The Boy Crisis: Experimental Evidence on the Acceptance of Males Falling Behind

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Abstract The 'boy crisis' prompts the question of whether people interpret inequalities differently depending on whether males or females are lagging behind. We study this question in a novel large-scale distributive experiment involving more than 5,000 Americans. Our data provide strong evidence of a gender bias against low-performing males, particularly among female participants. A large set of additional treatments establishes that the gender bias reflects statistical fairness discrimination. The study provides novel evidence on the nature of discrimination and on how males falling behind are perceived by society.

JEL: C91, D63, J16

Key words: gender bias, boy crisis, statistical fairness discrimination, large-scale experiment

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1 Introduction

Across the world, males occupy the majority of top-level jobs, head of government positions and national parliament seats, and in all societies there is still a significant gender wage gap. To illustrate, in the United States, women full-time workers earned on average 79 percent of what men did on an annual basis in 2014 (Blau and Kahn, 2017). Thus, there is still urgent need for political action to achieve gender equality for women.

The present paper is motivated by a different gender gap, often termed the 'boy crisis' (Autor and Wasserman, 2013). In education, it is by now well established that boys are lagging behind. In all but six OECD countries, a larger proportion of boys than girls do not attain the baseline level of proficiency in any of the core subjects; mathematics, reading and science (OECD, 2015). In the US for instance, the average percentage of students who do not attain the baseline proficiency level was 71% higher for boys than for girls. Boys are also dropping out of high school at higher rates than girls in most OECD countries. In higher education, females have surpassed the rate of males graduating in nearly all OECD countries, on average by 14 percentage points (OECD, 2016).

Similarly, in high-income countries there is a growing concern about the prospects for low-skilled males: "The decline in economic opportunities for low-skilled men and the possible negative effects of this trend on their well-being is a matter of increasingly urgent concern for policy makers and the general public" (Coile and Duggan (2019), p. 2). Males with less than four-year college education have seen a significant reduction in real income over the last decade in the US (Autor and Wasserman, 2013; Binder and Bound, 2019), and the percentage of idle young males and prime age males outside the labor force has increased (Blau and Kahn, 2013; Krueger, 2017). The prospects for males outside the labor force are dim, in particular for those from low-income households and for males with minority backgrounds. The likelihood of living in poverty is increased and their expected future health and emotional well-being is poor (Autor and Wasserman, 2013; Krueger, 2017; Council of Economic Advisers, 2016).

These striking empirical developments make it important to study whether people react more negatively to males falling behind than to females falling behind, since this may both reinforce the negative trend of low-performing males and shape our public responses to the 'boy crisis'. In this paper, we examine this question with a novel experimental approach, where we study peoples' views on income inequalities generated in a labor market. Our main focus is on whether people show less concern for income inequality when a male is falling behind than when a female is falling behind. We provide a simple theoretical framework to guide the empirical analysis, where we show how statistical fairness discrimination against male losers may occur if people perceive males to have a productivity advantage. The idea is that such an advantage makes people infer that male losers are likely to have exerted lower effort than female losers, and thus are less deserving of assistance.

To collect experimental data on a general population sample, we combine the infrastructure of a leading international data-collection agency and an online labor market (Almås, Cappelen, and Tungodden, 2016b). In the online labor market, we recruit more than 2,000 workers and generate inequalities by paying two workers differently for the same assignment. In our main treatments, the inequality is generated by paying the more productive worker (the winner) more than the less productive worker (the loser). We then ask a general population sample of more than 3,000 Americans to act as impartial spectators and make a decision on whether to redistribute earnings between the winner and the loser, where each spectator makes a real decision that has consequences for two workers. We randomly assign spectators into a treatment where the loser is a male or a treatment where the loser is a female. Our main interest is in studying whether the redistribution decision of the spectators depends on the gender of the loser. We run a set of additional treatments to study the underlying mechanisms of the spectator choices, where we vary the source of the inequality (merit or luck) and the gender-composition of the two workers (mixed-sex or single-sex).

Our main result is reported in Figure 1. In a large general population sample of Americans, we find a significant gender bias against male losers in the mixed-sex treatments when merit is the source of inequality. The left bar of Panel A shows the average share transferred by the spectators to the losing worker when a female is the least productive, and the right bar shows the average share transferred when a male is the least productive. The spectators transfer about 15% less to a male loser than to a female loser (23.1% versus 19.5%), and the share of spectators transferring nothing increases by 7.3 percentage points when the loser is a male. Panel B reports the difference in the average share transferred by the gender of the spectator, which shows that the gender bias is clearly driven by the female spectators, who transfer 25% less to the male losers than to the female losers.

[Figure 1 about here]

We further show that the gender bias against males does not reflect taste-based preferences among the spectators. In the treatments where the source of inequality is luck, the spectators transfer the same amount to male losers and to female losers. We also do not find any difference in spectator behavior between treatments where both workers are female or both workers are male, which suggests that the spectators do not find inequality more acceptable between males than between females. The findings are in line with our theoretical framework, and our preferred interpretation of the main result is that the gender bias in the mixed-sex merit setting reflects statistical fairness discrimination: spectators infer that male losers to a greater extent than female losers have exerted low effort and therefore consider them less deserving of assistance. The fact that we find the gender bias to be driven by female spectators suggests that females, to a greater extent than males, consider males to have a productivity advantage, and, as a result, are more likely to infer differently about the effort of male losers and female losers.

Our paper contributes to a number of different literatures. Our results shed light on the growing literature on the 'boy crisis', by providing evidence suggesting that the general public may view male losers differently from female losers. This may have important implications for the support for public policies targeting low-performing males, and for our understanding of gender-biased behavior. The existing literature in this area has largely focused on explaining the low performance of males with structural changes and socioeconomic developments (Almås, Cappelen, Salvanes, Sørensen, and Tungodden, 2016a; Autor and Wasserman, 2013; Autor, Figlio, Karbownik, Roth, and Wasserman, forthcoming; Bertrand and Pan, 2013; Binder and Bound, 2019; Krueger, 2017; Rosin, 2012), while the present paper focuses on how low-performing males are perceived by society. We show that people tend to interpret males falling behind as having exerted less effort than females falling behind, which may result in male losers being treated differently in school, at the workplace, and in the family. This may result in low-performing males ending up in a vicious circle where they lose their motivation to provide effort because they are not rewarded to the same extent as females in the same situation.

We further contribute to the literature on gender discrimination (Bertrand and Duflo, 2017), by providing novel evidence on a gender bias against low-performing males. A number of important papers have shown discrimination against females in different areas, including in hiring decisions (Goldin and Rouse, 2000; Coffman, Exley, and Niederle, 2019), task allocation (Babcock, Recalde, Vesterlund, and Weingart, 2017), bargaining (Castillo, Petrie, Torero, and Vesterlund, 2013; Exley, Niederle, and Vesterlund, forthcoming), teaching evaluations (Mengel, Sauermann, and Zölitz, 2018), and career development (Reuben, Sapienza, and Zingales, 2014), but recent research has also provided evidence of a gender bias against males in certain settings (Bohren, Imas, and Rosenberg, forthcoming; Heikensten and Isaksson, 2016; Mengel et al., 2018; Reynolds, Sjåstad, Howard, Okimoto, Baumeister, Aquino, and Kim, 2017; Williams and Ceci, 2015). In particular, Bohren et al. (forthcoming) find in a field experiment on an online mathematics forum for STEM-students and researchers that females initially face significant discrimination, but over time are favored over men. Our paper focuses on low-performing males in a distributive context, where we show, in a large-scale study of the general population in the United States, that people are less willing to assist males falling behind than females falling behind.

Our results also speak to the non-experimental studies of gender discrimination in schools (Breda and Ly, 2015; Cornwell, Mustard, and Van Parys, 2013; Falch and Naper, 2013; Lavy, 2008; Lavy and Sand, 2018; Lindahl, 2016; Terrier, 2016). Albeit with exceptions, accumulated evidence suggests that in developed countries, teacher grade setting is discriminatory against males in a range of subjects in kindergarten, primary school, high school and higher education. One of the challenges in this literature has been to disentangle a teacher gender bias from the effect of gender differences in non-cognitive skills on grade setting. The present study contributes to this literature by identifying that there is a gender bias against males in a performance-based environment, even in a setting in which non-cognitive skills cannot affect evaluations.

We more generally contribute to the discrimination literature by introducing, to our knowledge, the first study of statistical fairness discrimination, where people make inferences about the deservingness of a person based on observable characteristics. We believe that this mechanism speaks both to distributional settings, as is the focus in this paper, but also more generally to labor market and educational settings where a principal would like to reward effort. We also provide a new approach to disentangling statistical discrimination and taste-based discrimination (Bohren et al., forthcoming; Cettolin and Suetens, forthcoming; Fershtman and Gneezy, 2001; List, 2004), by randomly manipulating whether the spectators make a distributive decision in an environment where productivity or luck is the source of inequality.

Finally, our results contribute to the literature in behavioral economics investigating the role of gender in people's social preferences (Croson and Gneezy, 2009; Eckel and Grossman, 2008). Previous studies have varied the salience of recipient gender in stakeholder games such as the dictator game and the ultimatum game. A meta-study on dictator game experiments largely finds that females receive more than males in dictator games when recipient gender is made salient (Engel, 2011). For ultimatum games that vary recipient gender, individuals make higher offers to males compared to females (Eckel and Grossman, 2001; Solnick, 2001). In contrast to these previous studies, we examine gender bias in an impartial spectator decision, which provides a direct expression of the moral preferences of the participants (Cappelen, Konow, Sørensen, and Tungodden, 2013). In this setting, we show that there is a significant gender bias against males reflecting statistical fairness discrimination. More broadly, we also provide new evidence on how fairness preferences shape distributive behavior (Bolton and Ockenfels, 2000; Bortolotti, Soraperra, Sutter, and Zoller, 2017; Cappelen, Drange Hole, Sørensen, and Tungodden, 2007; Fehr and Schmidt, 1999; Konow, 2000), by showing how people's fairness considerations differ across contexts and depend on the source of inequality.

The paper is organized as follows: Section 2 describes the experimental design, Section 3 introduces a simple theoretical framework that guides our interpretation of the results, Section 4 outlines the main empirical strategy, Section 5 reports the main results and the heterogeneity results, while Section 6 concludes. Additional analysis is provided in Appendix A, and the complete instructions for both spectators and workers are provided in Appendix B.

2 Experimental design and participants

We first provide an overview of the general structure of the experiment, which builds on Almås et al. (2016b), before we turn to a detailed discussion of the participants and the experimental design.

Table 1 summarizes the main stages of the experiment. The experiment had two types of participants, *workers* and *spectators*. First, the workers completed an assignment. They were then matched in pairs and assigned different earnings. The spectators were randomly matched to one pair of workers and decided whether to redistribute earnings between the two workers. Finally, the workers were paid according to the spectator decisions.

[Table 1 about here]

2.1 The workers

The workers in the experiment were recruited from the international online labor market platform Amazon Mechanical Turk. This is a crowdsourcing web service that specializes in recruiting anonymous workers to complete small tasks online. When recruited, the workers were promised a participation fee of 2 USD and told that they could earn additional money, depending on the actions they and others would take in the experiment. We recruited 2,072 workers, 1,036 men and 1,036 women. Each worker completed three different tasks. After they had completed all three assignments, the workers were told how they would be paid for the assignments. Specifically, for each assignment, they were randomly matched in pairs, giving us 3,108 unique pairs workers conditional on assignment. In each such pair, one worker was initially assigned 6 USD and the other 0 USD. The workers were not told whether they had been assigned high or no initial earnings. They were told, however, that a third person, the spectator, would be informed about the assignment and the initial distribution of earnings. They were further informed that the spectator would be given the opportunity to redistribute the earnings between the two workers in the pair and thus determine how much they would actually be paid for the assignment. The workers received the participation fee immediately after they had completed the assignment and the income determined by the spectator within a few days after the spectators made their choice.

2.2 The spectators

The spectators in the experiment were recruited using the infrastructure of the data-collection agency TNS Gallup. We recruited 3,102 participants who constitute a nationally representative sample of the United States (+ 18 years old) on a limited set of observable characteristics (gender, age and geography). Each spectator was matched with a unique pair of workers and decided whether and how much of the initial earnings to redistribute.[1] We further collected background characteristics of the spectators in terms of gender, political orientation, income and age. Table 2 provides an overview of the background characteristics of the spectators and a comparison with US census data. The sample is largely gender-balanced, with 48.8% being males, and a median age of 41 years. The median yearly gross income before taxes is 55 000 USD and 33.7% state that they would vote Republican.[2] The sample is largely representative of the US population on these dimensions, even though we note that income is more compressed in the sample than in the population at large (which partly may reflect that self-reported income was restricted at the extremes).

[Table 2 about here]

2.3 General structure

In all treatments, the spectators made a decision in a situation where one worker had earnings of 6 USD and the other had earnings of 0 USD. The spectators were not informed about the nature of the tasks assigned to the workers, but about the age, nationality, and gender of the two workers. It was emphasised to the spectators that, in contrast to traditional survey questions, their choice would have consequences for a real life situation. They were given all the information provided to the workers. In particular, to minimize the role of worker expectations in the spectator choice, they were told that the workers would not at any point be informed about their initial earnings.

[1] Since we had 3,108 unique distributive situations and 3,102 spectators, we applied six spectator decisions twice.

[2] 4.8% of the spectators reported that they did not know or preferred to not state their income. Our results are robust to the removal of these participants.

2.4 Treatments

We implemented a between-subject design, where spectators were randomly assigned to treatments.

In the two main treatments, the mixed-sex merit treatments, the spectators considered a distributive situation involving a female worker and a male worker, where the initial inequality in earnings was determined by the productivity of the workers: the more productive worker earned 6 USD and the less productive worker earned 0 USD. The two treatments only differed in terms of whether the female or the male worker had been less productive, which allows us to identify the causal effect of the gender of the loser on the amount transferred to the loser. The experimental design thus allows us to study whether the spectators are more inequality accepting when a male falls behind then when a female falls behind.

To investigate the underlying mechanisms of the spectator behavior, we included six additional treatments. First, to study the role of the source of inequality, we implemented two additional treatments that mirrored the two main treatments but where the inequality in earnings was determined by luck; second, to study the role of the gender composition, we added four single-sex treatments that mirrored the four mixed-sex treatments. Table 3 provides an overview of the treatments and the number of participants in each treatment.[3]

[Table 3 about here]

3 Theoretical framework

We here provide a simple theoretical framework to guide the interpretation of the results.

The spectator decides on a distribution $(1-y, y)$ of income between two randomly matched workers $i = j, k$, where y is the share given to the worker with no initial earnings (the loser).

[3]We recruited the spectators in two rounds of data collection. In the first round, we recruited 2,052 US participants to act as spectators, who were randomly allocated to one of eight treatments. In the second round, to study the robustness of our findings, we recruited another 1,050 US participants. In this round, the participants were randomly allocated to one of the two main treatments. Individuals who participated in the first round of data collection were not permitted to participate in the second round. Table A.1 presents a balance test, where we show that the eight treatments are not significantly different from each other on any of the background characteristics in Table 2.

We assume that the spectators have the following model of how the productivity of a worker is determined, $r_i(g) = e_i + a(g) + \varepsilon_i$, where e_i is the worker's effort, $a(g)$ is a gender specific advantage, $g = f, m$, and ε_i is a normally distributed random shock, $\varepsilon_i \sim N(0, \sigma)$.[4] For simplicity, we consider only two effort levels, $e^h > e^l$, and we assume that the spectators believe that males and females have the same effort distribution, where $p(e^l)$ is the share of workers exerting low effort We normalize the gender specific advantage of females, $a(f) = 0$, such that $a(m) > 0$ would imply that males have a productivity advantage relative to females. We may interpret the productivity advantage in terms of ability, but it can also be interpreted more broadly as capturing any kind of advantage that makes one gender more productive than the other. Finally, we assume that the random shock is truncated, $\varepsilon_i \in (-1/2a(m), 1/2a(m))$, and that the gender specific advantage is restricted, $2|a(m)| < (e^h - e^l)$, which implies that a worker exerting high effort is always more productive than a worker exerting low effort.

We assume that the spectators care about fairness and that they consider the fair share to transfer to the losing worker, l, to be determined by the relative effort of the two workers. The spectators may also have a partial gender preference, as captured by the following utility function (Cappelen et al., 2013; Almås et al., 2016b):

$$V(y;\cdot) = -(y - h(E(e)))^2 - I\beta(g)y, \tag{1}$$

where $E(e = e_l/e_w)$ is the expected relative effort of the loser (e_l) compared to that of the winner (e_w). We assume that the fair share to the loser is increasing in the expected relative effort of the loser. The second term captures partial gender preferences, where I is an indicator variable taking the value one if this is a mixed-sex pair, g is the gender of the loser, and $\beta(g)$ is the strength of the gender preference, $\beta(m) = -\beta(f)$.

The optimal interior solution is given by:

$$y(E(e), g, I) = h(E(e)) - \frac{\beta(g)}{2}I \tag{2}$$

The model captures the two main approaches to discrimination in the eco-

[4] We do not have data that allow us to study whether the spectator's belief about the relationship between effort and productivity is misspecified, see Bohren et al. (forthcoming).

nomics literature. The first approach, developed by Becker (1957), introduces taste-based discrimination, where a distaste for a group of people (or favoritism of another) may lead to differential, negative treatment of its members. In our theoretical framework, spectators have taste-based discrimination if $\beta(g) \neq 0$. The second approach is statistical discrimination (Phelps, 1972; Arrow, 1973), where observable characteristics of individuals are used to proxy unobservable, but relevant, characteristics. Our model captures statistical fairness discrimination. The spectators' belief about the expected relative effort of the loser and the winner, and consequently what the spectators consider the fair share to give to the loser, depend on the signal they receive about the gender composition in the pair and the source of the inequality.

Let us now study the predictions of this model for the different treatments in our study. First, consider the mixed-sex merit treatments. Assume that the spectators believe that males have an advantage $a(m) > 0$. In this case, it follows from the model that a male worker will only have lower productivity than a female worker when he has exerted low effort and she has exerted high effort.[5] In all others cases, the female worker has lower productivity, including the cases where they both have exerted the same effort. Thus, assuming that the spectators have rational beliefs, the expected relative effort of the loser will be lower when there is a male loser than when there is a female loser. Hence, without taste-based gender preferences in favor of the male worker, the spectators would transfer less to a male loser than to a female loser in the mixed-sex merit treatments. More generally, we have the following observation:

Observation 1: *Statistical fairness discrimination would in mixed-sex merit treatments imply a smaller transfer to the loser of the gender that is considered to have an advantage.*

In the mixed-sex luck treatments, there is no signal of productivity that can lead to statistical fairness discrimination. Hence, any gender bias in the amount transferred to the loser in these treatments would have to reflect taste-based

[5]This follows straightforwardly from comparing the four possible scenarios: (i) a male k exerting low effort matched with a female j exerting low effort: $r_k(m) = e^l + a(m) + \varepsilon_k > r_j(f) = e^l + \varepsilon_j$, (ii) a male k exerting low effort matched with a female j exerting high effort: $r_k(m) = e^l + a(m) + \varepsilon_k < r_j(f) = e^h + \varepsilon_j$, (iii) a male k exerting high effort matched with a female j exerting low effort: $r_k(m) = e^h + a(m) + \varepsilon_k > r_j(f) = e^l + \varepsilon_j$, (iv) a male k exerting high effort matched with a female j exerting high effort: $r_k(m) = e^h + a(m) + \varepsilon_k > r_j(f) = e^h + \varepsilon_j$.

discrimination or that the spectators use gender as a signal for other morally relevant characteristics not captured by the fairness considerations.

Observation 2: *Statistical fairness discrimination would not affect spectator behavior in mixed-sex luck treatments, while taste-based discrimination would imply a smaller transfer to the loser of the gender that the spectators have a distaste for.*

Consider now the single-sex treatments. It follows by design that there cannot be any gender bias in these treatments, since the loser and the winner are of the same gender. However, our model still offers some predictions for the comparison of the single-sex treatments. Given the assumption that the effort distribution is the same for males and females, it follows that the likelihood of the loser having relatively low effort compared to the winner is the same in the two single-sex merit treatments.[6] Hence, we should observe the same spectator behavior in these two treatments. In the single-sex luck treatments, there is no productivity signal and the two workers are of the same gender, and thus we should also in these treatments expect the spectator behavior to be unaffected by the gender of the loser.

Observation 3: *Statistical fairness discrimination and taste-based discrimination should not make spectators transfer differently to male losers and female losers in the single-sex treatments.*

Finally, the model provides predictions for the comparison of the mixed-sex treatments and the single-sex treatments. In particular, statistical fairness discrimination implies that we should observe the lowest transfer to the male loser in the mixed-sex merit treatment, where a male loser provides the strongest signal of the loser having exerted low effort compared to the winner.[7]

Observation 4: *Statistical fairness discrimination would imply that we observe the lowest transfer to male losers in the mixed-sex merit treatments.*

[6] In the single-sex treatments, the likelihood of the loser having exerted low effort and the winner having exerted high effort is given by $2p(e^l)(1-p(e^l))$.

[7] This follows straightforwardly from the fact that the probability that the loser has exerted low effort compared to the winner $p(e_w > e_l)$ is equal to one in the mixed-sex merit treatment with a male loser and less than one in all the other treatments.

4 Empirical strategy

We here outline the main empirical strategy. We specified the empirical strategy in two pre-analysis plans, one for each round of data collection, registered at the AEA RCT Registry.

4.1 Main analysis

Our main variable of interest is the amount transferred to the losing worker by spectator i in the mixed-sex merit treatments. The main empirical specification used in the analysis of these two treatments is:

$$u_i = \alpha + \beta Maleloser_i + \gamma \mathbf{X}_i + \varepsilon_i, \tag{3}$$

where u_i is the standardized amount transferred by spectator i to the losing worker, $Maleloser_i$ is an indicator variable for spectator i belonging to the treatment where the losing worker is male, $\mathbf{X}_i$ is a vector of control variables, and ε_i is an error term. We regress (3) on the sample of spectators in the two mixed-sex merit treatments, with and without a set of pre-specified control variables (gender, political affiliation, income, age). The reference category in (3) is the treatment with a female loser, and β thus provides an estimate of the causal effect on the transfer to the loser of the loser being a male instead of a female. We also report (3) for the dependent variable being an indicator variable for spectators giving nothing to the losing worker.

For the mixed-sex merit treatments, we study heterogeneous effects based on the gender, political orientation, income and age of the spectators. For gender, we use the following specification:

$$u_i = \alpha + \beta_1 Maleloser_i + \beta_2 M_i + \beta_3 Maleloser \times M_i + \varepsilon_i, \tag{4}$$

where u_i is the standardized amount transferred by spectator i to the losing worker or the indicator variable for spectators giving nothing to the losing worker, $Maleloser_i$ is an indicator variable for spectator i being in a treatment where the losing worker is male, M_i is an indicator variable for spectator i being male, $Maleloser \times M_i$ is an interaction variable for spectator i being male and in a treatment where the losing worker is male, and ε_i is an error term. In this analysis, β_1 provides an estimate of the causal effect for female spectators of the loser being a male, $\beta_1 + \beta_3$ provides a corresponding estimate for the male spectators, and β_3 provides an estimate of whether the causal effect of the loser being male differs between male spectators and female spectators. We report corresponding regressions for the other dimensions of heterogeneity and a regression including interaction variables for all the background variables.

4.2 Mechanisms

To study the underlying mechanisms of the spectator choices, we provide a set of regressions involving the six additional treatments. First, we study the role of the losing gender in the two mixed-sex treatments where luck is the source of inequality, by reporting regressions using specifications (3) and (4). In addition, we include all the four mixed-sex treatments and run regressions where we interact the male loser indicator variable with an indicator variable for being in the treatment where luck is the source of inequality:

$$u_i = \alpha + \beta_1 Maleloser_i + \beta_2 Luck_i + \beta_3 Maleloser \times Luck_i + \gamma \mathbf{X}_i + \varepsilon_i. \qquad (5)$$

In this analysis, β_1 provides an estimate of the causal effect of the loser being a male in the mixed-sex treatment where the source of inequality is merit and $\beta_1 + \beta_3$ provides the corresponding estimate for the luck treatment, β_2 provides an estimate of whether the loser is treated differently in the merit treatment and the luck treatment, and β_3 provides an estimate of whether the effect of being a male loser differs between the merit and the luck treatment. We implement (5) for all participants in the mixed-sex treatments and separately for each subgroup defined by the background characteristics.

Second, we study the role of gender in the single-sex treatments. We report regressions corresponding to (3) and (4) separately for the two single-sex merit treatments and for the two single-sex luck treatments, where in both cases the treatment variation is the gender of the workers. Further, to study whether the male loser and the female loser in the mixed-sex merit treatments are treated differently from the average loser in the single-sex merit treatments, we run the following regression for the four merit treatments:

$$u_i = \alpha + \beta_1 MS - Maleloser_i + \beta_2 MS - Femaleloser_i + \gamma \mathbf{X}_i + \varepsilon_i, \qquad (6)$$

where $MS - Maleloser_i$ and $MS - Femaleloser_i$ are indicator variables for the spectator being in a mixed-sex merit treatment with a male loser and a female loser, respectively. In (6), the reference category is the pooled single-sex merit treatments, and thus β_1 and β_2 provide causal estimates of whether the male loser and the female loser in the mixed-sex merit treatments are treated differently from the average loser in the single-sex treatments. We report the regressions with and without control variables.

4.3 Multiple hypothesis testing

As a robustness check of our main results, we compute p-values adjusted for multiple hypothesis testing as described in Romano and Wolf (2016). We calculate unadjusted p-values as bootstrap p-values following Davison and Hinkley (1997) and compute p-values adjusted for stepdown multiple testing following the algorithm proposed by Romano and Wolf (2016). Bootstrapping is implemented with 10,000 replications.

5 Results

We first provide an overview of the spectator choices in the experiment. We then turn to the analysis of the main treatment effects, the heterogeneity analysis and the mechanisms.

5.1 The distributive decisions

Figure 2 presents a histogram of the spectator decisions pooled for all treatments.[8] We observe that the mode is to give nothing to the losing worker (31%), the average amount and the median amount transferred are 1.56 USD and 2 USD. A significant share of the spectators equalize the earnings (22%), while almost half of the spectators (44%) do not fully equalize but give some to the losing worker (1 USD or 2 USD). Interestingly, very few spectators (3%) give more to the losing worker than to the winning worker, which provides strong evidence against the spectators randomizing in their choices.

[8]Figure A.1 gives a disaggregated presentation by treatment. An overview of the distributive decisions by round is provided in Figure A.2.

[Figure 2 about here]

5.2 Main findings

We now turn to a regression analysis of our two main treatments, where we focus on whether the spectator choice is responsive to the gender of the loser. Table 4 reports the results for specification (3), where the dependent variable is the standardized amount transferred to the losing worker (columns 1-2) and the share of spectators giving nothing to the losing worker (columns 3-4).

[Table 4 about here]

We observe a significant gender bias in the spectator choices: the average amount transferred to the losing worker is reduced by 0.174 standard deviations ($p < 0.001$) when the losing worker is a male rather than a female (column 1), which corresponds to a 15% reduction in the amount transferred. In Table A.2, we show that the estimated causal effect is almost identical in the two rounds of data collection. We find the same qualitative result when we use the alternative outcome variable (column 3): the share of spectators giving nothing to the losing worker increases by 7.3 percentage points ($p = 0.003$) when the losing worker is a male rather than a female. These results remain practically unchanged when we include background variables for gender, political orientation, income and age (columns 2 and 4), and are robust to multiple hypothesis adjustment ($p = 0.003$, Table A.15). Thus, we can state our first main result:

Result 1: *We find strong evidence of a gender bias against male losers when the source of inequality is merit.*

With respect to the background variables, we observe in Table 4 that Republicans on average transfer significantly less than non-Republicans to the losing worker (0.173 standard deviations, $p = 0.001$), and are significantly more likely not to transfer anything to the loser (5.8 percentage points, $p = 0.026$). We do not observe any significant associations between the other background variables and the spectator choices.

In Table 5, we report the heterogeneity analysis, as specified in (4), focusing on the standardized amount transferred to the losing worker.[9]

[9] The full set of results are reported in Table A.3.

[Table 5 about here]

The gender bias against males is strikingly robust across the different subgroups (columns 1-4): the estimated causal effect of the loser being a male rather than a female is in all cases negative, the effect being statistically significant for all subgroups except for low income spectators and males. In particular, we observe a strong gender bias against males among the female spectators (0.283 standard deviations, $p < 0.001$), which is robust to multiple hypothesis adjustment ($p = 0.001$, Table A.16). The gender interaction effect is also large, significant and robust to the inclusion of all the interaction variables in the regression (0.23 standard deviations, $p = 0.025$) and robust to multiple hypothesis adjustment ($p = 0.085$, Table A.17). As shown in Table A.4, the patterns are the same when using the share transferring nothing to the losing worker.

Result 2: *We find a significant gender bias against male losers in almost all subgroups when the source of inequality is merit, and, in particular, among female spectators.*

The finding of a gender bias against males in the merit-sex treatments is in line with statistical fairness discrimination by spectators who consider males to have an advantage, as established in Observation 1 in our theoretical framework. However, from the mixed-sex merit treatments alone, we cannot rule out that this behavior reflects taste-based discrimination.

5.3 Mechanisms

In this section, we use our additional treatments to shed light on the underlying mechanisms driving the observed gender bias against male losers.

First, we study whether the gender bias against male losers reflects taste-based discrimination, by considering the distributive situations where the source of inequality is luck. In these situations, there is no productivity signal that can lead to statistical fairness discrimination, and thus the spectators believe that the expected effort of the winner and the loser is the same. However, in line with Observation 2, taste-based discrimination against males would imply a lower transfer to a male loser, both in the mixed-sex luck treatments and in the mixed-sex merit treatments. Table 6 reports the regressions using specification (3) for the two mixed-sex luck treatments, where the dependent variable is the standardized amount transferred to the losing worker in column 1 and the share of spectators giving nothing to the losing worker in column 4. Given that there is a significant gender interaction effect in the spectator behavior in the mixed-sex merit treatments, we also report this analysis separately for females (columns 2 and 5) and males (columns 3 and 6).

[Table 6 about here]

We do not find evidence of a gender bias in the spectator behavior in the mixed-sex luck treatments. The estimated male loser effect is small and not statistically significant both for the amount transferred to the loser (-0.043 standard deviations, $p = 0.629$) and for the share transferring nothing to the loser (0.002 standard deviations, $p = 0.957$). We further observe that there is no significant gender bias among female spectators or male spectators, and this pattern extends to all the other subgroups, see Table A.5. As shown in Table A.6, the subgroup patterns are largely robust to using the share of spectators giving nothing to the loser as the dependent variable.[10]

Result 3: *We find no robust evidence of a gender bias against male losers when the source of inequality is luck, which suggests that the spectator choices do not reflect taste-based preferences.*

In Table 7, we compare the spectator behavior in the mixed-sex merit treatments and mixed-sex luck treatments, using specification (5). We again observe that there is a highly significant male loser effect in the mixed-sex merit treatments, but no gender effect in the mixed-sex luck treatments.[11] The interaction effect is highly significant for female spectators: the male loser effect increases by 0.298 standard deviations in the mixed-sex merit treatments compared to the mixed-sex luck treatments (-0.266 standard deviations versus 0.032 standard deviations, $p = 0.020$), and the share transferring nothing to the male loser

[10]In Table A.6, we find some suggestive evidence of the high income group discriminating against males and the low-income group discriminating against females even when the source of inequality is luck, but these effects do not hold when adjusting for multiple hypothesis testing.

[11]In line with previous research (Almås et al., 2016b), we also observe that there is significantly more inequality acceptance when the source of inequality is merit than luck: on average, the share transferred to the loser when the source of inequality is merit is 0.594 standard deviations lower than when the source of inequality is luck ($p < 0.001$) and this pattern is robust across subgroups (in all cases, $p < 0.001$).

increases by 15.3 percentage points (0.128 percentage points versus -0.025 percentage points, $p = 0.020$). This provides evidence of the behavior of female spectators reflecting statistical fairness discrimination. In Table A.7 and Table A.8, we compare the spectator behavior in the mixed-sex merit treatments and mixed-sex luck treatments for all subgroups, where we also observe evidence of statistical fairness discrimination among low income spectators and older spectators. We should note, however, that the estimated interaction effects are not statistically significant if we adjust for the multiple testing of interaction effects between merit and luck for all subgroups, see Table A.18.

We now turn to an analysis of the single-sex treatments. In our theoretical framework, Observation 3, the spectators should not infer differently about the effort of the loser and the winner in the female and male single-sex merit treatments. An essential assumption underlying this observation is that spectators believe that males and females have the same underlying effort distribution. As shown in Table 8, using specification (3), the evidence is very much in line with this observation. The loser is not treated differently in the single-sex male treatments than in the single-sex female treatments. This finding is largely robust across subgroups, as shown in Tables A.9- A.12.[12]

Result 4: *We find no evidence of spectators choosing differently in single-sex male treatments and single-sex female treatments, which is consistent with spectators believing that males and females have the same effort distribution.*

This result thus suggests that the observed gender bias is not driven by spectators in general believing that males exert less effort than females. It is rather consistent with the idea formulated in the theory framework, namely that spectators believe that males have an advantage, which then implies that a male loser is a stronger signal of low effort than a female loser.

Finally, we compare the mixed-sex merit treatments and the single-sex merit treatments in Table 9, where we report regressions using specification (6). The theoretical framework, Observation 4, predicts that we should observe the lowest transfer to the loser in the mixed-sex treatment with a male loser, which is exactly what we observe The male losers losing to a female are disadvantaged

[12]The only exception is that low income spectators transfer significantly more to the loser in the single-sex male treatments than in the single-sex female treatments when luck is the source of inequality.

relative to the losers in the single-sex merit treatments: on average, these male losers receive 0.138 standard deviation less ($p = 0.015$) and female losers losing to a male receive 0.037 standard deviations more than the average loser in the single-sex treatments ($p = 0.518$). This pattern is driven by the female spectators, who give the male losers in the mixed-sex merit treatments 0.296 standard deviations less than the losers in the single-sex merit treatments ($p < 0.001$), while they give the female losers in the mixed-sex treatments almost the same as the losers in the single-sex merit treatments.[13] For the male spectators, we observe that both male and female losers in the mixed-sex merit treatments receive slightly more than the losers in the single-sex merit treatments, but these effects are not statistically significant.

Result 5: *We find strong evidence of the male losers in the mixed-sex merit treatments receiving less than the losers in the single-sex treatments and this pattern is driven by the female spectators.*

Taken together, our findings are consistent with a model of statistical fairness discrimination, where spectators perceive a male loser in a mixed-sex merit treatment as a particularly strong signal of low effort, and thus consider it fair to transfer less to male losers than to female losers.

6 Concluding remarks

The emergence of the 'boy crisis' prompts the question of whether people interpret gender inequalities differently depending on whether males or females are lagging behind. We study this question in a novel large-scale economic experiment conducted with a general population from the United States. The participants act as spectators and distribute earnings between two workers in a controlled labor market environment. When initial earnings are based on merit, we find that the spectators are gender-biased against males. We show that this gender bias is driven by female spectators and we provide evidence suggesting that the underlying mechanism is statistical fairness discrimination, where spectators interpret a male loser as someone who has exerted less effort than a female loser.

[13] Table A.13 and Table A.14 report this analysis for all subgroups and for the analysis where the dependent variable is the share giving nothing to the loser.

Our study provides new evidence on the nature of gender discrimination, by showing how the perception of females being disadvantaged may cause people to infer that low-performing males have exerted less effort than low-performing females. This mechanism speaks to the ‘boy crisis’, by calling attention to the possibility of a gender bias against low-performing males. Both in the educational system and at the workplace, a perception of males being advantaged may lead us to interpret a losing male, more than a losing female, as someone who has not exerted sufficient effort, and thus may find it fair that less resources are allocated to assist them. Notably, however, as evident from our theoretical model, statistical fairness discrimination may equally well work against females, in settings where females are perceived to have an advantage. This may for example be the case in settings where affirmative action for women is perceived to create an advantage for females (and not only remove a disadvantage), where people may infer that females falling behind have exerted low effort. More broadly, our findings speak to how we relate ourselves to individuals struggling in society. In an era where American politics has become “a personal responsibility crusade” (Hacker, 2006), it is of great importance that we better understand how we arrive at our views about whether individuals who are struggling should be held personally responsible for their situation (Moffitt, 2015).

The paper opens up several avenues for future research. First, it is important to understand whether the identified gender bias extends to other settings where males fall behind. In particular, it would be extremely interesting to study this in an educational setting, to link it even more closely to the existing field literature on the discrimination of boys in schools. Second, it would be interesting to study whether the observed gender bias of female spectators is specific to the gender domain or whether it reflects a more general behavioral phenomenon of disadvantaged groups. Finally, we believe that our experimental design is well suited for a number of different applications, including the study of ethnic discrimination and discrimination of immigrants. We believe that the idea of statistical fairness discrimination is powerful, and we hope that future research will further our understanding of this mechanism.

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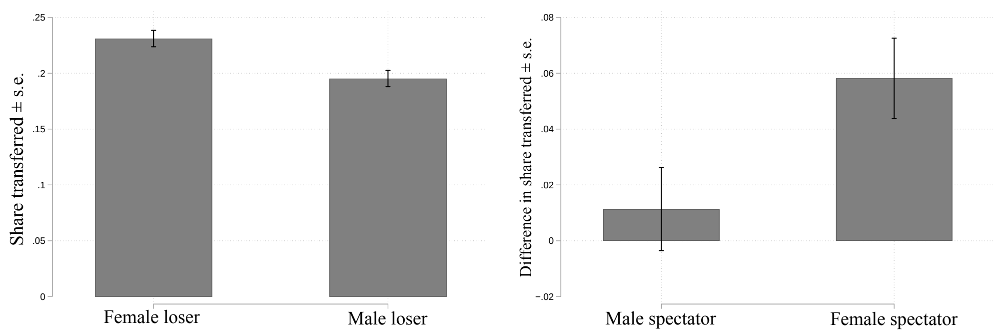
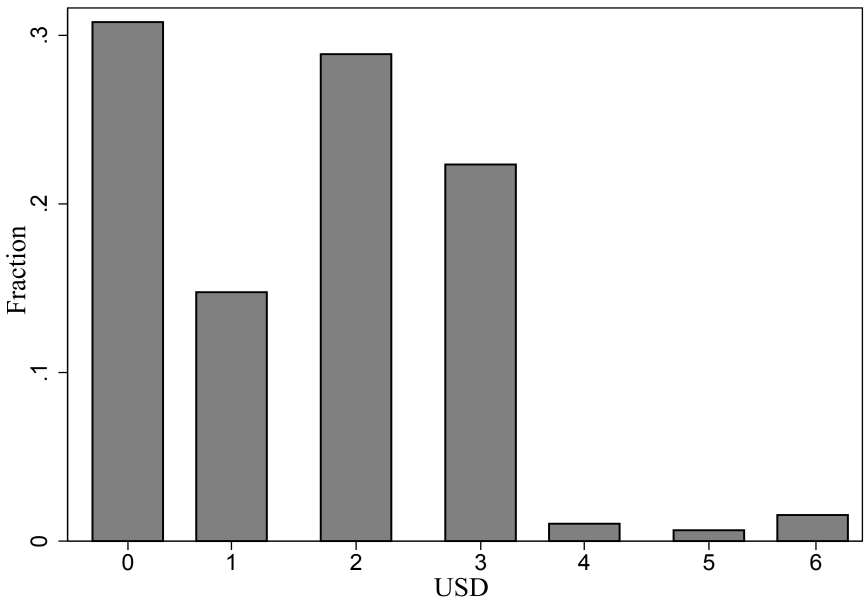
Figure 1: Main findings



Panel A: Share transferred to loser Panel B: Difference by spectator gender

Note: Panel A shows the mean share transferred to the female loser and the male loser in the mixed-sex merit treatments, while Panel B shows the difference in the mean share transferred in the same two main treatments by the spectator's gender. The standard errors are indicated by the bars.

Figure 2: Transfer to loser



Note: The figure shows the distribution of transfers (in USD) to the losing worker, pooled for all treatments.

Table 1: The stages of the experiment

1. **Work stage:** Workers complete an assignment.
2. **Earnings stage:** Workers matched in pairs. Assigned initial earnings according to treatment.
3. **Redistribution stage:** Each spectator decides for one pair of workers whether and how much to redistribute.
4. **Payment stage:** Workers in the pair paid according to the decision of the spectator.

Table 2: Descriptive statistics

	Spectator sample	**US**
Male (share)	0.488	0.492
Age (year)		
Median	41	46
p10	23	23
p90	59	72
Income (USD)		
Median	55000	57500
p10	19999	12500
p90	125000	167500
Republican (share)	0.337	0.270

Note: The table provides the descriptive statistics for the spectator sample and the US population. Sample (self-reported): The income variable is combined yearly income in USD (gross income before taxes are deducted) and given in standard categories where we use the mid-point in the category (see Appendix B.3 for a listing of income categories). A participant is classified as Republican if he or she would have voted for the Republican party if there was an election tomorrow. US: The share of males and the median age (+18) in the US are from the US Census Bureau, Population Division (2016 and 2017) (https://www.census.gov/quickfacts/ and https://www.census.gov/data/). The income data are based on the US Census Bureau, Current Population Survey together with the 2016 and 2017 Annual Social and Economic Supplement. Political affiliation is from Gallup (http://news.gallup.com/poll/).

Table 3: Treatments

	Mixed-sex		Single-sex	
	Female loser	Male loser	Female loser	Male loser
MERIT	N=782	N=782	N=257	N=256
LUCK	N=256	N=256	N=256	N=257

Note: The table provides an overview of the eight treatments in the experiment and the number of spectators in each treatment. The two main treatments are highlighted.

Table 4: Regression analysis: Transfer to loser

	Mixed-sex merit			
	Amount to loser (std)		Nothing to loser	
Male loser	-0.174	-0.173	0.073	0.073
	(0.050)	(0.050)	(0.024)	(0.024)
Male spectator		0.078		-0.011
		(0.050)		(0.024)
Republican		-0.173		0.058
		(0.054)		(0.026)
Low income		-0.011		0.009
		(0.052)		(0.025)
Low age		-0.005		-0.000
		(0.051)		(0.024)
Constant	0.066	0.092	0.335	0.318
	(0.051)	(0.068)	(0.024)	(0.033)
Observations	1564	1564	1564	1564
R^2	0.008	0.016	0.006	0.010

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker (columns 1 and 2) or an indicator variable for transferring nothing to the losing worker (columns 3 and 4). The sample and the basis for the standardization are the mixed-sex merit treatments. Male loser is an indicator for the spectator being in a treatment where the male has lost. Male spectator is an indicator variable for being male. Republican is an indicator for voting Republican. Low income is an indicator for having an income below $55,000 (which is the median income per year in the sample). Low age is an indicator for being below 41 years old (which is the median age in the sample). Included in all regressions, but not reported, is an indicator for the spectator participating in the second round of data collection. Standard errors in parentheses.

Table 5: Heterogeneity analysis: Amount to loser (std)

	Mixed-sex merit				
	Gender	Politics	Income	Age	All
Male loser	-0.283	-0.171	-0.228	-0.206	-0.378
	(0.070)	(0.061)	(0.065)	(0.071)	(0.105)
Male spectator*Male loser	0.228				0.230
	(0.101)				(0.101)
Republican*Male loser		-0.013			0.005
		(0.107)			(0.108)
Low income*Male loser			0.131		0.137
			(0.103)		(0.103)
Low age*Male loser				0.065	0.071
				(0.101)	(0.101)
Constant	0.108	0.141	0.110	0.098	0.219
	(0.050)	(0.044)	(0.047)	(0.051)	(0.076)
Controls	Yes	Yes	Yes	Yes	Yes
(Male loser+interaction)	-0.055	-0.184	-0.096	-0.141	
	(0.072)	(0.088)	(0.079)	(0.072)	
Observations	1564	1564	1564	1564	1564
R^2	0.012	0.014	0.009	0.008	0.020

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the mixed-sex merit treatments. Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser and Low age*Male loser are interactions between the respective characteristic and Male loser. Male loser+interaction is a linear combination of Male loser and the respective interaction. Each regression also includes the respective indicator variable interacted with Male loser (see Table A.3 for the full table). Standard errors in parentheses.

Table 6: Regression analysis: Transfer to loser

	Mixed-sex luck					
	Amount to loser (std)			Nothing to loser		
	All	Female	Male	All	Female	Male
Male loser	-0.043	0.012	-0.113	0.002	-0.023	0.034
	(0.089)	(0.120)	(0.132)	(0.038)	(0.052)	(0.057)
Male spectator	-0.108			0.036		
	(0.089)			(0.038)		
Republican	-0.140	-0.309	0.058	0.070	0.149	-0.020
	(0.094)	(0.126)	(0.142)	(0.041)	(0.054)	(0.061)
Low income	-0.027	-0.078	0.032	0.007	-0.004	0.020
	(0.092)	(0.120)	(0.140)	(0.039)	(0.052)	(0.060)
Low age	-0.108	-0.148	-0.026	-0.000	0.009	-0.030
	(0.089)	(0.120)	(0.133)	(0.038)	(0.052)	(0.057)
Constant	0.184	0.256	-0.014	0.198	0.184	0.257
	(0.104)	(0.127)	(0.137)	(0.045)	(0.055)	(0.059)
Observations	512	266	246	512	266	246
R^2	0.010	0.031	0.004	0.007	0.030	0.003

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker (columns 1-3) or an indicator variable for transferring nothing to the losing worker (columns 4-6). The sample and the basis for the standardization are the mixed-sex luck treatments: all spectators (columns 1 and 4), female spectators (columns 2 and 5), and male spectators (columns 3 and 6). Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Standard errors in parentheses.

Table 7: Regression analysis: Transfer to loser

	Mixed-sex merit vs. mixed-sex luck					
	Amount to loser (std)			Nothing to loser		
	Female	Male	All	Female	Male	All
Male loser	-0.266	-0.052	-0.163	0.128	0.016	0.073
	(0.064)	(0.074)	(0.048)	(0.033)	(0.034)	(0.024)
Luck	0.580	0.606	0.594	-0.062	-0.129	-0.095
	(0.100)	(0.119)	(0.077)	(0.051)	(0.055)	(0.038)
Luck*Male loser	0.298	-0.074	0.118	-0.153	0.017	-0.070
	(0.128)	(0.149)	(0.098)	(0.065)	(0.069)	(0.047)
Male spectator			0.027			0.000
			(0.042)			(0.021)
Republican	-0.225	-0.085	-0.158	0.099	0.020	0.060
	(0.060)	(0.069)	(0.045)	(0.031)	(0.032)	(0.022)
Low income	-0.048	0.021	-0.013	0.016	-0.000	0.008
	(0.056)	(0.067)	(0.043)	(0.029)	(0.031)	(0.021)
Low age	-0.064	0.008	-0.031	0.008	-0.011	-0.000
	(0.055)	(0.065)	(0.042)	(0.028)	(0.030)	(0.021)
Constant	0.063	-0.106	-0.035	0.255	0.371	0.312
	(0.077)	(0.088)	(0.062)	(0.040)	(0.041)	(0.030)
Male loser (luck)	0.032	-0.126	-0.045	-0.025	0.033	0.003
	(0.111)	(0.129)	(0.085)	(0.057)	(0.060)	(0.041)
Observations	1070	1006	2076	1070	1006	2076
R^2	0.131	0.053	0.085	0.039	0.009	0.019

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker (columns 1-3) or an indicator variable for transferring nothing to the losing worker (columns 4-6). The sample and the basis for the standardization are the mixed-sex treatments: female spectators (columns 1 and 4), male spectators (columns 2 and 5), and all spectators (columns 3 and 6). Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Luck is an indicator for spectators being in one of the luck treatments. Luck*Male loser is an interaction between Luck and Male loser. Male loser (luck) is a linear combination of Male loser and Luck*Male loser. Included in all regressions, but not reported, is an indicator for the spectator participating in the second round of data collection. Standard errors in parentheses.

Table 8: Regression analysis: Transfer to loser

	Single-sex							
	Merit				Luck			
	Amount to loser (std)		Nothing to loser		Amount to loser (std)		Nothing to loser	
Male loser	-0.040	-0.031	-0.007	-0.010	0.087	0.091	-0.001	-0.003
	(0.088)	(0.089)	(0.041)	(0.041)	(0.088)	(0.088)	(0.036)	(0.036)
Male spectator		-0.126		0.071		-0.020		-0.004
		(0.088)		(0.041)		(0.088)		(0.036)
Republican		-0.181		0.088		-0.259		0.091
		(0.095)		(0.044)		(0.092)		(0.038)
Low income		0.035		-0.018		-0.033		0.012
		(0.092)		(0.043)		(0.091)		(0.037)
Low age		0.113		-0.037		-0.125		0.029
		(0.088)		(0.041)		(0.089)		(0.037)
Constant	0.020	0.072	0.323	0.285	-0.044	0.136	0.215	0.165
	(0.062)	(0.100)	(0.029)	(0.047)	(0.063)	(0.102)	(0.026)	(0.042)
Observations	513	513	513	513	513	513	513	513
R^2	0.000	0.017	0.000	0.017	0.002	0.020	0.000	0.012

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker (columns 1-2 and 5-6) or an indicator variable for transferring nothing to the losing worker (columns 3-4 and 7-8). The sample and the basis for the standardization are the single-sex merit treatments (columns 1-4) and the single-sex luck treatments (columns 5-8). Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Standard errors in parentheses.

Table 9: Single-sex vs. mixed-sex merit: Amount to loser (std)

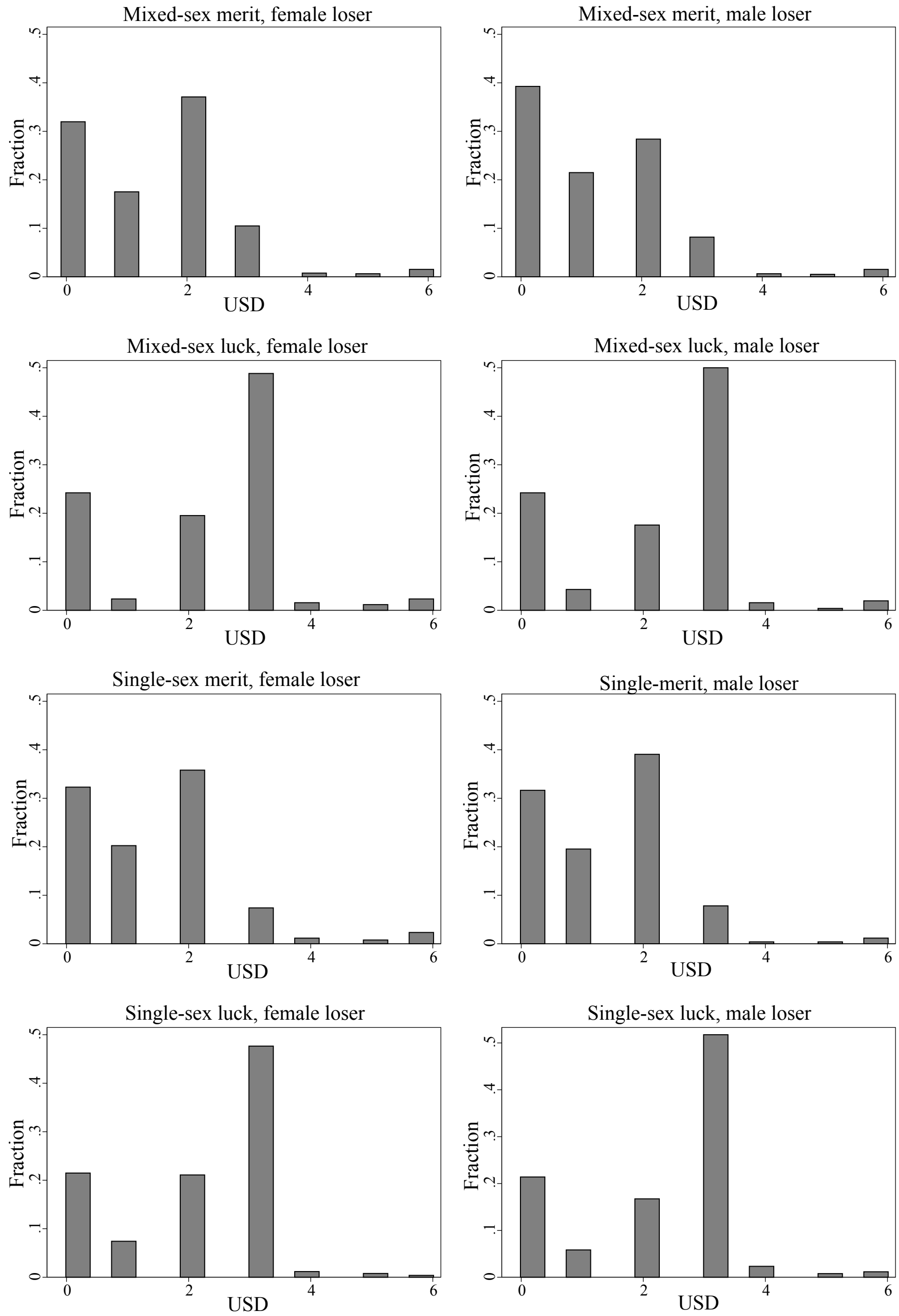
	Merit					
	All	All	Females	Females	Males	Males
MS-Male loser	-0.138	-0.137	-0.296	-0.292	0.028	0.024
	(0.057)	(0.057)	(0.075)	(0.075)	(0.085)	(0.085)
MS-Female loser	0.037	0.038	-0.012	-0.009	0.084	0.079
	(0.057)	(0.057)	(0.076)	(0.076)	(0.084)	(0.084)
Male spectator		0.028				
		(0.044)				
Republican		-0.175		-0.172		-0.175
		(0.047)		(0.063)		(0.070)
Low income		-0.001		-0.051		0.055
		(0.045)		(0.059)		(0.068)
Low age		0.023		0.044		-0.003
		(0.044)		(0.058)		(0.066)
Constant	0.038	0.070	0.108	0.157	-0.030	0.016
	(0.044)	(0.059)	(0.059)	(0.073)	(0.065)	(0.082)
MS-Male loser -	-0.175	-0.174	-0.284	-0.283	-0.055	-0.055
MS-Female loser	(0.050)	(0.050)	(0.067)	(0.067)	(0.076)	(0.076)
Observations	2077	2077	1057	1057	1020	1020
R^2	0.006	0.013	0.022	0.030	0.001	0.009

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the merit treatments: all spectators (columns 1 and 2), female spectators (columns 3 and 4), and male spectators (columns 5 and 6). The reference sample is the sample of spectators in the single-sex merit treatments. MS-Male loser is an indicator for the spectator being in a treatment where the male has lost to a female. MS-Female loser is an indicator for the spectator being in a treatment where the female has lost to a male. Male spectator, Republican, Low income and Low age are defined in Table 4. MS-Male loser - MS-Female loser is a linear combination of MS-Male loser and MS-Female loser. Standard errors in parentheses.

A Online Appendix: Additional analysis

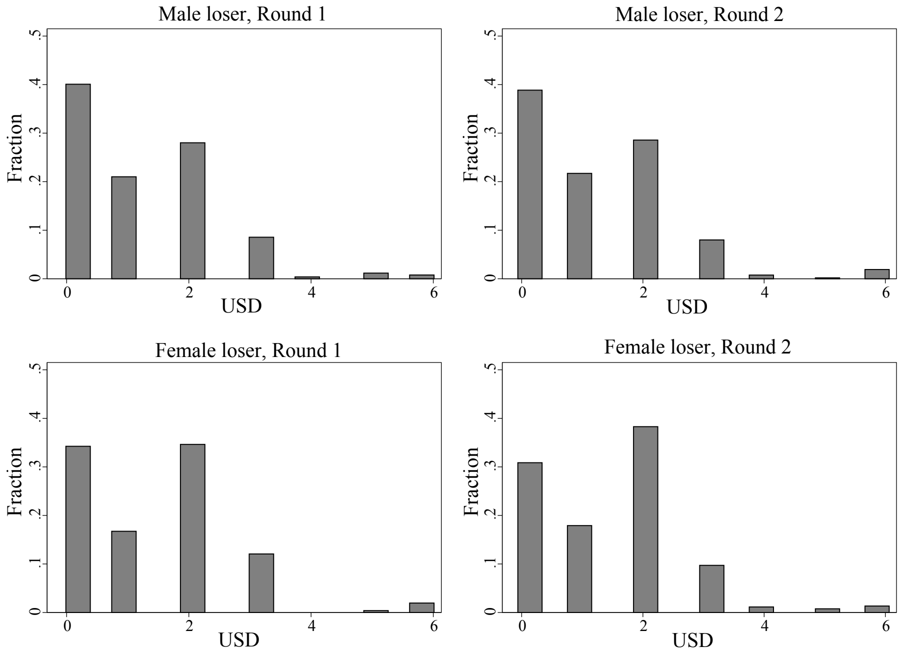
A.1 Figures and tables

Figure A.1: Distribution of transfers to loser by treatment



Note: The figure shows the distribution of transfers (in USD) to the losing worker by treatment.

Figure A.2: Distribution of transfers to loser in the mixed-sex merit treatments, by round



Note: The upper panels (lower panels) show the distribution of transfers (in USD) to the male loser (female loser) in the mixed-sex merit treatments by round.

Table A.1: Balance test

	Male	Republican	Income	Age
Mixed-sex merit male loser	-0.028 (0.025)	-0.005 (0.024)	2455.043 (2114.984)	0.921 (0.667)
Mixed-sex luck female loser	-0.020 (0.040)	0.026 (0.038)	538.868 (3356.926)	-0.075 (1.063)
Mixed-sex luck male loser	0.011 (0.040)	-0.013 (0.038)	8095.877 (3365.135)	1.332 (1.063)
Single-sex merit female loser	0.017 (0.040)	-0.010 (0.038)	3076.967 (3394.785)	0.869 (1.062)
Single-sex merit male loser	0.027 (0.040)	0.007 (0.038)	2361.561 (3373.458)	1.652 (1.063)
Single-sex luck female loser	-0.001 (0.040)	0.030 (0.038)	3184.619 (3373.458)	-0.571 (1.063)
Single-sex luck male loser	-0.002 (0.040)	0.075 (0.038)	657.073 (3365.135)	2.153 (1.062)
Included control:				
Round dummy	Yes	Yes	Yes	Yes
Observations	3102	3102	2954	3102
R^2	0.001	0.002	0.005	0.004
Prob > F	0.8637	0.4264	0.3692	0.1718

Note: The table reports OLS regressions with the different spectator background characteristics as dependent variables. For each background characteristic, we have reported the p-value of the joint F-test testing whether the eight treatments are significantly different from each other with respect to that background characteristic. The reference category across all regressions is the mixed-sex merit treatment where a female has lost. The dependent variable in column 1 is male, an indicator for being a male. The dependent variable in column 2 is republican, an indicator for wanting to vote republican. The dependent variable in column 3 is income. Income is the spectator's reported combined, yearly household income (gross income before taxes are deducted). The nine different income categories we used are specified in Appendix B.3. The spectators who did not know or want to state their income are not included in the sample in column 3. The dependent variable in column 4 is age, which reports the spectator's age in number of years. Included in all regressions, but not reported, is an indicator for the spectator participating in the second round of data collection. Standard errors in parentheses.

Table A.2: Regression analysis: Transfer to loser by round

A. Amount to loser (std)	Mixed-sex merit			
	Round 1		Round 2	
Male loser	-0.170	-0.169	-0.176	-0.175
	(0.088)	(0.088)	(0.062)	(0.061)
Male spectator		0.052		0.093
		(0.088)		(0.061)
Republican		-0.207		-0.161
		(0.095)		(0.066)
Low income		-0.018		-0.017
		(0.092)		(0.063)
Low age		0.127		-0.069
		(0.089)		(0.062)
Constant	0.064	0.049	0.098	0.147
	(0.062)	(0.103)	(0.044)	(0.072)
Observations	514	514	1050	1050
R^2	0.007	0.022	0.008	0.016
B. Nothing to loser	Mixed-sex merit			
	Round 1		Round 2	
Male loser	0.058	0.062	0.080	0.080
	(0.043)	(0.043)	(0.029)	(0.029)
Male spectator		0.020		-0.026
		(0.043)		(0.029)
Republican		0.077		0.050
		(0.046)		(0.032)
Low income		0.036		-0.001
		(0.045)		(0.030)
Low age		-0.031		0.014
		(0.043)		(0.030)
Constant	0.342	0.308	0.309	0.299
	(0.030)	(0.050)	(0.021)	(0.034)
Observations	514	514	1050	1050
R^2	0.004	0.011	0.007	0.010

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker (Panel A) or an indicator for the spectator transferring nothing to the losing worker (Panel B). The sample and the basis for the standardization are the mixed-sex merit treatments. Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Standard errors in parentheses.

Table A.3: Heterogeneity analysis: Amount to loser (std)

	Mixed-sex merit				
	Gender	Politics	Income	Age	All
Male loser	-0.283	-0.171	-0.228	-0.206	-0.378
	(0.070)	(0.061)	(0.065)	(0.071)	(0.105)
Male spectator*Male loser	0.228				0.230
	(0.101)				(0.101)
Republican*Male loser		-0.013			0.005
		(0.107)			(0.108)
Low income*Male loser			0.131		0.137
			(0.103)		(0.103)
Low age*Male loser				0.065	0.071
				(0.101)	(0.101)
Male spectator	-0.042				-0.036
	(0.071)				(0.071)
Republican		-0.161			-0.177
		(0.075)			(0.077)
Low income			-0.056		-0.078
			(0.072)		(0.073)
Low age				-0.020	-0.045
				(0.071)	(0.072)
Constant	0.108	0.141	0.110	0.098	0.219
	(0.050)	(0.044)	(0.047)	(0.051)	(0.076)
(Male loser+interaction)	-0.055	-0.184	-0.096	-0.141	
	(0.072)	(0.088)	(0.079)	(0.072)	
Observations	1564	1564	1564	1564	1564
R^2	0.012	0.014	0.009	0.008	0.020

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the mixed-sex merit treatments. Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser, Low age*Male loser and Male loser+interaction are defined in Table 5. Standard errors in parentheses.

Table A.4: Heterogeneity analysis: Nothing to loser

	Mixed-sex merit				
	Gender	Politics	Income	Age	All
Male loser	0.127	0.070	0.099	0.065	0.146
	(0.034)	(0.029)	(0.031)	(0.034)	(0.050)
Male spectator*Male loser	-0.112				-0.114
	(0.048)				(0.048)
Republican*Male loser		0.010			0.007
		(0.051)			(0.052)
Low income*Male loser			-0.065		-0.068
			(0.049)		(0.050)
Low age*Male loser				0.015	0.015
				(0.048)	(0.049)
Male spectator	0.046				0.044
	(0.034)				(0.034)
Republican		0.051			0.054
		(0.036)			(0.037)
Low income			0.034		0.041
			(0.035)		(0.035)
Low age				-0.013	-0.006
				(0.034)	(0.035)
Constant	0.297	0.303	0.306	0.326	0.265
	(0.024)	(0.021)	(0.022)	(0.024)	(0.037)
(Male loser+interaction)	0.015	0.080	0.034	0.081	
	(0.035)	(0.042)	(0.038)	(0.034)	
Observations	1564	1564	1564	1564	1564
R^2	0.009	0.009	0.007	0.006	0.014

Note: The table reports OLS regressions, where the dependent variable is an indicator for transferring nothing to the losing worker. The sample is the mixed-sex merit treatments. Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser, Low age*Male loser and Male loser+interaction are defined in Table 5. Standard errors in parentheses.

Table A.5: Heterogeneity analysis: Amount to loser (std)

	Mixed-sex luck					
	No interaction	Gender	Politics	Income	Age	All
Male loser	-0.033	0.051	-0.045	-0.187	0.069	-0.035
	(0.088)	(0.123)	(0.108)	(0.114)	(0.124)	(0.183)
Male spectator*Male loser		-0.169				-0.109
		(0.177)				(0.178)
Republican*Male loser			0.019			0.036
			(0.188)			(0.189)
Low income*Male loser				0.384		0.396
				(0.181)		(0.183)
Low age*Male loser					-0.219	-0.252
					(0.177)	(0.178)
Male spectator		-0.019				-0.039
		(0.125)				(0.126)
Republican			-0.143			-0.158
			(0.131)			(0.131)
Low income				-0.200		-0.215
				(0.126)		(0.127)
Low age					0.003	0.017
					(0.125)	(0.126)
Constant	0.017	0.026	0.067	0.103	0.015	0.174
	(0.063)	(0.085)	(0.078)	(0.083)	(0.090)	(0.133)
(Male loser+interaction)		-0.118	-0.026	0.197	-0.150	
		(0.128)	(0.154)	(0.140)	(0.126)	
Observations	512	512	512	512	512	512
R^2	0.000	0.005	0.004	0.009	0.006	0.024

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the mixed-sex luck treatments. Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser, Low age*Male loser and Male loser+interaction are defined in Table 5. Standard errors in parentheses.

Table A.6: Heterogeneity analysis: Nothing to loser

	Mixed-sex luck					
	No interaction	Gender	Politics	Income	Age	All
Male loser	0.000	-0.032	-0.019	0.082	-0.032	0.003
	(0.038)	(0.053)	(0.046)	(0.049)	(0.053)	(0.078)
Male spectator*Male loser		0.063				0.042
		(0.076)				(0.076)
Republican*Male loser			0.065			0.048
			(0.081)			(0.081)
Low income*Male loser				-0.207		-0.202
				(0.077)		(0.079)
Low age*Male loser					0.065	0.087
					(0.076)	(0.076)
Male spectator		0.003				0.009
		(0.054)				(0.054)
Republican			0.038			0.046
			(0.056)			(0.056)
Low income				0.097		0.104
				(0.054)		(0.054)
Low age					-0.035	-0.042
					(0.054)	(0.054)
Constant	0.242	0.241	0.229	0.200	0.260	0.199
	(0.027)	(0.037)	(0.033)	(0.035)	(0.039)	(0.057)
Male loser + interaction		0.032	0.046	-0.125	0.033	
		(0.055)	(0.066)	(0.060)	(0.054)	
Observations	512	512	512	512	512	512
R^2	0.000	0.003	0.007	0.014	0.001	0.025

Note: The table reports OLS regressions, where the dependent variable is an indicator variable for transferring nothing to the losing worker. The sample is the mixed-sex luck treatments. Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser, Low age*Male loser and Male loser+interaction are defined in Table 5. Standard errors in parentheses.

Table A.7: Regression analysis: Amount to loser (std)

	Mixed-sex merit vs. mixed-sex luck								
	Female	Male	Republican	Non-Republican	High income	Low income	High age	Low age	All
Male loser	-0.266	-0.052	-0.172	-0.164	-0.212	-0.086	-0.203	-0.127	-0.163
	(0.064)	(0.074)	(0.086)	(0.059)	(0.063)	(0.076)	(0.068)	(0.069)	(0.048)
Luck	0.580	0.606	0.611	0.575	0.663	0.498	0.625	0.550	0.594
	(0.100)	(0.119)	(0.135)	(0.094)	(0.102)	(0.119)	(0.110)	(0.108)	(0.077)
Luck*Male loser	0.298	-0.074	0.159	0.114	0.009	0.285	0.280	-0.046	0.118
	(0.128)	(0.149)	(0.173)	(0.118)	(0.126)	(0.155)	(0.137)	(0.140)	(0.098)
Male spectator			0.123	-0.012	0.006	0.068	0.004	0.066	0.027
			(0.075)	(0.051)	(0.055)	(0.067)	(0.059)	(0.060)	(0.042)
Republican	-0.225	-0.085			-0.184	-0.103	-0.246	-0.059	-0.158
	(0.060)	(0.069)			(0.057)	(0.076)	(0.062)	(0.067)	(0.045)
Low income	-0.048	0.021	0.043	-0.035			0.009	-0.041	-0.013
	(0.056)	(0.067)	(0.080)	(0.051)			(0.062)	(0.061)	(0.043)
Low age	-0.064	0.008	0.105	-0.092	-0.009	-0.075			-0.031
	(0.055)	(0.065)	(0.076)	(0.051)	(0.055)	(0.067)			(0.042)
Constant	0.063	-0.106	-0.343	0.041	-0.006	-0.078	-0.055	-0.042	-0.035
	(0.077)	(0.088)	(0.103)	(0.073)	(0.077)	(0.092)	(0.082)	(0.082)	(0.062)
Male loser (luck)	0.032	-0.126	-0.014	-0.050	-0.203	0.199	0.077	-0.173	-0.045
	(0.111)	(0.129)	(0.150)	(0.103)	(0.110)	(0.135)	(0.119)	(0.122)	(0.085)
Observations	1070	1006	686	1390	1235	841	1046	1030	2076
R^2	0.131	0.053	0.087	0.082	0.095	0.080	0.112	0.069	0.085

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the mixed-sex treatments, with the different subgroups (columns 1-8) and the full sample (column 9). Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Luck is an indicator for spectators being in the mixed-sex luck treatments. Luck*Male loser is an interaction between Luck and Male loser. Male loser (luck) is a linear combination of Male loser and Luck*Male loser. Included in all regressions, but not reported, is an indicator for the spectator participating in the second round of data collection. Standard errors in parentheses.

Table A.8: Regression analysis: Nothing to loser

	Mixed-sex merit vs. mixed-sex luck								
	Female	Male	Republican	Non-Republican	High income	Low income	High age	Low age	All
Male loser	0.128	0.016	0.081	0.072	0.100	0.036	0.072	0.081	0.073
	(0.033)	(0.034)	(0.042)	(0.028)	(0.031)	(0.037)	(0.033)	(0.034)	(0.024)
Luck	-0.062	-0.129	-0.107	-0.082	-0.114	-0.069	-0.092	-0.090	-0.095
	(0.051)	(0.055)	(0.066)	(0.046)	(0.049)	(0.058)	(0.054)	(0.053)	(0.038)
Luck*Male loser	-0.153	0.017	-0.047	-0.090	-0.015	-0.160	-0.103	-0.047	-0.070
	(0.065)	(0.069)	(0.085)	(0.057)	(0.061)	(0.076)	(0.067)	(0.068)	(0.047)
Male spectator			-0.058	0.024	0.002	-0.006	0.003	-0.009	0.000
			(0.037)	(0.025)	(0.026)	(0.033)	(0.029)	(0.029)	(0.021)
Republican	0.099	0.020			0.086	0.013	0.113	0.001	0.060
	(0.031)	(0.032)			(0.027)	(0.037)	(0.030)	(0.032)	(0.022)
Low income	0.016	-0.000	-0.039	0.027			0.023	-0.006	0.008
	(0.029)	(0.031)	(0.039)	(0.025)			(0.030)	(0.030)	(0.021)
Low age	0.008	-0.011	-0.075	0.033	0.011	-0.014			-0.000
	(0.028)	(0.030)	(0.037)	(0.025)	(0.027)	(0.033)			(0.021)
Constant	0.255	0.371	0.455	0.271	0.275	0.373	0.302	0.321	0.312
	(0.040)	(0.041)	(0.051)	(0.035)	(0.037)	(0.045)	(0.040)	(0.040)	(0.030)
Male loser (luck)	-0.025	0.033	0.034	-0.017	0.085	-0.124	-0.031	0.034	0.003
	(0.057)	(0.060)	(0.074)	(0.050)	(0.053)	(0.066)	(0.058)	(0.059)	(0.041)
Observations	1070	1006	686	1390	1235	841	1046	1030	2076
R^2	0.039	0.009	0.026	0.020	0.029	0.018	0.030	0.017	0.019

Note: The table reports OLS regressions, where the dependent variable is an indicator variable for transferring nothing to the losing worker. The sample is the mixed-sex treatments, with the different subgroups (columns 1-8) and the full sample (column 9). Male loser, Male spectator, Republican, Low income and Low age are defined in Table 4. Luck is an indicator for spectators who belong to either of the luck treatments. Luck*Male loser is an interaction between Luck and Male loser. Male loser (luck) is a linear combination of Male loser and Luck*Male loser. Included in all regressions, but not reported, is an indicator for the spectator participating in the second round of data collection. Standard errors in parentheses.

Table A.9: Heterogeneity analysis: Amount to loser (std)

	Single-sex merit					
	No interaction	Gender	Politics	Income	Age	All
Male loser	-0.040	-0.108	-0.075	-0.132	0.088	-0.109
	(0.088)	(0.126)	(0.107)	(0.111)	(0.122)	(0.181)
Male spectator*Male loser		0.137				0.147
		(0.177)				(0.177)
Republican*Male loser			0.118			0.130
			(0.188)			(0.190)
Low income*Male loser				0.237		0.227
				(0.184)		(0.185)
Low age*Male loser					-0.253	-0.257
					(0.177)	(0.177)
Male spectator		-0.207				-0.199
		(0.125)				(0.125)
Republican			-0.261			-0.242
			(0.134)			(0.134)
Low income				-0.064		-0.076
				(0.133)		(0.133)
Low age					0.244	0.240
					(0.125)	(0.124)
Constant	0.020	0.124	0.102	0.041	-0.104	0.099
	(0.062)	(0.088)	(0.075)	(0.076)	(0.089)	(0.125)
(Male loser+interaction)		0.028	0.043	0.106	-0.165	
		(0.124)	(0.155)	(0.147)	(0.128)	
Observations	513	513	513	513	513	513
R^2	0.000	0.006	0.010	0.005	0.008	0.026

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the single-sex merit treatments. Male loser is an indicator for the spectator being in a treatment of two males. Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser and Low age*Male loser are interactions between the respective characteristic and Male loser. Male loser+interaction is a linear combination of Male loser and the respective interaction. Standard errors in parentheses.

Table A.10: Heterogeneity analysis: Nothing to loser

	Single-sex merit					
	No interaction	Gender	Politics	Income	Age	All
Male loser	-0.007	-0.001	-0.003	0.020	-0.065	-0.033
	(0.041)	(0.059)	(0.050)	(0.052)	(0.057)	(0.084)
Male spectator*Male loser		-0.012				-0.017
		(0.082)				(0.083)
Republican*Male loser			-0.015			-0.019
			(0.088)			(0.089)
Low income*Male loser				-0.067		-0.054
				(0.086)		(0.087)
Low age*Male loser					0.118	0.122
					(0.083)	(0.083)
Male spectator		0.083				0.079
		(0.058)				(0.058)
Republican			0.105			0.097
			(0.063)			(0.063)
Low income				0.003		0.008
				(0.062)		(0.062)
Low age					-0.098	-0.097
					(0.058)	(0.058)
Constant	0.323	0.281	0.290	0.322	0.373	0.300
	(0.029)	(0.041)	(0.035)	(0.035)	(0.042)	(0.059)
Male loser + interaction		-0.013	-0.019	-0.046	0.053	
		(0.058)	(0.072)	(0.069)	(0.060)	
Observations	513	513	513	513	513	513
R^2	0.000	0.007	0.010	0.002	0.006	0.022

Note: The table reports OLS regressions, where the dependent variable is an indicator variable for transferring nothing to the losing worker. The sample is the single-sex merit treatments. Male loser is an indicator for the spectator being in a treatment of two males. Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser, Low age*Male loser and Male loser+interaction are defined in Table A.9. Standard errors in parentheses.

Table A.11: Heterogeneity analysis: Amount to loser (std)

	Single-sex luck					
	No interaction	Gender	Politics	Income	Age	All
Male loser	0.087	0.087	0.059	-0.079	-0.028	-0.194
	(0.088)	(0.123)	(0.111)	(0.112)	(0.124)	(0.183)
Male spectator*Male loser		0.000				-0.032
		(0.177)				(0.177)
Republican*Male loser			0.102			0.120
			(0.181)			(0.184)
Low income*Male loser				0.440		0.427
				(0.181)		(0.181)
Low age*Male loser					0.222	0.190
					(0.177)	(0.178)
Male spectator		-0.028				-0.010
		(0.125)				(0.125)
Republican			-0.292			-0.309
			(0.130)			(0.131)
Low income				-0.250		-0.245
				(0.129)		(0.129)
Low age					-0.202	-0.205
					(0.125)	(0.125)
Constant	-0.044	-0.030	0.060	0.048	0.062	0.269
	(0.063)	(0.087)	(0.077)	(0.078)	(0.090)	(0.126)
Male loser + interaction		0.087	0.161	0.360	0.194	
		(0.127)	(0.143)	(0.143)	(0.126)	
Observations	513	513	513	513	513	513
R^2	0.002	0.002	0.016	0.013	0.007	0.033

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the single-sex luck treatments. Male loser is an indicator for the spectator being in a treatment of two males. Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser, Low age*Male loser and Male loser+interaction are defined in Table A.9. Standard errors in parentheses.

Table A.12: Heterogeneity analysis: Nothing to loser

	Single-sex luck					
	No interaction	Gender	Politics	Income	Age	All
Male loser	-0.001	0.006	0.000	0.065	0.048	0.112
	(0.036)	(0.051)	(0.046)	(0.046)	(0.051)	(0.076)
Male spectator*Male loser		-0.014				-0.002
		(0.073)				(0.073)
Republican*Male loser			-0.013			-0.026
			(0.075)			(0.076)
Low income*Male loser				-0.173		-0.168
				(0.075)		(0.075)
Low age*Male loser					-0.098	-0.083
					(0.073)	(0.074)
Male spectator		0.006				0.001
		(0.052)				(0.052)
Republican			0.093			0.099
			(0.054)			(0.054)
Low income				0.098		0.096
				(0.053)		(0.053)
Low age					0.066	0.066
					(0.051)	(0.051)
Constant	0.215	0.212	0.182	0.179	0.180	0.110
	(0.026)	(0.036)	(0.032)	(0.032)	(0.037)	(0.052)
Male loser + interaction		-0.008	-0.013	-0.108	-0.050	
		(0.052)	(0.059)	(0.059)	(0.052)	
Observations	513	513	513	513	513	513
R^2	0.000	0.000	0.010	0.011	0.004	0.024

Note: The table reports OLS regressions, where the dependent variable is an indicator variable for transferring nothing to the losing worker. The sample is the single-sex luck treatments. Male loser is an indicator for the spectator being in a treatment of two males. Male spectator, Republican, Low income and Low age are defined in Table 4. Male spectator*Male loser, Republican*Male loser, Low income*Male loser, Low age*Male loser and Male loser+interaction are defined in Table A.9. Standard errors in parentheses.

Table A.13: Single-sex vs. mixed-sex merit: Amount to loser (std)

	Merit								
	All	Females	Males	Republican	Non-Republican	Low income	High income	Low age	High age
MS-Male loser	-0.137	-0.292	0.024	-0.120	-0.143	-0.122	-0.142	-0.170	-0.098
	(0.057)	(0.075)	(0.085)	(0.099)	(0.069)	(0.092)	(0.072)	(0.083)	(0.077)
MS-Female loser	0.038	-0.009	0.079	0.066	0.028	-0.030	0.084	-0.035	0.114
	(0.057)	(0.076)	(0.084)	(0.099)	(0.069)	(0.091)	(0.072)	(0.083)	(0.078)
Male spectator	0.028			0.029	0.033	0.100	-0.011	0.005	0.059
	(0.044)			(0.076)	(0.054)	(0.069)	(0.056)	(0.063)	(0.060)
Republican	-0.175	-0.172	-0.175			-0.104	-0.215	-0.128	-0.226
	(0.047)	(0.063)	(0.070)			(0.080)	(0.058)	(0.071)	(0.063)
Low income	-0.001	-0.051	0.055	0.096	-0.038			-0.081	0.084
	(0.045)	(0.059)	(0.068)	(0.082)	(0.054)			(0.065)	(0.062)
Low age	0.023	0.044	-0.003	0.106	-0.012	-0.079	0.090		
	(0.044)	(0.058)	(0.066)	(0.077)	(0.054)	(0.070)	(0.056)		
Constant	0.070	0.157	0.016	-0.188	0.109	0.091	0.058	0.165	-0.001
	(0.059)	(0.073)	(0.082)	(0.099)	(0.068)	(0.088)	(0.072)	(0.080)	(0.074)
MS-Male loser -	-0.174	-0.283	-0.055	-0.186	-0.172	-0.092	-0.225	-0.135	-0.212
MS-Female loser	(0.050)	(0.067)	(0.076)	(0.087)	(0.062)	(0.079)	(0.065)	(0.073)	(0.070)
Observations	2077	1057	1020	682	1395	824	1253	1021	1056
R^2	0.013	0.030	0.009	0.011	0.007	0.008	0.023	0.010	0.023

Note: The table reports OLS regressions, where the dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the merit treatments, with the full sample (column 1) and all the subgroups (columns 2-9). The reference sample is the spectators in the single-sex merit treatments. MS-Male loser is an indicator for the spectator being in a treatment where a male has lost to a female. MS-Female loser is an indicator for the spectator being in a treatment where a female has lost to a male. Male spectator, Republican, Low income and Low age are defined in Table 4. MS-Male loser - MS-Female loser is a linear combination of MS-Male loser and MS-Female loser. Standard errors in parentheses.

Table A.14: Single-sex vs. mixed-sex merit: Nothing to loser

	Merit								
	All	Females	Males	Republican	Non-Republican	Low income	High income	Low age	High age
MS-Male loser	0.073	0.141	0.002	0.050	0.083	0.074	0.073	0.095	0.052
	(0.027)	(0.038)	(0.039)	(0.049)	(0.032)	(0.044)	(0.034)	(0.039)	(0.037)
MS-Female loser	-0.000	0.015	-0.013	-0.033	0.012	0.040	-0.027	0.014	-0.018
	(0.027)	(0.038)	(0.038)	(0.048)	(0.032)	(0.044)	(0.034)	(0.039)	(0.038)
Male spectator	0.009			0.011	0.004	-0.022	0.027	0.021	-0.008
	(0.021)			(0.037)	(0.025)	(0.033)	(0.027)	(0.030)	(0.029)
Republican	0.065	0.060	0.069			0.026	0.086	0.009	0.114
	(0.022)	(0.032)	(0.032)			(0.038)	(0.028)	(0.033)	(0.031)
Low income	0.002	0.024	-0.023	-0.044	0.019			0.005	-0.006
	(0.021)	(0.030)	(0.031)	(0.040)	(0.025)			(0.031)	(0.030)
Low age	-0.008	-0.020	0.006	-0.081	0.025	0.003	-0.016		
	(0.021)	(0.029)	(0.030)	(0.038)	(0.025)	(0.034)	(0.027)		
Constant	0.297	0.263	0.338	0.428	0.267	0.302	0.294	0.284	0.305
	(0.028)	(0.036)	(0.037)	(0.049)	(0.032)	(0.042)	(0.034)	(0.037)	(0.036)
MS-Male loser -	0.073	0.127	0.015	0.083	0.072	0.034	0.100	0.080	0.070
MS-Female loser	(0.024)	(0.033)	(0.035)	(0.043)	(0.029)	(0.038)	(0.031)	(0.034)	(0.034)
Observations	2077	1057	1020	682	1395	824	1253	1021	1056
R^2	0.010	0.023	0.006	0.014	0.007	0.005	0.018	0.008	0.017

Note: The table reports OLS regressions, where the dependent variable is an indicator variable for transferring nothing to the losing worker. The sample is the merit treatments, with the full sample (column 1) and all the subgroups (columns 2-9). The reference sample is the spectators in the single-sex merit treatments. MS-Male loser is an indicator for the spectator being in a treatment where a male has lost to a female. MS-Female loser is an indicator for the spectator being in a treatment where a female has lost to a male. Male spectator, Republican, Low income and Low age are defined in Table 4. MS-Male loser - MS-Female loser is a linear combination of MS-Male loser and MS-Female loser. Standard errors in parentheses.

A.2 Multiple hypothesis testing

We here report the p-values adjusted for multiple hypothesis testing. We calculate unadjusted p-values as bootstrap p-values following Davison and Hinkley (1997) and compute p-values adjusted for stepdown multiple testing following the algorithm proposed by Romano and Wolf (2016). Bootstrapping is done with 10000 replications.

Table A.15: Multiple hypothesis adjustments: Average treatment effects (male loser vs. female loser)

	Differences	Unadjusted p-values	Romano-Wolf adjusted p-values
Mixed-sex			
Merit (male vs. female loser)	0.164	0.001	0.003
Luck (male vs. female loser)	-0.044	0.624	0.855
Single-sex			
Merit (male vs. female loser)	-0.035	0.665	0.855
Luck (male vs. female loser)	0.092	0.279	0.641

Note: The multiple hypothesis adjustment is based on the following OLS regression specification

$$u_i = \alpha + \beta_1 T2_i + \beta_2 T3_i + \beta_3 T4_i + \beta_4 T5_i + \beta_5 T6_i + \beta_6 T7_i + \beta_7 T8_i + \gamma \mathbf{X}_i + \varepsilon_i$$

where u_i is the standardized amount transferred by spectator i to the losing worker (based on the full sample). $\mathbf{X}_i$ is a vector of control variables and includes indicator variables for gender, political party, income and age as defined in Table 4, and ε_i is an error term. Column 1 reports the estimated treatment effects (the difference in the standardized amount transferred to a male loser and a female loser). Column 2 reports the unadjusted p-values and column 3 reports the Romano-Wolf adjusted p-values.

Table A.16: Multiple hypothesis adjustments: Treatment effect (male loser vs. female loser) in mixed-sex merit for all subgroups

	Differences	Unadjusted p-values	Romano-Wolf adjusted p-values
Female	-0.283	0.000	0.001
Male	-0.055	0.477	0.477
Republican	-0.184	0.035	0.136
Non-Republican	-0.171	0.006	0.028
High income	-0.228	0.001	0.003
Low income	-0.096	0.223	0.400
High age	-0.206	0.003	0.022
Low age	-0.141	0.051	0.140

Note: The multiple hypothesis adjustment is based on specification (4), one for each dimension: gender, political party, income and age. The dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the mixed-sex merit treatments. Column 1 reports the estimated treatment effects (the difference in the standardized amount transferred to a male loser and a female loser). Column 2 reports the unadjusted p-values and column 3 reports the Romano-Wolf adjusted p-values.

Table A.17: Multiple hypothesis adjustments: Subgroup differences in treatment effect (male loser vs. female loser) in mixed-sex merit

	Differences	Unadjusted p-values	Romano-Wolf adjusted p-values
Males vs. females	0.230	0.025	0.085
Republicans vs. non-republicans	0.005	0.959	0.959
Low inc. vs. high inc.	0.137	0.188	0.459
Low age vs high age	0.071	0.490	0.731

Note: The multiple hypothesis test is based on specification (4), including interaction variables and background variables for gender, political party, income and age as specified in Table 4 and Table 5. The dependent variable is the standardized amount transferred to the losing worker. The sample and the basis for the standardization are the mixed-sex merit treatments. Column 1 reports the estimated subgroup differences in treatment effect (the difference in the standardized amount transferred to a male loser and a female loser). Column 2 reports the unadjusted p-values and column 3 reports the Romano-Wolf adjusted p-values.

Table A.18: Multiple hypothesis adjustments: Difference in treatment effect (male loser vs. female loser) in mixed-sex luck vs. mixed-sex merit, for all subgroups:

	Differences	Unadjusted p-values	Romano-Wolf adjusted p-values
Female	0.305	0.028	0.187
Male	-0.076	0.627	0.923
Republican	0.135	0.479	0.878
Non-Republican	0.110	0.374	0.853
High income	0.008	0.953	0.953
Low income	0.286	0.084	0.335
High age	0.274	0.061	0.288
Low age	-0.052	0.723	0.923

Note: The multiple hypothesis test is based on OLS regressions with the standardized amount transferred to the losing worker as the dependent variable, one regression for each dimension of background characteristics; gender, political party, income and age. The sample and the basis for the standardization are the mixed-sex treatments. Each regression includes indicator variables Male loser, Male spectator, Republican, Low income and Low age as defined in Table 4, Luck and Luck*Male loser as defined in Table 7, and interaction variables between Male loser, between Luck and between Luck*Male loser and the relevant background characteristic. Included in all regressions, but not reported, is an indicator for the spectator participating in the second round of data collection. Column 1 reports the estimated differences in treatment effect (the difference in the standardized amount transferred to a male loser and a female loser) between the mixed-sex luck and the mixed-sex merit treatments for each subgroup, column 2 reports the unadjusted p-values, and column 3 reports the Romano-Wolf adjusted p-values.

B Online Appendix: Instructions

B.1 Instructions, main treatments

Treatment 1: Mixed-sex merit, losing female
In contrast to traditional survey questions that are about hypothetical situations, we now ask you to make a choice that has consequences for a real life situation. A few days ago two workers were recruited via an online labor market to conduct an assignment. They were both from the US; a man and a woman of the same age.

They were each paid a participation compensation of 2 USD regardless of what they would end up being paid for the assignment. After completing the assignment, they were told that their earnings from the assignment would be determined by their productivity. The most productive worker would earn 6 USD for the assignment and the other worker would earn nothing for the assignment. They were not informed about who was the most productive worker. However, they were told that a third person would be informed about the assignment and who was the most productive worker. They were also told that this third person would be given the opportunity to redistribute the earnings and thus determine how much they were paid for the assignment.

You are the third person and we now want you to choose whether to redistribute the earnings for the assignment between the two workers. Your decision is completely anonymous. The workers will receive the payment that you choose for the assignment within a few days, but will not receive any further information.

The man was most productive and earned 6 USD for the assignment. The woman was least productive and earned nothing for the assignment.

Please state which of the following alternatives you choose:

I do not redistribute:

- *The most productive worker is paid 6 USD and the least productive worker is paid 0 USD.*

I do redistribute:

- *The most productive worker is paid 5 USD and the least productive worker is paid 1 USD.*
- *The most productive worker is paid 4 USD and the least productive worker is paid 2 USD.*
- *The most productive worker is paid 3 USD and the least productive worker is paid 3 USD.*
- *The most productive worker is paid 2 USD and the least productive worker is paid 4 USD.*
- *The most productive worker is paid 1 USD and the least productive worker is paid 5 USD.*
- *The most productive worker is paid 0 USD and the least productive worker is paid 6 USD.*

B.2 Instructions, additional treatments

Treatment 3: Luck, mixed-sex, unlucky female
In contrast to traditional survey questions that are about hypothetical situations, we now ask you to make a choice that has consequences for a real life situation. A few days ago two workers were recruited via an online labor market to conduct an assignment. They were both from the US; a man and a woman of the same age.

They were each paid a participation compensation of 2 USD regardless of what they would end up being paid for the assignment. After completing the assignment, they were told that their earnings from the assignment would be determined by a lottery. The worker winning the lottery would earn 6 USD for the assignment and the other worker would earn nothing for the assignment. They were not informed about the outcome of the lottery. However, they were told that a third person would be informed about the assignment and the outcome of the lottery. They were also told that this third person would be given the opportunity to redistribute the earnings and thus determine how much they were paid for the assignment.

You are the third person and we now want you to choose whether to redistribute the earnings for the assignment between the two workers. Your decision is completely anonymous. The workers will receive the payment that you choose for the assignment within a few days, but will not receive any further information.

The man was lucky, won the lottery and earned 6 USD for the assignment. The woman was unlucky and earned nothing for the assignment.

Please state which of the following alternatives you choose:

I do not redistribute:

- *The lucky worker is paid 6 USD and the unlucky worker is paid 0 USD.*

I do redistribute:

- *The lucky worker is paid 5 USD and the unlucky worker is paid 1 USD.*
- *The lucky worker is paid 4 USD and the unlucky worker is paid 2 USD.*
- *The lucky worker is paid 3 USD and the unlucky worker is paid 3 USD.*
- *The lucky worker is paid 2 USD and the unlucky worker is paid 4 USD.*
- *The lucky worker is paid 1 USD and the unlucky worker is paid 5 USD.*
- *The lucky worker is paid 0 USD and the unlucky worker is paid 6 USD.*

Treatment 5: Merit, single-sex, two females

In contrast to traditional survey questions that are about hypothetical situations, we now ask you to make a choice that has consequences for a real life situation. A few days ago two workers were recruited via an online labor market to conduct an assignment. They were both from the US; two women of the same age.

They were each paid a participation compensation of 2 USD regardless of what they would end up being paid for the assignment. After completing the assignment, they were told that their earnings from the assignment would be determined by their productivity. The most productive worker would earn 6 USD *for the assignment and the other worker would earn nothing for the assignment. They were not informed about who was the most productive worker. However, they were told that a third person would be informed about the assignment and who was the most productive worker. They were also told that this third person would be given the opportunity to redistribute the earnings and thus determine how much they were paid for the assignment.*

You are the third person and we now want you to choose whether to redistribute the earnings for the assignment between the two workers. Your decision is completely anonymous. The workers will receive the payment that you choose for the assignment within a few days, but will not receive any further information.

One of the women was most productive and earned 6 USD for the assignment. The other woman was least productive and earned nothing for the assignment.

Please state which of the following alternatives you choose:

I do not redistribute:

- *The most productive worker is paid 6 USD and the least productive worker is paid 0 USD.*

I do redistribute:

- *The most productive worker is paid 5 USD and the least productive worker is paid 1 USD.*
- *The most productive worker is paid 4 USD and the least productive worker is paid 2 USD.*
- *The most productive worker is paid 3 USD and the least productive worker is paid 3 USD.*
- *The most productive worker is paid 2 USD and the least productive worker is paid 4 USD.*
- *The most productive worker is paid 1 USD and the least productive worker is paid 5 USD.*

- *The most productive worker is paid 0 USD and the least productive worker is paid 6 USD.*

B.3 Background questions

In addition, the spectators will answer the following set of background questions:

- (...) we would be grateful if you could type in your actual age below?
- Are you?
  - Male
  - Female
- In which region do you live? (State in the United States)
- What is your household's combined yearly income (gross income before taxes are deducted)?
  - Less than $20.000
  - $20.000 - $29.999
  - $30.000 - $39.999
  - $40.000 - $49.999
  - $50.000 - $59.999
  - $60.000 - $74.999
  - $75.000 - $99.999
  - $100.000 - $149.999
  - $150.000 or more
  - Do not know/prefer not to state
- Which political party would you vote for if there was an election tomorrow?
  - Republican
  - Democratic
  - Other

B.4 Beliefs and attitudes questions

Question 1) US 8th graders were tested in mathematics. How do you think the male students performed relative to the female students in

- a) mathematics?
  - Males much better
  - Males somewhat better
  - Equal performance
  - Females somewhat better
  - Females much better

We then asked the same question about reading (1b), by inserting reading instead of mathematics in the question structure above.

Question 2) Do you generally favor or oppose affirmative action programs for women?[14]

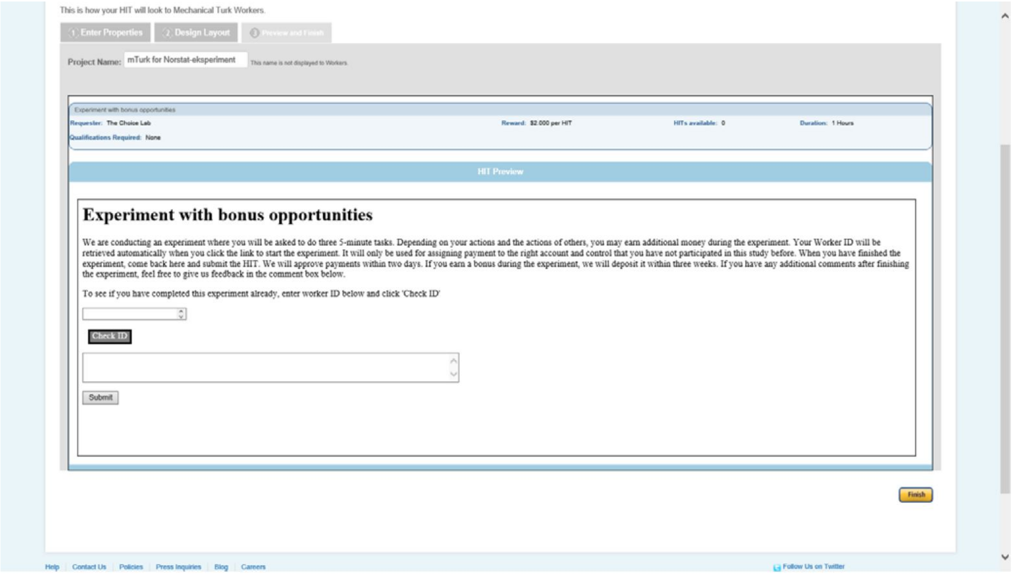
- Generally favor
- Generally oppose

B.5 HIT announcement and worker instructions

We recruited the workers in two rounds of data collection. The complete instructions for the workers in each of the two rounds are provided below. In the first round of data collection, we recruited 1370 workers, 685 men and 685 women living in the US. In the second round, we recruited 702 workers, 351 men and 351 women. In total, we ended up with 2055 unique pairs of assignments/workers in the first round of data collection and 1053 in the second.

[14]Question 1a and 1b are based on a nationally representative assessment conducted in 2015 by The National Assessment of Educational Progress (NAEP). Here, male and female 8th graders performed equally well on the mathematics test (each group with an average of 282 points), while females on average performed slightly better than males on the reading test (271 vs. 260 points). For more details, see http://www.nationsreportcard.gov/reading_math_2015/. Question 2 is taken from Gallup's Minority Rights and Relations survey conducted in 2015 with more than 2000 US adults. They found that 67% of Americans are in favor of affirmative action for women, with females being more prone to support it than males (72% vs. 62%).

B.5.1 Round 1


This is how your HIT will look to Mechanical Turk Workers.
1 Enter Properties
2 Design Layout
Project Name: mTurk for Norstat-eksperiment
This name is not displayed to Workers.
Experiment with bonus opportunities
Requester: The Choice Lab
Reward: $2.000 per HIT
HITs available: 0
Duration: 1 Hours
Qualifications Required: None
HIT Preview
Experiment with bonus opportunities
We are conducting an experiment where you will be asked to do three 5-minute tasks. Depending on your actions and the actions of others, you may earn additional money during the experiment. Your Worker ID will be retrieved automatically when you click the link to start the experiment. It will only be used for assigning payment to the right account and control that you have not participated in this study before. When you have finished the experiment, come back here and submit the HIT. We will approve payments within two days. If you earn a bonus during the experiment, we will deposit it within three weeks. If you have any additional comments after finishing the experiment, feel free to give us feedback in the comment box below.
To see if you have completed this experiment already, enter worker ID below and click 'Check ID'
Check ID
Submit
Finish
Help | Contact Us | Policies | Press Inquiries | Blog | Careers
Follow Us on Twitter

Introduction

Please read the instructions below carefully

General instructions:

The results from this experiment will be used in a research project. It is therefore important that you carefully read and follow all instructions. Note that you will remain anonymous throughout the experiment. We will only use your Worker ID to assign payments and check that you have not participated in this experiment before.

You will be paid a fixed participation fee of 2 USD and you may, depending on the actions you and others take, earn additional money.

You will be given detailed instructions on your screen before each part of the experiment. Please read the instructions to each part carefully.

If you have any questions regarding this experiment, you may contact thechoicelab@nhh.no

I have read and understood the above and want to participate in this study:

- ○ Yes
- ○ No

Part 1 - Production phase

Part 1 — Production phase

The first part of the experiment is a production phase where you are given three assignments to work on.

Go on to the next page to receive instructions for the first assignment.

Assignment 1 - Sentence unscrambling

Assignment 1:

In the first assignment you are asked to work on a sentence unscrambling task for 5 minutes. Your performance will not be measured as there is no right or wrong answer, but we do ask you to work continuously on this assignment.

Description of the assignment:
You will be shown five English words and are asked to form a sentence or an expression by using four of these words. This means that each sentence or expression must only contain four words.

For example, if the words given to you are **"wings, sun, the, has, jet"** then you can construct the sentence:
the jet has wings

Write the sentence or expression that you form into the blank space using your keyboard. Your answer will be submitted automatically after 20 seconds and you will auto-advance to five new words.

This assignment will last for 5 minutes and we ask you to work continuously. When you have read and understood the instructions press >> to start the assignment.

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STRONG WAS LONG THE HIKE

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GLASSES ARE PICTURE DIRTY HIS

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BASICS SHE SEDUCED THE INTRODUCED

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FINALLY IS ALWAYS HERE FRIDAY

You have now completed the first out of three assignments.

On the next page you will receive instructions for the second assignment.

Assignment 2 - Black cells

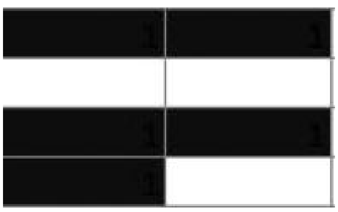
Assignment 2:

In the second assignment you are asked to work on a counting task for 5 minutes.

You are asked to count the number of black cells in a matrix similar to the one below (but bigger). You will auto-advance from each matrix after 60 seconds. On the following page you will then get to submit the number of black cells you counted, before moving on to another matrix. Your performance will be measured. The aim is to get the closest to the true number of black cells in each of the matrices. In the example matrix below, the correct number of black cells is five.

After this 5-minute assignment you will advance to the last assignment.

When you have read and understood the instructions press >> to start the assignment.



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Press >> to start go on to the next page.

You have now completed the second assignment.

On the next page you will receive instructions for the third and final assignment.

Assignment 3 - Code recognition

Assignment 3

In the third assignment you are asked to work on a code recognition task for 5 minutes. For this assignment we will measure your performance by the number of points you receive. You will be informed about your score on assignment 3 at the end of the assignment.

Description of the assignment:
On top of the page you will be shown a 3-digit code that you must find and check off from a matrix of 3-digit codes in random order. The assigned code will occur multiple times in the same matrix and you will be given 1 point for each correct marking. You will be subtracted 1 point if you check off a wrong code, but you will not lose any points for failing to check off all occurrences of the correct code.

Your matrix will be submitted automatically after 60 seconds and you will auto-advance to the next page. This assignment will last for 5 minutes and after 5 minutes you will be taken to the last part of the survey.

Below you are shown a simplified example to make sure you understand the assignment. When you have read and understood the instructions press >> to start the assignment.

This is an example:

The code you must check off is: 123

☐ **123**	☐ 283
☐ 231	☐ **123**
☐ 952	☐ 641
☐ 864	☐ 820
☐ **123**	☐ 462
☐ 791	☐ **123**

These page timer metrics will not be displayed to the recipient.

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Last Click: *0 seconds*

#QuestionText, TimingPageSubmit#: *0 seconds*

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☐ 180	☐ 847	☐ 843	☐ 738	☐ 302	☐ 301	☐ 191	☐ 379	☐ 881	☐ 632	☐ 821	☐ 534	☐ 525	☐ 191	☐ 584	☐ 302	☐ 276
☐ 808	☐ 918	☐ 678	☐ 555	☐ 656	☐ 559	☐ 281	☐ 720	☐ 390	☐ 834	☐ 557	☐ 116	☐ 234	☐ 229	☐ 157	☐ 302	☐ 616
☐ 787	☐ 478	☐ 856	☐ 412	☐ 832	☐ 848	☐ 305	☐ 406	☐ 746	☐ 288	☐ 843	☐ 997	☐ 926	☐ 302	☐ 427	☐ 302	☐ 302
☐ 616	☐ 500	☐ 549	☐ 345	☐ 587	☐ 844	☐ 185	☐ 409	☐ 591	☐ 302	☐ 964	☐ 353	☐ 350	☐ 709	☐ 916	☐ 398	☐ 998
☐ 908	☐ 227	☐ 302	☐ 219	☐ 424	☐ 372	☐ 738	☐ 800	☐ 356	☐ 326	☐ 408	☐ 782	☐ 273	☐ 898	☐ 730	☐ 628	☐ 116
☐ 825	☐ 675	☐ 260	☐ 661	☐ 585	☐ 109	☐ 690	☐ 677	☐ 760	☐ 419	☐ 536	☐ 282	☐ 364	☐ 114	☐ 516	☐ 731	☐ 213
☐ 574	☐ 810	☐ 394	☐ 113	☐ 578	☐ 909	☐ 302	☐ 509	☐ 588	☐ 907	☐ 197	☐ 302	☐ 256	☐ 160	☐ 607	☐ 302	☐ 971
☐ 843	☐ 578	☐ 711	☐ 718	☐ 595	☐ 869	☐ 562	☐ 652	☐ 980	☐ 387	☐ 332	☐ 745	☐ 664	☐ 236	☐ 308	☐ 259	☐ 341
☐ 170	☐ 154	☐ 302	☐ 839	☐ 438	☐ 597	☐ 102	☐ 150	☐ 336	☐ 118	☐ 434	☐ 378	☐ 941	☐ 750	☐ 309	☐ 244	☐ 626
☐ 705	☐ 729	☐ 161	☐ 158	☐ 749	☐ 302	☐ 871	☐ 706	☐ 220	☐ 964	☐ 280	☐ 460	☐ 848	☐ 225	☐ 302	☐ 692	☐ 437
☐ 959	☐ 293	☐ 206	☐ 434	☐ 302	☐ 319	☐ 321	☐ 655	☐ 428	☐ 390	☐ 269	☐ 302	☐ 735	☐ 671	☐ 738	☐ 326	☐ 331
☐ 401	☐ 302	☐ 880	☐ 352	☐ 450	☐ 919	☐ 547	☐ 673	☐ 302	☐ 254	☐ 158	☐ 614	☐ 302	☐ 596	☐ 519	☐ 472	☐ 984
☐ 675	☐ 852	☐ 857	☐ 180	☐ 593	☐ 340	☐ 869	☐ 146	☐ 772	☐ 182	☐ 885	☐ 302	☐ 786	☐ 899	☐ 302	☐ 376	☐ 302

You have now completed the third and final assignment. Your total score on Assignment 3 is **${gr://SC_af1QZozPqCuXWND/Score}.**

Press >> to continue to the next part of the experiment.

Part 2 - Determination payments - productivity

Part 2 – Determination of payments

You have now completed your work on all three assignments. We will now explain how you will be paid for this work. After you have completed this HIT, we will for each assignment match you with another participant who has completed the same assignment. The payments to you and the other participant is determined by a two-stage process. Below we explain this process in more detail.

First stage:

Assignment 1: For this assignment, your earnings are determined by a lottery where each of you with equal probability earns 6 USD or 0 USD.

Assignment 2: For this assignment, your earnings are determined by how productive you are. Your productivity in assignment 2 is measured by how close you got to the true number of black cells in each of the matrices. The participant who got closest to the true number of black cells in each of the matrices earns 6 USD and the other participant earns 0 USD. If you both have the same productivity, you will be matched with another participant.

Assignment 3: For this assignment, your earnings are again determined by how productive you are. Your productivity in assignment 3 is measured by your score on assignment 3. The participant with the highest score earns 6 USD and the other participant earns 0 USD. If you both have the same score, you will be matched with another participant.

Second stage:

For each assignment, a randomly selected third person will be given the opportunity to redistribute the earnings between you and the other participant. This person will not know the identity of you or the other participant, but will be informed about the nature of the assignment and your earnings for this assignment.

For each assignment, either you or the other participant earns 6 USD and the other participant earns 0 USD. If the third person chooses not to redistribute, each of you will be paid your earnings from the assignment. If the third person chooses to redistribute earnings for any of the assignments, increasing the payment of the participant with the low earnings by 1 USD decreases the other participant's payment by 1 USD.

You will receive your payments for the three assignments within three weeks and it will be paid separately from your fixed participation fee of 2 USD.

Please click >> to continue.

Part 2 - Determination payment - lottery

Part 2 – Determination of payments

You have now completed your work on all three assignments. We will now explain how you will be paid for this work. After you have completed this HIT, we will for each assignment match you with another participant who has completed the same assignment. The payments to you and the other participant is determined by a two-stage process. Below we explain this process in more detail.

First stage:

Assignment 1: For this assignment, your earnings are determined by a lottery where each of you with equal probability earns 6 USD or 0 USD.

Assignment 2: For this assignment, your earnings are determined by how productive you are. Your productivity in assignment 2 is measured by how close you got to the true number of black cells in each of the matrices. The participant who got closest to the true number of black cells in each of the matrices earns 6 USD and the other participant earns 0 USD. If you both have the same productivity, you will be matched with another participant.

Assignment 3: For this assignment, your earnings are determined in the same way as for assignment 1.

Second stage:

For each assignment, a randomly selected third person will be given the opportunity to redistribute the earnings between you and the other participant. This person will not know the identity of you or the other participant, but will be informed about the nature of the assignment and your earnings for this assignment.

For each assignment, either you or the other participant earns 6 USD and the other participant earns 0 USD. If the third person chooses not to redistribute, each of you will be paid your earnings from the assignment. If the third person chooses to redistribute earnings for any of the assignments, increasing the payment of the participant with the low earnings by 1 USD decreases the other participant's payment by 1 USD.

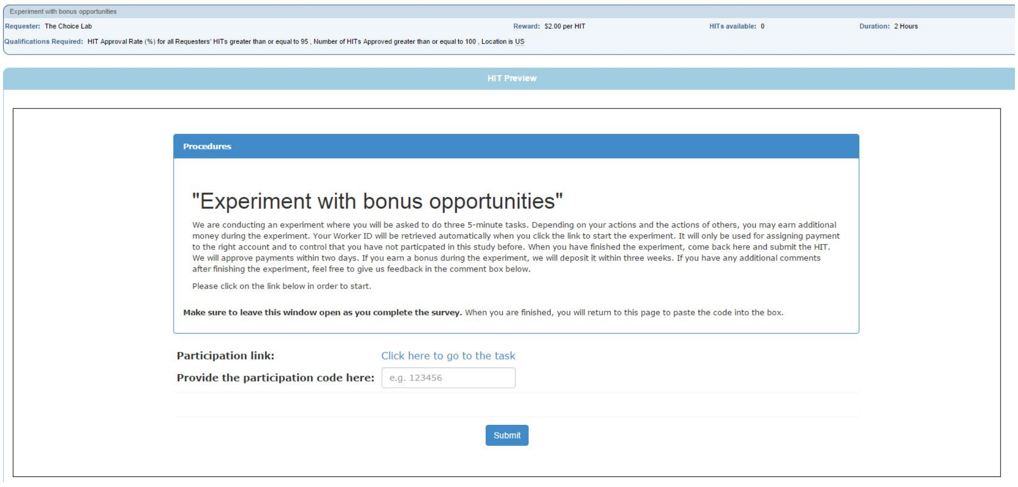
You will receive your payments for the three assignments within three weeks and it will be paid separately from your fixed participation fee of 2 USD.

Please click >> to continue.

Comment

Finally, if you have any comments or suggestions related to this experiment please write them down in the blank space below. Your feedback is very important to improve our research.

B.5.2 Round 2


Experiment with bonus opportunities

Requester: The Choice Lab   Reward: $2.00 per HIT   HITs available: 0   Duration: 2 Hours

Qualifications Required: HIT Approval Rate (%) for all Requesters' HITs greater than or equal to 95 , Number of HITs Approved greater than or equal to 100 , Location is US

HIT Preview

Procedures

"Experiment with bonus opportunities"

We are conducting an experiment where you will be asked to do three 5-minute tasks. Depending on your actions and the actions of others, you may earn additional money during the experiment. Your Worker ID will be retrieved automatically when you click the link to start the experiment. It will only be used for assigning payment to the right account and to control that you have not particpated in this study before. When you have finished the experiment, come back here and submit the HIT. We will approve payments within two days. If you earn a bonus during the experiment, we will deposit it within three weeks. If you have any additional comments after finishing the experiment, feel free to give us feedback in the comment box below.

Please click on the link below in order to start.

Make sure to leave this window open as you complete the survey. When you are finished, you will return to this page to paste the code into the box.

Participation link: Click here to go to the task

Provide the participation code here: e.g. 123456

Submit

Background questions

What is your current age?

- Less than 16
- 16-19
- 20-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65 or over

What is your gender?

- Male
- Female

Introduction

Please read the instructions below carefully

General instructions:

The results from this experiment will be used in a research project. It is therefore important that you carefully read and follow all instructions. Note that you will remain anonymous throughout the experiment. We will only use your Worker ID to assign payments and check that you have not participated in this experiment before.

You will be paid a fixed participation fee of 2 USD and you may, depending on the actions you and others take, earn additional money.

You will be given detailed instructions on your screen before each part of the experiment. Please read the instructions to each part carefully.

If you have any questions regarding this experiment, you may contact thechoicelab@nhh.no

I have read and understood the above and want to participate in this study:

- Yes
- No

Part 1 - Production phase

Part 1 — Production phase

The first part of the experiment is a production phase where you are given three assignments to work on.

Go on to the next page to receive instructions for the first assignment.

Assignment 1 - Black cells runde 2

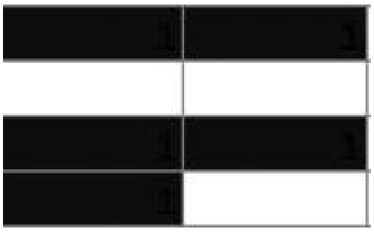
Assignment 1:

In the first assignment you are asked to work on a counting task for 5 minutes.

You are asked to count the number of black cells in a matrix similar to the one below (but bigger). You will auto-advance from each matrix after 60 seconds. Please remember to submit the number of black cells you counted within the 60 seconds. Your performance will be measured. The aim is to get the closest to the true number of black cells in each of the matrices. In the example matrix below, the correct number of black cells is five.

After this 5-minute assignment you will advance to the second assignment.

When you have read and understood the instructions press >> to start the assignment.



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How many black cells are there in matrix 1?

You have now completed the first assignment.

On the next page you will receive instructions for the second assignment.

Assignment 2 - Code recognition

Assignment 2

In the second assignment you are asked to work on a code recognition task for 5 minutes. For this assignment we will measure your performance by the number of points you receive. You will be informed about your score on assignment 3 at the end of the assignment.

Description of the assignment:
On top of the page you will be shown a 3-digit code that you must find and check off from a matrix of 3-digit codes in random order. The assigned code will occur multiple times in the same matrix and you will be given 1 point for each correct marking. You will be subtracted 1 point if you check off a wrong code, but you will not lose any points for failing to check off all occurrences of the correct code.

Your answer will be submitted automatically after 60 seconds and you will auto-advance to the next page. This assignment will last for 5 minutes and after 5 minutes you will be taken to the last assignment of the survey.

Below you are shown a simplified example to make sure you understand the assignment. When you have read and understood the instructions press >> to start the assignment.

This is an example:

The code you must check off is: 123

- ☐ **123**
- ☐ 231
- ☐ 952
- ☐ 864
- ☐ **123**
- ☐ 791
- ☐ 283
- ☐ **123**
- ☐ 641
- ☐ 820
- ☐ 462
- ☐ **123**

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The code you must check off is: 241

☐ 407	☐ 559	☐ 917	☐ 522	☐ 459	☐ 293	☐ 743	☐ 241	☐ 778	☐ 241	☐ 303	☐ 234	☐ 951	☐ 807	☐ 637	☐ 454	☐ 583
☐ 743	☐ 538	☐ 330	☐ 265	☐ 816	☐ 661	☐ 998	☐ 678	☐ 269	☐ 241	☐ 578	☐ 241	☐ 308	☐ 233	☐ 464	☐ 749	☐ 495
☐ 602	☐ 241	☐ 602	☐ 121	☐ 241	☐ 314	☐ 241	☐ 850	☐ 144	☐ 518	☐ 241	☐ 494	☐ 354	☐ 247	☐ 258	☐ 957	☐ 777
☐ 537	☐ 914	☐ 241	☐ 340	☐ 241	☐ 410	☐ 274	☐ 674	☐ 721	☐ 711	☐ 971	☐ 290	☐ 606	☐ 265	☐ 783	☐ 775	☐ 674
☐ 144	☐ 942	☐ 723	☐ 922	☐ 241	☐ 873	☐ 337	☐ 474	☐ 630	☐ 241	☐ 574	☐ 615	☐ 695	☐ 388	☐ 241	☐ 174	☐ 926
☐ 435	☐ 146	☐ 618	☐ 219	☐ 980	☐ 674	☐ 391	☐ 749	☐ 795	☐ 380	☐ 340	☐ 859	☐ 882	☐ 210	☐ 912	☐ 703	☐ 707
☐ 265	☐ 241	☐ 943	☐ 723	☐ 843	☐ 241	☐ 924	☐ 218	☐ 241	☐ 607	☐ 876	☐ 757	☐ 160	☐ 427	☐ 925	☐ 234	☐ 255
☐ 689	☐ 795	☐ 416	☐ 622	☐ 233	☐ 508	☐ 648	☐ 602	☐ 223	☐ 589	☐ 701	☐ 393	☐ 372	☐ 942	☐ 124	☐ 241	☐ 377
☐ 617	☐ 705	☐ 572	☐ 891	☐ 524	☐ 634	☐ 456	☐ 975	☐ 874	☐ 241	☐ 966	☐ 729	☐ 730	☐ 216	☐ 900	☐ 241	☐ 241
☐ 809	☐ 763	☐ 874	☐ 180	☐ 241	☐ 187	☐ 241	☐ 891	☐ 603	☐ 881	☐ 405	☐ 241	☐ 389	☐ 510	☐ 130	☐ 268	☐ 739
☐ 350	☐ 241	☐ 806	☐ 833	☐ 585	☐ 205	☐ 623	☐ 567	☐ 241	☐ 341	☐ 843	☐ 560	☐ 546	☐ 810	☐ 796	☐ 180	☐ 842
☐ 948	☐ 303	☐ 274	☐ 173	☐ 361	☐ 273	☐ 241	☐ 533	☐ 446	☐ 590	☐ 280	☐ 759	☐ 334	☐ 205	☐ 307	☐ 654	☐ 447
☐ 408	☐ 221	☐ 818	☐ 938	☐ 997	☐ 241	☐ 216	☐ 554	☐ 566	☐ 300	☐ 495	☐ 472	☐ 360	☐ 641	☐ 543	☐ 431	☐ 549
☐ 764	☐ 365	☐ 241	☐ 926	☐ 542	☐ 395	☐ 355	☐ 674	☐ 241	☐ 197	☐ 191	☐ 653	☐ 527	☐ 172	☐ 140	☐ 884	☐ 225
☐ 220	☐ 882	☐ 979	☐ 108	☐ 932	☐ 919	☐ 883	☐ 354	☐ 358	☐ 744	☐ 545	☐ 809	☐ 241	☐ 661	☐ 968	☐ 317	☐ 355
☐ 881	☐ 347	☐ 609	☐ 537	☐ 241	☐ 809	☐ 879	☐ 334	☐ 540	☐ 213	☐ 121	☐ 555	☐ 596	☐ 527	☐ 241	☐ 702	☐ 906
☐ 149	☐ 375	☐ 858	☐ 801	☐ 550	☐ 241	☐ 965	☐ 628	☐ 388	☐ 163	☐ 477	☐ 989	☐ 553	☐ 840	☐ 494	☐ 809	☐ 605

384	384	862	384	775	655	644	846	367	719	411	148	773	998	258	685	778
269	458	449	384	491	298	323	384	446	270	133	384	199	108	800	114	230

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210	454	384	833	302	226	508	328	302	842	302	427	930	790	464	932	302
898	592	900	871	409	302	428	379	708	586	201	428	160	301	710	145	550
583	669	199	465	443	252	474	547	473	945	904	337	501	269	300	847	498
825	638	334	863	302	299	302	469	426	903	566	189	244	333	208	302	202
180	847	843	738	302	301	191	379	881	632	821	534	525	191	584	302	276
808	918	678	555	656	559	281	720	390	834	557	116	234	229	157	302	616
787	478	856	412	832	848	305	406	746	288	843	997	926	302	427	302	302
616	500	549	345	587	844	185	409	591	302	964	353	350	709	916	398	998
908	227	302	219	424	372	738	800	356	326	408	782	273	898	730	628	116
825	675	260	661	585	109	690	677	760	419	536	282	364	114	516	731	213
574	810	394	113	578	909	302	509	588	907	197	302	256	160	607	302	971
843	578	711	718	595	869	562	652	980	387	332	745	664	236	308	259	341
170	154	302	839	438	597	102	150	336	118	434	378	941	750	309	244	626
705	729	161	158	749	302	871	706	220	964	280	460	848	225	302	692	437
959	293	206	434	302	319	321	655	428	390	269	302	735	671	738	326	331
401	302	880	352	450	919	547	673	302	254	158	614	302	596	519	472	984
675	852	857	180	593	340	869	146	772	182	885	302	786	899	302	376	302

You have now completed the second assignment. Your total score on Assignment 2 is **${gr://SC_af1QZozPqCuXWND/Score}.**

Press >> to continue to the third and final assignment.

Assignment 3 - Black cells

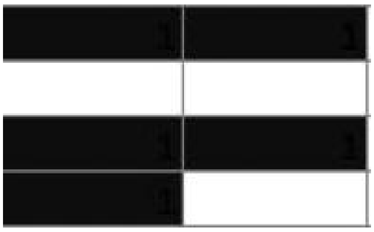
Assignment 3:

In the third and final assignment you are asked to once again work on a counting task for 5 minutes.

In the same way as in assignment 1, you are asked to count the number of black cells in a matrix similar to the one below (but bigger). You will auto-advance from each matrix after 60 seconds. Please remember to submit the number of black cells you counted within the 60 seconds. Your performance will be measured. The aim is to get the closest to the true number of black cells in each of the matrices. In the example matrix below, the correct number of black cells is five.

After this 5-minute assignment you have completed the final assignment and will advance to the last part of the experiment.

When you have read and understood the instructions press >> to start the assignment.



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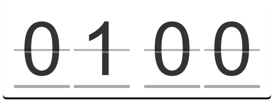

How many black cells are there in matrix 1?

You have now completed the third and final assignment.

Please press next >> to advance to the last part of the experiment.

Part 2 - Determination payments - productivity

Part 2 – Determination of payments

You have now completed your work on all three assignments. We will now explain how you will be paid for this work. After you have completed this HIT, we will for each assignment match you with another participant who has completed the same assignment. The payments to you and the other participant is determined by a two-stage process. Below we explain this process in more detail.

First stage:

Assignment 1: For this assignment, your earnings are determined by how productive you are. Your productivity in assignment 1 is measured by how close you got to the true number of black cells in each of the matrices. The participant who got closest to the true number of black cells in each of the matrices earns 6 USD and the other participant earns 0 USD. If you both have the same productivity, you will be matched with another participant.

Assignment 2: For this assignment, your earnings are again determined by how productive you are. Your productivity in assignment 2 is measured by your score on assignment 2. The participant with the highest score earns 6 USD and the other participant earns 0 USD. If you both have the same score, you will be matched with another participant.

Assignment 3: For this assignment, your earnings are determined by how productive you are in assignment 3 in the same way as for assignment 1.

Second stage:

For each assignment, a randomly selected third person will be given the opportunity to redistribute the earnings between you and the other participant. This person will not know the identity of you or the other participant, but will be informed about the nature of the assignment and your earnings for this assignment.

For each assignment, either you or the other participant earns 6 USD and the other participant earns 0 USD. If the third person chooses not to redistribute, each of you will be paid your earnings from the assignment. If the third person chooses to redistribute earnings for any of the assignments, increasing the payment of the participant with the low earnings by 1 USD decreases the other participant's payment by 1 USD.

You will receive your payments for the three assignments within three weeks and it will be paid separately from your fixed participation fee of 2 USD.

Please click >> to continue.

Comment

Finally, if you have any comments or suggestions related to this experiment please write them down in the blank space below. Your feedback is very important to improve our research.

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