Discrimination in an Online Labor Market

Sher Afghan Asad

05/07/18

Abstract

Add abstract at the end.

1 Introduction

A large body of literature in economics has demonstrated that discrimination – whether it be racial, religious, ethnic or gender in origin – is widespread in labor markets. The most common form of such discrimination studied is of the employer-to-employee kind, that shown by an employer from one group toward a potential or existing employee from another group. Such discrimination can be along an "extensive" margin (e.g., unwarranted low interviewing or hiring of job-seekers from a certain group) or along an "intensive margin" (e.g. deliberate unfairness in compensation, pecuniary or otherwise). Researchers have established that discrimination along either margin is emphatically costly and demoralizing to those being discriminated against: it may cause inefficiently-low job seeking or suboptimal investment in skill or human capital by disadvantaged workers (Coate & Loury, 1993); it may directly reduce their performance (Glover, Pallais, & Pariente, 2017).

However, almost all the literature on discrimination in economics has tend to investigate the issue on the premise that discrimination is driven by the employers i.e. employers have some animus or beliefs about the productivity of workers from disadvantaged group and that leads them to discriminate against the equally productive workers from the disadvantaged group in favor of workers from the advantaged group. In this study we investigate the issue from a different angle and see whether discrimination can run in opposite direction i.e. whether a worker from the advantaged (disadavantaged) group may exhibit bias towards the employer from the disadvantaged (advantaged) group. To our knowledge the possibility of discrimination from this direction has not been explored in the economics literature. Our research question is close to Glover et al. (2017); in their study the authors found that workers from disadvantaged group underprovide effort when working under the biased managers. However, our study is different in a sense that we argue that workers may underprovide effort even in the absence of bias from the employer. Ours is the only study which explore the possibility of bias driven from the worker side in the absence of any discrimination or anticipation of discrimination from the employer.

It is important to understand what we mean by discrimination from the worker side and why is it an important issue that needs investigation. We define worker discrimination as when employers from one group are treated differently (less favorably) than employers from another group with identical characteristics. For example, workers discriminate when they underprovide effort to employers from one group as compared to the other group with otherwise identical characteristics (such as wages, job conditions etc.). The investigation into this issue is important for several reasons. First, in the absence of perfectly enforcable contracts, this form of discrimination directly affects the profitability of the employers. Second, it can explain why employers tend to not hire workers from the opposite group (insert reference of study that defends segregation). If employers expect that workers from particular group are going to underprovide effort then it is rational for even unbiased employers to not hire from that group. Finally, this line of research can also explain why discrimination, even after various affirmative action policies by governments all over the world, continue to exist in one form or another (Bayer & Charles, 2017)(insert more reference saying discrimination exist). One possible explanation for why those policies haven't achieved the discrimination free society could be that those policies were aimed at employers and they were perceived as the only entity responsible for causing discrimination. However, our research identifies that discrimination can also be driven by those who are traditionally "discriminated against" and if one is to tackle the issue it needs to target both sides of market i.e. employers and workers.

Fundamentally, economists view discrimination as arising in one of two ways. Becker (1957) introduced the notion of taste-based discrimination postulating that discrimination exists because of prejudice/animus of the advantaged group toward the disadvantaged group. Phelps (1972) and Arrow (1973) instead view discrimination as statistical, in which, say, an advantaged group-employer, lacking information, say, on a disadvantaged group-worker, forms rational beliefs about the worker in terms of the aggregate distribution of group traits. It is important to define taste-based and statistical discrimination in the context of discrimination by workers. We define taste based discrimination as the discrimination that results because of animus or prejudice of workers towards the employer. For example, if a White worker, in the context of United States, prefers working for the White employer as compared to the equally rewarding opportunity from the Black employer, then we call this taste-based discrimination against the Black employer. Statistical discrimination from the worker side would be the discrimination that results when a worker, lacking information on the employer, forms beliefs about the desirability of the job with the employer using sterotypes about the group of employer. For example, a White worker may beleive that Blacks employers are generally less generous (in compensations; monetary or otherwise) towards their workers as compared to White employers and hence that lead them to discriminate against the Black employer in favor of the equally desirable job from the White employer.

The purpose of this research is simple, we investigate whether the discrimination can be driven from the worker side and which economic theory provides explanation for the existence of this kind of discrimiantion - taste or statistcal? Is it that workers exhibit distaste towards the employers from opposite group or is it that the discrimination is statistical in nature where workers have some beliefs or stereotypes towards the opposite group employer and they invoke those when working for the employer. The distinction is important because each kind of discrimination warrants different policy prescriptions for addressing the problem of discrimination. In this paper, we design an experiment to only allow the possibility of taste-based discrimination. So any observed discrimination can only be attributed to the taste of workers towards the employers.

To test whether workers discriminate in providing effort to the employer, we implemented an online experiment on Amazon Mechanical Turk.

(Carefully define taste based and statistical discrimination from the worker side.)

(Discrimination from coworkers (add relevant arguments here distinguishing it from discrimination towards employers).)

(Address the argument that workers should demand higher wages in the presence of discrimination.)

(Why not real effort task? Upwork workers work hard because they know they are monitored, so there is no issue of contract enforcement.)

(Why gift exchange framework? How is it any better than dictator/trust/ultimatum games that are used to study discrimination?)

(Why "make believe" environment?)

To address our research question we make use of the gift exchange framework pioneered by Akerlof (1982) and in an experimental setting by Fehr, Kirchsteiger, and Riedl (1993).

2 Model and Treatments

We closely follow the model of Dellavigna and Pope (2018) for the worker side and modify it to incorporate employer side and the possiblity of discrimination from worker side. Assuming risk neurtality, a worker $i \in \{B, W\}$ solves the following problem when working for an employer $j \in \{B, W\}$ where B and W denote the black or white race of an agent (employer or worker) respectively;

$$\underbrace{max}_{e_{ij} \geq 0} U_{ij} = \underbrace{max}_{e_{ij} \geq 0} (F_j + (s_{ij} + p)e_{ij} - c(e_{ij})) \tag{1}$$

where $e_{ij}$is the number of points (on a button-pressing task) scored by worker i when working for employer j, F_j is the fixed money paid by employer j for working on a task, s_{ij} (as in Dellavigna and Pope (2018)) captures the sense of duty, norm, intrinsict motivation, and competitiveness of worker towards the task. We argue that s_{ij} also include the taste (like or dislike) of worker i towards the employer j per unit of effort e_{ij}. p is the piece rate chosen by the employer

j, we allow employers to select piece rate from anywhere between 0 cents and 10 cents per 100 points (in increments of 3 cents). $c(e_{ij})$ is the cost of effort, following Dellavigna and Pope (2018) we assume cost fucntion to have either power or exponential functional form i.e.

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

or

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

These functions differ in their elasticity of effort with respect to the value of effort. Power cost function (2) characterize a costant elasticity of effort given by $1/\gamma$ while exponential cost function (3) implies a decreasing elasticity as effort increases. Both functions requires the estimation of unknowns k, and γ which we will back out using observed effort at different piece rates.

Solving 1 leads to following solution (when interior);

$$e^{\star}_{ij} = c'^{-1}\left(s_{ij} + p\right)$$

With power cost function this translates to;

$$e^{\star}_{ij} = \left(\frac{s_{ij} + p}{k}\right)^{1/\gamma}$$

While exponential cost function lead to the solution

$$e^{\star}_{ij} = \frac{1}{\gamma} log\left(\frac{s_{ij} + p}{k}\right)$$

We make a simplifying assumption that the workers of type i are homogenous given a treatment i.e. they will make the same effort choice in a given treatment.

2.1 Baseline Treatment

In the baseline treatment an employer chooses a wage, worker observes the wage and then work on the task. We allow employers to select any wage between 0 and 10 cents while workers work on a simple button-pressing task for 10 minutes[1]. From the MTurk standards this variation in piece rates is substantial for the 10 minute task. Employers also offer a flat fee (F_j) of \$1 to each worker.

These piece rates provide evidence on the responsiveness of effort to incentives for this particular task and hence allow us to estimate parameters of cost function which will be used to estimate other behavioral parameters.

Formally, in the baseline treatment, employer j selects a piece rate p for worker i, worker observe the piece rate p and then choose effort e_{ij} by maximizing 1. Worker do no observe the identity of the employer which implies that for

[1] We use the exact same task as in Dellavigna and Pope (2018)

any worker i, $s_{iW} = s_{iB} = s_i$. The equilibrium effort $e_i^{\star}$ in this treatment will be given as;

$$e_i^{\star} = c'^{-1}\left(s_i + p\right) \text{ for } i \in \{B, W\}$$

This treatment will give us the baseline measure of effort of worker i for the given piece rate p. For each i, the solution of effort has one behavioral unknown (s_i), and two unknowns from cost function (k and γ). We will back out these unknowns from the observed effort at different piece rates.

2.2 Race Salient Treatments

In the race salient treatment, workers will observe the race of the matched employer along with the selected piece rate and then work on a task. In the presence of group biases i.e. when workers derive different level of social preference for different employers' group then;

$$e_{ij}^{RS} = c'^{-1}\left(\left(s_i + \Delta s_{ij}^{p}\right) + p\right)$$

We are implicitly assuming $s_{ij} = s_i + \Delta s_{ij}$ i.e. the parameter s_{ij} can be separated into two components 1) s_i, which is independent of the employer type and include everything such as sense of duty, norm, intrinsict motivation, competitiveness of worker etc. and 2) Δs_{ij}, which represents additional utility or disutility from working for the employer of type j which we interpret as taste towards the employer a' la Becker (1957).

$\Delta s_{ij}^{RS} > 0$ $\left(\Delta s_{ij}^{RS} < 0\right)$ will represent the increase (decrease) in effort because of taste of worker i towards (against) the employer j. For $j \neq i$, $\Delta s_{ij}^{RS} < 0$ will be interpreted as the decrease in effort due to taste bias of worker i towards the opposite group employer j. In other words, the difference in provided effort between the white employer and black employer $\left(e_{iW}^{RS} - e_{iB}^{RS}\right)$ for a given piece rate is construed as a difference which is only driven by the taste bias of the workers of group i. The main goal of this research is to identify the parameter Δs_{ij}^{RS} at different piece rates.

3 Experiment Design

The main goal of this study is to document the evidence of discrimination in the online labor market. We designed the experiment to allow for the possibility of discrimination in effort by workers towards the employers.

3.1 Recruitment of Subjects

The subjects for this experiment were recruited from an online labor market, Amazon's Mechanical Turk. Mechanical Turk is a crowdsourcing web-service that allows employers (called requesters) 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 in research in economics and give access to large pool of applicants at a much cheaper rate hence allowing for the well powered study. See Paolacci, Chandler, and Ipeirotis (2010) and Paolacci and Chandler (2014) for discussion on demographic characteristics and representativeness of subjects from Mechanical Turk.

To recruite subjects we posted the screener survey as the HIT on Mechanical Turk with the following description *"Fill out this 2-minutes screener survey to qualify for the immediate second study (that study will take ~15 minutes and pay 1 dollar plus bonus). You MUST use your webcam and take a picture (following guidelines) to be considered for the study."*. We restricted the screener survey to subjects who (1) are from United States and (2) speak fluent english. The screener survey is given in the Appendix B.

Based on the responses in the screener survey, we invited participants above the age of 18 who reported their race as "Black or African American" or "White or Caucasian" to participate in the experiment. Everyone else was shown the exit screen.

Since our choice of task is same as Dellavigna and Pope (2018), we can use results from their study to determine the sample size that can achieve sufficient power for our study. Dellavigna and Pope (2018) found that the points scored in each treatment have a standard deviation of around 660 points. Assuming this standard deviation for each treatment and assuming a minimum detectable effect of 185 points between two treatments, we will need around 200 observations in each comparison group to have a power of 80 percent. This implies that we need 200 x 5= 1,000 observations in total for all five treatments. In our design one observation constitute two subjects - one employer and one worker - therefore we need to recruit around 400 subjects in each treatment implying a total sample of size 2000.

Based on the power calculations we recruited 600 subjects in each treatment which gave us 300 observations (two subjects (employer and worker) constitute one observation). We ideally need 500 observations for each racial combination of employer and worker in the race salient treatment i.e. Black Employer-Black Worker, Black Employer-White Worker, White Employer-Black Worker and White Employer-White Worker.

3.2 Task

We designed this experiment to observe whether workers discriminate in their effort when working for different employer types and then to back out the behavioral parameter of distaste. For this purpose we needed a task which is costly to workers. We settled on a button-pressing task as in Dellavigna and Pope (2018). The task involves alternating presses of "a" and "b" on keyboard for 10 minutes. We settled on this task because it is simple to understand and have features that parallel clerical jobs: it involves repetition and it gets tiring, thus testing the motivation of the workers.

3.3 Experiment Flow

The experiment proceeded as follows: (1) HIT was posted on Mechanical Turk for a screener survey, (2) subjects were presented with the consent form, (3) those who consented and met the criteria were shown a screen to initiate the experiement, (4) upon inititation a subject was randomly assigned to one of the treatment groups and then to the role of employer or worker. The first person to inititate the experiment was always assigned the role of employer while the second person was made the worker. One employer and one worker formed a group for this experiment. The flow of the screenshots of the screens that subjects saw are given in Appendix B. The application for the experiment was designed using oTree (Chen, Schonger, & Wickens, 2016).

The instructions to the employers and workers for each treatment are given in Appendix B.

3.3.1 Baseline Treatment

In the baseline treatment employers were informed (truthfully) that they will be paid 10 cents for every 100 points scored by the randomly matched worker and they can choose if they want to transfer part of 10 cents to workers as piece rate. Employers were allowed to select a piece rate of 0, 3, 6 or 9 cents for the matched worker. Employers did not know the identity of worker for whom the piece rate was selected neither did worker observe the identity of employer before starting to work. Once an employer selected a piece rate, a matched workers was informed of the selected piece rate and was given 10 minutes to work on the task.

3.3.2 Race Salient Treatment

The race salient treatment was identical to baseline treatment except that when a worker observed the selected piece rate, he/she also saw the picture that was taken by the matched employer when he/she selected the piece rate. When employers selected the piece rate they were instructed to write the selected piece rate on a piece of paper and take a picture with only the part of their hand showing in the picture. Showing hand with piece rate is a subtle way of revealing the race (Doleac & Stein, 2013) and avoid psychological confounds which are assoicated with facial pictures such as attractiveness and trustworthiness (Eckel & Petrie, 2011).

4 Structural Estimation

We designed our experiment with the structural model given in Section 2. The advantage of designing field experiments on the basis of model of behavior is that it allows researchers to estimate the nuisance parameters in the environment that is relevant to the decison making (DellaVigna, 2017). Because of the simplicity of our task, the only nuisance parameters are related to cost function. We will thus use data from baseline treatment to identify these parameters. Once we have the estimate of these nuisance parameters, we can estimate parameters of distaste using data from the race salient treatment. We will now present the estimation procedures and the resulting estimates.

4.1 Minimum Distance Estimation

We use data from baseline treatment, specifically the average effort corresponding to three piece rates (0 cents, 3 cents and 9 cents), to estimate $\hat{\gamma}$, $\hat{s}$, and $\hat{k}$. The estimates are presented in Table X for both power and exponential cost function. Given these estimates, we then back out the estimate of Δs_{ij} for each piece rate (0, 3, 6 or 9 cents) by using the average effort in the race salient treatment corresponding to the respective piece rate. For example, average effort by Black workers for White employers with piece rate of 0 cents in the race salient treatment is given as follows;

$$e_{BW}^{RS} = c'^{-1}\left(\left(s_B + \Delta s_{BW}^{p=0}\right)\right)$$

Given the estimates of $\hat{\gamma}$, $\hat{s}$, and $\hat{k}$, $\Delta s_{BW}^{p=0}$ is just identified.

References

Akerlof, G. A. (1982). Labor Contracts as Partial Gift Exchange. *The Quarterly Journal of Economics*, *97*(4), 543–569.

Arrow, K. J. (1973). The Theory of Discrimination. In *Discrimination in labor markets* (pp. 3–33).

Bayer, P., & Charles, K. K. (2017). Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men Since 1940. *The Quarterly Journal of Economics*, *133*(3), 1459–1501.

Becker, G. S. (1957). *The economics of discrimination*. University of Chicago Press.

Chen, D. L., Schonger, M., & Wickens, C. (2016). oTree-An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97.

Coate, S., & Loury, G. (1993). Will Affirmative-Action Policies Eliminate Negative Stereotypes ? *The American Economic Review*, *83*(5), 1220–1240.

DellaVigna, S. (2017). Structural Behavioral Economics. *Handbook of Behavioral Economics*(December).

Dellavigna, S., & Pope, D. (2018). What motivates effort? Evidence and expert forecasts. *Review of Economic Studies*, *85*(2), 1029–1069.

Doleac, J. L., & Stein, L. C. D. (2013). The visible hand: Race and online market outcomes. *Economic Journal*, *123*(572), 469–492.

Eckel, C. C., & Petrie, R. (2011). Face value. *American Economic Review*, *101*(4), 1497–1513.

Fehr, E., Kirchsteiger, G., & Riedl, A. (1993). Does Fairness Prevent Market Clearing ? An Experimental Investigation. *The Quarterly Journal of Economics*, *108* (2), 437–459.
Glover, D., Pallais, A., & Pariente, W. (2017). Discrimination as a Self-Fulflling Prophecy : Evidence from French Grocery Stores. *Quartely Journal of Economics*.
Paolacci, G., & Chandler, J. (2014). Inside the Turk: Understanding Mechanical Turk as a Participant Pool. *Current Directions in Psychological Science*, *23* (3), 184–188.
Paolacci, G., Chandler, J., & Ipeirotis, P. (2010). Running experiments on amazon mechanical turk. *Judgment and Decision making*, *5* (5), 411–419.
Phelps, E. S. (1972). The Statistical theory of Racism and Sexism. *American Economic Review*, *62* (4), 659–661.

A Estimation Appendix

A.1 Minimum Distance

We use data from baseline treatment to estimate parameters of cost function and baseline parameters. Given 8 moments (mean efforts from 4 different piece rates for each of the two types of workers) we are able to estimate 4 parameters s_B, s_W, γ and k . That is, we solve numerically the system of

$$\gamma log(e_i^p) + log(k) - log(s_i + p) = 0 \text{ for } p \in [0, 3, 6, 9] \text{ and } i \in \{B, W\}$$

B Experiment Material Appendix

B.1 Screener Survey