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The impact of discrimination on redistributive preferences and productivity: experimental evidence from the United States

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The impact of discrimination on redistributive preferences and productivity: experimental evidence from the United States

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Abstract

This study focuses on luck as a source of inequality, including (1) sheer luck and (2) luck that correlates with individual characteristics, such as gender and ethnicity. While the former is more random, the latter is more discriminatory. A strand of previous literature treats luck more generally, but this study distinguishes between different types of luck and investigates their distinct effects on redistributive preferences and productivity with the aid of experimental data. The study implements an online experiment on Amazon's Mechanical Turk with participants resident in the United States. Participants are informed about randomized payment schemes with or without discrimination on the grounds of gender or ethnicity. They earn money for performing a real-effort task and afterward have the chance to redistribute earnings. The key results of the study are: discrimination raises demand for redistribution more than sheer luck, especially when women are discriminated against, and ethnic discrimination reduces productivity marginally.

1. Introduction and background literature

We provide new insights into recent debates about how inequality is shaping redistributive preferences and productivity in the United States. Compared to Western Europe, income or wealth inequality has been relatively high and growing at an alarming rate in the United States since the 1980s (Piketty, 2014; Piketty and Saez, 2014; Atkinson, 2015; World Inequality Report, 2018). Interestingly, this observation has not come with growing demand for redistribution, especially for a highly democratic country as the United States (Kuziemko *et al.*, 2015). This is puzzling, given the “median-voter hypothesis”, which suggests that in a democracy the median voter will vote for greater redistribution in favor of the poor when inequality rises (Meltzer and Richard, 1981).

A possible explanation of this puzzle is that people have limited knowledge about inequality levels and trends (Norton and Ariely, 2011; Gimpelson and Treisman, 2017). Kuziemko *et al.* (2015) conduct randomized online experiments that provide information about the actual distribution of income in the United States. Though their “informational treatments” raise awareness of high levels of inequality, Kuziemko *et al.* (2015) generally find only slight demand for redistribution (measured as tax and transfer preferences) due to the lack of trust in the government. The authors highlight the exception of high responsiveness of estate tax preferences to information, which, they explain, might partly be the consequence of moral concerns about inheritance.

Perhaps, Americans demand redistribution in line with their perception of the fairness of the distribution. Recent studies seem to suggest that fairness is more important to people than equality (Akbaş *et al.*, 2016; Starmans *et al.*, 2017). Americans might prefer inequality that is fair to equality that is unfair. In a culture that is founded on democracy and meritocracy, there is the strong belief that equal opportunities abound for all, and everyone has a fair chance of becoming successful regardless of their initial conditions – what is touted as the “American Dream” (Piketty, 1995, 1998; Benabou and Ok, 2001; Alesina and La Ferrara, 2005). In the face of the hard facts, however, the American Dream is exaggerated (Chetty *et al.*, 2017; Pickett and Wilkinson, 2017).

Alesina and Angeletos (2005) present a theoretical explanation of why the United States seems to demand less redistribution than continental Europe. The United States operates at a low-redistribution, low-tax steady state, while continental Europe operates at a high-redistribution, high-tax steady state. This is the result of self-fulfilling beliefs: Americans generally think that people are poor because they do not work hard, while Europeans generally think that people are poor because they faced some bad luck or lack connections. Based on correlational studies, Americans generally believe in high prospects of upward social mobility and demand less redistribution, compared to continental Europe (Alesina and Angeletos, 2005; Alesina and La Ferrara, 2005; Alesina and Giuliano, 2009). But the experimental evidence has been less clear that people who believe in high prospects of upward social mobility demand less redistribution, and vice versa (Neustadt and Zweifel, 2009; Grimalda *et al.*, 2018).

The literature on fairness and demand for redistribution has largely taken a dichotomous approach, comparing attitudes toward inequality resulting from “effort” versus “luck” (Fong, 2001; Esarey *et al.*, 2012; Akbaş *et al.*, 2016; Lefgren *et al.*, 2016; Bortolotti *et al.*, 2017; Gee *et al.*, 2017). The clear conclusion from this experimental literature is that there is little or no demand for redistribution when the distribution is drawn by individual effort or performance (e.g., Lefgren *et al.*, 2016). People however demand redistribution “behind a veil of ignorance” when inequality is caused by luck. The important contribution of our study is the argument that there might be value in distinguishing between sheer luck and luck that correlates with individual identity (such as gender or ethnicity). The former may be more random, the latter may be more discriminatory. The former may be natural, the latter may be man-made or a social construct. The former may be more acceptable, the latter may be more upsetting. For instance, when the distribution is drawn by factors such as family and social connections, corruption, and cheating, there is greater demand for redistribution, even if this is costly (e.g., Bortolotti *et al.*, 2017).

A rich literature studies discrimination in the social sciences. Discrimination involves unequal access to schooling and health opportunities, as well as unequal treatment in the labor, housing, credit, consumer markets and other social spheres, on the basis of individual or group characteristics, such as age, gender, ethnicity or race, sexual orientation, religious beliefs, and such like. Economists have proposed two theories that explain discrimination in the labor market (Autor, 2003), namely “taste-based discrimination” (Becker, 1963) and “statistical discrimination” (Arrow, 1972; Phelps, 1972). The first theory suggests that employers have a “taste for discrimination” and is based on supply and demand dynamics of the labor market. It is costly for discriminating employers to discriminate, as they pay a higher wage rate to workers from the majority group. It is also costly for workers from the minority group to accept lower wages; they will not supply their labor services to discriminating employers, but to non-discriminating ones. Discrimination will be competed away in equilibrium, conditional on a large share of non-discriminating employers and a large number of workers in the minority group. Thus, discrimination persists because the conditions do not hold.

The second theory, “statistical discrimination”, has dominated the discourse on discrimination and is based on information asymmetries. It is costly for employers obtain accurate information about the skills of prospective workers, *a priori*. Employers rely on the signalling effects of observable characteristics of job applicants, such as their skin color or gender, to estimate the expected productivity of job applicants. Employers base their hiring decisions on known productivity levels of different types of workers, obtained from previous data. This argument rationalizes and perpetuates discrimination. Sociologists and psychologists have discussed possible underlying causes of discrimination, including prejudice (attitudes), racial and patriarchal stereotypes (beliefs), and racism (ideology) (e.g., Pager and Shepherd, 2008; Plous, 2010; Whitley Jr and Kite, 2016). Despite growth in legislation in the United States that protects the rights of

minorities, discrimination still lingers but often as a covert phenomenon (Pager and Shepherd, 2008; Milanovic, 2014).

A person's gender or ethnicity is luck at birth, also known as "initial brute luck", distinct from other forms of luck that people face later in life. On the one hand, it may be less contentious to compensate people for discrimination they face because of their identity (such as gender or ethnicity) for which they cannot be held accountable. In respect of the "principle of compensation" (Fleurbaey and Maniquet, 2011), the United States has witnessed policies of affirmative action, which aim to leverage the outcomes of underrepresented population sub-groups that have historically suffered discrimination, such as women and African Americans (Arcidiacono and Lovenheim, 2016; Naibandian, 2018; Sandberg, 2013; *The Economist*, 2018b). On the other hand, it may be more contentious to compensate people who have poor outcomes as a result of sheer luck or other forms of luck, such as "option luck" (e.g., the outcome of risk-taking), where the individual plays an initiating role. Even in such cases, people may nevertheless want to compensate or support victims of a black swan (e.g., bailouts). Taken together, it may be hard to draw clear conclusions about the fairness of outcomes produced by luck (Ferreira and Peragine, 2015). But for simplicity and for our purposes, we study sheer luck and initial brute luck, factors that are exogenous to the individual. While a strand of previous literature conflates such exogenous sources of inequality (Akbaş, Ariely and Yuksel, 2016; Gee, Migueis and Parsa, 2017), our study isolates and compares their distinct effects on redistributive preferences and productivity with the aid of experimental data.

Additionally, we contribute to the literature that studies the relationship between inequality and productivity. Recent research decomposes inequality into two main components, namely "inequality of opportunity" (i.e., inequality explained by differences in circumstances individuals face, often determined at birth, over which they have no control, such as their gender, ethnicity and parental socioeconomic background) and "inequality of effort" (i.e., inequality explained by differences in individual effort and decisions for which people can be held responsible) (Ferreira, 2007; Ferreira and Gignoux, 2011; Marrero and Rodríguez, 2013; Ferreira *et al.*, 2014; Brunori, *et al.*, 2015). The former is generally considered unfair, while the latter is generally considered fair. The above-cited researchers identify a residual component of inequality, which we may refer to as "inequality of luck". Some scholars have been skeptical about the role of talent, hard work, risk taking, and other meritocratic principles, and have emphasized the role of luck as an important source of variation in people outcomes (e.g., Frank, 2013; Biondo and Rapisarda, 2018), though luck could intersect both inequality of opportunity and inequality of effort (Lefranc *et al.* 2009). For example, Fleurbaey and Peragine (2013) argue that luck is a circumstance variable in determining inequality of opportunity.

At the macro level, it has been difficult to establish a clear relationship between inequality and subsequent growth (Barro, 2000; Banerjee and Duflo, 2003; Roodman, 2009). However, when

inequality is decomposed into inequality of opportunity and inequality of effort, the results are more interesting. As expected, Marrero and Rodríguez (2013) find a negative relationship between inequality of opportunity and growth and a positive relationship between inequality of effort and growth across 26 states in the United States. But Ferreira *et al.* (2018) do not find empirical support for such a relationship in cross-country regressions.

To our knowledge, researchers explain how inequality may affect productivity with at least two theories at the micro level, namely “stereotype threat” and “fair-wage hypothesis”. First, a large literature in social psychology discusses stereotype threat as “being at risk of confirming, as self-characteristic, a negative stereotype about one’s group” (Steele and Aronson, 1995, p.797). In other words, “stereotype threat is a situational phenomenon, leading to test performance decrements, in which a member of a stigmatized group feels pressured by the possibility of confirming or being judged by a negative stereotype” (Kit, Tuokko and Mateer, 2008, p.132). Over 300 experiments have studied this phenomenon in a wide range of social settings (Stroessner and Good, 2014). To set the stage for this body of literature, Steele and Aronson (1995) found that black college freshmen and sophomores in the United States underperform in standardized test scores compared to their white counterparts when race is made salient. Thus, students of color underperform relative to other students, not necessarily because they are less capable but because of stereotype threat. Further studies have found evidence for race-based stereotype threats. Hoff and Pandey (2006) exploit the fact that caste identity is physically unobservable to confirm stereotype threat among schoolchildren in India: when caste is publicly announced, low-caste schoolchildren underperform in solving mazes by 23%. Gender-based stereotype threats are also quite important in the literature. Davies, Spencer and Steele (2005) find that women had lower aspirations to take up leadership tasks after watching gender-stereotypic TV commercials. From a selected sample of University of Michigan students, Spencer, Steele and Quinn (1999) find that females performed poorly relative to males in a difficult GRE mathematics test designed to test stereotype threat.

Nguyen and Ryan (2008) conduct a meta-analysis that finds race-based stereotypes to have larger effect sizes than gender-based stereotypes (similar to what we find). Stereotype threat may inhibit performance because affected people redirect some effort from performing a given task to dealing with another concern psychologically – in this case, the negative stereotype about their group. In the end, they indeed underperform as they believed – a typical case of a self-fulfilling prophesy (Guyl et al., 2010). An important knowledge gap is that we do not know if it might trigger off the same or different effects on productivity when people are told they are unlucky or they just feel unlucky (without any connection to their identity). This study aims to fill this knowledge gap.

Second, the fair-wage hypothesis explains involuntary unemployment and wage inequality *within* firms or industries (Akerlof and Yellen, 1990; Gächter and Thöni, 2010; Kube *et al.*, 2012). The

seminal work of Akerlof and Yellen (1990, pp.256, 261) formalizes the concept that “if people do not get what they think they deserve, they get angry.....they try to get even.” According to the theory the authors proposed, workers withdraw effort when their actual wage falls short of their “fair wage”, but do not supply more effort when their actual wage exceeds their fair wage. The fair wage may be in reference to a wage at a previous time period [serially] (Bracha *et al.*, 2012), or the wage of peers or co-workers at a particular point in time [cross-sectionally] (Bewley, 1999).

A large number of experimental studies conducted in the laboratory (with costly or real-effort task) and in the field have tested the fair-wage hypothesis with mixed results – some confirming the hypothesis, and others not (Charness and Kuhn, 2007; Cohn, Fehr and Goette, 2008, 2015; Hennig-Schmidt, Rockenbach and Sadrieh, 2010; Bartling and von Siemens, 2011; Bracha, Gneezy and Loewenstein, 2012; Card *et al.*, 2012; Kube, Maréchal and Puppe, 2013; Liu-Kiel *et al.*, 2013; Cohn *et al.*, 2014; Dube, Giuliano and Leonard, 2015; Breza *et al.*, 2016; Grosch and Rau, 2017). Overall, more studies have confirmed the fair-wage hypothesis than rejected it. For experiments with real-effort tasks, some of the studies are the following: Harvard students lower labor supply significantly when they know they have lower pay rate, but knowing that they have a higher wage rate does not affect labor supply significantly (Bracha, Gneezy and Loewenstein, 2012). Students in Germany and China learn about having a disadvantageous wage inequality and this reduces their productivity (Liu-Kiel *et al.*, 2013). Students in Germany do not become less productive but become more antisocial (i.e., destroy more vouchers) when they face a discriminatory payment scheme; but once pay differences are justified by performance differences, antisocial behavior is not observed (Grosch and Rau, 2017).

The results of field experiments are similarly mixed. Cohn *et al.* (2008) find support for the fair-wage hypothesis in a study involving workers at a publishing house: workers who felt underpaid at the baseline wage distributed more copies but workers who felt adequately paid at baseline show no effect of increasing effort. Hennig-Schmidt, Rockenbach and Sadrieh (2010) hired students as research assistants and observe that wage increases and information on peer wages do not have a significant influence on the workers’ effort. In an additional laboratory experiment with real-effort task, the authors find a positive wage-effort relationship when information on employers’ surplus is known. Kube, Maréchal and Puppe (2013) announced a data entry job with a prospect of earning 15 euros at a German university library. On the day of work, three conditions were created: baseline (15 euros), pay cut (10 euros), pay raise (20 euros). The authors find reduction in work effort in pay cut condition, but no increase in work effort in pay raise condition. Dube, Giuliano and Leonard (2015) show that workers in a large US retail firm quit their jobs when their wage rate is less compared to their peers’ wage rate. In a field experiment with manufacturing workers in India, Breza *et al.* (2016) find that there is no longer reduction in productivity once wage inequality is known to be justifiably fair based on productivity differences at baseline. For all these studies, luck is, as it were, the source of discrimination, though it is not

based on identity. Our study add to the literature by considering not only discrimination by sheer luck, but also discrimination based on identity, such as gender and ethnicity.

The study implements a large randomized online experiment (N=8,514) on Amazon's Mechanical Turk (MTurk) to answer the following research questions: (1) What is the impact of gender discrimination on productivity and demand for redistribution? (2) What is the impact of ethnic discrimination on productivity and demand for redistribution? and (3) What is the impact of inequality of luck on productivity and demand for redistribution?

The experiment was conducted on a sample of adult residents of the United States.¹ The identification strategy rests on randomization. Different experimental conditions / treatments / groups that represent inequality of opportunity and inequality of luck are compared in terms of productivity and demand for redistribution. In particular, inequality of opportunity is presented in the form of a discriminatory payment scheme for performing a real-effort task – discriminatory on the grounds of gender or ethnicity. The real-effort task known as the “slider task” is used to elicit productivity in this study. In this task, study participants are asked to drag as many as 100 sliders to a pre-defined number ranging from 1 to 100 within 3 minutes. Productivity is measured as the total number of sliders correctly positioned. Redistributive preferences are elicited with a tax vote that is levied on participants' earnings from the slider task. Within each group, all participants vote a tax rate, but the effective tax applied on earnings is the median tax vote. Tax revenue is shared equally among all participants in each group. Though we do not have a progressive tax structure, the vote for redistribution is progressive in itself because relatively high earners share more earnings for a given tax rate.

Some of the key results of the study are the following. First, discrimination raises demand for redistribution more than sheer luck, especially when women are discriminated against. In terms of demand for redistribution, African / African American and Hispanic women are more reactive to gender discrimination than white women. Second, ethnic discrimination reduces productivity marginally, especially when non-whites are discriminated against. Third, gender discrimination has no effect on productivity because of countervailing effects from males (who increase their productivity) and females (who decrease their productivity, though not statistically significantly) when they face discrimination. Fourth, whites are less willing to equalize ethnic outcomes while males are more willing to equalize gender outcomes.

The rest of the paper is organized as follows. Section 2 explains the experimental design and methods. Section 3 discusses the experimental data. Section 4 presents the results and Section 5 checks the robustness of the results. Section 6 concludes.

¹ See the distribution of participants by state of residence in Supplemental Appendix A1.

2. Research methodology

2.1 Online survey instruments

At the start of this study, we sought and obtained ethical approval for the experiment from the Research Ethics Committee of ETH Zurich. This committee scrutinizes proposed research projects from ETH researchers to conform to widely accepted research codes and conducts. The committee reviews important elements of research projects, which include, *inter alia*, the sample size, informed consent of participants, confidentiality of personal data, voluntary participation of subjects, right to withdraw from the study, payments accruing to participants, time required to complete the study, expected risks of the study (e.g. discomfort) as well as precautionary measures.

The experiment was designed with Qualtrics, which is an online survey software, and implemented using participants recruited on Amazon's Mechanical Turk (MTurk) platform. A Qualtrics link is posted on the MTurk platform that directs prospective participants to the experiment.² MTurk is an online platform for securing jobs known as Human Intelligence Tasks (HITs) with voluntary participants mostly from the United States (Horton *et al.*, 2011; Goodman *et al.*, 2013; Sheehan and Pittman, 2016). MTurk is becoming popular in social science research as an important source of experimental data; more precisely, in the literature on redistributive preferences (e.g., Kuziemko *et al.*, 2015; Lefgren *et al.*, 2016). Due to the (low-cost) access to large non-student populations, it improves the external validity as well as the statistical power of experiments (Horton *et al.*, 2011; Goodman *et al.*, 2013; Sheehan and Pittman, 2016).

We collaborated with the ETH Decision Science Laboratory (DeSciL) to launch the experiment online. The Lab recruits MTurk workers from their subject pool of 30,000 to 50,000 on the Amazon's Mechanical Turk. The Lab launched the experiment online with an access code, which allowed interested participants to work on our Qualtrics link. Payments were made to participants upon providing a password, which was available only after they completed the survey. For a more homogeneous sample, only adult US residents (with IP addresses from the United States) were recruited into the study. On MTurk, US workers are screened by their Social Security Numbers, so that it is not possible to have multiple worker accounts (Sheehan and Pittman, 2016).³

² The Qualtrics link to the study is found at: https://descil.eu.qualtrics.com/jfe/form/SV_e5tIZEv4KNyWai9.

³ Unfortunately, it has been detected that the MTurk platform has been hacked into, contaminating data collected by researchers since March, 2018 – the same period within which our experiment was conducted (Bai, 2018). To diagnose the problem, the author recommends that the data be checked for multiple cases of “88639831” in the latitude field. Following this recommendation, we found 60 cases, representing 0.6% of the entire raw data. We do not include these data in all of our analysis.

2.2 Experimental design and identification

At the start of the experiment, participants are informed that they are in a group of 100 MTurk participants.⁴ Participants are informed they all receive the amount of \$1.00 for answering a couple of questions about themselves. (This amount is equivalent to the federal minimum wage of \$7.25/hour, as participants spend 11.5 minutes on average to complete the whole survey.) These questions include a number of socioeconomic and demographic questions; see Fig. 2 below for the experimental sequence. Participants are also informed that they will earn additional money depending on their performance in a slider task that will be explained to them later. At this stage, participants are randomized into different experimental conditions, which is determined by the payment information they receive later in the experiment.⁵

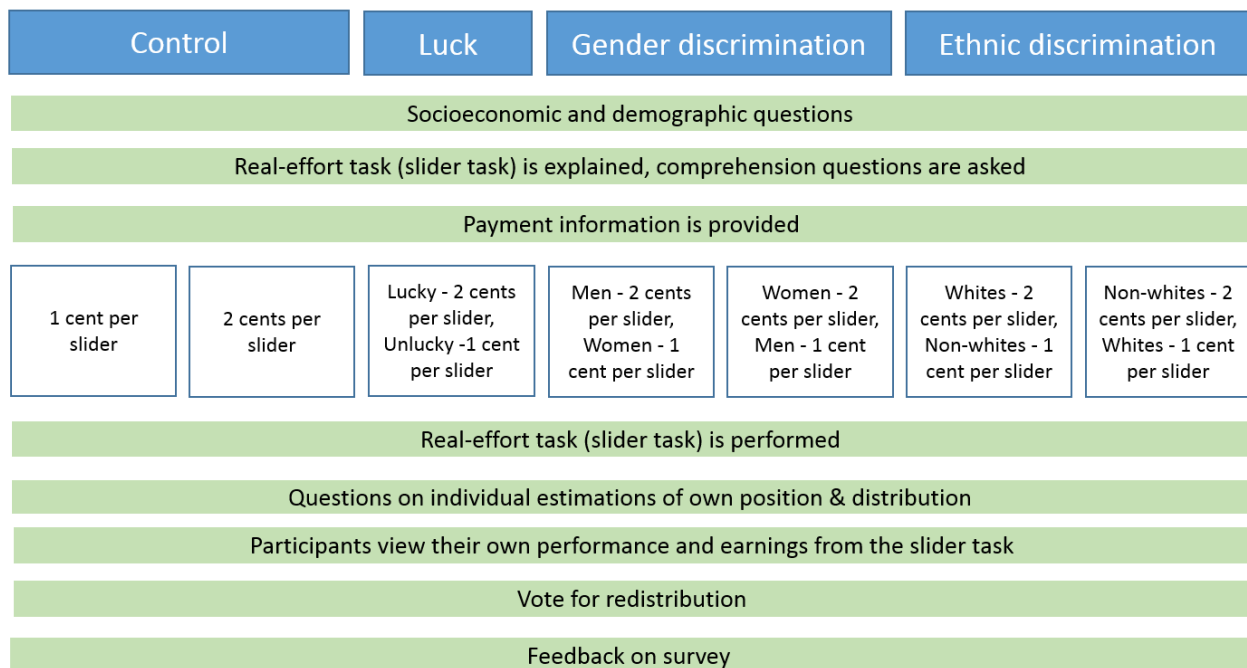


Fig. 2: Experimental sequence

With the Qualtrics program, participants are randomly drawn into 7 experimental conditions; see Figure 2. For the **Control** treatment, there are 2 conditions, namely “1 cent” [where all participants earn 1 cent for each slider correctly positioned] and “2 cents” [where all participants earn 2 cents for each slider correctly positioned]. For the **Luck** treatment, there is 1 condition,

⁴ The sample sizes of the different conditions/groups differ, based on power calculations we did. But the desired sample sizes for all groups are all in blocks of 100. See Supplemental Appendix A2 for desired sample sizes.

⁵ There is also a within-treatment randomization into two equally-sized sub-groups at this stage of the experiment. One sub-group receives information beforehand that at the end of the slider task their group will have the chance to make earnings more equal by voting on a tax rate to redistribute some of the money earned in the slider task. The other sub-group does not receive this tax information.

namely “Lucky 2c, Unlucky 1c” [where half of the participants are informed that they are randomly allocated to a sub-group called ‘Lucky group’ that earns 2 cents for each slider correctly positioned, and the remaining half of the participants are informed they are randomly allocated to a sub-group called ‘Unlucky group’ that earns 1 cent for each slider correctly positioned]. In the **Discrimination** treatment, there are 4 conditions, namely “Female 1c, Male 2c” [where females earn 1 cent and males earn 2 cents for each slider correctly positioned], “Female 2c, Male 1c” [where females earn 2 cents and males earn 1 cent for each slider correctly positioned], “Non-white 1c, White 2c” [where non-whites earn 1 cent and whites 2 cents for each slider correctly positioned] and “Non-white 2c, White 1c” [where non-whites earn 2 cents and whites earn 1 cents for each slider correctly positioned].⁶

After randomization, the real-effort task is explained, comprehension questions are asked, payment information is given for the real-effort task (see Fig. 3 below for examples), and the task is performed. Participants are then asked to guess their relative performance in the slider task, after which their performance and earnings are displayed. Next, we collect information on perceived earnings distributions in their respective groups. The vote on redistribution then takes place. Lastly, we ask a couple of questions about the survey, including whether participants think the payment scheme in the slider task is fair or discriminatory. The full questionnaire of the study is available in Supplemental Appendix A3.

Information on earnings!

50 of the 100 participants are randomly allocated to a group (called **Unlucky Group**) that earns **1 cent** per slider correctly positioned, and the other half (remaining 50 participants) are randomly allocated to a group (called **Lucky Group**) that earns **2 cents** per slider correctly positioned.

By chance, you are in the sub-group (called “**Unlucky Group**”) that earns **1 cent** per slider correctly positioned, which means a maximum of $100 \times 1 \text{ cent} = \1.00 .

⁶ For the gender and ethnicity conditions, we implement a within-treatment randomization in which some of the participants are reminded of their gender and ethnicity (to make their identities salient, similar to the luck condition) and some of the participants are not reminded of their gender and ethnicity (assuming that they feel attached to their identities). This within-treatment randomization was done with a second round of the experiment. Thus, in the first round, gender and ethnicity in the gender and ethnicity conditions were, respectively, not made salient. In the second round, we also re-adjusted the sample sizes of experimental conditions based on power calculations done with data from the first round. The aim was to improve statistical power of the study. See Supplemental Appendix A2 for sample sizes of experimental conditions in the first and second rounds of the experiment.

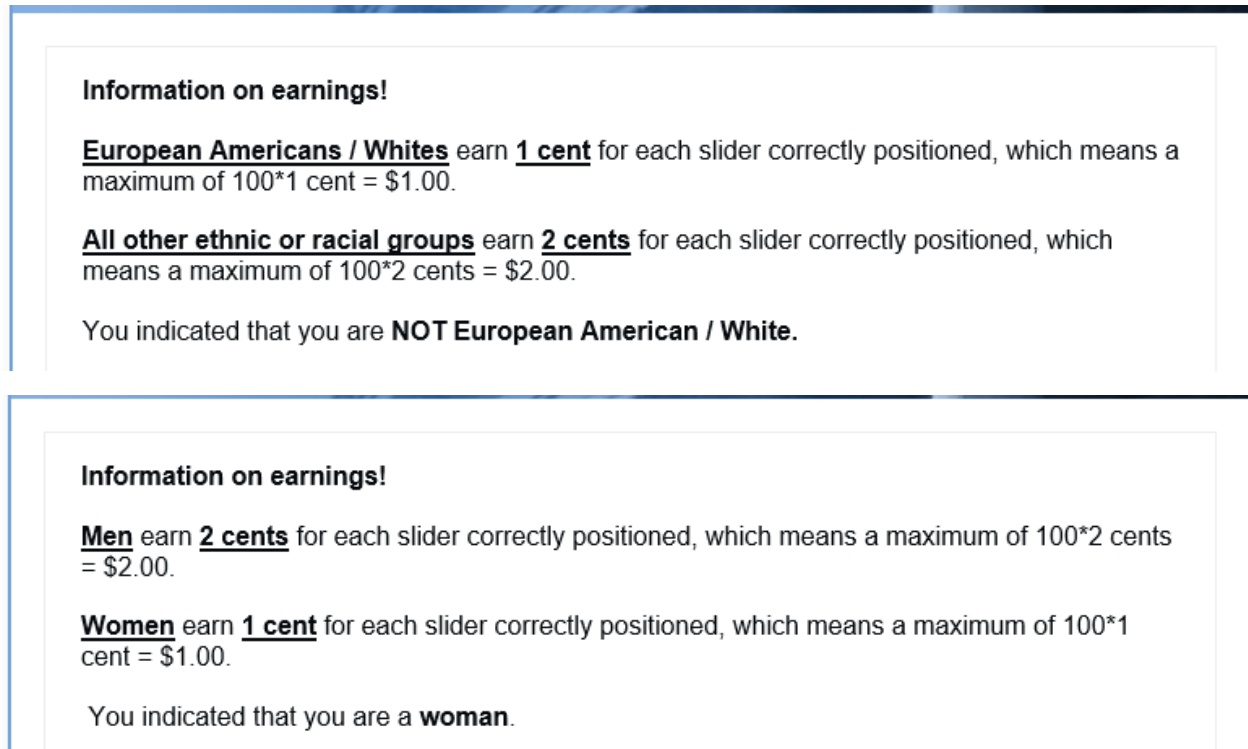


Fig. 3: Payment information – 3 examples of all 7 treatments

2.3 Dependent variables – productivity and demand for redistribution

The study selects a real-effort task, known as the “slider task”, to obtain variation in productivity, which is one of two dependent variables. Compared to costly effort, a real-effort task is particularly important for this experiment in order to elicit individual effort or performance levels (e.g., in labor market applications) (Gill and Prowse, 2013; Lezzi *et al.*, 2015). Social science researchers have used a wide array of real-effort tasks in experiments, including solving mazes, solving mathematics problems, counting, decoding, filling envelopes, answering general knowledge questions, word-search puzzles, slider task, and many other similar tasks requiring either physical and/or mental efforts. The chosen real-effort task for our purposes is the slider task, which has been shown to have a high level of variation in effort or performance levels compared to the other tasks (Gill and Prowse, 2013). In a slider task, a number of sliders are displayed on a computer screen each over a range of values 0 to 100, with the initial position of the slider being 0. Individuals are asked to use the computer mouse to move each slider to a pre-defined point (e.g. 58). They can try as many times as they wish until they have the slider at the pre-defined point. In this study, there are 100 sliders that could be positioned correctly for bonus earnings. This task is timed [3 minutes], and performance is rated based on the number of sliders correctly positioned when the time of the task elapses. Below is a snapshot of the slider task in Fig. 4. The slider task requires work but no specific skills, such that variation in performance are

more likely to be correlated with effort than with specific skills, such as for example word-search puzzles.

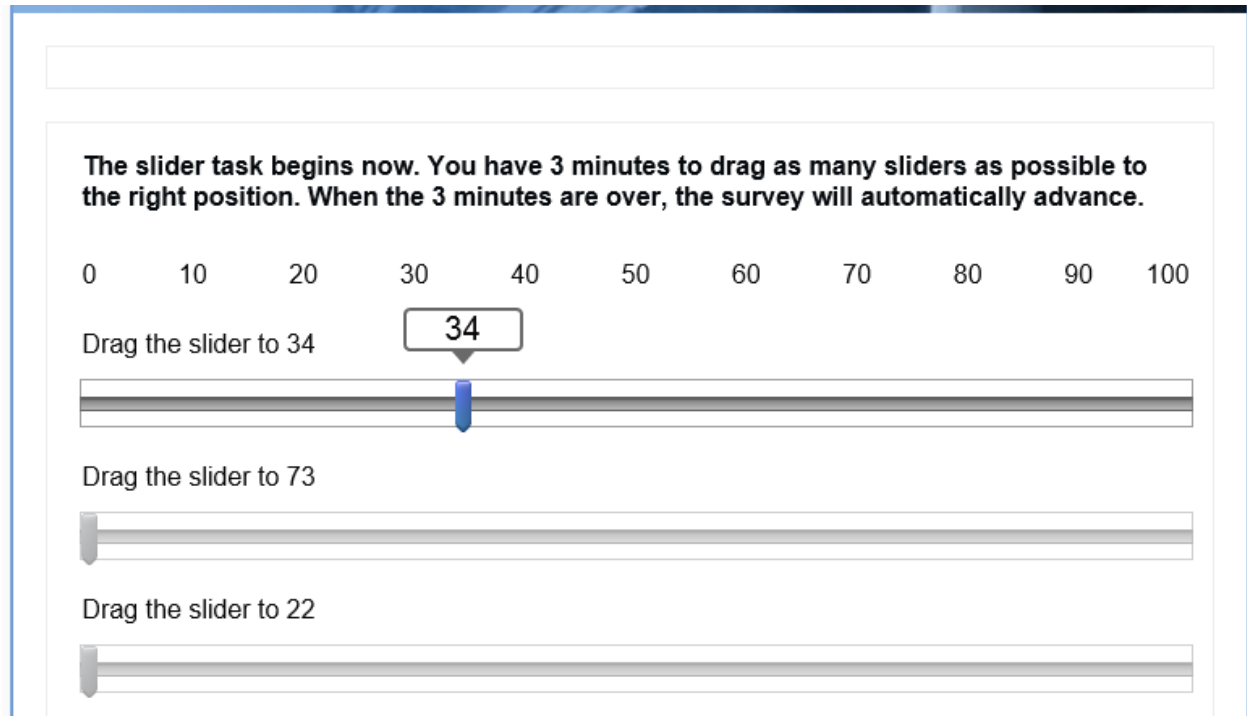


Fig. 4: Slider task (snapshot)

The second dependent variable is participants' vote for redistribution, measured as a preferred tax rate. In the real world, redistributive taxation is often implemented *ex ante* (i.e., people know the tax rates *before* choosing their effort levels). A large literature demonstrates people's aversion to *ex ante* tax rates above a certain threshold, where both work effort and tax revenue begin to decline (i.e., the Laffer curve phenomenon) (Sutter and Weck-Hannemann, 2003; Lévy-garboua *et al.*, 2006; Ottone and Ponzano, 2007; Ortona *et al.*, 2008; Kessler and Norton, 2016). Alternatively, the tax rate that people are both willing and able to vote for redistribution may be determined *ex post*. Our study contributes to the body of literature that investigates redistributive preferences *after* people have chosen their effort levels. For our experimental design, we follow relevant experimental literature that implements vote for redistribution in our design (Klor and Shayo, 2010; Esarey *et al.*, 2012; Großer and Reuben, 2013; Agranov and Palfrey, 2015; Lefgren *et al.*, 2016). Some percentage of every participant's earnings from the slider task is collected as tax and put into a group account. At the end of the study, every participant will receive an *equal* share of the group account. The process requires that participants vote their preferred tax rates (0 – 100%), and the median tax rate is selected as the effective tax rate for the group. This proportional tax scheme together with equal distribution to all group members is progressive: a higher (lower) tax rate would imply greater (less) support to participants with relatively low earnings.

2.4 Empirical strategy: main specifications

This study specifies an OLS model of the following form to run different types regressions, depending on the research questions of interest.

$$Y_i = \beta_0 + \sum_{i=1}^K \beta_i T_i + \sum_{i=1}^L \alpha_i X_i + e_i \quad (1)$$

where:

Y_i is the number of sliders correctly positioned or tax rate voted by participant,

T_i is a treatment dummy variable,

K is the total number of treatments,

X_i is an observable characteristic controlled for, such as a demographic characteristic,

L is the total number of observable characteristics controlled for, and

e_i is an error term assumed to be well-behaved.

To investigate the impact on discrimination and inequality of luck on productivity, let's elaborate and re-specify (1) as follows (while suppressing the subscripts):

$$\text{Sliders} = \beta_0 + \beta_1 f1m2 + \beta_2 f2m1 + \beta_3 nw1w2 + \beta_4 nw2w1 + \beta_5 \text{luck} + \alpha X + e \quad (2)$$

where:

Sliders is the number of sliders participants correctly position,

f1m2 is a dummy variable which indicates 1 if a participant is randomized into Female 1c, Male 2c condition and 0 otherwise,

f2m1 is a dummy variable which indicates 1 if a participant is randomized into Female 2c, Male 1c condition and 0 otherwise,

nw1w2 is a dummy variable which indicates 1 if a participant is randomized into Non-white 1c, White 2c condition and 0 otherwise,

nw2w1 is a dummy variable which indicates 1 if a participant is randomized into Non-white 2c, White 1c condition and 0 otherwise, and

luck is a dummy variable which indicates 1 if a participant is randomized into Lucky 2c, Unlucky 1c condition and 0 otherwise.

The control group for Equation (2) is the 1 cent condition together with 2 cents condition, since participants in these conditions earn equal rates for the same work done in their respective groups. Equation (2) is a productivity function that hypothesizes that $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5 < 0$. In other words, gender or ethnic discrimination decreases productivity, and inequality of luck decreases productivity.

Further, this study argues that inequality based on luck that correlates with individual identity is quite different from inequality based on sheer luck. To test this empirically in terms of productivity, we reformulate Equation (2) as follows:

$$\text{Sliders} = \beta_0 + \beta_1 f1m2 + \beta_2 f2m1 + \beta_3 nw1w2 + \beta_4 nw2w1 + \beta_5 1c + \beta_6 2c + \alpha X + e \quad (3)$$

where:

1c is a dummy variable which indicates 1 if a participant is randomized into 1 cent condition and 0 otherwise, and

2c is a dummy variable which indicates 1 if a participant is randomized into 2 cents condition and 0 otherwise.

The control group for Equation (2) is the Lucky 2c, Unlucky 1c condition. It is hypothesized that $\beta_1, \beta_2, \beta_3, \beta_4 < 0$. In other words, gender or ethnic discrimination decreases productivity more than inequality of luck.

To investigate the impact on discrimination and inequality of luck on demand for redistribution, let's elaborate and re-specify (1) as follows (while suppressing the subscripts):

$$\text{TaxRate} = \beta_0 + \beta_1 f1m2 + \beta_2 f2m1 + \beta_3 nw1w2 + \beta_4 nw2w1 + \beta_5 \text{luck} + \beta_6 \text{Sliders} + \beta_7 \text{SliderTaskEarnings} + \alpha X + e \quad (4)$$

where:

TaxRate is the tax rate voted by participants for redistribution, and

SliderTaskEarnings is participants' earnings from the slider task.

Note that Equation (4) additionally controls for productivity and earnings from the slider task, to correct for possible endogeneity due to omitted variable bias. By the experimental design, the vote for redistribution takes place after participants perform the slider task and earn some money as a result. Participants' voting decisions may be influenced by these factors independent of the treatment conditions they are in.

The control group for Equation (4) is the 1 cent condition together with 2 cents condition, since participants in these conditions earn equal rates for the same work done in their respective groups. Equation (2) is a function for demand for redistribution that hypothesizes that $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5 > 0$. In other words, gender or ethnic discrimination increases demand for redistribution, and inequality of luck increases demand for redistribution. Further, we test empirically whether inequality based on luck that correlates with individual identity is quite different from inequality based on sheer luck in terms of demand for redistribution with the following re-formulation of Equation (4).

$$TaxRate = \beta_0 + \beta_1 f1m2 + \beta_2 f2m1 + \beta_3 nw1w2 + \beta_4 nw2w1 + \beta_5 1c + \beta_6 2c + \beta_7 Sliders + \beta_8 SliderTaskEarnings + \alpha X + e \quad (5)$$

The control group for Equation (5) is the Lucky 2c, Unlucky 1c condition. It is hypothesized that $\beta_1, \beta_2, \beta_3, \beta_4 > 0$. In other words, gender or ethnic discrimination increases demand for redistribution more than inequality of luck.

Next, we investigate gender and ethnic attitudes to discrimination as well as good and bad luck in terms of both productivity and demand for redistribution. Sub-sample regressions also in the form of Equation (1) above are used for these analyses. The sub-sample regressions are restricted to sample sub-groups; such as, male only, female only, white only, and non-white only as well as white male only, white female, non-white male only, and non-white female only. These sub-sample analyses investigate interaction effects of our treatments. We estimate Equation (2) and (4) with 1 cent or 2 cents condition as control group. Relevant comparisons are made as to how different gender or ethnic groups respond or react to both favorable and unfavorable discrimination as well as good and bad luck. For these sub-sample analyses, the Lucky 2c, Unlucky 1c condition is separated into 2 different conditions, as Lucky 2c and Unlucky 1c.

3. Experimental data

3.1 External validity: MTurk data vs. US Census data

This study obtains experimental data from Amazon's Mechanical Turk (MTurk). Sheehan and Pittman (2016) discuss the resemblance of MTurk data to the US population. MTurk data match the US population better than student samples, but may not perfectly match national probability samples. In light of this, we compare our MTurk data to basic demographics of the US population in Table 1 below, to have an idea how nationally representative our data are. Our MTurk sample is somewhat similar to the US population, particularly in terms of unemployment rate. In terms of gender, Sheehan and Pittman (2016) note that the share of females on MTurk has decreased over time to 50%. We, however, find that females still dominate in our sample (55%). Nine percent of participants in our study have a high school diploma, while 14% of the US population have a high school diploma. Forty-one percent of participants in our study have a bachelor's degree, while 9% of the US population have a bachelor's degree. Thus, our sample is more educated than the US population on average. Middle-income earners are overrepresented in our sample; high- or low-income earners are underrepresented in our sample. Our sample is roughly representative of the racial or ethnic composition of the US population. It is hard to make concrete claims about ethnicity due to the following caveat. In our experiment, we record ethnicities based on how people describe themselves, which slightly differs from the classification of the US Census. In the US Census, people are identified as 'White alone', 'Black or African

American alone', 'Asian alone', and 'Hispanic or Latino' could be also be any of the other ethnicities.

Table 1: Comparing MTurk data to US Census data

Basic demographics	MTurk data	US Census data
Male	0.44	0.495
Female	0.55	0.504
High school diploma	0.094	0.14
Bachelor's degree	0.41	0.09
Unemployed (of labor force)	0.056	0.05
Earning less than \$10,000	0.044	0.06
Earning \$10,000 - \$59,999	0.525	0.43
Earning \$60,000 - \$99,999	0.26	0.23
Earning \$100,000 +	0.175	0.28
White (alone)	0.75	0.77
Black or African American (alone)	0.083	0.13
Asian (alone)	0.078	0.06
Hispanic or Latino	0.065	0.18

Notes: This table shows information on the share of selected indicators of gender, educational status, employment status, income status, and ethnicity in our MTurk sample or the US population.⁷

Additionally, our MTurk data are at least geographically representative of the US population at the state level; see Maps 1 and 2 in Supplemental Appendix A4.

3.2 Internal validity: Summary statistics and balance tests

This study utilizes information from a complete data set of 8,514 observations. The following are the numbers of observations by condition: 1 cent – 1,176; 2 cents – 1,180; Female 1c, Male 2c – 778; Female 2c, Male 1c – 780; Luck (Lucky/Unlucky) – 1,585; Non-white 1c, White 2c – 1,504; and Non-white 2c, White 1c – 1,511. The productivity of participants in the study is an average number of 43 sliders correctly positioned. Demand for redistribution is obtained as an average tax vote of 28%.⁸

⁷ The US Census data are obtained from the following links:

<https://www.statista.com/statistics/241488/population-of-the-us-by-sex-and-age/>,
<https://www.census.gov/quickfacts/fact/table/US/PST045217> and
<https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml>.

⁸ We identify and drop observations that might be outliers in terms of (1) productivity – the number of sliders correctly positioned, and/or (2) tax vote for redistribution. See Supplemental Appendix A5 for how the distributions of (1) and (2) look before and after dropping outliers.

Table 2 presents summary statistics and balance tests of the main control variables. The average age of participants is 36. The average household size is 3. Thirty-two percent of participants are single and not in a relationship, 26% are in a relationship, 41% are married, 1% are widowed. There are more females (55%) than males (44%), with the rest indicating “Other / Not prefer to tell”. Eight percent of participants describe themselves as African American / African, 8% Asian American / Asian, 75% European American, 7% Hispanic / Latino, and 2% indicate “Other / Prefer not to tell”. Alternatively, we have white and non-white sub-samples of the data. However, Asian Americans / Asians are excluded from the non-white category in all the data analysis presented in the Results section [Section 4], as they often do not face discrimination in the United States. Forty-five percent of participants report they have children. Seventy-eight percent of participants are employed, 6% are unemployed and looking for a job, 7% are students, and 9% are not in the labor force (e.g., retired). Forty-seven percent of participants report annual household income of less than \$50,000, 38% report annual household income of \$50,000 to \$99,999, and 15% report annual household income of \$100,000 and more.

In general, the F-tests do not reject the hypothesis that experimental conditions are not different from each other. Overall, the summary of the data described above is fairly similar across the different experimental conditions. Given that observables generally balance across all 7 experimental conditions, one can expect that these conditions are also similar across unobservables. Thus, randomization deals with possible endogeneity (more precisely, unobserved heterogeneity) that could contaminate the results of this study. However, we acknowledge that our randomization did not work perfectly; e.g., the rate of being in a relationship and the rate of being a migrant do not balance across all experimental conditions.

Table 2: Summary statistics & balance tests

Observables	Mean	F-statistic	p-value	Observables	Mean	F-statistic	p-value
Age	36	0.54	0.777	Full-time employment	0.55	1.56	0.154
Household size	3	1.97	0.067	Part-time employee	0.11	0.23	0.966
Single and not in a relationship	0.31	0.52	0.796	Self-employed or small business owner	0.11	0.48	0.822
In a relationship	0.26	2.50	0.020	Not in labor force (e.g., retired)	0.09	1.49	0.179
Married	0.41	1.82	0.091	Student	0.07	1.83	0.090
Widowed	0.10	0.28	0.945	Unemployed and looking for a job	0.06	0.61	0.724
Prefer not to tell civil status	0.01	0.95	0.455	Prefer not to tell employment status	0.01	0.38	0.892
Female	0.55	0.95	0.460	Low-income earners (<\$50,000)	0.47	1.3	0.253
Male	0.44	0.82	0.556	Middle class (\$50,000 - \$99,999)	0.38	0.68	0.666
Other gender / prefer not to tell	0.00	1.53	0.163	High-income earners (\$100,000 +)	0.15	1.2	0.304
African American / African	0.08	0.70	0.647	High school diploma	0.09	0.36	0.906
Asian American / Asian	0.08	1.12	0.347	Bachelor's Degree	0.41	1.01	0.415
European American / White	0.75	0.45	0.844	Graduate Degree (Master's, Ph.D.)	0.15	0.62	0.713
Hispanic / Latino	0.07	0.78	0.587	Some college, no degree	0.30	0.65	0.693
Other ethnicity / prefer not to tell	0.02	15.47	0.000	Some high school, no degree	0.01	1.24	0.284
Children - yes	0.45	1.10	0.357	Other educational status	0.04	1.16	0.325
Children - no	0.54	0.81	0.561	Prefer not to tell educational status	0.00	1.59	0.145
Children - prefer not to tell	0.01	1.22	0.292	Computer	0.89	0.27	0.950
Born in the US - yes	0.95	1.89	0.079	Smartphone	0.07	0.32	0.926
Born in the US - no	0.05	2.40	0.025	Tablet	0.03	0.79	0.580
Born in the US - prefer not to tell	0.01	0.67	0.676	Other device	0.01	0.8	0.572

Note: Not all observables have been displayed in this table.

4. Results

4.1 Relationship between inequality, productivity, and demand for redistribution

First, we explore the relationship between inequality, productivity, and redistribution from the experimental data. Table 3 below reports productivity, inequality and demand for redistribution observed within all groups. There is limited variation in productivity; productivity is highest in the Female 2c, Male 1c condition (43.4 sliders) and lowest in the Non-white 1c, White 2c condition (41.7 sliders). At the group level, inequality in earnings from the slider task is higher than inequality in productivity, particularly in the treatment groups. As is expected, redistribution reduces inequality within all groups and within the whole sample. See Appendix A graphical representation of the distribution of productivity as well as earning before and after redistribution. Unlike productivity, tax vote is more varied across conditions; tax rate is as low as 24.8% in the 2 cents condition and as high as 31.3% in the Female 1c, Male 2c condition. The effective tax rate applied and paid out in the experiment is the median tax rate within each group. The median tax rate is 20% for the whole sample as well as 5 of all 7 conditions. Median tax rate is lowest in the 2 cents condition (11%) and highest in the the Female 1c, Male 2c condition (23%).

Table 3: Group outcomes

Condition	Sliders - Mean	Gini - sliders	Gini - earnings before redistrib.	Gini - earnings after redistrib.	Tax - Mean	Tax - Median
1c	43	17.9	17.9	14.3	27	20
2c	42.6	18.1	18.1	15.4	24.8	11
f1m2	42.7	18.2	29.9	22.4	31.3	23
f2m1	43.4	17.6	22.3	17.8	26.7	20
luck	42.5	17.8	26.5	21.2	27.8	20
nw1w2	41.7	18	22.3	18.0	28.1	20
nw2w1	41.9	18	23.1	18.2	29.3	20
All	42.4	18	26.4	22.3	27.8	20

Notes: Productivity is the number of sliders correctly positioned. Gini coefficient obtained from productivity and earnings from slider task (before and after redistribution) as well as tax rate is reported as a percentage. Earnings before or after redistribution does not include the flat compensation of \$1.00 paid to all participants for their time.

Figure 5 shows a significant negative relationship between inequality in productivity in the slider task and productivity. At the group level, a point increase in inequality is associated with -1.63 reduction in productivity. Figure 6 shows a significant positive relationship between inequality in productivity in the slider task and demand for redistribution. At the group level, a point increase in inequality is associated with a 1.6 point increase in tax rate. These relationships still hold when one considers the inequality in earnings from slider task (before redistribution). Appendix A illustrates the aforementioned relationships graphically; see Fig. A4 and Fig. A5. These are interesting relationships, but are not causal. More rigorous analysis can be found in the next

sub-section that shows the impacts of our treatments on productivity and demand for redistribution.

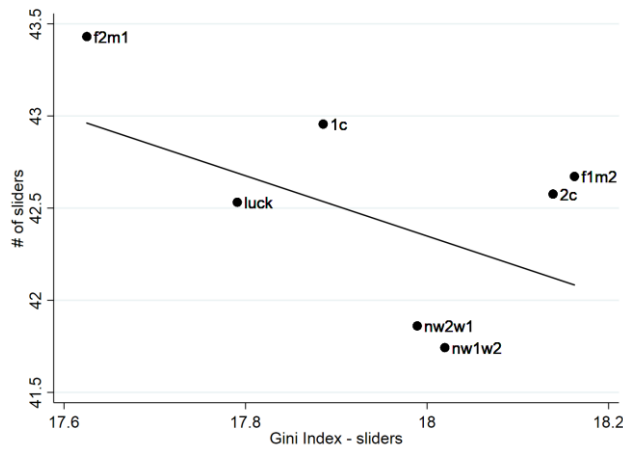


Fig. 5: Relationship between inequality and productivity

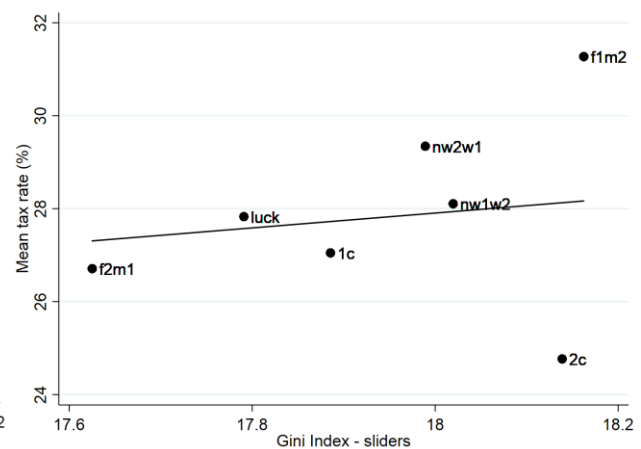


Fig. 6: Relationship between inequality and redistribution

4.2 Impact of discrimination on productivity and demand for redistribution

The main objective of this study is to investigate the impact of gender and ethnic discrimination, as well as inequality of luck, on productivity and redistributive preferences, for comparison. Table 4 presents important results of the study. The study finds that ethnic discrimination reduces productivity, whether non-white or whites are discriminated against in the payment scheme. The effects sizes are small relative to the average productivity of 42.4 sliders. When non-whites are discriminated against, productivity falls by 0.88 sliders; when whites are discriminated against, productivity falls by 0.65 sliders (see Table 4, column 1). Since our randomization was not perfect, observables are controlled for in all regressions. The control group for all the regressions in this table is the 1 cent condition together with the 2 cents condition. Discrimination by sheer luck does not affect productivity, while discrimination by ethnic identity (which is a specific type of luck) hurts productivity. Gender discrimination does not reduce productivity, whether females or males are discriminated against in the payment scheme. However, the study observes suggestive countervailing effects across genders, to be discussed in the next sub-section.

The study observes demand for redistribution in the presence of discrimination, especially when females or non-whites are discriminated against. In Table 4 (column 3), tax rate increases by about 6 percentage points when females are discriminated against. Tax rate increases by 3 percentage points when non-whites are discriminated against. Tax rate increases by 2 percentage points when whites are discriminated against. Inequality of luck also raises demand for redistribution, but less than inequality of opportunity, particularly when females are discriminated against (according to t-tests from results in Table 4, column 3). It is important to note that the effect sizes are larger in terms of redistributive preferences than productivity, both in absolute terms and

relative to average tax rate (28%) and average productivity (42.4 sliders) respectively. Further, no effects are observed whatsoever when females earn 2 cents and males earn 1 cent in both productivity and redistributive preferences.

Table 4: Main regressions I

	(1) Sliders	(2) Discriminatory	(3) Tax rate	(4) Discriminatory
1 cent & 2 cents	-	-	-	-
Female 1c, Male 2c	-0.131 (0.500)	0.602*** (0.0184)	5.591*** (1.210)	0.602*** (0.0182)
Female 2c, Male 1c	0.711 (0.494)	0.394*** (0.0202)	0.984 (1.153)	0.394*** (0.0200)
Non-white 1c, White 2c	-0.882** (0.393)	0.607*** (0.0142)	3.201*** (0.960)	0.625*** (0.0145)
Non-white 2c, White 1c	-0.654* (0.392)	0.520*** (0.0148)	2.101** (0.961)	0.506*** (0.0151)
Luck (Lucky/Unlucky)	-0.0590 (0.386)	0.0524*** (0.0120)	1.915** (0.909)	0.0530*** (0.0121)
Male	4.309*** (0.274)	-0.0212** (0.0101)	-2.587*** (0.655)	-0.0346*** (0.0102)
White	6.684*** (0.482)	0.0719*** (0.0172)	1.722 (1.116)	0.0498*** (0.0172)
Sliders			-0.0839** (0.0357)	0.00484*** (0.000539)
Earnings from slider task			-7.741*** (1.461)	-0.111*** (0.0225)
Constant	52.03*** (1.130)	0.0332 (0.0421)	35.18*** (3.092)	-0.130*** (0.0474)
Observables	Yes	Yes	Yes	Yes
Observations	7,515	7,515	7,515	7,515
Adjusted R-squared	0.308	0.296	0.022	0.303

Notes: Dependent variable for sliders regressions the number of sliders correctly positioned. Dependent variable for tax rate regressions is the tax vote (%) for redistribution. Discriminatory is a dependent variable which is a dummy for participants who say payment scheme is discriminatory. Estimates from the Discrimination regression are similar, whether or not control variables are included. Control group is 1 cent condition together with 2 cent condition. Explanatory variables are all dummies. Asian Americans / Asians are excluded from the regressions. Observables controlled for are basic demographic and socioeconomic characteristics, including age, household size, gender, ethnicity, employment status, income class, educational status, relationship status, citizenship, device used in performing slider task, and whether respondent has children or not. The tax rate equation controls for productivity in the slider task as well as the earnings from the slider task. This is to deal with endogeneity that results from the fact that the slider task precedes vote for redistribution in the experimental sequence. Robust standard errors are in parenthesis. Estimates are significant at the following significance levels: *** $p < 0.005$, ** $p < 0.025$, * $p < 0.05$. Since these tests are one-sided, the p-values are divided by 2, making them more powerful. Estimates that are not starred are not significant at the 5% level.

It appears that participants' fairness perceptions about the payment schemes mediate or predict the above-mentioned effects from Tables 4. In general, productivity and retributive effects of discrimination are observed when more participants think the payment scheme is discriminatory; see columns 2 and 4. When females earn 2 cents and males earn 1 cent (i.e., the treatment that has no effect of discrimination), the likelihood that participants think the payment scheme is discriminatory increases by only 40%, compared to participants in the control conditions. When females earn 1 cent and males earn 2 cents, the likelihood that participants think the payment scheme is discriminatory increases by 60%, compared to participants in the control conditions. When non-whites earn 1 cent and whites earn 2 cents, the likelihood that participants think the payment scheme is discriminatory increases by about 61%, compared to participants in the control conditions.

Table 5: Main regressions II

	(1) Sliders	(2) Discriminatory	(3) Tax rate	(4) Discriminatory
Luck (Lucky/Unlucky)	-	-	-	-
Female 1c, Male 2c	-0.0717 (0.524)	0.550*** (0.0197)	3.667*** (1.276)	0.549*** (0.0195)
Female 2c, Male 1c	0.770 (0.518)	0.342*** (0.0214)	-0.918 (1.220)	0.341*** (0.0212)
Non-white 1c, White 2c	-0.823* (0.423)	0.554*** (0.0158)	1.421 (1.047)	0.580*** (0.0163)
Non-white 2c, White 1c	-0.595 (0.423)	0.467*** (0.0165)	0.0502 (1.055)	0.445*** (0.0170)
1 cent	0.0743 (0.460)	-0.0564*** (0.0138)	-2.603** (1.159)	-0.0928*** (0.0152)
2 cents	0.0438 (0.459)	-0.0485*** (0.0140)	-1.239 (1.128)	-0.0139 (0.0153)
Male	4.309*** (0.274)	-0.0211** (0.0101)	-2.574*** (0.655)	-0.0339*** (0.0102)
White	6.684*** (0.482)	0.0719*** (0.0172)	1.717 (1.116)	0.0495*** (0.0172)
Sliders			-0.0695* (0.0386)	0.00567*** (0.000601)
Earnings from slider task			-8.690*** (1.760)	-0.166*** (0.0288)
Constant	51.97*** (1.130)	0.0856** (0.0428)	37.10*** (3.092)	-0.0774 (0.0480)
Observables	Yes	Yes	Yes	Yes
Observations	7,515	7,515	7,515	7,515

Adjusted R-squared	0.308	0.296	0.022	0.304
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Notes: All notes in the previous table [Table 4] apply, except that control group is the Luck condition.

When non-whites earn 2 cents and whites earn 1 cent, the likelihood that participants think the payment scheme is discriminatory increases by about 51%, compared to participants in the control conditions. See Appendix B for the graphs that illustrate the fairness perceptions in experimental conditions; gender conditions are disaggregated by gender groups, and ethnic conditions are disaggregated by ethnicity.

Next, we empirically investigate if sheer luck differs from luck based on identity, as argued by this study. The results in Table 5 provide some support for this claim. Productivity reduces by 0.8 sliders when non-whites are discriminated against, compared to the Luck condition. In terms of productivity, the remaining forms of discrimination are hardly distinguishable from luck, given our data. Tax rate increases by 3.7 percentage points when females are discriminated against, compared to the Luck condition. In terms of redistributive preferences, the remaining forms of discrimination are hardly distinguishable from luck, given our data.

Additionally, the main regressions in Tables 4 and 5 suggest the following general results: men are more productive in the slider task than women by 4 sliders, men are less willing to demand redistribution than women by 3 percentage points of tax rate, whites are more productive in the slider task than non-whites by 7 sliders, and whites are just as willing as non-whites to demand redistribution.

4.2 Sub-sample regressions – gender effects of discrimination

This sub-section discusses the responses of gender groups to disadvantageous and advantageous discrimination, as well as to bad and good luck. Appendix C reports a number of sub-sample regressions similar to the main regressions, though regressions are run on sub-samples (e.g., males only, females only). The relevant results are compiled in Table 5.

When men are discriminated against, they actually increase their productivity by 1.8 sliders compared with other men who also earn 1 cent but in a non-discriminatory, control condition. However, they do not demand more redistribution. Being unlucky does not affect their productivity and redistributive preferences, either. Men show no productivity effects for being lucky, but men demand redistribution even when they are on the advantageous side of discrimination. Their tax rate increases by 4.1 percentage points.

The productivity of women falls by 1 slider when they are discriminated against in favor of men, but this result is not statistically significant. The tax rate of women increases by 8.2 percentage points when they earn 1 cent and men earn 2 cents. The effect size is relatively large; thus, women seem to be bothered a lot if they suffer discrimination. Like men, being unlucky does not

affect the productivity of women. Unlike men, however, being unlucky increases the tax rate of women by 3 percentage points. Women become more productive when they are lucky, but are not more productive when they are on the advantageous side of discrimination. Moreover, women do not demand redistribution when they are on the advantageous side.

Table 5: Key results from sub-sample regressions		
Comparison (sample 1 vs. sample 2)	Sliders	Tax rate
<i>Male attitudes toward discrimination</i>		
1 cent (male) vs. f2m1 (male)	1.847**	-0.207
1 cent (male) vs. Unlucky (male)	0.0408	1.657
2 cents (male) vs. f1m2 (male)	-0.282	4.078**
2 cents (male) vs. Lucky (male)	-1.323	1.192
<i>Female attitudes toward discrimination</i>		
1 cent (female) vs. f1m2 (female)	-1.064	8.168***
1 cent (female) vs. Unlucky (female)	-0.639	3.117*
2 cents (female) vs. f2m1 (female)	0.937	0.649
2 cents (female) vs. Lucky (female)	1.354**	1.253
<i>White attitudes toward discrimination</i>		
1 cent (white) vs. nw2w1 (white)	-0.521	2.932**
1 cent (white) vs. Unlucky (white)	0.0909	3.847***
2 cents (white) vs. nw1w2 (white)	-0.66	4.437***
2 cents (white) vs. Lucky (white)	0.433	2.290*
<i>Non-white attitudes toward discrimination</i>		
1 cent (non-white) vs. nw1w2 (non-white)	-2.041*	1.505
1 cent (non-white) vs. Unlucky (non-white)	-1.688	-3.755
2 cents (non-white) vs. nw2w1 (non-white)	-0.909	-5.856**
2 cents (non-white) vs. Lucky (non-white)	-0.949	-3.219

Notes: These results are coefficients obtained from all sub-sample regressions in Appendix C that control for observables. Two conditions are compared based on identity. The coefficients indicate the difference between sample 2 and sample 1 [i.e., sample 2 – sample 1]. For the first line [1 cent (male) vs. f2m1 (male)], for example, the coefficient 1.847 means that men in the Female 1c, Male 1c condition correctly position 1.8 more sliders than men in the 1 cent condition.

4.3 Sub-sample regressions – ethnic effects of discrimination

This sub-section discusses the responses of ethnic groups to disadvantageous and advantageous discrimination, as well as to bad and good luck. Appendix C reports a number of sub-sample regressions similar to the main regressions, though regressions are run on sub-samples (e.g., white only, non-white only). The relevant results are compiled in Table 5.

When whites earn 1 cent and non-whites earn 2 cents, their productivity is not any different from when they earn 1 cent in a non-discriminatory control group. However, they are also non-reactive in terms of productivity when they feel unlucky, compared to whites who earn 1 cent with no feelings of bad luck.

With regard to demand for redistribution, whites are reactive. Their tax rate increases by 3.8 percentage points when they are just unlucky and 2.9 percentage points when they are on the disadvantageous side of discrimination. As indicated earlier, males are however not reactive when they earn 1 cent and females earn 2 cents. It is striking that males are generally more progressive than whites. When whites earn 2 cents and non-whites earn 1 cent, whites demand more redistribution to compensate non-whites; tax rate increases 4.4 percentage points. When discrimination favors them, both males and whites demand redistribution to compensate females and non-whites, respectively. But when discrimination does not favor them, males do not demand redistribution but whites do. Whites also demand more redistribution when they are just lucky, to compensate participants who are unlucky. Their tax rate increases by 2.3 percentage points.

Productivity falls by 2 sliders when non-whites are discriminated against, unlike whites who are unaffected by discrimination. (This result provides some evidence for the impact of stereotype threat.) Non-whites do not demand redistribution when they are discriminated against or just unlucky, compared to non-whites who earn exact same 1 cent in a control treatment where all participants are paid equally. The productivity of non-whites does not respond to being on the advantageous side of discrimination or being just lucky to earn 2 cents. As regards demand for redistribution, non-whites demand less redistribution (by 5.9 percentage points) compared to other non-whites who earn exact same 2 cents without any feelings of favor in the control treatment. As mentioned earlier, whites do the opposite in a similar situation.

4.4 Sub-sample regressions – gender & ethnicity interaction effects of discrimination

This sub-section investigates the effects of discrimination on productivity and demand for redistribution when one interacts both gender and ethnicity. Appendix D reports the results from a number of sub-sample regressions, which are run on more restricted sub-samples (e.g., white male only, white female only). The relevant coefficients are compiled in Table 6 and shed light on the results in Table 5 above. In other words, they show which gender or ethnic group drives the results in Table 5.

The following are ethnic attitudes toward gender discrimination. First, white males explain why males increase their productivity in the condition where males earn 1 cent and females earn 2 cents. Overall, males increase productivity by 1.8 sliders, but white males do increase their productivity by 2.3 sliders while non-white males do not respond to the treatment statistically. Second, males overall do not react in terms of their demand for redistribution when they are just

unlucky, but this is due to balancing effects from white males (who increase their tax rate by 3.9 percentage points) and non-white males (who decrease their tax rate by 8.1 percentage points). Third, males overall increase their demand for redistribution by 4.1 percentage points when females earn 1 cent and males earn 2 cents, but this is explained by white males. White males increase their tax rate by 4.9 percentage points, while non-white males do not statistically increase their tax rate significantly. Fourth, non-white females explain the relatively large effect size of 8.2 percentage increase in tax rate when females earn 1 cent and males earn 2 cents. Non-white females increase their tax rate by 11.4 percentage points, while white females increase their tax rate by 7.6 percentage points.

Table 6: Key results from sub-sample regressions - gender & ethnicity

Comparison (sample 1 vs. sample 2)	Sliders	Tax rate
1 cent (male) vs. f2m1 (male) - whites	2.252**	-0.197
1 cent (male) vs. f2m1 (male) - non-whites	0.344	0.909
1 cent (male) vs. Unlucky (male) - whites	0.141	3.901*
1 cent (male) vs. Unlucky (male) - non-whites	0.229	-8.131*
2 cents (male) vs. f1m2 (male) - whites	0.394	4.857**
2 cents (male) vs. f1m2 (male) - non-whites	-2.517	1.038
2 cents (male) vs. Lucky (male) - whites	-1.132	2.292
2 cents (male) vs. Lucky (male) - non-whites	-2.727	-4.865
1 cent (female) vs. f1m2 (female) - white	-1.097	7.636***
1 cent (female) vs. f1m2 (female) - non-white	-1.045	11.39**
1 cent (female) vs. Unlucky (female) - white	-0.156	3.839**
1 cent (female) vs. Unlucky (female) - non-white	-2.979*	-2.131
2 cents (female) vs. f2m1 (female) - whites	1.472**	3.624*
2 cents (female) vs. f2m1 (female) - non-whites	-1.634	-15.51***
2 cents (female) vs. Lucky (female) - whites	1.695**	2.275
2 cents (female) vs. Lucky (female) - non-whites	0.132	-4.483
1 cent (white) vs. nw2w1 (white) - male	-0.14	2.882
1 cent (white) vs. nw2w1 (white) - female	-0.947	3.092*
1 cent (white) vs. Unlucky (white) - male	0.141	3.901*
1 cent (white) vs. Unlucky (white) - female	-0.156	3.839**
2 cents (white) vs. nw1w2 (white) - male	-0.761	4.568***
2 cents (white) vs. nw1w2 (white) - female	-0.523	4.596***
2 cents (white) vs. Lucky (white) - male	-1.132	2.292
2 cents (white) vs. Lucky (white) - female	1.695**	2.275
1 cent (non-white) vs. nw1w2 (non-white) - male	-4.352**	-2.734
1 cent (non-white) vs. nw1w2 (non-white) - female	0.139	3.444
1 cent (non-white) vs. Unlucky (non-white) - male	0.229	-8.131*
1 cent (non-white) vs. Unlucky (non-white) - female	-2.979*	-2.131
2 cents (non-white) vs. nw2w1 (non-white) - male	-3.413*	-4.029
2 cents (non-white) vs. nw2w1 (non-white) - female	0.679	-7.974**

2 cents (non-white) vs. Lucky (non-white) - male	-2.727	-4.865
2 cents (non-white) vs. Lucky (non-white) - female	0.132	-4.483

Notes: These results are coefficients obtained from all sub-sample regressions in Appendix D. Two conditions are compared based on interacted identity, namely gender and ethnicity. The coefficients indicate the difference between sample 2 and sample 1 [i.e., sample 2 – sample 1]. For the first line [1 cent (male) vs. f2m1 (male) - whites], for example, the coefficient 2.252 means that white men in the Female 2c, Male 1c condition correctly position 2.3 more sliders than white men in the 1 cent condition.

Fifth, females overall increase their tax rate by 3.1 percentage points when they are just unlucky, but this effect is driven by white females whose tax rate increases by 3.8 percentage points. The relevant result from the non-white female sub-sample regression is not statistically significant. Sixth, females overall do not increase their tax rate when males earn 1 cent and females 2 cents, but this is due to the balancing effects of white females (who increase their tax rate by 3.6 percentage points) and non-white females (who decrease their tax rate by 15 percentage points). Seventh, females overall are more productive when they are lucky by 1.4 sliders. However, this effect is also driven by whites whose productivity increases by 1.7 sliders, and non-whites do not respond positively to good luck in terms of their productivity.

The following results are gender attitudes to ethnic discrimination. First, whites demand more redistribution by 2.9 percentage points in tax rate when they are on the disadvantageous side of ethnic discrimination. This effect is, however, driven by white females (whose tax rate increases by 3.1 percentage points) and not white males. Second, whites demand more redistribution by 3.8 percentage points in tax rate when they are just unlucky to earn 1 cent. This effect is driven by both the males (3.9 percentage points) and females (3.8 percentage points). Third, whites increase demand for redistribution by 4.4 percentage points in tax rate when they are on the advantageous side of discrimination, and this effect is driven by both the males (4.6 percentage points) and females (4.6 percentage points). Fourth, when whites are just lucky to earn 2 cents, whites increase their demand for redistribution by 2.3 percentage points, though this effect does not differ by gender.

Fifth, the productivity of non-whites falls by 2 sliders when they are on the disadvantageous side of discrimination. The source of this reduction is the males, who reduce their productivity by 4.4 sliders, and the females do not react in a statistically significant way. Lastly, non-white reduce their tax rate when they are on the advantageous side of ethnic discrimination by 5.9 percentage points. This result is driven by non-white females (whose tax rate reduces by 8 percentage points); non-white males also reduce their tax rate by 4 percentage points, but this estimate is not statistically significant.

5. Robustness checks

a. Time spent on treatment/payment information pages

To be double sure the treatment/payment information caused the effects the study reports, we check the time participants spent in reading the treatment/payment information by condition. It turns out that participants, on average, spend more time reading treatment/payment information that are longer, and vice versa. The Luck (Lucky/Unlucky) condition has the highest word count of 73, and the 1 cent or 2 cents condition has the lowest word count of 19. Participants in the former spend 72 seconds more in reading the payment information than participants in the latter. See Appendix E for a complete set of results. The same piece of information is given to all participants in all conditions to explain the vote for redistribution before they state their preferred tax rate. This information has a word count of 518. As expected, time spent does not differ by condition; see Appendix E again. Overall, if there is any variation in time spent reading the treatment/payment information that could influence our treatment effects, it is expected to be random across treatments.

b. Actual productivity vs. perceived productivity

Participants in the study were asked to make a guess on how many sliders they correctly positioned in the slider task. This is a measure of perceived productivity. This study finds slight reductions in actual productivity due to ethnic discrimination. We investigate if this result holds if we consider perceived productivity. Table F1 in Appendix F, the results suggest that actual productivity decreases by 0.88 sliders and perceived productivity decreases by 1.1 sliders when non-whites earn 1 cent and whites earn 2 cents for the same piece of work. These effect sizes are not statistically different from each other. Thus, the reduction in productivity brought about by ethnic discrimination is observed both objectively and subjectively.

Further, participants in the study were asked to make a guess on their performance in the slider task relative to other participants in their groups. They indicate whether they think their performance is far below, below, about, above, or far above average in their group. This is a measure of perceived performance relative to other participants. The actual data of performance of all participants in the slider task are grouped in 5 quantile categories, where 1 indicates “far below average” and 5 indicates “far above average”. We investigate whether the treatments generally impact participants’ actual or perceived productivity relative to other participants in their groups. Table F2 in Appendix F presents OLS estimates of sub-sample comparisons of the effects of different types of discrimination on productivity. The results buttress a key finding of the study, that men raise their productivity when they are discriminated against. This male attitude to gender discrimination is observed both objectively and subjectively.

c. Power calculations

This study finds effects of different types of discrimination that could be considered causal, or internally valid, as a result of randomization. However, a possible concern is that the experiment may be underpowered, regardless of the large sample size of the study, due to many different treatment conditions and sample sub-groups. In the event of insufficient statistical power, the study runs the risk of imprecise estimates. In other words, the probability of concluding that there is no effect when, in fact, there is an effect is low when power is high. To deal with possible power problems, we did power calculations from the results of a pilot of this study, and we did a second round of the real experiment to boost the power of the study (as mentioned earlier in Section 2.2). For validation, Appendix G shows results of power calculations we do again with actual data of the study. A power level of 80% and a significance level of 10% are selected for power calculations. Given the mean and standard deviation of productivity and redistributive demand in control groups, Appendix G shows the minimum detectable effect (MDE) sizes with the relevant sample sizes for all comparisons in the study. If the MDE is less than the actual effect size or coefficient reported in the study (in absolute terms), that means we have statistical power of at least 80% to detect an effect if there is one. If the MDE is greater than the actual effect size (in absolute terms), we have less than 80% power to detect an effect if there is one. The results from the power calculations show that the effects of discrimination observed in the main treatments of the study are well powered. However, power is reduced for effects in most of the sub-sample comparisons, where the sample sizes reduce. Overall, the redistributive effects of discrimination are not only larger but also more powered than the productivity effects. For example, we find that ethnic discrimination reduces productivity marginally, but also at less than 80% power. By contrast, both gender and ethnic discrimination raise demand for redistribution with at least 80% power.

d. Drop-out analysis

We separately analyze the incomplete data of some 161 participants who drop out in the course of the survey and are not part of the main analysis carried out in this study. This figure accounts for 1.86% of all observations in the raw data set, implying only limited loss of power for the whole study. Among other reasons, participants may drop out the survey because of fatigue, lack of interest, and resentment over the payment information, especially if they are discriminated against or are unlucky. In fact, one of the stages in the survey flow where drop-out rate peaks is just after payment information is provided; see Appendix H (Table H1). Drop-out rate does not differ significantly across all conditions. An ANOVA test does not reject the null hypothesis of equality of drop-out rate across all conditions ($F=0.31$, $p=0.9321$). After payment information is provided, an ANOVA test shows that drop-out rate is still statistically equal across all conditions ($F=1.49$, $p=0.1762$). However, a closer look at the data provides suggestive evidence that after payment information is provided, drop-out rate is relatively high in Non-white 2c, White 1c

condition [Appendix H (Table H2)]. Besides, the drop-out rate doubles for whites when they are discriminated against in the payment scheme and the drop-out rate doubles for Africans / African Americans also doubles when non-whites are discriminated against in the payment scheme [Appendix H (Table H3)].

6. Discussions and Conclusion

This study is a scientific contribution to the clarion call for “equal opportunity” in the United States. It analyzes experimental data to show how unequal opportunities based on gender and ethnic discrimination or sheer luck affect productivity and demand for redistribution in the United States. The study distinguishes between different sources of inequality and finds interesting results once inequality is viewed through the lens of perceived fairness. For instance, Kuziemko *et al.* (2015) find that participants in their MTurk experiment do not demand more redistribution in response to informational treatments about growing inequality (broadly defined) in the United States; but, once we present the case of unfair inequality based on gender and ethnicity, we find a positive response.

A few more general results and conclusions are worth mentioning and discussing. First, the men in our study are more productive in the slider task than women, probably because men are just better at computer games. Or, probably men are more concerned about poverty and women are more concerned about (unfair) inequality. When men are discriminated against in favor of women (i.e., when they earn 1 cent and women earn 2 cents), they increase their productivity to raise their earnings from the slider task. When women are discriminated against in favor of men (i.e., when they earn 1 cent and men earn 2 cents), they demand more redistribution, which is the largest effect size of the study.

Second, the results of the study may be picking up effects of the media in the United States. Calls for affirmative action in the United States have become more prevalent in recent times, though it emphasizes more gender equality than ethnic equality (Arcidiacono and Lovenheim, 2016; Naibandian, 2018; Sandberg, 2013; *The Economist*, 2018b). This could explain why whites admit ethnic discrimination just as much as men admit gender discrimination, but whites are less willing to equalize ethnic outcomes than men in equalizing gender outcomes. Comments from male participants in the Female 1c, Male 2c indicate that some men were quite uncomfortable that women were discriminated against (e.g., “I hope you're not actually paying women 50% less just to prove a point.”).

Third, the study acknowledges that the choice of 1 cent and 2 cents as the stakes in the experimental design has its pros and cons. On the one hand, discriminatory payment schemes presented in the ratio 1:2 (50% or 200%) is incredibly high and unrealistic. According to the U.S. Census Bureau, Current Population Survey, 1961 to 2017 Annual Social and Economic Supplements, the median earnings of females is about \$40,742 and the median earnings of males

is about \$51,212 in the US. This accounts for female-to-male earnings ratio of about 0.8. The Census Bureau also shows that household incomes differ in the US by ethnicity. The median household income of whites is about \$62,950, and for all other ethnic groups, it is about \$56,516. This accounts for a non-white-to-white household income ratio of about 0.9. These ratios only reflect inequality, and not discrimination as such. Controlling for skills, preferences, education, and other factors, discrimination will even be less severe than these ratios suggest.

On the other hand, the stakes used in this study (i.e., 1 cent and 2 cents, or maximum \$1 and \$2) are rather infinitesimal compared to the figures in the real world, but relevant for our purposes. In fact, experimental evidence is limited and inconclusive on whether people are more sensitive to income ratios or income gaps when making income comparison with a reference group (Cowell, 1992; Amiel and Cowell, 1999; Lembregts and Pandelaere, 2014; Ravallion, 2014). But due to the empirical regularity that logarithmized income fits life satisfaction and happiness better than income level (Kahneman and Deaton, 2010; Deaton, 2013), people may care more about percentage differences in income at higher levels of income and care more about absolute differences in income at lower levels of income. Thus, with stakes as small as 1 cent and 2 cents, the absolute difference of 1 cent (i.e., 2 cents – 1 cent) is more relevant to people than the ratio of 2 (i.e., 2 cents / 1 cent). Even if the absolute difference is too little, the study still finds robust effects of discrimination.

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Appendix

Appendix A: Productivity, inequality, and demand for redistribution

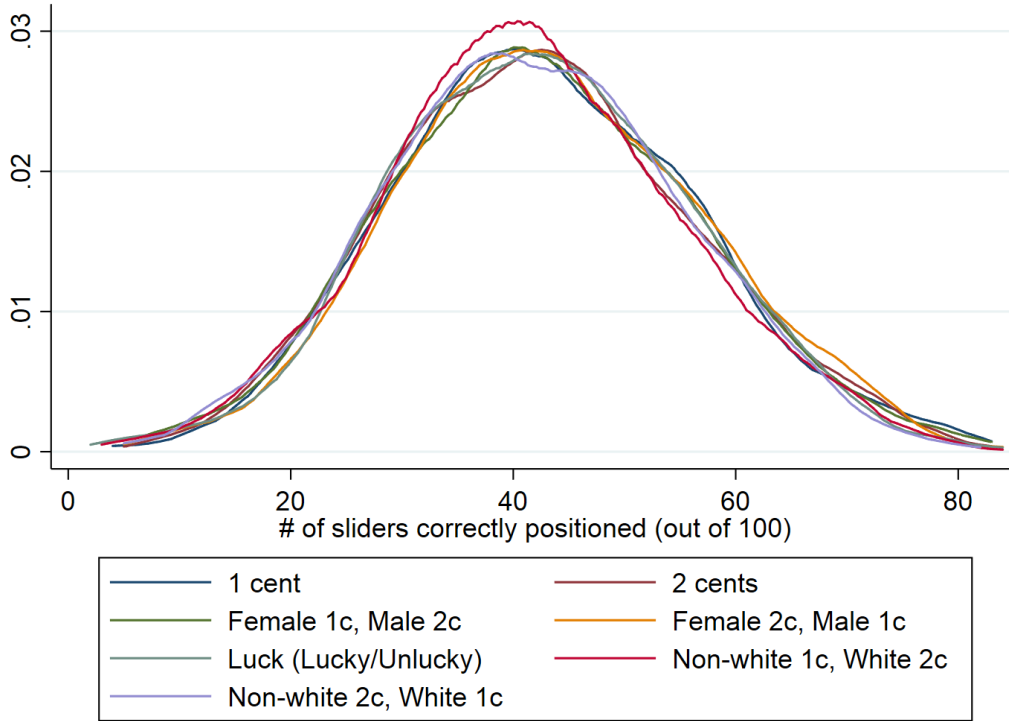


Fig. A1: Distribution of productivity in the slider task by condition

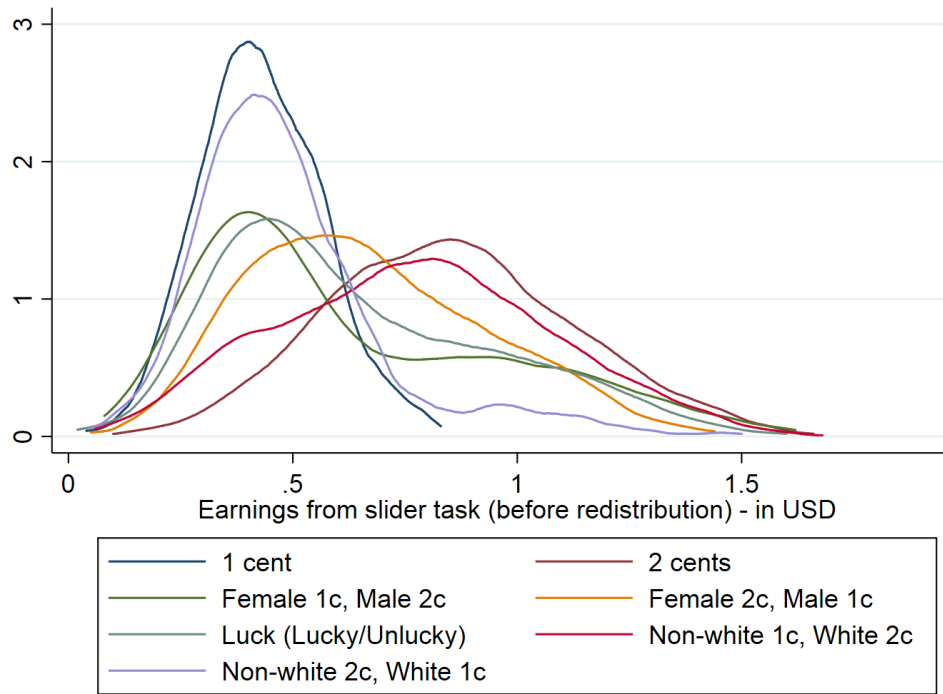


Fig. A2: Distribution of earnings from the slider task before redistribution by condition

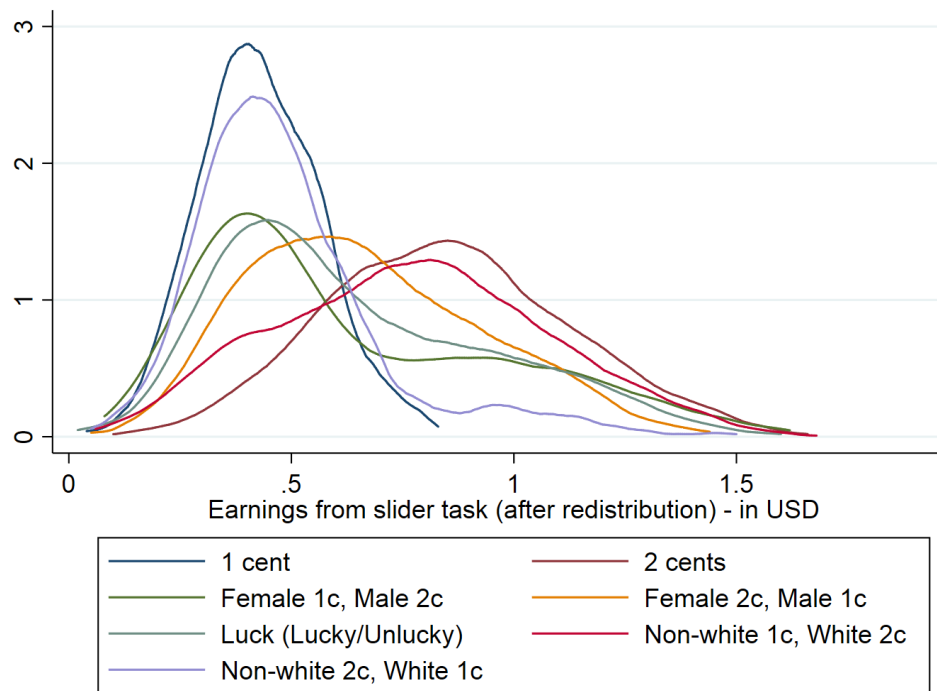


Fig. A3: Distribution of earnings from the slider task after redistribution by condition

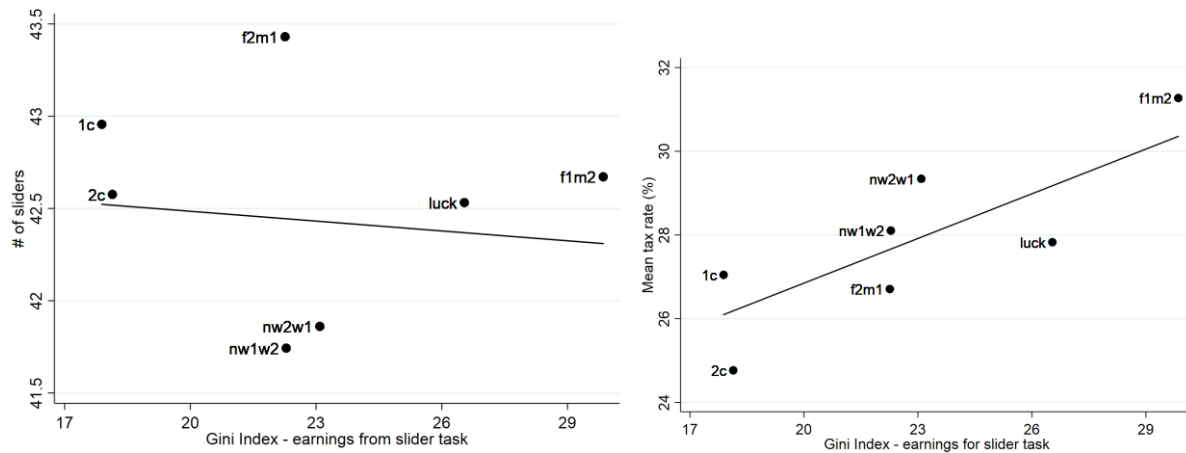


Fig. A4: Relationship between inequality and productivity
 Note: A point increase in Gini is associated with -0.02 reduction in productivity in the slider task (which is statistically significant).

Fig. A5: Relationship between inequality and redistribution
 Note: A point increase in Gini is associated with 0.4 raise in tax rate (which is statistically significant).

Appendix B: Fairness perceptions about payment schemes in the slider task

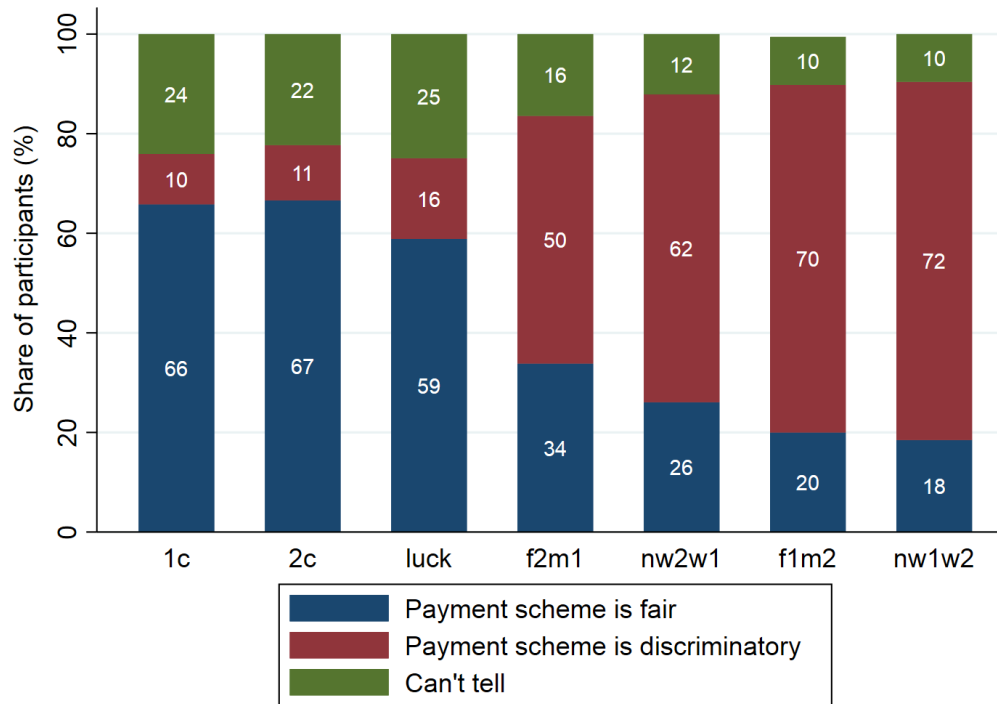


Fig. B1: Fairness perceptions about payment schemes in the slider task

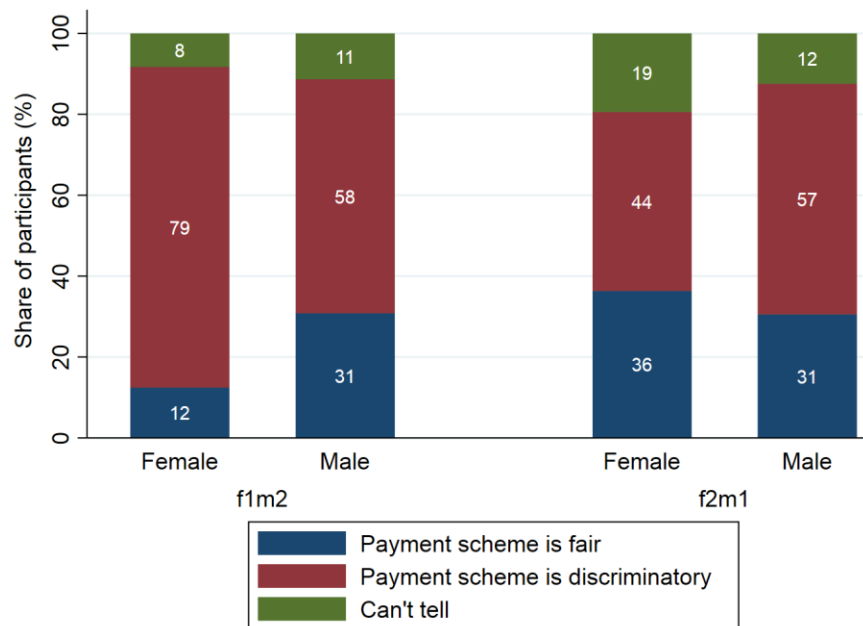


Fig. B2: Fairness perceptions in gender conditions by gender

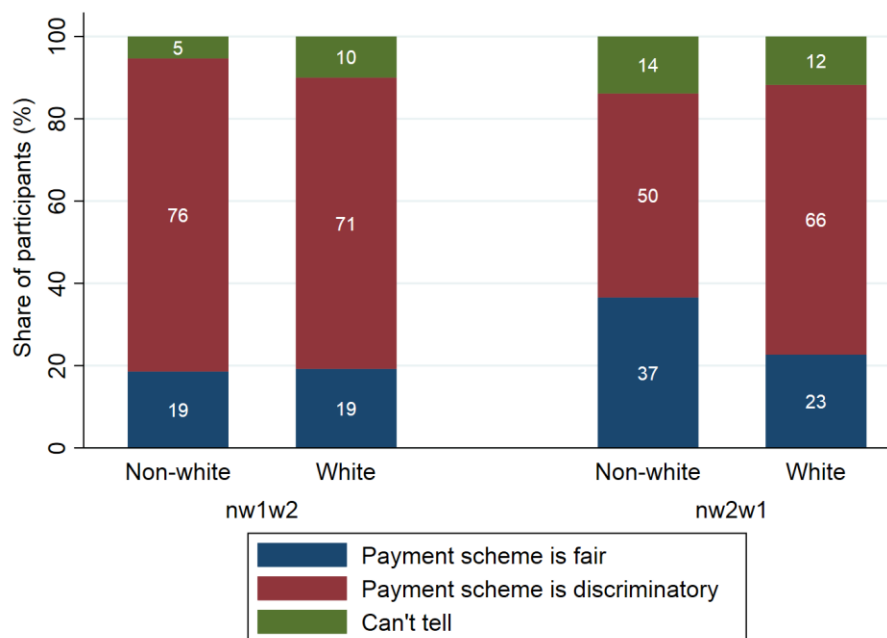


Fig. B3: Fairness perceptions in ethnic conditions by ethnicity (white vs. non-white)

Appendix C: Sub-sample regressions

Table C1: Male sub-group (disadvantaged)

	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	0.378 (1.034)	0.0408 (0.892)	2.048 (1.940)	1.657 (1.954)	0.0623** (0.0253)
Female 2c, Male 1c	1.911* (1.058)	1.847** (0.939)	-0.165 (1.922)	-0.207 (1.923)	0.468*** (0.0322)
Constant	42.26*** (0.876)	56.90*** (1.929)	35.34*** (2.260)	34.56*** (4.639)	0.0513** (0.0209)
Control for observables	No	Yes	No	Yes	No
Observations	3,296	3,296	3,296	3,296	3,296
Adjusted R-squared	0.012	0.256	0.018	0.024	0.251

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table C2: Male sub-group (advantaged)

(1)	(2)	(3)	(4)	(5)
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	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	-1.255 (1.057)	-1.323 (0.901)	1.396 (1.862)	1.192 (1.860)	0.0525* (0.0275)
Female 1c, Male 2c	-0.131 (1.054) (0.864)	-0.282 (0.906) (0.758)	4.035** (1.916) (2.135)	4.078** (1.918) (2.126)	0.454*** (0.0322) (0.0254)
Constant	43.45*** (0.860)	58.07*** (1.923)	33.61*** (2.281)	32.58*** (4.581)	0.0832*** (0.0215)
Control for observables	No	Yes	No	Yes	No
Observations	3,296	3,296	3,296	3,296	3,296
Adjusted R-squared	0.012	0.256	0.018	0.024	0.251

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table C3: Female sub-group (disadvantaged)					
	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	-1.272 (0.797)	-0.639 (0.669)	3.314* (1.772)	3.117* (1.776)	0.0483** (0.0227)
Female 1c, Male 2c	-1.113 (0.808)	-1.064 (0.695)	8.376*** (1.884)	8.168*** (1.881)	0.702*** (0.0241)
Constant	37.80*** (0.670)	52.28*** (1.404)	28.57*** (2.116)	32.51*** (4.497)	0.0611*** (0.0201)
Control for observables	No	Yes	No	Yes	No
Observations	4,219	4,219	4,219	4,219	4,219
Adjusted R-squared	0.011	0.295	0.010	0.012	0.335

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table C4: Female sub-group (advantaged)					
	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	1.428* (0.796)	1.354** (0.675)	1.019 (1.728)	1.253 (1.732)	0.0534** (0.0218)
Female 2c, Male 1c	0.822 (0.775)	0.937 (0.653)	0.484 (1.726)	0.649 (1.732)	0.360*** (0.0277)
Constant	36.48*** (0.656)	51.18*** (1.410)	32.34*** (2.149)	35.91*** (4.522)	0.0510*** (0.0185)
Control for observables	No	Yes	No	Yes	No
Observations	4,219	4,219	4,219	4,219	4,219
Adjusted R-squared	0.011	0.295	0.010	0.012	0.335

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table C5: White sub-group (disadvantaged)					
	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	-0.0413 (0.696)	0.0909 (0.597)	3.949*** (1.447)	3.847*** (1.448)	0.0603*** (0.0185)
Non-white 2c, White 1c	-0.635 (0.595)	-0.521 (0.502)	2.986** (1.225)	2.932** (1.223)	0.555*** (0.0176)
Constant	40.37*** (0.474)	60.15*** (1.186)	34.10*** (1.578)	36.95*** (3.555)	0.110*** (0.0115)
Control for observables	No	Yes	No	Yes	No
Observations	6,280	6,280	6,280	6,280	6,280
Adjusted R-squared	0.058	0.312	0.021	0.026	0.298

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table C6: White sub-group (advantaged)					
	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	0.659 (0.702)	0.433 (0.592)	2.166 (1.354)	2.290* (1.353)	0.0420** (0.0189)
Non-white 1c, White 2c	-0.566 (0.584)	-0.660 (0.508)	4.414*** (1.181)	4.437*** (1.180)	0.585*** (0.0177)
Constant	40.17*** (0.459)	60.14*** (1.188)	33.98*** (1.532)	36.70*** (3.557)	0.131*** (0.0120)
Control for observables	No	Yes	No	Yes	No
Observations	6,280	6,280	6,280	6,280	6,280
Adjusted R-squared	0.058	0.312	0.021	0.026	0.298

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table C7: Non-white sub-group (disadvantaged)					
	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	-2.893* (1.609)	-1.688 (1.393)	-3.979 (2.937)	-3.755 (2.978)	0.0207 (0.0406)
Non-white 1c, White 2c	-2.117 (1.386)	-2.041* (1.209)	1.590 (2.740)	1.505 (2.791)	0.637*** (0.0385)
Constant	38.30*** (1.067)	48.66*** (2.567)	27.93*** (3.364)	34.89*** (6.793)	0.121*** (0.0277)
Control for observables	No	Yes	No	Yes	No

Observations	1,235	1,235	1,235	1,235	1,235
Adjusted R-squared	0.045	0.268	0.020	0.018	0.275

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table C8: Non-white sub-group (advantaged)

	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	-1.810 (1.619)	-0.949 (1.491)	-2.583 (3.472)	-3.219 (3.538)	0.111*** (0.0413)
Non-white 2c, White 1c	-1.321 (1.311)	-0.909 (1.173)	-6.109** (2.695)	-5.856** (2.757)	0.433*** (0.0367)
Constant	38.26*** (1.029)	48.12*** (2.565)	41.24*** (3.485)	48.33*** (7.020)	0.0635*** (0.0203)
Control for observables	No	Yes	No	Yes	No
Observations	1,235	1,235	1,235	1,235	1,235
Adjusted R-squared	0.045	0.268	0.020	0.018	0.275

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Appendix D: Sub-sample regressions – Gender & Ethnicity

Table D1: White male sub-group (disadvantaged)

	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	0.976 (1.115)	0.141 (0.987)	4.422** (2.188)	3.901* (2.207)	0.0687** (0.0287)
Female 2c, Male 1c	2.594** (1.143)	2.252** (1.001)	0.00501 (2.099)	-0.197 (2.100)	0.475*** (0.0354)
Non-white 2c, White 1c	0.192 (0.915)	-0.140 (0.789)	3.003* (1.801)	2.882 (1.809)	0.567*** (0.0265)
Constant	45.79*** (0.699)	67.13*** (2.072)	36.27*** (2.745)	38.80*** (5.521)	0.105*** (0.0152)
Control for observables	No	Yes	No	Yes	No
Observations	2,730	2,730	2,730	2,730	2,730
Adjusted R-squared	0.001	0.249	0.022	0.030	0.253

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table D2: White male sub-group (advantaged)

	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	-0.905 (1.158)	-1.132 (0.988)	2.367 (1.987)	2.292 (1.978)	0.0367 (0.0301)
Female 1c, Male 2c	0.734 (1.151)	0.394 (1.006)	4.798** (2.085)	4.857** (2.089)	0.449*** (0.0357)
Non-white 1c, White 2c	-0.502 (0.976)	-0.761 (0.855)	4.329** (1.721)	4.568*** (1.724)	0.509*** (0.0283)
Constant	47.10*** (0.743)	68.43*** (2.105)	31.78*** (2.594)	33.76*** (5.445)	0.145*** (0.0182)
Control for observables	No	Yes	No	Yes	No
Observations	2,730	2,730	2,730	2,730	2,730
Adjusted R-squared	0.001	0.249	0.022	0.030	0.253

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table D3: White female sub-group (disadvantaged)

	(1)	(2)	(3)	(4)	(5)
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	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	-0.964 (0.881)	-0.156 (0.733)	3.924** (1.946)	3.839** (1.941)	0.0566** (0.0243)
Female 1c, Male 2c	-1.144 (0.888)	-1.097 (0.749)	7.704*** (2.042)	7.636*** (2.031)	0.735*** (0.0250)
Non-white 2c, White 1c	-1.419* (0.776)	-0.947 (0.645)	3.262* (1.674)	3.092* (1.673)	0.548*** (0.0236)
Constant	41.29*** (0.588)	59.03*** (1.382)	29.51*** (2.541)	32.48*** (5.054)	0.0998*** (0.0141)
Control for observables	No	Yes	No	Yes	No
Observations	3,550	3,550	3,550	3,550	3,550
Adjusted R-squared	0.003	0.301	0.011	0.015	0.344

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table D4: White female sub-group (advantaged)

	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	1.849** (0.864)	1.695** (0.716)	1.949 (1.847)	2.275 (1.853)	0.0466* (0.0241)
Female 2c, Male 1c	1.377 (0.848)	1.472** (0.708)	3.565* (1.873)	3.624* (1.876)	0.376*** (0.0307)
Non-white 1c, White 2c	-0.613 (0.709)	-0.523 (0.610)	4.485*** (1.621)	4.596*** (1.619)	0.643*** (0.0223)
Constant	39.77*** (0.542)	57.88*** (1.374)	33.12*** (2.510)	35.81*** (5.057)	0.108*** (0.0141)
Control for observables	No	Yes	No	Yes	No
Observations	3,550	3,550	3,550	3,550	3,550
Adjusted R-squared	0.003	0.301	0.011	0.015	0.344

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table D5: Non-white male sub-group (disadvantaged)

	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	-2.699 (2.696)	0.229 (2.338)	-8.267** (4.083)	-8.131* (4.406)	0.0302 (0.0515)
Female 2c, Male 1c	-1.587 (2.757)	0.344 (2.585)	-0.654 (4.838)	0.909 (4.969)	0.433*** (0.0768)
Non-white 1c, White 2c	-5.984*** (2.253)	-4.352** (1.999)	-2.319 (4.115)	-2.734 (4.255)	0.648*** (0.0561)
Constant	45.04*** (1.753)	54.17*** (4.163)	34.39*** (5.746)	30.64*** (10.32)	0.0769** (0.0304)
Control for observables	No	Yes	No	Yes	No

Observations	566	566	566	566	566
Adjusted R-squared	0.007	0.272	0.003	-0.016	0.256

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table D6: Non-white male sub-group (advantaged)					
	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	-2.661	-2.727	-2.443	-4.865	0.145**
	(2.609)	(2.237)	(5.165)	(5.298)	(0.0695)
Female 1c, Male 2c	-4.193	-2.517	1.007	1.038	0.479***
	(2.620)	(2.134)	(4.840)	(4.963)	(0.0754)
Non-white 2c, White 1c	-2.746	-3.413*	-2.794	-4.029	0.390***
	(2.078)	(1.787)	(3.958)	(4.077)	(0.0551)
Constant	45.23***	54.40***	37.88***	34.15***	0.0698**
	(1.510)	(3.992)	(5.925)	(10.41)	(0.0277)
Control for observables	No	Yes	No	Yes	No
Observations	566	566	566	566	566
Adjusted R-squared	0.007	0.272	0.003	-0.016	0.256

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table D7: Non-white female sub-group (disadvantaged)					
	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Unlucky 1c	-3.204*	-2.979*	0.130	-2.131	0.0146
	(1.812)	(1.562)	(4.251)	(4.380)	(0.0621)
Female 1c, Male 2c	-0.990	-1.045	12.52**	11.39**	0.521***
	(1.948)	(1.900)	(4.923)	(4.889)	(0.0747)
Non-white 1c, White 2c	0.822	0.139	4.064	3.444	0.624***
	(1.689)	(1.502)	(3.702)	(3.823)	(0.0533)
Constant	37.47***	48.54***	20.64***	41.14***	0.146***
	(1.218)	(3.259)	(5.439)	(10.44)	(0.0377)
Control for observables	No	Yes	No	Yes	No
Observations	669	669	669	669	669
Adjusted R-squared	-0.001	0.232	0.027	0.031	0.295

Notes: **Control group is 1 cent.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Table D8: Non-white female sub-group (advantaged)					
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	(1)	(2)	(3)	(4)	(5)
	Sliders	Sliders	Tax rate	Tax rate	Discriminatory
Lucky 2c	-0.943 (2.048)	0.132 (1.956)	-3.121 (4.694)	-4.483 (4.871)	0.0921* (0.0497)
Female 2c, Male 1c	-2.131 (1.888)	-1.634 (1.686)	-15.62*** (4.203)	-15.51*** (4.401)	0.274*** (0.0628)
Non-white 2c, White 1c	-0.00920 (1.651)	0.679 (1.523)	-9.128** (3.709)	-7.974** (3.822)	0.472*** (0.0490)
Constant	37.16*** (1.262)	47.39*** (3.432)	41.67*** (5.268)	59.38*** (10.57)	0.0435** (0.0214)
Control for observables	No	Yes	No	Yes	No
Observations	669	669	669	669	669
Adjusted R-squared	-0.001	0.232	0.027	0.031	0.295

Notes: **Control group is 2 cents.** All other notes from the main regression table in the paper apply, including all control variables. All other treatment dummies are included in the regressions but not displayed.

Appendix E: Time spent on treatment/payment information pages

Dependent variable: ln(time spent [in seconds] on treatment/information page)			
	(1)	(2)	
1 cent + 2 cents (19 words)	-	-	
Female 1c, Male 2c (36/43 words)	0.453*** (0.0270)	0.0316 (0.0196)	
Female 2c, Male 1c (36/43 words)	0.417*** (0.0274)	-0.00593 (0.0190)	
Non-white 1c, White 2c (44/53 words)	0.615*** (0.0227)	0.0193 (0.0161)	
Non-white 2c, White 1c (44/53 words)	0.570*** (0.0226)	0.00564 (0.0158)	
Luck [Lucky 2c, Unlucky 1c] (73 words)	0.724*** (0.0223)	0.000492 (0.0150)	
Constant	1.891*** (0.0754)	4.711*** (0.0518)	
Control variables - sliders	Yes	No	
Control variables - tax rate	No	Yes	
Observations	7,515	7,515	
Adjusted R-squared	0.180	0.074	
t-test/p-values:			
f1m2 = f2m1	0.26	0.1126	
f1m2 = nw1w2	0.00	0.5658	
f1m2 = nw2w1	0.00	0.2187	
f1m2 = luck	0.00	0.1309	
f2m1 = nw1w2	0.00	0.2231	
f2m1 = nw2w1	0.00	0.5716	
f2m1 = luck	0.00	0.7467	
nw1w2 = nw2w1	0.06	0.4650	
nw1w2 = luck	0.00	0.2764	
nw2w1 = luck	0.00	0.7586	

Notes: For column 1 - The word count for the payment information is provided in brackets. In the first round of the experiment, the word count for the gender and ethnicity conditions are 36 and 44 respectively. In the second round when gender and ethnicity are made salient, the word counts increase to 43 to 53 respectively. The control variables for the slider equation in all previous regressions are applied here. For column 2 – information provided to explain vote for redistribution to participants is the same across all conditions (518 words). The control variables for the tax rate equation in all previous regressions are applied here. Control group is 1 cent together with 2 cents condition. Dependent variable is the natural logarithm of time spent on information page (in seconds).

Appendix F: Actual vs. perceived productivity

Table F1: Actual & perceived productivity		
	(1) Actual productivity "# of correct sliders"	(2) Perceived productivity "# of correct sliders - own guess"
1 cent & 2 cents	-	-
Female 1c, Male 2c	-0.131 (0.500)	0.140 (0.747)
Female 2c, Male 1c	0.711 (0.494)	0.205 (0.709)
Non-white 1c, White 2c	-0.882** (0.393)	-1.113** (0.560)
Non-white 2c, White 1c	-0.654* (0.392)	-0.882 (0.568)
Luck (Lucky/Unlucky)	-0.0590 (0.386)	0.623 (0.567)
Male	4.309*** (0.274)	4.073*** (0.398)
White	6.684*** (0.482)	6.570*** (0.675)
Constant	52.03*** (1.130)	37.89*** (1.687)
Observables	Yes	Yes
Observations	7,515	7,515
Adj. R-squared	0.308	0.100

Note: The results in column 1 are same as in Table 4. All relevant notes in Table 4 apply here.

Table F2: Relative productivity - actual & perceived		
Comparison (sample 1 vs. sample 2)	Relative performance (actual, observed)	Relative performance (own guess, perceived)
<i>Male attitudes toward discrimination</i>		
1 cent (male) vs. f2m1 (male)	0.207**	0.149***
1 cent (male) vs. Unlucky (male)	0.0519	-0.0309
2 cents (male) vs. f1m2 (male)	0.0339	0.00764
2 cents (male) vs. Lucky (male)	-0.00129	-0.0779
<i>Female attitudes toward discrimination</i>		
1 cent (female) vs. f1m2 (female)	-0.0909	0.0339
1 cent (female) vs. Unlucky (female)	-0.0699	0.0529
2 cents (female) vs. f2m1 (female)	0.113	0.0469
2 cents (female) vs. Lucky (female)	0.125*	-0.00482
<i>White attitudes toward discrimination</i>		
1 cent (white) vs. nw2w1 (white)	-0.0235	0.00703
1 cent (white) vs. Unlucky (white)	0.0292	0.0174
2 cents (white) vs. nw1w2 (white)	-0.0578	0.00350
2 cents (white) vs. Lucky (white)	0.0600	0.00613
<i>Non-white attitudes toward discrimination</i>		
1 cent (non-white) vs. nw1w2 (non-white)	-0.156	0.122
1 cent (non-white) vs. Unlucky (non-white)	-0.154	0.0299
2 cents (non-white) vs. nw2w1 (non-white)	-0.00407	0.0355
2 cents (non-white) vs. Lucky (non-white)	-0.0820	0.000295

Notes: This table investigates the impact of treatments on the performance of participants relative to other participants in their groups, in terms of both observed and perceived effects. To obtain observations for relative performance (actual), the productivity data on all participants are grouped into 5 quantile categories: 1 – Far below average; 2 – Below average; 3 – About average; 4 – Above average; and 5 – Far above average. To obtain observations for relative performance (guess), we use data on self-evaluation of performance relative to others, coded as follows: 1 – Far below average; 2 – Below average; 3 – About average; 4 – Above average; and 5 – Far above average. The table summarizes relevant results from a number of sub-sample regressions, similar to regressions reported in Appendix D. These regressions tables are not reported for the lack of space.

Appendix G: Power calculations

Power calculations: main effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
Control group: 1 cent + 2 cents					
Female 1c, Male 2c	705	1.2537	-0.131	2.4474	5.591***
Female 2c, Male 1c	707	1.2518	0.711	2.4437	0.984
Non-white 1c, White 2c	1339	1.0060	-0.882**	1.9638	3.201***
Non-white 2c, White 1c	1354	1.0026	-0.654*	1.9571	2.101**
Luck (Lucky/Unlucky)	1442	0.9837	-0.059	1.9203	1.915**

Notes: Control group is 1 cent + 2 cents with N=2,129. Mean number of slider in the control group is 42.79 with as standard deviation of 13.58. Mean tax rate in the control group is 25.99% with a standard deviation of 26.51. A significance level of 10% and a power level of 80% are chosen for all computations. MDE is the minimum detectable effect size determined with the relevant parameters (i.e., mean and standard deviation in the control group as well as sample size in the experimental condition). Coefficient is the effect size obtained from the main regressions in the table. For comparison of effect sizes, take absolute figures.

Power calculations: main effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
Control group: Luck (Lucky/Unlucky)					
Female 1c, Male 2c	705	1.302	-0.0717	2.5786	3.667***
Female 2c, Male 1c	707	1.3012	0.770	2.5771	-0.918
Non-white 1c, White 2c	1339	1.0752	-0.823*	2.1295	1.421
Non-white 2c, White 1c	1354	1.0721	-0.595	2.1234	0.0502
1 cent	1060	1.1464	0.0743	2.2705	-2.603**
2 cents	1069	1.1436	0.0438	2.2649	-1.239

Notes: The parameters for sliders in the control group are: Mean=42.60; SD=13.34; N=1442. The parameters for tax rate (%) in the control group are: Mean=27.90; SD=26.42; N=1442. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
Control group: 1 cent (male)					
Female 2c, Male 1c (male)	299	2.2404	1.847**	4.0512	-0.207
Unlucky (male)	304	2.2274	0.0408	4.0276	1.657

Notes: The parameters for sliders in the control group are: Mean=45.57; SD=14.39; N=496. The parameters for tax rate (%) in the control group are: Mean=26.23; SD=26.02; N=496. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cents (male)</i>					
Female 1c, Male 2c (male)	312	2.2195	-0.282	3.944	4.078**
Lucky (male)	310	2.2226	-1.323	3.9495	1.192

Notes: The parameters for sliders in the control group are: Mean=46.59; SD=14.3; N=471. The parameters for tax rate (%) in the control group are: Mean=22.19; SD=25.41; N=471. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (female)</i>					
Female 1c, Male 2c (female)	393	1.7359	-1.064	3.7851	8.168***
Unlucky (female)	404	1.7219	-0.639	3.7546	3.117*

Notes: The parameters for sliders in the control group are: Mean=40.66; SD=12.41; N=560. The parameters for tax rate (%) in the control group are: Mean=27.75; SD=27.06; N=560. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cents (female)</i>					
Female 2c, Male 1c (female)	408	1.6512	0.937	3.6753	0.649
Lucky (female)	417	1.6406	1.354**	3.6517	1.253

Notes: The parameters for sliders in the control group are: Mean=39.5; SD=12.09; N=595. The parameters for tax rate (%) in the control group are: Mean=26.85; SD=26.91; N=595. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (white)</i>					
Non-white 2c, White 1c (white)	1112	1.301	-0.521	2.5538	2.932**
Unlucky (white)	583	1.5374	0.0909	3.0179	3.847***

Notes: The parameters for sliders in the control group are: Mean=43.39; SD=13.5; N=863. The parameters for tax rate (%) in the control group are: Mean=26.83; SD=26.5; N=863. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cents (white)</i>					
Non-white 1c, White 2c (white)	1122	1.3028	-0.66	2.4639	4.437***

Lucky (white)	605	1.5255	0.433	2.8851	2.290*
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Power calculations: main effects

Notes: The parameters for sliders in the control group are: Mean=41.07; SD=13.96; N=168. The parameters for tax rate (%) in the control group are: Mean=27.58; SD=26.26; N=168. All other notes in previous table apply.

Notes: The parameters for sliders in the control group are: Mean=41.13; SD=13.62; N=179. The parameters for tax rate (%) in the control group are: Mean=31.13; SD=28.64; N=179. All other notes in previous table apply.

Power calculations: sub-sample

Notes: The parameters for sliders in the control group are: Mean=45.79; SD=14.16; N=410. The parameters for tax rate (%) in the control group are: Mean=25.64; SD=25.80; N=410. All other notes in previous table apply.

Unlucky (non-white male)	56	5.7867	0.229	10.0547	-8.131*
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Notes: The parameters for sliders in the control group are: Mean=45.04; SD=15.47; N=78. The parameters for tax rate (%) in the control group are: Mean=28.77; SD=26.88; N=78. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cent (white male)</i>					
Female 1c, Male 2c (white male)	256	2.4758	0.394	4.132	4.857**
Lucky (white male)	259	2.4687	-1.132	4.1203	2.292

Notes: The parameters for sliders in the control group are: Mean=47.10; SD=14.35; N=373. The parameters for tax rate (%) in the control group are: Mean=20.57; SD=23.95; N=373. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cent (non-white male)</i>					
Female 1c, Male 2c (non-white male)	51	5.2773	-2.517	10.928	1.038
Lucky (non-white male)	42	5.6558	-2.727	11.712	-4.865

Notes: The parameters for sliders in the control group are: Mean=45.23; SD=13.99; N=86. The parameters for tax rate (%) in the control group are: Mean=27.37; SD=28.97; N=86. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (white female)</i>					
Female 1c, Male 2c (white female)	326	1.9282	-1.097	4.1901	7.636***
Unlucky (white female)	339	1.9073	-0.156	4.1447	3.839**

Notes: The parameters for sliders in the control group are: Mean=41.29; SD=12.48; N=451. The parameters for tax rate (%) in the control group are: Mean=27.80; SD=27.12; N=451. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (non-white female)</i>					
Female 1c, Male 2c (non-white female)	54	4.2452	-1.045	9.5433	11.39**
Unlucky (non-white female)	56	4.1963	-2.979*	9.4336	-2.131

Notes: The parameters for sliders in the control group are: Mean=37.47; SD=11.49; N=89. The parameters for tax rate (%) in the control group are: Mean=26.28; SD=25.83; N=89. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cent (white female)</i>					
Female 2c, Male 1c (white female)	337	1.7965	1.472**	4.0007	3.624*
Lucky (white female)	343	1.7865	1.695**	3.9783	2.275

Notes: The parameters for sliders in the control group are: Mean=39.77; SD=11.90; N=482. The parameters for tax rate (%) in the control group are: Mean=25.56; SD=26.50; N=482. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cent (non-white female)</i>					
Female 2c, Male 1c (non-white female)	63	4.222	-1.634	9.7908	-15.51***
Lucky (non-white female)	59	4.3061	0.132	9.9858	-4.483

Notes: The parameters for sliders in the control group are: Mean=37.16; SD=12.10; N=92. The parameters for tax rate (%) in the control group are: Mean=34.88; SD=28.06; N=92. All other notes in previous table apply.

Power calculations: sub-sample effects					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (white male)</i>					
Non-white 2c, White 1c (white male)	467	2.037	-0.14	3.7114	2.882
Unlucky (white male)	242	2.4418	0.141	4.4491	3.901*

Notes: The parameters for sliders in the control group are: Mean=45.79; SD=14.16; N=410. The parameters for tax rate (%) in the control group are: Mean=25.64; SD=25.80; N=410. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (white female)</i>					
Non-white 2c, White 1c (white female)	641	1.6297	-0.947	3.5414	3.092*
Unlucky (white female)	339	1.9073	-0.156	4.1447	3.839**

Notes: The parameters for sliders in the control group are: Mean=41.29; SD=12.48; N=451. The parameters for tax rate (%) in the control group are: Mean=27.80; SD=27.12; N=451. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cents (white male)</i>					
Non-white 1c, White 2c (white male)	485	2.1008	-0.761	3.5063	4.568***
Lucky (white male)	259	2.4687	-1.132	4.1203	2.292

Notes: The parameters for sliders in the control group are: Mean=47.10; SD=14.35; N=373. The parameters for tax rate (%) in the control group are: Mean=20.57; SD=23.95; N=373. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cents (white female)</i>					
Non-white 1c, White 2c (white female)	631	1.5295	-0.523	3.406	4.596***
Lucky (white female)	343	1.7865	1.695**	3.9783	2.275

Notes: The parameters for sliders in the control group are: Mean=39.77; SD=11.90; N=482. The parameters for tax rate (%) in the control group are: Mean=25.56; SD=26.50; N=482. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (non-white male)</i>					
Non-white 1c, White 2c (non-white male)	91	5.0985	-4.352**	8.8589	-2.734
Unlucky (non-white male)	56	5.7867	0.229	10.0547	-8.131*

Notes: The parameters for sliders in the control group are: Mean=45.04; SD=15.47; N=78. The parameters for tax rate (%) in the control group are: Mean=28.77; SD=26.88; N=78. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 1 cent (non-white female)</i>					
Non-white 1c, White 2c (non-white female)	126	3.3678	0.139	7.5709	3.444
Unlucky (non-white female)	56	4.1963	-2.979*	9.4336	-2.131

Notes: The parameters for sliders in the control group are: Mean=37.47; SD=11.49; N=89. The parameters for tax rate (%) in the control group are: Mean=26.28; SD=25.83; N=89. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cents (non-white male)</i>					
Non-white 2c, White 1c (non-white male)	111	4.2902	-3.413*	8.8841	-4.029
Lucky (non-white male)	42	5.6558	-2.727	11.7119	-4.865

Notes: The parameters for sliders in the control group are: Mean=45.23; SD=13.99; N=86. The parameters for tax rate (%) in the control group are: Mean=27.37; SD=28.97; N=86. All other notes in previous table apply.

Power calculations: sub-sample					
Condition	N	Sliders		Tax rate (%)	
		MDE	Coefficient	MDE	Coefficient
<i>Control group: 2 cents (non-white female)</i>					
Non-white 2c, White 1c (non-white female)	130	3.518	0.679	8.1582	-7.974**
Lucky (non-white female)	59	4.3061	0.132	9.9858	0.132

Notes: The parameters for sliders in the control group are: Mean=37.16; SD=12.10; N=92. The parameters for tax rate (%) in the control group are: Mean=34.88; SD=28.06; N=92. All other notes in previous table apply.

Appendix H: Drop-out analysis

Table H1: Drop-out analysis I			
Progress	Frequency	Percent	Stage in the survey flow
50	4	2.7	
51	7	4.73	Demographic and socioeconomic questions
52	3	2.03	
53	8	5.41	Demographic and socioeconomic questions
55	5	3.38	
56	1	0.68	
58	12	8.11	Slider task instructions
59	2	1.35	
60	13	8.78	Slider task (trial)
61	5	3.38	
62	12	8.11	Comprehension questions
63	11	7.43	Information is given that all Mturkers perform the same slider task with the same level of difficulty
64	6	4.05	
65	3	2.03	
66	5	3.38	
70	2	1.35	
71	1	0.68	
74	1	0.68	
77	1	0.68	
78	4	2.7	Payment information
79	12	8.11	Slider task
80	4	2.7	
81	3	2.03	
84	1	0.68	
85	3	2.03	
86	1	0.68	
87	1	0.68	
88	2	1.35	
90	3	2.03	
91	3	2.03	
92	3	2.03	
93	1	0.68	
94	3	2.03	
97	2	1.35	
Total	148	100	

Notes: The variable "Progress" in the Qualtrics data provides an "an exact percentage of how far [participants] got in the survey based on what question they left off on." Fields in yellow indicates a stage in survey flow where drop-out peaks. The field in red indicates the stage at/beyond which payment information is likely to be a reason participants drop out.

Table H2: Drop-out analysis II

Condition	Drop-outs if Progress>77		Completed survey		Drop-out as a share of completed (%)
	Number	Share (%)	Number	Share (%)	
1 cent	4	8.7	1088	13.86	0.37
2 cents	7	15.22	1097	13.98	0.64
Female 1c, Male 2c	1	2.17	719	9.16	0.14
Female 2c, Male 1c	2	4.35	720	9.17	0.28
Lucky 2c, Unlucky 1c	9	19.57	1474	18.78	0.61
Non-white 1c, White 2c	9	19.57	1370	17.46	0.66
Non-white 2c, White 1c	14	30.43	1380	17.58	1.01
Total	46	100	7848	100	0.59

Note: This table compares the number of participants that drop out rate at/beyond the stage in the survey flow when they are given treatment/payment information with the number of participants that completed the survey in each condition.

Table H3: Cross-tabulation - drop-outs vs. ethnicity in ethnicity conditions

	African/African American	European American/White	Hispanic	Total
Non-white 1c, White 2c	4 (66.67%)	5 (33.3%)	0 (0%)	9
Non-white 2c, White 1c	2 (33.3%)	10 (66.7%)	2 (100%)	14

Note: This table presents into the ethnic composition of participants who drop out at/beyond the stage in the survey flow when they are given treatment/payment information in the ethnicity conditions. The probability that a participant drops out who belongs to a particular ethnic group is given in brackets.