Racial Prejudice in the Workplace and Firm Boycotts

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ABSTRACT

I investigate the impact of contemporary grassroots boycotts on addressing racial discriminatory practices within a firm. Introducing new data on allegations of racial prejudice in the workplace, I show that when these allegations are more (randomly) prominent to prospective employees and consumers, foot traffic declines by 4-5% at stores located in predominantly non-white, young, or low-income zip codes. Additional results show that information cascades among internet platforms, shedding light into the mechanisms of a modern grassroots boycott. A randomized survey experiment confirms that consumers boycott a firm after learning about allegations of workplace racial prejudice, but not for other types of complains.

JEL Codes: D12, D22, D63, E24, G34, I14, J15, J22, J28, J71, J81, M14, M51

Keywords: *Prejudice; discrimination; boycotts, labor supply; consumer boycotting; job reviews; foot traffic; harassment; workplace; firm distress.*

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1 INTRODUCTION

Boycotts have played a crucial role in social justice movements in the U.S., particularly for black Americans (Biggs and Andrews, 2015; Chong, 2014; Morris, 1999; Weems, 1995; Wright, 1999). For example, the "Don't Buy Where You Can't Work" campaign of the 1930s, a precursor to the economic boycotts of the Civil Rights Movement, encouraged black Americans to boycott white-owned businesses in Chicago that refused to hire black workers (Ware, 1986). This movement spread to various U.S. cities and succeeded in creating new jobs for black Americans (Skotnes, 1994).

Recent data shows that boycotts remain a common practice in the United States. Approximately 38% of U.S. consumers boycotted at least one firm in 2020.[1] Nearly half of these consumers consider a company's treatment of its employees in their decision, and a quarter of them boycott in response to a company's involvement in a racist incident. However, modern boycotts differ significantly from those in the past. As information now easily flows through online platforms, modern grassroots boycotts may be carried out without organized coordination. Individuals may independently choose to boycott a company, but their combined actions can have a significant impact on targeted firms. Internet platforms, and its network structure, could trigger cascade effects. Yet, empirical evidence on the inner workings of contemporary grassroots boycotts and, more importantly, their effectiveness in impacting targeted firms is still limited.

Analyzing job reviews from a job-search website that receives 270 million monthly visits, this paper introduces new data on allegations of workplace racial prejudice (hereafter, "racialized reviews"). I identify over 10,000 allegations for the largest U.S. stores starting in 2012. With this data, I examine whether consumers and prospective employees boycott a firm after information on day-to-day allegations of workplace prejudice become public. To identify this hypothesis, I take advantage of a random feature in the publication process of job reviews that makes some reviews more prominent to website users. The findings indicate that when an allegation of racial preju-

[1] http://www.lendingtree.com/credit-cards/study/boycotting-companies-political-pandemic-reasons/

dice becomes public in a specific firm-city, monthly foot traffic decreases by 4–5% (21 to 25 unique monthly visitors) in stores located in zip codes with a high proportion of non-white, young, or low-income individuals. This impact remains statistically significant for 9 months after publication, and it is substantially larger in zip codes where Blacks and Hispanics have greater access to broadband internet. Shedding light on how modern grassroots boycotts work, I also show that information quickly spreads from the job-search website to other internet platforms commonly read by consumers.

A randomized survey conducted on MTurk confirms that prospective employees and consumers are willing to boycott a firm that tolerates racial prejudice in the workplace. The survey shows that when information on workplace racial prejudice becomes salient to individuals, they are less likely to submit job applications and purchase goods and services from the firm. The effect is larger for females and racial minorities. The survey also shows negative reviews that do not mention racism—i.e., reviews that discuss bad management, favoritism, or long hours—have no impact on consumer demand. These findings show that allegations of workplace racial prejudice have implications on firms that differ from those for other workplace dysfunctions.

A simple reputation model rationalizes the results (Kreps et al., 1982). Prospective employees and consumers do not directly observe the workplace but they have a preference for a workplace free of discrimination. Firms have an incentive to build reputation since it equates to more "cooperation" from stakeholders. When allegations of workplace racial prejudice become public, consumers learn that firms deviate from good behavior, and in response punish the firm. In this framework, firms with higher reputation experience a larger punishment.[2] Further, in the presence of network effects, individual punishments might aggregate to a sizable impact, demonstrating that consumers can discipline firms.

Workplace prejudice data is obtained from Indeed.com. Among job search platforms, In-

[2]Consistently, I show that firms with a higher reputation (higher ESG index) experience larger drops in foot traffic after a racialized review becomes public. The differences are larger when focusing on the Social score, and smaller when using the Environment score of the ESG index.

deed.com has had the largest web traffic since 2012. For example, on October 2021, Indeed.com received over 270 million U.S. monthly visitors, a figure equivalent to those for Foxnews.com or NYtimes.com. Complaints about racial prejudice in the workplace are obtained through job reviews published on the website.[3] A review is published for a specific city where a company is located. I collect all reviews on Indeed.com for the 6,000 largest U.S. firms with a storefront. The sample spans a large number of firms, including McDonald's, Walmart, Home Depot, Chase, Marriott Hotel, AT&T, BP, Autozone, and Walgreens. I obtain a total of 7 million employer reviews from 2012 through 2021. Many companies have a large amount of reviews. For example, McDonald's and Walmart each have over 200,000 reviews. Firm boycotts are measured using foot traffic data from Safegraph from 2018 through 2021. This data uses GPS locations of 18 million anonymized mobile phones representative of the U.S. population and is available for each U.S. store.

Reviews reporting prejudice exist in every state, but there is a larger per capita incidence in southern U.S. states. I compare the per capita incidence of racialized reviews with self-reported measures of prejudice in Charles and Guryan (2008). Locations where individuals are more likely to not vote for a Black president correlate with more allegations of workplace prejudice per capita. Further, locations where more individuals support laws against interracial marriage have higher incidence of workplace prejudice reports per capita. Workplace prejudice reviews per capita is also negatively correlated with the Black-white wage gap.

To address endogeneity concerns, I exploit the fact that some reviews may be more salient to website visitors for random reasons. Specifically, employee reviews submitted to Indeed.com in a given day are audited in batches prior to publication, typically once a day, at an uncertain time. Since reviews are released in chronological order on the firm's profile on Indeed, this process randomizes the position where a job review is published among those in the same batch. Job reviews submitted immediately after (before) the auditing time are more likely to be published at the top

[3]Indeed.com introduced an employer review system in 2012 to improve their user service. They ask job seekers to review their work experience at firms listed on their resumes. Each anonymous review contains a textual review, ratings on several aspects of a company, and some information about the reviewer. In the textual review, current and former employees may report any comment regarding their experience at the firm.

(bottom) of the firm's profile page on Indeed. This placement only depends on the combination of when the review is submitted and audited. Since auditing time is uncertain, placement is random. Therefore, some racialized reviews are published at the top of the webpage, while others are published at the bottom of the webpage.

I confirm empirically that the likelihood of being the top review is random among a batch of submitted reviews. I show that when N reviews are submitted on a given day, the likelihood that a racialized review appears at the top of the webpage equals $1/N$. This evidence alleviates concerns that racialized reviews are placed systematically in specific positions on the webpage. To further confirm this point, I show that a long list of observables, including several characteristics of the firm and textual review, are economically and statistically identical between top and non-top racialized reviews. I then assume that a racialized review that appears at the top of a webpage is more salient than other reviews, and this salience increases with the size of the batch of submitted reviews in a given day.[4] Thus, a racialized review is considered treated if published at the top of a webpage, and control if it is published anywhere else.

The results show that when an allegation of racial prejudice becomes public, establishments located in zip codes that are predominately non-white, young, and low-income experience a decline of four to five percentage points in monthly visitors. This drop is observed in firms with fewer than five stores per city. For firms with more than five stores per city, the effect is not statistically different than zero. Since job reviews on Indeed.com only identify the firm name and city, this is consistent with individuals boycotting a firm only when they have some degree of confidence of the establishment under accusation. Lastly, an event-plot analysis shows that the effect persists for about nine months.

Next, I document the underpinnings of a grassroots boycott. I first show that information on workplace racial prejudice in the job-search website quickly cascades to the largest consumer review website, Yelp.com. I use the same baseline empirical design but change the outcome variable

[4] When the daily batch of reviews is large, the likelihood that a non-top review is published at the bottom of the webpage is larger. The difference between a top and non-top review is then larger.

to the number of very negative reviews (1- or 2-star reviews) observed on Yelp.com. The results show that, in the same month, when a racialized review becomes more salient on Indeed.com, the number of negative reviews increases on Yelp.com. This result is driven by 1-star reviews. A small fraction of reviews mention words related to racism. An event-plot analysis shows that this spike in negative consumer reviews only lasts for three months post-publication on the job-search website.[5] Since information spreads through internet platforms, boycotts are more likely to occur when individuals have better access to the internet. I test this prediction. Following the publication of a racialized review, the impact on foot-traffic is indeed larger in stores situated in zip codes where Black and Hispanic individuals have greater access to broadband internet.

I then turn to a randomized survey experiment on MTurk to provide further evidence on the boycotting mechanism. The experiment consists of showing job ads accompanied by job reviews to a representative sample of individuals. I select a sample of job ads from firms in my dataset and use real job reviews for those companies, but randomly select the reviews shown. All participants are shown two positive reviews, and a third review randomly picked from the following set: (i) review associated with an episode of racial prejudice, (ii) non-racialized but very negative review, or (iii) another positive review about the company. I then ask several questions, including whether participants are interested in submitting a job application and whether they would change their consumer behavior and boycott the firm.

The randomized survey results show several patterns consistent with boycotting. First, awareness of a racialized review reduces by 12 percentage points the likelihood of submitting a job application. Second, salience of a review reporting racial prejudice increases the likelihood of consumer boycotting by 7.5 percentage points. Third, these effects are largest for non-whites and females, and lowest for white males. Fourth, awareness of a very negative non-racialized review has no impact on consumer behavior, but it reduces the likelihood of submitting a job application by 6.5 percentage points. Lastly, results are strongest when racialized reviews are written by employees

[5] As 1-star reviews can damage a company's rating on Yelp.com, it can take several months for a company to recover its prior rating (Luca, 2016).

in higher-ranked occupations. Collectively, these findings show that some prospective employees and consumers have strong preferences against workplace racial prejudice.

This paper shows that an allegation of racial prejudice in the workplace can lead to a firm boycott with large implications for targeted firms. The paper also shows that internet platforms play a crucial role for contemporary grassroots boycotts. Internet platforms, and its network structure, allows for cascade effects. Lastly, the paper shows that consumers can monitor firms and discipline them for discriminatory practices in the workplace.

Related literature. This paper contributes to several strands of literature. First, it builds upon the existing literature in economics and sociology that focuses on boycotts (Besley and Ghatak, 2007; Biggs and Andrews, 2015; Broccardo et al., 2022; Caren et al., 2020; Chong, 2014; Gurun et al., 2020; Morris, 1999; Weems, 1995; Wright, 1999); and the literature that examines the roots and consequences of protest movements (Bursztyn et al., 2020, 2021a, 2022; Huet-Vaughn, 2015; Madestam et al., 2013; Nathan et al., 2020). Morris (1999) argues that the Civil Rights Movement was able to overthrow the southern Jim Crow regime because of its successful use of mass nonviolent direct action. Biggs and Andrews (2015) find that sit-in protests increase the probability of desegregation. Caren et al. (2020) review recent research focusing on how movements are shaped by the media environment and how the media environment has reshaped participation in boycotts. More recently, Broccardo et al. (2022) consider boycott strategies in promoting socially desirable outcomes in companies. This paper shows that consumers and prospective employees boycott a firm after learning about allegations of racial prejudice within a firm. It also illustrates that the combined efforts of individuals, although taken individually, have a significant impact on the targeted firms. Key to this effect is the role of online platforms in disseminating information.[6]

Second, it adds to the literature that studies racial prejudice in labor markets (Charles and Guryan, 2008; Glover et al., 2017; Haaland and Roth, 2023; Hedegaard and Tyran, 2018; Hjort, 2014;

[6] Johnson (2020) highlights the impact of publicly announcing a facility's violations of safety and health regulations through press releases. Their evidence suggests that peer firms are more likely to improve compliance in order to avoid negative costly reactions from workers.

Rubinstein and Brenner, 2014). Charles and Guryan (2008) suggest that one-quarter of the racial wage gap is due to prejudice. Glover et al. (2017) shows that when minority cashiers are scheduled to work with managers who are biased, they are less productive. Hjort (2014) shows that inter-ethnic rivalries lower allocative efficiency. Barnes (2022) shows that employee morale declines after EEOC announcements of major discrimination cases. Others have shown the implications of prejudice in different markets (Alan et al., 2020; Bursztyn et al., 2021b; Card et al., 2008; Cutler et al., 1999; Fisman et al., 2017; Lowe, 2021; Schindler and Westcott, 2021). This paper introduces new data on racial prejudice in the workplace, and shows that firms incur a significant revenue loss when prospective employees and consumers learn about these practices.

Third, an extensive literature in health economics, psychology, and public health has shown the individual perils of racial prejudice and harassment in the workplace. Harassment leads to worse physical health (Krieger et al., 2008; Okechukwu et al., 2014), job satisfaction (Antecol and Cobb-Clark, 2009; Shields and Price, 2002), and mental health outcomes (Richman et al., 1999). Sexual harassment in the workplace poses a danger that increases the obstacles for women seeking leadership positions (Folke et al., 2020). When harassed, victims are more likely to exit the workplace, resulting in more gender segregation and a wider wage gap (Folke and Rickne, 2022). This paper provides evidence consistent with potential employees avoiding companies that exhibit racial prejudice practices in the workplace. Additionally, it shows that consumers exhibit preferences against firms that permit racial harassment in the workplace.

Fourth, the paper is connected to the literature on consumer discrimination (Bar and Zussman, 2017; Cook et al., 2023; Gil and Marion, 2018; Holzer and Ihlanfeldt, 1998). Holzer and Ihlanfeldt (1998) show that the racial composition of an establishment's customers has significant effects on the race of who gets hired. Bar and Zussman (2017) find that a significant share of Jewish customers prefer to receive services from firms employing Jewish rather than Arab workers. Gil and Marion (2018) find that that revenues of Washington D.C. theaters fell after the 1953 desegregation of movie theaters. Cook et al. (2023) construct a national data set of nondiscriminatory establishments from 1936 to 1966. They find that the share of nondiscriminatory establishments grew faster in locations with larger increases in the share of the Black population. This paper shows that consumers can also discipline firms to prevent discriminatory practices within a firm.

Fifth, the paper also contributes to the literature on job culture and firm value (Gorton and Zentefis, 2020; Graham et al., 2017; Grennan, 2020; Guiso et al., 2015; Li et al., 2020; Lins et al., 2017; Martinez et al., 2015; Song and Thakor, 2019). This literature aims to understand how job culture impacts firm value. For example, Guiso et al. (2015) study which dimensions of corporate culture are related to a firm's performance. Martinez et al. (2015) examine the effect of management on corporate culture. But corporate culture entails many attributes. I focus on racial prejudice and show that the effects on firm outcomes differ substantially from other job culture factors—i.e., bad management, favoritism, or long hours.

Lastly, the paper highlights the importance of (former) rank-and-file employees. A nascent literature in finance shows the impact of rank-and-file workers on firm outcomes (Agrawal et al., 2021; Belo et al., 2017; Edmans, 2011; Hacamo and Kleiner, 2022). Since the majority of job reviews are posted by former employees, the current paper shows that former employees might affect firm outcomes by alleviating asymmetric information about workplace practices.

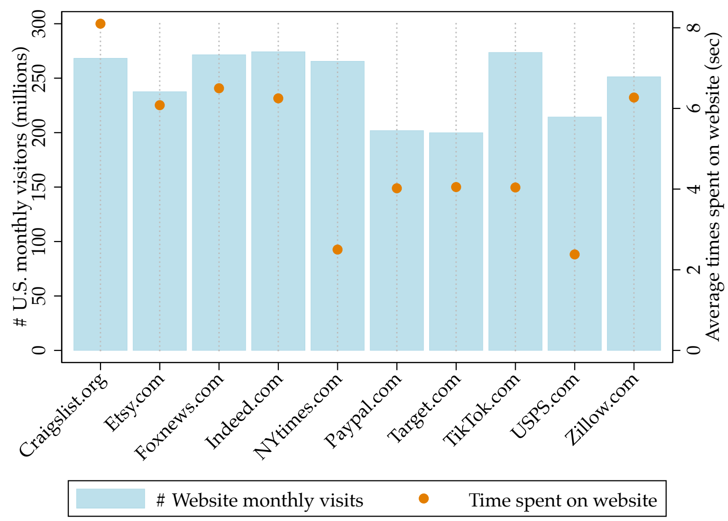
2 DATA

2.1 Racial prejudice data

Data on incidences of racial prejudice is scarce. Beyond large lawsuits and cases covered in news media, data available to prospective employees and consumers is limited. Researchers may measure workplace prejudice through anonymous complaints (i.e., EEOC), but these data is not readily available to other market participants. Furthermore, since it is costly to sue employers or even to report complaints to governmental institutions, prejudice and racial harassment are often underreported (Aguilar and Baek, 2020; Cheng and Hsiaw, forthcoming; Dahl and Knepper, 2021).

These limitations prevent information regarding prejudice incidents to be quickly incorporated by all market participants. Internet platforms, such as Indeed.com, that allow employees to report anonymous reviews about their workplace may provide an opportunity for prospective employees and consumers to learn about racist or discriminatory practices in organizations.

Figure 1: Web traffic on Indeed.com and other prominent websites



Notes: The bar column depicts the number of website visits originated from the US. The dot plot shows the average time spent on each website. Both data charts report data for October 2021. Data is from from Similarweb.com.

Indeed.com aggregates job listings from thousands of websites and offers a resume repository service that allows job seekers to easily apply for jobs. Indeed.com has been the highest-traffic job-search website in the United States since 2010. Figure 1 shows the web traffic on Indeed.com and other prominent websites. In October 2021, Indeed.com received over 270 million monthly U.S. visitors. This number of webpage visits is similar to those for Foxnews.com, NYtimes.com, or Craiglist.org; and is larger than Paypal.com, Zillow.com, or Target.com. These numbers suggest that information published on their website is likely to receive a large amount of attention.

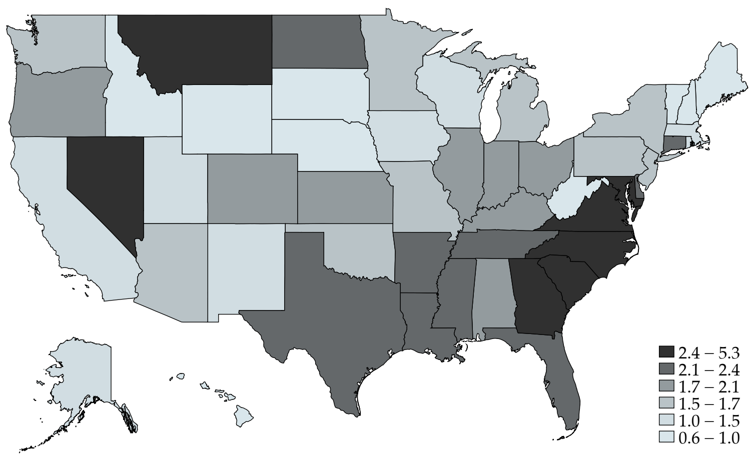
Indeed.com introduced an employer review system in 2012. A review contains a textual review, ratings on several aspects of a company, and some information about the reviewer: occupation, location, and employment status, and a date. Reviewers may also rate a company with an overall rating, and five additional dimensions: job work/life balance; compensation/benefits; job security/advancement; management; and job culture. Ratings may vary from one to five stars. In the textual review, current and former employees report any comment regarding their experience at the firm.

I collect all reviews on Indeed.com for the 6,000 largest U.S. firms with a storefront—e.g., McDonald's, Walmart, Home Depot, Chase, Bank of America, Marriott Hotel, AT&T, BP, AutoZone, Walgreens, among others—and obtained a total of 7 million employer reviews. Most companies have a large amount of reviews. For example, McDonald's and Walmart have each over 200,000 reviews. Approximately 70% of reviewers are former employees, and 50% of the reviews were posted after 2018. Most reviews are positive, but over 20% are negative ones.

Identifying racial prejudice. I parse all reviews to find those associated with racial prejudice. The process involves three steps. First, I search for words associated with racial prejudice in the textual review content (i.e., racist, racism, harassment, discrimination, slur, prejudice, among others). The full list of words is reported in Table A.1 Internet Appendix. More than 93% of tagged reviews contain one of four words: racist, racism, discrimination, or racial. Reading a random sample of tagged reviews shows that some are clearly associated with racial prejudice while others are not. For example, the word "racist" almost always pins down a racial prejudice complaint, while the word "discrimination" leads to several instances unrelated to prejudice.

Second, I search among tagged reviews in the first step for additional words (e.g., minority, race, Hispanic, Black, among others). This second list of words is also reported in Table A.2 in the Internet Appendix. In some cases, I impose the second word to be in same sentence. For example, "discrimination" and "black" need to be in same sentence. The first and second step lead to almost 12,000 reviews associated with racial prejudice. Lastly, a team of trained research assistants verify every review in the final list and exclude misclassified reviews, including reviews associated with consumer discrimination. This process identifies over 10,000 episodes of racial prejudice in the workplace between 2012 and 2021.

Figure 2: Geographical distribution of racial prejudice reports



Notes: This figure maps the number of incidents of racial prejudice in the workplace per 100,000 residents, for each state in the U.S.

Figure 2 depicts the distribution across U.S. states of racialized reviews per 100,000 residents. The lowest states have around 0.6 reviews that report prejudice per capita, while the highest states have four or more racial incidents per capita during the sample period. The two states with the lowest number of racialized reviews per capita are Hawaii and Maine, and the ones with the highest number of racialized reviews per capita are Georgia and Nevada. The largest incidence of racialized reviews occurs in southern U.S. states. Further, Figure A.1 in the Internet Appendix shows that, at the state-level, the number of racialized reviews per capita correlates with the share of non-white population.

Table A.3 reports the top 10 firms with the highest incidence of racialized reviews in the sample. Walmart, McDonald's, and Target have the highest number of incidents. Wendy's, Lowe's, and CVS have the lowest number of incidents among the top 10. There is a large variation across firms. For example, McDonald's has 2.2 reported prejudice incidents per 100 stores, while Burger King only has 1.2 reported incidents per 100 stores during the sample period.[7] Table 1 tests this conjecture. It regresses the incidence of prejudice in the workplace on a constant and different levels of fixed effects. The regression sample includes the sample of firms with a complaint of workplace prejudice and all other firms in the same county and 6-digit NAICS industry. Firm fixed effects explain 28.43% of the variation of prejudice incidents, while county or industry fixed effects only explain 8.79% and 3.25% of the variation, respectively. This is consistent with recent evidence in the literature (Kline et al., 2022).

Table 1: Variation of workplace prejudice

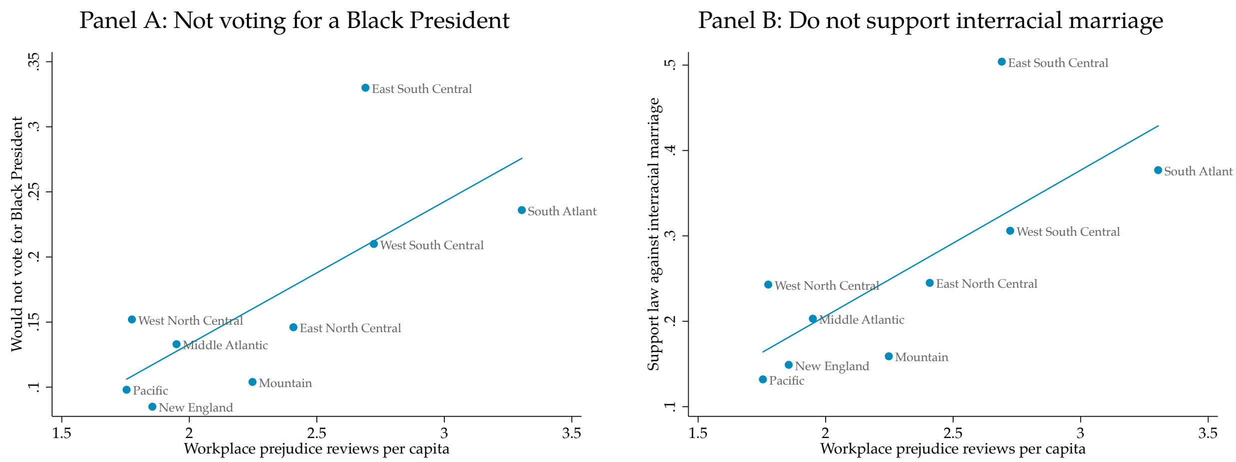
	Workplace Prejudice Report		
	Industry	Geography	Firm
R^2	8.79%	3.25%	28.43%
Industry FE	Yes	No	No
County FE	No	Yes	No
Firm FE	No	No	Yes

Notes: This table reports the R^2 of a regression that only includes a constant and fixed-effects. The sample consists of a panel with all firm-county observations when an instance of racial prejudice was reported, and all other firms that share the same 6-digit NAICS codes in the same county. The outcome variable is the likelihood that an instance of workplace racial prejudice is reported on Indeed.com. The first, second, and third column include industry, geography, and firm fixed-effects, respectively.

I also confirm that the fraction of prejudiced reviews per capita correlates with the measures of self-reported prejudice introduced by Charles and Guryan (2008). Figure 3, Panel A, shows a correlation between locations where individuals are less likely to vote for a Black president and those with more incidents of workplace prejudice per capita. Figure 3, Panel B shows a similar pattern for locations where more individuals support laws against interracial marriage.

[7]These figures are based on the number of establishments estimated from ScrapeHero.com. McDonald's and Burger King have 13,237 and 7,257 locations, respectively.

Figure 3: Workplace prejudice and self-reported measures of prejudice



Notes: The y-axis uses data from nine census divisions on the mean response among whites on two questions from the General Social Survey (GSS) about racial prejudice. The x-axis in both panels uses data on instances of racial prejudice in the workplace per 100,000 residents.

Figure A.2 shows that racialized reviews per capita correlate negatively with the Black-white wage gap. Census divisions where there are more racialized reviews per capita are also those with high wage gaps between Black and white people.

2.2 Foot-traffic data

I measure firm performance with foot traffic data provided by Safegraph. These data use GPS locations of 18 million anonymized mobile phones representative of the U.S. population, and are available for each store in the U.S. The dataset starts in January 2018 and provides the number of daily visitors, including stores visited before and after, and the census tract of the visitor's residence. Data is available for every single establishment for the 6,000 largest U.S. brands.

3 EMPIRICAL DESIGN

It is challenging to identify the causal effect of a reported incident of workplace prejudice on consumer demand. Omitted variables and reverse causality can contaminate a naive regression of consumer demand on a measure of reported prejudice incidents. This is because underperforming firms might have worse job culture, which in turn might lead to a higher number of reported episodes of racial prejudice. Or firms with low quality managers might have more instances of reported prejudice and simultaneously worse consumer demand. As these instances of workplace racial prejudice are being reported, consumer demand and labor supply might be declining, making it difficult to identify the paper's hypothesis.

To address these identification challenges, I introduce an empirical design that uses exogenous variation on salience of job reviews. The design exploits the process that Indeed.com uses to audit reviews before publishing them on the website. Due to the timing of this process, some reviews become more salient to users due to reasons unrelated to their content. This section describes this design, presents empirical evidence validating the design, and lays out the regression specification.

3.1 Firm's webpage profile

Understanding how reviews are published on Indeed's website is key to deriving the empirical design. Each firm has a profile page on Indeed.com. A firm's profile contains a snapshot of the firm. A prospective employee may learn more about a firm from job reviews of current and former employees for any establishment in the *Reviews* tab. Figure A.3 provides an example of Walmart's reviews tab in November 2019. Here an employee can see the history of all Walmart's reviews for any location. Reviews are automatically ordered from the most recent to the oldest by default. The first page shows the 20 most recent reviews.[8] An example of a review is provided in Figure A.4.

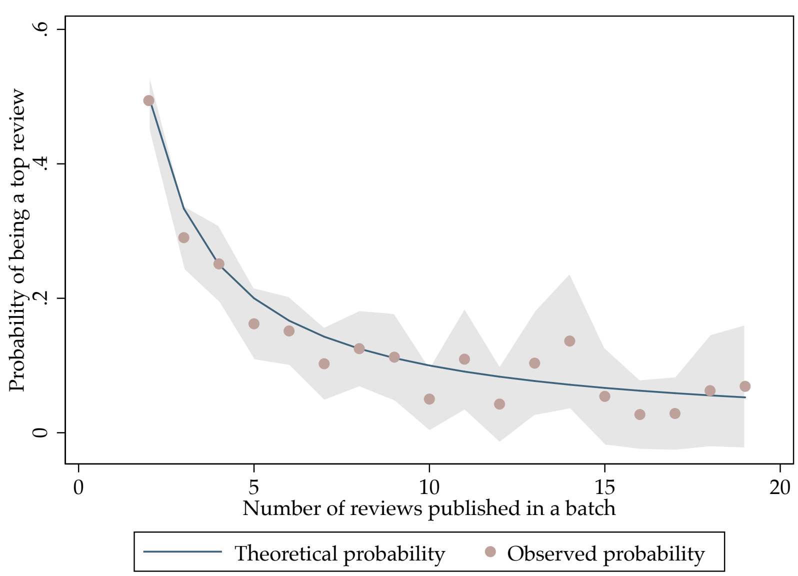
[8] In late 2020, Indeed.com started to feature one review.

3.2 Identification strategy

Indeed reserves the right to deny the publication of any submitted review to prevent the publication of fake reviews. As such, they audit every submitted review, and commit to do so within 24 hours. Reviews are audited in batches and typically published the following day. For most firms, reviews are audited once a day. The time of auditing is however uncertain. A daily inspection of the website confirms that this review process is a current practice, and Wayback Machine shows that this practice is in place since the introduction of the review system.

Since reviews are released in chronological order on a firm's profile on Indeed.com, this process randomizes the position where a job review is published among those in the same batch. Some racialized reviews are published at the top of the webpage (*top review*), while others are published at the bottom of the webpage. This placement only depends on the combination of when the review is submitted and audited. Since auditing timing is uncertain for a given firm, placement is random.

Figure 4: Likelihood that a racialized review is a *top review*



Notes: This picture depicts the theoretical and observed probability that a racialized review is a top review. The theoretical probability equal $1/N$, where N is the number of reviews submitted on the same day than the racialized review.

Data on the publication position of racialized reviews confirms empirically that the likelihood of being a top review is random among a batch. When $N-1$ non-racialized reviews are published together with a racialized review on the same day, the *theoretical probability* that a racialized review is a top review is $1/N$. Figure 4 plots this theoretical probability against the observed probability. The figure also includes confidence intervals. The plot shows that the observed probability is not statistically different than the theoretical probability. This evidence suggests that there is no manipulation from Indeed.com in trying to place racialized reviews in specific positions on the webpage. If Indeed tries to help some firms by publishing racialized reviews systematically at the bottom of the webpage, the observed probability should be systematically below the theoretical probability. This is not confirmed empirically.

To strengthen this point, I also show that the characteristics of top racialized reviews are similar to non-top racialized reviews. Table 2 reports this evidence. A long list of observables is economically and statistically identical between these two groups. For example, the likelihood of mentioning the word racist words ("racist," "racism," or "slur") is 70% in both groups. The average length of a review is 363 words in both groups, and the likelihood of using harsh words (e.g., "horrible," "hate," "terrible," or "awful") is equal in both types of reviews. The average overall rating is 1.51 in top reviews and 1.52 in non-top reviews. The table shows other observables that are similar between these two groups. This evidence helps demonstrate that the publication position on the webpage is random.

A racialized review is then considered treated if it is a top review among a batch of submitted reviews, and control otherwise. I hypothesize that a review that is published on the top of a webpage is more salient than other reviews. As treatment reviews receive more attention, their information content is more likely to propagate to other internet platforms, including consumer reviews. This propagation through internet platforms can amplify the differences in salience between first position and others. Moreover, salience should be larger when the batch of submitted reviews is larger. This is because the likelihood that a non-top racilized review is at the bottom of the webpage increases with the size of total number of submitted reviews. I test this conjecture in the Results section.

Table 2: Balancing tests between top and non-top reviews

	Top reviews	Non-top reviews	Difference
	Mean (SD)	Mean (SD)	Mean-diff (t-stat)
Job review characteristics			
Racist words	0.70	0.70	0.01
	(0.46)	(0.46)	(0.23)
Harsh words	0.20	0.19	-0.02
	(0.40)	(0.39)	(-0.81)
Review length	362.55	361.18	-1.36
	(294.51)	(268.24)	(-0.10)
Overall rating	1.51	1.53	0.01
	(0.75)	(0.75)	(0.38)
Culture rating	1.39	1.42	0.03
	(0.89)	(0.91)	(0.58)
Firm characteristics			
Yelp review	3.53	3.31	-0.22
	(10.68)	(7.55)	(-0.39)
Num 1-star Yelp reviews	1.60	1.62	0.02
	(4.78)	(4.03)	(0.06)
Num 2-star Yelp reviews	0.41	0.36	-0.05
	(1.50)	(1.05)	(-0.67)
High Prejudice State	0.49	0.48	-0.02
	(0.50)	(0.50)	(-0.61)
Republican 2016 Pres. State	0.60	0.61	0.01
	(0.49)	(0.49)	(0.40)
Number establishments per county	9.71	11.30	1.58
	(28.26)	(22.66)	(1.18)
Restaurants	0.27	0.30	0.03
	(0.44)	(0.46)	(1.54)
Groceries	0.08	0.08	-0.01
	(0.28)	(0.27)	(-0.47)
Clothing stores	0.07	0.05	-0.02
	(0.26)	(0.22)	(-1.65)

Notes: This table reports the average characteristics for top and non-top racialized reviews. A top review is a racialized review that appeared on the top of a webpage, while a non-top review is published anywhere else. *Racist words* is an indicator if the review text includes the words "racist," "racism," or "slur". *Harsh words* is an indicator if the review text includes the words "horrible," "hate," "terrible," or "awful". *Overall* and *Culture rating* is the employer rating given by the submitter of the racialized review. *Yelp review* if the average Yelp review on the month when the racialized review was submitted. *Number of 1- and 2-star Yelp reviews* are the number of 1- and 2-star Yelp reviews on the month when the racialized review appeared on Indeed.

3.3 Regression specification

To implement the empirical design, I only focus on stores where a racialized review was reported on Indeed.com. Further, I only consider racialized reviews that were published on a day with at least another non-racialized review. The empirical design compares firms that experienced an instance of racial prejudice in the workplace that was reported on Indeed, but some receive more attention than others. A firm i in county c is considered treated if a racialized review is a top review, and control if the racialized review is published anywhere else expect the first position. I then estimate the following regression:

$$\text{Y}_{ict} = \beta \times \text{Post}_t \times \text{Treatment}_{ic} + A_{ic} + B_t + \varepsilon_{ict} \tag{1}$$

where *Treament*$_{ic}$ equals one when a racialized review for firm i in county c is a top review, and zero otherwise. If a certain firm i in county c has multiple racialized reviews, I only consider the first one.[9] Treatment remains equal to one after the first review is published. *Post*$_t$ equals one for all months after a racialized review becomes public. Y_{ict} is the foot traffic of firm i in county c in year-month t. Since foot-traffic is only available starting in January 2018, the regression sample starts in January 2018 and ends in May 2021.

The specification includes fixed effects for a firm i in county c (A_{ic}) and for a year-month t (B_t). Technically, one should control for the size of the batch of reviews published with the racialized review, but this variable is absorbed by the fixed effect A_{ic}. Robustness tests also include industry-year fixed effects. Errors are always clustered at the industry level using 3-digit NAICS codes. Lastly, estimates from a staggered difference-and-differences may be biased in the presence of treatment effect heterogeneity (Borusyak et al., 2022; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). To alleviate concerns that the above estimates are biased, I report the estimates of a differences-in-differences model based on Callaway and Sant'Anna (2021).

[9]Only 9% of firm-city pairs have repeated incidents of racialized reviews.

3.4 Transmission of information

To shed light on the inner workings of a boycott, I provide additional evidence that information reported on Indeed percolates to other internet platforms, especially those that are more commonly read by consumers. I hand-collect data on consumer reviews on Yelp.com for all firms in cities for which a racialized review was reported on Indeed. While I obtain this data for each establishment, I aggregate these reviews at the firm-city level to match the employee review dataset. I then estimate a regression specification similar to (1), but replace the outcome variable, Y_{ict}, with the number of negative reviews or the number of reviews mentioning racism. This regression tests whether users of the online job-search platform intentionally propagate information on workplace prejudice to an online platform to form a boycott movement.

4 Randomized survey experiment

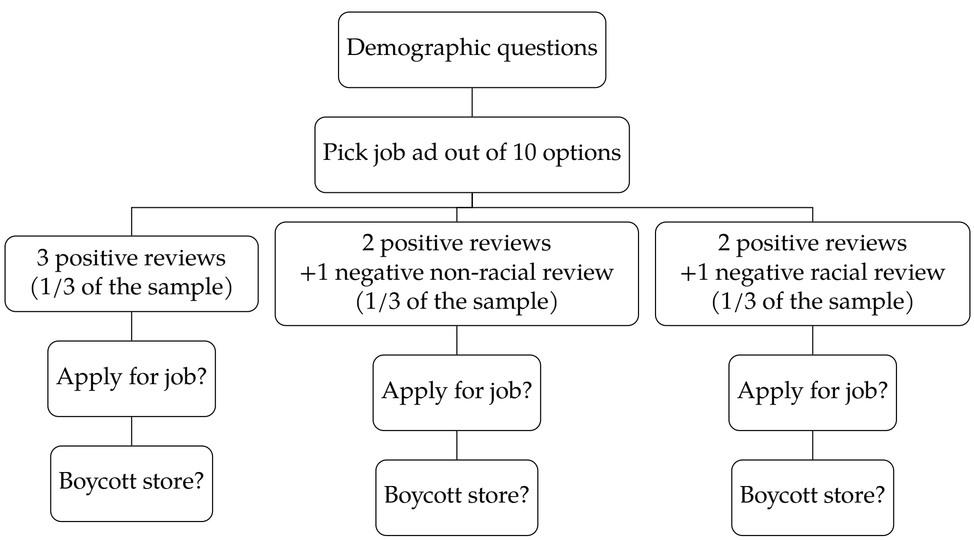
To provide additional evidence of the boycotting mechanism, I conduct a randomized survey experiment with participants who are likely users of Indeed.com. The experiment consists on showing job ads accompanied by job reviews to a representative sample of individuals to understand their job and consumer preferences.

The randomized survey is conducted on Amazon Mechanical Turk (MTurk). MTurk is a web-based platform that allows requesters to post small tasks (HITs) to be performed by humans. Potential workers browse through postings and choose whether to complete a task for the offered price. Mturk has been widely used among economists to conduct surveys and experiments (De Quidt et al., 2018; DellaVigna and Pope, 2018; Fisman et al., 2020; Kuziemko et al., 2015). I choose participants located in the U.S., with at least 1,000 completed jobs, and an approval rate higher than 95%.

Each participant was paid to answer 10 questions, including demographic queries. The survey took 3–4 minutes to complete. Regarding demographic data, I asked participants about their employment status, gender, race, ethnicity, age, and household income—the specific questions are available in section B of the Internet Appendix. After filtering responses that did not complete successfully the re-captcha, the final sample contains 2,217 unique participants. Table A.4 summarizes the characteristics of the participants: 45% are female, 69% are white, 10% are Black, and 14% are Hispanic. The average participant age is 39.6. And over 34% of participants live in a household that makes more than $75,000 per year.

The randomized survey is structured as follows. First, I ask a few demographic questions, which complement the information provided by MTurk. Second, I confirm if participants use Indeed.com. Whether users are familiar with Indeed.com is not critical for this part of the study, since we only want to understand the behavior of job seeker. Figure A.5 shows that 50% of the survey participants are Indeed.com users, it is the most popular job-search website among survey participants.[10]

Figure 5: Survey design



Notes: This chart summarizes the survey design.

[10] There are no differences between users and non-users of Indeed.com.

I then present participants with 10 different job-ad titles and ask them to pick one ad. Job ads are selected for firms that are included in the dataset. I use real job reviews for these companies, but randomly select the reviews shown. All participants are shown two positive reviews, and a third review randomly picked from the following set: (i) review associated with an episode of racial prejudice, (ii) non-racialized negative review, or (iii) positive review about the company. Figures A.6 and A.7 in the Internet Appendix provide examples of racialized and negative non-racialized reviews. I then ask several questions, including whether they are interested in submitting an application to the job post, and whether they think they would change their consumer behavior. The Internet Appendix details all survey questions. Figure 5 summarizes the survey dynamics.

5 RESULTS

5.1 Summary statistics

The regression dataset only contains racialized reviews reported on days when at least more than one non-racialized review was reported.[11] Table 3 reports summary statistics of the regression sample. The median firm has four stores per county, and each store receives on average of 414 unique monthly visitors. Over 30% of the observations in the sample are restaurants, 6% are clothing stores, and almost 8% are groceries stores. The average number of monthly 1-star (2-stars) Yelp reviews is 1.49 (0.32), the average ESG index from Sustainalytics is 57.5. The sample only includes ESG index data from companies that are publicly listed.

[11]This condition stems from the identification strategy.

Table 3: Summary statistics of observational data

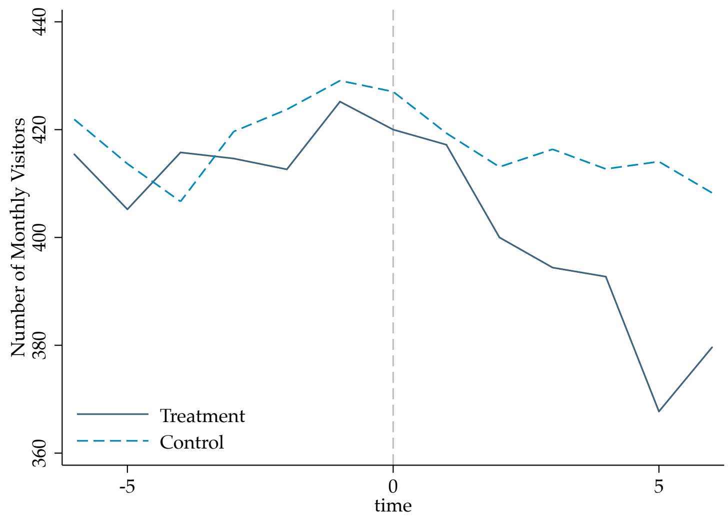
	N	Mean	Std	10th	50th	90th
Monthly #visitors	88,365	414.2	566.7	22	231.1	1019.4
Number establishments per county	88,365	11.1	24.1	1	4	28
Clothing stores	88,365	0.055	0.23	0	0	0
Groceries	88,365	0.079	0.27	0	0	0
Restaurants	88,365	0.30	0.46	0	0	1
Num 1-star Yelp reviews	69,098	1.49	4.19	0	0	4
Num 2-star Yelp reviews	69,098	0.32	1.06	0	0	1
ESG index	38,465	57.5	7.12	48.8	57.0	65.8
ESG-social score	38,465	54.6	8.13	45.6	52.8	63.9
ESG-enviornmental score	38,465	57.1	13.2	38.7	57.3	75.8

Notes: This table reports the summary statistics of the full sample. The description and computation of each variable is detailed in the Internet Appendix.

5.2 Average number of visitors

Before introducing the regression estimates, I examine the average number of monthly visitors in the treatment and control group, before and after a racially-prejudiced review becomes public. Figure 6 demonstrates that the unconditional averages are similar before a racialized review becomes public. The plot also shows that prior to publication of a racialized review, the number of visitors is not declining. This alleviates concerns that firms might be underperforming prior to the publication of racial prejudice reviews.

Figure 6: Average number of monthly visitors



Notes: This figure depicts the average number of monthly visitors in the treatment and control groups around the time when a racialized review appears on Indeed.com. This figure focuses on racial reviews published on days when 10 or fewer reviews are published.

After a review becomes public, the number of monthly visitors declines for both groups of establishments since all reviews are published on a popular job-search platform. But the decline is larger for those in the treatment group since their reviews are more salient to website visitors. This evidence lends support to the hypothesis of the paper. The publication of a racialized review potentially has a large effect on consumer demand. In the next section, I conduct a formal comparison between these two groups using the aforementioned empirical design.

5.3 Do consumers boycott a firm after a racial prejudice review becomes public?

Table 4 reports the estimates of the model detailed in section 3. The model exploits that, due to the timing of when the review is submitted and audited by Indeed.com, some reviews might be published in the top of the webpage. I assume that these reviews are more salient and receive more attention than others published elsewhere on the webpage.

The point estimates vary between -21 to -25 monthly customers, and are statistically significant at the 1% level in all specifications. Column (1) only includes firm-county and year-month fixed effects. Column (2) adds industry-year fixed effects, column (3) adds the number of establishments for a firm-county, and column (4) reports the Callaway and Sant'Anna (2021) DiD estimator. The point estimates barely vary across specifications. They imply that awareness of one report of prejudice reduces the number of monthly visitors by 5.2% (=21.73/414.2) after publication.

Table 4: Workplace racial prejudice and consumer demand

	Monthly Visitors per Store			
				CS DiD
Treatment × Post	-24.813***	-23.264***	-23.095***	-21.73**
	(-3.36)	(-3.43)	(-3.38)	(-2.45)
Number establishments per county			-2.139**	
			(-2.52)	
Firm × County FE	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes
Industry × Year	No	Yes	Yes	No
N	87,848	87,848	87,848	87,848
R-squared	0.908	0.914	0.914	-

Notes: This table reports the estimates of regression model (1) when a total of 20 or fewer reviews are published on the same day than the racialized review. The outcome variable is the number of monthly visitors. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a racialized review is a top review and zero otherwise. *Number establishments per county* is the total number of establishments for a given firm in a given county. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

The results reported in Table 4 focus on racialized reviews published on a day when 20 or fewer reviews were published for the same firm. The salience conjecture suggests that the effects should be stronger in days when the batch of published reviews for a firm is large (N). For example, if we compare racialized reviews published on days when only two reviews are submitted to the website for a firm, one should not observe a large effect between a top and non-top racialized review. Both racialized reviews should experience similar visibility. In contrast, if a racialized review is published on a day together with 19 non-racialized reviews, a top racialized review might be compared with a non-top racialized review published on the bottom of the webpage. The effects on visibility and foot traffic should be much larger in this latter case.

Table 5 confirms this conjecture. The effect is smallest when only a small batch of reviews for a firm is published in a given day, and largest when many reviews are published on the same day. For instance, when a racialized review is published together with four or fewer non-racialized reviews ($N \leq 5$), the reduction in foot traffic is only 3%. In contrast, when a racialized review is published together with 39 or fewer non-racialized reviews ($N \leq 40$), the reduction in foot traffic is almost 7%.

Table 5: Do results depend on total #reviews that appear on the same day?

	Monthly Visitors per Store					
	$N \leq 5$	$N \leq 10$	$N \leq 15$	$N \leq 20$	$N \leq 30$	$N \leq 40$
Treatment × Post	-13.759*	-15.955**	-20.863***	-23.264***	-25.353***	-26.817***
	(-1.84)	(-2.07)	(-3.18)	(-3.43)	(-3.65)	(-3.79)
Firm × County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
N	47,989	71,104	81,232	87,848	94,237	97,162
R-squared	0.910	0.910	0.914	0.914	0.916	0.919

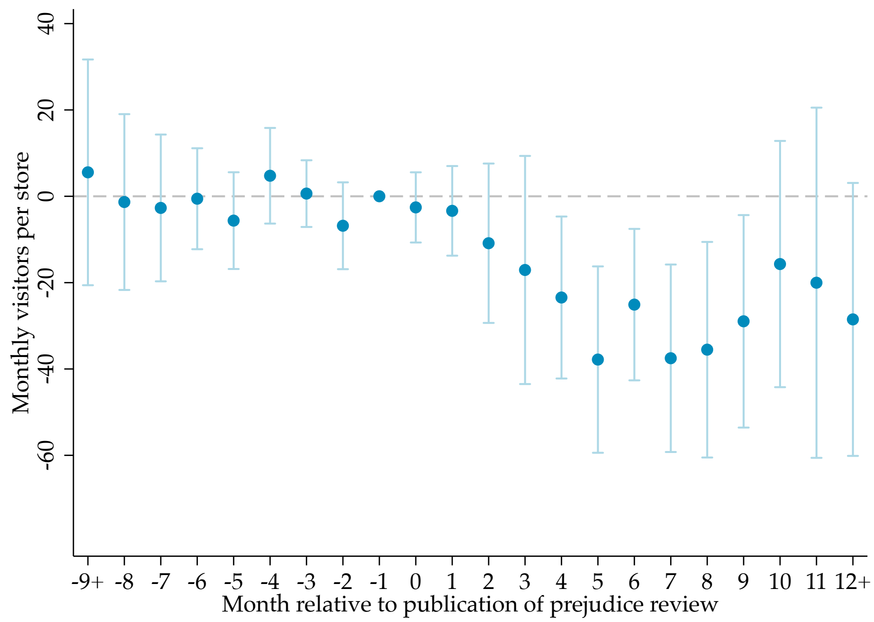
Notes: This table reports the estimates of regression model (1) varying the total number of reviews published on the same day. N is the total number of reviews published on the same day when the racialized prejudice review appears on Indeed. The outcome variable is the number of monthly visitors. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a racialized review is a top review and zero otherwise. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Event-study plot and pre-trends. Next, I test the parallel trends assumption with an event plot analysis. Figure 7 depicts the estimates and 95% confidence intervals of the following model:

$$\begin{aligned} Y_{ict} &= \sum_{m=-9}^{12} \beta_m \times 1_{t,m} \times \text{Treatment}_{ic} \\ &+ A_{ic} + B_t + \varepsilon_{ict} \end{aligned} \tag{2}$$

where m refers to the month relative to when the racial prejudice becomes public. $1_{t,m=-9}$ and $1_{t,m=12}$ are binary dummies that equal one for all months prior and after to $m = -9$ and $m = 12$, respectively. All other $1_{t,m}$ equal one for month m and zero otherwise. The outcome variable is the monthly foot traffic.

Figure 7: Event plot analysis



Notes: This figure provides a test to the parallel trends assumption. It reports the point estimates β_m coefficients from model (2), including the 95% confidence intervals.

The event plots show several patterns. First, there are no pre-trends prior to the month when racially-prejudiced reviews are published. The Wald test fails to reject that the coefficients prior to publication are equal to zero. Second, the even-plot analysis rejects a time trend confounding factor. Third, foot traffic starts a steady decline after the racialized review is published and reaches its lowest value five months post-publication. Fourth, the effect seems to revert back after nine months, suggesting that the drop in foot traffic is not permanent.[12] Taken together, these findings paint a better picture on how consumer demand is affected by the publication of a workplace-prejudice review, and strengthen the causal arguments laid out in the previous section.

[12]Figure A.8 reports parallel trends using the DD estimator by Callaway and Sant'Anna (2021). The event plot provides the same inferences as Figure 7.

Table 6: Heterogeneity Across Firms and Time

	Number of stores per city		Pre- and post-covid	
	(1)	(2)	(3)	(4)
	$\leq$ 5 stores/city	$>$ 5 stores/city	Pre Feb-2020	Post Feb-2020
Treatment $\times$ Post	-34.431***	-4.639	-20.034***	-13.566
	(-2.80)	(-0.61)	(-3.67)	(-1.22)
Firm $\times$ County FE	Yes	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes	Yes
Industry $\times$ Year	Yes	Yes	Yes	Yes
N	51,732	36,092	61,797	33,428
R-squared	0.909	0.937	0.957	0.917

Notes: This table reports the estimates of regression model (1) when a total of 20 or fewer reviews are published on the same day than the racialized review. The outcome variable is the number of monthly visitors. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a racialized review is a top review and zero otherwise. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Heterogeneity. The results exhibit an interesting amount of heterogeneity. First, the results are mostly driven by firms that have fewer than five establishments in a city. Since job reviews on Indeed.com only identify the firm name and city, this is consistent with prospective employees and consumers boycotting a firm only when they have some degree of confidence of the establishment at fault. The first two columns of Table 6 report these results. Second, the effect is larger prior to February 2020. This alleviates concerns that the magnitudes might be larger due to issues related to the pandemic lockdown. It also shows that the effects are larger during a time when labor supply is not tight.

I also show that the effect is prevalent across several industries. Table A.5 in the Internet Appendix reports the estimates for restaurants, groceries, and clothing stores. The effect on foot traffic after consumers learn about a workplace-prejudice event is similar across industries. I also show in Table A.6 that the point estimates are almost equal between firms in states that voted for the Republican and Democratic parties, respectively, in the 2016 presidential elections.[13]

[13] Table A.7 shows a similar finding after splitting the sample between states with high and low self-reported levels of racial prejudice.

5.4 Identifying a grassroots boycott

Next, I illustrate the mechanisms behind a grassroots boycott. First, I demonstrate that boycotts occur in zip codes where residents are more sensitivity to discrimination practices. Second, I provide evidence on how a grassroots boycott spreads information to other constituents. Lastly, I present the results of a randomized survey conducted on MTurk demonstrating that both prospective employees and consumers are likely to boycott a company when they learn about racial prejudice in the workplace.

5.4.1 Do boycotts happen close to those more sensitive to discrimination?

Grassroots boycotts based on racial discrimination are more likely to be successful in stores frequented by young, non-white, and low-income individuals (e.g., Biggs and Andrews, 2015; Ware, 1986). Boycotts should also be more credible when there are alternative stores available to choose from. In addition, since information spreads quickly through internet platforms, boycotts are more likely to occur when individuals have better access to the internet. I test these predictions in this section.

First, I test whether boycotts are more likely to occur in stores located in zip codes that are predominately non-white, young, and low-income. Second, I test whether the effects are larger in zip codes where Blacks and Hispanics have great access to broadband internet. Lastly, I examine whether the impact of boycotts is more pronounced in counties where targeted stores face larger competition. Table 7 and 8 report the results of these tests. The outcome variable, with the exception of columns (7) and (8) in Table 7, is calculated by splitting stores into zip codes with high and low values of a specific characteristic and then aggregating foot-traffic for each group of stores at the county level. For columns (7) and (8) in Table 7, the outcome variable is similar to the baseline regressions, but the estimation is done by splitting counties into high and low competition per capita, which is defined as the number of different brands (in the same 6-digit NAICS code) in a county divided by the county's population.

Table 7: Do effects vary with demographics and competition?

	Zip code demographics (store location)						Competition (county)	
	Race		Income		Age		Brands per capita	
	(1) White	(2) Non-white	(3) High	(4) Low	(5) Old	(6) Young	(7) Low	(8) High
Treatment × Post	2.310	-21.710**	-12.280	-26.941***	-1.917	-26.131***	-13.546	-25.263***
	(0.28)	(-2.49)	(-1.35)	(-2.72)	(-0.30)	(-3.30)	(-1.50)	(-3.75)
Firm × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	35,436	78,544	65,692	63,689	39,765	81,816	43,475	43,463
R-squared	0.911	0.915	0.914	0.908	0.902	0.916	0.917	0.913

Notes: This table reports the estimates of regression model (1) when a total of 20 or fewer reviews are published on the same day than the racialized review. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a racialized review is a top review and zero otherwise. A zip code is considered white is the fraction of non-white population is lower than 20%. A zip code is regarded as high-income if above the sample median. A zip code considered young if the average age is below the sample median. A county is considered high competition if the number of brands per capita is above 6.6 brands per million people. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table 7 shows that, after a racialized reviews becomes public, foot-traffic declines almost uniquely in zip codes that are predominately non-white, young, and low income. This is consistent with the existing evidence on boycotts (e.g., Biggs and Andrews, 2015; Ware, 1986). Furthermore, consistent with a credible boycott, the effects are significantly larger in counties with more competition.

Table 8 illustrates that following the publication of a racialized review, the impact on foot-traffic is notably greater in stores in zip codes where Black and Hispanic individuals have greater access to broadband internet. This aligns with how stakeholders learn about incidents of discrimination. Information regarding racial prejudice in the workplace is primarily disseminated via large internet platforms. While this information may eventually reach individuals without internet access through word of mouth, it is likely that the effects are more pronounced in stores located near those who have better access to internet.

Table 8: Are effects larger in zip codes where minorities have better access to internet?

	Zip code internet access (store location)			
	% Blacks w/ broadband		% Hispanics w/ broadband	
	(1) Low	(2) High	(3) Low	(4) High
Treatment × Post	-15.287*	-25.281***	-1.016	-19.811**
	(-1.95)	(-2.98)	(-0.18)	(-2.69)
Firm × County FE	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes
N	53,131	75,861	54,244	77,274
R-squared	0.908	0.914	0.912	0.914

Notes: This table reports the estimates of regression model (1) when a total of 20 or fewer reviews are published on the same day than the racialized review. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a racialized review is a top review and zero otherwise. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

5.4.2 Transmission of information to consumers

While it is possible that the decline in foot traffic might be explained by job seekers who are also consumers, a boycott by consumers is more credible if we observe that information reported on the job search website diffuses to other platforms, especially those used by millions of consumers. I test in this section whether information trickles from Indeed.com to Yelp.com, one of the largest U.S. websites for crowd-sourced reviews about businesses. As of December 2021, over 240 million reviews were available on the platform. In 2021, Yelp had 46 million unique visitors to its desktop webpages and over 56 million unique visitors to its mobile sites. In March 2021, Yelp.com received 151 million website visits. Over 50% of the company's audience has an annual household income of more than $100,000.[14]

I search for consumer reviews on Yelp for all establishments in a city where an incident of racial prejudice was reported. I then construct a panel similar to the panel used in the baseline regression. The outcome variable is the number of very negative reviews on Yelp. To ensure that

[14] Information obtained Yelp Inc. Annual Report 10-K in 2021.

relatively balanced panel, I impose that a firm in a city needs to have at least 25 reviews on Yelp.[15] I then run a model similar to (1) where I include all racialized reviews that were published on Indeed.com when 40 or fewer reviews were published on the same day. Table A.8 in the Internet Appendix reports a table with different thresholds for the total number of reviews published on the same day, similarly to Table 5.

Table 9: Does information percolate from Indeed to Yelp?

	Bad Yelp review		1-star Yelp	2-star Yelp	Mention Racism
	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.267***		0.200***	0.066	0.009***
	(3.89)		(3.94)	(1.45)	(3.30)
Treatment × Post$_{t=0,1,2}$		0.327***			
		(3.38)			
Treatment × Post$_{t>2}$		0.228*			
		(1.82)			
Firm × County FE	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes	Yes
Industry × County × Year	Yes	Yes	Yes	Yes	Yes
N	45,482	45,482	45,482	45,482	45,482
R-squared	0.831	0.831	0.817	0.625	0.185

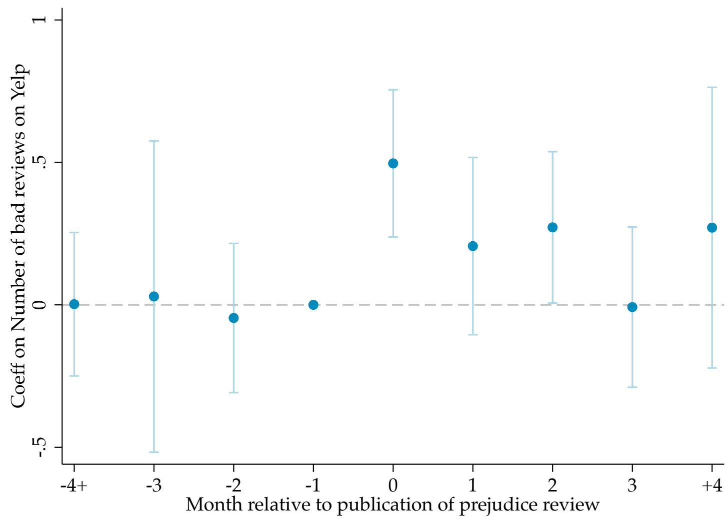
Notes: This table reports the estimates of regression model (1) when 40 or fewer reviews are published on the same day than the racialized review. The outcome variable is the number of bad reviews on Yelp. A bad review on Yelp is a 1- or 2-star review. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a racialized review is a top review and zero otherwise. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table 9 shows that the likelihood of having very negative reviews on Yelp.com is larger when a racialized review is more salient in the job-search platform. Column (1) shows that when a racialized review is a top review, there is an increase of 0.267 very negative reviews on Yelp.com. Column (2) shows that the effect is concentrated in the first three months. Columns (3) and (4) show that the likelihood of a 1-star review is significantly larger than the likelihood of a 2-star review. And column (5) shows that there is an increased change of mentioning the word "racism" or "racist" in the review, however small.

[15]Results are robust to other cutoffs, including 10, 20, and 50.

Figure 8 reports an event plot for the effect on very negative reviews on Yelp. Strikingly, there is no difference in the likelihood of very negative reviews on Yelp prior to the salience treatment in the job-search platform. The plot also shows that there is an immediate discrete jump in negative reviews on Yelp in the same month when a racialized review becomes more salient to job searchers. One could argue that very negative reviews on Yelp cause (former) employees to report racialized prejudice incidences on Indeed.com, but given the empirical design, it would have to be the case that more reporting on Yelp leads to reviews being top reviews on Indeed.com. As shown in section 3, the position where reviews are published on the webpage is close to random, making this alternative explanation of the results very implausible.

Figure 8: Event plot analysis for bad reviews on Yelp



Notes: This figure provides a test to the parallel trends assumption. It reports the point estimates β_m coefficients from a model similar to (2), including the 95% confidence intervals. The outcome variable is the number of bad reviews on Yelp. The plot only reports the coefficients for 4 months before and after the treatment effect on the job search platform.

The transmission of information from Indeed.com to Yelp.com suggests that some job searchers take action after learning about racial prejudice in the workplace. The evidence is consistent with some consumers punishing a firm for deviating from good behavior. The written reviews on Yelp reveal that some reviews mention racism, but many do not, indicating that consumer reviews on Yelp might make general negative statements about the business, which can have far-reaching implications for consumer demand.

5.4.3 Randomized Survey

To further understand the importance of the underlying mechanisms in the paper, I conduct a randomized experiment on MTurk with individuals who use Indeed.com. The experiment consists of showing job ads accompanied by job reviews to a representative sample of individuals to understand their job and consumer preferences. I select a sample of job ads from firms in the dataset, and then use real job reviews for those companies, but randomly select which ones are presented to each survey participant. I then ask several questions, including whether they are interested in submitting an application to the job post, and whether they would go back to the store if the company in the survey is a store where they usually shop. Section 4 details the design of the survey, Figure 5 provides a schematic diagram of the survey, and the Internet Appendix reports the all survey questions.

Table 10 and 11 report the likelihood that respondents will boycott the firm by estimating the following regression model:

$$\begin{aligned} \text{Apply for job/Consumer boycott}_i &= \beta_1 \times \text{Racialized review}_i \\ &+ \beta_2 \times \text{Negative non-racialized review}_i + \varepsilon_i, \end{aligned} \tag{3}$$

where *Consumer boycott* equals one if participants answer "Somewhat unlikely," or "Extremely unlikely" to the following question: "If this employer is a store where you usually shop, what is the likelihood that you will go back to the store?". *Racialized review* equals one if a participant was shown a negative racialized review, and *Negative non-racialized review* equals one if a participant was shown a negative non-racialized review. Figures A.6 and A.7 in the Internet Appendix provide examples of racialized and negative non-racialized reviews. Since one-third of the sample only views positive reviews, β_1 and β_2 measure the likelihood of consumer boycotting after a negative review is shown, relative to a positive review.

Table 10: Do racial prejudice reviews affect consumer demand on MTurk?

	Consumer boycotting					
	(1) All	(2) All	(3) Non-white	(4) Non-white	(5) White F	(6) White M
Racialized review	0.075^{***}		0.104^{***}		0.075^{***}	0.049^{**}
	(5.33)		(3.80)		(3.33)	(2.08)
Negative non-racialized review	0.021	0.021	0.031	0.031	0.023	0.013
	(1.54)	(1.54)	(1.09)	(1.10)	(1.05)	(0.56)
Racialized review (Sr. IT Analyst)		0.097^{***}		0.159^{***}		
		(4.81)		(4.08)		
Racialized review (Customer Assoc.)		0.022		0.035		
		(1.14)		(0.92)		
Racialized review (Manager)		0.110^{***}		0.121^{***}		
		(5.45)		(3.09)		
N	2,217	2,217	678	678	724	800
R-squared	0.013	0.020	0.022	0.032	0.016	0.006

Notes: This table reports the regressions using model (3). *Consumer boycotting* is a binary variable equal to one if the participant answer "Somewhat unlikely," or "Extremely unlikely" to the following question: "If this employer is a store where you usually shop, what is the likelihood that you will go back to the store?". *Racialized review* is a job review that mentions an instance of racial prejudice in the workplace. *Negative non-racialized review* is a negative review that does not mention racial prejudice. Figures A.6 and A.7 in the Internet Appendix provide examples of these reviews. *Racialized review* (*Sr. IT Analyst*) is racialized review written by a former employee with a *Sr. IT Analyst* job title. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table 10 reports the results and shows several interesting patterns. First, awareness of a negative non-racialized review has no impact on consumer behavior. Second, a report of racial prejudice increases the likelihood of consumer boycotting by 7.5 percentage points. Third, this effect is largest for non-whites and lowest for white males. Last, reviews from higher ranked employees are more likely to impact the likelihood of consumer boycotting. By and large, these findings align with the evidence shown with observational data. Reports of prejudice impact store foot traffic, but reviews about other workplace dysfunctions do not affect the likelihood that prospective employees boycott a store.

Table 11: Do racial prejudice reviews affect labor supply?

	Apply for Job					
	(1) All	(2) All	(3) Non-white	(4) Non-white	(5) White F	(6) White M
Racialized review	-0.123***		-0.140***		-0.143***	-0.091***
	(-7.14)		(-4.37)		(-4.86)	(-3.15)
Negative non-racialized review	-0.065***	-0.065***	-0.093***	-0.093***	-0.083***	-0.029
	(-3.80)	(-3.81)	(-2.86)	(-2.86)	(-2.85)	(-1.01)
Racialized review (Sr. IT Analyst)		-0.147***		-0.160***		
		(-5.94)		(-3.49)		
Racialized review (Customer Assoc.)		-0.079***		-0.100**		
		(-3.28)		(-2.21)		
Racialized review (Manager)		-0.147***		-0.163***		
		(-5.94)		(-3.54)		
N	2217	2217	678	678	724	800
R-squared	0.023	0.026	0.029	0.031	0.032	0.013

Notes: This table reports the regressions using model (3). The outcome variable is a binary variable equal to one if the participant answer yes to the following question: "Are you still interested in applying for this job?". *Racialized review* is a job review that mentions an instance of racial prejudice in the workplace. *Negative non-racialized review* is a negative review that does not mention racial prejudice. Figures A.6 and A.7 in the Internet Appendix provide examples of these reviews. *Racialized review* (*Sr. IT Analyst*) is racialized review written by a former employee with a *Sr. IT Analyst* job title. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table 11 reports the survey results for the likelihood that respondents will submit a job application. There are several conclusions that we can infer from these estimates. First, a racialized review decreases the likelihood that a job seeker applies for a job by 12 percentage points, while a non-racialized review only leads to a decline of six percentage points. Second, the effect of a racialized review on job applications is twice as large for Black job applicants. Third, the effect is larger for white females than for white males.

I also examine the heterogeneity of the results across different characteristics in Table A.9 and Table A.10. First, Black people are two times more likely to consumer boycott a store than Hispanic people. Second, younger individuals are slightly more likely to boycott the store as consumers than older ones. Across the board, negative non-racialized reviews have no effect on likelihood of consumer boycotting. In applying for a job, Hispanics are more likely to boycott than Blacks after learning about a racialized review. Lastly, there is no discernible difference between young and older individuals in their likelihood of applying for a job after learning about prejudice in the workplace.

By and large, the results of the randomized survey experiment lend strong support that consumers and prospective employees are likely to boycott a firm after learning about an instance of racial prejudice in the workplace. In contrast, consumers do not boycott a firm after learning about non-racialized negative reviews, and are almost as half as likely to not apply for a job.

5.5 Reputation

The findings of this paper can be rationalized with a reputation framework Kreps et al. (1982). In this framework, individuals do not observe workplace practices but they have a preference for goods produced in a workplace free of racial prejudice. Firms will then have an incentive to build a reputation that they keep a workplace free of prejudiced practices, since higher reputation leads to more "cooperation" from all stakeholders. However, when a racialized review becomes public, prospective employees and consumers learn that firms deviate from good behavior, and in response they "punish" the company. The higher the reputation, the larger the punishment.

To provide support to this framework, I obtain ESG scores from Sustainalytics. Sustainalytics constructs ESG scores based on several data sources items, and compiles an ESG index according to a proprietary algorithm. I obtain the E, S, and G category scores and an aggregated ESG score for 2018.[16] Results are reported in Table 12. Consistent with a reputation model, firms with higher ESG scores experience larger drops in foot traffic after a racialized review becomes public. Surprisingly, these difference is larger when using the Social score, and in contrast, smaller when considering the Environment score from the ESG index.

[16] In the SustainAbility survey, Sustainalytics was mentioned as one of the most high-quality and useful providers by both investors and industry experts.

Table 12: Effect for firms with high and low ESG index

	ESG - Total score		ESG - Social score		ESG - Enviro. score	
	(1)	(2)	(3)	(4)	(5)	(6)
	$\leq p_{50th}$	$> p_{50th}$	$\leq p_{50th}$	$> p_{50th}$	$\leq p_{50th}$	$> p_{50th}$
Treatment × Post	-14.464**	-40.319***	-12.117	-51.805***	-23.868***	-35.832**
	(-2.11)	(-2.95)	(-0.81)	(-4.76)	(-2.83)	(-2.07)
Firm × County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
N	23,336	23,267	22,096	24,507	25,325	21,278
R-squared	0.947	0.958	0.972	0.933	0.912	0.969

Notes: This table reports the estimates of regression model (1) when a total of 20 or fewer reviews are published on the same day than the racialized review. ESG scores are from Sustainalytics. The higher the index the better the score. The outcome variable is the number of monthly visitors. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a racialized review is a top review and zero otherwise. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

6 CONCLUDING REMARKS

Racial discrimination in the workplace has severe consequences for the health and well-being of employees. Achieving an equal society requires eliminating prejudice in the workplace. This often involves raising public awareness of instances of racial bias, including organizing protests and boycotts. Historically, coordinating boycotts and protests has been a significant undertaking, but the introduction of online platforms might have change significantly the costs of modern boycotts. This paper sheds light on contemporary boycotts by exploring whether individuals independently choosing to boycott a company results in a substantial overall boycott of the targeted firm.

The paper shows that when one allegation of prejudice in a specific firm-city becomes public, foot traffic drops by 4–5% in stores located in zip codes that are predominantly non-white, young, and low-income. It also shows that information spreads quickly among internet platforms. Contemporary grassroots boycotts are distinct from those of the Civil Rights Movement. Today, individuals may choose to boycott a company independently, but their combined actions can still impact targeted firms. As such, companies are more easily monitored by consumers and face significant costs if discriminatory practices occur in the workplace. Lastly, the novel data introduced in the paper should lead to future research that investigates the origins and implications of racial prejudice in the workplace.

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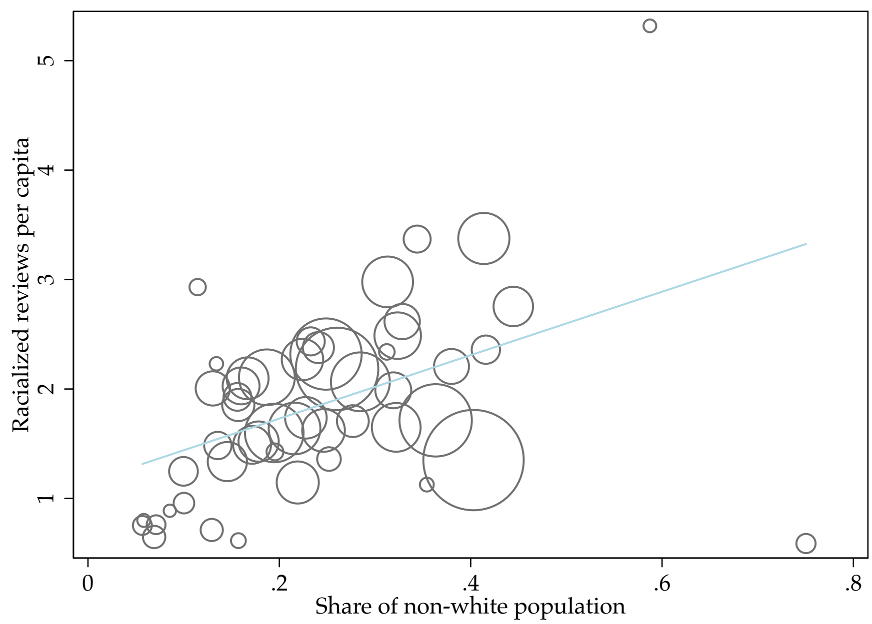
INTERNET APPENDIX

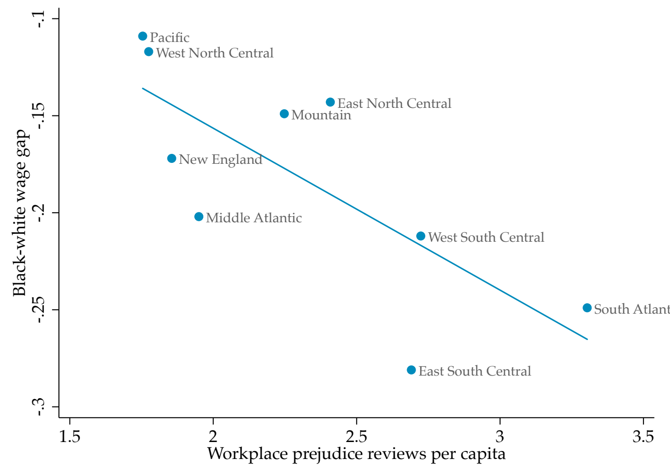
A ADDITIONAL TABLES AND FIGURES

Figure A.1: Racialized reviews per capita and share of Non-white population



Notes: This figure reports the correlation between the number of incidents of workplace racial prejudice per capita and the share of non-white population. Each dot represents a U.S. state and its size is proportional to the total population in the state. The fitted line between the x and y variable is reported in light blue.

Figure A.2: Workplace prejudice and Black-white wage gap



Notes: The y-axis uses data from nine census divisions on the Black-white wage gap. This data was directly obtained from Charles and Guryan (2008). The x-axis panels uses data on number of instances of racial prejudice in the workplace per 100,000 residents.

Figure A.3: Firm homepage

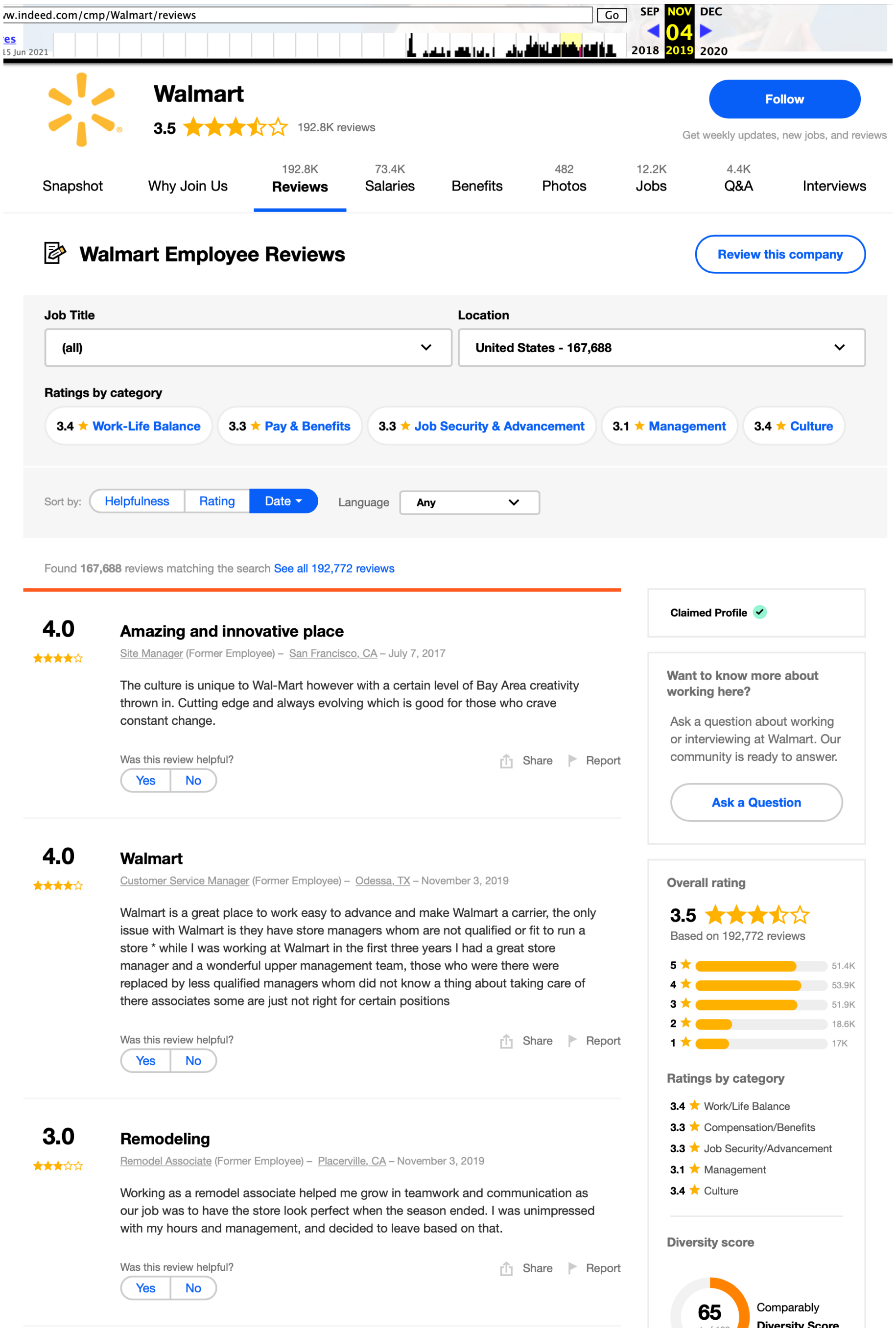
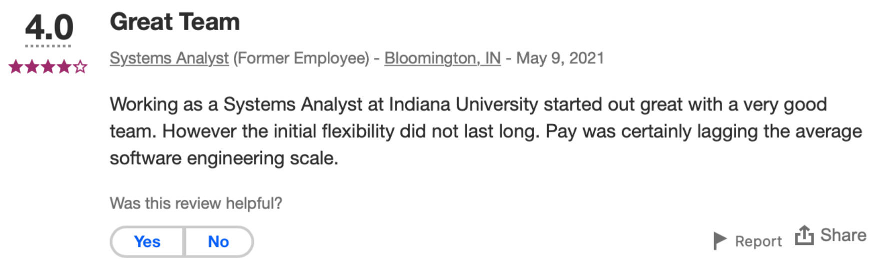


Figure A.4: Example of a review

Panel A: Example of a review



Panel B: Detailed ratings

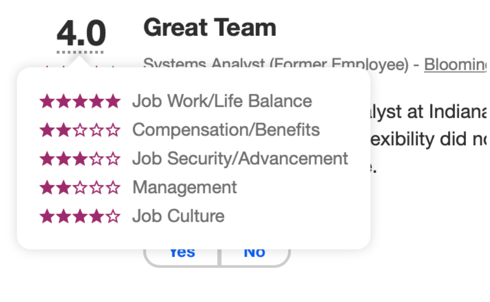
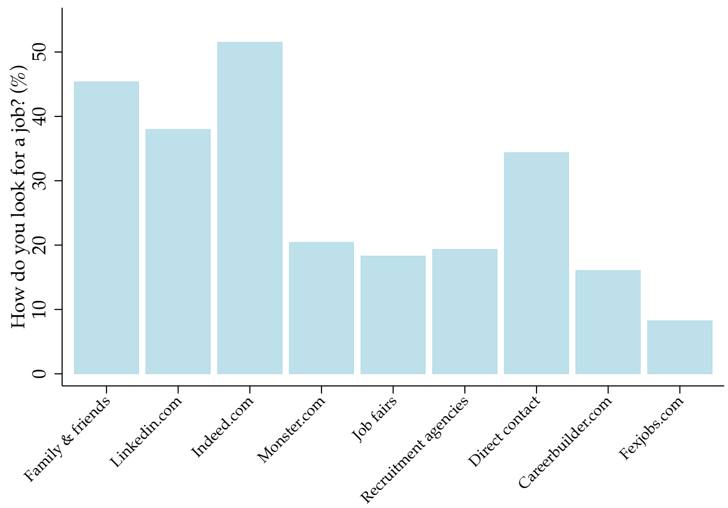


Figure A.5: Most popular platforms to find a job



Notes: This chart summarizes the survey response to the question "How do you usually look for a job?". Respondents were allowed to pick multiple choices.

Figure A.6: Example of racial harassment reviews

Panel A: First example

1.0

Worst location to work

Manager (Current Employee) - [redacted] - August 21, 2020

The general manager is racist and acts accordingly and only hires minorities so she can tell at them everyday and disrespect them.
Anytime she is wrong she and she knows it. She starts firing people who know.

Was this review helpful?

Yes No Report Share

Panel B: Second example

1.0

terrible

Customer Service Associate (Current Employee) - [redacted] - April 24, 2021

everything nothing is really worth is. management is terrible and don't care about you. show favoritism to certain colors of race and make you do things out of your control.

Pros
nothing

Cons
everything

Was this review helpful?

Yes No Report Share

Panel C: Third example

1.0

Not diverse

Sr. IT Analyst of Global Infrastructure (Former Employee) - [redacted] - September 15, 2019

In one word, I would summarize: racist.

Sounds harsh, but the treatment received is much harsher.
There is a deception or divesity, but it's more like they hire the amount of minorities to satisfy a quota.
Good ol' boy system.
Talent and skill has no value, only who you know or how long you've been there.

Was this review helpful?

Yes 5 No Report Share

Figure A.7: Example of bad management reviews

Panel A: First example

1.0

★☆☆☆☆

Negative workplace

Customer Service Representative (Current Employee) - [redacted] - April 5, 2021

GO work somewhere else. Long hours bad pay not many opportunities for raises or promotions. When you do get a promotion it'll be a lot more work for barely any pay.

Was this review helpful?

Yes 1 No Report Share

Panel B: Second example

1.0

★☆☆☆☆

bad

Shift Supervisor (Former Employee) - [redacted] - April 21, 2021

overall bad experience. I would not recommend working here long term. Upper management is a joke. Don't bother working hard for a promotion, be lazy that'll get you promoted quick.

✓ **Pros**

Nothing

✕ **Cons**

everything

Was this review helpful?

Yes No Report Share

Panel C: Third example

1.0

★☆☆☆☆

Use to be good

[redacted] Technician (Current Employee) - [redacted] - November 5, 2020

It use to be a good place to work and move up now the place is just a job. They want you to consider it a career but pay you like a job. They've taken away all
The positions so there is no extra pay and more work most people don't have set schedules and there is no structure

✓ **Pros**

If you been there long enough you might have decent pay

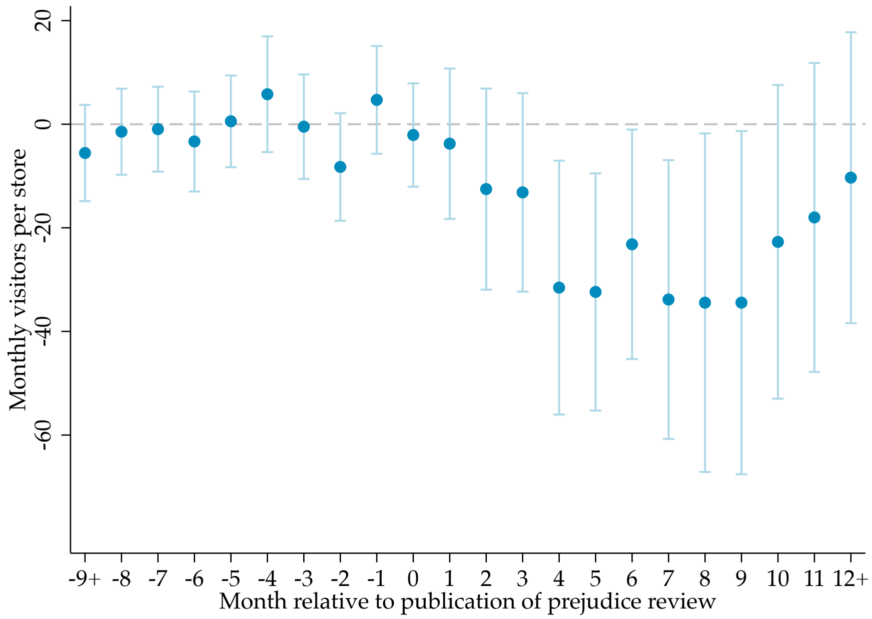
✕ **Cons**

Everything

Was this review helpful?

Yes No Report Share

Figure A.8: Event plot analysis



Notes: This figure provides a test to the parallel trends assumption. It reports the period by period point estimates using the Difference-in-Differences estimator from Callaway and Sant'Anna (2021), including the 95% confidence intervals.

Table A.1: Primary Root Words in Prejudice Reviews

Primary root words	Frequency (%)	Primary root words	Frequency (%)
racist	60.13	disrespect, racial	0.16
racism	13.08	racial, racist	0.16
racial	4.99	favorit, racist	0.18
favorit	2.91	racial, disrespect	0.13
discrimin	2.75	racial, hate	0.13
slur, racial	0.83	bias, racist	0.11
discrimin, racial	0.69	discrimin, favorit	0.11
bias	0.64	privilege	0.11
harass	0.59	racist, favorit	0.11
racial, slur	0.59	slur, racial, racist	0.11
disrespect	0.56	discrimin, harass	0.08
prejudice	0.61	discrimin, racist	0.08
racial, discrimin	0.51	disrespect, favorit	0.08
favorit, racial	0.48	favorit, prejudice	0.08
racist, racism	0.48	insult	0.08
hate	0.56	racial, prejudice	0.08
racism, racist	0.35	racial, racism	0.08
bias, racial	0.27	racist, harass	0.08
harass, racial	0.24	segregat	0.08
hostil	0.24	stereotyp	0.08
racial, bias	0.24	bias, favorit, racial	0.05
racial, favorit	0.24	bully, discrimin	0.05
racial, harass	0.21	disrespect, racism, hostil	0.05
bully	0.19	disrespect, racist	0.05
racist, racial	0.24	favorit, discrimin	0.05

Notes: This table reports the list of words found in employee reviews related to prejudice. This is the list of first words, which means that often they had to be found in conjunction with a second word reported in Table A.2.

Table A.2: Secondary Words in Prejudice Reviews

Second root words
african
asian
black
caucasian
chinese
cultures
ethnicity
hispanic
immigrant
immigration
indian
latina
latino
mexican
middle east
minorities
minority
pakistani
skin color
white

Notes: This table reports the list of words found in employee reviews related to prejudice. This is the list of second words, which means that they had to be found in conjunction with a first word reported in Table A.1.

Table A.3: Companies with largest incidence of workplace prejudice

Firm	Total # Racial Reviews	Sample Fraction
Walmart	364	3.07%
MacDonald's	293	2.47%
Target	109	0.92%
Home Depot	105	0.89%
Burger King	91	0.77%
Walgreens	79	0.67%
Amazon	77	0.65%
Wendy's	76	0.64%
Lowe's	74	0.62%
CVS	71	0.60%

Notes: This table reports the firms in the sample with the largest incidence of workplace prejudice. The second column reports the total count, and the third column reports the sample fraction.

Table A.4: Summary statistics of survey data

	N	Mean	Std	10th	50th	90th
Female	2,192	0.45	0.50	0	0	1
White (non-Hispanic)	2,217	0.69	0.46	0	1	1
Black	2,217	0.098	0.30	0	0	0
Hispanic	2,217	0.14	0.34	0	0	1
Age	2,217	39.6	10.3	28	37	56
Household income $\geq$ 75k	2,217	0.34	0.47	0	0	1
Consumer boycotting	2,217	0.080	0.27	0	0	0
Apply for job	2,217	0.87	0.34	0	1	1

Notes: This table reports the summary statistics of the survey data. *Consumer boycotting* is a binary variable equal to one if the participant answer "Somewhat unlikely," or "Extremely unlikely" to the following question: "If this employer is a store where you usually shop, what is the likelihood that you will go back to the store?". *Apply for job* is a binary variable equal to one if the participant answer yes to the following question: "Are you still interested in applying for this job?".

Table A.5: Effect across industries

	Monthly Visitors per Store		
	(1) Restaurants	(2) Groceries	(3) Clothing
Treatment × Post	-32.562***	-30.992***	-43.261***
	(-6.84)	(-3.82)	(-4.53)
Firm × County FE	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes
Industry × Year	Yes	Yes	Yes
N	26,624	6,957	13,621
R-squared	0.858	0.922	0.932

Notes: This table reports the estimates of regression model (1). Definition of industries is based on NAICS codes. The outcome variable is the number of monthly visitors. Post is a variable equal to one after the racial prejudice report becomes public. *Treatment* equals one when a review is a top-review and zero otherwise. Number establishments in county is the total number of establishments for a given firm in a given county. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table A.6: Republican versus Democratic states

	Monthly Visitors per Store	
	(1)	(2)
	Republican state	Democratic state
Treatment × Post	-21.421**	-21.887*
	(-2.44)	(-1.78)
Firm × County FE	Yes	Yes
Year × Month FE	Yes	Yes
Industry × Year	Yes	Yes
N	53,655	34,193
R-squared	0.915	0.917

Notes: This table reports the estimates of regression model (1). The political leaning of an U.S. state is estimated using the outcome of the 2016 presidential election. The outcome variable is the number of monthly visitors. Post is a variable equal to one after the racial prejudice report becomes public. *Treatment* equals one when a review is a top-review and zero otherwise. Number establishments in county is the total number of establishments for a given firm in a given county. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table A.7: Low vs high prejudice areas

	Monthly Visitors per Store	
	Self-reported prejudice	
	(1) High	(2) Low
Treatment × Post	-22.757*	-26.788**
	(-1.69)	(-2.61)
Firm × County FE	Yes	Yes
Year × Month FE	Yes	Yes
Industry × Year	Yes	Yes
N	46,854	50,308
R-squared	0.919	0.921

Notes: This table reports the estimates of regression model (1). Self-reported prejudice is based on two questions from General Social Survey (GSS) about racial prejudice that were used in Charles and Guryan (2008). The first question asks survey participants whether they would not vote for a Black President, and the second question asks participants whether they support a law against interracial marriage. I define high prejudice states as those in census divisions with the highest scores in these questions. This set of states includes Alabama, District of Columbia, Florida, Georgia, Kentucky, Maryland, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. The outcome variable is the number of monthly visitors. Post is a variable equal to one after the racial prejudice report becomes public. *Treatment* equals one when a review is a top-review and zero otherwise. Number establishments in county is the total number of establishments for a given firm in a given county. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table A.8: Do racial prejudice reviews affect likelihood of bad yelp reviews?

	Likelihood of bad yelp reviews					
	$N \leq 5$	$N \leq 10$	$N \leq 15$	$N \leq 20$	$N \leq 30$	$N \leq 40$
Treatment × Post	0.123**	0.127**	0.169***	0.203***	0.254***	0.267***
	(2.15)	(2.12)	(3.65)	(4.18)	(4.70)	(3.89)
Firm × County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year						
N	18,582	30,372	35,593	40,073	43,961	45,482
R-squared	0.807	0.817	0.818	0.821	0.830	0.831

Notes: This table reports the estimates of regression model (1) varying the total number of reviews published on the same day. N is the total number of reviews published on the same day when the racialized prejudice review appears on Indeed. The outcome variable is the number of bad reviews on Yelp. A bad review on Yelp is a 1- or 2-star review. *Post* is a variable equal to one after the racial prejudice appears on Indeed. *Treatment* equals one when a raicalized review is a top review and zero otherwise. Errors are clustered at the industry level using 3-digit NAICS codes. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table A.9: Do racial prejudice reviews affect consumer demand?

	Non-white		Age	
	(1)	(2)	(3)	(4)
	Hispanic	Black	$\geq$40	<40
Racialized review	0.086**	0.172***	0.066***	0.079***
	(1.98)	(3.37)	(3.39)	(3.97)
Negative non-racialized review	0.056	0.041	0.023	0.019
	(1.24)	(0.82)	(1.22)	(0.95)
N	305	217	956	1261
R-squared	0.013	0.053	0.012	0.014

Notes: This table reports the regressions using model (3). *Racialized review* is a job review that mentions an instance of racial prejudice in the workplace. *Negative non-racialized review* is a negative review that does not mention racial prejudice. Figures A.6 and A.7 in the Internet Appendix provide examples of these reviews. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

Table A.10: Do Racial prejudice reviews affect labor supply?

	Non-white		Age	
	(1)	(2)	(3)	(4)
	Black	Hispanic	$\geq$40	$<$40
Racialized review	-0.091**	-0.234***	-0.128***	-0.121***
	(-2.33)	(-4.06)	(-4.87)	(-5.26)
Negative non-racialized review	-0.077*	-0.115**	-0.056**	-0.073***
	(-1.87)	(-2.02)	(-2.16)	(-3.16)
N	305	217	956	1,261
R-squared	0.020	0.072	0.024	0.022

Notes: This table reports the regressions using model (3). The outcome variable is a binary variable equal to one if the participant answer yes to the following question: "Are you still interested in applying for this job?". *Racialized review* is a job review that mentions an instance of racial prejudice in the workplace. *Negative non-racialized review* is a negative review that does not mention racial prejudice. Figures A.6 and A.7 in the Internet Appendix provide examples of these reviews. t-statistics are in parentheses. Statistic significance: ***=1%; **=5%; and *=10%.

B RANDOMIZED SURVEY QUESTIONS

1. Are you currently employed?

    - Yes, full-time
    - Yes, part-time
    - No

2. How do you usually look for a job? (multiple choices allowed)

    - Monster.com
    - Indeed.com
    - Linkedin.com
    - CareerBuilder.com
    - Friends and Family
    - Contact companies directly
    - Job fairs
    - Recruitment/staffing agencies
    - Glassdoor.com
    - Flexjobs.com

3. We would like you to consider the job openings below. Please choose one job that you may be interested in applying for. Job details will be shown after you pick one option.

    - Restaurant General Manager
    - Cashier/Counter Service
    - Retail Sales Consultant

- Supervisor Marketing Strategy
- Store Manager
- Associate Manager Marketing
- Bank Teller
- Assistant Manager - Room Operations
- Faculty Assistant
- Commercial Sales Manager

4. (A full job description based on a real job ad is shown)

5. We would like you to consider a few company reviews. Please read them carefully. Do not write anything in the text boxes below each review. Just click next at the bottom. These are real company reviews. A few details have been redacted to protect confidentiality.

   (Three random reviews are shown. There are three positive reviews, three bad non-racial reviews, and three racial reviews. The randomization scheme is described in the results section.)

6. Are you still interested in applying for this job?

   - Yes
   - No

7. Why aren't you interested in this job?

   - I am not qualified for this job
   - I did not like the company reviews

- I am no longer interested in the job
- Other, please list why.

8. If this employer is a store where you usually shop, what is the likelihood that you will go back to the store?
    - Extremely unlikely
    - Somewhat unlikely
    - Neither likely nor unlikely
    - Somewhat likely
    - Extremely likely

9. To which gender identity do you most identify?
    - Female
    - Male
    - Transgender
    - Non-binary/non-conforming
    - Not Listed: _____
    - Prefer not to respond

10. What is your race?
    - White
    - Black or African American
    - American Indian or Alaska Native

- Asian Indian
- Chinese
- Other Asian
- Native Hawaiian
- Other Pacific Islander
- Other: _____
- Prefer not to respond

11. Are you hispanic?
    - Yes
    - No

12. How old are you?

13. What's your total annual household income?
    - Under $10k
    - $10k to $40k
    - $40k to $75k
    - $75k to $100k
    - $100k or more