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DISCUSSION PAPER SERIES

IZA DP No. 13012

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ABSTRACT

Do Workers Discriminate against Their Out-group Employers? Evidence from the Gig Economy*

We study possible worker-to-employer discrimination manifested via social preferences in an online labor market. Specifically, we ask, do workers exhibit positive social preferences for an out-race employer relative to an otherwise-identical, own-race one? We run a well-powered, model-based experiment wherein we recruit 6,000 workers from Amazon's M-Turk platform for a real-effort task and randomly (and unobtrusively) reveal to them the racial identity of their non-fictitious employer. Strikingly, we find strong evidence of race-based altruism – white workers, even when they do not benefit personally, work relatively harder to generate more income for black employers. Self-declared white Republicans and Independents exhibit significantly more altruism relative to Democrats. Notably, the altruism does not seem to be driven by race-specific beliefs about the income status of the employers. Our results suggest the possibility that pro-social behavior of whites toward blacks, atypical in traditional labor markets, may emerge in the gig economy where associative (dis)taste is naturally muted due to limited social contact.

JEL Classification: J71, D91, C93

Keywords: discrimination, worker-to-employer, social preferences, taste-based discrimination, Gig Economy, mechanical turk, Structural Behavioral Economics

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1 Introduction

By construction, *Homo economicus* is self-interested and only takes actions that maximize his/her payoffs. By way of contrast, *Homo behavioralis*, in addition to being self-interested is also endowed with social preferences, a concern for how his/her actions affect the payoffs of others. These "others" could belong to his in-group, a group he identifies with and whose membership gives him a sense of belonging. Everyone else, by definition, is in his out-group. *Homo behavioralis* may harbor negative social preferences urging him to discriminate against others; or the preferences could be positive and take the form of prosocial behavior – actions taken with an intent to benefit others with no expectation of personal benefit.

This paper is aimed at detecting evidence of positive or negative social preferences within the context of labor markets. The experimental setting is an U.S. based online labor market (loosely, "gig economy") and group identity is assumed to be racial in origin. Within this environment, we ask, is there evidence that whites systematically treat blacks differently from how they treat fellow whites? We depart from a half-century of research in labor economics that views this issue largely as unidirectional, emanating from employers and directed toward their employees.[1] Instead, we ask, is there evidence that white *workers* in the gig economy treat their black *employers* better or worse than how they treat their otherwise-identical, white employers?

A series of questions come up right away. Why is it interesting to study discrimination or pro-social behavior of workers toward employers? Is there any evidence of this? And, why the gig economy? We take these up one by one. That workers may treat their out-race employers differently may, at first glance, seem implausible; after all, it is mostly bosses who get to frame labor contracts and surely within the bounds of such contracts there cannot be much room left for workers to mistreat out-group bosses. Our view is that this first-pass line of thinking is limited. While admittedly it is easier for bosses to maltreat out-group workers, the latter are also keenly aware that the effort they put in, the diligence or care they show on the job, crucially affects the bottomline of their bosses. Moreover, as is well known, labor contracts are often "incomplete": they leave workers a considerable degree of discretion over work effort. It is therefore conceivable that a worker with substantial leeway over effort makes very different effort choices reflecting his underlying differential social preferences. For instance, a black worker may choose to work harder for a black boss because of his desire to a) see his boss succeed even if it does not benefit him personally (**altruism** à la Simon (1993)), and b) return any respect or kindness he receives from his boss (**reciprocity** à la Akerlof (1982)).

Second, there is important evidence that workers care about the social identity of their bosses and differentially perform for in versus out-group employers. Sundstrom (1994), focusing on U.S. urban labor markets 1910-1950, notes "one of the most widely noted rules of the southern labor market was

[1] See Riach and Rich (2002), Charles and Guryan (2011), Rich (2014), Bertrand and Duflo (2017), and Neumark (2018) for a review of this literature.

that blacks were not to supervise whites...[because it] would plainly invert the appropriate hierarchy" which meant "blacks were generally absent from supervisory positions". White employees simply did not wish to receive orders from (or work under) black supervisors. More recently, Glover, Pallais, and Pariente (2017) study whether discriminatory beliefs held by bosses directly affect minority workers' job performance in a real-world workplace. They investigate the performance of cashiers in a French grocery store chain, and find when "minority cashiers, but not majority cashiers, are scheduled to work with managers who are biased (as determined by an Implicit Association Test), they are absent more often, spend less time at work, scan items more slowly, and take more time between customers." The upshot is, workers *do* adjust their effort based on the social identity of their bosses, and may perform better when paired with own-group managers than out-group ones.[2]

And why study this question in the confines of the gig economy? To be clear, a gig economy is one where independent workers are paid by the gig (i.e., for a task or a project) as opposed to the traditional economy where workers are paid a salary or hourly wage as part of a contract. One important distinction is that in the gig economy, particularly of the digital-platform type, there is little scope for close or repeated interactions between the employer and the employee; hence, associative distaste or liking is unlikely to be activated.[3] This means, if we are to detect any race-based differences in social preferences (altruism or reciprocity) in our gig economy setting, it will not be because of associative distaste or liking. Another critical difference is the vastly dissimilar "power dynamic" between worker and boss. In a gig economy, workers retain a lot of power in the worker-employer relationship: they may shirk under a particular employer or easily switch employers without losing much "employment rent".[4] This new power dynamic makes the gig economy an ideal setting to study *worker-to-boss* discrimination, much more so than the conventional labor market setting.[5,6]

To the end of answering our research question, we run a well-powered, AEA preregistered, model-based experiment using 6,000 white subjects from one of the largest gig economy platforms: Amazon's Mechanical Turk (M-Turk).[7] Specifically, our experimental design uses U.S. based subjects from M-

[2]Oh (2019) finds that 43% of Indian workers "refuse to spend ten minutes working on tasks associated with other castes, even when offered ten times their daily wage" suggesting the important role of social identity in determining work-related decisions.

[3]While our work is focused on an online labor market, others such as TaskRabbit offer tasks situated in the physical world and cover household errands and skilled tasks such as minor home repairs, assembling Ikea furniture, where the scope for more interaction between worker and boss, and hence, more associative (dis) taste, is clearly higher.

[4]After all, a typical Uber driver (or a M-Turker), each a worker, may work for ten "employers" in a day and ten different ones the very next day!

[5]Allport (1954) classic *The Nature of Prejudice*, (Chapter 16 'The Effect of Contact') argued for bringing members of different groups together in face-to-face encounters to reduce inter-group hostility. Significantly, he was of the view that direct inter-group contact would effectively reduce out-group prejudice if it involved equal status among the participants. We posit that the gig economy allows the worker and the employer to be of "equal status" and that, in and of itself, may reduce inter-group hostility even when no direct contact à la Allport is initiated.

[6]There are ancillary reasons why our focus on the gig economy is pertinent. The argument is often made that blacks, often the victim of discrimination in conventional labor markets, would gravitate to the gig economy because of reduced expectations of discrimination in the latter. We would want to know, are those expectations likely to be satisfied? Also, other than Cook, Diamond, Hall, List, and Oyer (2019), it is not known whether long-established routes of discrimination researched on traditional labor markets with conventional worker-boss power dynamics will continue to operate in the dawning gig economy.

[7]Roughly 50% of M-Turkers are from the United States. Based on 2015 data, about 77% are non-Hispanic white and only 6% are non-Hispanic black (Hitlin, 2016). The results reported below are for U.S.-based white workers, by far the vast majority of workers on M-Turk and in our sample.

Turk (recruited as "workers") and black and white student subjects (recruited as "employers") from a major U.S. public university. The interaction between a worker and an employer is kept one-shot, as is typical in the gig economy, so that confounding reputation effects (of the kind that naturally emerge in Glover et al. (2017)) do not enter. In the experiment, workers engage in a real-effort task for a pre-assigned, non-fictitious employer. The real-effort task (unlike monetized costs in studies such as Charness, Rigotti, and Rustichini (2007); Fershtman and Gneezy (2001)) entails a real utility cost of effort because it requires a worker to alternately press the 'a' and 'b' buttons on a keyboard for up to 10 minutes. Workers do not get to select their employer but are free to decide how much effort to provide on the task (an 'incomplete contract' environment). [8] The worker's performance is measured by the number of times the buttons are alternately pressed, and the worker is informed (truthfully) of the payoff the employer will receive due to the worker's performance. Race-dependent social preferences are potentially activated in some treatments by unobtrusively revealing the employer's race to the matched worker.

The design is tightly connected to a simple structural model à la DellaVigna, List, Malmendier, and Rao (2016), in which workers have race-dependent social preferences towards their employer and maximize utility from the provision of costly effort. Inspired by Doleac and Stein (2013), we take the approach of revealing race indirectly via the revelation of skin color and voice: employer-subjects are videotaped while they read off a script explaining and demonstrating the task for the workers. The camera placement only captures the hand of the employer along with the movement of the fingers alternating 'a' and 'b' button presses. Other identifiers, such as the face, are not revealed. This allows us to reveal or conceal race without sacrificing either privacy or anonymity. In the neutral treatments, gloves and other clothing hide the skin entirely. The worker is aware of being matched to an employer but is unaware of any identity clues. We make every effort to check that race, when revealed, is correctly perceived. In the experiment, we introduce a total of ten treatment variations. In the first three, we vary the piece rate with an aim to identify and estimate the cost-of-effort function. Here, the worker is not given any information about the existence of (non-existent) employer; any earnings from his/her effort choices go entirely to the worker. The next set of three treatments aim to a) detect the baseline level of altruism towards the hidden race of the employer (altruism netural) and b) estimate race-specific altruism towards the revealed race of the employer (altruism black and altruism white). The final treatments are designed to a) detect the baseline level of reciprocity towards the hidden race of the employer (reciprocity neutral) and b) estimate the race-specific variations in reciprocity towards the revealed race of the employer (reciprocity black and reciprocity white). Thus, the ten treatments

[8] Traditionally, discrimination in labor markets is understood to arise in two main ways. Becker (1957) introduced the notion of taste-based discrimination postulating that discrimination exists because of a prejudice/animus towards the members of the disadvantaged group. On the other hand, Phelps (1972) theorized that discrimination might be statistical – an employer, lacking information about a job-seeker's productivity, forms beliefs about it based on the person's group identity and the aggregate productivity distribution of the group to which the person belongs. In our experiment, the employers do not get to make any strategic choices (such as wage offers, payments, minutes of work, work times, etc.). This eliminates most channels for statistical discrimination by workers.

help us identify the cost-of-effort function and social-preference parameters (altruism and reciprocity) of the structural model separately for neutral (hidden race), black, and white employers.

Our findings reported in terms of average effort by white workers are as follows. First, not surprisingly, incentives via piece rates have a strong, statistically-significant effect on effort. Second, as in DellaVigna and Pope (2018), we detect statistically significant evidence for altruism: workers put more effort when they know their work benefits an employer of unknown race ("altruism-neutral treatment") as compared to the piece rate 0-cent treatment where neither the worker nor the employer earns any payoff attributable to worker effort. Parenthetically, there is no evidence of reciprocity.

Strikingly, white workers are significantly more altruistic towards black employers than white employers – categorically, they do not discriminate against their black employers. In addition to being statistically significant at the 2% level, the difference in effort provision is non-trivial. To see this, consider a baseline level of altruism, defined as the differential effort provided by white workers knowing their effort enhances the payoff of an unknown race employer versus their effort when the piece rate is 0-cent and no employer exists. Our results indicate that the differential effort by white workers knowing their effort enhances the payoff of a white vs. a black employer is 75% of this baseline. Also, the differential effort by workers knowing their effort enhances the payoff of a black vs. an unknown-race employer is 45% of the baseline. The structural estimation exercise also reveals that black employers get 5% more effort than white employers at a 0-piece rate. Collectively, these represent persuasive evidence of pro-social behavior by whites toward black employers.

What explains this pro-social behavior? Is it racial heterophily? Is it "white guilt"? We did not collect data from M-Turk workers on any measure of racial bias such as the Implicit Association Test (IAT).[9] However, we combined IAT data from Project Implicit with county-level knowledge of worker residence. We find that the pro-social response towards black employers is partially driven by workers from areas with low implicit bias against blacks. Peeking further, we find if we split the IAT data into two halves (top and bottom), the pro-black altruism is highly significant for workers in the bottom half – those residing in the "least racist" counties – and is insignificant for those in the top half.[10] We also test (albeit, somewhat crudely) and reject the hypothesis that the differentially altruistic response toward black employers is driven by worker beliefs about the income status of their employers. Interestingly, we find workers who are self-declared Republicans and Independents exert significantly more effort for their black employers as compared to Democrats.

[9]Perhaps the most well known measure of racial bias is the Implicit Association Test (IAT) which measures the "strength of association between categories such as European American versus African-American and words such as joy, laughter, and happy versus hurt, evil, and awful that represent categories of good versus bad." Upwards of 80% of whites in nationally representative American samples have shown an implicit preference for whites over blacks (Triplett, 2012).

[10]It is tempting to draw conclusions about "white guilt", a supposedly collective guilt felt by whites for their group's actions toward blacks, not necessarily for their own actions. As Chudy, Piston, and Shipper (2019) point out "...whites who hold collective guilt acknowledge that their group is responsible for black suffering and that the inter-group relationship needs to be repaired." Just because someone lives in a county where an average person registers low animus toward African Americans in an IAT test does not mean such people will wish to do something to repair the aforementioned inter-group relationship. In our case, though, unlike research that relies on survey-based measures of white guilt, we are able to detect evidence of whites doing *something extra for blacks even when they do not need to*.

In terms of the value-added to the literature, our primary contribution is to showcase the importance of looking at the worker-to-employer social preference angle. Our finding is interesting because it raises the possibility that positive social preference toward blacks, rarely detected in traditional labor markets, may emerge in environments such as the gig economy where associative distaste is naturally muted. Bear in mind, ours is a well-powered, AEA pre-registered experiment which would have detected preference-based discrimination had it existed on the M-Turk platform; the fact we don't is encouraging, seeing how the gig economy is expanding (Katz & Krueger, 2019). Further, it is oft-repeated that the relative lack of success of black-owned businesses or the diminished presence of blacks in leadership positions in the United States is a major concern among policy makers; more so, because "business ownership has historically been a route of economic advancement for disadvantaged groups" (Fairlie & Robb, 2007). Our study can offer a partial answer in the negative to the following question: do entrepreneurial blacks shy away from business because they rationally fear discrimination by majority white workers? Curiously, our finding also shuts down another line of thinking connected to the issue of anticipation of discrimination. There is considerable evidence that employer-to-employee discrimination is mostly taste-based.[11] What if it is being miss-classified? What if an employer discriminates against his out-race workers because he rationally believes/anticipates being discriminated against by them? In that case, the employer-to- employee discrimination ought to be characterized as statistical. Within the confines of our environment, our finding that workers do not discriminate against their out-race employers essentially shuts down any rational expectation of bias an employer may have. Incorrect beliefs may persist, though (Bohren et al., 2019).

Our research is related to an emerging literature in economics studying discrimination by subordinates (Abel, 2019; Ayalew, Manian, & Sheth, 2018; Chakraborty & Serra, 2019; Grossman, Eckel, Komai, & Zhan, 2019). This literature focuses on gender as group identity and mostly finds belief-based discrimination against female leaders. Another study on Amazon's Mechanical Turk by Abel (2019) finds that workers do not discriminate in effort choices when they work for women leaders, even though the feedback from them is perceived as being less pleasant than from a male leader. Ours is the first to investigate the possibility of race-based discrimination by subordinates in the U.S. Evidence from Benson, Board, and Meyer-ter Vehn (2019) suggests that workers' performance is influenced by the social identity of their boss. They chalk it to the fact that bosses can better screen applicants from their own race. Our study shuts down this "selection effect" and yet finds no evidence of race-based discrimination by workers. Our result, along with that in Abel (2019), reaffirms our conclusion that worker-to-boss discrimination is less likely to elicit itself in a gig economy.

The rest of the paper proceeds as follows. In Section 2, we present the model of behavior and produce the treatments to identify the parameters of interest. In Section 3, we present the experiment

[11] Indeed, 97% of the papers on discrimination against disadvantaged groups published in top economics outlets find significant evidence for it (Bohren, Haggag, Imas, & Pope, 2019; Lane, 2016). A caveat: though, none of this research looks at the worker-to-boss discrimination angle.

design. Section 4 summarizes the data. In Section 5, we present the results followed by structural estimation in Section 6; concluding remarks are in Section 7.

2 Model and Treatments

In this section, we present the model of behavior that is used to design the experiment. The model explains a worker's effort choice given the monetary and non-monetary incentives and costs of working for an employer. Our design is inspired by DellaVigna et al. (2016) modified to permit discrimination from the workers' side. In the setup, workers choose how much effort to provide on a real-effort task.

A risk-neutral worker, working for an employer j, $j \in \{Neutral, Black, White\}$, receives utility[12]

$$U_j \equiv (\ F + (s + \rho_j \mathbb{1}_{Gift} + \alpha_j v + p)e_j - c(e_j)). \tag{1}$$

Here, e_j is the number of points (on the button-pressing task) scored by the worker when working for an employer j, F is the fixed participation fee he receives , and s captures a sense of duty, norm, intrinsic motivation, and competitiveness of the worker towards the task and is independent of the employer. ρ_j is the reciprocity parameter per unit of effort which is activated whenever employer j awards a gift to the worker à la Gneezy and List (2006). $\mathbb{1}_{Gift}$ is an indicator function which assumes a value 1 when a gift is rewarded by the employer, 0 otherwise. α_j captures the altruistic preference of a worker towards employer j per unit of effort à la Becker (1974), where v is the (race independent and exogenous) value to the employer of a unit of effort by the worker. Note that our notion of altruism captures "pure altruism" as well as "warm glow" of the workers (DellaVigna et al. (2016)): we don't aim to disentangle the two. p is the piece rate per unit of effort. $c(e_j)$ is the cost of effort function, assumed, for now, to be the same for all workers. We assume the regularity conditions $c'(.) > 0$, $c''(.) > 0$, and $lim_{e \to \infty} c'(e) = \infty$. The upshot is that effort is costly but helps generate both a) a private benefit (via, *F*, *s* and *p*) that would appeal to *Homo economicus*, and b) a part (via α and ρ) that would appeal to *Homo behavioralis*.

Following DellaVigna and Pope (2018) and DellaVigna et al. (2016), we analyze the optimality conditions assuming two different functional forms for the cost of effort function : a power function and an exponential function i.e.,

$$c(e) = \frac{ke^{1+\gamma}}{1+\gamma}, \tag{2}$$

and

$$c(e) = \frac{kexp^{\gamma e}}{\gamma} \tag{3}$$

[12]We assume risk neutrality because the stakes are too small for the curvature of the preferences to matter. It also leaves us with one less parameter to estimate.

The power cost function (2) characterizes a constant elasticity of effort with respect to return to effort given by $1/\gamma$, while the exponential function (3) represents decreasing elasticity of effort with respect to return to effort given by $1/log(r/k)$, where r is the return to the effort. Workers' effort at different piece rates can be used to identify and structurally estimate both parameters of the cost-of-effort functions, namely, k and γ.

A worker solves the problem, $\underset{e_j \geq 0}{max}\, U_j$. The interior solution is characterized by:

$$e_j^\star = c'^{-1}\left(s + \rho_j \mathbb{1}_{Gift} + \alpha_j v + p\right) \tag{4}$$

which, for the power cost function, yields :

$$e_j^\star = \left(\frac{s + \rho_j \mathbb{1}_{Gift} + \alpha_j v + p}{k}\right)^{1/\gamma},$$

and

$$e_j^\star = \frac{1}{\gamma} ln\left(\frac{s + \rho_j \mathbb{1}_{Gift} + \alpha_j v + p}{k}\right)$$

for the exponential form.

We start by making the simplifying assumption that workers are homogeneous given a treatment i.e., they will make the same effort choice as any other worker assigned to the same treatment. We later relax this assumption to account for heterogeneity in effort within a treatment. Our goal is to identify the parameters of the model just described. To that end, we design our treatments by varying the incentives and behavioral motivators for the workers.

2.1 Piece Rate Treatments

Here, all else same, each worker works on a task at a given piece rate of either 0, 3, 6 or 9 cents per unit of effort (calibrated to 100 points scored on the task). The piece rates generate income in addition to the $1 fixed participation fee, *F*. By M-Turk standards, this amount of variation in piece rates is substantial enough to elicit significant changes in effort thereby allowing us to estimate the baseline parameters (s, k, and γ) which, in turn, are used to estimate other behavioral parameters.

Formally, in the piece rate treatments, a worker observes a piece rate p and then chooses effort e_j. There is no corresponding employer j present in these treatments. This shuts down altruism and reciprocity right away: for any worker, $\alpha_j = 0$ and $\mathbb{1}_{Gift} = 0$. The equilibrium efforts $e_j^\star$ in these treatments is thus given as:

$$e_p^\star = c'^{-1}\left(s + p\right) \text{ for } p \in \{0, 3, 6, 9\}$$

The solution of effort has one behavioral unknown (s), and two unknowns from the cost function (k

and γ). To back these out, we use effort corresponding to three different piece rates which gives us three equations to identify these parameters.

2.2 Altruism Treatments

In the altruism treatments, each worker is matched (see below for details) to an employer (truthfully) and he/she observes the (true) value of his/her effort to the matched employer. Specifically, each participant knows that an employer earns 1 cent for every 100 points scored by the matched worker. So as to not contaminate social preference with individual benefit, we set the piece rate to 0 in the three altruism treatments. In the first treatment (altruism baseline) a worker knows he/she has been matched to an employer but does not observe the employer's identity. In the 'altruism black' and 'altruism white' treatments, the worker observes the matched employer to be black and white, respectively.

Formally, in the altruism treatments, a worker observes the zero piece rate ($p = 0$), the value of the unit of effort to the employer j ($v = 0.01$), and then chooses effort e_j by maximizing (1). There is no gift from the employer implying $\mathbb{1}_{Gift} = 0$. The equilibrium efforts $e_j^\star$ in these treatments is, thus, given as:

$$e_j^\star = c'^{-1}\left(s + \alpha_j v\right) \text{ for } j \in \{Neutral, Black, White\}.$$

We are implicitly assuming that the altruism parameter can vary by the employer's group identity. For instance, $\alpha_{White} > \alpha_{Black}$ ($\alpha_{White} < \alpha_{Black}$) represents stronger (weaker) altruistic feelings for white as opposed to black employers. (As will be clear soon, all the workers in our sample are white which means α_j represents the strength of altruism a white worker feels for the jth employer.) Notice, since the piece rate is held fixed at 0 and reciprocity is shut out, the difference in effort provision between the 'altruism white' and 'altruism black' treatments is indentifiable as resulting solely from the employer-race-dependent altruistic preferences of the workers. The three altruism treatments help us identify $\alpha_{Neutral}$, α_{Black}, and α_{White}, given the baseline parameters.

2.3 Reciprocity Treatments

Reciprocity treatments build on the altruism treatments and add a positive monetary gift (20 cents) from the employer to the worker. The remaining details are exactly the same as in altruism treatments. Thus, the equilibrium effort is given as;

$$e_j^\star = c'^{-1}\left(s + \alpha_j v + \rho_j\right) \text{ for } j \in \{Neutral, Black, White\}$$

As above, we are implicitly assuming that the reciprocity parameter may be different for each employer's group identity. In other words, controlling for the differences in altruism, the difference in effort between the treatments 'reciprocity white' and 'reciprocity black' is interpreted as resulting solely from the differential reciprocity preferences of the workers. The three reciprocity treatments help us identify $\rho_{Neutral}$, ρ_{Black}, and ρ_{White} given the baseline and altruism parameters.

3 Experiment Design

The main goal of this study is to investigate the possibility of discrimination by workers towards their out-group employers in an online labor market. Our variable of choice is effort provision and the margin of choice is intensive. Our experiment is designed to ensure that observed differences in effort provision can only realize because of the race-dependent social preferences of workers. That is, if we detect any discrimination, it will be entirely driven by taste parameters; after all, we rule out the possibility of statistical discrimination by making it clear that employers will not get to make any payoff-relevant (or otherwise) choices after workers have finished working on the task.

3.1 Task

We need a task that is costly, effort-wise, to workers but is not meaningful in any way to a particular race. The task must require no special ability either. We settled on a button-pressing task as in DellaVigna and Pope (2018). The task involves alternating presses of "a" and "b" on a keyboard for 10 minutes. We chose it because it is simple to understand and has features that parallel clerical jobs: it involves repetition, it gets tiring (and boring), and therefore tests the motivation of the workers to stick to it and bring benefits to himself or his employer.

3.2 Race Revelation

We take the approach of revealing race via the revelation of skin color (Doleac & Stein, 2013). To that end, we record videos of employers in otherwise-identical scenarios as they read off a script explaining and demonstrating the task. The camera placement only captures the hand of the employer along with the movement of the fingers alternating 'a' and 'b' button presses. Other identifiers, such as the face, are not captured in the video to avoid psychological confounds often associated with faces, such as attractiveness and trustworthiness (Eckel & Petrie, 2011). The employer's hand is bare or covered (with full sleeves and latex gloves) depending on the assigned treatment. For black employers, we restrict the sample to participants with darker skin tone to avoid any ambiguity about the race of the person. We mute the voice for the videos in the neutral treatments. We program each video to play with subtitles to aid easier understanding of the instructions. The sample video links for each treatment are given in Table 1.

3.3 Experiment Flow

The experiment proceeds as follows: (1) First, we recruit employers, students from a major public university in the U.S. Midwest and record videos of them explaining the task, 2) next, we post a HIT on Amazon's Mechanical Turk inviting M-Turkers to take a screener survey , (3) we invite those who meet the recruitment criteria (undisclosed) and consent to participate to initiate the experiment, (4) upon initiation, we assign each subject to one of the aforediscussed treatment groups. Following Czibor, Jimenez-Gomez, and List (2019), we use the blocked randomization design to assign subjects to treatments. We define blocks based on demographic information collected in the screener survey (Gender, Age, Race, Education, Income, Political Party Affiliation, and the Most-Lived U.S. state),[13] Next, (5) we present instructions to each subject in a pre-recorded video (based on the assigned treatment). We program our study to *require* each worker to watch the assigned video. Finally, (6) we elicit incentivised beliefs from each worker about their matched employer,[14,15] and 7) workers start to work on the task for a maximum of 10-minutes.

3.3.1 Piece Rate Treatments

In the piece rate treatments, each worker sees a video demonstrating a task with a script: "*On the next page, you will play a simple button-pressing task. The object of the task is to alternately press the 'a' and 'b' buttons on your keyboard as quickly as possible for ten minutes. Every time you successfully press the 'a' and then the 'b' button, you will receive a point. Note that points will only be rewarded when you alternate button pushes: just pressing the 'a' or 'b' button without alternating between the two will not result in points. Buttons must be pressed by hand only (key-bindings or automated button-pushing programs/scripts cannot be used), or task will not be approved. Feel free to score as many points as you can.*" The final line is tailored to the assigned treatment (0, 3, 6 or 9 cents). The wording is provided in Table 1. Even though piece rates are framed in units of 100 points, workers are paid continuously for each point scored and are able to see the earned bonus in real time as they score points.

3.3.2 Social Preference Treatments

In the altruism and reciprocity treatments, each video starts with the introduction by the employer: "*Hi, I am another participant in this study who is matched to you. In this study, you will work on a*

[13] See Cavaille (2018) for instructions on implementing sequential blocked randomization for online experiments.

[14] The elicitation of beliefs *before* workers start work on the task serves two purposes: 1) it provides us with data on workers' beliefs about the identity of their employer, and 2) it allows for the identity of the employer to become salient to the worker; importantly, it renders prominence to the seemingly-obvious fact that the worker is indeed matched to a real person whose payoff will be influenced by the worker's choices. We believe prior belief elicitation serves to increase salience of employer identity (and yes, that includes race) but does not amount to targeted priming about race. Bear in mind that workers are not just asked to report their beliefs on race but also about other identities, such as, gender, age, income, and education of the employer.

[15] To discourage random guessing in the belief elicitation part, participants are informed that an incorrect guess will lead to a deduction of 2 cents from their final earnings.

Table 1: Summary of treatments

Category	**Treatment Wording**	**Voice**	**Skin Color**	**Sample Video**
(1)	**(2)**	**(3)**	**(4)**	**(5)**
Piece Rate	Your score will not affect your payment in any way.	Muted	Concealed	Link
	As a bonus, you will be paid an extra 3 cents for every 100 points that you score.	Muted	Concealed	Link
	As a bonus, you will be paid an extra 6 cents for every 100 points that you score.	Muted	Concealed	Link
	As a bonus, you will be paid an extra 9 cents for every 100 points that you score.	Muted	Concealed	Link
Altruism	I will earn 1 cent for every 100 points that you score. Your score will not affect your payment in any way.	Muted	Concealed	Link
	I will earn 1 cent for every 100 points that you score. Your score will not affect your payment in any way.	Black	Black	Link
	I will earn 1 cent for every 100 points that you score. Your score will not affect your payment in any way.	White	White	Link
Reciprocity	I will earn 1 cent for every 100 points that you score. In appreciation to you for performing this task, I have decided to pay you extra 20 cents as a bonus. Your score will not affect your payment in any way.	Muted	Concealed	Link
	I will earn 1 cent for every 100 points that you score. In appreciation to you for performing this task, I have decided to pay you extra 20 cents as a bonus. Your score will not affect your payment in any way.	Black	Black	Link
	I will earn 1 cent for every 100 points that you score. In appreciation to you for performing this task, I have decided to pay you extra 20 cents as a bonus. Your score will not affect your payment in any way.	White	White	Link

Notes: The table list all the treatments in this study. Each piece rate treatment differs just in the last line of the script, uses no audio, and conceals the skin color of the hand. Social preference treatments (altruism and reciprocity) begin with the introduction of the employer (in the first person), explain the task using the same script as in piece rate treatments and then differ only in the last paragraph of the script. Both altruism and reciprocity categories have three treatments, each with black, white, and concealed skin tone of the employer (using gloves). In the social preference treatments of concealed skin tone, the ratio of black and white employers is 1:1.

simple button-pressing task, and I will earn some money depending on how well you do on the task." Thereafter, the script follows the same instructions as in piece rate treatments with the last paragraph being tailored to the social preference treatment in question. The wording is provided in Table 1. There are three treatments each in the category of altruism and reciprocity. Altruism-baseline and reciprocity-baseline conceals the skin color of the employer in the video using latex gloves. The voice in the baseline treatments is also muted so as not to reveal any racial markers present in the voice. We recruit an equal number of black and white employers in the neutral treatments. The videos shown to workers in the altruism black (white), and reciprocity black (white) clearly reveal the black (white) skins of the employers respectively.

3.4 Recruitment of Subjects

3.4.1 Recruitment of Employers

To recruit employers, we invite male student subjects over the age of 18 from a major public university in the U.S. Midwest who racially identify as either African American or Caucasian. We restrict our sample to male and U.S.-based employer-subjects to avoid confounds arising from identity effects of gender and nationality effects. Holding the sample size fixed and restricting it to one social identity give us extra statistical power and thereby ability to draw more credible inferences. We restrict the sample to employer subjects who are either black or white (we exclude Asians and Latinos, for example) because we believe our race-revelation mechanism works best in the context of these two races. When an employer-subject arrived at the lab, they filled out a short demographic survey and was then randomly assigned to one of six social preference treatments. Based on the assigned treatment, subjects read from the script and demonstrate the task on a video. Each subject was paid $5 for participation and an additional variable amount (average of $17.5) depending on their matched worker's performance. Our final sample include six employers in each social preference treatment (in all, 36 employers, 18 blacks and 18 whites).

3.4.2 Recruitment of Workers

We recruit workers from Amazon's Mechanical Turk, a popular crowd-sourcing web-service that allows employers (called requester) to get tasks (called Human Intelligence Tasks (HITs)) executed by employees (called workers) in exchange for a wage (called reward). Mechanical Turk is a widely used platform for research in economics and allows access to a large pool of applicants at an affordable rate.[16]

We post a screener survey as the HIT on M-Turk with the following description "*Fill out this 2-minute screener survey to qualify for a study that starts immediately, take up to 15 minutes, and pays participation bonus $1 with scope to earn extra. You will be required to watch and listen to a video. Do*

[16] See Paolacci, Chandler, and Ipeirotis (2010) and Paolacci and Chandler (2014) for a discussion on demographic characteristics and representation of subjects from M-Turk.

NOT take this study on mobile.". The responses to the screener survey allows us to pick participants that satisfy the criteria listed above. Based on power considerations and a pilot we conducted, we found it difficult to recruit sufficient number of black workers from M-Turk . Perforce, we restrict attention to white workers and study their effort choices for black versus white employers. We paid 15-cents to each potential subject for filling out the screener survey. On average, the workers in our sample earned $1.72 (including $0.15 for the screener survey, $1.0 for participation, and upto $0.1 for belief elicitation questions).

3.5 Pre-registration

We pre-registered the design on AEA RCT registry as AEARCTR-0003885. Since our task is the same as used in DellaVigna and Pope (2018), we can use results from their study to determine the sample size needed to achieve sufficient power for our study. DellaVigna and Pope (2018) find that the points scored across all treatments have a standard deviation of around 660 . Assuming this standard deviation for each treatment and assuming a minimum detectable effect of 0.2 standard deviations between two treatments, we needed around 400 subjects in each treatment to have a power of 80 percent. This implies that we needed 400 x 10 = 4,000 observations in total for all ten treatments. We pre-registered the rule for sample size collection: we aimed to recruit 6,000 worker-subjects from M-Turk within the first three weeks of posting the experiment. Our data collection went slower than anticipated, and we ended up recruiting subjects from August 5th, 2019 to October 24th, 2019. In our registration, we had also planned to recruit self-identified black workers, which as explained above, did not work out.

4 Data

4.1 Employers

The demographic characteristics of the employer subjects in each treatment are presented in Table B1.

4.1.1 Pre-Testing of Videos

To verify whether the videos accurately reveal race , we test them using an independent sample of U.S.-based, white subjects from Academic Prolific, a data collection platform. We used them instead of M-Turk to ensure that our M-Turk recruits could not have watched these videos before they participate in our experiment. Each subject was asked to identify the race of the person in a randomly-assigned video. See Figure 1 for a graphical representation of average perception of race across treatments. Overall, race is correctly perceived more than 80 percent of the time for all the race-salient treatments: – our race revelation mechanism works. For the race-neutral treatments, only less than 30 percent of the participants could guess the rac, probably the result of random guessing. The pairwise

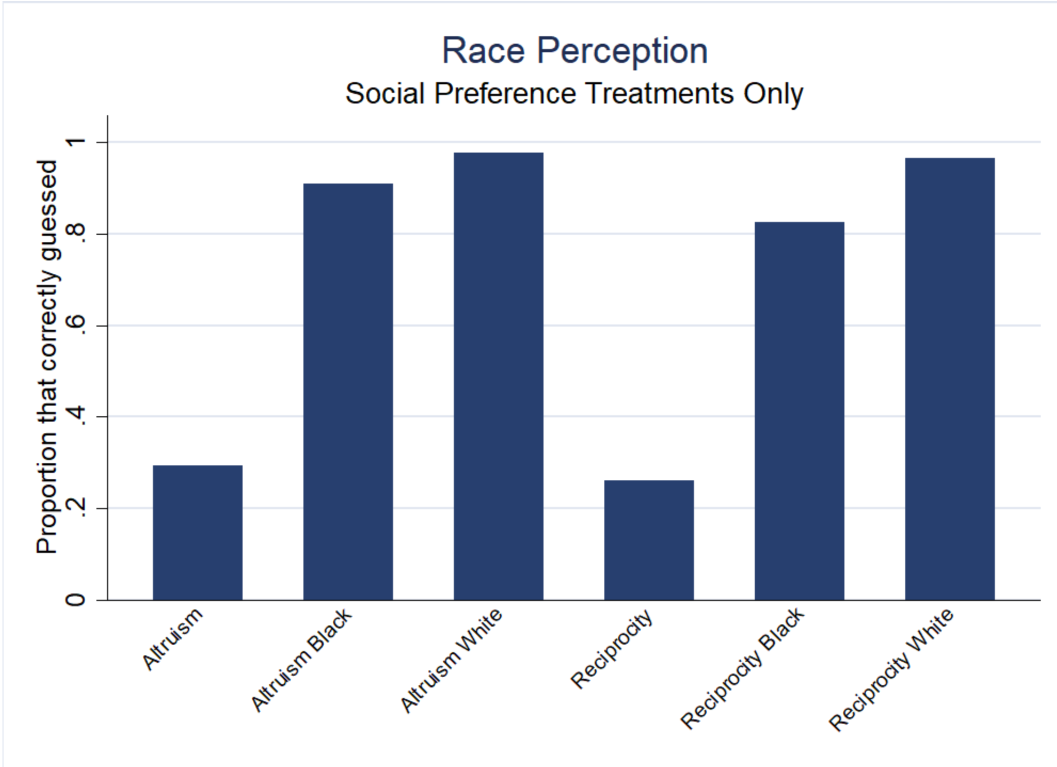


Figure 1: Race Perception

Notes: This figure shows the proportion of individuals who were able to correctly guess the race of the employer after watching a video.

comparisons of race perception among these treatments is presented in Table B2. The results suggest that the race-neutral treatments (altruism and reciprocity) are statistically indistinguishable from each other and significantly different from race-salient treatments. The perception of race in the treatments 'Altruism Black' and 'Altruism White' is statistically indistinguishable; however 'Reciprocity Black' is not perceived as accurately as 'Reciprocity White'.

Participants also evaluated the videos in race-salient treatments for perception of skin color; the results are presented in Figure 2. Overall, blacks' skin is correctly perceived to be of darker tone and whites' of lighter tone. The pairwise comparisons of skin color perception among these treatments is presented in Table B2. The results suggest black treatments are statistically indistinguishable from each other and are significantly different from white treatments.

Finally, to check whether subjects in the videos were not perceived differently on soft personality traits such as friendliness, professionalism, clarity etc., we get these videos rated on those traits. The results for positive and negative traits are presented in Figure A1 and A2 of the Appendix A respectively. Pairwise comparisons of means across all the social-preference treatments suggest only the reciprocity-black treatment is perceived to be significantly higher on positive traits while all other treatments are statistically indistinguishable from each other on both positive and negative traits (see Table B3 of the

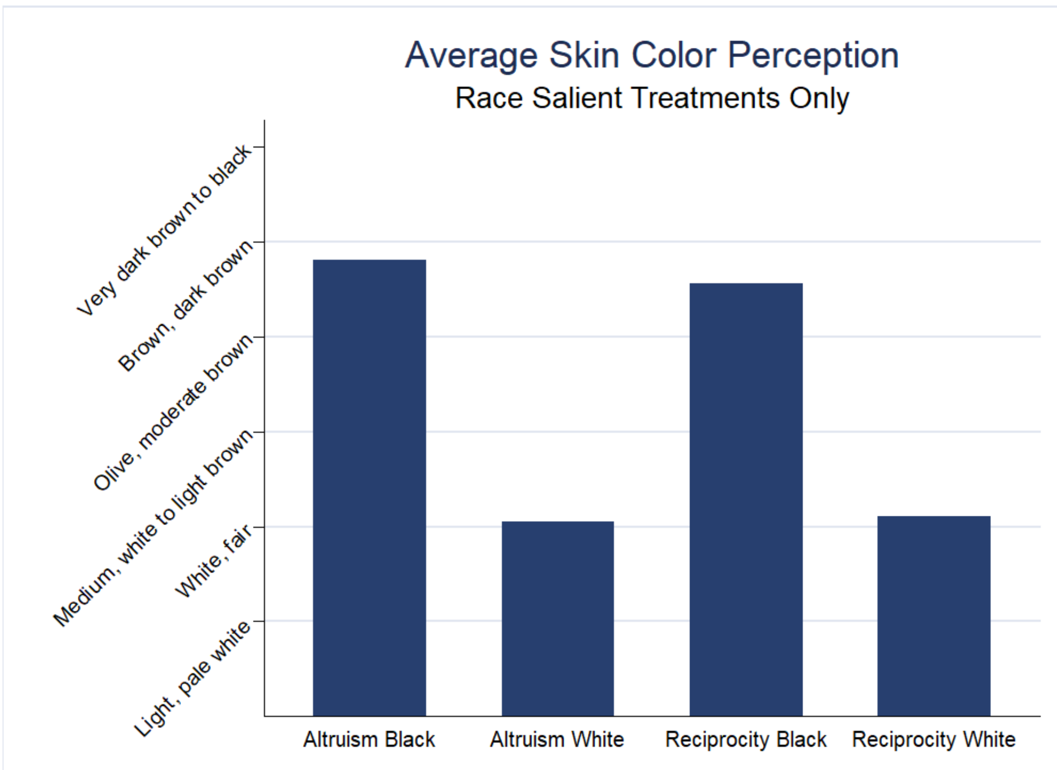


Figure 2: Skin Color Perception

Notes: This figure shows the average perceived skin tone accross the race salient treatments.

Appendix B).

4.2 Workers

As per the pre-registration, we apply the following restrictions to the collected data: (1) we drop 17 participants who scored above 4,000 points as this is physically impossible in the 10- minute time-frame – likely, these users used some automated programs to score points;[17], 2) we drop 64 workers who scored zero points as this may reflect some malfunction or technical problem in the recording of points;[18] (3) we drop 4 observations of workers who participate more than once;[19] (4) we dropped two observations from workers who somehow managed to take this study from outside the United States.[20]

The final sample consists of 5,945 workers and the summary statistics are presented in Table 2. Our sample over represents women, young, educated, middle-income, and Democrats as compared to the U.S. labor force. This is typical of the population on online platforms. We present results of productivity by demographics in Table B10. Overall in our sample, men and younger workers are more productive than women and older workers respectively. We present test-of-balance of demographic variables across ten treatments in Table B4 of the the Appendix B. The treatments are balanced on all the observed variables, no surprise since we use blocked randomization to assign subjects to treatments. Since worker characteristics are balanced across treatments, there is no reason to believe that more/less productive workers are assigned to any specific treatment.

5 Results

We present average effort by workers (recall, all our workers are white) against each treatment in column 1 of Table 3 and in Figure 3. Overall, it is evident that incentives have a strong effect on effort, raising performance from 1627 points (piece rate of 0) to 2060 points (3-cent piece rate) and 2127 points (9-cent piece rate).[21] The standard error for the mean effort per treatment is around 30 points or less, implying that differences across treatments larger than 85 points are statistically significant.

How do we detect altruism? We compute the average effort of workers in the altruism-neutral treatment; recall, these are workers who know they are matched to an employer but don't know his race. We compare that to the average effort of workers who are not matched to any employer and are offered a 0-cent piece rate. We find statistically significant evidence for altruism: workers put more effort in the altruism-neutral treatment as compared to the piece rate 0-cent treatment. The one

[17] We instructed each worker up-front to not use any automated scripts/programs .

[18] These workers are spread across all treatments, and there is no systematic difference in workers scoring zero points for any particular treatment or employer.

[19] A worker can participate in our study only once; these exceptions must be an error on the part of M-Turk.

[20] The study was restricted to U.S.-based workers. Presumably, these participants used a proxy server or VPN to mask their origin but we could spot them from the GPS coordinates recorded by Qualtrics.

[21] Workers' positive effort in the 0-cent treatment is explained by the parameter s of the model in Section 2. Part of the positive effort could also be workers' unsubstantiated fear of being rejected for not scoring enough points.

Table 2: Summary Statistics, Worker Sample

	(1) Sample	(2) US Labor Force
Gender		
Female	0.58	0.47
Male	0.41	0.53
Race		
White or Caucasian	1.00	0.78
Age		
18-24	0.12	0.11
25-30	0.38	0.14
31-40	0.26	0.22
41-50	0.14	0.21
51-64	0.08	0.25
65 and over	0.03	0.06
Education		
Less than high school	0.01	0.14
High school or equivalent	0.13	0.39
Some college	0.28	0.35
College graduate	0.41	0.30
Graduate or professional degree	0.18	0.18
Income		
Less than $20,000	0.17	0.20
$20,000 - $44,999	0.31	0.26
$45,000 - $99,999	0.38	0.33
$100,000 - $149,999	0.09	0.12
$150,000+	0.03	0.08
Political Affiliation		
Democrat	0.39	0.31
Independent	0.28	0.38
Republican	0.27	0.29
Most lived US State		
Blue	0.31	0.47
Red	0.20	0.14
Swing	0.49	0.39
Observations	5945	162075000

Notes: The table presents demographic information of worker subjects. Column (1) presents proportion of the worker subjects by their gender, race, age, education, income, party, and the most lived state in the United States. Column (2) presents these demographics for US labor force based on 2018 numbers from Bureau of Labor Statistics/Current Population Survey. Estimates of population by political affiliation and by blue, red, and swing state are based on Gallup polling survey 2019.

Table 3: Effort by Treatment

	(1) All Workers		(2) Correctly Perceived Race	
	N	Mean (s.e)	N	Mean (s.e)
Piece Rate - 0 cents	599	1627.07	599	1627.07
		(28.56)		(28.56)
Piece Rate - 3 cents	595	2059.83	595	2059.83
		(24.19)		(24.19)
Piece Rate - 6 cents	592	2046.68	592	2046.68
		(23.62)		(23.62)
Piece Rate - 9 cents	588	2127.37	588	2127.37
		(23.01)		(23.01)
Altruism - Neutral	591	1746.06	261	1724.87
		(29.15)		(43.70)
Altruism - Black	601	1798.37	494	1807.68
		(27.55)		(29.58)
Altruism - White	592	1708.09	557	1715.24
		(28.90)		(29.52)
Reciprocity - Neutral	608	1771.15	265	1766.99
		(27.95)		(41.63)
Reciprocity - Black	590	1803.61	470	1818.78
		(26.95)		(29.73)
Reciprocity - White	589	1798.23	561	1803.75
		(29.58)		(30.33)
Total	5945	1848.08	4982	1865.98
		(8.80)		(9.49)

Notes: The table presents the effort choices in each treatment. Column 1 reports the effort choices by all the workers, column 2 reports the effort choices by workers who were able to correctly perceive the race of the employer as neutral, black or white in social preference treatments.

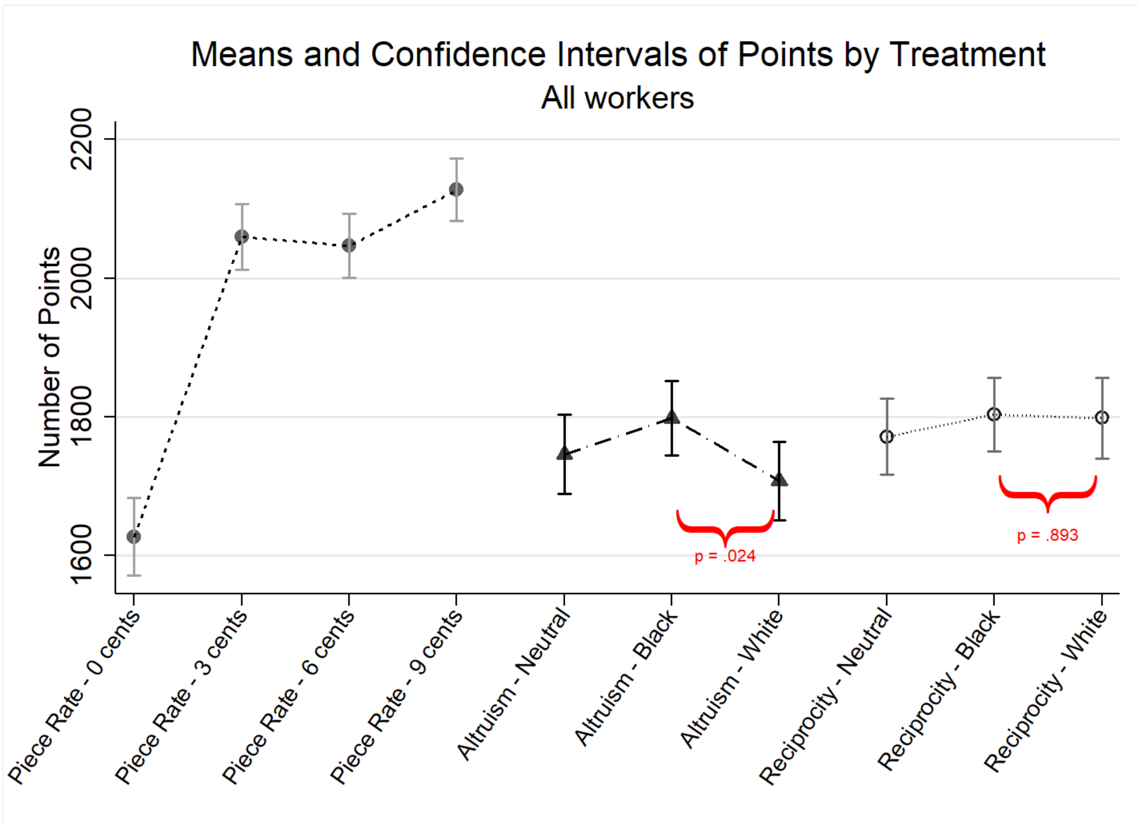


Figure 3: Effort by Treatment - All Workers

Notes: This figure presents the average score and confidence interval for each of ten treatments for all workers. Each treatment has about 590 participants.

cent return to the employer induces an effort of 1746 points as compared to 1627 points in the 0-cent treatment.

Next, we wish to compare the strength of the altruism preference across black and white employers. To that end, we compute the average effort of workers in the altruism-black treatment to those in the altruism-white treatment. Strikingly, workers are significantly more altruistic towards black employers than white employers. The average effort for black employers is 1798 points, which is significantly higher ($p = 0.024$) than the same for white employers (1708 points). However, note that in the altruism treatments, average effort forany race employer is not significantly different from the same for a race-neutral employer .

In the reciprocity treatments, the worker receives an unanticipated gift of 20-cents (in addition to all other earnings) from the employer, unconditional on performance. This gift does not induce a significant increase in effort as compared to the altruism treatment (1771 points in the reciprocity-neutral treatment as compared to 1746 points in the altruism-neutral treatment). The reciprocal response to the employer's racial identity is also insignificant, implying that, on average, workers do not reciprocate towards any employer race. This result is consistent with the literature which finds weak evidence for positive reciprocity (such as Kube, Maréchal, and Puppe (2006)).

In column 2 of Table 3, we restrict the analysis to only workers who could correctly guess the race of the employer in the social preference treatments. This does not substantially affect the direction or magnitude of the results.

Although our treatments are balanced on observed worker and employer characteristics, for robustness sake we present the regression results from regressing "Points" scored on the employer racial identity and controlling for these variables in the Table 4. We observe that workers' pro-altruistic response for black employers stays significant even after controlling for the demographic variables. Controlling for employer fixed effects makes the altruism effect larger in magnitude, but is no longer statistically significant presumably because of lower power to detect the effect size (via loss in degrees of freedom).[22] The reciprocity response stays statistically indifferent from zero for all the specifications.

We also test (do not report) whether the altruistic response toward black employers is driven by the workers' beliefs about the income of their employers. For example, it is conceivable white workers are inequity averse and believe they ought to work harder to generate more income for blacks who they perceive to have low income. If that is the case, then any observed positive altruism towards black employers would , in fact, capture positive altruism towards the low-income group. However, since we do not observe differential beliefs about the income of black and white employers, we are certain the higher altruistic response towards blacks is most likely not driven by differential beliefs about the income of the employers.[23]

[22]The employer fixed effect controls for the personality traits of the employer which may have had an effect on a worker's effort choice.

[23]It is important to note that we allow for only two perceptions about income (greater than $45k and less than $45k per year). Also, any variation in beliefs about income may be pure noise, given that nothing other than skin color is observable .

Table 4: Social Preference Treatments - Robustness

	Altruism			Reciprocity		
	(1)	(2)	(3)	(4)	(5)	(6)
White or Caucasian	-90.28*	-84.51*	-124.1	-5.379	-1.803	-70.48
	(39.92)	(40.77)	(99.48)	(40.01)	(40.89)	(102.3)
Constant	1798.4***	1822.5***	1709.2***	1803.6***	1772.0***	1753.7***
	(28.12)	(294.0)	(302.1)	(28.28)	(289.2)	(300.0)
Demographic Controls	No	Yes	Yes	No	Yes	Yes
Employer Fixed Effects	No	No	Yes	No	No	Yes
Observations	1193	1138	1138	1179	1126	1126

Notes: The table presents the estimates from an OLS regression of Points in the race salient social preference treatments on the employer's race. The omitted category is the Black employer. Demographic controls include age, gender, education, income, political affiliation and the voting pattern of the most lived state (red, blue, or swing) of the worker. There are total of 12 employer fixed effects for each of altruism and reciprocity treatments. Standard errors in parentheses. for p < 0.05, ** for p < 0.01, and *** for p< 0.001*

5.1 Distribution of Effort

Beyond average effort, we present the distribution of effort from all the treatments in Figure A3 of the Appendix A and by each treatment in Figure A4 of the Appendix A. Overall, very few workers score below 500 points and even fewer score above 3000 points.

Figure 4a presents the cumulative distribution function for the piece rate treatments. Incentives induce a clear rightward shift in effort relative to the 0-cent treatment. However, there is not much change in effort between the 3-cent and the 6-cent treatments. Figure 4b shows strong evidence for altruistic preferences as observed by the clear rightward shift of the effort distribution in the altruism treatment as compared to the 0-cent treatment. The effort distribution in the reciprocity treatment is indistinguishable from the altruism treatment, implying a lack of reciprocal preferences. Figure 4c shows that altruism is stronger towards blacks as compared to whites while the cumulative density function is indistinguishable for reciprocity-black and reciprocity-white treatments. Quantile regression estimates for effort (not tabulated) show that black employers get higher effort than white employers at each quantile for the altruism treatments. This shows that the altruistic response for the black employers is coming from the *entire* effort distribution and not just from one particular part. On the other hand, there is no difference between black and white employers for the reciprocity treatments at any quantile.

5.2 Evolution of Effort

We present the evolution of effort over the 10-minute period in Figure 5. Figure 5b shows that, in the social preference treatments, effort declines over time presumably due to boredom and tiredness. And yet, interestingly,the piece rate treatments are able to sustain consistently higher effort throughout the

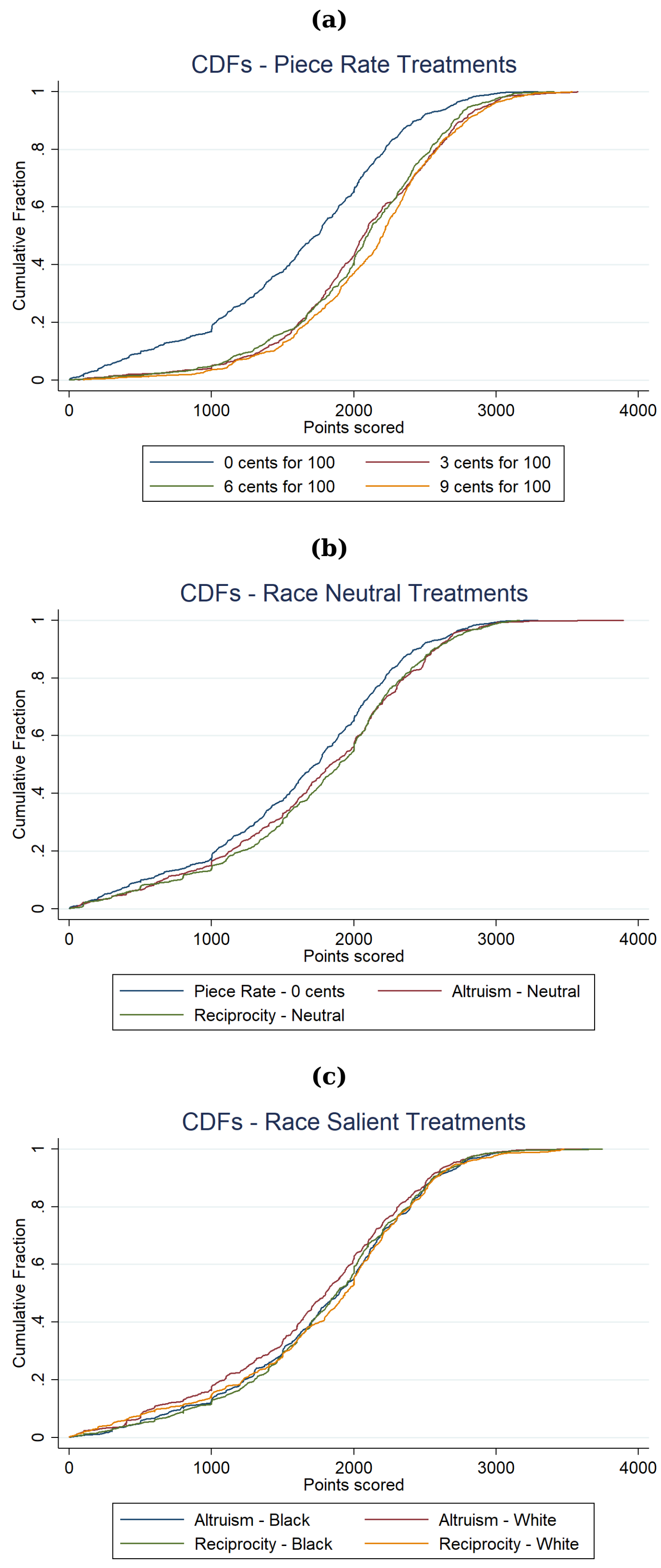


Figure 4: Cumulative distribution function

Notes: The figure presents the cumulative distribution function of points for the workers in each of the treatments featured. The sample size in each treatment is approximately 590 subjects. Figure a features the four piece rate treatments (no piece rate, 3-cent per 100 points, 6 cents per 100 points, and 9 cents per 100 points). Figure b presents the results for the race-neutral treatments. Figure c presents the results for the race-salient treatments.

entire time interval (Figure 5a), with workers in the 9-cent treatment pushing extra hard near the end.

5.3 Heterogeneity

5.3.1 Heterogeneity by Demographics

To examine the heterogeneity in our average treatment effects based on demographic characteristics of the sample, we present the conditional average treatment effects in Table B5 and B6 of the Appendix B for altruism treatments and in Table B7 and B8 of the Appendix B for reciprocity treatments. Overall, we do not find evidence of heterogeneity on the basis of gender, age, education, income, and state voting pattern for both altruism and reciprocity treatments. However, we do find evidence for heterogeneity in altruism on the basis of party affiliation:Republicans and Independents exert significantly more effort than Democrats for black employers relative to white employers, indicating the presence of pro-black, altruistic preferences among Republicans and Independents as compared to Democrats.

5.3.2 Heterogeneity by the share of black population in the neighborhood

Following Andreoni, Payne, Smith, and Karp (2016), we explore the effects of local racial composition on social preferences of the workers in our sample. We condition on the zip code level racial composition of the worker and examine the difference in effort provided to black versus white employers. Figure 6 presents the conditional average treatment effects for each decile of the share of black population for workers who correctly perceived the employer race. Overall, the difference in effort provided to the black versus white employers is statically zero at each level of black share of population.

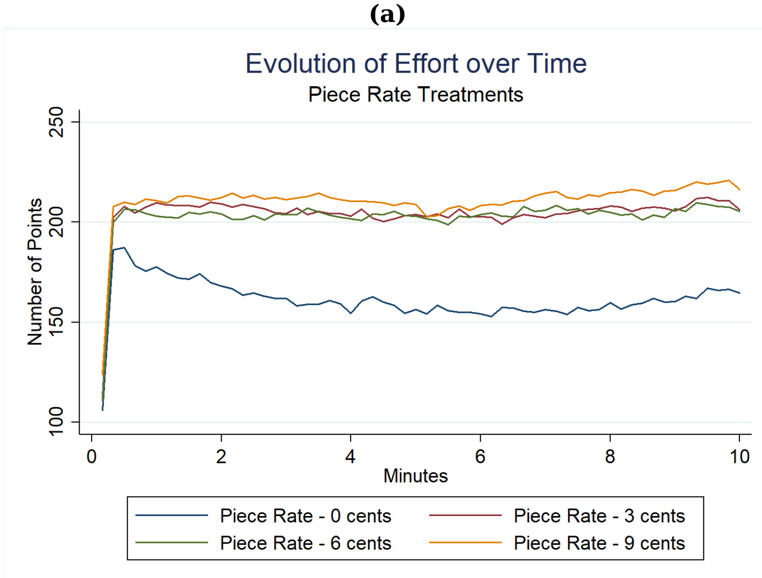
5.3.3 Heterogeneity by Geographical Area

It is a well established fact that racial disparities are not equally distributed across the U.S. We present the summary of workers performance by their geographical area in Table 5. Interestingly, there is a weak evidence in favor of workers from South being relatively more pro-social to black employers. This is surprising given that the average implicit bias against blacks (see next subsection) in the South is higher than in the other regions of the U.S.

5.3.4 Heterogeneity by Implicit Biases

We examine the heterogeneity in treatment effects based on the implicit biases of workers as measured by the implicit association test (IAT). IATs are widely used in social psychology to measure implicit and unconscious biases towards a particular group. The test involves categorizing two sets of words to the left or right hand side of the computer screen. Implicit bias is measured by a time difference in associating good or bad words to the relevant group identities. The idea is that making a response is easier when closely related items share categorization to the same side of the screen. In case of race

(a)



(b)

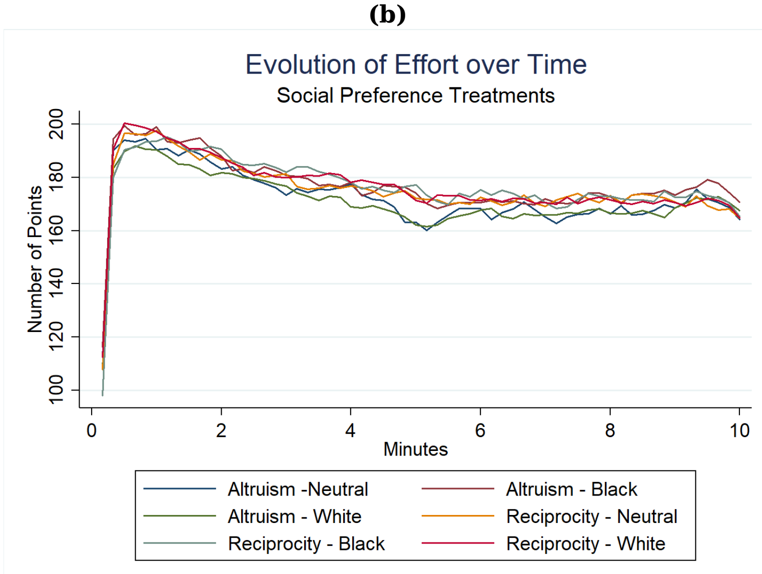
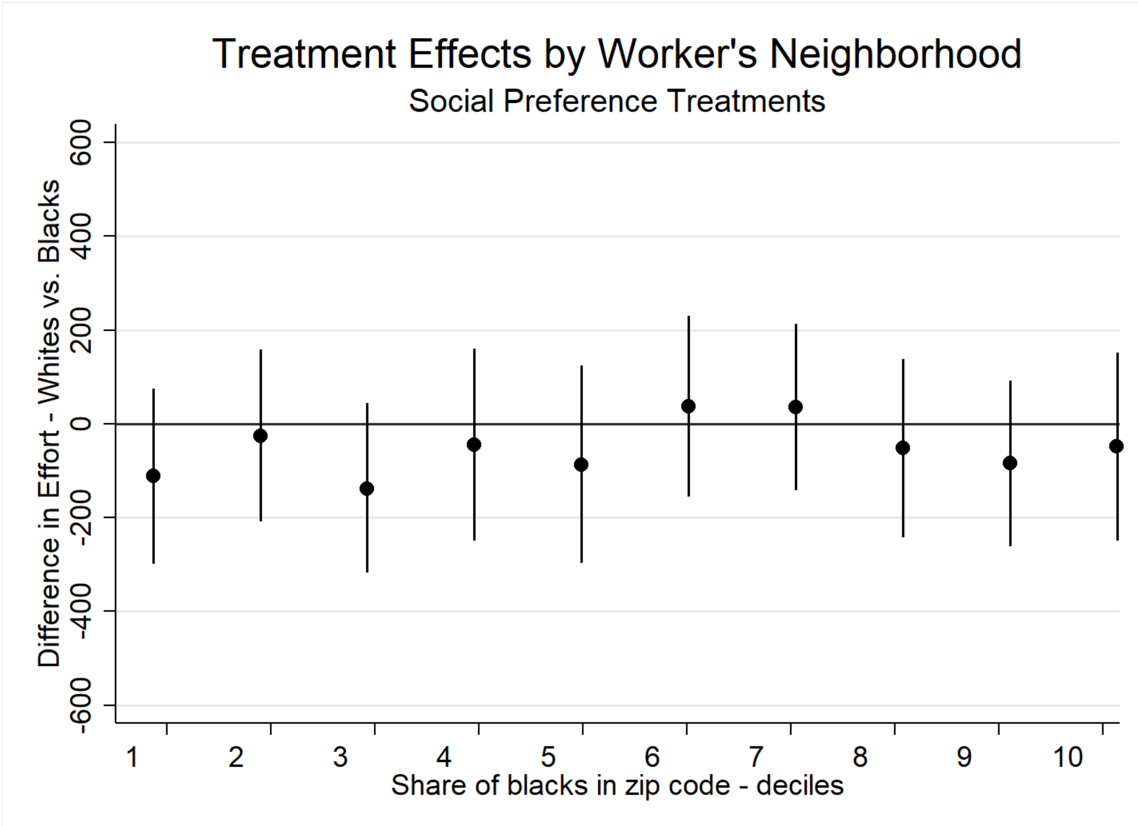


Figure 5: Evolution of effort over time

Notes: This figure presents the effort over time for selected treatments. The y axis indicates the average number of points scored in that treatment per minute.

Figure 6: Treatment effects by local racial composition



Notes: The figure presents the conditional average treatment effects (conditioned on the share of blacks in a zip code). The x-axis represents deciles of the share of black population in a zip code. Measure of conditional treatment effect is obtained by pooling data from race salient social preference treatments of workers who could correctly perceive the employer race and running a regression of Points on Employer Race for each decile of the black share. The cutoff values of the deciles are 0, 0.009, 0.018, 0.03, 0.045, 0.065, 0.094, 0.137, 0.207, and 0.351.

Table 5: Heterogeneity by Geographical Area

	Regions			
	(1)	(2)	(3)	(4)
	North East	Mid West	South	West
White or Caucasian	-34.55	-36.83	-72.28	-31.67
	(72.20)	(57.17)	(48.99)	(73.74)
Constant	3083.1	1634.6	1366.0	1630.7
	(737.4)	(390.5)	(333.7)	(438.9)
Demographic Controls	Yes	Yes	Yes	Yes
Observations	377	529	771	405

Notes: The table presents the conditional average treatment effect by the geographical location of the worker. Measure of conditional treatment effect is obtained by pooling data from race salient social preference treatments of workers who could correctly perceive the employer race and running a regression of Points on Employer Race for each geographical region. Standard errors in parenthesis.

IAT, we would say that one has an implicit preference for white people relative to black people if they are faster to categorize words when white face and good words (friend, glorious, enjoy, joyous, terrific, beautiful, magnificent, and fabulous) share a response key and black faces and bad words (detest, poison, nasty, disgust, pain, despise, sadness, evil) share a response key, relative to the reverse.

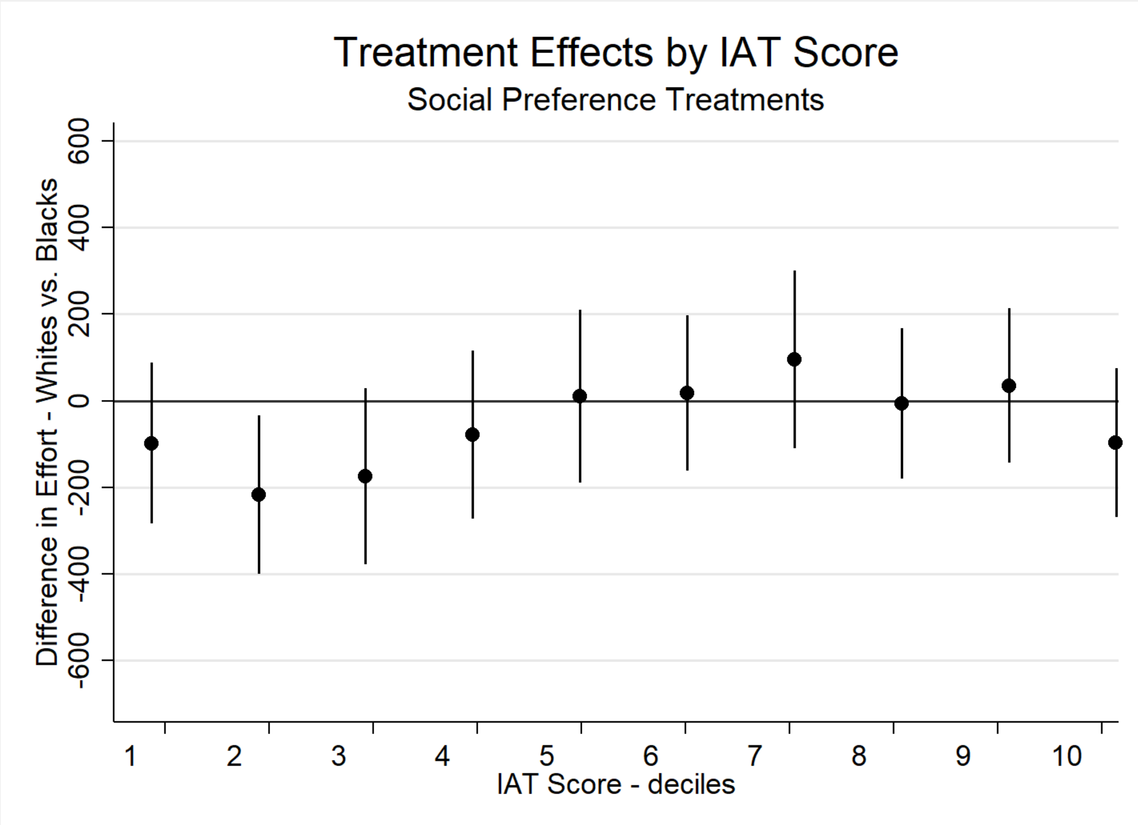
For this study, we did not conduct IAT test for individual workers. Instead we proxy the IAT score of individual worker by using the geo-coded race IAT data by Project Implicit, which provides historical record of tests taken on the project's website. These tests can be taken by anyone from anywhere in the world. For our purpose, we restrict to white individuals from the United States and use the data from more than two million test takers between 2006 to 2018. We map the county level (lowest available resolution) IAT score to workers in our sample based on the worker's geographic location. Our worker sample comes from 190 counties spanning all 50 states in the U.S.

Typical thresholds found in the literature (Greenwald, Nosek, & Banaji, 2003; Hahn, Judd, Hirsh, & Blair, 2014; Rooth, 2010) are as follows: IAT scores below -0.15 indicate some preference for minorities; scores between -0.15 and 0.15 indicate little to no bias; scores between 0.15 and 0.35 indicate a slight bias against minorities; and scores above 0.35 show moderate to severe bias against minorities. The average score (standard deviation) of white test takers in our sample is 0.38 (0.42) implying, on average, white people have moderate to severe implicit bias against blacks. Like black share, we explore the effects of local IAT score on the social preferences of workers in our sample. We condition on the county level IAT score of the worker and examine the difference in effort provided for black versus white employers. Figure 7 presents the conditional average treatment effects for each decile of the IAT score for workers who could correctly perceive the employer race. Overall, there is some indication that workers with relatively low implicit bias exhibit higher social preference towards the black employers as compared to white employers. However, at relatively higher level of implicit biases, the difference in effort is statistically zero. Restricting to two quantiles of IAT score clearly shows (Table 6) that black employers get significantly higher effort than white employers in the lower quantile (lower implicit bias), while there is no difference in effort provision for black and white employers in the upper quantile (higher implicit bias).

6 Estimates of Behavioral Parameters

We designed our experiment to go with the structural model outlined in Section 2. The advantage of designing field experiments on the basis of a model of behavior is that it allows researchers to estimate the nuisance parameters in the environment that are relevant to decision making (DellaVigna, 2018). Because of the simplicity of our task, there are only three nuisance parameters we need to estimate. We use data from the piece rate treatments to identify these parameters. Subsequently, we estimate the deeper behavioral parameters of interest using data from the social preference treatments. We

Figure 7: CATE by IAT deciles



Notes: The figure presents the conditional average treatment effects (conditioned on the IAT score of the worker's county). The x-axis represents deciles of the IAT score at county level. Measure of treatment effect is obtained by pooling data from race salient social preference treatments of workers who could perceive the employer race correctly and running a regression of Points on Employer Race for each decile of the IAT score. The cutoff values of the deciles are 0.295, 0.349, 0.376, 0.381, 0.386, 0.396, 0.404, 0.413, 0.415, and 0.444.

Table 6: CATE by IAT Quantiles - Bottom and Top

	Implicit Bias of Worker's County	
	(1)	(2)
	Lower Implicit Bias	Higher Implicit Bias
White or Caucasian	-120.0**	28.84
	(43.83)	(41.11)
Constant	1372.3***	2043.4***
	(280.0)	(301.4)
Demographic Controls	Yes	Yes
Observations	1057	1010

Notes: The table presents the conditional average treatment effect by the bottom and top quantile of the IAT score of the worker's county. Measure of conditional treatment effect is obtained by pooling data from race salient social preference treatments of workers who could correctly perceive the employer race and running a regression of Points on Employer Race for bottom (column 1) and top (column 2) quantile of IAT score. Standard errors in parenthesis.

closely follow the estimation procedure in DellaVigna and Pope (2018) .

6.1 Minimum-Distance Estimation

We first use minimum-distance estimation method to estimate these parameters. In minimum distance estimation, one identifies the set of moments in the data (average effort) and then finds the set of model parameters that minimizes the distance between the empirical moments and the theory-predicted moments. To estimate nuisance parameters, we use the average effort corresponding to the three piece rates (0 cents, 3 cents and 9 cents), to estimate γ, s, and k. Specifically, in the case of the power cost function, to estimate nuisance parameters, we use first moments from the piece rate treatments and solve the following equations

$$\bar{e}_p = \frac{1}{\gamma}\left[log(s+p) - log(k)\right] \text{ for } p \in \{0, 0.03, 0.09\}$$

where $\bar{e}_p$ is the average effort in the piece rate p treatment. These parameters estimates are used to draw the marginal cost and marginal benefit curve in Figure 8.

Once these parameters are estimated, we use average effort corresponding to altruism neutral, altruism black and altruism white treatment to estimate behavioral parameters $\alpha_{Neutral}$, α_{Black}, and α_{White} respectively. Specifically, for the power cost function, we solve the following equations for α_j for $j \in \{Neutral, Black, White\}$ taking estimates of γ, s, and k as given

$$log(\bar{e}_{\alpha_j}) = \frac{1}{\gamma}\left[log(s+\alpha_j v) - log(k)\right] \text{ for } j \in \{Neutral, Black, White\}$$

where $\bar{e}_{\alpha_j}$ is the average effort in the altruism j treatment.

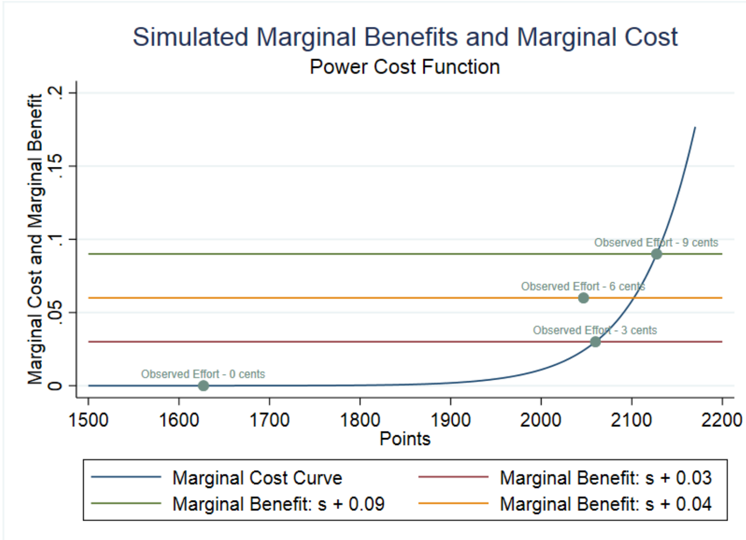
Similarly, to calculate reciprocity parameters for neutral ($\rho_{Neutral}$), black (ρ_{Black}) and white (ρ_{White}) employers, we use average effort from reciprocity neutral, reciprocity black, and reciprocity white treatments and solve the following equations taking estimates of γ, s, k, and α_j for $j \in \{Neutral, Black, White\}$ as given:

$$log(\bar{e}_{\rho_j}) = \frac{1}{\gamma}\left[log(s+\rho_j+\alpha_j v) - log(k)\right] \text{ for } j \in \{Neutral, Black, White\}$$

where $\bar{e}_{\rho_j}$ is the average effort in the reciprocity j treatment.

Estimates using the exponential cost function are similarly calculated. Table 7 presents the parameter estimates for power cost function (column 1) and exponential cost function (column 3). The standard errors for these parameter estimates are estimated using a bootstrap procedure with a thousand draws.

Figure 8: Illustration of the Model: Marginal Benefits and Cost Curves



Notes: The figure presents the marginal benefit and marginal cost curves using minimum-distance estimates for the power cost function.

6.2 Non-Linear Least Squares Estimation

The minimum distance estimator solely relies on the moment, and hence, does not use all the variation in the data. There are methods such as maximum likelihood and non-linear least squares that can be used to estimate these parameters using all the variation present in the data. We use non-linear least square method to estimate these parameters allowing for the heterogeneous cost of effort. Allowing for a heterogeneous marginal cost of effort in 1, we assume for a worker i, for a power cost case, $c(e_{ij}) = \frac{ke_{ij}^{1+\gamma}}{1+\gamma} exp(-\gamma\epsilon_{ij})$ with $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$. The first order condition 4 can then be written as;

$$s + 1_{Gift}\rho_j + \alpha_j v + p - ke_{ij}^{\gamma} exp(-\gamma\epsilon_{ij}) = 0$$

Taking the last term to the right and taking logs, we obtain

$$log(s + 1_{Gift}\rho_j + \alpha_j v + p) + \epsilon_{ij} = log(k) + \gamma log(e_{ij}) - \gamma\epsilon_{ij}$$

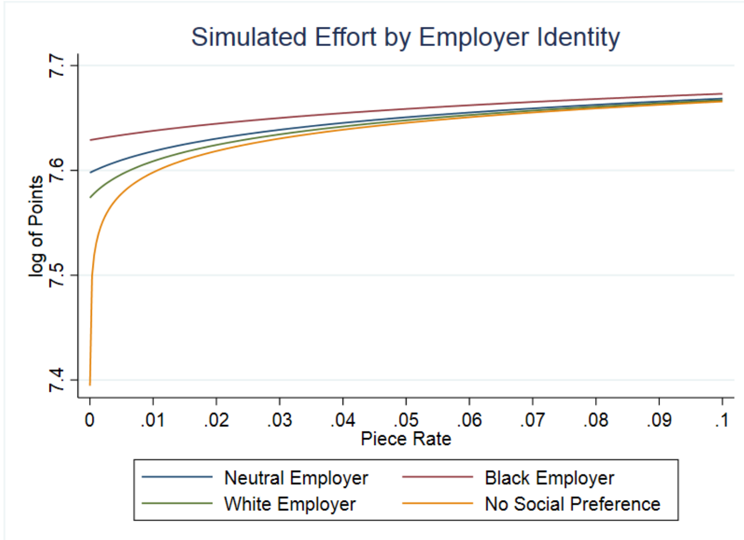
Solving for $log(e_{ij})$, we obtain the estimating equation

$$log(e_{ij}) = \frac{1}{\gamma}\left[log(s + 1_{Gift}\rho_j + \alpha_j v + p) - log(k)\right] + \epsilon_{ij}. \quad (5)$$

Similarly using exponential cost function, we get

$$e_{ij} = \frac{1}{\gamma}\left[log(s + 1_{Gift}\rho_j + \alpha_j v + p) - log(k)\right] + \epsilon_{ij}. \quad (6)$$

Figure 9: Simulated Effort by Employer Race at Different Piece Rates



Notes: The figure presents the simulated effort using the parameter estimates from table 7 for power cost, minimum distance specification. Neutral/Black/White employer uses the respected social preference parameter estimates to calculate the predicted effort at each piece rate. No Social Preference assumes that altruism and reciprocity estimates are zero.

Equations 5 and 6 can be estimated using non-linear least squares (NLS). Table 7 presents the NLS parameter estimates for power cost function (column 2) and exponential cost function (column 4). The NLS parameter estimates are nearly identical to those computed with minimum-distance estimation for the exponential cost case. The model predictions are also very similar .

The NLS estimates for the power cost function yield a lower curvature than the minimum-distance estimates ($\hat{\gamma}_{NLS} = 20.29$ versus $\hat{\gamma}_{MD} = 34.05$). The NLS model matches expected log effort, while the minimum-distance matches the log of expected effort. Both NLS and minimum-distance fit the in-sample moments and make similar predictions for the 6-cent piece rate treatment.

The parameter estimate for 'altruism black' is significantly higher than 'altruism white' in all the specifications, indicating that white workers have significantly higher altruistic preferences for black employers as compared to white employers. The reciprocity estimates indicate a null effect from the gift for any employer in all the specifications. Even though the parameter values are close to zero, but they translate to meaningful differences in effort provided to black and white employers at the zero piece rate. Figure 9 presents the simulated effort for neutral, black and white employer using parameter estimates along with zero social-preference case. Black employers receive around five percent higher effort than white employers at the zero piece rate. The difference between black and white employers becomes negligible at higher piece rates because workers respond much more to monetary incentives as compared to social preferences.

Table 7: Parameter Estimates

	Power cost of effort		Exponential cost of effort	
	Minimum distance estimator on average effort	NLS on Individual effort	Minimum distance estimator on average effort	NLS on individual effort
	(1)	(2)	(3)	(4)
Baseline Parameters				
Curvature γ of cost of effort function	34.05	20.30	0.0163	0.0163
	(15.9)	(8.85)	(.0207)	(.00807)
Intrinsic motivation s (cents per point)	0.00000977	0.00000802	0.0000264	0.0000264
	(.000246)	(.000032)	(.000389)	(.000101)
Level k of cost of effort function	4.50e-115	2.98e-70	8.58e-17	8.58e-17
	(2.7e-46)	(2.5e-68)	(7.1e-09)	(1.5e-15)
Altruism Parameters				
Altruism α_{Neutral} towards neutral employer	0.00983	0.000426	0.0156	0.0156
	(.00779)	(.0017)	(.0103)	(.0427)
Altruism α_{Black} towards black employer	0.0285	0.000776	0.0402	0.0402
	(.0186)	(.00274)	(.0226)	(.0953)
Altruism α_{White} towards white employer	0.00413	0.000270	0.00722	0.00722
	(.00367)	(.00129)	(.00552)	(.0215)
Reciprocity Parameters				
Reciprocity ρ_{Neutral} towards neutral employer	0.0000676	0.0000272	0.0000921	0.00124
	(.000136)	(.000103)	(.000173)	(.00318)
Reciprocity ρ_{Black} towards black employer	0.0000307	0.0000395	0.0000381	0.00220
	(.000265)	(.00014)	(.000308)	(.00513)
Reciprocity ρ_{White} towards white employer	0.000243	0.0000255	0.000328	0.00200
	(.00021)	(.0001)	(.000257)	(.00477)
Implied effort at 6-cents		expected log effort		
(observed effort 2047, log 7.624)	2102	7.746	2102	2102.4

Notes: This table reports the structural estimates of the model in section 2. Column (1) and (3) use a minimum-distance estimator employing three moments (average effort in three piece rate treatments) and three parameters (γ , s and k), and is thus exactly identified. Column (2) and (4) use a non-linear least squares employing individual effort in all the treatments and thus estimating all the parameters simultaneously. We use power cost (column 1 and 2) and exponential cost (column 3 and 4) function to estimate the model. Implied effort is calculated using estimated parameters for each model. For the altruism parameters, the baseline parameters are taken as given and the average effort for neutral, black, and white employers is used to estimate $\alpha_{Neutral}$, α_{Black}, and α_{White} from the altruism treatments. Similarly for the reciprocity parameters, the baseline and altruism parameters are taken as given and the average effort corresponding to reciprocity neutral, reciprocity black, and reciprocity white is used to estimate $\rho_{Neutral}$, ρ_{Black}, and ρ_{White}. Standard errors for minimum-distance estimator are calculated by taking a bootstrap sample of 1000 draws and recalculating these parameters for each draw.

7 Conclusion

Economic historians record a time in US labor history when white workers openly militated against receiving orders from (or working under) black supervisors. Things have changed. “[W]hile overt racism was implicated in the past, it is behavioral differences that lie at the root of racial inequality in contemporary America” (Loury, 1998). What are these behavioral differences? Now that overt racism is either deemed illegal or too difficult to practice openly, have white workers stopped discriminating against black employers? This paper uses insights from behavioral and experimental economics to shed light on this enduring issue in American labor markets. The narrower question we ask is, do workers with a considerable degree of discretion over work effort display differential, race-dependent social preferences toward their out-race employers?

The experimental setting is an online labor market - Amazon’s Mechanical Turk (M-Turk). In this gig economy, workers and employers are at arms length and the worker is involved in a real-effort task for a pre-assigned, non-fictitious, black or white employer. The possibility of race-dependent social preferences is activated by unobtrusively revealing the employer’s race to the matched worker. We detect statistically significant evidence for altruism: workers put more effort when they know their work benefits the employer (altruism neutral treatment) as compared to a treatment where neither the worker nor the employer benefits from worker effort. Most importantly, white workers are significantly more altruistic towards black employers than white employers. Importantly, this result is not driven by beliefs white workers have for the income status of their black employers. Not only is this finding statistically significant at the 2% level, the difference in effort provision is economically powerful as well. There is suggestive evidence that the higher effort towards black employers is driven by workers with relatively low implicit bias against blacks.

Our results suggest that preference-based discrimination against minorities may dampen as traditional labor markets get replaced with gig economy ones. Indeed, our results are roughly in line with a new body of research that finds a general erosion of racially-motivated discrimination in hiring in U.S. labor markets. Lahey and Oxley (2018) finds while “younger white applicants are preferred to younger black applicants, this preference diminishes with age as white applicants become less attractive and black applicants become more attractive. Indeed, we find no preference for white compared to black applicants in their 50s, and black applicants are even preferred in some specifications.”

That is not to say that racial discrimination is disappearing or will soon, nor do we suggest that pro-social behavior of whites towards blacks is omnipresent. Indeed, the pro-sociality may vanish in settings where employer-worker engagement is longer and involves physical interaction. Likewise, we recognize that unlike the current focus on the intensive margin of worker effort, understanding social preferences on the extensive margin may be equally important; after all, it is possible workers from the dominant group may systematically select out of (not even apply for) jobs posted by disadvantaged-group employers, thereby limiting the labor resources at the disposal of said employers. In short, if workers are given agency in who they work for, they may well avoid out-race employers. We aim to study the extensive margin angle to worker-to-employer discrimination in future research. Our work also does not suggest that asking whether workers differentially treat their out-race bosses in traditional labor markets is not interesting. Far from it. The questions we ask, could in principle, be asked in the sort of field setting studied in Breza, Kaur, and Shamdasani (2017) where the researchers set up their own factory workshops in Odisha, India to employ 378 workers full-time for one month in seasonal manufacturing jobs. We leave this to future research.

We recognize that we do not offer a clear answer to the question, what explains the pro-social behavior of white workers towards black employers? That question deserves full attention and it will in our future work. We present some evidence to knock down some explanations such as "it is driven entirely by the beliefs whites have about black incomes and the fact that whites are inequity averse". Another explanation that is sometimes offered – social desirability bias: people want to appear as nice (non-racist) to the experimenter which is why they put more effort for black employers. For one, the identity of the experimenters was never made salient to the subjects. Second, in order for a white subject to put more effort for black relative to white employers because of his social desirability bias, he must know what the experimenter deems as appropriate levels of effort toward black and white employers. Also bear in mind that the game ends after the worker has finished the task. Subsequent to that, there is no possibility of communication (and everyone knows this ex ante) between the employer and the worker implying the worker could not be motivated by a desire to signal anything to the employer. In particular, given the one-shot nature of the encounter, even if the worker has an innate preference to be well regarded by the other race, there is no possibility for the other race to react to that preference.

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A Miscellaneous Figures

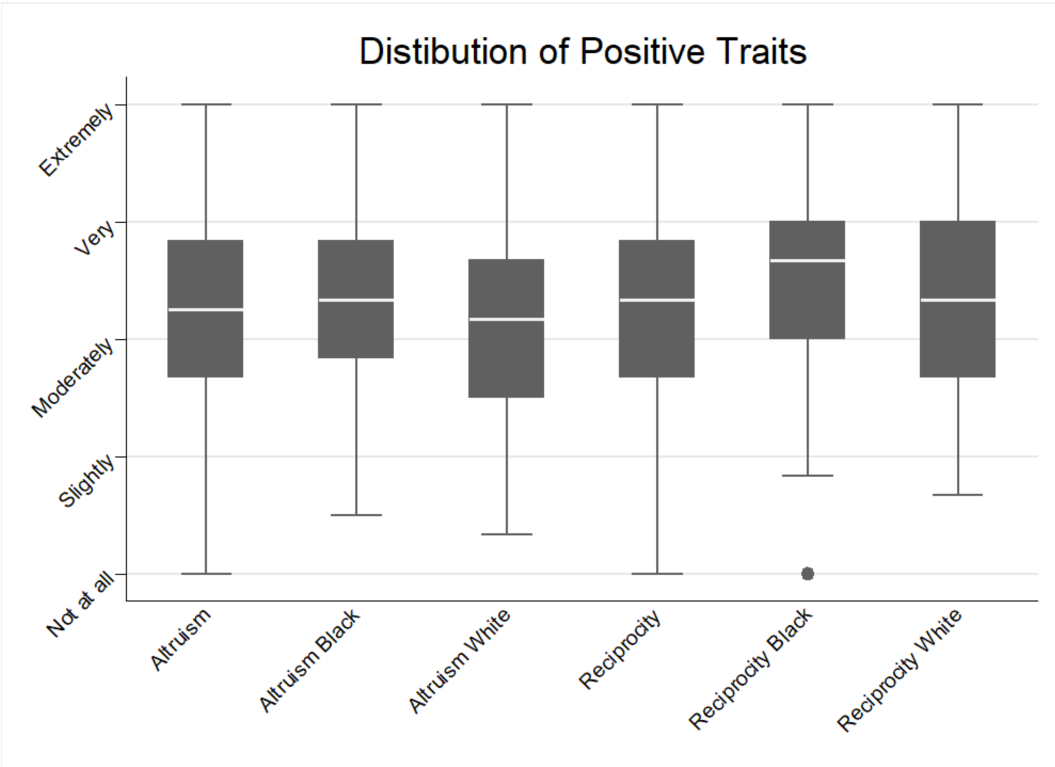

Figure A1: Perception of Positive Personality Traits

Notes: This figure presents the box-plot of average of positive traits as rated by the evaluators. After the evaluators watched the video they were asked "Please rate the following characteristics about the the person in the above video". The positive traits were friendliness, confidence, encouragement, trustfulness, clarity, and motivation .

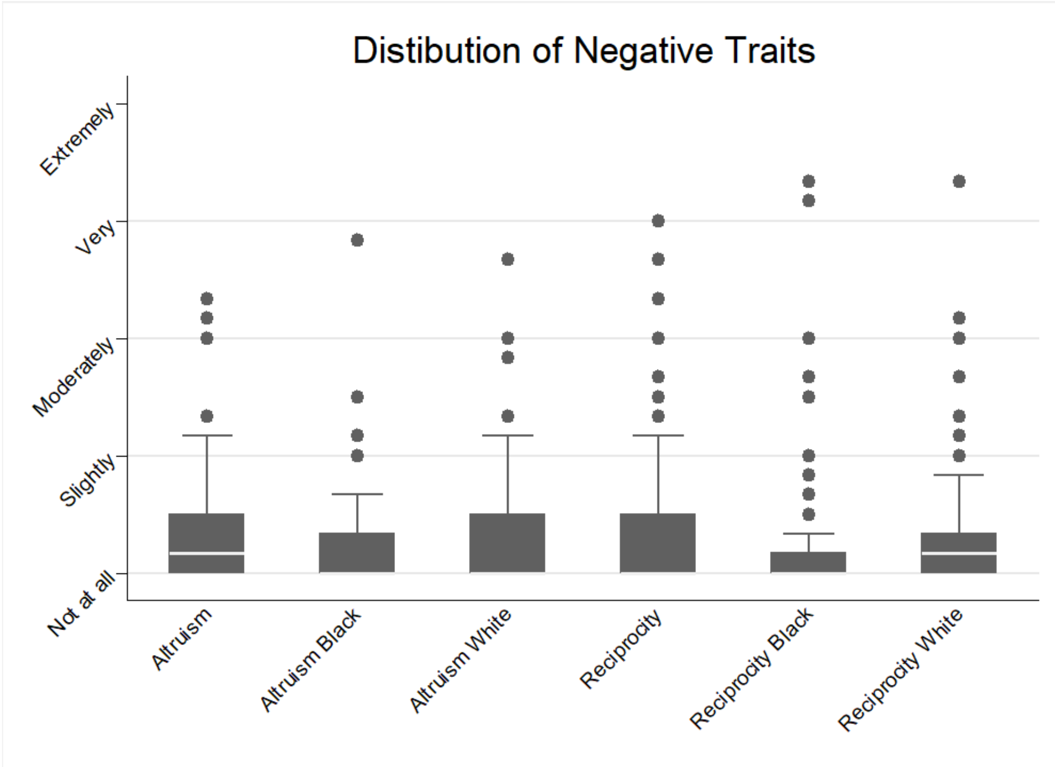

Figure A2: Perception of Negative Personality Traits

Notes: This figure presents the box-plot of average rating of negative traits by the evaluators. After the evaluators watched the video they were asked "Please rate the following characteristics about the person in the above video". The negative traits were arrogance, laziness, bossinesss, rudeness, hostility, and undermining.

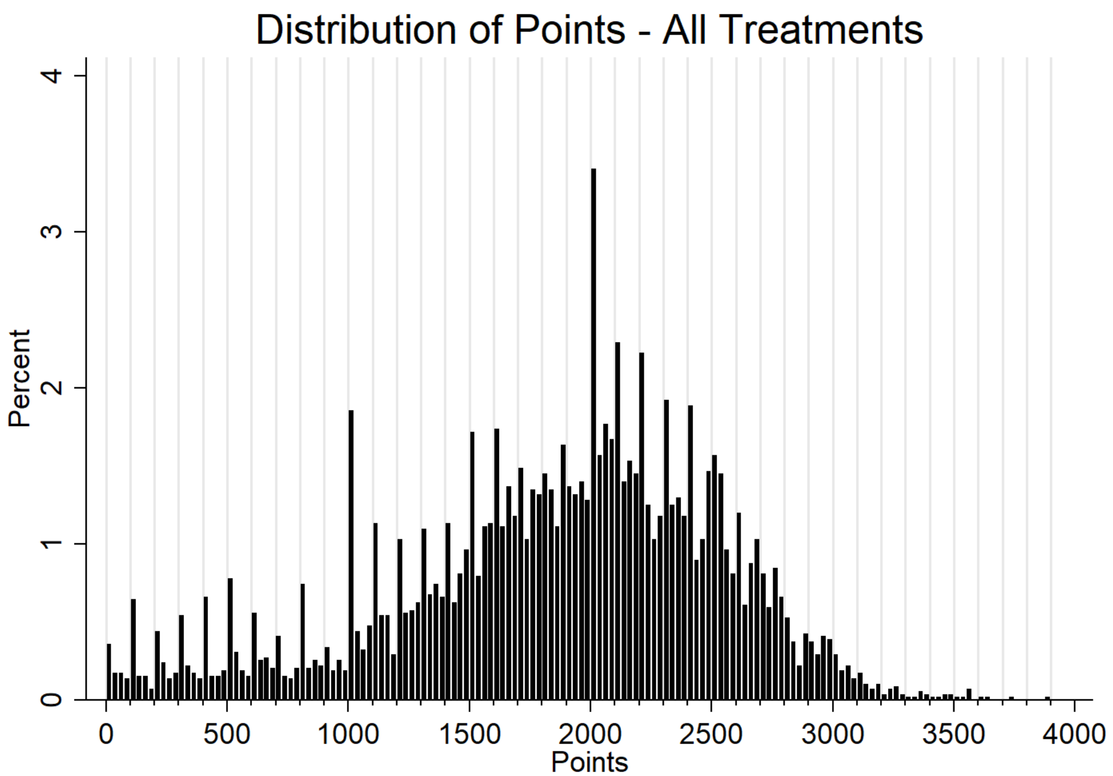

Figure A3: Distribution of effort

Notes: This figure plots a histogram of the observed points over all 10 treatments.

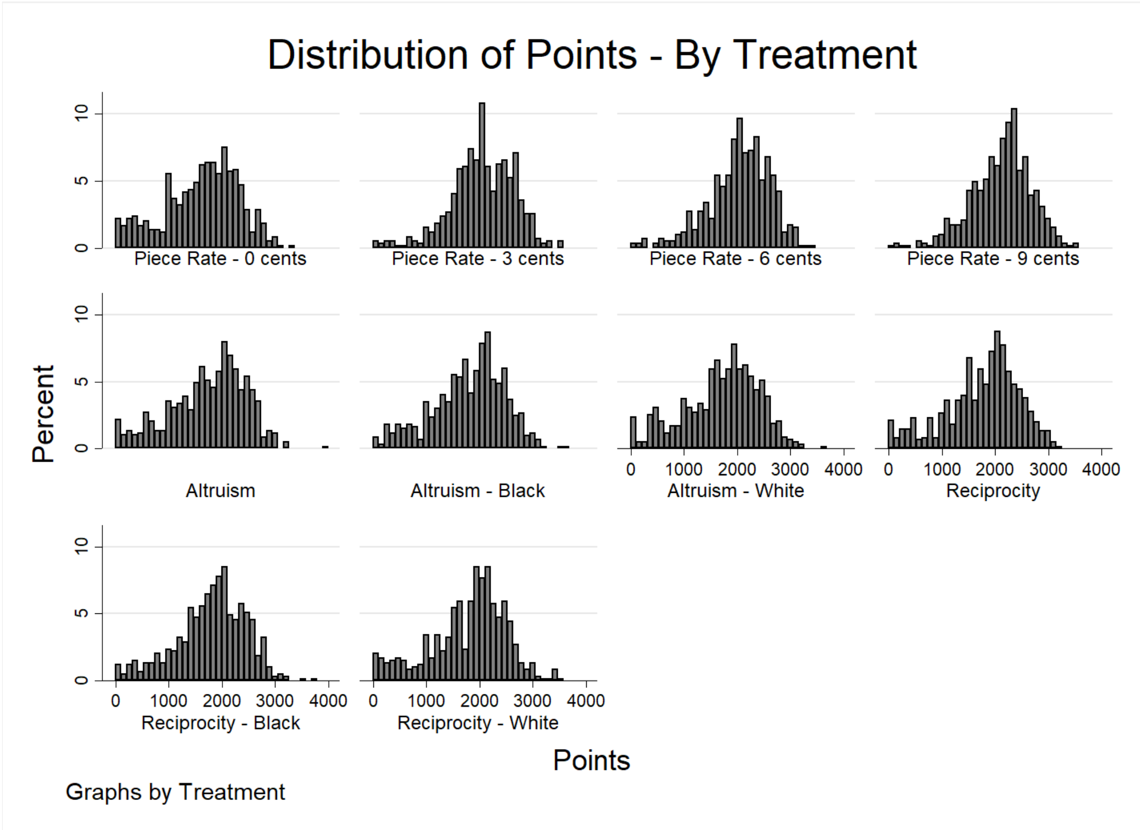

Figure A4: Distribution of effort by Treatment

Notes: This figure plots a histogram of the observed points by each of the 10 treatments.

B Miscellaneous Tables

Table B1: Demographic Information of Employer Subjects

	(1) All Subjects	(2) Blacks	(3) Whites
Gender			
Male	1.00	1.00	1.00
Female	0.00	0.00	0.00
Race			
Black or African American	0.50	1.00	0.00
White or Caucasian	0.50	0.00	1.00
Age			
18-24	0.78	0.61	0.94
25-34	0.14	0.22	0.06
35-44	0.06	0.11	0.00
45-54	0.03	0.06	0.00
Education			
High school or equivalent	0.06	0.00	0.11
Some college	0.64	0.50	0.78
College graduate	0.19	0.28	0.11
Master's degree	0.08	0.17	0.00
Doctoral degree	0.03	0.06	0.00
Most lived state			
Blue	0.28	0.22	0.33
Red	0.03	0.06	0.00
Swing	0.69	0.72	0.67
Observations	36	18	18

Notes: The table presents demographic information of employer subjects. Column (1) presents proportion of all the employer subjects by their gender, race, age and education. Column (2) and column (3) presents these information for only black and white employers respectively.

Table B2: Test of Difference of Perception of Race and Skin Color

Panel A: Average Perception of Race

	(1) Race Perception		
	Proportion	SE	Group
Altruism	0.29	(0.03)	1
Altruism Black	0.91	(0.03)	23
Altruism White	0.98	(0.03)	3
Reciprocity	0.26	(0.03)	1
Reciprocity Black	0.83	(0.03)	2
Reciprocity White	0.96	(0.03)	3
Degrees of Freedom	1016		

Panel B: Average Perception of Skin Color

	(1) Skin Color Perception		
	Mean	SE	Group
Altruism Black	4.81	(0.05)	1
Altruism White	2.05	(0.05)	2
Reciprocity Black	4.57	(0.05)	1
Reciprocity White	2.11	(0.05)	2
Degrees of Freedom	667		

Notes: Panel A presents the proportion of subjects who could correctly guess the race of the employer in the video. Panel B presents the average skin color as perceived by the subjects in each treatment. The skin color can vary from 1 to 6 where 1 represents the 'light, pale white' while 6 represents the 'very dark brown to black' skin tone. Proportions sharing a digit in the 'Group' column are not significantly different at the 5% level. The comparisonwise error rate is adjusted using the Bonferroni method.

Table B3: Test of Difference of Personality Traits

	(1) Positive Traits			(2) Negative Traits		
	Mean	SE	Group	Mean	SE	Group
Altruism	3.27	(0.07)	12	1.33	(0.04)	12
Altruism Black	3.33	(0.07)	12	1.19	(0.04)	1
Altruism White	3.15	(0.07)	1	1.30	(0.04)	12
Reciprocity	3.26	(0.07)	12	1.38	(0.04)	2
Reciprocity Black	3.51	(0.07)	2	1.24	(0.04)	12
Reciprocity White	3.28	(0.07)	12	1.28	(0.04)	12
Degrees of Freedom	852			929		

Notes: The table presents the average of perceived positive and negative traits across the social preference treatments. The perception of the trait can vary from 1-Not at all to 5-Extremely. Positive Trait is constructed by taking an average of the ratings on; friendliness, confidence, encouragement, trustfulness, clarity, and motivation . Negative Trait is constructed by taking an average of the ratings on; arrogance, laziness, bossinesss, rudeness, hostility, and undermining. Means sharing a digit in the group label are not significantly different at the 5% level. The comparisonwise error rate is adjusted using the Bonferroni method.

Table B9: Social Preference Treatments - Robustness, Employer Race Correctly Perceived

	Altruism			Reciprocity		
	(1)	(2)	(3)	(4)	(5)	(6)
White or Caucasian	-92.45*	-92.45*	-25.12	-15.02	-5.901	-33.61
	(41.94)	(42.97)	(106.6)	(42.88)	(43.80)	(108.6)
Constant	1807.7***	1703.7***	1487.5***	1818.8***	1788.0***	1739.3***
	(30.53)	(316.5)	(325.1)	(31.63)	(290.1)	(303.7)
Demographic Controls	No	Yes	Yes	No	Yes	Yes
Employer Fixed Effects	No	No	Yes	No	No	Yes
Observations	1051	1000	1000	1031	986	986

Notes: The table presents the estimates from an OLS regression of Points in the race salient social preference treatments on the employer's race for workers who could correctly perceive the race of the employer. The omitted category is the Black employer. Demographic controls include age, gender, education, income, political affiliation and the voting pattern of the most lived state (red, blue, or swing) of the worker. There are total of 12 employer fixed effects for each of altruism and reciprocity treatments. Standard errors in parentheses.

Table B4: Balance Check

	$\chi 2$ (p-value)
Gender	
Female	8.414 (0.493)
Age	
25-30	11.03 (0.273)
31-40	10.98 (0.277)
41-50	14.95 (0.0924)
51-64	11.04 (0.273)
65 and over	10.19 (0.335)
Education	
High school or equivalent	3.744 (0.927)
Some college	2.884 (0.969)
College graduate	3.511 (0.941)
Graduate or professional degree	2.753 (0.973)
Income	
$20,000 - $44,999	6.928 (0.645)
$45,000 - $99,999	10.38 (0.321)
$100,000 - $149,999	10.13 (0.340)
$150,000+	11.01 (0.275)
Most lived US State	
Blue	4.953 (0.838)
Red	9.193 (0.420)
Party	
Democrat	5.939 (0.746)
Republican	12.65 (0.179)
Observations	5945

Notes: The table presents the $\chi 2$ *and corresponding p-values of the likelihood ratio (LR) test of the equality of each coefficient from multinomial-logit regression of Treatment status on the demographic variables.*

Table B5: Heterogeneous Treatment Effects - Altruism Treatments

	(1) Gender	(2) Age	(3) Education
White or Caucasian	-60.32	16.31	-128.2
	(52.19)	(116.6)	(115.2)
Male	154.6**		
	(56.95)		
White or Caucasian × Male	-74.43		
	(80.90)		
Age 25 - 34		35.29	
		(90.83)	
Age 35 - 44		63.93	
		(95.68)	
Age 45 - 54		-23.21	
		(111.1)	
Age 55 - 64		-243.6	
		(129.3)	
Age 65 or older		-46.72	
		(194.5)	
White or Caucasian × Age 25 - 34		-125.9	
		(133.2)	
White or Caucasian × Age 35 - 44		-152.5	
		(140.8)	
White or Caucasian × Age 45 - 54		-96.19	
		(158.2)	
White or Caucasian × Age 55 - 64		46.03	
		(184.5)	
White or Caucasian × Age 65 or older		-275.0	
		(281.4)	
Some college			-130.2
			(95.29)
College graduate			-198.7*
			(87.83)
Graduate or professional degree			-160.0
			(100.2)
White or Caucasian × Some college			127.9
			(139.2)
White or Caucasian × College graduate			3.194
			(129.7)
White or Caucasian × Graduate or professional degree			36.75
			(149.4)
Constant	1735.0***	1790.5***	1946.4***
	(36.82)	(78.53)	(76.77)
Observations	1187	1192	1193

Notes: The table presents the estimates from an OLS regression of Points in the race salient altruism treatments on the employer's race. The omitted employer is the Black employer. Column (1), (2), and (3) test for the heterogeneity in treatment effects by gender, age, and education respectively. The omitted categories for gender, age, and education are female, age between 18 and 24, and high school or less. Standard errors in parentheses.

Table B6: Heterogeneous Treatment Effects - Altruism Treatments

	(1) Income	(2) Political Affiliation	(3) State Voting Pattern
White or Caucasian	26.40	-156.7*	-32.94
	(98.09)	(71.10)	(72.13)
Income \$20,000 - \$44,999	31.32		
	(85.53)		
Income \$45,000 - \$99,999	42.77		
	(83.30)		
Income \$100,000 - \$149,999	1.883		
	(119.2)		
Income \$150,000+	86.45		
	(177.0)		
White or Caucasian × Income \$20,000 - \$44,999	-185.3		
	(121.3)		
White or Caucasian × Income \$45,000 - \$99,999	-110.1		
	(117.6)		
White or Caucasian × Income \$100,000 - \$149,999	-33.72		
	(165.7)		
White or Caucasian × Income \$150,000+	-190.2		
	(250.1)		
Democrat		-109.3	
		(66.71)	
Republican		31.42	
		(73.48)	
White or Caucasian × Democrat		168.2	
		(95.54)	
White or Caucasian × Republican		-14.72	
		(104.3)	
Red			144.9
			(82.31)
Swing			76.50
			(64.10)
White or Caucasian × Red			-212.3
			(115.3)
White or Caucasian × Swing			-31.55
			(91.68)
Constant	1763.5***	1830.7***	1732.9***
	(69.71)	(49.26)	(50.37)
Observations	1167	1171	1193

Notes: The table presents the estimates from an OLS regression of Points in the race salient altruism treatments on the employer's race. The omitted employer is the Black employer. Column (1), (2), and (3) test for the heterogeneity in treatment effects by income, political affiliation, and the voting pattern of the most lived state (red, blue, or swing) of the worker, respectively. The omitted categories for income, political affiliation, and state voting pattern are less than \$20,000, democrat, and blue state. Standard errors in parentheses.

Table B7: Heterogeneous Treatment Effects - Reciprocity Treatments

	(1) Gender	(2) Age	(3) Education
White or Caucasian	42.95	-0.996	58.85
	(52.94)	(112.1)	(113.7)
Male	171.1**		
	(57.27)		
White or Caucasian × Male	-113.1		
	(81.06)		
Age 25 - 34		-100.2	
		(89.40)	
Age 35 - 44		-119.0	
		(95.48)	
Age 45 - 54		-216.9*	
		(109.7)	
Age 55 - 64		-319.6*	
		(131.3)	
Age 65 or older		-520.6**	
		(167.4)	
White or Caucasian × Age 25 - 34		24.34	
		(129.5)	
White or Caucasian × Age 35 - 44		-4.573	
		(136.9)	
White or Caucasian × Age 45 - 54		-63.38	
		(156.9)	
White or Caucasian × Age 55 - 64		-110.6	
		(180.6)	
White or Caucasian × Age 65 or older		303.7	
		(243.0)	
Some college			190.1*
			(93.43)
College graduate			20.81
			(89.36)
Graduate or professional degree			-24.39
			(100.4)
White or Caucasian × Some college			-117.5
			(135.9)
White or Caucasian × College graduate			-63.39
			(129.5)
White or Caucasian × Graduate or professional degree			-42.49
			(149.5)
Constant	1731.1***	1941.5***	1747.4***
	(37.40)	(77.08)	(77.05)
Observations	1170	1176	1178

Notes: The table presents the estimates from an OLS regression of Points in the race salient reciprocity treatments on the employer's race. The omitted employer is the Black employer. Column (1), (2), and (3) test for the heterogeneity in treatment effects by gender, age, and education respectively. The omitted categories for gender, age, and education are female, age between 18 and 24, and high school or less. Standard errors in parentheses.

Table B8: Heterogeneous Treatment Effects - Reciprocity Treatments

	(1) Income	(2) Political Affiliation	(3) State Voting Pattern
White or Caucasian	85.03	49.63	-67.15
	(100.9)	(62.58)	(72.69)
Income \$20,000 - \$44,999	15.20		
	(88.56)		
Income \$45,000 - \$99,999	100.2		
	(86.06)		
Income \$100,000 - \$149,999	98.32		
	(116.9)		
Income \$150,000+	29.43		
	(219.8)		
White or Caucasian × Income \$20,000 - \$44,999	37.44		
	(123.4)		
White or Caucasian × Income \$45,000 - \$99,999	-195.8		
	(119.2)		
White or Caucasian × Income \$100,000 - \$149,999	-325.6		
	(170.2)		
White or Caucasian × Income \$150,000+	-63.35		
	(284.5)		
Independent		134.1*	
		(66.38)	
Republican		76.13	
		(71.70)	
White or Caucasian × Independent		-127.8	
		(94.79)	
White or Caucasian × Republican		-35.17	
		(101.7)	
Red			12.30
			(82.52)
Swing			16.26
			(64.50)
White or Caucasian × Red			89.20
			(117.8)
White or Caucasian × Swing			86.19
			(91.82)
Constant	1752.3***	1729.4***	1793.2***
	(73.27)	(44.43)	(50.53)
Observations	1161	1149	1179

Notes: The table presents the estimates from an OLS regression of Points in the race salient reciprocity treatments on the employer's race. The omitted employer is the Black employer. Column (1), (2), and (3) test for the heterogeneity in treatment effects by income, political affiliation, and the voting pattern of the most lived state (red, blue, or swing) of the worker respectively. The omitted categories for income, political affiliation, and state voting pattern are less than \$20,000, democrat, and blue state. Standard errors in parentheses.

Table B10: Overall Productivity by Demographics

	(1) Points
Gender	
Female	-135.42 (17.77)
Age	
25-30	-26.53 (29.58)
31-40	-83.18 (31.39)
41-50	-126.63 (35.09)
51-64	-257.55 (40.42)
65 and over	-356.25 (58.48)
Education	
Some college	1.78 (29.12)
College graduate	-96.92 (28.06)
Graduate or professional degree	-97.23 (32.92)
Prefer not to answer	-1260.07 (472.82)
Income	
$20,000 - $44,999	33.00 (25.98)
$45,000 - $99,999	40.73 (26.24)
$100,000 - $149,999	84.57 (37.01)
$150,000+	91.32 (54.65)
Party	
Democrat	-60.48 (20.59)
Republican	-25.35 (22.64)
Most lived US State	
Blue	-47.50 (20.02)
Red	-13.10 (23.06)
Constant	2074.68 (38.74)
Observations	5945
R^2	0.034
F	11.68

Notes: The table presents the estimates of an OLS regression of points scored on worker demographics. Standard errors in parentheses.

C Experiment Material

Iowa State University
Department of Economics
Consent for Participation in Research

Title of Study: Decisions in Labor Market
Investigator: Sher Afghan Asad, Ritwik Banerjee, Joydeep Bhattacharya

This brief screener is a part of a research project at Iowa State University. You will receive $0.05 for completing the screener, which is used to see if you are eligible for the full study. Individuals who qualify for the study will be invited to participate in a 15-minute study for the pay of 1 dollar plus bonus. If you do not qualify for participation based on this screening questionnaire, all the information about you will be destroyed.

Description of Procedures
To be considered for participation in the study, you will have to answer a few demographic questions. Once you have answered those questions, you may be invited to participate in the full study. In the full study, you may be randomly matched with another participant and you will then work on a simple task that may affect your and your matched participant earnings. The experiment will last for approximately 15 minutes. You will be given more information about the structure of the study in the instructions.

Risks or Discomforts
There are no foreseeable risks currently in participating in the study.

Benefits
If you decide to participate in this study, there are no direct benefits to you. It is hoped that the information gained in this study will benefit the field of economics by providing more insight into the process of how decisions are made in the labor markets.

Costs and Compensation
You will not bear any costs from participating in this study. If you participate you will spend no longer than 15 minutes completing procedures. Participants will earn $1 for participating in the experiment and a bonus amount depending on the decisions in the experiment. Your final compensation will vary depending on your and your randomly matched participant choices.

Participant Rights

Participating in this study is completely voluntary. You may choose not to take part in the study or to stop participating at any time, for any reason, without penalty or negative consequences. If you have any questions about the rights of research subjects or research-related injury, please contact the IRB Administrator, 515-294-4566, IRB@iastate.edu, or Director, 515-294-3115, Office for Responsible Research, Iowa State University, Ames, Iowa 50011.

Confidentiality

This consent form and any other documents identifying participants will be kept confidential to the extent permitted by applicable laws and regulations and will not be made publicly available. However, federal government regulatory agencies, auditing departments of Iowa State University, and the Institutional Review Board (a committee that reviews and approves human subject research studies) may inspect and/or copy study records for quality assurance and data analysis. These records may contain private information. This experiment is approved by the Institutional Review Board at Iowa State University (ISU IRB: 18-201-01, Approved Date: 03/25/2019, Expiration Date: 07/17/2020). It is assured that the confidentiality of your data and the choices that you make in the study will be strictly maintained. To ensure confidentiality to the extent permitted by law, the following measures will be taken: Data will be stored on a secure cloud-based drive (Dropbox) under password protection. Your identifiable information will be separated from your decisions in the experiment. When we report results, we will group responses in aggregate; individual responses will not be shared. Please be aware that any work performed on Amazon MTurk can potentially be linked to information about you on your Amazon profile. We will not be accessing any information about you that you may have put on your Amazon public profile page. We will store your MTurk worker ID separately from the other information you provide to us.

Future Use of Data

De-identified information collected about you during this study may be shared with other researchers or used for future research studies. We will not obtain additional informed consent from you before sharing the de-identified data.

Questions

You are encouraged to ask questions at any time during this study. For further information about the study, contact Sher Afghan Asad at 515-735-6309 or saasad@iastate.edu or Joydeep Bhattacharya at joydeep@iastate.edu.

Consent and Authorization Provisions

By clicking the box below, you acknowledge, that you voluntarily agree to participate in this study, that the study has been explained to you, that you have been given the time to read the document, and that your questions have been satisfactorily answered. You may print a copy of this informed consent document for your records.

If you don't agree with this consent document, then close this form and return the HIT.

○ I acknowledge that I have read the material above and I agree to participate in the study.

Subjects who consent to participating in the study will fill out this screener survey before being considered for participation in this study.

Thank you for participating. Now that you have started, **you may not restart** this survey at any point or else your HIT will be rejected.

Please answer the following questions to the best of your ability.

Gender you most closely identify with:

- ◯ Male
- ◯ Female
- ◯ Prefer not to answer
- ◯ Other

Race you most closely identify with:

- ◯ American Indian or Alaskan Native
- ◯ Asian
- ◯ Black or African American
- ◯ Hispanic or Latino
- ◯ Native Hawaiian or other Pacific Islander
- ◯ White or Caucasian
- ◯ Prefer not to answer
- ◯ Other

If “White or Caucasian” is not selected, survey will end with 5 cents compensation.

Age (in years):

- ◯ Under 18
- ◯ 18 - 24
- ◯ 25 - 34
- ◯ 35 - 44
- ◯ 45 - 54
- ◯ 55 - 64
- ◯ 65 or older
- ◯ Prefer not to answer

If "Under 18" is selected, survey will end with 5 cents compensation.

Highest education level reached:

- Less than high school
- High school or equivalent
- Vocational / Technical School
- Some college
- College graduate
- Master's degree
- Professional degree
- Doctoral degree
- Prefer not to answer

Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or something else?

- Republican
- Democrat
- Independent
- Other
- No preference

Annual pre-tax income

- Less than $10,000
- $10,000 - $19,999
- $20,000 - $29,999
- $30,000 - $44,999
- $45,000 - $99,999
- $100,000 - $149,999
- $150,000 - $199,999
- $200,000+
- Prefer not to answer

In which US state have you resided the longest?

Subjects who report their race as "White or Caucasian", age as above 18, and their device type is not mobile will be shown the following screen. Rest of them will be shown the exit screen with 5 cents compensation.

Congratulations! You meet the criteria to participate in the full study.

This study will take up to 10 minutes, pay a bonus of 1 dollar and possibly an additional amount depending on your decisions in the study.

Make sure that you are not distracted for the next 10 minutes. Once you click next, you may not restart this study at any point or else your HIT will be rejected. When you are ready, click next to begin.

You may have to click the next button multiple times to move forward.

Participants will be blocked randomized to one of the ten treatments when they click next.

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Instructions for each treatment will be explained in the video.

The script of each video will differ only on the incentive and bonus structure, the video format will be same for each treatment. The video will only show the hands of the other participant demonstrating the task. The skin will be revealed/concealed (using gloves) in the video depending on the assigned treatment. The next few pages presents the interface for each treatment.

Instructions for piece rate treatments. The videos have the hands covered in gloves and the audio is muted.

The following video explains what you are supposed to do in this study. You **MUST watch** this ~1-minute video to continue with the study.

The video has no sound, please carefully read the captions.

Below is an example of how the task will work. Try pressing `a' and `b' alternatively to score points. We have limited the point total below to a maximum of 5 as this is just practice, but the overall task will not have a limit.

Press `a' then `b'...

Points: 0

Proceed to the next page when you are ready to play the task. Your 10-minute task will begin immediately when the page loads.

The next button will appear only after you have finished watching a video. PLEASE WATCH AND LISTEN TO THE VIDEO TO CONTINUE.

Instructions for race neutral treatments. The videos have the hands covered in gloves and the audio is muted.

The following video explains what you are supposed to do in this study. You **MUST watch** this ~1-minute video to continue with the study.

The person in the video is **another participant** in the study. The video has no sound, please carefully read the captions.

The payment to the other participant will be paid in a couple of weeks. The proof of payment will be posted here. The ID of your other participant (assigned by us) is 18.

Below is an example of how the task will work. Try pressing `a' and `b' alternatively to score points. We have limited the point total below to a maximum of 5 as this is just practice, but the overall task will not have a limit.

Press `a' then `b'...

Points: 0

The next page will ask you some questions about the other participant. You will play the task after answering those questions.

The next button will appear only after you have finished watching a video. PLEASE WATCH AND LISTEN TO THE VIDEO TO CONTINUE.

Instructions for race salient treatments. The videos have the bare hands and the audio is not muted.

The following video explains what you are supposed to do in this study. You **MUST watch** this ~1-minute video to continue with the study.

The person in the video is **another participant** in the study.

The payment to the other participant will be paid in a couple of weeks. The proof of payment will be posted here. The ID of your other participant (assigned by us) is 62.

Below is an example of how the task will work. Try pressing `a' and `b' alternatively to score points. We have limited the point total below to a maximum of 5 as this is just practice, but the overall task will not have a limit.

Press `a' then `b'...

Points: 0

The next page will ask you some questions about the other participant. You will play the task after answering those questions.

The next button will appear only after you have finished watching a video. PLEASE WATCH AND LISTEN TO THE VIDEO TO CONTINUE.

These questions are presented only in the race salient and race neutral treatments.

Before you play the task, please give your **best guess** about the participant in the video. For each question, you will be paid **an extra 2 cents** as bonus if your guess is correct, we will **deduct 2 cents** from your final bonus payment if your guess is incorrect. Select "Cannot decide" if you cannot decide between the two options, in which case **no extra amount** will be rewarded or deducted for that question.

The other participant is either male or female, please guess the gender of the other participant?

- Male
- Female
- Cannot decide

The other participant's income is either less than or greater than $45,000, please guess the income of the other participant?

- Less than $45,000
- Greater than $45,000
- Cannot decide

The other participant's education is either 'below college' or 'some college or above', please guess the highest education level attained by the other participant.

- Below college
- Some college or above
- Cannot decide

The other participant is either black or white, please guess the race of the other participant?

- Black or African American
- White or Caucasian
- Cannot decide

The other participant is either 'under 35' or '35 or above', please guess the age group of the the other participant?

- Under 35
- 35 or above
- Cannot decide

Proceed to the next page when you are ready to play the task. Your 10-minute task will begin immediately when the page loads.

Task screen for Altruism Black treatment

0845

Press 'a' then 'b'...

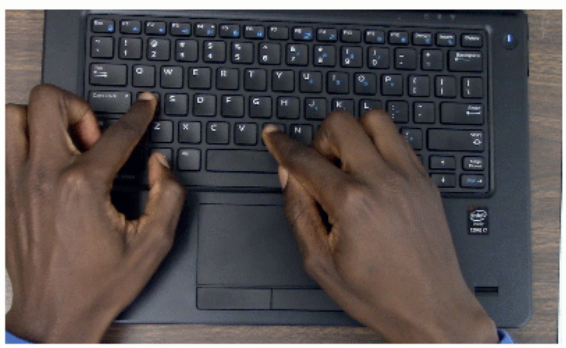
Points: 155

Your bonus payout: $1

Other participant's earning: $ 0.016

The other participant will be paid 1 cent for every 100 points that you score.

Your score will not affect your payment in any way.



Demonstration of the task by the other participant

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

Task screen for Altruism Neutral treatment

0918

Press 'a' then 'b'...

Points: 110

Your bonus payout: $1
Other participant's earning: $ 0.011

The other participant will be paid 1 cent for every 100 points that you score.

Your score will not affect your payment in any way.

Demonstration of the task by the other participant

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

Task screen for Altruism White treatment

0924

Press 'a' then 'b'...

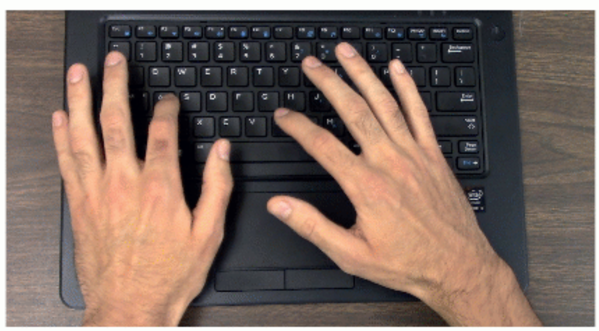
Points: 132

Your bonus payout: $1

Other participant's earning: $ 0.013

The other participant will be paid 1 cent for every 100 points that you score.

Your score will not affect your payment in any way.



Demonstration of the task by the other participant

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

Task screen for Piece Rate - 0 cents treatment

0938

Press 'a' then 'b'...

Points: 57
Your bonus payout: $1

Your score will not affect your payment in any way.

Demonstration of the task

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

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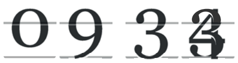
Task screen for Piece Rate - 3 cents treatment



Press 'a' then 'b'...

Points: 44
Your bonus payout: $1 + 0.013

As a bonus, you will be paid an extra 3 cents for every 100 points that you score.

Demonstration of the task

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

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Task screen for Piece Rate - 6 cents treatment

0 9 0 0

Press 'a' then 'b'...

Points: 38

Your bonus payout: $1 + 0.023

As a bonus, you will be paid an extra 6 cents for every 100 points that you score.

Demonstration of the task

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

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Task screen for Piece Rate - 9 cents treatment

0916

Press 'a' then 'b'...

Points: 68

Your bonus payout: $1 + 0.061

As a bonus, you will be paid an extra 9 cents for every 100 points that you score.

Demonstration of the task

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

Powered by Qualtrics

Task screen for Reciprocity Black treatment

0929

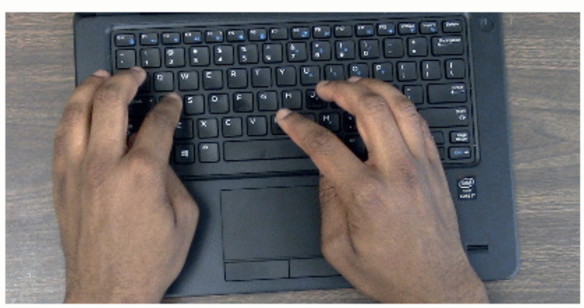
Press 'a' then 'b'...

Points: 117
Your bonus payout: $1 + 0.2
Other participant's earning: $ 0.012

The other participant will be paid 1 cent for every 100 points that you score.

In appreciation to you for performing this task, the other participant has decided to pay you an extra 20 cents as a bonus.

Your score will not affect your payment in any way.



Demonstration of the task by the other participant

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

Task screen for Reciprocity Neutral treatment

0914

Press 'a' then 'b'...

Points: 114

Your bonus payout: $1 + 0.2
Other participant's earning: $ 0.011

The other participant will be paid 1 cent for every 100 points that you score.

In appreciation to you for performing this task, the other participant has decided to pay you an extra 20 cents as a bonus.

Your score will not affect your payment in any way.

Demonstration of the task by the other participant

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

Task screen for Reciprocity White treatment

0908

Press 'a' then 'b'...

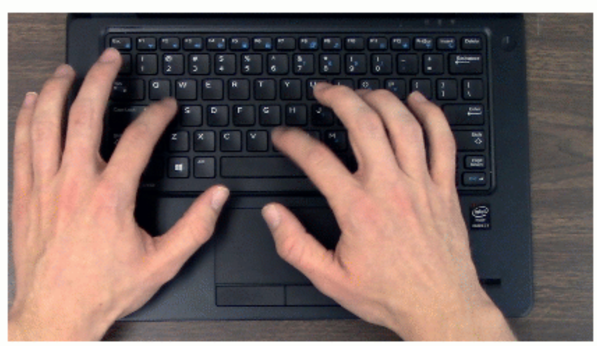
Points: 138

Your bonus payout: $1 + 0.2
Other participant's earning: $ 0.014

The other participant will be paid 1 cent for every 100 points that you score.

In appreciation to you for performing this task, the other participant has decided to pay you an extra 20 cents as a bonus.

Your score will not affect your payment in any way.



Demonstration of the task by the other participant

This page will automatically submit after 10 minutes are over. Do NOT refresh / reload this page.

Here is the summary of what happened in the experiment.

Points Scored: 38
Your Bonus Payout: $1.023

Please note that any bonus payment must be approved before they are given. Your bonus amount (if any) will be paid in 24 hours.

Did you have any questions, concerns or comments about this study? If so, enter them here.:

On the next screen, you will be given a survey code that you must enter into the textbox on Mechanical Turk to get paid.

Thank you for participating in this study.

Your MTurk completion code is: 28377

It is **very important** that you do not share any of your results and that you do not provide any details about this study to other potential participants. We trust in you to keep this study and your results confidential.

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