele by networking to find new customers and generate lists of prospective clients</li> <li>•Prepared activity reports with the interpretation, implementation and enforce company policies, strategies and procedures</li> <li>•Monitor insurance claims to ensure they are settled equitably for both the client and the insurer</li> <li>•Inspect property, examining its general condition, type of construction, age, and other characteristics, to decide if it is a good insurance risk</li> <li>•Resolved clients' claim issues in assistance of manager</li> </ul>
Infield 2	Insurance Sales Agent	<ul style="list-style-type: none"> <li>•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</li> <li>•Strive to achieve optimum customer satisfaction and access coverage, liability and damage</li> <li>•Responsible for appointing a legal representative for the court cases and communicating with the agents to resolve the issues</li> <li>•Ensure that policy requirements are fulfilled, including any necessary medical examinations and the completion of appropriate forms</li> <li>•Calculate premiums and establish payment method</li> </ul>
Internship 1	Intern	<ul style="list-style-type: none"> <li>•Asked probing and challenging questions to uncover a prospective clients needs</li> <li>•Identified and understood a prospect's needs to help create solutions</li> <li>•Handled objections and effectively built relationships</li> </ul>
Internship 2	Intern	<ul style="list-style-type: none"> <li>•Asked probing and challenging questions to uncover a prospective clients needs</li> <li>•Identified and understood a prospect's needs to help create solutions</li> <li>•Handled objections and effectively built relationships</li> </ul>

Marketing		
	Job Title	Resume Description
Infield 1	Marketing Specialist	<ul style="list-style-type: none"> <li>•Conducted qualitative and quantitative research to help guide new creative efforts</li> <li>•Evaluated all potential sponsorship/partnership opportunities</li> <li>•Researched multi-channel marketing efforts of five key advertisers to prepare comprehensive report on how to target consumers for agency-wide project</li> <li>•Directed and manage 4 internal staff and network of 3 external local-market agencies/consultants</li> <li>•Developed, sold, moderated, and interpreted results for more than 100 qualitative focus groups and one-on-one sessions for firm</li> <li>•Evaluated target markets and proposed marketing strategies</li> <li>•Turned 17% sales decline into 20% increase in two years by overhauling entire marketing effort and launching company's first-ever national advertising campaign</li> </ul>
Infield 2	Marketing Specialist	<ul style="list-style-type: none"> <li>•Analyzed regular corporate retail sales reports and tailor each local marketing profit-plan with retail leadership</li> <li>•Programs increased average store traffic 21% and sales averaging 12%, contributing to unprecedented growth</li> <li>•Explored multi-cultural trends and developed volumetric sales analysis to convince firm to address diverse "non-traditional" audiences across all brands</li> <li>•Created 5 integrated and multi-tiered new store opening programs in domestic &amp; international locations</li> <li>•Designed, developed and implemented marketing and sales campaigns, fundraisers, employee incentive programs and contests</li> <li>•Introduced planning discipline and mass advertising techniques to entertainment retailer with more than ten million in sales</li> <li>•Managed all phases of direct mail projects; monitored production teams; recruited and guided vendors; oversaw print operations and coordinated mailing process</li> </ul>
Internship 1	Marketing Business Analyst Intern	<ul style="list-style-type: none"> <li>•Analyzed the divisional business to identify problems, opportunities, and trends</li> <li>•Executed elements of the marketing plan, including price promotions</li> <li>•Managed multiple projects</li> </ul>
Internship 2	Marketing Business Analyst Intern	<ul style="list-style-type: none"> <li>•Analyzed the divisional business to identify problems, opportunities, and trends</li> <li>•Executed elements of the marketing plan, including price promotions</li> <li>•Managed multiple projects</li> </ul>

Sales		
	Job Title	Resume Description
Infield 1	Sales Representative	<ul style="list-style-type: none"> <li>•Sold and marketed packaging products to manufacturers in a two-state territory</li> <li>•Managed account base of 70 which is an increase of 14 accounts over from previous year</li> <li>•Assigned responsibility to mentor/develop three inside salespeople for promotion to outside sales positions</li> <li>•Recaptured 4 lost accounts during first year of employment</li> <li>•Developed strong referral system which provides continuous leads for new business development</li> <li>•Exceptional leadership, organizational, oral/written communication, interpersonal, analytical, and problem resolution skills</li> <li>•Named "Salesman of the Month" four times during work tenure</li> </ul>
Infield 2	Sales Consultant	<ul style="list-style-type: none"> <li>•Proactive leader with refined business acumen and exemplary people skills. Facilitate a team approach to achieve organizational objectives, increase productivity and enhance employee morale</li> <li>•Helped develop an expansive plan to increase sales by over 30% over the next five years</li> <li>•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.</li> <li>•Quick study, with an ability to easily grasp and put into application new ideas, concepts, methods and technologies</li> <li>•Dedicated, innovative and self-motivated team player/builder</li> <li>•Thrive in both independent and collaborative work environments</li> <li>•Review product pricing and gross margin goals for existing products annually</li> </ul>
Internship 1	Sales Intern	<ul style="list-style-type: none"> <li>•Assisted sales representatives, who sold Auto, Home, Life, and other insurance products</li> <li>•Spent time out of the office observing and assisting with sales events</li> <li>•Worked with Sales Reps to identify prospective customers using established lead methods</li> </ul>
Internship 2	Sales Future Leader Intern	<ul style="list-style-type: none"> <li>•Utilized analytical and fact-based selling skills to grow volume, revenue, and profitability goals for the assigned territory</li> <li>•Activated local and national marketplace initiatives and promotions through merchandising products and building creative displays</li> <li>•Performed at a fast pace in a self-motivated position</li> </ul>

Out-of-Field & College		
	Job Title	Resume Description
Outfield 1	Sales Associate <sup>1</sup>	<ul style="list-style-type: none"> <li>•Team leader in sales for two consecutive months</li> <li>•Greet patrons at door and assisted them in locating their desired purchases</li> <li>•Manage sales desk while assisting customers with purchase</li> <li>•Promote company brands whenever possible</li> <li>•Communicate to manager any possible areas of improving the customer service experience</li> <li>•Restock items on sales floor as needed</li> <li>•Handle customer complaints and problems in the most efficient way possible</li> </ul>
Outfield 2	Retail Associate	<ul style="list-style-type: none"> <li>•Open and close cash registers, performing tasks such as counting money, separating charge slips, coupons, and vouchers, balancing cash drawers, and making deposits</li> <li>•Recommend, select, and help locate or obtain merchandise based on customer needs and desires</li> <li>•Describe merchandise and explain use, operation, and care of merchandise to customers</li> <li>•Place special orders or call other stores to find desired items</li> </ul>
College 1	Barista	<ul style="list-style-type: none"> <li>•Ensured counters, customer areas are neat, clean and presentable</li> <li>•Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment</li> <li>•Served food, beverages, or desserts to customers in a fast paced environment</li> <li>•Followed cash handling procedures and cash register policies</li> </ul>
College 2	Tutor <sup>2</sup>	<ul style="list-style-type: none"> <li>•Worked with students to help them better understand _____<sup>3</sup> concepts</li> <li>•Identified the preferred communication style of the students and adjusted tutorial sessions accordingly</li> <li>•Taught tailored large-group review sessions before exams</li> </ul>
College 3	Customer Service Representative	<ul style="list-style-type: none"> <li>•Served as a resource by providing accurate and current information regarding recreation and university-related programs and facilities</li> <li>•Maintained current certifications in first aid, CPR, and AED.</li> <li>•Counseled peers on personal, academic, and career concerns</li> <li>•Assist with data entry of fitness and intramural participants into Access database and IMTrack</li> </ul>
College 4	Sales Associate	<ul style="list-style-type: none"> <li>•Asked lifestyle questions to thoroughly understand customer needs, offers relevant services, solutions, and accessories so customer can make informed decision to complete their purchase</li> <li>•Leveraged on-line resources, tools, and peer knowledge to self-train</li> <li>•Utilized all relevant sales tools to drive profitable growth</li> </ul>

*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

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### **ABC University**

Bachelor of Science, May 2010  
Management

## Work Experience

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### **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

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University of ABC  
Bachelor of [Science](#), May 2010  
Psychology  
GPA 3.9

## Work Experience

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### ***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

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## Education

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Bachelor of Science, May 2010  
University of ABC  
Management

## Work Experience

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*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 Sliph  
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 Beasley (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 and Employment Prospects

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

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

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  $\beta_1$ , 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  $\beta_2$ . 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, Work Experience, and Employment Prospects

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  $\beta_3$  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 8

To produce the estimates presented in Table 8, we use three different regression models. The first regression equation of interest is

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

The subscripts  $i$ ,  $m$ ,  $c$ ,  $f$  and  $j$  and the variables  $interview$ ,  $black$ ,  $\mathbf{X}$ ,  $\phi$  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

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

The subscripts  $i$ ,  $m$ ,  $c$ ,  $f$  and  $j$  and the variables  $interview$ ,  $black$ ,  $bus$ ,  $\mathbf{X}$ ,  $\phi$ , 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

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

The subscripts  $i$ ,  $m$ ,  $c$ ,  $f$  and  $j$  and the variables  $black$ ,  $bus$ ,  $intern$ ,  $\mathbf{X}$ ,  $\phi$ , 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  $\beta_1$  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: résumé Characteristics, Definitions, and Means**

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Variable Name	Variable Definitions	Mean
<i>black</i>	=1 if applicant has a distinctively black name	0.497
<i>female</i>	=1 if applicant has a distinctively female name	0.499
<i>econ</i>	=1 if applicant has a Bachelor's degree in Economics	0.115
<i>finance</i>	=1 if applicant has a Bachelor's degree in Finance	0.101
<i>acctg</i>	=1 if applicant has a Bachelor's degree in Accounting	0.112
<i>mgmt</i>	=1 if applicant has a Bachelor's degree in Management	0.114
<i>mkt</i>	=1 if applicant has a Bachelor's degree in Marketing	0.111
<i>eng</i>	=1 if applicant has a Bachelor's degree in English	0.110
<i>psych</i>	=1 if applicant has a Bachelor's degree in Psychology	0.114
<i>bio</i>	=1 if applicant has a Bachelor's degree in Biology	0.116
<i>hist</i>	=1 if applicant has a Bachelor's degree in History	0.108
<i>nogap</i>	=1 if applicant has a no gap in their work history	0.255
<i>front3</i>	=1 if applicant has a 3-month gap in their work history after finishing degree	0.125
<i>front6</i>	=1 if applicant has a 6-month gap in their work history after finishing degree	0.121
<i>front12</i>	=1 if applicant has a 12-month gap in their work history after finishing degree	0.125
<i>back3</i>	=1 if applicant has a current 3-month gap in their work history	0.124
<i>back6</i>	=1 if applicant has a current 6-month gap in their work history	0.123
<i>back12</i>	=1 if applicant has a current 12-month gap in their work history	0.127
<i>intern</i>	=1 if applicant worked as an intern while completing their degree	0.248
<i>infield</i>	=1 if applicant worked in the field for which they are applying for a job	0.500
<i>highses</i>	=1 if applicant has an address in a high-socioeconomic-status area	0.499
<i>honors</i>	=1 if applicant reports completing their degree with an Honor's distinction	0.248
<i>gpa</i>	=1 if applicant reports a grade point average (GPA) of 3.9 on their résumé	0.249
<i>exp</i>	Number of months that applicant has worked since completing their degree	30.02

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**Table A2: Race-Gender Interactions and Interview Rates**

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Regression Estimates</i>						
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)
<i>Linear Combinations</i>						
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	9397	9397	9397	9397	9397	9397

*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. ‘Resume’ represents controls for the randomized resume 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)
<i>Specification 1:</i>				
Black	-0.031*** (0.008)	-0.018 (0.013)	-0.011 (0.014)	0.008 (0.017)
<i>Specification 2:</i>				
Black	-0.032*** (0.009)	-0.021* (0.009)	-0.011 (0.014)	0.008 (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 full set of control variables.

**Table A4: Race, Work Experience, and Interview Rates**

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

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

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*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**

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

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*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.