Discrimination Against Black and Hispanic Americans is Highest in Hiring and Housing Contexts: A Meta-Analysis of Correspondence Audits

S. Michael Gaddis[a,b,1], **Edvard Nergård Larsen**[c], **Charles Crabtree**[d], **and John B. Holbein**[e]

[a]Department of Sociology, University of California, Los Angeles; [b]California Center for Population Research, University of California, Los Angeles; [c]Department of Sociology and Human Geography, University of Oslo; [d]Department of Government, Dartmouth College; [e]Frank Batten School of Leadership and Public Policy, University of Virginia

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To what extent does racial/ethnic discrimination in America differ across contexts? In this paper, we provide the largest and most comprehensive review of racial/ethnic discrimination research to date. We conducted a meta-analysis of 78 correspondence audits in the United States, representing over half a million applications, emails, and other forms of correspondence that occur in all aspects of modern society, including the hiring, housing, medical, public services, and education sectors. We find that racial/ethnic discrimination in the United States continues to be a large problem, but discrimination against racial/ethnic minorities simultaneously exhibits a substantial amount of contextual heterogeneity not recognized in previous discrimination research. Discrimination against Black Americans is most common in hiring, followed by the rental housing context. Discrimination against Hispanic Americans is highest in hiring, but discrimination in other contexts is considerably lower. Although discrimination occurs in education, medical, and public services contexts, it is far less common in these sectors. Altogether, our findings suggest that discrimination is more common in economic contexts that are more resource-intensive and have higher stakes, despite stronger legal protections against discrimination in those same contexts. Our work confirms that racial/ethnic discrimination in the United States continues to be a persistent and pervasive phenomenon that impacts many core parts of the lives of Black and Hispanic Americans and simultaneously reinforces and exacerbates existing inequalities.

racial/ethnic discrimination | correspondence audit | field experiment | meta-analysis

One of America's enduring legacies is the many active and antagonistic acts of violence, prejudice, bias, and discrimination directed at its racial/ethnic minority citizens. Given this, scholars have long sought to measure and understand the causes, scope, size, and consequences of acts of racial/ethnic discrimination. Since the 1970s, researchers have conducted well-controlled experiments that measure the extent of racial and ethnic discrimination across many contexts, including hiring (1, 2), housing (3, 4), government and public services (5, 6), higher education (7, 8), and medicine (9, 10), among others (see (11)). These studies have crossed disciplinary boundaries and have been published in top journals across economics, management, political science, psychology, public administration/policy, sociology, and other fields. Despite a large—and ever-growing—literature using experiments to study racial/ethnic discrimination, current research lacks a cohesive and comprehensive assessment of the extent, nature, and scope of discrimination that racial/ethnic minorities face across the many sectors of American life. The largely piecemeal approach to understanding racial/ethnic discrimination has deepened scholarly and public knowledge about the prevalence of the phenomena but limited our ability to come to a consensus about where, when, and how discrimination impacts the lived experience of millions of racial/ethnic minority Americans in their search for jobs, housing, education, healthcare, and various other public services.

In this paper, we aim to fill this gap by bringing together **all** of the available correspondence audits of racial/ethnic discrimination against the two largest racial/ethnic minority groups in the United States—Black and Hispanic Americans. Correspondence audits are a specific type of field experiment in which researchers manipulate some signal (e.g., name, appearance) related to a personal characteristic (e.g., race, gender, sexual orientation) to examine discrimination on the basis of that characteristic. These experiments allow scholars to make strong causal claims about the "what," "where," and "when" aspects of discrimination (12). Correspondence audits present a means for researchers to covertly examine real-world behavior and as such offer a marked methodological improvement over surveys that examine attitudes, opinions, or self-reported

Significance Statement

We report the results from a meta-analysis of all (n=78) publicly available correspondence audits testing for racial/ethnic discrimination against Black and Hispanic Americans. Our meta-analysis is the largest conducted to date—incorporating over 500,000 instances of correspondence. We compare levels of discrimination across multiple aspects of American life including hiring, rental housing, public services, higher education, medical, and other contexts. Our results corroborate that discrimination against Black and Hispanic Americans is persistent and pervasive. Importantly, our results show that discrimination is largest in hiring and rental housing contexts compared to other contexts. Thus, discrimination in the United States is more common in contexts where interactions are resource-intensive, that have higher stakes, and that have the greatest legal protections against discrimination.

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[1]To whom correspondence should be addressed. E-mail: mgaddis@soc.ucla.edu

behavior toward members of certain groups, which may be plagued by Hawthorne effects, social desirability bias, or other measurement and methodological issues (11, 13, 14).

Many scholars in the social sciences have used the correspondence audit method to document discriminatory behavior (11, 12, 15). As prominent social scientists who led the charge in using audits to study discrimination, Pager and Shepherd note that this approach is particularly well-suited to capture the "unequal treatment of persons or groups on the basis of their race or ethnicity" (16, 182). A panel convened by the National Research Council of the National Academies recommended the audit method as a particular valuable tool in understanding racial/ethnic discrimination and federal courts have acknowledged the importance of audits (17, 18). Given these features, the audit method has been especially prevalent during the past decade (for summaries of this literature, see (3, 11, 19–22)).

Despite the widespread use of correspondence audits documenting racial/ethnic discrimination, few meta-analyses or broad examinations of prior work exist. To our knowledge, only three such studies have attempted to synthesize prior research from the U.S. in a systematic fashion. In the first, Quillian et al. use a meta-analysis to examine hiring discrimination against Black and Hispanic Americans through 2015 and find that levels of racial/ethnic discrimination in the labor market did not change much between 1990 to 2015 (21). In the second, Quillian et al. use similar data to examine how much discrimination varies between the initial contact stage and follow-ups during the hiring process (23). In the third, Quillian et al. present the results of another meta-analysis showing that levels of discrimination against Black and Hispanic people in the housing market declined from 1976-2016 (24). Although these three studies are vitally important in their own right, the purpose and scope of each of these studies is substantially different than ours and leave some important questions unanswered.

First, we do not know the extent to which racial/ethnic discrimination against Black and Hispanic Americans varies systematically across contexts. That is to say, based on previous work, we do not know the extent to which discrimination in the labor and housing markets are the proverbial high-water mark for discrimination in the United States or, rather, whether discrimination in these economic transactions mirrors discrimination in the many other aspects of day-to-day life. In addition to searching for a job and housing, Americans spend much of their time searching for quality education, high quality medical care, and access to other vitally important public services. Collectively, these experiences form an important part of the bedrock of citizens' lived experience that previous research has often ignored. Furthermore, employment and housing are the two sectors that are afforded the greatest legal protections and enforcement mechanisms by the federal government to protect against racial/ethnic discrimination. The threat of legal penalties should theoretically limit levels of discrimination in these contexts compared to other contexts with less civil rights protection.

Second, audits of racial/ethnic discrimination have historically focused on examining differences between White and Black Americans. Examinations of racial/ethnic discrimination against Hispanic Americans and other racial/ethnic groups have began in earnest only recently. In compiling the present research, we found that 61.8% of the correspondence audits examining racial/ethnic discrimination against Hispanic Americans in the United States were published since the beginning of 2018. Without additional study, the only meta-analytic estimates we have for levels of discrimination against Hispanic Americans include nine studies of employment discrimination (21) and eight studies of housing discrimination (24). This is an important gap in our understanding of how the nearly 61 million Americans (who represent just under 20% of the population) in this ethnic minority experience discrimination across multiple contexts in their lives.

Third, the previously discussed meta-analyses covered a total of two contexts through 2010 (23), 2015 (21), and 2016 (24). However recent years have seen an explosion of correspondence audits testing for racial/ethnic discrimination. In the past half-decade alone, for instance, the number of correspondence audits testing for bias against Black Americans has more than tripled. In their meta-analysis on hiring specifically, Quillian et al. (21) use data from 24 studies representing nearly 56,000 pieces of correspondence; however, our meta-analysis across contexts through 2021 includes 78 studies representing over 500,000 pieces of correspondence. The size of our dataset and samples represented therein allows us to definitively compare levels of racial/ethnic discrimination across contexts, increasing external validity, ecological validity, and statistical power. Moreover, we include only correspondence audits, minimizing significant differences in the method itself across studies and focusing our examination of racial/ethnic discrimination on studies that occurred only in the 21st century.

Our paper helps fill these important gaps and examines racial/ethnic discrimination across contexts in the 21st century. We conduct a meta-analysis of 78 correspondence audit studies (165 total data points) representing over half a million applications, emails, and other instances of correspondence. For a full explanation of how we compiled this sample and the meta-analytic methods that we use to estimate discrimination across studies, see the Materials and Methods section below.

To preview our results, our findings corroborate that discrimination against Black Americans continues to occur in the hiring sector. Moreover, for both Black and Hispanic Americans, discrimination in hiring is greater than in other contexts. In the rental housing market, racial/ethnic discrimination is substantial and second only to hiring discrimination for Black Americans, but is much less severe for Hispanic Americans. In public services, higher education, and medical contexts, racial/ethnic discrimination against Black and Hispanic Americans is substantively small and statistically insignificant. Finally, although we find that racial/ethnic discrimination is pervasive across contexts, there is evidence of favorable treatment toward Black or Hispanic Americans in some instances.

Research Question

Does racial/ethnic discrimination vary by the context under examination? For example, are there larger gaps in White/Black outcomes in correspondence audits of hiring rather than rental housing, education, medicine, or public services?

Materials and Methods

To address our research question, we followed a procedure similar to a recent meta-analysis of audit studies of hiring discrimination (21). First, we created a comprehensive list of all known correspondence audits examining racial/ethnic discrimination that fit specific criteria. Second, we coded key data about each of the studies to create an analysis dataset. Third, we conducted a meta-analysis using multiple meta-regression models to address our research question. Below, we discuss each of these steps in detail.

Creating a Comprehensive List of Known Correspondence Audits. In general, an audit study is a type of field experiment that permits researchers to examine difficult to detect behavior, such as racial/ethnic and gender discrimination, and decision-making in real-world scenarios. In-person audits use actors or testers who are trained to perform in specific scenarios (e.g., interactions with employers or real estate agents) where discrimination might occur. Correspondence audits examine potential discrimination in similar situations, but all interactions occur through correspondence (e.g., emails or online applications), eliminating the need for and costs associated with using actors or testers to engage in real-time human interactions (11, 15).

To create a comprehensive list of all known correspondence audits examining racial/ethnic discrimination, we first established three rules. We limited our examination to studies that (1) were conducted in the U.S. or Canada, (2) examined responses for both Blacks and Whites *or* Hispanics and Whites, and (3) signaled race/ethnicity through names. We placed no restrictions on discipline or context. We included published peer-reviewed studies and publicly available working papers. We did not include in-person audit studies due to the significantly different nature of the method and because nearly all in-person audit studies occur in hiring and housing contexts (11).

We began by searching Google Scholar, the National Bureau of Economic Research (NBER), and the Social Science Research Network (SSRN) for the terms "audit study," "correspondence audit," "correspondence study," "correspondence test," "discrimination experiment," "paired test," and "situation experiment," all common terms broadly used to describe correspondence audits of discrimination (11). We then cross-checked citations of important empirical, methodological, and review articles and books in the audit literature. Finally, we reached out via email and social media to scholars who have conducted empirical or methodological work on correspondence audits in the past to identify studies we might have missed.

In total, we identified 76 research studies using a correspondence audit to examine responses for Blacks and Whites and 36 research studies for Hispanics and Whites. In two cases, we could not obtain the necessary information from publicly available materials nor after contacting the authors for additional information. In these cases our request was either refused (25) or could not be fulfilled due to data availability issues (26). Thus, our final dataset includes 74 studies using a correspondence audit to examine responses for Blacks and Whites and 34 studies for Hispanics and Whites. In total, we have a set of 78 unique studies because many studies examine responses for both Blacks and Hispanics. The full list of studies is available in the Supporting Information Appendix Section 1.

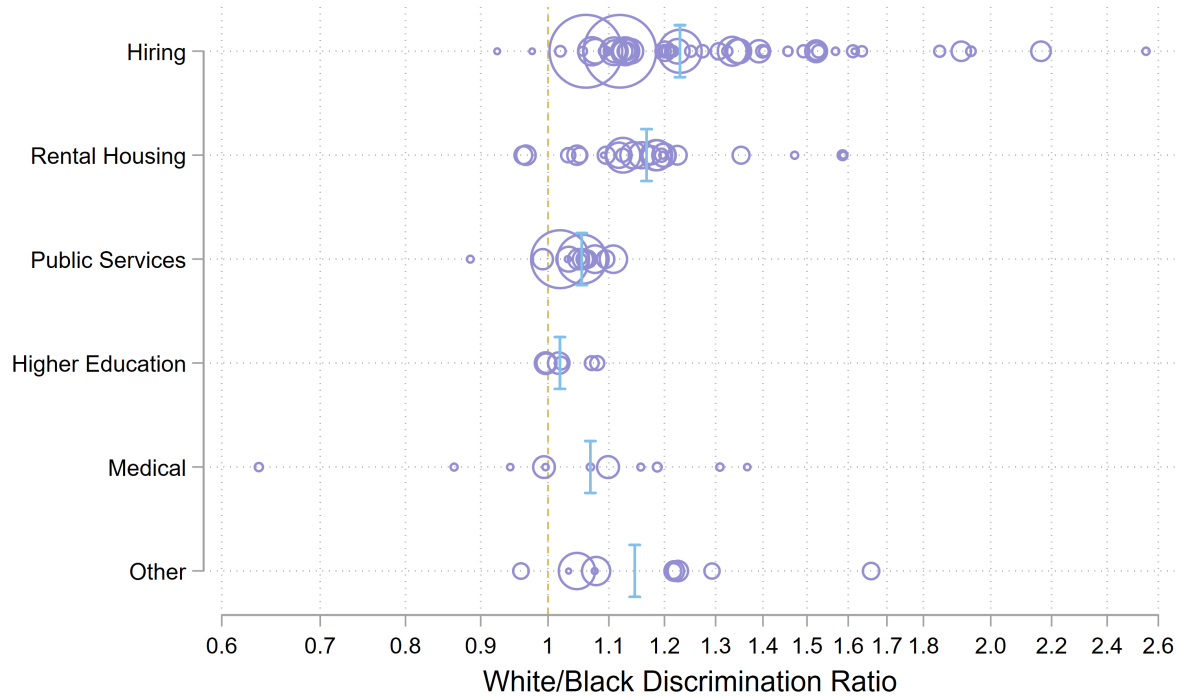
Coding the Correspondence Audits. Next, we recorded data about the sample size and response rate (overall and by race/gender) for each study. We then created a list of environmental and design factors that researchers often manipulate in correspondence audits which may influence estimates of discrimination. We identified six such factors: context of discrimination (i.e., hiring, rental housing, higher education, medical, public services, and a residual "other" category), gender(s) examined (i.e., male, female, or both), time period (recorded as month and year of the beginning and end of data collection), geographic location(s), use of last names to signal race/ethnicity (27–29), and use of a matched or within-subjects design (30).

Our choices in coding the context of discrimination are critically important to our research question and analysis. We began with a broad list of potential contexts, initially coding in these categories: hiring (31 / 49), higher education – admissions (3 / 4), higher education – professors (1 / 2), housing – mortgage (1 / 1), housing – rental (15 / 24), housing – roommate (1 / 1), housing – short term rental (2 / 3), medical (7 / 11), public services (10 / 14), retail services (1 / 2), religious (1 / 1), and rideshare (1 / 2). The first number for each context indicates the number of studies and the second number indicates the number of data points examining White/Black discrimination. We decided to combine categories where appropriate to increase the sample size within each context of discrimination value. Our final categories for analysis are hiring, higher education, medical, public services, rental housing, and "other." Thus, our residual other category includes housing – mortgage, housing – roommate, housing – short term rental, retail services, religious, and rideshare. The majority of studies and data points are from two contexts: hiring and rental housing. Table S2.1 in the Supporting Information Appendix Section 2 shows the number of studies and data points for each of these categories.

Additionally, for our analyses, we recoded time period into a binary variable to indicate whether data collection occurred during a recession, and we recoded geographic location into a binary variable to indicate whether data collection occurred in urban areas only. We describe our selection and coding of each of these environmental and design factors in more detail in the Supporting Information Appendix Section 2.

Meta-Analysis Models. Because some studies only include one gender, or have different sample sizes by gender, we treat each study-by-gender data point as a separate observation in the analysis. Our dependent variable of interest is the response discrimination ratio from each study-by-gender data point. We define the response discrimination ratio as the study-by-gender response rate for Whites divided by the response rate for Blacks (or Hispanics). Each racial response rate is the number of positive responses divided by the number of total correspondence sent (e.g., applications, emails) for that group by gender in a single study. In other words, if the Black male response rate in a study is 0.1 and the White male response rate in a study is 0.2, the discrimination ratio is $0.2/0.1 = 2.0$. A discrimination ratio of 1 indicates equal treatment, i.e., no discrimination against Blacks or Hispanics. A discrimination ratio below

Fig. 1. White/Black Racial/Ethnic Discrimination by Context



Note: Each data point represents a gender-specific study-level discrimination ratio (White response rate / Black response rate). Marker size varies by the sample size of each data point. Blue lines indicate median discrimination ratios by context of discrimination. Results shown on logged scale. N=74 studies / N=114 data points.

1 indicates favorable treatment toward Blacks or Hispanics and a discrimination ratio above 1 indicates discrimination against Blacks or Hispanics. The use of the discrimination ratio in this manner for meta-analysis work is established practice (21, 24, 31, 32). Moreover, this measure balances the three criteria recommended for a summary statistic in meta-analysis: consistency, mathematical properties, and ease of interpretation (33). We examine alternative dependent variables in the Supporting Information Appendix Section 3.

Researchers typically rely on either fixed- or random-effects regression models when conducting meta-analyses (34–36). In short, fixed-effects models are more appropriate when a researcher (1) assumes homogeneity of a population effect size and (2) wishes to make conditional inference only about the observed set of studies. Moreover, random-effects models are more appropriate when a researcher (1) assumes heterogeneity of a population effect size and (2) wishes to generalize beyond the observed set of studies.

A collection of correspondence audits examining discrimination is likely to contain significant heterogeneity in effect sizes, even if those estimates are within a single context (e.g., hiring). This is due to variation in unobserved contextual, design, and implementation characteristics not captured by additional covariates. To investigate heterogeneity between studies and between and within contexts, we examine forest plots and summary statistics (36). We provide details about these analyses, which confirm significant heterogeneity across multiple dimensions, in the Supplemental Information Appendix Section 3. Thus, these analyses suggest that a random-effects meta-analysis model is more appropriate than a fixed-effects meta-analysis model (33, 36).

We specify a random-effects meta-regression model estimated by restricted maximum likelihood using the meta regress function in Stata/MP version 16.1 (37). The general form equation for this model is:

$$\ln\,(y_i) = x_i\beta + u_i + \varepsilon_i, \text{ where } u_i \sim N(0,\tau^2) \text{ and } \varepsilon_i \sim N(0,\sigma_i^2)$$

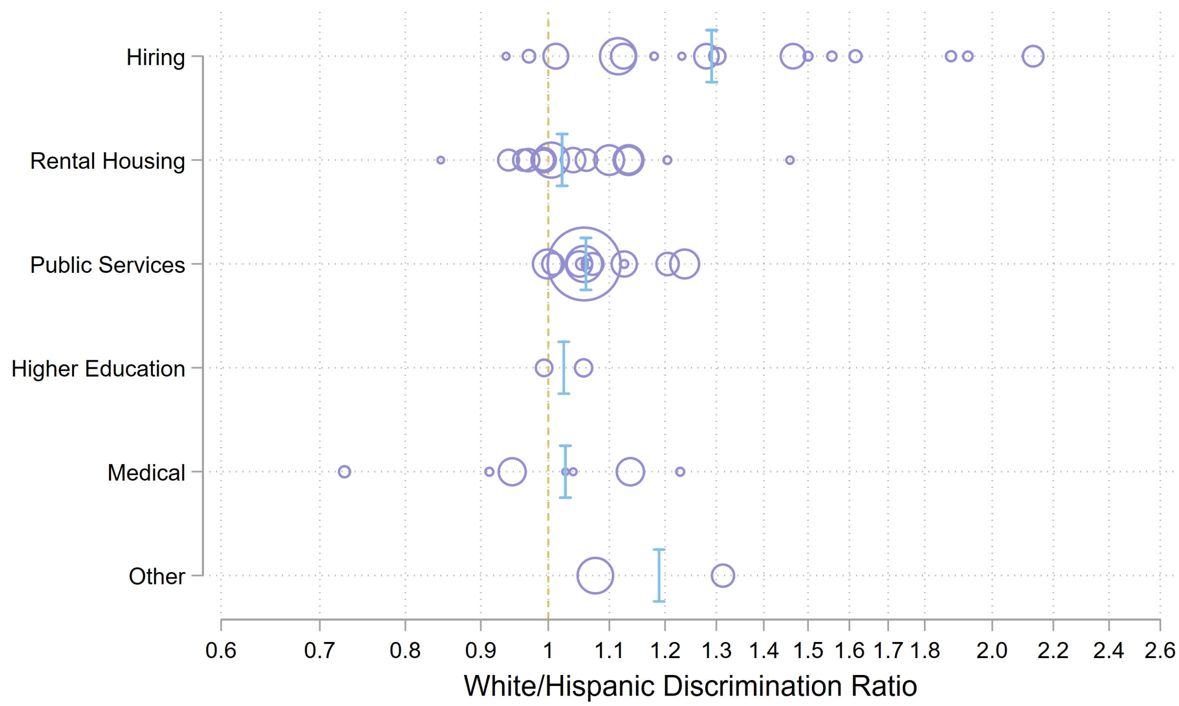
Here, $\ln\,(y_i)$ is the natural log of the discrimination ratio, a transformation recommended for meta-regression when using count data or ratios (33, 36), β is a $k \times 1$ vector of coefficients (including a constant), x_i is a $1 \times k$ vector of covariate values in study i (including a 1 for the constant). u_i is a random effect describing the study-specific deviation from the distribution mean that is normally distributed with a mean of 0 and standard deviation of τ, where τ^2 is the residual between-study variance (or random-effect variance). ε_i is a random error term describing sampling variability that is normally distributed with a mean of 0 and standard deviation of σ, where σ_i^2 is the observed variance of the log discrimination ratio in study i. We include the six environmental and design factors discussed above as covariates.

In addition to our random-effects regression models, we also specify a fixed-effect meta-regression model using the meta regress function in Stata/MP version 16.1 (37). The general form equation for this model is:

$$\ln\,(y_i) = x_i\beta + \varepsilon_i, \text{ where } \varepsilon_i \sim N(0,\sigma_i^2)$$

Here, the equation is similar to the previous equation, but without the random effect describing the study-specific

Fig. 2. White/Hispanic Racial/Ethnic Discrimination by Context



Note: Each data point represents a gender-specific study-level discrimination ratio (White response rate / Hispanic response rate) Marker size varies by the sample size of each data point. Blue lines indicate median discrimination ratios by context of discrimination. Results shown on logged scale. N=34 studies / N=53 data points.

deviation from the distribution mean. We examine the results from this model because small-sample bias among the studies included in a meta-analysis could lead to more biased estimates from a random-effects model and less biased estimates from a fixed-effect model (38–40). Although we believe the random-effects models are more appropriate, we also examine the results from a fixed-effect model as a type of robustness check (41). We present figures showing adjusted predictions for each context of discrimination (i.e., hiring, rental housing, higher education, medical, public services, and other) with other covariates set at their means. These figures include the adjusted predictions at the means for (1) a base random-effects model, (2) a random-effects model including all covariates, and (3) a fixed-effect model including all covariates.

Results

In Figures 1 and 2, we present the study-by-gender data points by context of discrimination. Each data point is a lavender circle that scales by sample size. Each context of discrimination includes a blue line denoting the median value of the discrimination ratio for that context.

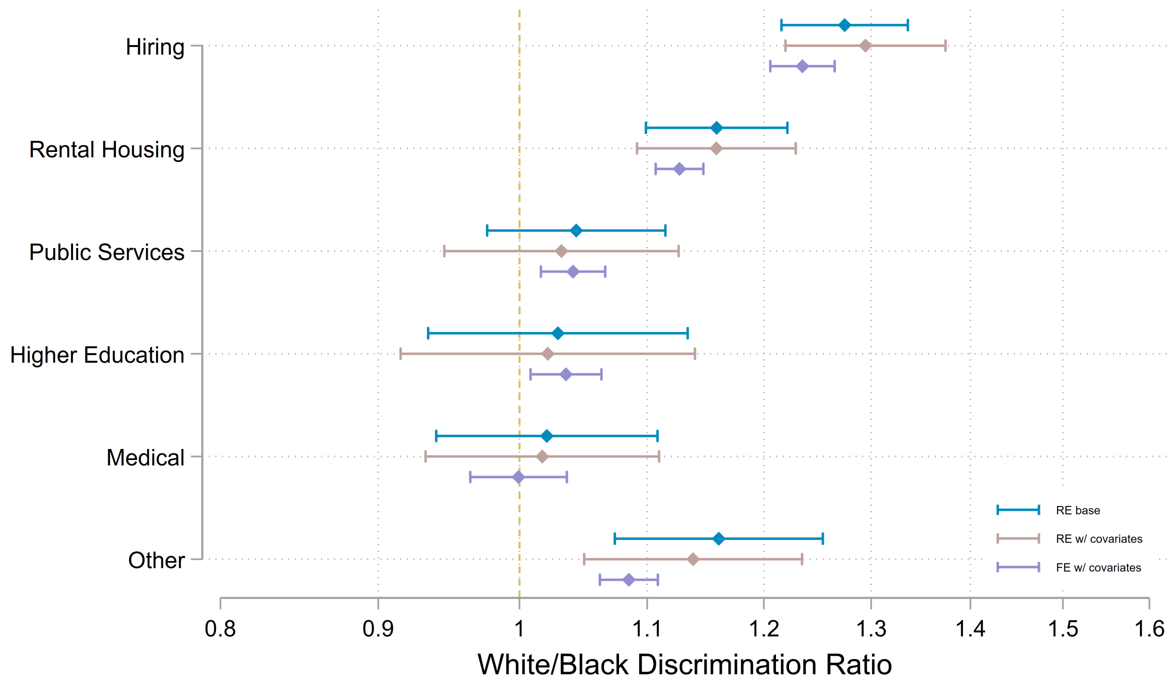
Figure 1 shows that the median White/Black discrimination ratio is highest in hiring contexts (∼1.229), slightly lower in rental housing contexts (∼1.167), slightly lower in "other" contexts (∼1.145), and close to 1 for medical (∼1.068), public services (∼1.054), and higher education (∼1.019) contexts. Additionally of note, 14 of 114 data points (12.3%) have a discrimination ratio below 1, indicating favorable treatment toward Black Americans. Five such data points occur in the medical context.

Figure 2 shows that the median White/Hispanic discrimination ratio is highest in hiring contexts (∼1.291), lower in "other" contexts (∼1.189), and close to 1 for public services (∼1.060), medical (∼1.027), higher education (∼1.024), and rental housing (∼1.022) contexts. Additionally of note, 13 of 53 data points (26.4%) have a discrimination ratio below 1, indicating favorable treatment toward Hispanic Americans. Six such data points occur in the rental housing context.

In Figures 3 and 4 we present the point estimates and 95% confidence intervals representing the adjusted predictions at the means for each context of discrimination. The results shown in blue are from a random-effects meta-regression model with no additional covariates. The results shown in rose are from a random-effects meta-regression model with our full set of covariates. The results shown in lavender are from a fixed-effect meta-regression model with our full set of covariates. We describe each of these models in more detail and present the full regression tables in the Supplemental Information Appendix Section 3.

The results from Figure 3 show that racial/ethnic discrimination against Black Americans is statistically significantly greater in hiring contexts compared to all other contexts of discrimination. The point estimates from these three models range from 1.24 to 1.29. These results indicate that for every 100 positives responses a Black job applicant receives, a comparable White job applicant will receive between 124 and 129 responses. The median positive response rate for White job applicants across all White/Black hiring studies in our meta-analysis is 18.75%. Thus, these combined results suggest that while a White job applicant would need to submit

Fig. 3. Adjusted Predictions at the Means - White/Black Racial/Ethnic Discrimination by Context of Correspondence Audit



Note: Each line represents the 95% confidence interval of adjusted predictions at the means from a model estimating the discrimination ratio. Models 1 and 2 are random-effects (RE) meta-regression models. Model 3 is a fixed-effect (FE) meta-regression model. Model 1 includes no additional covariates. Models 2 and 3 include the full set of covariates. Results shown on logged scale. Full results shown in Supplemental Table S3.1.

53 applications to receive 10 positive responses, a Black job applicant would need to submit approximately 68 applications to receive 10 positive responses.

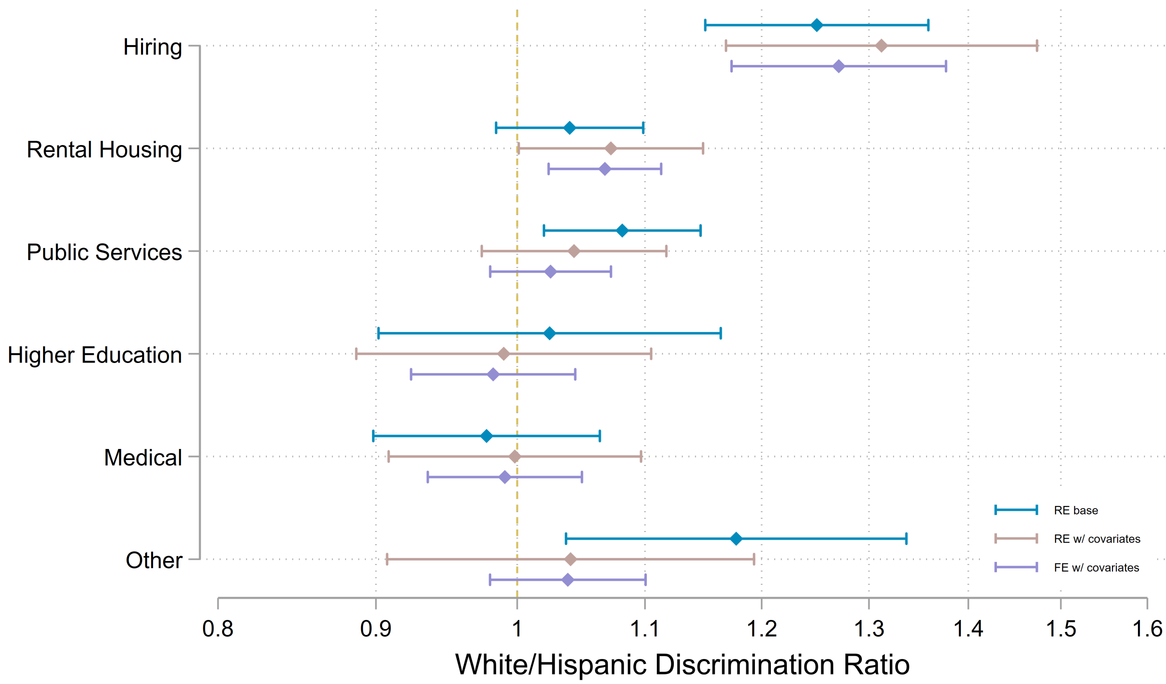
Additionally, we find that racial/ethnic discrimination against Black Americans is statistically significantly greater in rental housing contexts compared to all other contexts of discrimination except hiring and "other" contexts. The point estimates from these three models range from 1.13 to 1.16. Again, for every 100 positive responses a Black rental applicant receives, a comparable White rental applicant will receive between 113 and 116 responses. The median positive response rate for White rental applicants across all White/Black rental housing studies in our meta-analysis is 42.82%. Thus, while a White rental applicant would need to submit 23 applications to receive 10 positive responses, a Black rental applicant would need to submit approximately 27 applications to receive 10 positive responses.

These results for hiring and rental housing contexts hold whether we examine random-effects meta-regression models with or without covariates or a fixed-effect meta-regression model, and are robust to other alternative model specifications (see Supplemental Information Appendix Section 3). Furthermore, the random-effects meta-regression models show that racial/ethnic discrimination against Black Americans is statistically insignificant across the body of public services, higher education, and medical studies. In the fixed-effect model, the point estimates for discrimination in public services (1.04) and higher education (1.03) contexts are substantively small, although statistically significant; the effect for discrimination in the medical context is not statistically significant.

The results from Figure 4 show that racial/ethnic discrimination against Hispanic Americans is statistically significantly greater in hiring contexts compared to all other contexts of discrimination, except the comparison of "other" with hiring in the base random-effects model. The point estimates from these three models range from 1.25 to 1.31. These results indicate that for every 100 positives responses a Hispanic job applicant receives, a comparable White job applicant will receive between 125 and 131 responses. The median positive response rate for White job applicants across all White/Hispanic hiring studies in our meta-analysis is 19.17%. Thus, these combined results suggest that while a White job applicant would need to submit 52 applications to receive 10 positive responses, a Hispanic job applicant would need to submit approximately 67 applications to receive 10 positive responses. These results for the hiring context are robust across random-effects and fixed-effect meta-regression models, and are robust to other alternative model specifications (see Supplemental Information Appendix Section 3).

In most other contexts, racial/ethnic discrimination against Hispanic Americans is statistically insignificant. However, we urge caution in interpreting this findings, since these estimates have wide confidence intervals, largely due to the smaller sample size compared to estimates of White/Black discrimination ratios. One notable exception is that our estimates of discrimination against Hispanic Americans in rental housing are significant for Model 2 (1.07; 95% CI: 1.00-1.15) and Model 3 (1.07; 95% CI: 1.02-1.11). It is important to note that racial/ethnic discrimination is much less severe against Hispanic Americans than Black Americans in the rental housing

Fig. 4. Adjusted Predictions at the Means - White/Hispanic Racial/Ethnic Discrimination by Context of Correspondence Audit



Note: Each line represents the 95% confidence interval of adjusted predictions at the means from a model estimating the discrimination ratio. Models 1 and 2 are random-effects (RE) meta-regression models. Model 3 is a fixed-effect (FE) meta-regression model. Model 1 includes no additional covariates. Models 2 and 3 include the full set of covariates. Results shown on logged scale. Full results shown in Supplemental Table S3.2.

context.

Discussion

Our results highlight five important points. First, for both Black and Hispanic Americans, discrimination in hiring is greater than in other contexts. Second, for Black Americans, discrimination in the rental housing market is greater than in all other contexts except for hiring and the "other" context. Third, for Hispanic Americans, discrimination in the rental housing market is less severe than for Black Americans. Fourth, racial/ethnic discrimination against Black and Hispanic Americans in public services, higher education, and medical contexts is substantively small and statistically insignificant. Fifth, although we find that racial/ethnic discrimination is pervasive across contexts, there is favorable treatment for Black or Hispanic Americans in 16.2% of the observations in our meta-analysis.

Thus, our findings suggest that racial/ethnic discrimination is greater in contexts (e.g., hiring and rental housing) with four things in common. Hiring and housing contexts (1) are two of the most important economic contexts in society, (2) include interactions that are resource-intensive, (3) have higher stakes for both decision makers and applicants, and (4) have the greatest legal protections against discrimination.

Continued high-levels of racial/ethnic discrimination in the hiring and housing sectors is concerning and important for many reasons. These high levels of discrimination in the employment and housing search processes align with the staggering inequalities in economic outcomes that Black and Hispanic Americans face in the United States. While any degree of discrimination is—in our view—repugnant, the much lower levels of discrimination against Black and Hispanic Americans in educational, medical, and public service interactions portends more equitable treatment in these sectors. Inequities in these non-economic domains persist, however, and remain a problem for the United States as a whole.

In what represents an important puzzle, employment and housing are also the very contexts where explicit federal laws make discrimination illegal. The Civil Rights Act of 1964 legally prohibited racial/ethnic discrimination in employment, and housing discrimination was later outlawed via the Fair Housing Act of 1968. Moreover, government agencies, activist scholars, and other community advocate groups have a history of conducting similar audits in the employment and housing sectors as a means of uncovering, and often prosecuting those responsible for, racial/ethnic discrimination (11, 12, 42). Anti-discrimination law and small-scale audit studies of discrimination have been joined by large-scale audit research projects sponsored by government agencies and court approval of the use of these methods to establish legal standing in discrimination lawsuits (43, 44). The threat of legal penalties and the significant attention placed on documenting and stopping racial/ethnic discrimination should theoretically reduce the amount of discrimination that occurs in a particular context. Thus, it is surprising that, instead, we find significantly lower levels of racial/ethnic discrimination in contexts with minimal legal protections, enforcement mechanisms, and attention toward discrimination.

Alternatively, we might consider that the federal government was particularly prescient in identifying and targeting legal action in the contexts where racial/ethnic discrimination was most severe. It is somewhat unclear whether current federal legislation is ineffective in reducing discrimination or we have reached the limits of what any public policy can accomplish to reduce or eliminate discrimination. Moreover, we have no way to observe the counterfactual world where 1960s civil rights legislation was not enacted and examine whether discrimination would be more severe absent anti-discrimination legislation.

Our research spotlights the importance and necessity of correspondence audits examining racial/ethnic discrimination across a variety of contexts. Although we find lower levels of discrimination in contexts outside of hiring and rental housing, levels of racial/ethnic discrimination may change over time or be present in contexts heretofore unexplored. Additional research is needed to uncover the mechanisms and reasons behind discrimination, which may help elucidate why racial/ethnic discrimination is more prevalent in certain contexts. Finally, future research should examine additional heterogeneity both within and between contexts. We believe our findings are important in shaping a broad understanding of racial/ethnic discrimination in the U.S., but also raise many questions for social scientists and policymakers alike.

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SUPPORTING INFORMATION APPENDIX

for

Discrimination Against Black and Hispanic Americans is Highest in Hiring and Housing Contexts: A Meta-Analysis of Correspondence Audits

S. Michael Gaddis[1,2*], Edvard Negård Larsen[3], Charles Crabtree[4], and John B. Holbein[5]

1 Department of Sociology, University of California, Los Angeles

2 California Center for Population Research, University of California, Los Angeles

3 Department of Sociology and Human Geography, University of Oslo

4 Department of Government, Dartmouth College

5 Frank Batten School of Leadership and Public Policy, University of Virginia

∗ To whom correspondence should be addressed; E-mail: mgaddis@soc.ucla.edu

TABLE OF CONTENTS

Section 1. Creating a Comprehensive List of Known Correspondence Audits

To conduct our research, we followed a procedure similar to a recent meta-analysis of audit studies of hiring discrimination (79). First, we created a comprehensive list of all known correspondence audits examining racial discrimination that fit specific criteria. Second, we coded key data about each of the studies to create an analysis dataset. Third, we conducted a meta-analysis using multiple meta-regression models to address our research questions. Below, we discuss each of these steps in detail.

In general, an audit study is a type of field experiment that permits researchers to examine difficult to detect behavior, such as racial and gender discrimination, and decision-making in real-world scenarios. In-person audits use live human beings who are trained to perform in specific scenarios (e.g., interactions with employers or real estate agents) where discrimination might occur. Correspondence audits examine potential discrimination in similar situations, but all interactions occur through correspondence (e.g., emails or online applications), eliminating the need for trained human beings (80).

To create a comprehensive list of all known correspondence audits examining racial discrimination, we first specified three important criteria. We limited our examination to studies that (1) were conducted in the U.S. or Canada, (2) examined responses for both Blacks and Whites *or* Hispanics and Whites, and (3) signaled race/ethnicity through names. We placed no restrictions on discipline or context. We included published peer-reviewed studies and publicly available working papers. We did not include in-person audit studies due to the significantly different nature of the method and because nearly all in-person audit studies occur in employment and housing contexts (80).

We began by searching Google Scholar, the National Bureau of Economic Research (NBER), and the Social Science Research Network (SSRN) for the terms "audit study," "correspondence audit," "correspondence study," "correspondence test," "discrimination experiment," "paired test," and "situation experiment," all common terms broadly used to describe correspondence audits of discrimination (80). We then cross-checked citations of important empirical, methodological, and review articles and books in the audit literature. Finally, we reached out via email and social media to scholars who have conducted empirical or methodological work on correspondence audits in the past to identify studies we might have missed.

In total, we identified 76 research studies using a correspondence audit to examine responses for Blacks and Whites and 36 research studies for Hispanics and Whites. In two cases, we could not obtain the necessary information from publicly available materials nor after contacting the authors for additional information. In these cases, our request was either refused (81) or could not be fulfilled due to data availability issues (82). Thus, our final dataset includes 74 studies using a correspondence audit to examine responses for Blacks and Whites and 34 studies for Hispanics and Whites. In total, we have a set of 78 unique studies because some studies examine responses for both Blacks and Hispanics. The full list of studies is provided in Table S1.1.

Table S1.1. Full List of Studies in Meta-Analysis

#	Authors	Year	Context	Black / Hispanic / Both	Male / Female / Both
1	Lodder, McFarland, and White	2003	Hiring	Black	Female
2	Bertrand and Mullainathan	2004	Hiring	Black	Both
3	Carpusor and Loges	2006	Rental Housing	Black	Male
4	Berk	2008	Hiring	Hispanic	Both
5	Galgano	2009	Hiring	Black	Female
6	Kleykamp	2009	Hiring	Both	Male
7	Friedman, Squires, and Galvan	2010	Rental Housing	Both	Male
8	Butler and Broockman	2011	Public Services	Black	Male
9	Hanson and Hawley	2011	Rental Housing	Black	Male
10	Hogan and Berry	2011	Rental Housing	Black	Both
11	Jacquemet and Yannelis	2012	Hiring	Black	Female
12	Milkman, Akinola, and Chugh	2012	Higher Education	Both	Both
13	Feldman and Weseley	2013	Rental Housing	Both	Both
14	Ameri	2014	Hiring	Black	Male
15	Butler	2014	Public Services	Both	Both
16	Ewens, Tomlin, and Wang	2014	Rental Housing	Black	Both
17	Hanson and Santas	2014	Rental Housing	Hispanic	Male
18	Decker et al.	2015	Hiring	Both	Male
19	Gaddis	2015	Hiring	Black	Both
20	Nunley et al.	2015	Hiring	Black	Both
21	Sharma, Mitra, and Stano	2015	Medical	Both	Both
22	White, Nathan, and Faller	2015	Public Services	Hispanic	Male
23	Wright et al.	2015	Other	Both	Male
24	Darolia et al.	2016	Hiring	Both	Both
25	Hanson et al.	2016	Other	Black	Male
26	Kang et al.	2016	Hiring	Black	Male
27	Kugelmass	2016	Medical	Black	Both
28	Shin et al.	2016	Medical	Black	Female
29	Butler and Crabtree	2017	Public Services	Black	Both
30	Edelman, Luca, and Svirsky	2017	Other	Black	Both
31	Einstein and Glick	2017	Public Services	Both	Both
32	Feldberg and Kim	2017	Other	Black	Both
33	Hanson	2017	Higher Education	Black	Both
34	Phillips	2017	Rental Housing	Black	Both
35	Agan and Starr	2018	Hiring	Black	Male

36	Gell-Redman et al.	2018	Public Services	Both	Male
37	Kalla, Rosenbluth, Teele	2018	Public Services	Hispanic	Both
38	Moore	2018	Rental Housing	Both	Female
39	Murchie and Pang	2018	Rental Housing	Both	Both
40	Pedulla	2018	Hiring	Black	Both
41	Boyd-Swan and Herbst	2019	Hiring	Both	Female
42	Fang, Guess, and Humphreys	2019	Rental Housing	Both	Both
43	Giulietti, Tonin, and Vlassopoulos	2019	Public Services	Black	Male
44	Leasure	2019	Hiring	Black	Male
45	Leech, Irby-Shasanmi, and Mitchell	2019	Medical	Black	Female
46	Mobasseri	2019	Hiring	Both	Male
47	Schwegman	2019	Rental Housing	Both	Both
48	Bennett	2020	Hiring	Black	Both
49	Button et al.	2020	Medical	Both	Both
50	Cui, Li, and Zhang	2020	Other	Black	Male
51	Druckman and Shafranek	2020	Higher Education	Black	Male
52	Gaddis	2020	Hiring	Black	Both
53	Gaddis and Ghoshal	2020	Other	Both	Female
54	Ge et al.	2020	Other	Black	Both
55	Henkels	2020	Rental Housing	Black	Male
56	Hughes et al.	2020	Public Services	Both	Male
57	Leasure and Kaminski	2020	Hiring	Black	Male
58	Leasure and Zhang	2020	Hiring	Black	Female
59	Phillips	2020	Hiring	Black	Both
60	Wisniewski and Walker	2020	Medical	Both	Female
61	Yemane	2020	Hiring	Both	Both
62	Brown and Hilbig	2021	Higher Education	Black	Male
63	Flippen	2021	Rental Housing	Both	Female
64	Gaddis	2021	Hiring	Black	Both
65	Gaddis et al.	2021	Public Services	Both	Both
66	Gorzig and Rho	2021	Hiring	Black	Both
67	Gorzig and Rho	2021	Hiring	Black	Both
68	Kirk and Rovira	2021	Hiring	Black	Both
69	Kline, Rose, and Walters	2021	Hiring	Black	Both
70	Lennon	2021	Hiring	Both	Both
71	Mai	2021	Hiring	Both	Both
72	Murchie, Pang, and Schwegman	2021	Rental Housing	Black	Both
73	Paul et al.	2021	Hiring	Both	Both

74	Pedulla et al.	2021	Hiring	Black	Both
75	Wisniewski et al.	2021	Medical	Both	Both
76	Christensen, Sarmiento-Barbieri, and Timmins	Forth.	Rental Housing	Both	Both
77	Landgrave and Weller	Forth.	Public Services	Both	Male
78	Oberfield and Incantalupo	Forth.	Public Services	Black	Male

Note: Each number corresponds to the citation with full reference information at the end of this document. Year indicates the year of the publication or working paper.

Section 2. Coding Data from the Correspondence Audits

When possible, we coded all data from the correspondence audits using publicly available information (i.e., details in the publication or working paper, supplemental information, and online data repository). When we could not gather all of the information we needed from these sources, we contacted authors directly via email to request additional details.

First, we recorded data about the sample size and response rate for each study. We calculated the total response rate (total response / total sample size), the racial response rates (e.g., White response / White sample size; Black response / Black sample size), and the gender-specific racial response rates (e.g., White male response / White male sample size; Black female response / Black female sample size). In the present research, we only use the gender-specific racial response rates. We choose to use gender-specific racial response rates because (a) some studies only include one gender and (b) some studies have different sample sizes by gender. Among our total set of 78 studies, 42 (53.8%) include both genders, 25 (32.1%) include male names only, and 11 (14.1%) include female names only. Additionally, racial discrimination varies within and between studies by gender. Thus, our decision is based on multiple empirically-centered reasons.

Second, we recorded data about the context of discrimination. We began with a broad list of potential contexts, initially coding in these categories: hiring (31 / 49), higher education – admissions (3 / 4), higher education – professors (1 / 2), housing – mortgage (1 / 1), housing – rental (15 / 24), housing – roommate (1 / 1), housing – short term rental (2 / 3), medical (7 / 11), public services (10 / 14), retail services (1 / 2), religious (1 / 1), and rideshare (1 / 2). The first number for each context indicates the number of studies and the second number indicates the number of data points examining White/Black discrimination. We decided to combine categories where appropriate to increase the sample size within each context of discrimination value. Our final categories for analysis are hiring, higher education, medical, public services, rental housing, and other. Thus, our residual other category includes housing – mortgage, housing – roommate, housing – short term rental, retail services, religious, and rideshare. The majority of studies and data points are from two contexts: hiring and rental housing. Table S2.1 shows the number of studies and data points for each of these categories.

Third, we recorded data about the time period of data collection. We coded the month and year of the beginning and end of data collection for each study. If a study included more than one start and stop in data collection, we recorded that as well. In the present research, we recoded this information into a binary variable to indicate whether data collection occurred during a recession using data from the NBER's "U.S. Business Cycle Expansions and Contractions" (83).

Fourth, we recorded data about the geographic location(s) of data collection. We coded the names of the cities in which data collection took place. In the present research, we recoded this information into a binary variable to indicate whether data collection occurred in urban areas only.

Fifth, we recorded data about the last names used to signal race/ethnicity of Blacks or Hispanics in each study. We used data from the U.S. Census on the racial composition of common last names (84). If a study included only last names for Blacks that belonged to Blacks in the population at rates ≥ 50%, we coded the study as using only Black last names. If a study included only last names for Blacks that belonged to Blacks in the population at rates < 50%, we coded the study as using only White last names. If a study included some of each type of name, we coded the study as using mixed last names. If a study did not include last names at all, we coded the study as such. We did the same thing for Hispanic names by subbing in Hispanic for Black.

Finally, we recorded data about whether each study used a matched or within-subjects design. In this type of design, researchers send more than one query or piece of correspondence to each respondent. For example, in a hiring discrimination study, a researcher would send two or more applications per job advertisement sampled.

In Table S2.1, we show the descriptive statistics for the number of data points and studies for both our White/Black analysis sample and our White/Hispanic analysis sample. This table shows that the majority of studies and data points occur across two contexts: hiring and rental housing. The third most common context is public services.

Table S2.1. Descriptive Statistics

	White/Black Number (%) of Data Points	White/Hispanic Number (%) of Data Points	White/Black Number (%) of Studies	White/Hispanic Number (%) of Studies
Context: Hiring	49 (43.0%)	16 (30.2%)	31 (41.9%)	10 (29.4%)
Context: Rental Housing	24 (21.1%)	14 (26.4%)	15 (20.3%)	9 (26.5%)
Context: Higher Education	6 (5.3%)	2 (3.8%)	4 (5.4%)	1 (2.9%)
Context: Medical	11 (9.7%)	7 (13.2%)	7 (9.5%)	4 (11.8%)
Context: Public Services	14 (12.3%)	12 (22.6%)	10 (13.5%)	8 (23.5%)
Context: Other	10 (8.8%)	2 (3.8%)	7 (9.5%)	2 (5.9%)
Gender: Male	63 (55.3%)	29 (54.7%)	23 (31.1%)	10 (29.4%)
Gender: Female	51 (44.7%)	24 (45.3%)	11 (14.9%)	5 (14.7%)
Gender: Both	xx	xx	40 (54.1%)	19 (55.9%)
Time: Period of Recession	13 (11.4%)	3 (5.7%)	9 (12.2%)	2 (5.9%)
Geography: Urban Only	72 (63.2%)	23 (43.4%)	47 (63.5%)	16 (47.1%)
Racial/Ethnic Last Names: All Racial/Ethnic	63 (55.3%)	51 (96.2%)	42 (56.8%)	32 (94.1%)
Racial/Ethnic Last Names: All White	10 (8.8%)	1 (1.9%)	6 (8.1%)	1 (2.9%)
Racial/Ethnic Last Names: Mixed	34 (29.8%)	1 (1.9%)	22 (29.7%)	1 (2.9%)
Racial/Ethnic Last Names: None	7 (6.1%)	0 (0.0%)	4 (5.4%)	0 (0.0%)
Design: Matched	62 (54.4%)	21 (39.6%)	38 (51.4%)	14 (41.2%)
Total	114	53	74	34

Note:

Section 3. Meta-Analysis Models

Calculating the Dependent Variable – The Discrimination Ratio

Because some studies only include one gender, or have different sample sizes by gender, we treat each study-by-gender data point as a separate observation in the analysis. Our dependent variable of interest is the response discrimination ratio from each study-by-gender data point. We define the response discrimination ratio as the study-by-gender response rate for Whites divided by the response rate for Blacks (or Hispanics). Each racial response rate is the number of positive responses divided by the number of total correspondence sent (e.g., applications, emails) for that group by gender in a single study. This is represented by the following equation:

$$DR_{gi} = \frac{\frac{r_{wgi}}{n_{wgi}}}{\frac{r_{mgi}}{n_{mgi}}}$$

Where DR_{gi} is the discrimination ratio for gender *g* in study *i*, r_{wgi} is the number of positive responses for *Whites* of gender *g* in study i, n_{wgi} is the number of total correspondence sent for *Whites* of gender *g* in study *i*, r_{mgi} is the number of positive responses for *minorities* of gender *g* in study *i,* and n_{mgi} is the number of total correspondence sent for *minorities* of gender *g* in study *i*. When calculated this way, the discrimination ratio is a relative, rather than absolute, measure that allows for straight-forward interpretation. This relative measures also permits comparison across different contexts of discrimination that have different baseline response rates. The discrimination ratio is effectively a risk ratio or relative risk measure. These types of measures are commonly used in meta-analyses of dichotomous data from experiments (85-86).

In other words, if the Black male response rate in a study is 0.1 and the White male response rate in a study is 0.2, the discrimination ratio is 0.2/0.1 = 2.0. A discrimination ratio of 1 indicates equal treatment, i.e., no discrimination against Blacks or Hispanics. A discrimination ratio below 1 indicates favorable treatment toward Blacks or Hispanics and a discrimination ratio above 1 indicates discrimination against Blacks or Hispanics. The use of the discrimination ratio in this manner for meta-analysis work is established practice (87-90). Moreover, this measure balances the three criteria recommended for a summary statistic in meta-analysis: consistency, mathematical properties, and ease of interpretation (85).

Finally, after we calculate each discrimination ratio, we transform this measure using the natural logarithm of the discrimination ratio. This allows us to work with a dependent variable that is approximately normally distributed. This is a standard procedure recommended for meta-regression when using count data or ratios (85-86).

Calculating the Variance of the Discrimination Ratio

Next, we must calculate the within-study sampling variance of the estimate of the discrimination ratio for each study. Using dichotomous data and a risk ratio outcome measure, the equation to calculate the variance is:

$$\mathrm{Var}(\ln(\mathrm{DR}_{gi})) = \frac{1}{\mathrm{r}_{wgi}} - \frac{1}{\mathrm{n}_{wgi}} + \frac{1}{\mathrm{r}_{mgi}} - \frac{1}{\mathrm{n}_{mgi}}$$

Where DR_{gi} is the discrimination ratio for gender *g* in study *i*, r_{wgi} is the number of positive responses for *Whites* of gender *g* in study i, n_{wgi} is the number of total correspondence sent for *Whites* of gender *g* in study *i*, r_{mgi} is the number of positive responses for *minorities* of gender *g* in study *i*, and n_{mgi} is the number of total correspondence sent for *minorities* of gender *g* in study *i*.

Forest Plots

In Figures S3.1 and S3.2, we present the forest plots for White/Black and White/Hispanic discrimination effect sizes by context of discrimination using the meta forestplot function in Stata/MP version 16.1.

Figure S3.1 shows that the overall White/Black discrimination ratio (reported as log risk-ratio) is θ = 0.144 with a 95% confidence interval of 0.114 to 0.175 (exponentiated DR = 1.155; 95% CI: 1.121 – 1.191). The overall between-study variation of the effect sizes is reported as I^2, or the percentage of the variability that is due to heterogeneity rather than sampling error. The overall I^2 is estimated to be 93.29%, which indicates the presence of high heterogeneity (91). Even in this preliminary examination, we find that the estimated discrimination effect within hiring (θ = 0.247; 95% CI: 0.194 – 0.300) is significantly different from rental housing (θ = 0.145; 95% CI: 0.100 – 0.190), higher education (θ = 0.021; 95% CI: -0.005 – 0.046), medical (θ = 0.028; 95% CI: -0.097 – 0.152), and public services (θ = 0.048; 95% CI: 0.028 – 0.068). However, the estimated discrimination effect within hiring is not significantly different from the "other" category of contexts (θ = 0.150; 95% CI: 0.058 – 0.243).

Figure S3.2 shows that the overall White/Hispanic discrimination effect is θ = 0.078 with a 95% confidence interval of 0.042 to 0.114 (exponentiated DR = 1.081; 95% CI: 1.043 – 1.121). The overall I^2 is estimated to be 85.09%, which indicates the presence of high heterogeneity (91). Even in this preliminary examination, we find that the estimated discrimination effect within hiring (θ = 0.242; 95% CI: 0.131 – 0.352) is significantly different from rental housing (θ = 0.038; 95% CI: -0.000 – 0.076), higher education (θ = 0.024; 95% CI: -0.036 – 0.085), medical (θ = -0.017; 95% CI: -0.149 – 0.114), and public services (θ = 0.061; 95% CI: 0.045 – 0.078). However, the estimated discrimination effect within hiring is not significantly different from the "other" category of contexts (θ = 0.169; 95% CI: -0.026 – 0.364), due to a large confidence interval.

Meta-Regression Models

The forest plot analyses above are based on random-effects models. Researchers typically rely on either fixed- or random-effects regression models when conducting meta-analyses (86, 92-93). In short, fixed-effects models are more appropriate when a researcher (1) assumes homogeneity of a population effect size and (2) wishes to make conditional inference only about the observed set of studies. Moreover, random-effects models are more appropriate when a researcher (1) assumes heterogeneity of a population effect size and (2) wishes to generalize beyond the observed set of studies.

A collection of correspondence audits examining discrimination is likely to contain significant heterogeneity in effect sizes, even if those estimates are within a single context (e.g., hiring). This is due to variation in unobserved contextual, design, and implementation characteristics not captured by additional modeling covariates. Generally, traditional meta-analysis is concerned with identifying an estimate of a true effect size among a series of similar treatments and expect that heterogeneity might exist among subgroups. For example, a meta-analysis examining the efficacy of a vaccine might assume one true effect size in preventing death in the aggregate, with the expectation that heterogeneity exists based on individuals' pre-existing conditions.

Our analyses of heterogeneity are, perhaps, different than many traditional meta-analyses. We are interested in comparing the true effect size across different contexts of discrimination, with the expectation that at least some of these contexts should be significantly different than others. Thus, we want to adjust or control for other types of heterogeneity (e.g., observed and unobserved differences between studies).

Our forest plots, the basis of our primary research question, and the guidelines from meta-analysis texts suggest that a random-effects meta-analysis model is more appropriate than a fixed-effects meta-analysis model (85-86).

We specify a random-effects meta-regression model estimated by restricted maximum likelihood using the meta regress function in Stata/MP version 16.1 (94). The general form equation for this model is:

$$\ln\,(y_i) = x_i\beta + u_i + \varepsilon_i, \text{ where } u_i \sim N(0, \tau^2) \text{ and } \varepsilon_i \sim N(0, \sigma_i^2)$$

Here, $\ln(y_i)$ is the natural log of the discrimination ratio, a transformation recommended for meta-regression when using count data or ratios (85-86), β is a $k \times 1$ vector of coefficients (including a constant), x_i is a 1 x k vector of covariate values in study i (including a 1 for the constant). u_i is a random effect describing the study-specific deviation from the distribution mean that is normally distributed with a mean of 0 and standard deviation of τ, where τ^2 is the residual between-study variance (or random-effect variance). ε_i is a random error term describing sampling variability that is normally distributed with a mean of 0 and standard deviation of σ, where $\sigma^2{}_i$ is the observed variance of the log discrimination ratio in study i. We include the six environmental and design factors discussed above as covariates.

In addition to our random-effects regression models, we also specify a fixed-effect meta-regression model using the meta regress function in Stata/MP version 16.1 (94). The general form equation for this model is:

$$\ln\ (y_i) = x_i\beta + \varepsilon_i,\ \text{where } \varepsilon_i \sim N(0, \sigma_i^2)$$

Here, the equation is similar to the previous equation, but without the random effect describing the study-specific deviation from the distribution mean. We examine the results from this model because small-sample bias among the studies included in a meta-analysis can lead to more biased estimates from a random-effects model and less biased estimates from a fixed-effect (95-97). Although we believe the random-effects models are more appropriate, we also examine the results from a fixed-effect model as a type of robustness check (98).

Main Results

In Table S3.1, we present the main results for our meta-regression models predicting the White/Black discrimination ratio. Our dependent variable is the discrimination ratio (risk ratio or relative risk variable), presented on a natural log scale and multiplied by 100 for readability. We also multiply the standard deviation by 100 correct for this scaling. Model 1 is a baseline random-effects (RE) meta-regression model estimated by restricted maximum likelihood. Model 2 adds covariates. Model 3 is a fixed-effect (FE) meta-regression model estimated using inverse variance and includes covariates. Table 3.2 is similar, but presents results for the White/Hispanic discrimination ratio instead.

Regardless of the model specification, the results in Table S3.1 show that White/Black discrimination in the hiring context is significantly larger than in any other context. The results in Table S3.2 present a similar story for White/Hispanic discrimination, although discrimination in the "other" context is not significantly different from hiring in Model 1.

In the main paper, we present figures showing adjusted predictions for each context of discrimination (i.e., hiring, rental housing, higher education, medical, public services, and other) with other covariates set at their means. These figures include the adjusted predictions at the means based on each of three models in Table S3.1 (main paper: Figure 3) and Table S3.2 (main paper: Figure 4).

Robustness Checks / Sensitivity Analyses

Following the advice of one of the main textbooks on meta-analysis (86), we examine a series of sensitivity analyses by examining alternative models, examining our main models with exclusion of some data, and examining our main models with different dependent variables.

First, we specify the fixed-effect meta-regression models (Model 3 in Tables S3.1 and S3.2) as a robustness check of our main random-effects findings. Compared to the random-effects models with covariates, the fixed-effect models have coefficients that are closer to zero and much smaller standard errors. Thus, the adjusted prediction confidence intervals from the fixed-effect models are smaller than those from the random-effects models (see Figures 3 and 4). However, the substantive story we glean from the fixed-effect models is essentially the same as from the random-effects models.

Second, we examine alternative specifications predicting the White/Black discrimination ratio by excluding the smallest studies (n<500; Table S3.3) and the largest studies (n>10,000; Table S3.4). We choose to examine models without these extreme data points to be certain that they do not influence our findings. In Table S3.3, we present the results of models that exclude 13 small studies and 21 total observations. Our findings are mostly robust to this specification, although discrimination in the “other” context is not significantly different from hiring in Models 1 and 2. However, the coefficients for “other” context are still in the expected direction. In Table S3.4, we present the results of models that exclude 4 large studies and 6 total observations. Our findings are mostly robust to this specification, although discrimination in the “other” context is only significantly different from hiring in Model 1 at $p < 0.10$. Once again, the coefficient for “other” context are still in the expected direction. We do not examine similar alternative specifications predicting the White/Hispanic discrimination ratio because the sample size for those models is already smaller.

Finally, we discuss alternative specifications using two different dependent variables. Beyond a risk ratio (our main DV, the discrimination ratio, is a type of risk ratio), scholars can also examine an odds ratio and/or a risk difference using meta-analysis. We believe the risk difference measure is inappropriate for our analysis because it is an absolute measure. In other words, the risk difference measure does not account for differences in baseline responses, which is critical to comparing across contexts of discrimination.

An odds ratio is simply the ratio of two odds. Similar to a risk ratio, the odds ratio measure is a relative measure. However, a risk ratio is arguably easier to interpret than an odds ratio. Additionally, as pointed out in (87), correspondence audits often use a risk ratio as a measure of discrimination, but rarely use an odds ratio. Nonetheless, we believe there is value in examining an alternative specification using the odds ratio as the dependent variable. The odds ratio is the study-by-gender odds of response for Whites divided by the study-by-gender odds of response for Blacks (or Hispanics). Each racial odds rate is the number of positive responses for that group divided by the number of total correspondence sent (e.g., applications, emails) minus the number of positive responses for that group by gender in a single study. This is represented by the following equation:

$$\mathbf{OddsRatio}_{gi} = \frac{\dfrac{\mathrm{r}_{wgi}}{\mathrm{n}_{wgi} - \mathrm{r}_{wgi}}}{\dfrac{\mathrm{r}_{mgi}}{\mathrm{n}_{mgi} - \mathrm{r}_{mgi}}}$$

Again, we transform this measure using the natural logarithm of the odds ratio. The equation to calculate the variance is:

$$\mathrm{Var}(\ln(\mathrm{OddsRatio}_{gi})) = \frac{1}{\mathrm{r}_{wgi}} + \frac{1}{\mathrm{n}_{wgi} - \mathrm{r}_{wgi}} + \frac{1}{\mathrm{r}_{mgi}} + \frac{1}{\mathrm{n}_{mgi} - \mathrm{r}_{mgi}}$$

In Table S3.5, we present the results of models with the odds ratio as the dependent variable. Our findings are mostly robust to this specification, although discrimination in the rental housing and "other" contexts are not significantly different from hiring in Models 1 and 2. However, the coefficients for both of these contexts in Model 2 and the rental housing context in Model 1 are still in the expected direction.

Figure S3.1. Forest Plot of White/Black Racial Discrimination by Context of Discrimination

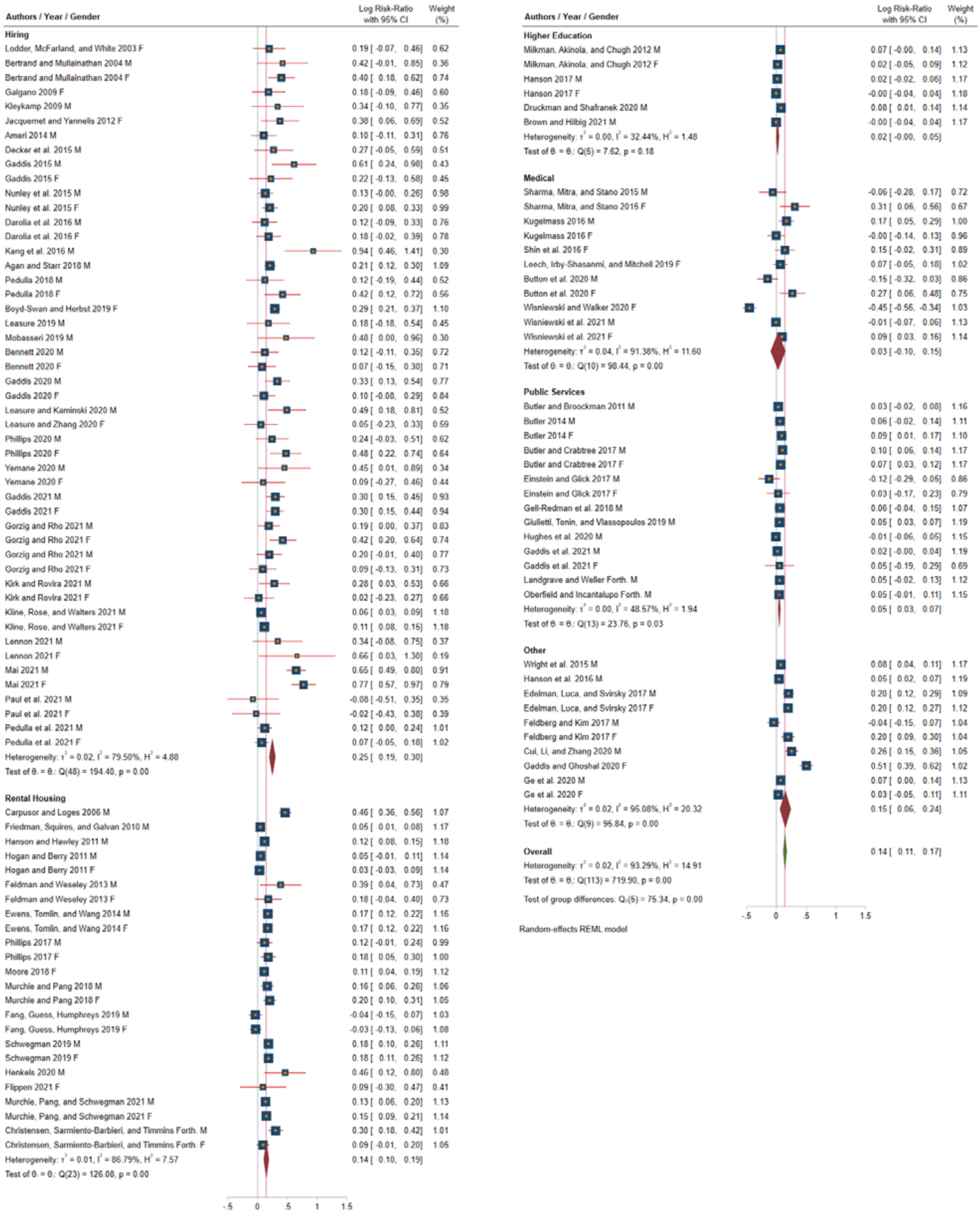

Figure S3.2. Forest Plot of White/Hispanic Racial Discrimination by Context of Discrimination

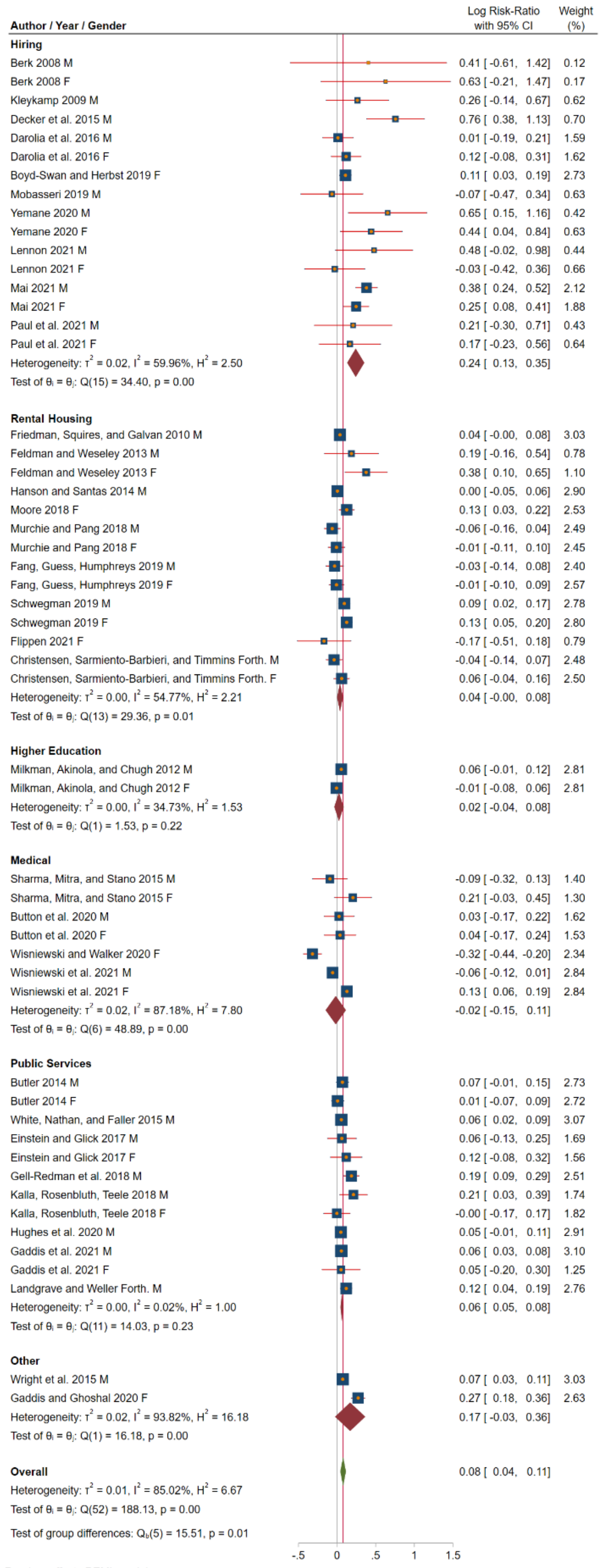

Table S3.1. Regression Models Predicting White/Black Discrimination Ratio

	(1) RE	(2) RE	(3) FE
Context (ref: Hiring)			
Rental Housing	-9.550**	-11.128**	-9.173***
	(3.612)	(4.109)	(1.459)
Higher Education	-21.396***	-23.705***	-17.645***
	(5.494)	(6.956)	(1.853)
Medical	-22.221***	-24.114***	-21.185***
	(4.850)	(5.589)	(2.278)
Public Services	-20.026***	-22.684***	-17.118***
	(4.159)	(6.189)	(1.873)
Other	-9.391*	-12.860*	-12.954***
	(4.634)	(5.429)	(1.719)
Gender: Female		0.518	1.995*
		(2.787)	(0.873)
Time: Period of Recession		-11.165*	-8.074***
		(4.601)	(1.331)
Geography: Urban Only		0.316	3.266**
		(3.956)	(1.227)
Racial/Ethnic Last Names (ref: All Black)			
All White		-6.092	-10.218***
		(5.637)	(2.443)
Mixed		-1.393	-2.578**
		(3.322)	(0.967)
None		-2.160	-0.333
		(5.563)	(1.66)
Design: Matched		-2.552	-2.999**
		(3.564)	(1.058)
Constant	24.264***	28.952***	22.398***
	(2.406)	(5.376)	(1.846)
N (studies)	74	74	74
N (observations)	114	114	114

Note: Dependent variable = discrimination ratio, natural log scale, multiplied by 100 for readability. Models 1 and 2 are random-effects (RE) meta-regression models estimated by restricted maximum likelihood. Model 3 is a fixed-effect (FE) meta-regression model estimated using inverse variance.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S3.2. Regression Models Predicting White/Hispanic Discrimination Ratio

	(1) RE	(2) RE	(3) FE
Context (ref: Hiring)			
Rental Housing	-18.433***	-20.182***	-17.444***
	(5.085)	(4.814)	(3.355)
Higher Education	-19.927**	-28.175**	-25.778***
	(7.773)	(9.323)	(6.129)
Medical	-24.632***	-27.346**	-24.906***
	(6.050)	(9.116)	(6.108)
Public Services	-14.510**	-22.931**	-21.495***
	(5.187)	(8.356)	(5.888)
Other	-6.013	-23.189*	-20.21**
	(7.744)	(10.499)	(6.207)
Gender: Female		0.150	1.334
		(2.941)	(1.753)
Time: Period of Recession		2.308	3.856
		(5.944)	(2.768)
Geography: Urban Only		-5.633	-7.197*
		(4.642)	(2.857)
Racial/Ethnic Last Names (ref: All Hispanic)			
All White		-29.517**	-28.597***
		(10.924)	(7.163)
Mixed		29.943*	28.985***
		(13.261)	(7.585)
Design: Matched		-4.526	-3.188
		(4.939)	(3.378)
Constant	22.347***	30.521***	27.542***
	(4.245)	(8.207)	(5.870)
N (studies)	34	34	34
N (observations)	53	53	53

Note: Dependent variable = discrimination ratio, natural log scale, multiplied by 100 for readability. Models 1 and 2 are random-effects (RE) meta-regression models estimated by restricted maximum likelihood. Model 3 is a fixed-effect (FE) meta-regression model estimated using inverse variance.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S3.3. Alternative Specification 1: Regression Models Predicting White/Black Discrimination Ratio

	(1) RE	(2) RE	(3) FE
Context (ref: Hiring)			
Rental Housing	-10.346**	-13.475**	-11.276***
	(3.723)	(4.458)	(1.548)
Higher Education	-21.206***	-20.675**	-15.982***
	(5.500)	(7.430)	(1.927)
Medical	-28.513***	-28.615***	-21.948***
	(6.775)	(7.662)	(2.660)
Public Services	-18.802***	-18.244**	-15.702***
	(4.334)	(6.903)	(1.953)
Other	-6.719	-9.208	-10.370***
	(5.066)	(5.891)	(1.836)
Gender: Female		0.457	1.947*
		(2.950)	(0.898)
Time: Period of Recession		-12.745**	-6.821***
		(4.936)	(1.400)
Geography: Urban Only		2.803	6.120***
		(4.469)	(1.416)
Racial/Ethnic Last Names (ref: All Black)			
All White		-10.447	-12.230***
		(7.166)	(2.736)
Mixed		0.096	-1.638+
		(3.398)	(0.994)
None		3.533	5.706*
		(7.593)	(2.249)
Design: Matched		-1.009	-4.089***
		(3.993)	(1.144)
Constant	24.074***	25.355***	20.893***
	(2.469)	(6.146)	(1.932)
N (studies)	61	61	61
N (observations)	93	93	93

Note: Dependent variable = discrimination ratio, natural log scale, multiplied by 100 for readability. Models 1 and 2 are random-effects (RE) meta-regression models estimated by restricted maximum likelihood. Model 3 is a fixed-effect (FE) meta-regression model estimated using inverse variance. Data points with n<500 are excluded (13 studies and 21 observations are excluded).

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S3.4. Alternative Specification 2: Regression Models Predicting White/Black Discrimination Ratio

	(1) RE	(2) RE	(3) FE
Context (ref: Hiring)			
Rental Housing	-11.156^{**}	-11.997^{**}	-11.176^{***}
	(3.759)	(4.423)	(1.930)
Higher Education	-23.020^{***}	-26.640^{**}	-22.245^{***}
	(5.640)	(7.636)	(2.673)
Medical	-23.821^{***}	-25.454^{***}	-24.118^{***}
	(4.983)	(5.934)	(2.709)
Public Services	-21.533^{***}	-24.713^{**}	-18.942^{***}
	(4.566)	(6.947)	(2.758)
Other	-9.699^{+}	-12.202^{*}	-13.550^{***}
	(4.983)	(6.057)	(2.523)
Gender: Female		-0.129	0.785
		(2.965)	(0.965)
Time: Period of Recession		-9.773^{+}	-7.900^{***}
		(5.259)	(1.756)
Geography: Urban Only		-2.363	0.152
		(4.667)	(1.606)
Racial/Ethnic Last Names (ref: All Black)			
All White		-4.998	-9.903^{***}
		(5.947)	(2.482)
Mixed		-0.822	-2.818^{*}
		(3.732)	(1.260)
None		-2.719	-1.373
		(5.907)	(1.822)
Design: Matched		-1.290	-1.284
		(3.869)	(1.341)
Constant	25.889^{***}	31.214^{***}	26.670^{***}
	(2.584)	(5.795)	(2.500)
N (studies)	70	70	70
N (observations)	108	108	108

Note: Dependent variable = discrimination ratio, natural log scale, multiplied by 100 for readability. Models 1 and 2 are random-effects (RE) meta-regression models estimated by restricted maximum likelihood. Model 3 is a fixed-effect (FE) meta-regression model estimated using inverse variance. Data points with n>10,000 are excluded (4 studies and 6 observations are excluded).

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S3.5. Alternative Specification 3: Regression Models Predicting White/Black Discrimination Odds Ratio

	(1) RE	(2) RE	(3) FE
Context (ref: Hiring)			
Rental Housing	-1.438	-4.778	-4.796^{+}
	(6.253)	(7.422)	(2.778)
Higher Education	-20.909*	-20.337	-14.753**
	(10.427)	(13.085)	(4.839)
Medical	-25.597**	-29.342**	-18.270***
	(9.470)	(11.115)	(5.051)
Public Services	-20.328**	-23.288*	-12.949***
	(7.392)	(11.125)	(3.884)
Other	3.689	-1.511	0.667
	(8.858)	(10.093)	(3.476)
Gender: Female		-0.682	3.873*
		(5.038)	(1.599)
Time: Period of Recession		-12.888	-8.639**
		(8.098)	(2.950)
Geography: Urban Only		5.516	8.013***
		(7.577)	(2.496)
Racial/Ethnic Last Names (ref: All Black)			
All White		-14.173	-7.442
		(10.375)	(5.363)
Mixed		-4.193	-1.841
		(5.942)	(2.016)
None		5.739	5.415
		(12.458)	(3.978)
Design: Matched		-8.339	-4.352^{+}
		(6.629)	(2.484)
Constant	30.260***	37.252***	24.313***
	(3.804)	(9.452)	(3.763)
N (studies)	74	74	74
N (observations)	114	114	114

Note: Dependent variable = odds ratio, natural log scale, multiplied by 100 for readability. Models 1 and 2 are random-effects (RE) meta-regression models estimated by restricted maximum likelihood. Model 3 is a fixed-effect (FE) meta-regression model estimated using inverse variance.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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