University-Level Recruiting and Black Underrepresentation in the Auditing Profession

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Abstract: For decades, Black people have been earning accounting degrees at high rates and, since the 1960s, the auditing profession has been making highly publicized efforts to increase the hiring and retention of Black workers. Yet, today, Black people remain underrepresented among auditors. Why? One theory is that Black underrepresentation in auditing is partially a consequence of the recruiting practices of auditing firms, which some argue is targeted at universities with few Black graduates. In this study, we use novel data on the hiring practices of auditing firms to test this theory. We find evidence that big N and non-big N audit firms hire significantly fewer graduates from universities with high levels of Black representation, a result that is robust to the inclusion of a number of controls including measures of university, business school, and accounting program quality. Further analyses suggest that the negative association between high Black representation and audit firm hiring is partially attributable to racially biased hiring practices of the audit firms and partially attributable to a limited supply of qualified Black accounting graduates. Our evidence also suggests that a significant portion of the problem of Black underrepresentation in the auditing profession could be corrected at low cost and without reducing the quality of people hired if audit firms were to reallocate recruiting resources across schools.

Keywords: Audit Firms, Professional Services Firms, Diversity, Institutional Racism, Discrimination

I. INTRODUCTION

Black people[1] have long been underrepresented in the auditing profession when it is compared to other American professions (Hammond 1997 and 2002; Mitchel 1969 and 1976). They are still underrepresented in auditing today (AICPA 2012, Department of the Treasury 2008, Hammond 2004, Madsen 2013, Moyes et al. 2000). This is, perhaps, surprising given the significant efforts on the part of the auditing profession, beginning in the 1960s, to recruit and retain minority-race employees (AICPA 2012, Hammond 1997, Hammond and Streeter 1994, Moyes et al. 2000), and given evidence that, from 1968 through 2010, Black college freshmen have planned to major in accounting at particularly high rates, Black college graduates have been particularly likely to hold accounting degrees, and Black auditors[2] have been paid similarly to White auditors while this has not been the case for many other jobs (Madsen 2013). Why, given the profession's interest in hiring Black workers, Black college students' interest in becoming accountants, and equal pay for Black auditors, are Black people still distinctively poorly represented in the auditing profession? In this study, we assemble a novel dataset describing, for university-years between 2001 and 2014, counts of graduates hired by audit firms, the racial composition of graduating accounting classes, and school quality, and find evidence that audit

[1] Throughout this study, we refer to the demographic group of interest as "Black people." People in this group are categorized as "Black" or "Black, African American, or Negro" in our datasets. Alternatives to the term "Black people" we might have chosen include "African Americans," "Black Americans," or "Blacks" (Harris 2014). We do not use these terms because 1) we do not narrow our sample to consider only American citizens and it would, therefore, be inaccurate to refer to the group we study as Americans, and 2) we prefer to use the term "Black" as an adjective but not a noun, consistent with many journalistic style guides (e.g. http://www.nabj.org/?styleguideA). In addition, we have chosen to capitalize the proper names of all nationalities, people, races, or tribes following the logic in Tharps (2014).

[2] In the interest of readability, we use the term "audit firms" to refer to firms that provide auditing services, including the large professional services firms that provide auditing services as part of their portfolio of services, and the term "auditors" to refer to all employees of these firms. The largest of these firms are today referred to as the "big 4". We call other audit firms "non-big 4 firms". We recognize that many of these firms provide a large number of services in addition to audit services, and that many of their employees do not provide audit services on their jobs. Alternative labels for these firms could include CPA firms and professional services firms. We do not use "CPA firms" because not all employees of these firms are CPAs and we do not use "professional services firms" because it is vague.

firms consistently hire fewer graduates from universities with high Black representation among accounting graduates, even after controlling for university, business school, and accounting program quality.

The negative association we document between high Black representation and audit firm hiring could be interpreted as a consequence of forces limiting the demand of audit firms for Black workers, including intentional racism or unintentional "institutional racism" resulting from historical racism combined with the tradition that audit firms hire from the same universities over time. Conversely, the association could be due to forces limiting the supply of qualified Black workers, including the quality of the accounting education delivered by accounting programs with high Black representation. It is often difficult to distinguish demand-side theories from supply-side theories empirically. In our main tests, when we control for measures of university, business school, and accounting program quality, the negative association between hiring and Black representation weakens. This is consistent with supply-side theories and suggests that low hiring from programs with large numbers of Black graduates is partially attributable to the fact that these programs are of somewhat lower quality. Following our main empirical tests, we perform further tests to help us understand the role of demand-side forces in explaining our results and find evidence consistent with demand-side forces playing an important role.

Overt racism has long been taboo and, as a consequence, the racially biased behaviors and practices that persist today are typically subtle. A form of subtle bias that is applicable to our study is institutional racism, which is "unwitting racism" that "can arise because of lack of understanding, ignorance or mistaken beliefs" and which often persists because it represents "the 'traditional' way of doing things" (Macpherson 1999, 6.16). The negative association we document between audit firm hiring and Black representation in accounting programs could potentially be an unintended consequence of audit firm recruiting practices if three conditions are met: 1) audit firms, at some point in history, focused recruiting at universities with fewer Black students, 2) audit firms tend to hire from the same universities over time, and 3) the racial make-up of students at a given university is consistent over time. In supplemental tests, we find support for each of these conditions, suggesting that, while we cannot rule out more explicit and intentional forms of racism, institutional racism is a plausible explanation for the tendency of audit firms to hire less from universities with high Black representation.

If at least part of the negative association between audit firm hiring and Black representation among accounting graduates is a consequence of unwitting institutional racism, there is reason to believe that Black underrepresentation is at least partially correctable at low cost once the problem is recognized. We provide evidence that there is a large sample of universities exhibiting low Black representation from which auditing firms hire large numbers of graduates ("over-recruited universities") and that there is also a large sample of universities of equal or better quality exhibiting high Black representation from which auditing firms hire few graduates ("under-recruited Black universities"). By shifting recruiting resources from over-recruited to under-recruited Black universities, the audit firms could increase Black representation in their workforce without reducing the quality of schools from which they hire. While our measures of quality of accounting graduates are coarse (institution-specific, rather than individual), we believe our analyses illustrate how audit firms could conduct similar tests using quality measures from their own personnel files.

Our tests rely on three sources of data. First, we collect data characterizing U.S. universities, business programs, and accounting programs for each of the years 2001-2014 in terms of their sizes, locations, highest level of degrees offered, the races of their accounting and business graduates, and their admission standards from the Integrated Postsecondary Education Data System (IPEDS), which is a program of the U.S. Department of Education. Second, using the LinkedIn social network, we collect estimates of the numbers of auditors newly hired by audit firms for each of the years 2001-2014 from a sample of the 506 U.S. universities with the largest accounting programs. We also collect data on the number of people on LinkedIn who graduated from each of our 506 universities who have ever worked for one of the top 27 audit firms as a means of examining historical hiring practices at these firms. Third, we collect data on the quality rankings of accounting graduate programs and MBA programs from U.S. News and World Report for each of the years 2001-2014. Together, our sample includes data describing 125,278 people hired by big N auditors, 39,430 people hired by non-big N auditors, and 6,424 university-years.

Our study is subject to some limitations. First, to attribute our results to supply-side or demand-side forces, we would need to effectively measure the quality of accounting graduates using the same criteria audit firms use. These criteria are not publicly known and, if known, would likely be very difficult to aggregate across large samples like ours. We control for various quality measures and find that they may reduce, but do not eliminate the negative association between hiring and Black representation. A second limitation is that our hiring data characterize only audit firm hiring that we can observe on LinkedIn. There is, therefore, a risk that our results could be explained by systematic differences in the rates at which auditors of differing races have LinkedIn profiles. To address this concern, we examine whether Black accounting graduates appear to be underrepresented on LinkedIn relative to other data sources and find that they do not. In sum, the primary limitations of this study are due to a lack of data characterizing the quality attributes of accounting graduates that are valued by auditing firms, measures of these attributes across graduates by race, and accurate counts of hires by race. We have done our best to address our research question with available data. However, this is an area in which a cooperative effort involving researchers and the auditing firms, which likely have more data on hiring and employee quality in personnel files, would be particularly valuable. With these limitations in mind, this study offers new insights because it is the first to use large-sample data on audit firm hiring behavior to empirically evaluate the puzzle of Black underrepresentation in the auditing profession and offer suggestions on how the auditing firms, which are eager to increase the diversity of their employees, could better address the problem of Black underrepresentation.

Section 2 develops our hypothesis. Section 3 discusses our sample and main variables. Section 4 presents results of our tests examining the association between audit firm hiring and university diversity. Section 5 discusses conclusions.

II. HYPOTHESIS DEVELOPMENT

Existing theories about the causes of Black underrepresentation in the auditing profession can be divided into supply-side theories and demand-side theories. Supply-side theories seek to explain low Black representation in auditing as a consequence of low interest among young Black people in becoming auditors, or of low quality of the Black accounting graduates who could potentially become auditors. Reasons proposed for low Black interest in auditing include that young Black people either do not develop a positive view of the auditing profession because they have little exposure to Black role models in the profession, or that they develop a particularly negative view of the auditing profession because of historical racism or unflattering portrayals of accountants in the media (AICPA 2012, CPA Journal Panel 1999, Crocket 2009, Department of the Treasury 2008, Hammond 2004, Moyes et al. 2000, Polley 2014, Ross et al.

2014, Sanders 2007). The allegedly poorer quality of Black potential auditors is said to be a consequence, among other things, of a lack of familiarity among Black people with the business world and traditional norms of business (Glover et al. 1999; Hammond 2004, 5-6; Moyes et al. 2000, 43).

Demand-side theories seek to explain Black underrepresentation in the auditing profession as a consequence of intentionally or unintentionally biased behavior by decision makers within audit firms that create disadvantages for potential Black auditors. These effects reduce the numbers hired and handicap Black auditors once they enter the profession, reducing the numbers retained and promoted. The primary reason given for allegedly continued racial bias in audit firm hiring and promotion is a history of particularly persistent racial uniformity within audit firms. This uniformity may be due to organizational apathy, as firms, for public relations and legal reasons, care about appearing interested in increasing Black representation in auditing, but may actually fall short in making structural changes in hiring, retention and culture to bring it about (Glover et al. 1999; Hammond 2004, 1; Moyes et al. 2000). Some demand-side theorists discuss the claim that the quality of potential Black auditors is low and suggest that this could be due to biases among audit firm employees tasked with evaluating Black applicants and employees. Specifically, Black applicants and auditors may be held to a higher standard than others (Glover et al. 1999; Hammond 2004, 5-6; Mitchel and Flintall, 1990; Moyes et al. 2000).

Existing evidence does not support the popular subset of supply-side theories relating to interest among Black people in becoming auditors. If a lack of interest in accounting on the part of Black people were causing their underrepresentation in auditing, one would expect that Black people entering college would express interest in earning an accounting degree at low rates relative to other degrees and that Black college graduates would hold accounting degrees at low rates relative to other college degrees. The evidence suggests that neither of these is true. Madsen (2013) shows, using data from large-sample surveys of incoming college freshmen in the 1970s-1990s, that over these years more than 10% of freshmen expressing an interest in accounting have been Black, a value that is larger than that for 80% of college degrees. In addition, Black college graduates are particularly likely to hold accounting degrees, and, if auditing firms hired a representative sample of accounting graduates, they would have far greater Black representation than they do (Hammond 2004, Madsen 2013). There is not evidence evaluating differences in applicant quality and job performance between Black and non-Black audit firm employees. Even if differences were identified, it is notoriously difficult to untangle whether measured differences capture meaningful racial differences or are simply a consequence of biased or misinterpreted measurement (Heckman 1998, Pager and Shepherd 2008, Snyderman and Rothman 1987).

The evidence that demand-side theories can explain Black underrepresentation in auditing is strong for years before the late 1960s, when audit firms were overtly discriminatory (Hammond 2002, Mitchel 1969). More recent evidence regarding demand-side theories is limited and anecdotal. Broadly speaking, there continue to be significant racial disparities in the U.S. across many domains (e.g. incarceration rates, incomes, health outcomes, and test scores), with research suggesting that they can be attributed, in part at least, to the effects of low visibility forms of discrimination operating through such things as implicitly racist attitudes and the effects of historical racism (Darity and Mason 1998, Pager 2007, Pager and Shepherd 2008, Pettit and Western 2004, Sommers and Ellsworth 2001, Williams and Mohammed 2009).[3] There is a large racial divide in public opinions about the causes of such disparities, with Black people in the 2000s being nearly twice as likely as White people to believe discrimination is a primary cause

[3] There is debate in the economics literature about the extent to which racial differences in such things as income persist in the presence of thorough controls for intelligence and other hard to measure dimensions of human capital. For examples, and from both sides of the debate, see Darity and Mason (1998) and Heckman (1998).

of disparities when it comes to jobs, income, and housing (60.2% versus 31.7%).[4] Concern among Black people about the impact of ongoing discrimination is also apparent in survey research studying the experiences of Black employees of the audit firms (Glover et al. 2000, Moyes et al. 2000). Glover et al. (2000) survey Black employees of the then big 6 audit firms and include some open ended questions eliciting opinions about discrimination. New employees frequently noted with approval the visible diversity efforts of the firms, but many long-term employees did not believe that the firms' diversity efforts were effective or sincere (Glover et al. 2000, 188).

Mitchel (1969) documents low representation of Black people in the auditing profession. Using surveys, he finds that while CPA firms explained this underrepresentation using supply theories, Black colleges and Black CPAs attributed it to demand theories (see also JOA 1969). Mitchel recommended several solutions to the problem, including increased hiring at predominantly black colleges, arguing that "increasing the number of blacks and other minority groups in the CPA profession is not an unsurmountable task" (Mitchel 1969, 47).[5] In the decades since Mitchel (1969), audit firms have made "many highly publicized attempts to increase the diversity of students studying accounting and entering the accounting profession" (AICPA 2012, 39). However, while Black representation in auditing has increased, modern evaluations of diversity in auditing find that Black people are still underrepresented in auditing relative to expectations (Department of the Treasury 2008, AICPA 2012, Ross et al. 2014) and relative to other comparable professions (Hammond 2004, Madsen 2013). This suggests that the audit

[4] These values are the authors' own calculations using data from the General Social Survey. See http://gss.norc.org/documents/codebook/GSS_Codebook.pdf page 455 and http://gss.norc.org/.

[5] In 1969, Bert Mitchel, a Black member of the AICPA's newly formed Committee on Recruitment from Disadvantaged Groups, published this study as an early attempt to address institutional racism in the audit profession.

profession may have a more significant problem than other fields in recruiting and retaining Black workers.

Consistent with Mitchel's (1969) survey results, there remains a consensus among commentators representing audit firms that Black underrepresentation in auditing is primarily a supply-side problem. Black workers are said to lack interest in becoming auditors because of, among other things, a lack of Black role models in the profession (CPA Journal Panel 1999, Polley 2014, Ross et al. 2014, Sanders 2007). However, many Black auditors continue to attribute Black underrepresentation in auditing to problems with the demand for Black workers and unequal treatment for Black workers once they enter the auditing profession (Crocket 2009, CPA Journal Panel 1999, Glover et al. 2000, Moyes et al. 2000). Further, recently published reports commissioned to evaluate the auditing profession and plan for its future identify increasing minority representation as a critical but achievable goal and make recommendations to solve the problem which include both 1) greater outreach to high school students and improved quality of introductory accounting classes at community colleges to improve the supply of Black students into accounting, and 2) increased recruitment from historically Black colleges and universities to improve job prospects for Black graduates (AICPA 2012, Department of the Treasury 2008). This study is intended to contribute to the latter effort.

Existing evidence suggests that the point in the pipeline at which potential Black accountants are most potently filtered away from the profession is the time between graduation from college, roughly 6% to 8% of accounting graduates are Black (Hammond 2004, Madsen 2013), and hiring by audit firms, roughly 4% of newly hired auditors are Black.[6] One respondent in Glover et al. (2000), repeats the argument, dating back to Mitchel (1969), that Black underrepresentation in auditing is a consequence of audit firm recruiting practices, saying, "I do

[6] This 4% figure is calculated from data presented in the AICPA's "trends" reports (AICPA 2011, 2015).

not believe my firm has a strong commitment to diversity... this is exemplified by the schools the firm recruits from, which do not have many minorities in the first place" (Glover et al. 2000, 188). In this study, we focus on the hiring decision and examine whether auditing firms make that decision differently for accounting programs with high Black representation. This leads to our hypothesis:

> H_1: Accounting graduates from universities with higher Black representation are hired by auditing firms at a lower rate.

In sections 3 and 4, we describe our data and the results of our hypothesis tests. We then discuss supplemental tests, in which we show that our finding that audit firm hiring is negatively associated with Black representation in an accounting program is potentially a consequence of unintentional institutional racism rather than intentional or overt racism (the demand-side argument), and at most responsible for about 14% of the difference between Black representation in the auditing profession and Black representation in an average U.S. profession.

III. SAMPLE, MAIN VARIABLES, AND DESCRIPTIVE STATISTICS

Sample

Our data describing universities come from the Integrated Postsecondary Education Data System (IPEDS), which is a program of the U.S. Department of Education through a branch called the National Center for Education Statistics (NCES). The NCES runs a program called the Institute of Education Sciences that is in charge of maintaining the IPEDS.[7] The IPEDS includes data from all universities that participate in federal financial aid programs, called Title IV-eligible institutions, as well as other institutions that voluntarily report information to IPEDS.[8]

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[7] See https://nces.ed.gov/ipeds/datacenter/.

[8] We believe that universities voluntarily report data to IPEDS because they want to be included in the IPEDS College Navigator, a website designed to help prospective college applicants find schools that suit them.

Title IV-eligible institutions are required by the Higher Education Act of 1965 to report the data provided in the IPEDS. IPEDS contains information about, among other things, university locations, enrollee test scores, admission rates, the number and racial makeup of graduates by degree program, and Carnegie Classifications of universities.[9]

In our analyses, our primary independent variables are based on IPEDS data describing the numbers and races/ethnicities of accounting graduates. We examine Black representation among accounting graduates in order to test our hypothesis, but we also examine Hispanic representation for exploratory purposes because of evidence that many important outcomes differ for Hispanic people when compared to White people (Pager and Shepherd 2010), and because there is little evaluation of Hispanic experiences in auditing in the literature (Goldstein 2013). Many important U.S. universities do not offer accounting degrees, generally offering instead degrees in business administration with the option to specialize in accounting. We identify these universities in the IPEDS and estimate values for the diversity and numbers of accounting graduates. Specifically, we assume that the representation of Black and Hispanic people among graduates with degrees specializing in accounting is equal to the representation of these groups among all students in schools with accounting programs. We calculate that, for schools with accounting programs, the number of accounting graduates amounts to 14% on average of the number of business graduates. For universities without separate accounting programs we assume the number of graduates specializing in accounting is equal to 14% of the number of business graduates. In addition, because we cannot distinguish degree levels of people on LinkedIn (from which, as we discuss next, we obtain hiring counts by university-year), we pool IPEDS data for bachelor's and master's degrees in all of our tests (specifically, we pool observations with

[9] Carnegie Classifications are intended to group comparable schools together and focus on the highest degrees offered by the institutions as well as their research intensity. See: http://carnegieclassifications.iu.edu/.

awlevel values between 5 and 8 in IPEDS). Finally, some IPEDS universities report that significant numbers of graduates are of unknown races. Given that we are interested in race, we exclude university-years in which more than 33% of graduates are of unknown race.

We collect data on audit firm hiring from publicly available employee biographical information posted on LinkedIn. Specifically, we collect data describing hiring counts for 506 universities with the largest business programs over our sample period, based on IPEDS data. We required that each of these universities has data on standardized test scores, granted bachelor's degrees or higher, and was not a "specialty school" in a discipline other than business.[10] These universities were responsible for, on average, 90.92% of accounting graduates in the IPEDS database over 2000-2014. After this process, we have a dataset describing, by university-year, the number of people on LinkedIn newly hired, and the number of people ever employed, by the top 27 audit firms. We classify the auditors as big N auditors and non-big N auditors in the analyses. Data describing accounting and MBA quality rankings by university-year are from U.S. News and World Report's Academic Insights.

< Table 1 about here >

The interpretability of our results depends on Black auditors using LinkedIn at similar rates as non-Black auditors. In Table 1 we show that they likely do. It shows, for the years 2001 to 2014, minority race and ethnicity representation among accounting graduates in our IPEDS sample, estimates of Black and Hispanic representation among audit firm hires produced from our LinkedIn hiring data and IPEDS data, and Black and Hispanic representation among audit firm hires as estimated by the AICPA in their "trends" reports (AICPA 2011, 2015). We estimate Black and Hispanic representation among people hired by the audit firms in our dataset by

[10] Specifically, we retain universities with *Carnegie Classification* values between 15 (Doctoral/Research Universities - Extensive) and 33 (Baccalaureate/Associates Colleges) as well as values equal to 55 (Schools of Business Management).

assuming that the hires we observe on LinkedIn, which are counts by university-year but for which we have no race/ethnicity information, were drawn randomly from the graduates of their universities in the year they were hired. This amounts to calculating weighted averages of our IPEDS Black and Hispanic representation data where the weights are the numbers of hires from a given university-year that we observe on LinkedIn. At the bottom of the table, we display simple averages of the annual averages (summing the values displayed in the table and dividing by the number of years represented) and also weighted averages that take into account the number of people contributing to the value each year (total graduates for IPEDS and total hires for LinkedIn and "trends" data). IPEDS data in Table 1 shows that Black representation among accounting graduates has been fairly stable over our sample period, averaging about 6.75% while Hispanic representation increased from 6.7% in 2001 to 9.6% in 2014. Comparing graduate data with hiring data, it is apparent that Black and Hispanic representation among accounting graduates is higher than their representation among newly hired auditors, which confirms that audit firms do not hire a random sample of all accounting graduates. The estimates of Black representation among newly hired auditors that we estimate from LinkedIn and IPEDS are quite comparable to values from the "trends" reports, which suggests that Black people newly hired by audit firms have LinkedIn profiles at rates that are similar to rates for non-Black people. This is evidence that our LinkedIn counts are not biased downward for schools with large numbers of Black graduates. The estimates of Hispanic representation among newly hired auditors that we estimate from LinkedIn and IPEDS are slightly lower than those in the "trends" data.

Main Variables

Because we are interested in audit firm hiring at universities with high Black representation, we transform IPEDS raw racial data to make it more interpretable. We first calculate the proportion of accounting graduates from university i in year t that were either Black or Hispanic. We then generate for Black and Hispanic representation, three indicator variables which are equal to one for university-years with Black or Hispanic representation in the top 60th to 75th percentiles of universities in our sample, the top 75th to 90th percentiles, and the top 90th to 100th percentiles, and zero otherwise. These transformations facilitate interpretation of our coefficients, enable us to focus on schools with high Black and Hispanic representation, and enable us to evaluate whether the strength of the association between audit firm hiring and Black and Hispanic representation varies as representation reaches higher levels. These variables, and all others used in this study, are defined in Appendix A. IPEDS provides data on the number of applicants to a university and the number of freshman applications and admissions, and we use these values to calculate *admission rate*. We also transform Carnegie Classification from IPEDS into a series of indicator variables characterizing universities by the level of the highest degrees offered (bachelor's/associates, bachelor's, master's, and doctoral).

Universities also report to IPEDS the 25th and 75th percentiles of the test scores of admitted students that were used to make admissions decisions, including as many as three from the SAT (critical reading, math, and writing) and as many as four from the ACT (composite, English, math, and writing). We believe it is valuable to include a measure of the relative test score performance of incoming students as a means of characterizing school quality, but universities in the sample do not use a consistent set of test scores. We create a variable called *test scores* that is intended to characterize the relative rankings of universities in terms of the test scores of incoming students that is comparable across tests and covers as much of our sample as possible. To create this variable, we use all universities in the IPEDS sample and we first calculate the percentile ranks of the 75th percentile scores reported for each university-year for each test score reported, with high scores ranking near the 100th percentile and low scores ranking near the 0th percentile. We then take the average percentile rank across all reported tests, ignoring missing values, for each university-year. The result is a set of values between 0 and 1 covering nearly all of our sample and measuring the relative performance of incoming students on whatever standardized tests each university uses to make admissions decisions for each university-year relative to all U.S. universities in IPEDS. We transform accounting and MBA program ranks into indicator variables. For accounting and MBA ranks, we have indicators equal to one for rankings from 1 to 10, from 11 to 20, and from 20 to 30, and zero otherwise. Because U.S. News provides rankings for much larger numbers of MBA programs than accounting programs, we also have indicators for MBA rankings equal to 1 for rankings from 31 to 50, and 50 to 100, and zero otherwise.

< Table 2 about here >

Descriptive Statistics

Table 2 summarizes our hiring and *ever employed* counts. Panel A describes the frequency with which big N and non-big N firms hired various numbers of people according to our LinkedIn data across our sample of university years. It shows that big N firms hired zero people in 15% of university-years in our sample and that non-big N firms hire zero people in 23% of university-years. The most frequently hired numbers in the sample are between one and ten people, suggesting that both big N (46.3% of observations are in this range) and non-big N (58.7%) firms tend to hire small numbers of people from many schools. Larger hiring counts are less frequent, with 97% of university-years experiencing 100 or fewer hires by big N firms and 30 or fewer hires by non-big N firms. Panel B of Table 2 shows total hiring and the total number of people ever employed by big N and non-big N firms in our sample. Together, our sample includes 125,278 people hired by big N firms, 39,430 people hired by non-big N firms, 744,078 people ever employed by big N firms, and 243,533 people ever employed by non-big N firms. Panel C of Table 2 describes the coverage of our sample by comparing hiring totals in our data to hiring totals estimated by the AICPA in the years covered by their recurring “trends” reports (AICPA 2011, 2015). Over the sample period, our LinkedIn totals comprise between 29% and 49% of all hiring by audit firms in the United States.

< Table 3 about here >

Table 3 shows descriptive statistics for the variables used in our multivariate analyses calculated over the pooled sample. The IPEDS sample contains 27,717 university-years, we have LinkedIn hiring data for a total of 7,074 of these university-years, and 6,424 of these have the required racial data in IPEDS. Most variables in Table 3 are available for 6,424 university-years, but *admission rate* and *test scores* are available in somewhat fewer years. On average, big N firms hire 19.5 graduates and non-big N firms hire 6.1 from our sample universities each year. Roughly 7% of the accounting graduates in the sample are Black and 8% are Hispanic. An average graduating class from our accounting programs is about 96 students with business graduates numbering about 676 students on average. Most of the schools in the sample are considered master’s degree granting institutions (51%) or doctoral degree granting institutions (41%). The average admission rate for our sample is 67%, but is as high as 100% and as low as 7%. The average university in our sample has a *test scores* value of 61%, indicating that they accept students with slightly higher standardized test scores than the average U.S university, which is, by definition, at the 50th percentile.

< Table 4 about here >

Table 4 reports univariate correlations among our variables. We include continuous measures of Black and Hispanic representation rather than our indicator variables to make the size of the table more manageable. Table 4 shows that big N and non-big N hiring counts are highly correlated (0.74), suggesting that auditing firms tend to hire from the same set of schools. Counts of people on LinkedIn graduating from each school that have ever been employed by an auditor are highly correlated with new hiring counts from that school (0.95 for big N and 0.90 for non-big N auditors). Black and Hispanic representation among graduates is negatively associated with both new hiring and historical hiring by audit firms from a university. The correlations between hiring counts and school quality measures are generally positive and significant, consistent with audit firms hiring more from higher quality schools. The coefficients on quality measures are generally larger for big N hiring than for non-big N hiring, suggesting that big N auditors are more sensitive to school quality than non-big N auditors. Because lower admission rates signal higher quality, the signs of the correlations between admission rates and hiring counts are negative, consistent with more hiring at higher quality schools. Hiring counts are positively associated with schools size and the square of school size, suggesting that auditing firms hire more graduates from larger programs.

IV. EMPIRICAL RESULTS

Univariate Results

Table 5 shows a univariate analysis of the association between high Black representation and audit firm hiring. Considering no controls, there is a negative association between increasing Black and Hispanic representation and hiring counts. As a baseline, Big N auditors hire about 24% of the graduates of programs without high Black or Hispanic representation. Table 5 also shows that Big N auditors hire about 17% of graduates from programs with Black representation in the top 60 to 75 percentiles, about 13% from programs with Black representation in the top 75 to 90 percentiles, and about 8% from programs with Black representation in the top 90 to 100 percentiles. For Hispanic people, hiring counts are higher than average for programs with graduates in the top 60 to 75 percentiles, with big N firms hiring about 26% of graduates from these programs. However, this rate drops to about 20% for programs with Hispanic representation in the top 75 to 90 percentiles and about 7% for the top 90 to 100 percentiles.

< Table 5 about here >

Multivariate Tests

The dependent variables in our multivariate tests are counts of the numbers of graduates hired by university-year. Count data are not normally distributed and are typically modelled using a class of non-linear models developed to deal with the distinctive characteristics of count distributions.[11] In our multivariate tests, we use zero inflated negative binomial (ZINB) models, which we find fit our data better than the alternatives.[12] Conceptually, ZINB models separate the estimation sample into two latent or unobserved subsamples, one in which the count will always be zero, and another in which the count may sometimes be zero but has a positive probability of being greater than zero. Estimation then involves: estimating the probability that an observation

[11] This discussion is based on Hilbe (2014) and Long and Freese (2014).

[12] For each of our models, we compared Poisson, negative binomial, and ZINB results in terms of goodness of fit using measures calculated by the *fitstat* command from Long and Freese (2014). We find that Poisson models are never preferred to either negative binomial or ZINB models according to these measures and also find that ZINB models appear to fit the data better in most cases. The Poisson and negative binomial distributions are popularly used in count data models. The Poisson distribution has the unusual feature that its mean is assumed to be equal to its variance. In practice, this assumption is often violated because of a problem called "overdispersion," which means that there is more variability in the data than assumed by the distribution. Overdispersion is especially likely to be a problem when the data includes a lot of zero counts. Table 3 shows that our hiring data has variances (calculated by squaring the reported standard-deviations) that are much higher than their means, signifying that our dependent variables are likely overdispersed. Overdispersed count data containing a lot of zeros can be econometrically dealt with in a number of ways. The simplest way is to relax the assumption of the Poisson distribution that mean equals variance by allowing the variance to differ from the mean and estimating a new parameter characterizing variance. This is what negative binomial models do, with the parameter estimating variance typically called "alpha." When alpha equals 1, the negative binomial distribution is identical to the Poisson distribution. Tests comparing Poisson models against negative binomial models evaluate whether alpha equals one, with significant differences indicating that the negative binomial model is preferred to the Poisson model.

is in the "always zero" or "not always zero" subsample, modeling the probabilities of observing different counts for observations in the "not always zero" group, and then computing coefficients by mixing the probabilities from the two groups.[13]

As with all non-linear models, raw coefficients in ZINB models are not easily interpreted, so we convert them into "factor change coefficients," which indicate how many times larger or smaller (the factor change) the outcome is expected to be for a unit change in X (in the "binary equation" models, factor change coefficients are equivalent to odds ratios). ZINB models involve the estimation of a "binary equation," which estimates the probability that observations are in the "always zero" versus "not always zero" subsamples, and a "count equation," which estimates the probability of various counts in the "not always zero" subsample. All tables displaying regression results show the "count equation" results at the top and the "binary equation" results at the bottom. Coefficients in the count model describe the associations between the independent variables and the count. Our discussion of results focusses on the coefficients from the count equations because our purpose is to examine variation in hiring counts. Coefficients in the binary model are interpretable as odds ratios explaining the likelihood that an observation will have a zero count. This can be confusing because it is essentially a logit in which zero counts are treated as ones and non-zero counts are treated as zeros, but it is the standard method. In most cases, we include the same independent variables in the "binary equation" and the "count equation." In addition, we report coefficients labelled "log alpha," which characterize the dispersion parameter in the negative binomial count model. Statistically significant log alpha coefficients suggest that

[13] While negative binomial models deal with dispersion with more flexibility than Poisson models, data can still be overdispersed relative to negative binomial assumptions, particularly, again, when there are many zero counts. In cases where data are overdispersed from the perspective of both the Poisson and negative binomial models, they can be modeled using either a two-stage "hurdle model" or a "mixed model." In hurdle models, the first step in estimation is to use a logit to predict whether the dependent variable is equal to zero and the second step is to use a Poisson or negative binomial model to estimate counts for observations that do not have a high probability of being equal to zero. Mixed models also use a logit combined with a Poisson or negative binomial model but they estimate stage one and stage two simultaneously. ZINB models, which we use in our tables, are mixed models.

negative binomial models are preferable to Poisson models. In untabulated analyses, we find that logit models using the same variables as our binary equations have pseudo R^2 values ranging from 30% to 40%, consistent with fairly good fits.

< Table 6 about here >

Table 6 shows results from estimating four multivariate models, two each explaining hiring by big N and non-big N audit firms. In columns 1 and 3, we estimate simple models including our race indicators, controls for accounting program sizes, and region and year indicator variables. We add various controls for university, MBA, and accounting program quality to the count and binary equations in columns 2 and 4. The columns labelled "Diff." show differences between the coefficients on the Black representation indicator variables when we include these controls. The results for the binary equations at the bottom of Table 6 show that the coefficients on the race indicator variables are mostly statistically insignificant, consistent with the incidence of zero hiring counts not being well explained by high Black and Hispanic representation. Program size is fairly consistently negatively associated with zero-hiring counts (factor change coefficients less than one), signifying that larger universities are less likely to place no students in audit firms. School quality variables in columns 2 and 4 are strongly negatively associated with zero hiring counts, consistent with audit firms being more likely to hire from higher quality schools. Accounting and MBA ranks are both negatively associated with zero hiring counts for big N auditors while, for non-big N auditors, accounting ranks are negatively associated with zero hiring counts while MBA ranks are not.

Our main results are from estimations of the ZINB "count equations" at the top of Table 6. They show that high Black representation among accounting graduates is strongly negatively associated with hiring counts, and that this negative relationship strengthens as Black representation becomes higher. This is the case for big N and non-big N auditors and holds when we add controls for university, MBA, and accounting program quality, as well as year and region indicator variables, though the size of the coefficients on our Black representation measures falls when we add these controls. These changes in the sizes of the coefficients on the Black representation indicator variables are all statistically significant with controls causing larger declines for big 4 auditors than non-big 4 auditors, and larger declines as Black representation increases. The declines in the magnitudes of the negative association between Black representation and auditor hiring counts after adding school quality measures are consistent with the supply-side argument that relatively lower quality of the graduates of accounting programs with high Black representation (whether because of their qualifications when entering school or the quality of the education delivered by these schools) limits the numbers of these graduates hired by audit firms. Overall, the evidence in Table 6 supports our hypothesis. Our exploratory analysis of Hispanic representation and hiring yields weak evidence that high Hispanic representation is negatively associated with hiring by non-big N auditors, but only for Hispanic representation in the top ten percentiles. This coefficient on the indicator variable for Hispanic representation in the top ten percentiles is also statistically significant and less than one in column 1, the big N equation with no quality controls, but it is no longer statistically significantly different from one in the presence of controls in column 2.

To illustrate the interpretation of factor change coefficients on indicator variables in our setting, consider the coefficient on the "Black graduate percentage in the 60^{th} to 75^{th} percentiles" variable in column 2, which is equal to 0.852 and is statistically significant at the $p < 0.01$ level. This coefficient signifies that the number of people hired by big N auditors is lower by a factor of 0.852 for universities with Black representation among graduates in the 60^{th} to 75^{th} percentiles when all else is held constant. This is an economically large coefficient. Mean big N hiring is 19.5 in our sample. Our column 2 results suggest that, for a university with Black representation in the 60th to 75th percentiles and average in other respects, the number of graduates hired is expected to be 16.6 (19.5 * 0.852) rather than 19.5. As for control variables in the count equations, as one might expect, audit firms hire more from larger accounting programs. Big N audit firms hire more from higher quality schools while non-big N audit firms' hiring is sensitive to only some of our measures of quality, including whether the school offers master or doctoral degrees and the test scores.

Demand-Side Argument

In this section, we evaluate why high Black and Hispanic representation are associated with lower hiring counts using demand-side theories. Table 7 shows results from estimations of models like those in Table 6, columns 2 and 4, but which include, in addition to all of our other controls, our measures of the number of people ever hired from a given university by a big N or non-big N auditor (columns 1 and 3) as well as interactions of our *ever hired* counts with the race indicator variables (columns 2 and 4). Coefficients on the interaction terms that are greater than one would signify that the negative association between high Black and Hispanic representation is weakening while coefficients less than one would signify that it is strengthening. We find, in columns 1 and 3, that the inclusion of *ever hired* counts reduces the magnitude and statistical significance of all of the coefficients on the race variables that were statistically significant in Table 6. This suggests that auditors tend to hire from the same universities over time, and that these universities tend to be those with fewer Black (representation lower than the 60th percentile) and Hispanic (representation lower than the 90th percentile) graduates. Thus, the negative association between Black and Hispanic representation and auditor hiring counts could at least partially be explained by loyalty among recruiters to their alma maters.

< Table 7 about here >

Table 7, Columns 2 and 4, show that many of the coefficients on the interactions between high Black and Hispanic representation and *ever hired* are greater than one and statistically significant. This suggests that, while audit firms tend to hire more from schools with lower Black and Hispanic representation, in cases where audit firms have a historical recruiting relationship with universities with high Black (representation higher than the 60th percentile) or Hispanic (representation higher than the 90th percentile) representation, they tend to hire more from these schools. This is consistent with audit firms seeking to increase their hiring of Black and Hispanic auditors using a strategy that emphasizes hiring at diverse schools, but only when they have previously hired large numbers of auditors from these schools.

We further examine whether the hiring bias against universities with high Black representation could be an unintentional consequence of alma mater loyalty among audit firm recruiters, and could, therefore, potentially be a case of institutional racism rather than intentional racism. As explained in the introduction, racial bias in hiring could plausibly be unintentional if three conditions are met: 1) that, at some point in the past, audit firms intentionally developed recruiting relationships with universities that had particularly few Black graduates, 2) that audit firms tend to hire from the same universities over time, and 3) that the racial make-up of students at a given university is relatively stable over time so that universities with high Black representation in the past tend to have high Black representation today. Historical evidence confirms condition one, that auditing firms have a history of racially discriminatory hiring practices. Before the Civil Rights Movement, audit firms intentionally focused recruiting at schools without large numbers of Black graduates, and even the small numbers of Black graduates from these schools were intentionally excluded from the auditing profession (Glover et al. 2000; Hammond 2002, Ch. 1-6; Hammond and Streeter 1994; Mitchel 1969). Black accountants recall being told in job interviews "we do not hire Negroes," a policy that was justified by racial prejudices either on the part of the White audit firm employees themselves or because audit firm recruiters believed that clients would object to the presence of Black auditors (Hammond 2002, 61-62; Hammond and Streeter 1994; Mitchel 1969).

Condition two is confirmed by our finding in Table 7 that *ever employed* counts are strongly positively associated with hiring counts. To test condition three, we collect data from all IPEDS universities about the levels of Black and Hispanic representation among their entire student populations in 1980 (the earliest available year) and 2014 and examine the correlation in Black and Hispanic representation at a given university in 1980 with that university's representation in 2014. The sample includes the 1,735 universities that have the required data. We find that the correlations for both Black and Hispanic representation are 0.89 ($p < 0.01$), consistent with very high stability in the racial makeup of students attending each university over time. This evidence supports condition three.

Together, the evidence suggests that it is plausible that the audit firms are sincerely trying to increase Black and Hispanic representation by more aggressively recruiting graduates of universities from which they have hired in the past when these graduates are Black or Hispanic. But this strategy has not been very successful and the auditing profession remains far less diverse than the US population and also far less diverse than other professions. Our evidence suggests that Black representation in the audit firms would increase if they expanded their diversity efforts to include reallocating recruiting resources across schools, something that would require breaking the tradition of hiring from the same set of schools over time.

Supplemental Analyses

Thus far, we have documented that audit firms hire more from universities with lower Black and Hispanic representation, that audit firms also hire more from universities from which they have hired previously, that audit firms tend to hire more people from universities with high Black representation *if* they have previously hired a lot from that university, and that at least some of the lower hiring from accounting programs with high Black representation could be explained by the quality of the graduates of these programs. While our evidence suggests that lower hiring from accounting programs with high Black representation contributes to Black underrepresentation in the auditing profession, it is not clear from our analyses thus far how impactful the bias we document against hiring from accounting programs with high Black representation likely is. How much of the problem of Black underrepresentation in the auditing profession could it explain?

To estimate the power of our findings to explain the distinctively low representation of Black people in auditing, we first estimate the number of additional Black hires that would be needed to make Black representation among newly hired auditors comparable to the racial composition of an average profession as estimated by Madsen (2013). Madsen (2013, Table 1 Panel A) shows that average Black representation in a sample of U.S. professions during the 2000s was about 7%. The estimate we produce using LinkedIn of the number of Black people among newly hired auditors over our sample period is 7,186 of 164,708 total hires (4.36%). For Black representation among newly hired auditors from our LinkedIn sample to become comparable to Black representation in other similar occupations, auditors would have had to hire an additional 4,400 Black auditors.[14] We use a ZINB model to predict the total numbers of people that would be hired by either a big N or non-big N audit firm from each university-year observation in our sample if the racial composition of the accounting programs were not observable. Specifically, we take predicted total hiring counts from a ZINB model that includes as predictors program size, size squared, accounting and MBA rank indicators, Carnegie Classification indicators, admission rate, and test score percentile. Using this predicted count, we calculate the number of Black hires we would expect if audit firm hiring matched our race-blind predicted hiring (this calculation is the same weighted average calculation displayed in Table 1 except that the weights are predicted hiring counts instead of actual hiring counts). We estimate that race blind hiring would produce 7,787 Black hires, or 601 additional Black hires over our sample period. These additional 601 Black hires amount to 13.7% of the 4,400 additional Black hires that would be needed to bring Black hiring up to 7%, the level of Black representation in Madsen's (2013) sample of professions. These calculations suggest that if university recruiting were blind to race, Black representation in the auditing profession would materially improve, but not by enough to bring Black representation in auditing up to the level achieved by other U.S. professions.

Time Trends

In this subsection, we examine whether the negative association between high Black and Hispanic representation and hiring counts is changing over time for big N and non-big N firms. These test involve creating an indicator variable equal to zero for years early in the sample period and equal to one for years later in the sample period. We then repeat regressions like those in columns 2 and 4 of Table 6 (including our more exhaustive list of controls) with our high

[14] Bringing Black representation among newly hired auditors up to the level of Black representation in other U.S. professions would be desirable, but it is a relatively low bar. This is because Black representation among newly hired professionals is likely higher than among professionals hired in the more distant past.

Black and Hispanic representation variables interacted with this *late* indicator variable. We define *late* to be equal to one for the years 2009-2014, splitting our sample years roughly in half, and for the years 2004-2014, roughly identifying pre- and post-SOX periods. Table 8 reports the results. Several of the interactions in our "count equations" where *late* is 2009-2014 have coefficients less than one, consistent with a negative association between high Black representation and hiring counts that is strengthening over time. This result applies to big N firms and non-big N firms. When *late* is defined as 2004-2014, some of the interactions of *late* with high Hispanic representation for non-Big N hiring are greater than one, suggesting that non-Big N firms have increased their hiring from schools with high Hispanic representation since 2004.

< Table 8 about here >

Illustrating How Recruiting Resources could be Reallocated to Increase Black Representation in the Auditing Profession

If the negative association between audit firm hiring and Black representation that we document is a consequence of unwitting bias caused by outdated racially motivated recruiting practices that have been carried by tradition into the present, we propose that it is likely correctable at low cost if audit firms were to broaden their minority recruiting strategies to include reallocating recruiting resources to a new set of universities. Table 9 illustrates examples of how this might be done. We first adapt our models of big N hiring counts by dropping all race variables and then use these models to estimate the numbers of people we expect the big N audit firms to hire from each university in each year when the analysis is race-blind. We then compare these predicted counts, which are insensitive to race, against the numbers of people actually hired to get prediction errors. We call universities with positive errors "over-recruited" universities because audit firms are hiring more from these universities than a race-blind model predicts, and we call universities with negative errors “under-recruited.” We propose that audit firms could increase Black representation among their hires if they were to reallocate recruiting resources away from over-recruited universities that have particularly few Black graduates to under-recruited universities of similar or better quality that have particularly many Black graduates. In Table 9, we display a number of over-recruited schools (defined in Table 9 to be those with hiring errors over all the years in the sample which total more than 20), with particularly few Black graduates (defined in Table 9 as average Black representation of less than 3%) which we have matched against under-recruited schools (defined in Table 9 as schools with prediction errors summing to less than -20) with particularly many Black graduates (defined in Table 9 as average Black representation of more than 6%) to illustrate specific recruiting reallocations that would increase Black representation among new hires that our data suggest are possible.

< Table 9 about here >

Table 9 shows the 66 universities in our sample that are over-recruited universities with low Black representation. We pair each, when possible, with a matching under-recruited university with high Black representation. Universities in Table 9 are ranked first by average accounting rank, second by average MBA rank, and third by average *test scores*. To describe the importance of universities with ranked accounting programs, ranked MBA programs but not ranked accounting programs, and unranked accounting and MBA programs for audit firm hiring, we calculate the percentage of big N and non-big N hiring from each category of schools in our sample. We find that big N (non-big N) auditors hire 33.5% (22.7%) of their new employees from schools with ranked accounting programs, 49.8% (52.3%) from schools with ranked MBA programs but unranked accounting programs, and 16.7% (25%) from schools with unranked accounting and MBA programs. Table 9 shows, first, that there are several over-recruited universities with low Black representation among universities with ranked accounting programs, but there are no examples of universities with ranked accounting programs that are also under-recruited and have high Black representation. This is likely a consequence of the fact that only two universities with ranked accounting programs also have high Black representation.[15] This is significant, in part, because it illustrates the limitations of the strategy we advocate in this study, reallocation of recruiting resources across equally ranked universities, for increasing Black representation in auditing. While our results suggest that our approach can increase Black representation in auditing at relatively low cost, the approach is of little use for the highest ranked accounting programs, from which big N auditors hire more than a third, and non-big N auditors hire more than a fifth, of their new workers. This highlights the continued importance of efforts to increase the rates at which Black people graduate from the highest quality accounting programs.

For over-recruited/low Black representation schools with ranked MBA programs, but unranked accounting programs, we identify a number of matches among under-recruited/high Black representation schools when we require the high Black representation matches have higher ranked MBA programs and higher test score percentiles. Reallocation of recruiting among these schools would counter the bias we document in audit firm hiring and increase Black representation in the auditing profession given that auditing firms hire about half of their workers from such schools. Similarly, at the bottom of Table 9, we are able to match many of the over-recruited/low Black representation schools with unranked accounting and MBA programs to schools with better *test scores* and high Black representation. We recognize that Table 9 is limited because our hiring data, though they are the best that has been assembled by researchers

[15] These are the University of Virginia, with Black representation of 9.03% on average, and Georgia State University, with Black representation of 23.24% on average. Both of these schools are over-recruited according to our models.

to date, are incomplete, and because our Table 9 results suggest that our IPEDS and rankings data do not enable us to characterize the quality of accounting graduates with the precision that audit firm recruiters likely can. But the audit firms likely have the information that would be needed to improve upon our Table 9 results (more complete hiring data and specific knowledge of the quality attributes they value). We hope that Table 9 illustrates how the firms themselves, perhaps in cooperation with researchers, might identify how their university recruiting decisions might be adjusted to improve Black representation while also improving or holding constant the quality of new hires.

V. CONCLUSIONS

Prior literature shows that audit firms have a history of explicit racism but that they began working to reverse the effects of this racist history beginning in the 1970s. These efforts continue today, but there is evidence that Black people remain under-represented in auditing compared to other similar professions, despite evidence that Black students want to become accountants and that Black workers are paid well in auditing relative to other professions. Why is this so?

The evidence in this study suggests that one cause is audit firm recruiting practices. Our evidence suggests that audit firms tend to hire from roughly the same set of schools year after year and that these schools, on average, have particularly few Black accounting graduates. This is an important finding because it can both explain the puzzling shortage of Black auditors despite efforts by the firms to increase their diversity and because it implies a simple solution to at least this part of the problem. Decision makers at audit firms in the past may have intentionally, and for racist reasons, forged recruiting relationships with universities that had few Black students. Black people may be underrepresented among auditors today, in part, because these schools continue to have few Black students and audit firms continue focusing recruiting at these schools, for reasons which could be completely unrelated to race. Our evidence supports this explanation, and implies that up to 14% of the problem of Black underrepresentation in auditing relative to other U.S. professions could be corrected if audit firms reallocated their recruiting resources in an effort to hire more graduates of high quality schools with high Black representation from which the firms have not recruited heavily in the past.

Black underrepresentation in the auditing profession is an old and stubborn problem that will likely require careful study to better diagnose it, significant investment to treat it, and significant time for the treatments to take effect. A cooperative effort on the part of audit firms, which have access to data and expertise that would enable more thorough evaluation of Black underrepresentation among auditors, and researchers, who have the tools to rigorously examine the data and systematize the institutional knowledge possessed by audit firm recruiters, would likely be very fruitful. In this study, we assemble a novel dataset characterizing hiring by audit firms from U.S. universities, find that it appears to be racially biased, and propose a method of reversing this bias. Much more similar work will be required before we can, at last, solve the puzzle of distinctive Black underrepresentation among auditors.

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Appendix A
Variable Definitions

Label	Source	Definition
Big N Hiring	LinkedIn	A count of individuals on LinkedIn who graduated from university i and began working at a big N auditor in year t. Big N auditors are KPMG, EY, PWC, Deloitte, and Arthur Andersen.
Non-Big N Hiring	LinkedIn	A count of individuals on LinkedIn who graduated from university i and began working at a non-big N auditor in year t. Non-big N auditors are WeiserMazars, Citrin Cooperman, Parente Beard, Carr Riggs & Ingram, Wipfli, Eide Baily, UHY, Rothstein Kass, EisnerAmper, Baker Tilly Virchow Krause, Dixon Hughes Goodman, Keller Marcum, Moss Adams, Plante Moran, BKD, CBIZ, CohnReznick, CliftonLarsonAllen, Crowe Horwath, BDO, Grant Thornton, and McGladrey.
Accounting Graduates	IPEDS	The number of people graduating with accounting degrees from university i in year t.
Business Graduates	IPEDS	The number of people graduating with business degrees from university i in year t. Information on business graduate numbers and races are used in cases where a university has no accounting graduates.
Big N Alumni	LinkedIn	A count of individuals on LinkedIn who graduated from university i who report working at a big N auditor in year t. This value excludes individuals newly hired in year t.
Non-Big N Alumni	LinkedIn	A count of individuals on LinkedIn who graduated from university i who report working at a non-big N auditor in year t. This value excludes individuals newly hired in year t.
Top X to Y Accounting	U.S. News	An indicator variable equal to 1 if university i is ranked by U.S. News in the top X to Y accounting programs in year t and zero otherwise.
Top X to Y MBA	U.S. News	An indicator variable equal to 1 if university i is ranked by U.S. News in the top X to Y MBA programs in year t and zero otherwise.
Carnegie Bachelor's/ Associates's	IPEDS	An indicator variable equal to 1 if university i has a Carnegie Classification indicating it is a bachelor's/associate's degree college (codes equal to 33) and zero otherwise.
Carnegie Bachelor's	IPEDS	An indicator variable equal to 1 if university i has a Carnegie Classification indicating it is a baccalaureate college (codes greater than 30 and less than 33) and zero otherwise.
Carnegie Master's	IPEDS	An indicator variable equal to 1 if university i has a Carnegie Classification indicating it is a master's degree college or university (codes in the 20s) and zero otherwise.
Carnegie Doctoral	IPEDS	An indicator variable equal to 1 if university i has a Carnegie Classification indicating it is a doctoral/research university (codes in the 10s) and zero otherwise.
Percent of Graduates who are Z	IPEDS	The percent of accounting graduates from university i in year t who are of race Z where Z is Black, or Hispanic.
Z Graduate Percentage in the X to Y	IPEDS	An indicator variable equal to 1 if the percentile rank of the representation of individuals of race Z among the accounting graduates from university i in year t is between X and Y and zero

Percentiles		otherwise.
Admission Rate	IPEDS	The number of students admitted by university i in year t divided by the number of applicants to university i in year t.
Test Scores	IPEDS	A measure of the rank of the test scores of incoming college freshman. The variable is calculated from a series of IPEDS variables measuring the 75th percentile ranks on seven different standardized tests, or test sections, of incoming college freshman to university i in year t. To maximize the number of universities we can compare using test scores, we first transform each of the seven scores into percentiles among all universities reporting the score in year t. We then average these percentiles for each test reported by university i in year t, yielding an average percentile rank for university i in year t on all tests reported. Values near 1 represent high scores and values near zero represent low scores.
Region	IPEDS	Indicator variables equal to 1 for a given geographical region and zero otherwise. Regions are: New England, Mid East, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains, and Far West.
Late		An indicator variable either: equal to 1 if the year is greater than 2008 and zero otherwise, or equal to 1 if the year is greater than 2003 and zero otherwise.

TABLE 1
Racial Diversity of Accounting Graduates and Auditor Hires in Three Datasets over Time

	All Graduates IPEDS (Bach and Mast)				Estimates from LinkedIn Hires (Bach and Mast)		AICPA Trends Hires (Bach and Mast)	
Year	Black	Hispanic	Other Minority	Unknown Race	Black	Hispanic	Black	Hispanic
2001	6.7%	6.7%	6.5%	7.8%	4.67%	4.60%	3%	6%
2002	6.9%	6.8%	6.5%	8.7%	4.60%	4.71%	3%	6%
2003	6.9%	7.0%	6.6%	8.6%	4.77%	4.85%	5%	4%
2004	6.9%	7.2%	6.9%	9.2%	4.70%	5.15%	3%	8%
2005	6.6%	7.0%	7.4%	9.9%	4.74%	4.87%		
2006	7.0%	7.7%	8.0%	9.7%	4.65%	5.08%		
2007	7.1%	7.1%	8.2%	9.4%	4.57%	4.86%	8%	4%
2008	6.8%	7.7%	8.0%	9.6%	4.47%	5.25%	4%	4%
2009	7.2%	7.5%	7.7%	10.2%	4.24%	5.38%		
2010	6.7%	8.0%	8.1%	10.7%	4.46%	5.40%	4%	7%
2011	6.5%	7.7%	8.8%	10.3%	4.13%	5.42%		
2012	6.3%	8.1%	9.1%	11.0%	4.10%	5.81%	4%	6%
2013	6.6%	8.6%	8.9%	11.7%	3.96%	6.19%		
2014	6.3%	9.6%	8.8%	11.0%	4.22%	6.62%	3%	8%
Average	6.75%	7.63%	7.84%	9.84%	4.45%	5.30%	4.11%	5.89%
Weighted Ave.	6.72%	7.73%	7.98%	10.00%	4.36%	5.45%	4.27%	6.01%

Values in this table are estimates of the racial diversity of people graduating from accounting programs and of people hired by audit firms. We calculate values in the first four columns using the IPEDS. We calculate values in the fifth and sixth columns using data from LinkedIn. We calculate values in the seventh and eighth columns using data from AICPA publications (AICPA 2011, 2015). Values include graduates of both bachelor's and master's degree programs. The row labelled "Average" shows simple averages of the yearly values in each column. The row labelled "Weighted Ave." shows weighted averages of the yearly values where the weights are the numbers of people used to compute the value.

TABLE 2
Descriptive Statistics for Hiring Data

Panel A: Frequencies of Hiring Counts from U.S. Universities for Big N and Non-Big N Auditors

	Big N Hiring Count Frequencies			Non-Big N Hiring Count Frequencies		
Number of People Hired in a University-Year	Freq.	Percent	Cumulative	Freq.	Percent	Cumulative
0	961	15.0	15.0	1,479	23.0	23.0
1 - 10	2,976	46.3	61.3	3,768	58.7	81.7
11 - 20	930	14.5	75.8	734	11.4	93.1
21 - 30	423	6.6	82.4	255	4.0	97.1
31 - 40	263	4.1	86.4	114	1.8	98.9
41 - 50	186	2.9	89.3	30	0.5	99.3
51 - 60	134	2.1	91.4	17	0.3	99.6
61 - 70	87	1.4	92.8	14	0.2	99.8
71 - 80	94	1.5	94.2	6	0.1	99.9
81 - 90	50	0.8	95.0	1	0.0	99.9
91 - 100	62	1.0	96.0	4	0.1	100.0
100+	258	4.0	96.9	2	0.0	100.0

Panel B: Total Hiring and Total People Ever Employed by Big and Non-Big Auditors in LinkedIn Sample

	Hiring	Ever Employed
Big N	125,278	744,078
Non-Big N	39,430	243,533

Panel C: Our LinkedIn Sample's Coverage of the Population of Audit Firm Hires by Year

	AICPA "Trends" Hiring			LinkedIn Hiring			
Year	Bachelor's	Master's	Total	Big N	Non-Big N	Total	Coverage
2001	13,335	3,035	16,370	5,057	965	6,022	37%
2002	12,630	3,295	15,925	3,771	897	4,668	29%
2003	13,270	3,555	16,825	4,456	1,271	5,727	34%
2004	14,985	4,720	19,705	6,272	1,823	8,095	41%
2005				7,619	2,670	10,289	
2006				8,351	2,994	11,345	
2007	28,025	8,087	36,112	9,036	3,294	12,330	34%
2008	19,110	6,378	25,488	8,685	3,353	12,038	47%
2009				7,921	2,274	10,195	
2010	19,870	13,451	33,321	10,389	3,042	13,431	40%
2011				15,253	4,497	19,750	
2012	23,793	16,557	40,350	14,987	4,637	19,624	49%
2013				13,998	4,808	18,806	
2014	24,931	18,321	43,252	9,483	2,905	12,388	29%

We calculate "Hiring" and "Ever Employed" values in this table using data from LinkedIn. Values in Panel C under the heading "AICPA 'Trends' Hiring" are taken from AICPA publications (AICPA 2011, 2015).

TABLE 3
Descriptive Statistics

	N	Mean	Std. Dev.	Min	Max
Big N Hiring	6,424	19.50	36.03	0	374
Non-Big N Hiring	6,424	6.14	9.40	0	107
Percent of Graduates who are Black	6,424	0.07	0.11	0	1
Black Representation 60-75th Percentiles	6,424	0.15	0.36	0	1
Black Representation 75-90th Percentiles	6,424	0.15	0.36	0	1
Black Representation 90-100th Percentiles	6,424	0.10	0.30	0	1
Percent of Graduates who are Hispanic	6,424	0.08	0.16	0	1
Hispanic Representation 60-75th Percentiles	6,424	0.15	0.35	0	1
Hispanic Representation 75-90th Percentiles	6,424	0.15	0.36	0	1
Hispanic Representation 90-100th Percentiles	6,424	0.10	0.29	0	1
Accounting Graduates	6,424	95.62	93.01	0	842
Business Graduates	6,424	676.40	548.59	3	6621
Big N Ever Employed	6,424	96.33	163.70	0	1565
Non-Big N Ever Employed	6,424	31.77	46.83	0	475
Top 10 Accounting	6,424	0.01	0.12	0	1
Top 11 to 20 Accounting	6,424	0.01	0.11	0	1
Top 21 to 30 Accounting	6,424	0.01	0.12	0	1
Top 10 MBA	6,424	0.01	0.08	0	1
Top 11 to 20 MBA	6,424	0.01	0.12	0	1
Top 21 to 30 MBA	6,424	0.02	0.14	0	1
Top 31 to 50 MBA	6,424	0.03	0.18	0	1
Top 51 to 100 MBA	6,424	0.08	0.27	0	1
Carnegie Bachelor’s/Associate’s	6,424	0.02	0.14	0	1
Carnegie Bachelor's	6,424	0.06	0.24	0	1
Carnegie Master's	6,424	0.51	0.50	0	1
Carnegie Doctoral	6,424	0.41	0.49	0	1
Admission Rate	6,220	0.67	0.17	0.07	1
Test Scores	5,996	0.61	0.24	0	1

Values in this table are calculated using our merged sample. “Big N Hiring” and “Non-Big N Hiring” are hiring counts by university-year taken from LinkedIn. “Percent of Graduates who are Black/Hispanic” are continuous measures of Black and Hispanic representation among accounting graduates and “Black/Hispanic Representation ### Percentiles” are indicator variables for differing levels of high Black and Hispanic representation taken from IPEDS. “Accounting Graduates” and “Business Graduates” are counts of the total numbers of accounting and business graduates by university-year taken from IPEDS. “Big N Ever Employed” and “Non-Big N Ever Employed” are counts of the numbers of people on LinkedIn whose resumes indicate that they were ever employed by a big N or non-big N auditor. “Top ## Accounting” and “Top ## MBA” are indicator variables equal to 1 for university-years with accounting or MBA programs ranked in U.S. News within the ranking range indicated and zero otherwise. “Carnegie…” are indicator variables equal to 1 for a selection of Carnegie Classifications in IPEDS and zero otherwise. “Admission Rate” is a measure of the percentage of applicants who were admitted in a given university-year taken from IPEDS. “Test Scores” is a measure of the percentile rank of the test scores of incoming freshmen at each university in each year with universities with relatively high test scores in a given year receiving values near 1 and universities with relatively low test scores in a given year receiving values near 0. Data used to calculate “Test Scores” were taken from IPEDS. Detailed variables definitions are in Appendix A.

TABLE 4
Correlations among Variables Used in Multi-Variate Tests

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Big N Hiring																				
2 Non-Big N Hiring	0.74																			
3 Big N Ever Employed	0.95	0.72																		
4 Non-Big N Ever Emp	0.73	0.90	0.76																	
5 Black Representation	-0.12	-0.15	-0.13	-0.16																
6 Hispanic Rep	-0.05	-0.07	-0.06	-0.08	-0.01†															
7 Top 10 Accounting	0.44	0.27	0.46	0.31	-0.05	-0.02†														
8 Top 11 to 20 Acctg	0.31	0.19	0.30	0.20	-0.05	-0.02	-0.01†													
9 Top 21 to 30 Acctg	0.23	0.23	0.22	0.20	-0.05	-0.02†	-0.01†	-0.01†												
10 Top 10 MBA	0.14	0.04	0.16	0.07	-0.03	-0.02†	0.26	0.14	0.07											
11 Top 11 to 20 MBA	0.32	0.10	0.33	0.12	-0.04	-0.02†	0.39	0.18	0.15	-0.01†										
12 Top 21 to 30 MBA	0.31	0.23	0.30	0.25	-0.05	-0.04	0.18	0.18	0.12	-0.01†	-0.02†									
13 Top 31 to 50 MBA	0.38	0.30	0.39	0.29	-0.06	-0.04	0.08	0.21	0.28	-0.02†	-0.02	-0.03								
14 Top 51 to 100 MBA	0.21	0.20	0.20	0.18	-0.04	-0.05	-0.04	-0.02	-0.01†	-0.03	-0.04	-0.05	-0.06							
15 Admission Rate	-0.32	-0.13	-0.33	-0.13	-0.09	-0.13	-0.17	-0.13	-0.05	-0.19	-0.25	-0.13	-0.13	-0.09						
16 Test Scores	0.47	0.36	0.49	0.36	-0.27	-0.22	0.18	0.15	0.14	0.13	0.19	0.20	0.24	0.29	-0.26					
17 Carnegie Bachelor's	-0.11	-0.12	-0.12	-0.13	0.09	-0.04	-0.03	-0.03	-0.03	-0.02†	-0.03	-0.04	-0.05	-0.07	0.00†	-0.12				
18 Carnegie Master's	-0.37	-0.30	-0.39	-0.30	0.02†	0.05	-0.12	-0.11	-0.11	-0.08	-0.13	-0.15	-0.20	-0.26	0.13	-0.35	-0.24			
19 Carnegie Doctoral	0.44	0.37	0.46	0.38	-0.05	-0.06	0.14	0.13	0.13	0.10	0.15	0.18	0.22	0.30	-0.12	0.44	-0.20	-0.87		
20 Program Size	0.61	0.64	0.63	0.64	-0.07	0.04	0.27	0.16	0.17	0.02†	0.12	0.16	0.27	0.26	-0.17	0.27	-0.12	-0.31	0.39	
21 Program Size ^ 2	0.55	0.58	0.57	0.57	-0.04	0.03	0.33	0.11	0.13	0.00†	0.11	0.13	0.25	0.19	-0.16	0.20	-0.07	-0.19	0.24	0.89

Values in this table are Pearson correlation coefficients calculated using our merged sample. Nearly every coefficient in the table is statistically significant at the $p < 0.01$ level. A small number of the coefficients are statistically significant at the $p = 0.05$ level, and these are marked with a †. “Big N Hiring” and “Non-Big N Hiring” are hiring counts by university-year taken from LinkedIn. “Big N Ever Employed” and “Non-Big N Ever Employed” are counts of the numbers of people on LinkedIn whose resumes indicate that they were ever employed by a big N or non-big N auditor. “Black/Hispanic Representation” are continuous measures of Black and Hispanic representation among accounting graduates taken from IPEDS. “Top ## Accounting” and “Top ## MBA” are indicator variables equal to 1 for university-years with accounting or MBA programs ranked in U.S. News within the ranking range indicated and zero otherwise. “Admission Rate” is a measure of the percentage of applicants who were admitted in a given university-year taken from IPEDS. “Test Scores” is a measure of the percentile rank of the test scores of incoming freshmen at each in each year with universities with relatively high test scores in a given year receiving values near 1 and universities with relatively low test scores in a given year receiving values near 0. Data used to calculate “Test Scores” were taken from IPEDS. “Carnegie…” are indicator variables equal to 1 for a selection of Carnegie Classifications in IPEDS and zero otherwise. “Program Size” is the total number of accounting graduates by university-year taken from IPEDS. Detailed variables definitions are in Appendix A.

TABLE 5
Average Hiring from Universities with High Black and Hispanic Representation

	Big N Hiring	Non-Big N Hiring	Total Graduates	Big N %	Non-Big N %
Black Representation in the 60-75th Percentiles	17.72	5.77	106.62	16.62%	5.42%
Black Representation in the 75-90th Percentiles	12.40	4.21	93.41	13.27%	4.51%
Black Representation in the 90-100th Percentiles	5.55	1.87	72.33	7.68%	2.59%
Hispanic Representation in the 60-75th Percentiles	30.08	7.71	113.85	26.42%	6.78%
Hispanic Representation in the 75-90th Percentiles	24.79	7.04	124.49	19.92%	5.66%
Hispanic Representation in the 90-100th Percentiles	6.78	2.74	91.97	7.37%	2.98%
Univ. without High Black or Hisp. Representation	21.59	7.60	88.87	24.29%	8.55%

This table shows estimates of the numbers of graduates of accounting programs with and without high Black and Hispanic representation who were hired by big N and non-big N auditing firms and of the total numbers of graduates from these programs. The columns labeled "Big N %" and "Non-Big N %" show the percent of all graduates hired by big and non-big N firms.

TABLE 6
Audit Firm Recruiting from Universities with High Black or Hispanic Representation

	Big N			Non-Big N		
	1	2	Diff.	3	4	Diff.
Count equation: Factor change in expected count of audit firm hires for observations not likely to be zero						
Black Representation in the 60-75th Percentiles	0.725***	0.852***	-0.13**	0.743***	0.792***	-0.05*
Black Representation in the 75-90th Percentiles	0.545***	0.770***	-0.23***	0.578***	0.670***	-0.09***
Black Representation in the 90-100th Percentiles	0.376***	0.783*	-0.41***	0.387***	0.510***	-0.12***
Hispanic Representation in the 60-75th Percentiles	1.170**	0.993		1.023	0.973	
Hispanic Representation in the 75-90th Percentiles	0.928	1.082		0.947	1.011	
Hispanic Representation in the 90-100th Percentiles	0.458***	0.848		0.622***	0.785**	
Program Size	1.014***	1.009***		1.011***	1.008***	
Program Size Squared	1.000***	1.000***		1.000***	1.000***	
Top 10 Accounting		1.444*			1.314	
Top 11 to 20 Accounting		1.214			1.055	
Top 21 to 30 Accounting		1.114			1.226*	
Top 10 MBA		1.338			0.973	
Top 11 to 20 MBA		1.706**			0.909	
Top 21 to 30 MBA		1.847***			1.160	
Top 31 to 50 MBA		1.388***			0.993	
Top 51 to 100 MBA		1.188**			1.022	
Carnegie Bachelor's		0.656			1.075	
Carnegie Master's		0.974			1.869*	
Carnegie Doctoral		1.646*			2.505**	
Admission Rate		0.610**			0.802	
Test Scores		7.177***			2.151***	
Constant	5.581***	1.804*		2.397***	0.901	
Log(Alpha)	1.036	0.401***		0.507***	0.384***	
N (University-Years)	6,424	5,993		6,424	5,993	
University-Years with Zero Big N Hires	961	820		1,479	1,274	
Includes Year Dummies and Region Dummies	Yes	Yes		Yes	Yes	

Interpretation of coefficients from the count models: When all else is held constant, the number of people audit firms are expected to hire for a given university-year is different by a factor of *[coefficient on x]* for a one unit increase in x.

	Big N		Non-Big N	
	1	2	3	4
Binary equation: Factor change in odds that the hiring count is always zero				
Black Representation in the 60-75th Percentiles	0.255*	0.840	1.233	1.120
Black Representation in the 75-90th Percentiles	0.392*	1.189	0.747	0.846
Black Representation in the 90-100th Percentiles	0.462	0.896	0.534	0.406
Hispanic Representation in the 60-75th Percentiles	0.893	0.814	0.702	0.651
Hispanic Representation in the 75-90th Percentiles	1.789	1.567	1.943	1.647
Hispanic Representation in the 90-100th Percentiles	0.192	1.485	1.461	1.386
Program Size	0.913***	0.972	0.957**	0.963***
Program Size Squared	1.000***	1.000	1.000	1.000***
Top 10 Accounting		0.000***		0.000***
Top 11 to 20 Accounting		0.000***		0.000***
Top 21 to 30 Accounting		5.700*		0.000***
Top 10 MBA		0.000***		16.172
Top 11 to 20 MBA		0.000***		2.884
Top 21 to 30 MBA		0.000***		0.425
Top 31 to 50 MBA		0.000***		0.401
Top 51 to 100 MBA		0.000***		0.442
Carnegie Bachelor's		0.522		1.866
Carnegie Master's		0.164**		1.846
Carnegie Doctoral		0.086*		1.591
Admission Rate		0.287		0.420

Test Scores		0.279		0.140**
Constant	1.806	13.223**	0.706	2.012

Interpretation of coefficients from the binary models: When all else is held constant, the likelihood that audit firms will hire zero people for a given university-year is different by a factor of *[coefficient on x]* for a one unit increase in x.

Models in this table explain the count of newly hired individuals from university i in year t by big N or non-big N auditors and are estimated using zero inflated negative binomial (ZINB) regressions. ZINB models separate the estimation sample into two latent or unobserved subsamples, one in which the count will always be zero, and another in which the count may sometimes be zero but has a positive probability of being greater than zero. Estimation involves: estimating the probability that an observation is in the "always zero" or "not always zero" subsample using a logit model, modeling the probabilities of observing different counts for observations in the "not always zero" group using a negative binomial model, and then computing coefficients by mixing the probabilities from the two groups. Values in the section of the table labelled "count equation" describe the results of the zero inflated negative binomial estimation of hiring counts by university-year. Values in the section of the table labelled "binary equation" describe the results of the logit estimation explaining the likelihood that a university-year has a zero count. Errors are clustered by university. The dependent variables are hiring counts by university-year taken from LinkedIn for big N auditors in columns 1 and 2 and non-big N auditors in columns 3 and 4. "Black/Hispanic Representation ### Percentiles" are indicator variables for differing levels of high Black and Hispanic representation taken from IPEDS. "Program Size" is the total number of accounting graduates by university-year taken from IPEDS. "Top ## Accounting" and "Top ## MBA" are indicator variables equal to 1 for university-years with accounting or MBA programs ranked in U.S. News within the ranking range indicated and zero otherwise. "Carnegie…" are indicator variables equal to 1 for a selection of Carnegie Classifications in IPEDS and zero otherwise. "Admission Rate" is a measure of the percentage of applicants who were admitted in a given university-year taken from IPEDS. "Test Scores" is a measure of the percentile rank of the test scores of incoming freshmen at each in each year with universities with relatively high test scores in a given year receiving values near 1 and universities with relatively low test scores in a given year receiving values near 0. Data used to calculate "Test Scores" were taken from IPEDS. "Year dummies" are indicator variables equal to one for years in the sample and zero otherwise. "Region dummies" are indicator variable equal to one for IPEDS regions and zero otherwise. Detailed variables definitions are in Appendix A.

TABLE 7
Hiring in the Past and Audit Firm Recruiting from Universities with High Black or Hispanic Representation

	Big N		Non-Big N	
	1	2	3	4
Count equation: Factor change in expected count of audit firm hires for observations not likely to be zero				
Black Representation in the 60-75th Percentiles	0.947	0.817***	0.921**	0.783***
Black Representation in the 75-90th Percentiles	0.896**	0.760***	0.834***	0.699***
Black Representation in the 90-100th Percentiles	0.846*	0.641***	0.655***	0.446***
Hispanic Representation in the 60-75th Percentiles	0.981	1.104**	0.972	1.046
Hispanic Representation in the 75-90th Percentiles	1.013	1.176**	0.971	1.106
Hispanic Representation in the 90-100th Percentiles	0.892	0.805**	0.850**	0.703***
Ever Employed * Black Rep 60-75		1.001***		1.003***
Ever Employed * Black Rep 75-90		1.002		1.004
Ever Employed * Black Rep 90-100		1.004***		1.015***
Ever Employed * Hispanic Rep 60-75		0.999***		0.998
Ever Employed * Hispanic Rep 75-90		0.999***		0.998
Ever Employed * Hispanic Rep 90-100		1.002**		1.005***
Ever Employed	1.003***	1.004***	1.011***	1.011***
Constant	2.548***	2.800***	1.765*	1.857**
Log(Alpha)	0.241***	0.224***	0.173***	0.159***
N (University-Years)	5,993	5,993	5,993	5,993
University-Years with Zero Hires	820	820	1274	1,274
Count and Binary Equations Include:				
Program Size and Square of Program Size Controls	Yes	Yes	Yes	Yes
School Quality Controls	Yes	Yes	Yes	Yes
Year & Region Dummies	Yes	Yes	Yes	Yes

Interpretation of coefficients from the count models: When all else is held constant, the number of people audit firms are expected to hire for a given university-year is different by a factor of *[coefficient on x]* for a one unit increase in x.

	Big N		Non-Big N	
	1	2	3	4
Binary equation: Factor change in odds that the hiring count is always zero				
Black Representation in the 60-75th Percentiles	0.839	0.779	1.336	1.150
Black Representation in the 75-90th Percentiles	1.035	0.958	1.213	1.049
Black Representation in the 90-100th Percentiles	0.998	0.851	0.663*	0.429***
Hispanic Representation in the 60-75th Percentiles	1.287	1.359	0.952	1.030
Hispanic Representation in the 75-90th Percentiles	1.340	1.428	1.264	1.418
Hispanic Representation in the 90-100th Percentiles	1.175	1.092	1.023	0.887
Ever Employed	0.705***	0.706***	0.632***	0.636***
Constant	5.718***	5.864***	2.607	2.525

Interpretation of coefficients from the binary models: When all else is held constant, the likelihood that audit firms will hire zero people for a given university-year is different by a factor of *[coefficient on x]* for a one unit increase in x.

Models in this table explain the count of newly hired individuals from university i in year t by big N or non-big N auditors and are estimated using zero inflated negative binomial (ZINB) regressions. ZINB models separate the estimation sample into two latent or unobserved subsamples, one in which the count will always be zero, and another in which the count may sometimes be zero but has a positive probability of being greater than zero. Estimation involves: estimating the probability that an observation is in the "always zero" or "not always zero" subsample using a logit model, modeling the probabilities of observing different counts for observations in the "not always zero" group using a negative binomial model, and then computing coefficients by mixing the probabilities from the two groups. Values in the section of the table labelled "count equation" describe the results of the zero inflated negative binomial estimation of hiring counts by university-year. Values in the section of the table labelled "binary equation" describe the results of the logit estimation explaining the likelihood that a university-year has a zero count. Errors are clustered by university. The dependent variables are hiring counts by university-year taken from LinkedIn for big N auditors in columns 1 and 2 and non-big N auditors in columns 3 and 4. “Black/Hispanic Representation ### Percentiles” are indicator variables for differing levels of high Black and Hispanic representation taken from IPEDS. “Ever employed” is a count of the number of people on LinkedIn from a given university-year that report ever having worked for a big N (columns 1 and 2) or non-big N (columns 3 and 4) auditor. A number of control variables are included in both the count and equations but their coefficients are not displayed. They are as follows. “Program Size” is the total number of accounting graduates by university-year taken from IPEDS. “Top ## Accounting” and “Top ## MBA” are indicator variables equal to 1 for university-years with accounting or MBA programs ranked in U.S. News within the ranking range indicated and zero otherwise. “Carnegie…” are indicator variables equal to 1 for a selection of Carnegie Classifications in IPEDS and zero otherwise. “Admission Rate” is a measure of the percentage of applicants who were admitted in a given university-year taken from IPEDS. “Test Scores” is a measure of the percentile rank of the test scores of incoming freshmen at each in each year with universities with relatively high test scores in a given year receiving values near 1 and universities with relatively low test scores in a given year receiving values near 0. Data used to calculate “Test Scores” were taken from IPEDS. “Year dummies” are indicator variables equal to one for years in the sample and zero otherwise. “Region dummies” are indicator variable equal to one for IPEDS regions and zero otherwise. Detailed variables definitions are in Appendix A.

TABLE 8
Audit Firm Recruiting from Universities with High Black or Hispanic Representation Over Time

	Late is 2009-2014		Late is 2004-2014	
	Big N	Non-Big N	Big N	Non-Big N
Count equation: Factor change in expected count of audit firm hires for observations not likely to be zero				
Black Representation in the 60-75th Percentiles	0.909**	0.801***	0.937	0.745***
Black Representation in the 75-90th Percentiles	0.843**	0.719***	0.893	0.719**
Black Representation in the 90-100th Percentiles	0.768**	0.570***	0.731**	0.577***
Hispanic Representation in the 60-75th Percentiles	0.975	0.932	0.971	0.844
Hispanic Representation in the 75-90th Percentiles	1.113	1.001	1.053	0.875
Hispanic Representation in the 90-100th Percentiles	0.907	0.769*	1.008	0.573***
Late * Black Representation in the 60-75th Percentiles	0.887*	0.974	0.891	1.065
Late * Black Representation in the 75-90th Percentiles	0.847**	0.864**	0.830*	0.927
Late * Black Representation in the 90-100th Percentiles	1.049	0.798*	1.102	0.868
Late * Hispanic Representation in the 60-75th Percentiles	1.016	1.085	1.024	1.176
Late * Hispanic Representation in the 75-90th Percentiles	0.901	1.020	1.027	1.182*
Late * Hispanic Representation in the 90-100th Percentiles	0.852*	1.044	0.818	1.419**
Late	0.986	0.888**	1.656***	1.797***
Constant	1.777*	0.906	1.090	0.497*
Log(Alpha)	0.379***	0.384***	0.401***	0.382***
N (University-Years)	5,993	5,993	5,993	5,993
University-Years with Zero Big N Hires	820	1,274	820	1,274
Includes Size and Quality Controls	Yes	Yes	Yes	Yes
Includes Year Dummies	Yes	Yes	Yes	Yes
Includes Region Dummies	Yes	Yes	Yes	Yes

Interpretation of coefficients from the count models: When all else is held constant, the number of people audit firms are expected to hire for a given university-year is different by a factor of *[coefficient on x]* for a one unit increase in x.

	Late is 2009-2014		Late is 2004-2014	
	Big N	Non-Big N	Big N	Non-Big N
Binary equation: Factor change in odds that the hiring count is always zero				
Black Representation in the 60-75th Percentiles	0.942	0.885	0.216	0.000
Black Representation in the 75-90th Percentiles	1.329	1.132	1.039	0.698
Black Representation in the 90-100th Percentiles	1.195	0.763	1.146	0.821
Hispanic Representation in the 60-75th Percentiles	0.753	0.670	1.316	1.425
Hispanic Representation in the 75-90th Percentiles	1.242	1.840	0.662	1.513
Hispanic Representation in the 90-100th Percentiles	1.130	1.570	2.213	0.887
Late * Black Representation in the 60-75th Percentiles	1.088	1.570	4.926	3037362.404
Late * Black Representation in the 75-90th Percentiles	1.205	0.537	1.203	1.335
Late * Black Representation in the 90-100th Percentiles	0.460	0.293	0.766	0.445
Late * Hispanic Representation in the 60-75th Percentiles	0.818	0.920	0.502	0.374
Late * Hispanic Representation in the 75-90th Percentiles	1.089	0.836	2.701	1.056
Late * Hispanic Representation in the 90-100th Percentiles	1.468	0.744	0.668	1.669
Late	0.486*	1.687	1.051	0.343***
Constant	9.733**	2.248	11.876*	5.820

Interpretation of coefficients from the binary models: When all else is held constant, the likelihood that audit firms will hire zero people for a given university-year is different by a factor of *[coefficient on x]* for a one unit increase in x.

Models in this table explain the count of newly hired individuals from university i in year t by big N or non-big N auditors and are estimated using zero inflated negative binomial (ZINB) regressions. ZINB models separate the estimation sample into two latent or unobserved subsamples, one in which the count will always be zero, and another in which the count may sometimes be zero but has a positive probability of being greater than zero. Estimation involves: estimating the probability that an observation is in the "always zero" or "not always zero" subsample using a logit model, modeling the probabilities of observing different counts for observations in the "not always zero" group using a negative binomial model, and then computing coefficients by mixing the probabilities from the two groups. Values in the section of the table labelled "count equation" describe the results of the zero inflated negative binomial estimation of hiring counts by university-year. Values in the section of the table labelled "binary equation" describe the results of the logit estimation explaining the likelihood that a university-year has a zero count. Errors are clustered by university. The dependent variables are hiring counts by university-year taken from LinkedIn for big N auditors in columns 1 and 2 and non-big N auditors in columns 3 and 4. "Black/Hispanic Representation ### Percentiles" are indicator variables for differing levels of high Black and Hispanic representation taken from IPEDS. "Late" is an indicator variable equal to one for later years and zero for earlier years, where later years are those after 2008 (columns 1 and 2) or after 2003 (columns 3 and 4). A number of control variables are included in both the count and equations but their coefficients are not displayed. They are as follows. "Program Size" is the total number of accounting graduates by university-year taken from IPEDS. "Top ## Accounting" and "Top ## MBA" are indicator variables equal to 1 for university-years with accounting or MBA programs ranked in U.S. News within the ranking range indicated and zero otherwise. "Carnegie…" are indicator variables equal to 1 for a selection of Carnegie Classifications in IPEDS and zero otherwise. "Admission Rate" is a measure of the percentage of applicants who were admitted in a given university-year taken from IPEDS. "Test Scores" is a measure of the percentile rank of the test scores of incoming freshmen at each in each year with universities with relatively high test scores in a given year receiving values near 1 and universities with relatively low test scores in a given year receiving values near 0. Data used to calculate "Test Scores" were taken from IPEDS. "Year dummies" are indicator variables equal to one for years in the sample and zero otherwise. "Region dummies" are indicator variable equal to one for IPEDS regions and zero otherwise. Detailed variables definitions are in Appendix A.

TABLE 9

Over-Recruited Universities with Few Black Graduates Matched with Under-Recruited Universities of Equal or Better Quality with Many Black Graduates

	Total Predicted	Total Hired	Total Error	Acct Grads	Black %	Acct Rank	MBA Rank	Test %ile		Total Predicted	Total Hired	Total Error	Acct Grads	Black %	Acct Rank	MBA Rank	Test %ile
University of Michigan-Ann Arbor	734	1,656	922	734	2.36%	4.7	11.4	0.97									
U. of North Carolina at Chapel Hill	1,152	1,195	43	1,621	2.89%	10.1	19.4	0.96									
Brigham Young University	1,835	1,939	104	4,247	0.05%	10.7	34.6	0.94									
Indiana University-Bloomington	197	1,151	954	196	2.53%	11.3	23.0	0.85									
University of California-Berkeley	1,157	1,309	152	1,431	1.41%	16.3	7.6	0.98									
Texas A & M University	1,707	2,313	606	5,790	1.85%	25.6	35.4	0.87									
University of Iowa	492	609	117	2,188	0.44%	26.1	42.5	0.87									
University of Arizona	457	567	110	2,406	0.98%	26.3	49.1	0.74									
John Carroll University	90	243	153	682	1.39%	27.0	.	0.72									
U. of Minnesota-Twin Cities	627	887	260	1,762	1.92%	.	25.6	0.92									
Vanderbilt University	181	362	181	152	1.15%	.	29.8	0.99	Washington University	287	231	-56	623	6.07%	.	28.4	0.99
Wake Forest University	221	244	23	558	1.39%	.	43.6	0.96									
Babson College	88	238	150	167	2.46%	.	53.3	0.92	U. of Maryland-College Park	2,212	2,124	-88	3,337	10.79%	.	37.2	0.95
University of Missouri-Columbia	587	715	128	3,256	2.84%	.	60.9	0.88	Rice University	303	183	-120	386	6.68%	.	38.6	0.99
U. of Colorado at Boulder	352	586	234	1,796	1.04%	.	64.8	0.86	The U. of Texas at Dallas	902	272	-630	3,422	7.16%	.	58.6	0.92
Boston University	20	57	37	2	0.00%	.	70.0	0.96									
Baylor University	495	673	178	2,044	2.95%	.	72.0	0.87									
Santa Clara University	198	403	205	870	0.68%	.	76.7	0.89									
Texas Christian University	313	360	47	1,223	1.44%	.	84.0	0.82	North Carolina State University	740	646	-94	3,049	7.88%	.	70.9	0.84
Saint Louis U.-Main Campus	188	379	191	629	2.60%	.	90.5	0.92									
Lehigh University	672	911	239	1,400	0.62%	.	92.8	0.94									
Miami University-Oxford	943	1,340	397	3,650	1.45%	.	97.8	0.89									
University of Kansas Main Campus	480	611	131	3,016	1.22%	.	99.4	0.85									
University of Denver	230	462	232	1,111	0.99%	.	100.5	0.87									
California Polytechnic State U.	245	770	525	830	1.20%	.	105.7	0.87									
San Diego State University	200	271	71	919	1.72%	.	106.3	0.60									
University of St Thomas	175	344	169	1,248	1.95%	.	107.0	0.80	Howard University	317	272	-45	508	80.93%	.	102.8	0.84
Ohio University-Main Campus	201	513	312	1,176	2.18%	.	110.3	0.68									
Texas Tech University	414	486	72	2,997	1.58%	.	110.6	0.69	University of Central Florida	945	447	-498	4,911	6.35%	.	103.4	0.77
Truman State University	152	198	46	1,382	2.14%	.	113.3	0.93									
James Madison University	224	998	774	2,114	2.31%	.	114.0	0.77									
West Virginia University	209	294	85	1,975	1.98%	.	118.8	0.57	Temple University	762	669	-93	2,690	15.42%	.	60.5	0.65
University of Scranton	149	213	64	859	0.27%	.	120.0	0.70	U. of Cincinnati-Main Campus	431	364	-67	2,052	8.14%	.	99.9	0.76
University of Dayton	251	341	90	1,021	1.77%	.	124.0	0.81									
The U. of Montana-Missoula	116	159	43	984	0.29%	.	125.5	0.62									
Kansas State University	109	146	37	1,072	0.84%	.	130.3	0.71									
Fairfield University	122	301	179	643	1.78%	.	133.3	0.80	U. of South Carolina at Columbia	585	0	-585	2,464	8.60%	.	63.8	0.82

San Jose State University	69	508	439	684	0.69%	.	134.0	0.44	Arkansas State U.-Main Campus	62	19	-43	987	6.28%	.	131.0	0.51
Northern Illinois University	435	460	25	3,726	2.72%	.	137.0	0.54	Rutgers University-Newark	813	415	-398	3,686	13.79%	.	64.3	0.55
Kent State U.-Main Campus	168	215	47	1,611	2.84%	.	137.5	0.51	Florida International University	528	484	-44	4,076	7.62%	.	137.9	0.60
University of North Dakota-Main	94	182	88	756	0.15%	.	154.5	0.65	Mississippi State University	277	152	-125	1,369	10.32%	.	138.3	0.83
Appalachian State University	143	167	24	1,576	1.12%	.	176.3	0.69									
U. of Wisconsin-Whitewater	171	209	38	2,616	1.34%	.	178.0	0.54									
Saint Cloud State University	43	70	27	1,183	1.44%	.	213.0	0.42	La Salle University	107	7	-100	1,129	9.83%	.	165.0	0.48
Shippensburg U. of Pennsylvania	62	93	31	688	2.90%	.	213.0	0.38	Louisiana Tech University	91	55	-36	541	9.27%	.	179.0	0.59
Eastern Washington University	83	115	32	777	1.06%	.	228.0	0.41	University of South Alabama	97	43	-54	837	9.56%	.	213.0	0.49
University of Richmond	101	403	302	685	2.19%	.	.	0.95	Johns Hopkins University	619	398	-221	1,198	14.56%	.	.	0.99
Villanova University	564	1,334	770	2,247	1.78%	.	.	0.94	Stevens Institute of Technology	80	10	-70	235	6.59%	.	.	0.95
The College of New Jersey	235	289	54	690	2.48%	.	.	0.92									
Creighton University	77	141	64	480	1.61%	.	.	0.89									
U. of California-Santa Barbara	450	922	472	1,052	1.07%	.	.	0.88									
Marquette University	346	473	127	1,313	1.20%	.	.	0.88									
Rutgers University-New Brunswick	539	1,296	757	1,437	2.93%	.	.	0.87									
Butler University	113	177	64	501	2.15%	.	.	0.87									
Providence College	161	287	126	571	0.96%	.	.	0.84	U of Alabama in Huntsville	213	23	-190	908	10.09%	.	.	0.84
U. of California-Santa Clara	270	317	47	567	2.16%	.	.	0.81	Florida Tech. - Melbourne	106	29	-77	247	12.72%	.	.	0.83
Colorado State University	257	286	29	1,869	1.81%	.	.	0.76	Suny at Stony Brook	191	77	-114	421	8.56%	.	.	0.81
Westminster College	15	57	42	72	0.00%	.	.	0.73	Campbell University	82	26	-56	444	14.38%	.	.	0.79
Siena College	152	186	34	1,409	1.37%	.	.	0.71	University of Louisville	274	133	-141	1,550	8.35%	.	.	0.77
Bryant College	264	498	234	1,870	2.17%	.	.	0.66	Indiana Wesleyan University	191	39	-152	1,808	11.87%	.	.	0.74
University of Northern Iowa	96	190	94	1,819	0.59%	.	.	0.63	University of Missouri-St Louis	213	97	-116	1,841	6.65%	.	.	0.73
Oakland University	177	205	28	1,174	2.70%	.	.	0.58	U. of Alabama at Birmingham	279	140	-139	1,674	17.72%	.	.	0.73
Central Michigan University	144	224	80	1,180	2.76%	.	.	0.52	Belhaven College	24	1	-23	97	13.27%	.	.	0.69
Sonoma State University	73	155	82	669	1.18%	.	.	0.45	Suny College at New Paltz	147	65	-82	700	6.49%	.	.	0.68
California State U.-Fullerton	28	84	56	472	0.74%	.	.	0.37	Adelphi University	169	0	-169	397	8.45%	.	.	0.67
California State U.-Northridge	121	277	156	2,641	2.86%	.	.	0.19	Palm Beach Atlantic College-West	50	9	-41	328	15.20%	.	.	0.61

"Total predicted" is a hiring count for each university (averaged over the years in our sample period) which is predicted by a version of our Table 6 models that has been adapted to be race-blind. Specifically, the model is a ZINB model explaining total hiring by big N and non-big N auditing firms (big N and non-big N hiring added together) across our sample of university years which includes, as right-hand-side variables in the count model, program size, size squared, our top accounting and top MBA program rank indicator variables, Carnegie classification indicator variables, admission rates, test scores, and region and year indicator variables. The binary model includes as right-hand-side variables program size, size squared, Carnegie classification indicator variables, admission rates, and test scores. Errors are clustered by university. Predictions from these models are "race-blind" because they exclude all of our measures of racial representation. We then compare these predicted hiring counts against actual hiring counts to find hiring errors. We call universities with positive average hiring errors "over-recruited universities" and universities with negative average hiring errors "under-recruited universities". The table shows, on the left, a list of the over-recruited schools with particularly few Black graduates (3% or fewer) ordered first by average accounting program rank, then by average MBA program rank, then by average test score percentile. On the right, the table shows under-recruited schools with relatively many Black graduates (6% or more) which have been matched to over-recruited schools such that the under-recruited schools are at least as high in quality as the over-recruited school to which it is matched. Audit firms could increase the number of Black hires without reducing the quality of schools from which they hire (as far as quality is captured by our measures) by shifting recruiting resources away from the schools on the left-hand-side of the table and to the schools on the right-hand-side of the table.