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The Demographic Context of Hiring Discrimination: Evidence from a Field Experiment in 50 Metropolitan Statistical Areas

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Abstract

How do the demographic contexts of urban labor markets correlate with the extent to which racial and ethnic minorities are disadvantaged at the hiring stage? This paper builds on two branches of labor market stratification literature to link demographic contexts of labor markets to race- and ethnicity-based hiring discrimination that manifest within them. Relying on a unique large-scale field experiment that involved submitting nearly 12,000 fictitious resumes to real job postings across 50 major urban areas, I found that Black population size is associated with greater discrimination against Black candidates, providing support for the "visibility-discrimination" thesis. I also show that this thesis cannot be extended straightforwardly to comparisons between Whites and other ethnic minority groups: I found no evidence of an association between Latino and Asian concentration and the

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labor market outcomes of those groups relative to Whites. The paper concludes with theoretical implications for studies of race and stratification, labor markets, and urban inequalities.

Keywords
race, discrimination, labor market, field experiment

Racial discrimination in hiring remains an important feature in contemporary labor markets, and operates as a key mechanism for reproduction of racial inequality in various areas of social life. Sociological research offers ample evidence of how ethnic minorities are disadvantaged at the hiring stage and how the intensity of such discrimination persists over time (Pager, 2003; Pedulla, 2018; Quillian et al., 2017). While much is known about how discrimination varies across *time* (Quillian et al., 2017), evidence on how it varies across *places* is more sparse. In particular, very limited sociological evidence is available on how racial discrimination in hiring is contextualized in social places, and how the structural characteristics of such places matter for processes leading to stratified outcomes among marginalized groups. Addressing this gap, this study asks: "How do the demographic contexts of urban labor markets correlate with the extent to which racial and ethnic minorities are disadvantaged at the hiring stage?" While theoretically and practically important, this critical research question remains underexplored.

Two broad areas of literature may yield key theoretical insight on this question: [1] demographic contexts of labor market inequality using survey data, and [2] hiring discrimination using field experiments. The theoretical roots of the first area of literature can be traced back to arguments on the association between group size and social stratification (Allport, 1954; Blalock, 1956). This line of thought maintains that discrimination varies across places as a response to group threat, which is often measured by demographic composition or group size. From the late 1970s to the 1990s, a number of theoretical developments and empirical tests of this perspective emerged (Beggs et al., 1997; Burr et al., 1991; Cohen, 1998; Frisbie & Neidert, 1977; Tienda & Lii, 1987). These studies assessed how group sizes relate to numerous outcomes – earnings, unemployment, occupational segregation, poverty etc. – but did not analyze variation in hiring discrimination itself. Scholarship in this tradition became scarcer since the mid-2000s.

In contrast, audit studies look directly at hiring discrimination. This sociological literature originated in the 1970s with HUD's search for evidence of racial discrimination in the housing market (Pager, 2007), but it was not until the mid-2000s – with pioneering studies such as Pager (2003) – that sociologists saw a proliferation of audit studies that analyzed how racial discrimination persists in large urban labor markets (Gaddis, 2014; Pager et al., 2009; Pedulla, 2016).

Each of these fields of literature developed at different times and consequently made limited references to one another. I argue that to shed light on the research question, these bodies of work should be connected because they have strengths and weaknesses complementary to one another. On the one hand, studies on hiring inequities, using field experiments, are effective at detecting discrimination but are under-contextualized because they typically cover a relatively small number of major cities (for important exceptions, see Weisshaar, 2018 and Kroft et al., 2013).[1] On the other hand, research on how ethnic minority concentration matters for socioeconomic inequality deeply contextualizes stratification but lacks the methodological tools to estimate discrimination in hiring.

This study explores how demographic contexts of labor markets correlate with race- and ethnicity-based hiring discrimination that manifest within those social milieus. The research question also drives the empirical strategy of generating a large-scale field experiment that covers a broad range of urban sites and jobseekers' racial/ethnic identities, while simultaneously preserving the methodological advantages associated with traditional audit studies. This paper presents results from an original field experiment in which applications from fictitious candidates of four different racial/ethnic groups (White, Asian, Latino, and Black) were submitted to job openings in 50 Metropolitan Statistical Areas (MSAs). This geographical coverage allows gauging the extent to which the chance of getting a job interview is correlated with variation in ethnic minority concentration.

This research contributes to both literatures. It brings the insights on the role of demographic contexts to bear on questions of how discrimination in hiring varies across labor markets. Doing so advances the research on consequences of demographic contexts of labor markets by directly testing its very *core* argument – the relationship between proportions of ethnic minority and discrimination. This paper also pushes the audit study literature forward by putting discrimination in urban demographic contexts, shifting away from a focus on identifying the level of discrimination in a relatively small number of major markets. This contribution is a timely one, given that research "on the contextual variation of employer hiring is still at an early stage," and in light of the "pressing need for more research on the contextual factors that may limit or enhance employers' discretion in personnel decisions" (Bills et al., 2017, p. 296). Additionally, the study further advances knowledge by including four racial/ethnic groups in the design and joins a growing number of experimental studies that examine discrimination against Asian and Latino jobseekers.

Field Experiments on Employers' Discriminatory Behavior

Scholarly accounts reveal consistent evidence of employers' discriminatory behavior. Ethnic minority applicants are selected at much lower rates compared to otherwise similar White jobseekers (Bertrand & Mullainathan, 2004; Gaddis, 2014; Pager, 2003; Pager et al., 2009; Pedulla, 2016), and the level of discrimination that Black applicants face has remained consistent over the last 30 years (Quillian et al., 2017). Field experiments dominate this area of sociological inquiry. The audit method embodies several unique features. The ability to identify specific experimental conditions that give rise to observed differentials in hiring, to make causal estimations, and to rule out alternative explanations make audit and correspondent studies particularly conducive to examining discrimination. Scholars generally consider audit studies "the only method that can reliably document discrimination in a fashion that is difficult to debate" (Quillian, 2006, pp. 303–4). Leveraging these important advantages, research using audit methods has been successful at detecting discrimination at the hiring stage. However, audit studies have limitations. Critics of this method point to several concerns: internal validity, generalizability, inflated effect size, and other ethical issues (Pager, 2007). I argue that another limitation of existing audit studies stems from the fact that they are typically conducted within a small number of experimental sites. This limitation challenges scholars' attempts to explore how characteristics of the sites correlate with dynamics of hiring discrimination reported. By undertheorizing urban sites, existing studies assume that hiring officers are relatively autonomous agents who discriminate in response to experimentally-manipulated signals, as opposed to actors whose actions are conditioned by demographic and economic forces that shape social arenas in which they operate. The literature on hiring discrimination still lacks studies that explicitly conceptualize urban sites as social arenas in which discrimination manifests and specifically situate discriminatory behaviors in the structural context of metropolitan areas.

Why should hiring discrimination be contextualized in urban areas? Theoretically, discrimination is a socially constructed process where discriminatory acts are conditioned by social settings. Hiring officers are gatekeepers constrained by structural forces beyond themselves and the organizations they represent. Since the process of discrimination is embedded in larger metropolitan contexts, characteristics of urban sites are theoretically expected to relate to employers' decision-making, which in turn matters for stratified outcomes among jobseekers of different marginalized categories.

Therefore, it is important to explore how such contextualization takes place and to unpack how variation in attributes of urban sites might correlate with differences in race- and ethnicity-based hiring discrimination in different labor markets. Such a task would deepen our understanding of how urban conditions relate to hiring discrimination and labor market stratification more broadly. Besides being theoretically important, situating hiring discrimination in different urban contexts embodies practical significance. Some of the most prominent audit studies took place in just a few major cities: New York City (Pager et al., 2009); Chicago and Boston (Bertrand & Mullainathan, 2004); and New York City, Atlanta, Los Angeles, Chicago, and Boston (Pedulla, 2016). Since millions of jobseekers live outside of megalopolises, it is crucial to widen the scope of existing field experiments to analyze how hiring discrimination varies across a broader range of cities. Understanding how employment discrimination and social stratification more generally manifest across labor markets that vary in terms of population, racial makeup, and economic conditions, could yield initiatives that contribute to reducing inequality in urban areas.

Demographic Context of Labor Market Stratification

A long line of research has explored the relationship between ethnic minority demographic composition and labor market stratification within cities. The "visibility-discrimination" thesis is the most developed and supported argument linking labor markets' demographic structure to racial discrimination (Beggs et al., 1997; Burr et al., 1991; Frisbie & Neidert, 1977). At the core of the thesis is how Whites' reactions to the rising number of ethnic minorities causally determine intergroup socioeconomic inequality within given ecological units. The thesis predicts that in response to the socioeconomic threats associated with the increasing sizes of ethnic minority subgroups, the racial majority will respond by: [1] raising the level of racial prejudice, and [2] mobilizing its existing resources to raise the barrier of access to various social goods, including good jobs with long-term contracts and decent pay, in order to maintain its privileged position (Blalock, 1967). Additionally, labor markets are organized along racial lines with the racially dominant group concentrated at the top and subordinate groups at the bottom

(Lieberson, 1980). Enlarged ethnic minority group sizes boost the supply of ethnic minority labor, providing the context for job segregation: racial minorities, particularly Blacks, are channeled into predominantly Black jobs, thereby increasing job segregation along racial lines. This process also benefits Whites since they can vacate non-desirable jobs – now filled by ethnic minorities – to obtain positions higher in the occupational hierarchy at the expense of ethnic minorities (Semyonov et al., 2000). In sum, a high concentration of racial/ethnic minorities is expected to be correlated with higher levels of inequality, either through increased discrimination or channeling of ethnic minorities into low-paid and undesirable jobs. This paper uses the visibility-discrimination thesis as a key guideline to explore ethnic minority population size relates to discrimination in hiring in metropolitan areas.

Contrastingly, some scholars argue that ethnic minority concentration might not correlate with heightened discrimination. Contact theory (Allport, 1954; Pettigrew, 2021) maintains that, under certain circumstances, intergroup hostility might be reduced through contact between different racial/ethnic groups. Under this premise, employers in certain cities might be less racially biased since they are more likely to interact – professionally or otherwise – with people of color. Furthermore, higher proportions of ethnic minorities can increase the number of minority-owned businesses. The presence of these decision-makers might benefit ethnic minority jobseekers who might be less likely to be rejected on the basis of "cultural fit" – a factor that has been used as a proxy for ethnic-based discrimination (Bye et al., 2014). Despite competing hypotheses on the linkages between percent ethnic minority and stratified outcomes, empirical evidence overwhelmingly shows a positive correlation between ethnic minority concentration and various measures of socioeconomic inequality (Beggs et al., 1997; Blalock, 1956; Frisbie & Neidert, 1977; Johnson et al., 2012; Semyonov et al., 2000; Tomaskovic-Devey & Roscigno, 1996).

There are two important limitations to the literature linking proportions of ethnic minority populations and labor market stratification. First, sociological work focuses almost exclusively on Black-White differences and pays insufficient attention to Latinos and Asians in the multiracial setting of U.S urban labor markets. A few sociological studies, such as Tienda and Lii (1987), have considered the role of Latinos, but Asians remain largely understudied. While convincing evidence shows that Black-White inequality widens as the Black population increases (Fossett & Kiecolt, 1989; Quillian, 1996), it is unclear if this finding extends to Asians and Latinos. It is possible that Whites perceive all ethnic minorities, including Asians and Latinos, to be equally as threatening as Blacks. In this case, the level of animosity and discriminatory behavior should be evenly distributed across all ethnic minority groups. However, the notions of "model minority" and "honorary whites"

(Tuan, 1998; Zhou, 2004) suggest that Asians might not be discriminated against as severely as Blacks due to their high educational and socioeconomic attainment. Latinos represent a broad group consisting of different ethnic identities. The variation in terms of racial proximity to Whiteness complicates the intensity of discrimination that Latinos might face (Tienda & Lii, 1987). It is therefore possible that concentration of Asians and Latinos in a given area does not correlate with the same labor market outcomes for two groups in the ways that the Black concentration associate with Black workers' employment prospects.

Second, in this literature, larger Black population has been shown to widen White-Black inequality in several labor market outcomes such as: income and earnings (Cohen, 2001; Tienda & Lii, 1987), poverty (Tomaskovic-Devey & Roscigno, 1996), occupational segregation (Huffman & Cohen, 2004; Semyonov et al., 2000), and unemployment (D'Amico & Maxwell, 1995). Hiring discrimination is largely overlooked in the literature. It is important to fill this gap because the linkage between proportions of ethnic minority and discrimination has only been inferred, not directly tested since the aforementioned studies were not designed explicitly to detect discrimination. This study directly observes the association between demographic context and discrimination – a key mechanism for racial stratification that previous studies hinted at without being able to test.

This research builds on insights from the two area of literatures to explore how urban labor market contexts might correlate with race- and ethnicity-based discrimination in hiring within those settings. This paper leverage empirical data from a multi-site large-scale experiment, one involving fictitious resumes submitted to real job openings in 50 cities. By expanding the geographical scope of existing audit studies and including Asians and Latinos in the design, this research takes a step forward in examining the linkages between urban context and racial discrimination in hiring. The following section describes the field experiment and the methodological approaches used to link Black, Asian, and Latino concentration with the hiring gaps between each ethnic minority group and Whites.

Data and Methods

The Field Experiment

From January to March 2017, I submitted 11,871 experimentally manipulated fictitious resumes to real job openings in 50 large MSAs.[2] I chose the top 50 MSAs based on 2016 Census population estimates.[3] The selected sites show considerable regional variation, with 17 Southern, 10 Midwestern, 12

Western, and 11 Northeastern MSAs. Resumes were submitted for three job types: marketing, sales, and administrative assistant. These job types are routinely chosen in audit studies, and are common in all major cities. To select job openings across cities, I used a VisualBasic code that returns a list of all openings with corresponding keywords within 25 miles of the MSA's central city. I then kept only one listing per employer to avoid overburdening the same employer with more than one pair of resumes. I deleted all jobs that were not full-time, were entry-level, or could not be applied for directly from the job board. Once I obtained the final list, its order was randomized to minimize any potential researcher's bias.

Consistent with other audit studies, I signaled race using racialized names. To reduce potential confounds between race and class, following Gaddis (2014), I obtained birth record data and extracted racialized names while accounting for mothers' educational level. I used vital statistics data from the California Department of Public Health, which has information on all babies born in 1989 and 1990 in the state. I selected those two years because the fictitious candidates would be in their late 20s in 2017. I used the same procedure to select names for all four racial/ethnic groups. I chose names that are at least 75% born to mothers of a particular race/ethnicity, and are generally comparable with respect to percent being born to mothers who attended college. I used two names for each race-gender combination, resulting in a total of 16 names (4 race/ethnicities * 2 genders * 2 names). The names selected were: Edward Henson, Frank Flanagan (White Male); Jessica Stallings, Chelsie Langley (White Female); Terrell Washington, Tyrone Winston (Black Male); Ebony Jefferson, Tanisha Muhammad (Black Female); Nelson Rodrigues, Gabriel Pereira (Latino Male); Monica Fernandes, Veronica Gomes (Latino Female); Jacky Zhou, Winson Kong (Asian Male), and Winnie Yin, Kimmy Zhu (Asian Female).[4] To ensure that candidates sent comparable class signals, besides accounting for mothers' education level, I designed the resumes so that all candidates graduated from top-20 universities with similar prestige. I split the MSAs into four census regions (Northeast, Midwest, South, and West). From each region, I selected two large public degree-granting institutions that did not differ in their 2016 *U.S News* rankings by a margin greater than 2. Another critical issue with signaling race was immigration status; I attempted to remove potential employer immigration-related concerns by adding variations of this phrase to resumes: "Legally authorized to work for any U.S employer."

Besides race, I also manipulated candidates' most recent work experience across three types of employment histories. After college graduation, all candidates had two jobs. For the third job, applicants were randomly assigned one of three categories: full-time, freelance, or unemployed. These categories cover a wide range of possible employment types in the labor market. The experiment thus simultaneously varied along two axes – four race/ethnicity and three employment histories – creating a total of 12 profiles and nearly 1,000 observations per experimental condition. For each job opening, I sent a pair of applications.[5] The first applicant was randomly chosen from a set of 12 profiles, and the second one was chosen so that either attribute (race and work) did not overlap with the first candidate.[6]

To make sure that candidates lived in equivalent neighborhoods, I selected apartment complexes whose monthly rent for a one-bedroom was generally comparable to the MSA's average. To the extent possible, I made sure the addresses were within the same neighborhood. The addresses for the complexes were real, but the apartment numbers were fictitious. For each MSA, I purchased eight phone area-code-specific numbers for each race-gender combination to indicate that candidates were local. For each of the eight race-gender combinations, I asked one person fitting that profile to record a voicemail greeting message. The messages were generic and the accents neutral, both regionally and ethnically.

I used three sets of codes to complete the submission process. The first code automatically populated resume templates with candidates' relevant information (names, addresses, schools, etc.). The code converted the resumes to a pdf formatting and deleted potentially revealing metadata. The second code automatically filled the application forms on the job board's interface, drastically reducing the time it took to submit applications. Lastly, for additional safety, I purchased two Internet Protocol (IP) cloaking services. I used one set of IP addresses to submit the first application and another for the second. This step reduced possible suspicion from employers' and the job-board's server. After submitting the first application, I allowed a 24-h waiting period prior to submitting the second one. After 15 weeks from the submission date, I considered the application failed. The data collection finished when the number of callbacks/email-backs were coded and the employers' identification deleted, per IRB requirement.

MSA-Level Predictors

In addition to the experimental data, this research also combined MSA-level variables as measures of urban context. The racial/ethnic composition was measured by proportion Black, Asian, and Latino. In addition, I included a variable capturing proportion ethnic minority within a given MSA. Although this paper focused primarily on the role of ethnic minority composition, the literature identified several possible drivers of labor market inequality, which I included as controls. For local economic conditions, following Huffman and Cohen (2004), I used the unemployment rate as a proxy for short-term economic vitality and net percent migration as a measure of long-term regional economic vitality. Additionally, I incorporated two measures of cities' industrial structure: percent employed in manufacturing and in services. Finally, I also included population and a dummy variable to account for regional variation. All non-dummy variables were standardized. Table 1 presents descriptive statistics pertaining to all variables used in the analysis.

Analytical Strategy

The nesting nature of applicants within labor markets calls for multilevel estimation techniques. My research question calls for not only controls at the individual- and MSA-level, but also cross-level interactions. To that end, I specified an intercept-and-slope-as-outcome model, which permits tests of variability in coefficients across two levels of analysis (Raudenbush & Bryk, 2002). For instance, this model allows me to test for whether the odds of getting a callback at the individual level for a Black person is conditional on MSA-level Black concentration. Given the binary nature of the outcome (callback vs. non-callback), I used a generalized model with a logit link. At the individual level, the model is specified as:

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{0j} + \beta_{1j}Black + \beta_{2j}Asian + \beta_{3j}Latino + \beta_{4j}Freelance + \beta_{5j}FullTime + \beta_{6j}Adm + \beta_{7j}Markt + r_{ij} \tag{1}$$

The dependent variable is the log odds of individuals getting a callback versus not getting one in MSA j. β_{0j} is the intercept for job market j, or the log odds of getting a callback for an unemployed White candidate looking for a job in sales. β_{1j}, β_{2j}, and β_{3j} represent the differences in log odds of getting a callback in MSA j between Whites and Blacks, Whites and Asians, and Whites and Latinos, respectively. With Whites being the baseline category, a negative coefficient suggests that minorities are less likely to get a callback than Whites. I did not control for gender because I did not vary gender within pairs and because I used job type specifically to determine applicants' gender.[7]

At level 2, the intercept (β_{0j}) and the slopes (β_{1j}, β_{2j}, β_{3j}) are allowed to vary across urban sites and modeled as functions of demographic variables

Table 1. Definition, Source, and Descriptive Statistics for Metropolitan Statistical Area - Level Predictors.

Variable	Definition	Descriptive Statistics Min	Max	Mean	Standard Deviation
Demographic Composition					
Proportion Ethnic Minority[a]	Share of non-White population aged 18–65	0.11	0.65	0.35	0.15
Proportion Black	Share of Black population aged 18–65	0.01	0.45	0.14	0.09
Proportion Asian	Share of Asian population aged 18–65	0.01	0.33	0.06	0.05
Proportion Latino	Share of Latino population aged 18–65	0.01	0.52	0.15	0.13
Industrial Makeup					
Percent Manufacturing[b]	Share of manufacturing employment	2.90	20.70	9.67	3.70
Percent Service[c]	Share of service employment	14.50	29.60	17.48	2.30
Economic Condition					
Unemployment Rate[d]	Percent of the civilian labor force unemployed	3.20	5.90	4.50	0.70
Percent net migration[e]	Cumulative estimates of Resident Population change from 2010 to 2015, percent	–0.80	16.60	5.90	3.90
Control Variables					
Population (thousands)[f]	Total population from 18–65	483.30	12112.10	2073.00	1073.50
Region	4 Census Regions (Midwest, Northeast, South, West)				

Sources. [a]Data for racial composition come from the U.S. Census Bureau 2012 Intercensal Population Estimates.
[b]Data come from estimates of "civilian employed population 16 years and over – Manufacturing. ACS 2016.
[c]Data come from estimates of "civilian employed population 16 years and over – Service occupations. ACS 2016.
[d]Unemployment rates data come estimates of "Unemployment Rates for Metropolitan Areas, Not Seasonally Adjusted", Bureau of Labor Statistics. February 2017.
[e]Migration data come from the U.S Census 2015 Population Estimates;
[f]Data on population come from the U.S Census Intercensal Population Estimate.

and controls. I specified three sets of models. For simplicity, I only show the equation when "proportion Black" is the main level-2 demographic predictor

$$\begin{aligned}
\beta_{0j} &= \gamma_{00} + \gamma_{01}\text{Prop.Black}_j + \gamma_{02}W_{1j} + \ldots + \gamma_{0s}W_{sj} + u_{oj} \\
\beta_{1j} &= \gamma_{10} + \gamma_{11}\text{Prop.Black}_j + \gamma_{12}W_{1j} + \ldots + \gamma_{1s}W_{sj} + u_{1j} \\
\beta_{2j} &= \gamma_{20} + \gamma_{21}\text{Prop.Black}_j + \gamma_{22}W_{1j} + \ldots + \gamma_{2s}W_{sj} + u_{2j} \\
\beta_{3j} &= \gamma_{30} + \gamma_{31}\text{Prop.Black}_j + \gamma_{32}W_{1j} + \ldots + \gamma_{3s}W_{sj} + u_{3j}
\end{aligned} \tag{2}$$

This modeling strategy suggests that the odds of getting a callback by different race/ethnic groups vis-à-vis Whites across MSAs may be explained by MSA-level characteristics such as demographic composition, industry/economic conditions, and population. The ways in which the hypotheses are set up directly determine this modeling strategy. γ_{00} is the average intercept across cities. γ_{01} represents the effect of labor market proportion Black on β_{0j}. γ_{11} represents the cross-level interaction estimating how much the effect of being Black on receiving a callback varies by proportion Black in labor markets. *If the net effect of this coefficient is negative and significant, then Black applicants' relative odds of getting a callback are reduced in labor markets with a larger Black population.* $W_{1j}..W_{sj}$ represent a set of control variables, and $u_{oj}..u_{3j}$ are level-2 random effects. The effects of level-1 control variables do not vary across MSAs.

Results

Main Effect of Race: Callback Rates Variation among Racial/Ethnic Groups

Figure 1 shows the percentage of applications from workers of different racial/ethnic backgrounds that generate callbacks from employers. Ethnic minority applicants have lower callback rates than their White counterparts. The callback rate that Whites received is significantly higher than the rate for Asians (22.00% versus 17.67%, $p < .01$), for Latinos (22.00% versus 16.01%, $p < .01$), and for Blacks (22.00% versus 10.97%, $p < .01$). Black applicants have significantly lower callback rates than their Latino and Asian counterparts. There is no statistically significant difference between the callback rates that Asians and Latinos received (17.67% versus 16.01%, $p = .09$). In sum, results of the experiment show that White workers are selected at the top of the hiring queue, Black workers at the bottom, with Asians and Latinos in between.

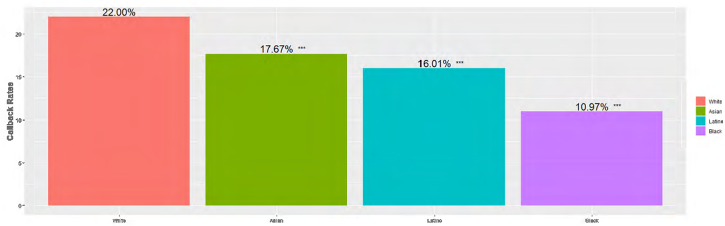

Figure 1. Callback rates by race/ethnicity.
Source. Original experimental audit study data. *Note.* All statistical tests are two-sample tests for equality of proportions. Statistical significance are reported from tests that compare the callback rates of White candidates and comparable ethnic minority candidates. * $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed tests).

Table 2 presents two intercept-as-outcome models, which allow for the variability in odds of getting a callback to be modeled simultaneously by individual-level and MSA-level factors. Unlike the intercept-and-slope-as-outcome models in subsequent tables, the models presented here assume that the association between MSA-level factors and the odds of candidates receiving a callback (or the slopes) do not vary across MSAs. The specifications show the main effects of variables at both levels. The first model includes applicant race/ethnicity, job type, and employment history at the individual-level and proportion minorities at the MSA-level. The second one contains all variables in the first model, but also adds measures of economic conditions and industrial structures, along with population and region controls.[8]

The results affirm findings presented in Figure 1. At the individual level, the coefficients associated with Asian, Latino, and Black are negative and in descending order in both models. These coefficients indicate that ethnic minorities are selected at significantly lower rates relative to otherwise comparable White counterparts. According to model 2, *ceteris paribus,* being Asian decreases the odds of being selected by about 23 percent and being Black reduces the chances of being invited to a job interview by 56 percent. Similarly, having a Latino name lowers the odds of receiving a callback by about 33 percent. At the MSA-level, proportion Black seems to decrease the odds of getting a callback for all candidates in model 1, but this effect is no longer statistically significant in model 2. Unemployment rate is negatively associated with candidates' chances of being selected: an increase in one standard deviation – or 0.7 percent – of unemployment rate is associated with a 9 percent reduction in odds of being invited for an interview. This finding makes substantive sense. A rise in unemployment results

Table 2. Intercept-as-Outcome Hierarchical Generalized Linear Models Predicting the Odds of Getting a Callback.

	Callback vs. No- Callback	
	Model 1 (1)	Model 2 (2)
Individual-level		
Race/Ethnicity (ref = White)		
Asian	−.2633***	−.2643***
	(.0665)	(.0665)
Black	−.8345***	−.8378***
	(.0748)	(.0748)
Latino	−.4024***	−.4046***
	(.0681)	(.0681)
Employment Histories (ref = Unemployed)		
Freelance	.4876***	.4897***
	(.0672)	(.0672)
Full-Time	.8621***	.8635***
	(.0643)	(.0643)
Job Type (ref = Sales)		
Admin	−.5328***	−.5319***
	(.0604)	(.0604)
Marketing	−.6114***	−.6169***
	(.0615)	(.0615)
MSA-level		
Prop. Black	−.1504***	−.0948
	(.0381)	(.0546)
Prop. Asian	−.0544	−.0594
	(.0387)	(.0441)
Prop. Latino	−.0365	.0426
	(.0378)	(.0542)
Unemployment Rates		−.0999*
		(.0495)
Percent net migration (logged)		−.0335
		(.0670)
Percent Manufacturing (logged)		.0351
		(.0579)
Percent services (logged)		−.0131
		(.0554)
Population (logged)		−.0307
		(.0418)

(continued)

Table 2. Continued.

	Callback vs. No- Callback	
	Model 1 (1)	Model 2 (2)
Region control		Yes
Constant	−1.4082*** (.0739)	−1.3011*** (.1075)
N	11,871	11,871
Log Likelihood	−5,103.76	−5,098.17
AIC	10,231.51	10,236.35
BIC	10,320.10	10,383.99

Note. Standardized coefficients with standard errors in parentheses; * $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed tests)

in larger pools of presumably qualified candidates, which in turns increases employers' latitude in hiring and decreases the odds of a given candidate being selected.

Interactions Between Race and Place: Concentration and Ethnic Minority/White Callback Ratios

Figure 2 includes several boxplots showing the regional variation of the ethnic minority/White callback ratios. These ratios were obtained by dividing the raw callback rates of ethnic minorities to those of Whites. Any ratios below 1 indicate that employers favor White applicants over comparable ethnic minority ones. The dotted line that crosses the vertical axis at 1 signifies parity with Whites. Any ratios below this line suggest that employers favor White applicants over ethnic minority ones, and vice versa. The racial gaps narrow as the ratios approach 1. The Black/White callback ratio is widest in the South and smaller in the Midwest, West, and Northeast. There does not seem to be a large difference in hiring gap between these three regions. The regional patterns of the racial hiring gap are similar for Asians and Latinos. Both groups are most likely to get callbacks in the Midwest, least likely in the Northeast, with the Western and Southern regions in between. For Asians and Latinos, given their substantial concentration in the Northwestern and Southwestern regions, the fact that they are more likely to get job interviews in the Midwest might simply be a consequence of their willingness to relocate (Kulkarni, 2008). Generally, these results show broad parallels with the ones reported in studies analyzing the racial *wage*

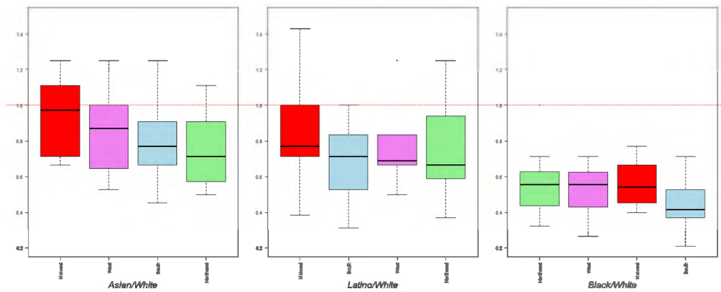

Figure 2. Regional variation of the ethnic minority/White callback ratios.
Source. Original experimental audit study data.

gap across regions (Cohen, 1998; McCall, 2001). These parallels suggest that different facets of labor market stratification might manifest in conjunction: in labor markets where ethnic minorities are unlikely to be *paid* as much as Whites, they are also unlikely to be *hired* as frequently as Whites.

Figure 3 offers a series of scatterplots of the 50 MSAs with ethnic minority concentration on the horizontal axes and the ethnic minority/White callback ratios on the vertical ones. The plots also include different shape-coded data points for each regions, and three regression lines that arise from three equations with the outcomes variables being the callback gaps and the only predictors being the corresponding percent ethnic minority in a given MSA.

A steep downward trend emerges in the scatterplot linking percent Black to the Black/White callback ratio, suggesting a negative association between Black concentration and Black hiring success relative to Whites. The plot also shows several MSAs – many of them Southern – concentrating in the lower right quadrant, indicating that these are urban sites where a high percentage of Blacks and higher rates of hiring discrimination against Black candidates co-exist. While the Southern MSAs also tend to cluster around the trend line, their Midwestern and Northeastern counterparts display a more complex pattern by being slightly further away from such line. The Western MSAs follow a more vertical pattern due to the narrow range of MSA percent Black (from 1.3% in Salt Lake City, UT MSA to 10.1% in Las Vegas-Paradise, NV MSA).[9]

The plot linking percent Asian to the Asian/White callback ratio in hiring shows a marginally upward trend, suggesting that Asians' relative hiring outcomes might slightly increase in cities with higher Asian concentration. However, it is evident that the slope is not as steep as the one in the first scatterplot and that some West-coast MSAs are primary drivers of the trend[10]. No clear pattern emerges for percent Latino in the third scatterplot. The generally

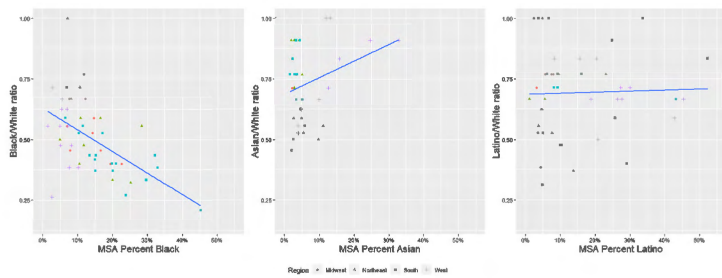

Figure 3. Scatterplots linking ethnic minority/White callback ratios and corresponding minority concentration in labor markets.
Source. Original experimental audit study data.

flat trendline suggests a weak association between percent Latino and the Latino/White callback ratio.

The next set of regression tables analyzes the extent to which these regression lines change when more predictors are added to the equations. Table 3 displays a series of parameters from seven mixed effect logistic regression models. These models are specified as intercept-and-slope-as-outcome models and are mathematically denoted by formulae (1) and (2). In these models, the callback gaps between ethnic minority groups and Whites are predicted by different combinations of MSA-level predictors. Models 1.1 and 1.2 include proportion Black as the key level-2 independent variable. Models 2.1 and 2.2 focus on proportion Asian, while models 3.1 and 3.2 on proportion Latinos. Model 4 includes all three racial/ethnic groups in the same specification. While model 1.1 includes the key predictor and two economic condition variables (unemployment rate and net percent migration), model 1.2 adds two measures of industrial structures (percent employed in manufacturing and in services). The two subsequent sets of models (2.1–2.2 and 3.1–3.2) follow the same structure of specification. All models include population and region as control.

At the individual-level, Tables 2 and 3 yield consistent results as the coefficients of employment history, and job type variables remain largely unchanged. At the MSA-level, the intercept $\gamma 10$ represents the difference between Whites and Blacks in the log-odds of getting a callback when all other predictors are at their mean levels. According to model 1.2, in an MSA with 13.7% percent Black and all other MSA-level predictors at their means, being Black is predicted to reduce the odds of getting a callback by about 54 percent relative to being White. Recall that $\gamma 11$ is the coefficient denoting the effect of MSA-level percent Black on the relative odds of a

Table 3. Intercept- and Slopes-as-Outcome Hierarchical Generalized Linear Models Predicting the Odds of Getting a Callback

Independent and Control Variables	Model 1.1		Model 1.2		Model 2.1		Model 2.2		Model 3.1		Model 3.2		Model 4	
Fixed Effects														
Individual-Level														
Employment Histories (ref = Unemployed)														
Freelance	.4907	***	.4894	***	.4901	***	.4888	***	.4905	***	.4899	***	.4887	***
Full-Time	.8640	***	.8646	***	.8646	***	.8647	***	.8644	***	.8643	***	.8651	***
Job Type (ref = Sales)														
Admin	−.5318	***	−.5327	***	−.5286	***	−.5307	***	−.5297	***	−.5313	***	−.5349	***
Marketing	−.6155	***	−.6162	***	−.6146	***	−.6172	***	−.6149	***	−.6174	***	−.6174	***
MSA-Level														
Black-White Gap ($\beta 1j$)														
Intercept ($\gamma 10$)	−.7804	***	−.7783	***	−.7701	***	−.8149	***	−.7429	***	−.7717	***	−.8558	***
Prop. Black ($\gamma 11$)	−.2191	*	−.2739	*									−.3133	*
Prop. Asian					−.1020		−.1130						−.0761	
Prop. Latino									−.0633		−.0695		−.1560	
Unemployment Rates	−.0266		.0272		−.0567		−.0482		−.0270		−.0363		.0529	
	.0827		.0307		.1567		.1882		.1874		.2179		.1033	

(continued)

Table 3. Continued.

Independent and Control Variables	Model 1.1	Model 1.2	Model 2.1	Model 2.2	Model 3.1	Model 3.2	Model 4
Percent Net Migration							
Percent Manufacturing		−.0995		.0671		.0675	−.0883
Percent Service		−.1104		.0671		.0315	−.0654
Population	.0402	.0435	.0406	.0532	.0385	.0473	.1279
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asian-White Gap (β2j)							
Intercept (γ20)	−.1626	−.1963	−.0735	−.1380	−.1238	−.1883	−.1573
Prop. Black (γ21)	−0.1532	−0.1345					−.1709
Prop. Asian			.1037	.0879			.1057
Prop. Latino					−.0061	−.0072	−.0702
Unemployment Rates	.0847	.0997	.0861	.0727	.0711	.0638	.1265
Percent Net Migration	−.0606	−.0305	−.0036	.0429	−.0010	.0516	−.0207
Percent Manufacturing		.0489		.1166		.1264	.0277
Percent Service		−.0233		.0391		.0350	.0017
Population	.0082	.0138	−.0386	−.0214	−.0075	.0064	.0130

(continued)

Table 3. Continued.

Independent and Control Variables	Model 1.1	Model 1.2	Model 2.1	Model 2.2	Model 3.1	Model 3.2	Model 4
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Latino-White Gap (β3j)							
Intercept (γ30)	−.3193	−.3397	−.2809	−.3585	−.2634	−.3337	−.3839 *
Prop. Black (γ31)	−.2138 *	−.1937					−.2185
Prop. Asian			−.0449	−.0578			−.0329
Prop. Latino					−.0080	−.0357	−.0965
Unemployment Rates	.0196	.0174	−.0062	−.0367	.0024	−.0286	.0319
Percent Net Migration	−.0253	−.0003	.0547	.0229	.0576	.1328	.0411
Percent Manufacturing		.0451		.1608		.1604	.0510
Percent Service		.0094		.0820		.1029	.0372
Population	.0096	.0132	−.0041	.0163	−.0126	.0135	.0627
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept (β0j)							
Intercept (γ00)	−1.3332	−1.3310 ***	−1.3600 ***	−1.3619 ***	−1.3124 ***	−1.3126 ***	−1.3354 ***
Prop. Black (γ01)	−.0004	.0078					.0495
Prop. Asian			−.0546	−.0549			−.0652
Prop. Latino					.0798	.0874	.1090

(continued)

Table 3. Continued.

Independent and Control Variables	Model 1.1	Model 1.2	Model 2.1	Model 2.2	Model 3.1	Model 3.2	Model 4
Unemployment Rates	−.1061	−.1178	−.1131	−.1202	−.1312	−.1251	−.1453
Percent Net Migration	−.0314	−.0227	−.0313	−.0246	−.0747	−.0779	−.0545
Percent Manufacturing		.0162		.0160		−.0034	.0273
Percent Service		.0230		.0149		−.0175	−.0121
Population	−.0429	−.0436	−.0292	−.0279	−.0759	−.0776	−.0704
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random Effects							
Intercept	.0252	.0252	.0235	.0235	.0225	.0227	.0208
Black	.0011	.0010	.0001	.0000	.0005	.0002	.0009
Asian	.0007	.0009	.0003	.0000	.0001	.0001	.0002
Latino	.0011	.0012	.0002	.0002	.0004	.0000	.0010
AIC	10271.8	10285.6	10280.3	10289.9	10284.1	10294.3	10294.3
BIC	10611.3	10684.2	10619.9	10688.6	10623.6	10692.9	10751.9
Log Likelihood	−5089.9	−5088.8	−5094.2	−5091.0	−5096.0	−5093.1	−5085.1
Number of Cluster	50						
Number of Observations	11,871						

Note. Standardized coefficients with standard errors in parentheses; * $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed tests).

Black applicant receiving a callback. Models 1.1, 1.2, and 4 include this coefficient. In all three models, this coefficient is negative and statistically significant. This result means that as the proportion of Black population increases, Black candidates' relative odds of getting callbacks are reduced. Since, all else being constant, Black candidates are less likely to get a callback relative to their White counterparts, the β_{1j} coefficient is negative (see formula 1). As proportion Black in MSAs increases, this coefficient becomes more negative with an increasing absolute value. This result suggests that the gap in callback rates between Whites and Blacks increases in labor markets with higher proportions of Blacks. According to model 4, for every 9 percent – or one standard deviation – increase in Black population at a given metropolitan area, the odds of getting a callback for Black candidates in that area is predicted to decrease by roughly 27 percent $(1-\varepsilon^{-.31})$ relative to otherwise similar White counterparts. No other control variables operate as a consistent factor in predicting the Black-White gap in callback rates.

As for coefficient terms predicting the Asian-White gap, the coefficients associated with proportion Asian are included in Models 2.1, 2.2, and 4. These coefficients are positive and non-significant in all models, suggesting that an increase in Asian population is associated with a decrease in the Asian-White callback gap, but these associations are not significantly different from zero. As for differences in callback rates between Latino and Whites, proportion Latino seem to be increasing the Latino-White callback gap, but the coefficients are non-significant. It is worth noting that proportion Black also seems to decrease the odds of getting a callback for Latino candidates (see coefficient $\gamma 31$) in model 1.1, but this effect is only present in one specification and is not robust across models. In addition, various control variables seem to have no consistent association with the callback gaps between racial/ethnic groups.

Figure 4 shows the predicted probability of getting a callback for ethnic minority and White applicants in the y-axis and the MSA percentage of Black, Asian, and Latinos in the x-axis. The predicted probabilities have been derived from model 4. According to the plot on the left, White candidates' chances of getting a callback seem to remain stable as MSA percent Black increases (the confidence intervals indicate that the slope is not statistically significantly different from a horizontal line). The opposite is true for Black workers. In an MSA with about 10% Black concentration, the predicted probability of getting a callback for Black applicants is about 11 percent. When the Black share of the population increases to 30%, the predicted probability falls to about 6.25 percent. The White-Black callback gap keeps widening as shares of the Black population increases. Therefore, after controlling for individual- and MSA-level characteristics, I might

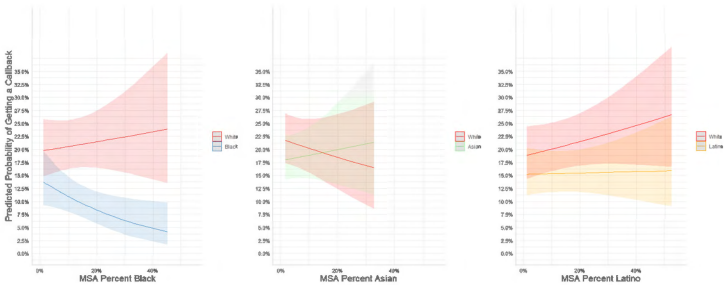

Figure 4. Predicted probabilities of getting a callback for White and ethnic minority candidates by ethnic minority concentration.
Source. Original experimental audit study data.

conclude that Black workers have a harder time getting an invitation for a job interview in areas with higher levels of Black population. The plot in the middle links MSA percent Asian with the predicted probabilities of getting a callback for Asian and White candidates. The plot indicates that White applicants' chances decrease and Asian applicants' chances increase as MSA percent Asian increases. This finding should be interpreted cautiously for two reasons. First, the effects of proportion Asian on the Asian-White gap in Table 3 were found to be non-significant. Second, the x-axis coordinate of the crossover point is at about 15%. This suggests that in cities with more than 15% Asians, Asians have higher predicted probabilities of getting a callback than Whites. Out of 50 MSAs in the sample, there are only three MSAs with more than 15% Asians (Los Angeles-Long Beach-Santa Ana at 15.9%, San Francisco-Oakland-Fremont at 24.6%, and San Jose-Sunnyvale-Santa Clara at 32.8%). The non-robust finding might thus be driven by only a few Californian MSAs. Finally, the plot linking MSA percent Latino to the White-Latino callback gap indicates that as the percent Latino in an MSA increases, the predicted probability of White candidates getting a callback rises faster than that of Latino candidates. However, recall that this effect – as shown in Table 3 – is statistically non-significant.

Discussion and Conclusion

Despite the substantial interest by sociologists in issues operating at the intersection of race, work, and place, the question: "How do demographic contexts of urban labor markets relate to the intensity of racial- and ethnic-based discrimination in hiring that takes place in those markets?" Two bodies of work can shed light on that question: [1] the literature on the relationship between ethnic minority size and stratified outcomes using survey data, and [2] the scholarship on racial discrimination in hiring using field experiments. Even though these literatures developed independently, they should be connected to answer the research question given the complementary nature of their strengths and weaknesses.

My research builds on theoretical insights from both bodies of work to derive predictions about how the demographic composition of labor markets correlate with the relative likelihood of ethnic minority candidates getting a job. Empirically, my study uses a large-scale experiment that includes submitting nearly 12,000 fictitious resumes from applicants of four racial/ethnic groups to real job openings in 50 MSAs. This research makes important contributions to both literatures. It advances visibility-discrimination scholarship by [1] using a unique database to *directly* test its fundamental premise – the relationship between group size and discrimination, and [2] moving beyond the Black-White gap and focusing also on the labor market experiences of Asians and Latinos. It contributes to audit studies by widening its geographical coverage and situating hiring discrimination in urban contexts. With respect to findings, in line with the visibility-discrimination thesis, I found that the relative labor market disadvantage of Blacks intensifies in areas with higher Black concentration. However, the linkage between demographic concentration and hiring inequities does not extend to other ethnic minority groups; the proportions of Asians and Latinos in MSAs do not significantly predict the Asian-White and Latino-White gaps in hiring. These findings do not provide support to the overflow or contact thesis, as increased percent ethnic minority do not seem to relate to lessened discrimination.

This study generates important findings and implications. Prior to discussing the key finding – the interactive effect between race and place – it is worth discussing the main effect of race, specifically the causal effect of being Asian on getting a job interview. Substantial debates are generated around the question: "Have Asians achieved labor market parity with Whites?" (Kim & Sakamoto, 2010) in the United States. However, with rare exceptions, like Kang et al. (2016), existing work focuses only on earning differentials. Scholars note that several factors could affect this differential: immigration status, region, educational history, social support, etc. By providing a causal estimate of how much Asians are disadvantaged at the hiring stage, while accounting for all non-experimentally manipulated factors, my study extends existing theoretical and empirical accounts. I find that, *ceteris paribus*, compared to their White counterparts, the odds of Asian jobseekers getting an interview is 23% lower. In light of Kim and Sakamoto (2010)'s findings that some Asian Americans *do not* appear to be significantly disadvantaged in terms of earnings, this finding indicates that Asian Americans might face some barriers to gaining entry to organizations. This result complicates this literature, given the multi-stage nature of the process of labor market stratification. The answer to the question about Asians' labor market parity with Whites might be conditional upon which stage of the labor market discrimination is being discussed.

This paper shows that the "visibility-discrimination" thesis is helpful to explain the discrimination that Black workers face at the hiring stage. Together with other evidence showing the linkages between Black concentration and a variety of negative outcomes for Blacks (D'Amico & Maxwell, 1995; Frisbie & Neidert, 1977; Semyonov et al., 2000; Tomaskovic-Devey & Roscigno, 1996), this finding highlights the unique dynamics of discrimination that African-Americans face in the labor market and in society more generally. While a higher concentration of Blacks could provide a context for heightened taste-based and statistic-based discrimination against Blacks as hypothesized, the *job segregation* thesis can provide a plausible explanation to the association observed. Huffman and Cohen (2004) outlined two mechanisms linking Black concentration to Black-White inequality – job segregation and devaluation – and found support for the former. In my study, none of the three job types considered – marketing, administrative assistant, and sales – are Black-dominated occupations. The percentages of Black workers in these job types are 5, 8.6, and 11, respectively (BLS, 2016). The racial discrimination against Black applicants detected might result from employers funneling Black applicants into lower-paying and Black-dominated jobs, instead of giving them a chance to get middle-class, white-collar jobs that require college degrees.

The findings that Black applicants experience disadvantages that correlate with percent Black – while Asians and Latinos do not – suggest that the visibility-discrimination does not extend in a straightforward way to Asians and Latinos. The presence of Asians and Latinos in urban areas do not seem to be correlated with White antipathy toward these racial/ethnic groups (Dixon & Rosenbaum, 2004; Taylor, 1998), and do not correlate with these groups' labor market performances in the same ways that Black concentration relates to Black-White inequality. In sum, this research offers qualified support for the "visibility-discrimination" thesis. The findings demonstrate that while the thesis extends to hiring discrimination and applies to the case of Black workers, it has limitations in explaining sources of discrimination that other minorities might face in the labor market.

It is worth noting that the large number of fictitious resumes represents a significant scale-up from previous work. Given the scope of the experiment, it is important to make sure employers were not unnecessarily overburdened.

To that end, after recording the callback, I immediately replied to the employer that the application had been withdrawn. No employers were notified later than 24 h after their initial reply. This procedure also minimized the risk of employers selecting fictitious candidates over actual jobseekers. Consequently, overall risks to employers were none or minimal.

While 50 MSAs represent a substantial improvement from previous experimental designs, this number of level-2 observations is not a large one in the statistical sense. Given the relatively small n and the cross-sectional nature of the data, it is difficult to pinpoint the exact mechanisms linking percent Black and the Black-White callback gap. Therefore, while one of the goals of this project is to contribute to the visibility-discrimination thesis, it is worth exploring mechanisms beyond threat and visibility that might be linking percent ethnic minority with increased inequality. Hiring outcome inequities might not be solely motivated by racial animus or group threat. Besides "taste-based discrimination" (Becker, 1957), there are theoretical grounds to expect that percent Black in the labor market also increases the level of "statistical discrimination" (Aigner & Cain, 1977) that Black workers might encounter. Various studies have found that Black concentration is correlated with Black workers having lower wages (Beggs et al., 1997; Cohen, 1998, 2001; McCall, 2001), higher rates of poverty (Tomaskovic-Devey & Roscigno, 1996), and higher odds of working in unskilled and low-skilled occupations (Semyonov et al., 1984; Semyonov et al., 2000) than Whites. Such labor market outcomes drive down the group average measures on which employers rely to make predictions about Black workers' potential productivity, as the statistical discrimination perspective would expect. Some employers operate in labor markets where Black workers face low levels of occupational attainment, which are also markets with a high concentration of Blacks. When making hiring decisions, such employers might believe that Black workers belong to an ethnic minority group that on average underperforms the majority, and thus are unjustifiably less incentivized to hiring competent Black workers. While this study is not designed to adjudicate the taste versus statistical discrimination debate, the results provide an interesting descriptive fact that could motivate further tests to tease out these competing frameworks.

While the visibility-discrimination perspective focuses on dynamics of discrimination in areas characterized by high percent ethnic minority, it is worth discussing how hiring practices might play out in areas with low concentrations of people of color. Employers are increasingly concerned about promoting organizational diversity, either as a genuine effort to increase their competitive advantage in recruiting skilled workers or as a strategy to manage their public reputation as equality-oriented organizations (Cook &

Glass, 2014; Cox, 2001; Kelly & Dobbin, 1998; Yang & Konrad, 2011). It could be the case that, while all employers are concerned about having some diversity in racial/ethnic terms – even in the realm of tokenism – within their organizations, the diversity level is harder to meet in cities with low concentrations of people of color. In such cities, with a high percentage of Whites, one would expect lower levels of discrimination against ethnic minorities. This diversity-tokenism explanation, which predicts less discrimination in low percent ethnic minority cities, could operate as an alternative explanation to the visibility-discrimination thesis. The difference between these perspectives stems from their focuses on two different ends of the ethnic minority concentration spectrum.

In addition, some socio-historical processes might be connected to both proportion of ethnic minority and employment opportunity disparities. For instance, Acharya et al. (2016) demonstrated that a legacy of slavery still affects Southern White racial attitudes. Southern Whites now living in counties that had a high proportion of slaves in 1860 were found more likely to oppose affirmative action, demonstrate racial resentment, and have colder attitudes toward African-Americans than were Whites living in areas that had a lower proportion of slaves. While this argument is specific to the South, the fact that my study observed anti-Black hiring discrimination in all regions could perhaps demonstrate the lasting and widespread impact of the legacy of slavery on modern inequality. Beyond this factor, it is worth noting that urban places are complicated milieus with various contexts: economic, cultural, residential, religious, etc. This research only deals with demographic contexts – or ethnic minority concentration, to be precise. Other attributes of urban areas, such as segregation, gentrification, or sociocultural history, are admittedly underexplored. This limitation is a necessary one both theoretically and empirically. Focusing only on demographic context allows the manuscript to concentrate on and contribute to a few key theoretical perspectives. Incorporating other contexts likely requires engagement with different areas of literature and potentially distracts the paper from its core focus. Future studies are encouraged to include an even larger number of MSAs in their design and to grapple with other characteristics of these urban sites to better represent the U.S. labor market landscapes.

This study is a part of a larger research that focus on race/ethnicity and employment history as individual-level drivers of unequal hiring outcomes (see Mai, 2021). It is not designed to examine the intersections between race/ethnicity and various other factors such as gender and job type. Studies that aim to analyze different combinations of several axes of stratification will require a substantially larger sample size than the one presented in this study. That is because the inclusion and systemic variation of levels of different predictors would exponentially increase the number of experimental cells and thus significantly drive up the number of fictitious resumes being submitted. In order to keep the project focused on the key predictor of interest, I did not vary gender within audit pairs.[11] While the question of how race intersects with gender or job type is an undeniably interesting one, it is simply beyond the scope of this research.

In addition, the study could not cover ethnic heterogeneity within racial groups. It is very likely that Indian- and Japanese-Americans will fare differently than Bhutanese- or Cambodian-Americans in the hiring process. The intensity of hiring discrimination likely varies across Cuban-, Mexican-, and Puerto Rican-Americans. The beauty of the experimental method lies in its simplicity and the ability to pinpoint a specific cause. Adding another signal immensely complicates the design and theorization, while making it very difficult to identify the exact cause of discrimination. Relatedly, at the design stage, I had to use Chinese names to represent Asian candidates. While this decision is not ideal given the complexity and heterogeneity within the Asian-American community, it is a necessary one. The inclusion of more racial/ethnic categories would, as stated, radically increase the required experimental cells and resumes submitted, rendering the project unmanageable. Chinese-Americans are the largest subgroup of Asian origin in the United States, but they are better-resourced with a higher level of education and income relative to other subgroups such as Vietnamese, Hmong, and Laotians. Little is known about how sensitive employers are to names belonging to different racial/ethnic subgroups, so it is unclear how this decision might have affected results. As it is almost impossible for the current study to include all racial ethnic subgroups, due to the massive number of experimental cells generated, future studies should look into variations in labor market outcomes of different subgroups within the same racial/ethnic group.[12]

This research also has broader implications for the debate in racial stratification literature on how the color line is drawn in modern society. Changing demographics in the U.S. raise critical questions about how the traditional Black-White delineation might transform in light of the growing presence of Asians and Latinos (Lee & Bean, 2007). Some scholars maintain that the line is drawn between “Whites” and “non-Whites” (Hollinger, 2006) with all “people of color” sharing subordinate status vis-à-vis the White majority. Scholarship in the Black/Non-Black or the Black exceptionalism camp, on the other hand, argues that due to the unique history of oppression and persistent segregation, Black individuals are pushed to the bottom of the racial/ethnic hierarchy while other ethnic minority groups are not (Yancey, 2003).

An original account of the “visibility-discrimination” thesis asserts: “Provided minority competition underlies prejudice, there should be a positive relationship between minority percentage and discrimination"(Blalock, 1967, p. 183). The language used in this theorization seems to indicate that the White-ethnic minority separation operates along the White/Non-White divide. However, the dynamics of racial stratification in the labor market that my study uncovers are more consistent with the Black/Non-Black or Black exceptionalism perspective. In case of hiring, that Black applicants are most disadvantaged at the hiring stage and the consequences are amplified in cities with higher Black concentration. Furthermore, these associations do not apply to Asians and Latinos. These findings suggest that Blacks experience alienation and ostracism in a way that Asians and Latinos do not. The contextualized labor market disadvantages, therefore, stem specifically from being Black, rather than being an ethnic minority. The findings thus suggest that the "visibility-discrimination" thesis should be re-interpreted and reframed through the lens of the Black exceptionalism perspective, rather than the White/non-White delineation based on which it was originally theorized.

The findings presented are also relevant for public policies. The finding, that when other factors – observed and unobserved – are accounted for racial/ethnic minorities are still disadvantaged at the hiring stage compared to Whites, indicates a stronger need for enforcement of anti-discrimination laws. However, the extent to which minorities experience discrimination is conditioned by the demographic variation of the areas where they live. Policymakers should take ethnic minority size seriously, as this factor has important implications for how various norms of enforcements should be used in different geographical areas to improve the equality of opportunity at the local level.

This research addresses several gaps and provides inroads into an important yet understudied question of how urban context is crucial in understanding employers' discriminatory behavior in hiring. It synthesizes insights from two largely independent fields of literature and contributes to both. The theoretical goal of this research drives the expansion of existing resume audit studies to accommodate a larger number of experimental sites, which constitutes the study's empirical contribution. Altogether, these theoretical and empirical contributions expand our understanding of how racial/ethnic discrimination is embedded in urban contexts, with implications for understanding the complex ways in which race and place intersect to generate unequal structures of opportunities in modern society.

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Notes

1. Another exception might be Mobasseri (2019). While both Mobasseri (2019) and this study are interested in how place matters for labor market outcomes, the difference stems from the analytical scopes of the two studies. Mobasseri (2019) analyzes how callback rates vary across multiple neighborhoods within the same city, while the examines how hiring outcomes vary across different cities within one country.
2. I planned to submit 12,000 resumes to 6,000 openings, but only 11,871 applications were sent out. This 1.07% attrition rate results from cases for which I was able to submit the first application, but the job posting closed before I sent the second one.
3. From the original list of the 50 most populous MSAs, I replaced Virginia Beach-Norfolk-Newport News, VA-NC and Birmingham-Hoover, AL with Bridgeport-Stamford-Norwalk, CT and Omaha-Council Bluffs, NE-IA due to the lack of job openings in the former two MSAs. Since I conducted pilot studies in St. Louis, MO-IL and Milwaukee-Waukesha-West Allis, WI, I replaced those with Grand Rapids-Wyoming, MI and Rochester, NY.
4. After finishing data collection, I used two-tailed, two-proportion z-tests to show non-significant differences (at the 0.05 level) between callback rates for two

names associated with each racial/ethnic-gender combination. These results showed that employers did not discriminate based on these names.

5. It is important to discuss a possible design drawback here. I intended, as much as possible, to create comparable employment histories across 50 MSAs. However, I must acknowledge that work histories unavoidably might not always be perfectly comparable across different urban areas. In most cases, I relied on large national brands such as Bank of America, Lowe's Home Improvement Store, and Allstate Insurance, etc. However, in some cases, I also relied on smaller local brands. For instance, for the sales job, I used large car dealerships, which exist in all MSAs. It is possible that these car dealerships might not be totally comparable. For example, "AutoNation Nissan" in Memphis may not be as prestigious as "Berger Chevrolet" in Grand Rapids. Future research could do well to provide more guidelines on how to create credible and comparable employment histories across urban areas.
6. This restriction created an advantage for the experiment: Gaddis (2014, p. 1459) posits that "employers do not focus on a single difference between candidates. It is highly unlikely that employers in real-world scenarios have to make the unrealistic choices that the typical matched-pair process requires of them, potentially inflating the estimates of characteristics such as race in prior audits."
7. In this study, employers received resumes from two applicants who were either both men or both women. All applicants for sales jobs were men, and all applicants for administrative assistant positions were women. I randomly assigned gender to applicants for marketing jobs. These gender assignments were somewhat consistent with the gender breakdown of the job types. According to the BLS (2016), secretaries and administrative assistant positions are dominated by women (94.6% of total employed). Employment of marketing specialists is about evenly split between men and women (55% women). Although the gender distribution of sales jobs is even (49% women), to keep the number of men and women applicants close to each other, I made sure that sales jobs were men only.
8. The results are generally consistent when the region dummy variable excluded.
9. While this observation indicates possible regional variation, the Region*Percent Black variables did not yield statistical significance in any regression models. This result indicates that the linkages between percent Black and the Black-White callback gap do not significantly vary by region.
10. The four MSAs that are closest to the regression lines are all in California: Los Angeles-Long Beach-Santa Ana, San Diego-Carlsbad-San Marcos, San Francisco-Oakland-Fremont, and San Jose-Sunnyvale-Santa Clara.
11. I ran a robustness check model with gender as a control variable. In this model, I could not include "job type" as a control due to the collinearity between gender and job type. In this model, the main findings remained unchanged: Percent

Black was correlated with a large Black-White callback gap, while Percent Asian and Percent Latino showed no association with the Asian/White and Latino-White callback gap, respectively. Men did have higher odds of getting a callback than women, but this might be largely driven by the fact that employers in sales were more likely to callback applicants than their counterparts in administrative assistant jobs and marketing. When the sample was limited to marketing jobs only, there was no difference in callback rates between men and women.

12. For robustness checks, I explored how the concentration of three Asian and two Latino subgroups might be correlated with various White-ethnic minority callback gaps. Consistent with key reported results, percent Chinese-, Korean-, and Vietnamese-Americans are not significantly correlated with the White-Asian callback gap. Similarly, percent Mexican- and Cuban-American are not correlated with the measures of White-Latino hiring inequality. These results are available upon request.

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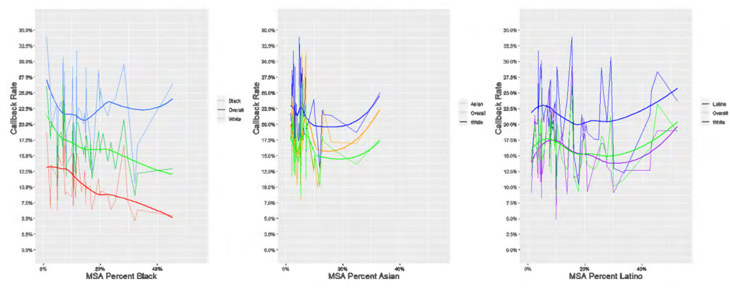
Appendix A. Raw Callback Rates and Ethnic Minority Percent



Source. Original experimental audit study data.