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Overconfidence and gender gaps in redistributive preferences: Cross-Country experimental evidence

Thomas Buser[a], Gianluca Grimalda[b], Louis Putterman[c,*], Joël van der Weele[d]

[a] University of Amsterdam and Tinbergen Institute, School of Economics, Roetersstraat 11, Amsterdam 1018WB, The Netherlands
[b] Kiel Institute for the World Economy, Germany
[c] Brown University, United States
[d] University of Amsterdam and Tinbergen Institute, Netherlands

ABSTRACT

Gender differences in voting patterns and political attitudes towards redistribution are well-documented. The experimental gender literature suggests several plausible behavioral explanations behind these differences, relating to gender differences in confidence concerning future income position, risk aversion, and social preferences. We use data from lab experiments on preferences for redistribution conducted in the U.S. and several European countries to investigate gender differences and their causes. On aggregate, women's demand for redistribution is higher than men's, but the differences vary considerably across locations and countries. Moreover, the gender difference appears only when the source of inequality is based on relative abilities, but not when it is based on luck. Our most robust finding is that across all sampled locations, men's relatively higher (over)confidence in their abilities, in comparison to women, leads them to specify lower redistribution levels. We discuss the role of confidence in accounting for gender differences in political and redistributive choices outside the lab.

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1. Introduction

In many Western countries, attitudes towards redistribution differ by gender. Based on data from large-scale surveys such as the World Values Survey or the General Social Survey, multiple studies find that, conditional on socio-economic controls, women are more in favor of governments redistributing incomes than are men (Alesina and Giuliano, 2010; Luttmer and Singhal, 2011). Consistent with such attitudes, women show higher support for left-wing parties than men, resulting in substantial voting gaps at the polls (Shapiro and Mahajan, 1986; Inglehart and Norris, 2000; Giger, 2009).

Findings from the experimental behavioral economics literature, surveyed in more detail below, suggest three main explanations for these gender gaps. First, the experimental literature finds that men are typically more (over)confident than women concerning their own abilities and more likely to overestimate their relative or future income. Second, women are consistently found to be more risk averse, which could translate into higher support for redistribution as a form of insurance

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against income uncertainty. Third, some studies find that women make more egalitarian choices, although these gender differences seem to depend on the details of the experimental setting. However, these gender disparities have not been directly linked to redistributive preferences.

We study the behavioral roots of gender differences in political attitudes and assess the importance of the mechanisms illustrated above, using experimental data from two studies: Durante et al. (2014, henceforth DPW) and Grimalda et al. (2018, henceforth GFS). These studies share a similar design, in which participants in groups of 21 can redistribute an initial unequal income distribution. Depending on the experimental condition, a participant's initial position in the income distribution is either random, based on the average income at their place of familial residence, or determined by their relative performance in a cognitive or effort task. Participants then choose tax (redistribution) rates under three different scenarios: as an impartial observer, behind a veil of ignorance where participants' own incomes are affected by taxation but they are ignorant of their exact place in the initial income distribution, and with full knowledge of their position in the distribution. The experiments were conducted at eight different locations in the US, Italy, Germany and Norway.[1]

We find that, when choosing behind a veil of ignorance, gender differences in redistributive choices are quite variable across locations and even within countries. However, one consistent pattern is that, on aggregate as well as in most locations, women favor higher tax rates than men when initial income depends on performance in a task, but not when it is allocated randomly or on the basis of a participant's place of origin. We show that most of this difference is due to men being more (over)confident than women in their own relative performance, conditional on actual rank. Risk preferences explain a much smaller part of the gender difference. The capacity of (over)confidence to explain gender differences extends to all of our eight locations and is robust across a range of model specifications. Consistent with this finding, gender differences disappear when uncertainty about income is removed. When subjects choose as impartial observers for redistribution between others, we find similar patterns to those observed for choices behind the veil of ignorance, albeit somewhat smaller in size. We provide suggestive evidence that the same motives, in particular male overconfidence, play a role in both decisions, implying that subjects consider their own potential income position even when making choices for others.

Our paper contributes to the literature in several ways. First, our results add to the empirical literature in economics and political science about preferences for redistribution, which is mostly based on survey evidence. While many survey studies can control for income, it is harder to control for income expectations and risk attitudes. By contrast, the laboratory allows us to use monetary tradeoffs to tease apart different potential sources of the gender gap, highlighting the role of uncertainty and confidence about future income. Second, in doing so, we also contribute to the experimental economics literature, which has explored gender differences in redistribution mostly in two-person games. DPW and GFS elicit tax choices in larger groups (21 subjects) and with a pre- and post-tax incomes setting that is suggestive of a macro-economic or political economy framing. Third, the combination of data from multiple countries and multiple locations within each country goes beyond the scope of most studies, and allows us to show which effects are robust across countries and which are not. In the literature review below, we specify our contributions to different aspects of the empirical literature on gender differences.

2. Literature

There is a substantial literature in experimental economics and psychology on gender differences in economic preferences and choices. Here, we discuss briefly the main gender differences found in the experimental economics literature that are relevant for the literature on redistribution as well as gender differences in political attitudes and voting behavior.

Social preferences in experiments. The experimental economics literature on social preferences mostly uses simple division games such as dictator and ultimatum games or dilemma situations like the public goods game to measure preferences for fairness or concern with social outcomes. Decisions in these games reveal whether people are willing to sacrifice in order to improve the income of others. Several surveys look at gender differences in such social preferences. Croson and Gneezy (2009) survey a large number of studies, and conclude that there is no strong support for gender differences, although women's social decisions are more context dependent than men's, i.e. more reactive to manipulations in framing and incentives. Engel (2011) shows in a meta study of the dictator game that women are marginally more generous than men. Eckel and Grossman (2008a) find that there are no large differences in social decisions in public good, ultimatum and dictator games when subjects are exposed to risk. However, when risk plays no role, women make less individually oriented and more socially oriented decisions. Cappelen et al. (2015) find that gender differences in trust games are more pronounced in a representative sample of the population than in the student samples that are usually used in experiments. Similarly, Falk et al. (2018) elicit preferences for altruism, positive and negative reciprocity using incentivized elicitation and self-reported measures in a worldwide data collection effort. They find that women are more altruistic and more inclined to positive, and less to negative reciprocity than men. When it comes to equality-efficiency tradeoffs, several papers find that

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[1] The latest version of GFS does not yet include analysis of German data, because these data have been more recently collected. Nevertheless, the experimental design and the protocol used in Germany are the same as those used in other three countries. All procedures documented in Section 3.2 apply to German data.

women are more focused on equality than men (e.g. Andreoni and Vesterlund, 2001; Schildberg-Hörisch, 2010; Cappelen et al., 2014; Fisman et al., 2017; Mueller and Renes, 2019).

We show that gender differences in preferences for redistribution are not universal across locations in Western countries. Moreover, they are driven by subjective perceptions of performance, and hence appear only in situations with uncertainty about income. The absence of gender differences when performance is irrelevant is in line with Ackert et al. (2007), who find no gender differences in redistributive tax choices in groups of 9 people with randomly allocated endowments. Our results also complement recent work by Ranehill and Weber (2017), who investigate preferences for redistribution in group settings in the laboratory, with an explicit focus on gender and group leadership. They find that women are more likely to vote for redistribution, and that the gender gap declines (but does not disappear) when controlling for risk preferences and beliefs about relative performance. While there are many differences between the two settings, the similarity of the findings between the two studies shows the robustness of these results.

Risk aversion. There is clear evidence that women on average are more risk averse than men. Croson and Gneezy (2009) survey ten experimental studies that elicit risk preferences using both real and hypothetical gambles. All studies find that women are (weakly) more risk averse than men. This conclusion is echoed by field studies that look at portfolio selection. Eckel and Grossman (2008b) survey studies in experimental economics and also conclude that women take less risk, although the effect is not universal across studies. Charness and Gneezy (2012) survey a particular risk preference elicitation method, the Investment Game of Gneezy and Potters (1997), and find that men take substantially more risk than women.[2]

In another influential approach, Dohmen et al. (2011) use self-assessed risk aversion in surveys and validate their measures experimentally. They show that women are much less likely to take risk in general, as well as in all surveyed specific domains (car driving, finance, sports and leisure, health, and career). Buser et al. (2020), using the same measure of self-assessed general risk taking, find a significant gender difference in a representative sample of the Dutch population. Falk et al. (2018) use experimentally validated self-reported measures in a worldwide preference elicitation, and again find that women are more risk averse. Byrnes et al. (1999) conduct a meta-analysis with 150 studies in psychology, using a broad range of risky behaviors like smoking, driving and gambling. The elicitation methods include self-reports, incentivized experiments and observed choices. The study finds that in most categories, men take more risks than women.

Our study shows that such gender differences partly explain redistributive choices in the laboratory, although the effect is smaller than that of overconfidence. Our results on the role of risk aversion are in line with the recent study by Gärtner et al. (2017), who show that risk aversion predicts demand for redistribution in a representative panel of the Swedish population and mediates the relationship between gender and the demand for redistribution.

Overconfidence. A large literature shows that people are generally overconfident about their own abilities (Moore and Healy, 2008). There is evidence from a range of methods that men are generally more confident – and hence more overconfident – than are women. For example, Deaux and Farris (1977) find that men evaluate their task performance more favorably than women, and tend to attribute their performance more to skill rather than luck. Lundeberg et al. (1994) find that women are less likely to be overconfident about the accuracy of (wrong) answers to exam questions. Estes and Hosseini (1988) ask people to evaluate the financial report of a company and decide upon a (fictional) investment in the company. They find that men are more confident about the correctness of their investment decision. Niederle and Vesterlund (2007) administer a number-addition task in groups of four, and measure beliefs about relative performance, giving a $1 reward for a correct assessment of performance ranks. Despite there being no gender difference in actual performance, they find that 75 percent of the men think they are the best performer in their group of four, while only 43 percent of the women hold this belief. This result has been replicated many times (Niederle, 2015). Buser et al. (2018) do a similar exercise for three different cognitive tasks, and find that, controlling for ability, women are on average 3 percentage points less confident that they are above the median performance in their group (see also Möbius et al., 2011, who use an IQ test). There is evidence that the gender gap in overconfidence is greatest for tasks that are perceived to be "masculine", like mathematical exercises (e.g. Beyer and Bowden, 1997).

The literature on gender differences in overconfidence typically stresses choices related to ability or financial investments. Our paper extends these applications by showing how the gender difference in overconfidence shapes political choices in the lab. We find that confidence about personal performance explains not only the choice to redistribute money towards oneself, but also "impartial" redistribution decisions where only the income of others is at stake.

Political preferences for redistribution. Surveys yield quite consistent evidence for gender differences in redistributive attitudes. Early studies simply compare self-reported attitudes between the sexes. Using the General Social Survey and several other surveys, Shapiro and Mahajan (1986) find about a 3 percentage point gender difference in support for economic policies to help the poor and targeted groups, with women being more in favor. Using the American National Election Study, Howell and Day (2000) find that more egalitarian attitudes and a higher valuation of helping others explain much of the

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[2] Filippin and Crosetto (2016) offer a more nuanced conclusion from their own literature survey: gender effects depend on the details of the task, like the presence of a safe option. Analyzing almost 100 studies using the Holt and Laury (2002) risk elicitation task, they find evidence of a small gender difference of about 1/6th of a standard deviation.

political gender gap on redistributive attitudes. Eagly et al. (2004) find that women score higher on "socially compassionate" values, and these scores are mediated by self-reported ideological values (e.g. conservatism and support for social equality).

Several studies have used stated support for redistribution as an independent variable in regression analyses on background variables including gender. Alesina and La Ferrara (2005) show a highly significant gender dummy in the General Social Survey, controlling for income and education. Inglehart and Norris (2000) and Alesina and Giuliano (2010) echo these results across countries, using the World Values Survey, and Luttmer and Singhal (2011) find the same result in Europe using the European Social Survey. Funk and Gathmann (2015) use data from telephone surveys that follow individual voting behavior in Swiss referenda, and find that women are more prone to vote for generous welfare policies. Morton et al. (2017), using large-scale survey data from Denmark, confirm that women have a more left-wing ideology and show that gender differences in personality traits are an explanatory factor.

Our study investigates the origins of these survey findings in detail, and suggests they may be rooted in gender differences in subjective perceptions of future income, something we discuss in more detail in the conclusion section of this paper.

Voting patterns. In political science, much attention has been given to the gender gap in voting behavior. In the U.S., women vote more Democratic starting in the 1970s (Shapiro and Mahajan, 1986; Manza and Brooks, 1998). The gender gap has grown over time, with the 24 percentage points gender gap in the 2016 presidential elections being the largest in U.S. history, and a substantial gender gap showing up in the polling for the 2020 elections (at the time of writing).[3] The gender voting gap has also been documented in European countries, where women generally vote for more "left-wing" parties (Inglehart and Norris, 2000; Giger, 2009). Note however that this voting gap is a phenomenon that has emerged only over the last decades, with women more likely to back conservative parties before the 1970s. This suggests that preferences for redistribution cannot be the only reason for voting gender gaps, but other, structural factors are at work as well (Manza and Brooks, 1998; Iversen and Rosenbluth, 2006).

3. Design

In this study, we use existing data from DPW and GFS. As the design of GFS was inspired by DPW, we start by outlining the design of DPW. In the second part of this section, we discuss the main differences of GFS with respect to DPW.

3.1. Design of the DPW study

Sixteen experimental sessions with twenty-one subjects each were conducted in a computer lab at Brown University. A total of 336 undergraduate students from a wide range of disciplines participated. Each session, which took about 90 minutes, began with instructions on participants' computer screens being read aloud by the experimenter. Subjects were promised a \$5 show-up fee and were told there would be an additional payoff, the size of which would depend on the outcome of the experiment.

The core decisions, made in two sequential "parts," centered on the choice of tax rates that could partly or wholly equalize an unequal set of twenty pre-tax payoffs, ranging from \$0.11 to \$100. These income levels were chosen in proportion to the pre-tax incomes of given twentieths (vigintiles) of the United States population, based on U.S. Census data for the year 2000. In each part, participants chose a tax rate between 0% and 100%, in increments of 10%. One individual's choice was randomly implemented for the session ex post ("Decisive Individual"), with each participants' choice being equally likely to be decisive. The chosen tax rate was applied to the pre-tax income distribution and the tax proceeds were distributed equally amongst all participants (except one, as we explain below). Thus, a tax rate of 0% left the original pre-tax distribution in place, while a tax rate of 100% induced full income equality. The consequences of each tax choice for the post-tax income distribution were introduced verbally, graphically and by means of a formula.

In each part, subjects made decisions under four different conditions, each with another base (method) for assigning pre-tax earnings, one of which was randomly selected near the end of the session. A different tax rate could be chosen by each subject for each of the four conditions. Specifically, there were two methods the experimenters expected to be viewed as arbitrary by subjects—strictly random assignment (henceforth dubbed Random) and assignment based on parental socioeconomic status (where initial income increased with the average income in the subject's place of origin, henceforth dubbed Origin). The two remaining methods were expected to be viewed by some as bases of just claims or entitlement—performance on a general knowledge Quiz, and success playing a computer game, Tetris. We henceforth combine decisions for the Quiz and Tetris conditions (and for two similar conditions in GFS) under the heading Performance.[4]

In Part 1 of the experiment, the decision-maker was in the role of a "disinterested observer", and her tax choice redistributed earnings among the other twenty participants. To place the decision-maker in as disinterested a position as possible, subjects were truthfully informed that if randomly selected as the decisive individual, their own earnings would be randomly drawn from a uniform distribution over a small interval (of span \$2.00) with the minimum value set at the

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[3] See https://www.washingtonpost.com/news/wonk/wp/2016/11/09/men-handed-trump-the-election/?utm_term=.0cef91f7e4d8.

[4] Place of origin information was obtained during the initial log in procedure before any information about the experiment, and the Quiz and Tetris tasks were completed by all participants following their tax decisions in the second part of the experiment.

average of the pre-tax earnings of the remaining twenty subjects, $19.80.[5] Subjects completed the comprehension questions and decisions of Part 1, knowing only that another experimental part sharing some (but not all) features would follow, and that each part was equally likely to determine their earnings.

In Part 2, the decision-maker was among the twenty participants whose income was affected by the tax choice, but subjects chose their favored tax rate from behind a veil of ignorance about what their own pre-tax earnings would be.[6] After reading the Part 2 instructions and answering the comprehension questions for that part, subjects were asked to predict their relative ranking under each method apart from the Random one.[7]

After the completion of Part 2 and the Quiz and Tetris tasks, a coin toss decided whether Part 1 or Part 2 would determine earnings. If Part 2 was selected, each participant was then shown her pre-tax earnings rank and (without prior notice) given the option to change her tax choice(s). This decision, dubbed Part 3, generated a third take on redistribution: decisions by interested parties after lifting the veil of ignorance. Subjects received no feedback regarding others' tax decisions and learned their relative performance in the Quiz and Tetris portions only if Part 2 was chosen by the subsequent coin toss, leading to the invitation to reconsider taxes.

Before concluding the session and learning their payoffs, subjects participated in an incentivized task consisting of five choices between a certain payment and a lottery. This task was designed to elicit risk attitudes using the "multiple price list" method introduced by Harrison and Rutström (2008). Subjects also answered a background survey including a series of questions on personal characteristics and attitudes.

In order to gauge strength of preference for equalizing income, subjects were randomly assigned a direct cost of either zero, $0.25, $0.50 or $1.00 per 10% increment of selected tax rate (so, for instance, selecting a tax rate of 80% cost $4.00 in the $0.50 tax cost treatment). This tax cost is identical for all subjects in the same session and constant across the three parts of the experiment.[8] Apart from this tax cost, the other dimension which varied across sessions was a shrinkage of the redistributed amounts, representing an "efficiency loss" or a "leaky bucket effect". This loss was 0% in some sessions, where subjects heard no mention of it, or equal to 12.5% or 25% of taxed-and-redistributed earnings in others.[9] The crossing of the four tax costs with three efficiency loss rates yields 12 treatments. Two sessions of each treatment with efficiency loss 0, and one session of each treatment with efficiency loss 12.5% and 25%, were conducted.

A more detailed description of the design including the instruction materials can be found in DPW. All the instructions are available at: https://www.brown.edu/Research/IDE/walkthrough.

3.2. Design of the GFS study

The design of GFS was directly modeled upon that of DPW, so the two experiments share their most essential features. In both studies, all participants chose tax rates between 0% and 100% for a group of 21 individuals. Experimental choices in GFS had the same content as in DPW and followed the same sequence. The decision by the "disinterested observer" was made first and preceded the decision made behind the veil of ignorance. The decision made with full information over one's earnings was taken at the end of the choices on redistribution. As in DPW, this last decision was presented as an opportunity to revise a previously made decision. After the indication of the preferred tax rate, subjects were asked to indicate their expectations over their pre-tax earnings. A risk-aversion task involving a decision between a lottery and a fixed payment was run at the end of the session, prior to the administration of a demographic and attitudinal questionnaire. For all choices, the decision of a randomly selected "Decisive Individual" would be applied to the whole group, as in DPW.

Pre-tax earnings were determined in GFS according to four different conditions, two of which - namely, the Random and Origin conditions - were the same as in DPW. The other two conditions were based on the relative performance in tasks, as in DPW, but used different tasks (Raven's IQ test and a letter-finding task). Since no significant differences emerge in redistribution rates in these two performance-based tasks, they have been merged in GFS, as well as in DPW. The key terms used to illustrate decisions - such as "Decisive Individual", "Tax", "Transfer", "Earnings" - were the same in the two studies, thus ensuring that the framing of the choices is comparable.

In GFS, instructions were translated from the English original into the other languages used in the experiment, that is, Italian and German, and then back-translated in order to ensure comparability of the texts (Roth et al., 1991).[10] Sessions

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[5] The random element prevented subjects from finding out one was the "decisive individual" at the session's conclusion, which might potentially induce social discomfort.

[6] Because the decider stood as a bystander to a group of twenty others in Part 1, but was one of the twenty directly affected by the tax in Part 2 and Part 3, symmetry called for random selection of one of the twenty non-decisive subjects to receive an amount drawn from the $19.80 to $21.80 interval if Part 1 were not selected. This randomly selected twenty-first individual was thus unaffected by the chosen tax rate, as the decider would be under a Part 1 outcome.

[7] In estimating their rank, subjects chose one of seven ranges grouping together ranks 1–2, 3–5, 6–8, 9–11, 12–14, 15–17, 18–20. In addition, subjects indicated whether they were "very confident", "somewhat confident" or "not confident at all" about their predictions.

[8] Subjects in the $0 tax cost treatment heard nothing about such costs existing in other sessions, just as subjects in each of the other treatments knew of the parameters of their own treatment only.

[9] Note that the decider' s income was not affected by efficiency loss, if present, in case a Part 1 decision was implemented, but she was affected if Part 2 (3) was applied.

[10] Given the high level of proficiency of Norwegian students with the English language, instructions in Norway were given in English. Norwegian assistants were present during the sessions to help with translation, in the very rare occasions this was needed.

were run following an identical protocol, and one of the authors conducted all sessions in Italy, the US and Norway, and monitored all sessions run in Germany. 59 sessions were performed on university campuses in seven cities in four different countries: Milan and Salerno in Italy, Oxford (MS) and Pullman (WA) in the U.S., Oslo in Norway, and Munich and Bremen in Germany. In each of these locations, 168 university students were recruited, whose families were residents either of the region (or U.S. state) where the university is located, or surrounding regions (states).[11]

There are nonetheless relevant differences from DPW, due to the comparative focus of GFS. Most notably, the pre-tax earnings distribution in GFS was linear and symmetric around the median, instead of reproducing the income distribution of the U.S. as in DPW. This ensured that subjects in each location were presented with the same pre-tax earnings distribution. Consequently, the distribution of pre-tax earnings was more compressed in GFS than in DPW. Pre-tax earnings varied from $1.30 for the poorest to $27.30 for the richest participant at the U.S. site of Pullman (WA) in GFS, versus the $0.11 and $100 range in DPW. The variation of pre-tax earnings in the European locations was the same as in the U.S. locations covered in GFS, with monetary quantities adjusted to be equivalent in terms of Purchasing Power Parity[12] (Roth et al., 1991).

The comparative research focus followed by GFS also led them to vary the source of the initial income inequality (Random, Origin, Performance) between subjects rather than within. GFS hypothesized that reward of performance would play a prominent part in explaining cross-country differences, and they felt that this aspect could be more clearly captured in a between-subjects design. Consequently, whereas in DPW the different sources of inequality were conditions present in each treatment, they constituted separate treatments in GFS. Other procedural and methodological differences between the two studies are reported in Appendix 4. A more detailed description of the protocol followed in GFS may be found in GFS (2018), along with the instructions.

While we do not want to downplay the differences, we believe that the choices in the two studies can be meaningfully compared. Furthermore, our econometric analyses always includes location fixed effects, which control for such methodological differences. Moreover, in the appendix we perform an extensive series of robustness checks, interact confidence and risk measurements with dummies for data origin (DPW vs. GFS), and use non-parametric versions of our confidence and risk controls. None of these checks alter our results, reinforcing our confidence in the robustness of our findings.

4. Results

In this section, we analyze gender differences in chosen tax rates and the extent to which they are explained by gender differences in overconfidence, risk aversion and social preferences. We first present our measures of risk aversion and political attitudes, and document patterns that are in line with the previous literature. We then focus on choices behind the veil of ignorance in part 2 of the experiment, since this arguably lies closest to "real life" situations where risk, confidence and preferences all potentially play a role. We will then compare these results to the choices made for others in a disinterested role and choices made with full knowledge of the place in the income distribution.

4.1. Gender differences in attitudes

In both studies, the post-experimental questionnaires elicited risk aversion[13], self-rated survey attitudes towards redistribution[14], and political philosophy (where higher values mean more left-wing).[15] Fig. 1 shows gender differences in these attitudes. The data replicate patterns in the literature, as women are significantly more in favor of redistribution and more left-leaning. Women also make significantly more risk-averse choices in the risk task.

4.2. Redistribution choices behind the veil of ignorance

In Part 2, the chosen tax rate affects the decider's own income, although his/her relative position in the income distribution is uncertain. Overall, aggregating data across locations and experimental conditions, we find a significant gender effect. On average, women demand about 7% more redistribution than men. The difference is statistically significant (p<0.01; see

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[11] Three additional sessions had to be conducted in Oxford (MS), because technical problems with the recruiting systems did not guarantee the required turnout of 21 individuals in the three initial sessions. The residence of students' families was ascertained in a pre-screening questionnaire that subjects had to fill in to take part in the research. Participants who stated a location for their family outside the targeted regions/states in the post-experiment questionnaire have been removed from the dataset.

[12] The value of the token was also adjusted within country in GFS to take into account differences in Purchasing Power Parity across locations. As a result, token values were 8% smaller in Oxford (MS) than Pullman (WA), and also 8% smaller in Salerno than Milan.

[13] Both DPW and GFS assess risk aversion through incentivized lottery choices. The measures have been standardized to have a range from 1 (most risk seeking) to 15 (most risk averse). See appendix for details.

[14] In DPW, attitudes towards redistribution are measured by the question "In general, do you think there is too little income redistribution". Answers are on a scale from 1 (disagree strongly) to 7 (agree strongly). In GFS, it is based on the question "Do you think gov't should reduce income differences?". Answers are on a scale from 1 (disagree strongly) to 5 (agree strongly). For the GFS data, the variable has been rescaled to have a range of 1 to 7 (see appendix).

[15] In DPW, political philosophy is measured by the question "Which of the following best describes your political philosophy (ideology)?" Answers are on a scale from 1 (very conservative) to 7 (very liberal). In GFS, it is based on the question "In political issues people often refer to positions of 'left' and 'right'. Where would you locate your opinions in the following scale, where 1 means 'Left' and 10 means 'Right'?". For the GFS data, the variable has been rescaled to have a range of 1 to 7 (see appendix).
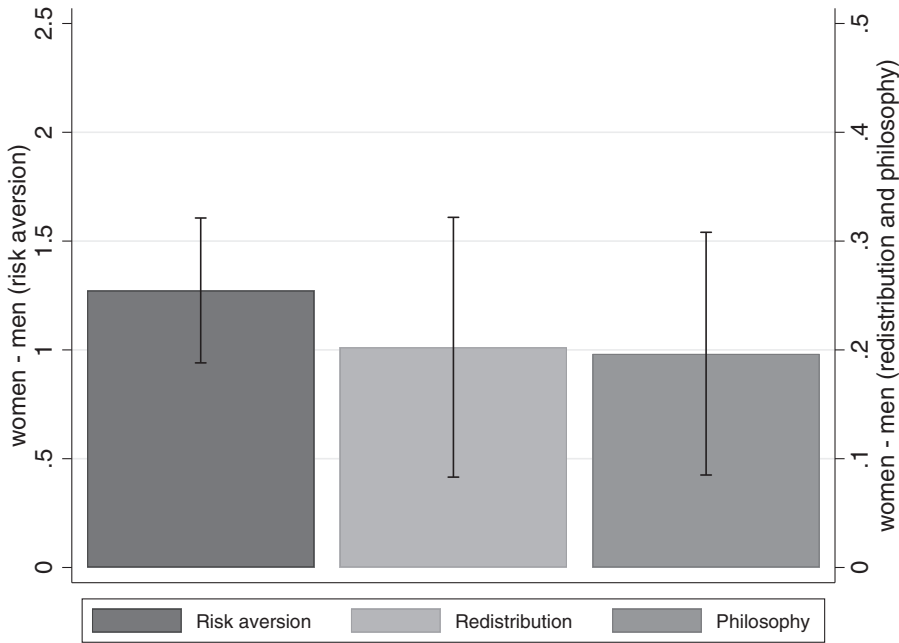
Fig. 1. Gender differences in attitudes. Note: The bars show gender differences whereby a positive value means a higher average value for women. Risk aversion is based on incentivized choices and is measured on a scale from 0 to 15. "Redistribution" means attitudes towards redistribution, where higher means more favorable, and is measured on a scale from 1 to 7. "Philosophy" means political philosophy on a left-right scale, where higher means more left-leaning, and is measured on a scale from 1 to 7. Error bars represent 95-percent confidence intervals.

Table 1
Gender differences in tax rates (Part 2: behind the veil of ignorance).

	(1) All	(2) Random	(3) Origin	(4) Performance
Female	6.749***	-0.0658	4.521	11.49***
	(1.700)	(2.701)	(2.890)	(1.978)
p-val. vs. (2)			0.175	0.000
Observations	2565	644	628	1293
R^2	0.019	0.034	0.009	0.042

Note: The table shows coefficients from OLS regressions. p-values for the difference in the Female coefficient between regressions stem from OLS regressions interacting the female dummy with a condition dummy. All regressions control for site fixed effects. Standard errors in parentheses are clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 1, column 1). Nevertheless, this general result does not hold uniformly across experimental conditions.[16] As shown in Fig. 2, gender differences completely disappear when pre-tax income is randomly determined, as men and women on average both favor a tax rate of 52 percent (p=0.91, *t*-test). When income is based on subjects' origins, men choose somewhat lower tax rates (44 percent vs. 48 percent). This difference is not statistically significant at conventional levels (p=0.13). Table 1 reports coefficients from regressions of a female dummy on chosen tax rates in the different conditions and also reports p-values for the difference in the female coefficient between conditions. The difference in the gender effect between the Random and Origins conditions is not statistically significant.

It is only in the Performance condition that women redistribute significantly more than men, as men favor substantially lower tax rates in this case (31 percent vs. 43 percent; p<0.01). The data thus show that men are less in favor of redistribution when income differences are based on performance than when they are based on luck or origin. This ten-

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[16] While the methods for determining pre-tax income vary by treatment (i.e. between subjects) in GFS, they are administered sequentially to each subject in DPW (i.e. the design is within subject), as noted above. For convenience, we use the term "condition" in the remainder of the paper to cover both cases.
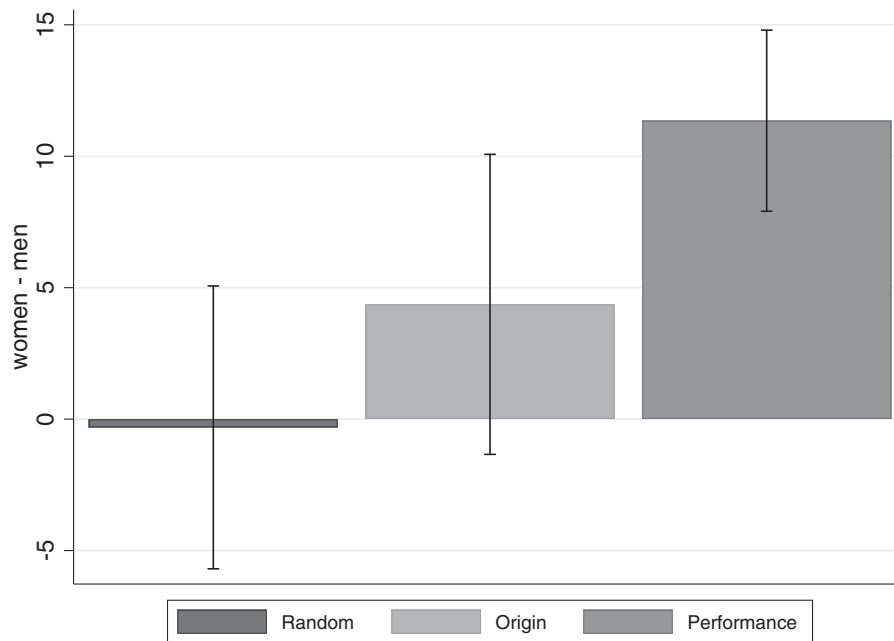
Fig. 2. Gender difference in chosen tax rates by condition (Part 2: behind the veil of ignorance). Note: The bars show gender differences in average chosen tax rates in each condition whereby a positive value means a higher average tax rate for women. Error bars represent 95% confidence intervals.

Table 2
Gender difference in confidence.

	(1) Origin	(2) Performance
Female	-0.692*	-2.350***
	(0.385)	(0.234)
Rank dummies	√	√
Observations	628	1293
R^2	0.148	0.168

Note: The table shows coefficients from OLS regressions. All regressions control for rank dummies and site fixed effects. Standard errors in parentheses are clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

dency is significantly weaker for women. Table 1 shows that the difference in the gender effect between the Random and Performance conditions is large (11.5 percentage points) and statistically significant.

We will now analyze the possible determinants of gender differences in the Performance condition, in comparison with the other conditions. Given that no significant gender difference in chosen tax rates is observed when income is randomly allocated, gender differences in pure preferences for equality are unlikely to be the main explanation (we will come back to this below in our discussion of Part 1). We will therefore concentrate on gender differences in risk aversion and (over)confidence as alternative potential explanation. Here, we define overconfidence as the expected rank in the income distribution minus the actual rank. Since our expectations were elicited over bins of three ranks, we took the average of these three ranks.

Fig. 3 shows the rank expectations of experimental subjects by true rank and gender. There is little variation in average estimated ranks across the performance distribution. That is, subjects are on average quite bad at estimating their relative performance (the correlation between true and guessed rank is highly statistically significant but quite weak at 0.23). This also means that subjects in the lower half of the performance distribution tend to be overconfident and subjects in the upper half of the performance distribution tend to be underconfident. Fig. 3 also clearly demonstrates that men are more confident than women about their rank across the whole performance distribution. In Table 2, we regress the expected
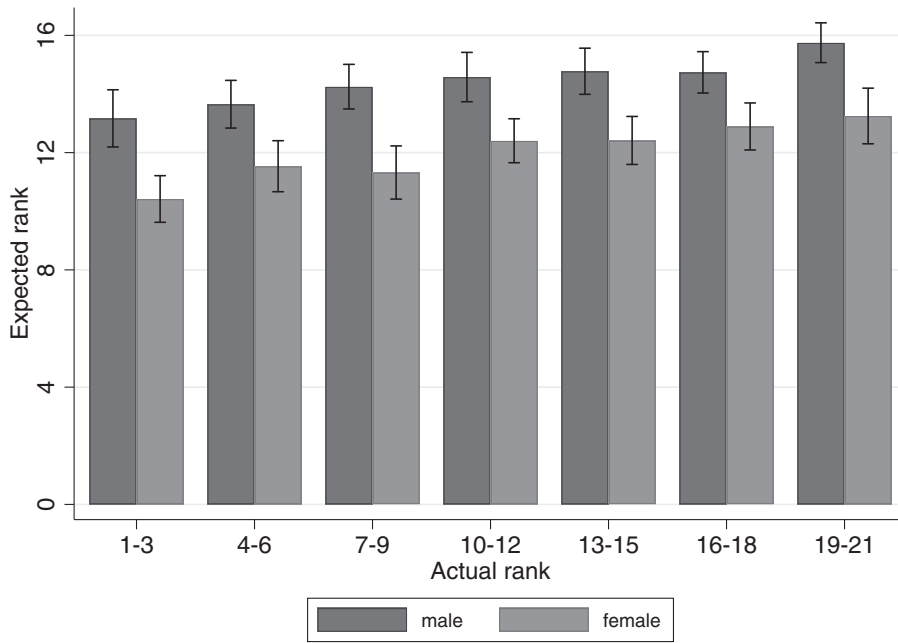
Fig. 3. Confidence by gender and true rank. Note: Error bars represent 95% confidence intervals.

Table 3
The effect of confidence and risk aversion on the gender difference in Part 2 tax choice.

	(1) Random	(2) Random	(3) Origin	(4) Origin	(5) Origin	(6) Origin	(7) Perform.	(8) Perform.	(9) Perform.	(10) Perform.
Female	-0.104	-1.177	3.957	2.559	1.617	0.402	10.26***	8.986***	5.041**	4.232**
	(2.707)	(2.724)	(2.826)	(2.855)	(2.562)	(2.575)	(1.979)	(1.985)	(2.073)	(2.069)
Actual Rank	-0.123	-0.122	-1.251***	-1.179***	-3.720***	-3.639***	-0.839***	-0.809***	-2.736***	-2.643***
	(0.224)	(0.224)	(0.235)	(0.235)	(0.280)	(0.283)	(0.148)	(0.148)	(0.272)	(0.275)
Risk aversion		0.707**		1.014***		0.893***		0.909***		0.704***
		(0.338)		(0.339)		(0.317)		(0.246)		(0.248)
Overconfidence					-3.316***	-3.293***			-2.211***	-2.131***
					(0.285)	(0.284)			(0.263)	(0.264)
p-value (Δ Female)		0.053		0.018	0.067	0.009		0.001	0.000	0.000
Observations	644	644	628	628	628	628	1293	1292	1293	1292
R^2	0.034	0.042	0.053	0.065	0.243	0.252	0.067	0.082	0.138	0.147

Note: The table shows coefficients from OLS regressions. All regressions control for site fixed effects. The p-values for the change in the female coefficient are bootstrapped (10,000 repetitions, stratified by gender and site). The p-value in column 2 refers to the change in the female coefficient relative to column 1, the p-values in columns 4–6 are relative to column 3, and the p-values in columns 8–10 are relative to column 7. Standard errors in parentheses are clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01

rank on true rank and a gender dummy.[17] Men expect to rank 2.4 places higher compared to women with the same actual performance level. Men are also marginally significantly more confident about their rank in the Origin condition where they expect to rank 0.7 places higher than women conditional on true rank.

We will now investigate whether these differences in (over)confidence, and the previously demonstrated differences in risk attitudes, can provide an explanation for the gender differences in chosen tax rates. In Table 3, we regress chosen tax rates on gender and actual rank. In Column 7, we restrict the sample to observations from the Performance conditions, confirming that there is a significant gender difference in tax rates of 10.3 percentage points when controlling for actual rank (and therefore income). The explanatory power of risk attitudes for this gender difference in tax rates is modest: the

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[17] Recall from Footnote [7] that expectations were measured over bins that grouped together multiple ranks. Here, we use the midpoint of each bin as a measure of expected rank.

gender coefficient is reduced by 12 percent when the risk aversion control is added in Column 8. When we control for overconfidence (that is, guessed rank minus actual rank) in Column 9, the coefficient on the gender dummy is reduced by 51 percent. Together, confidence and risk attitudes can explain 59 percent of the gender difference in tax rates in the Performance condition. The table also reports bootstrapped p-values for the significance of the change in the female coefficient caused by controlling for risk attitudes and confidence. Both changes are statistically significant at the 1-percent level. Keeping in mind that our controls are surely measured with error, we conclude that a major part of the difference in gender gaps between the Random and Performance conditions in Part 2 (choices behind a veil of ignorance) can be explained by these two factors, with gender differences in confidence playing by far the largest role.[18]

In Table 3, we also investigate whether gender differences in confidence and risk attitudes can explain the smaller gender difference in favored tax rates in the Origins condition (Columns 3 to 6). Controlling for risk attitudes reduces the gender coefficient by 35 percent and controlling for confidence leads to a reduction of 59 percent. Together the two factors explain almost the entire gap. While the estimates of the initial gender gap in the Origins condition are fairly imprecise and not statistically significant, the effects of confidence and risk attitudes on the gender gap are statistically significant. The same applies in the case of the Random condition (Columns 1 and 2) where controlling for risk attitudes changes the gender coefficient slightly but significantly.[19]

4.3. Results by country and site

While all the DPW data stem from a single site (Brown University in Providence, Rhode Island), the GFS data were collected at seven sites in four countries. Figs. A1 and A2 in Appendix 1 report the gender difference in desired tax rate between the Random and and Performance conditions - as reported in Table 1 - broken down by location. Fig. A1 shows that gender effects vary considerably across locations, and in some cases, even within the same country. For instance, in Pullman, WA, men tend on average to demand *more* redistribution than women, while the opposite is the case in Providence, RI and Oxford, MS. In Salerno (Italy), men demand more redistribution than women in both Performance and Random conditions, while in Milan (Italy) men demand more redistribution in Random but less in Performance than women. In both German locations, men demand more redistribution than women in the Random condition, but the opposite is true in the Performance condition. It has to be said that, although the two datasets are of similar size (1340 observations for DPW and 1225 observations for GFS), the sample sizes by site are necessarily much smaller in the GFS data (168 to 219 observations per site) which renders the estimates at the level of location a lot less precise. Most of the differences reported above are in fact not statistically significant. In the light of this variability across locations, the result that in the aggregate women demand more redistribution than men should be taken with caution.

Despite these differences in gender effects across locations, we observe high consistency across locations in the other results documented above, in particular the explanatory role of overconfidence. Figure 4 shows the gender coefficient in the Performance condition. In *all* locations, we observe a negative shift in this coefficient when we control for risk attitudes and overconfidence, like in Columns 7 to 10 of Table 3. Thus, in all locations overconfidence and risk aversion lead men to demand less redistribution than they would if their beliefs and risk preferences resembled those of women. Fig. A5 in the appendix shows a similar robustness of this result when we aggregate by country.

Consistent with this finding, Fig. A2 in the appendix shows that relative to men, women tend to demand *more* redistribution in the Performance than in the Random condition in six out of eight locations. Again, these effects are imprecisely estimated in individual locations in GFS, but these differences in tax preference between conditions are much more concordant across locations than are the gender differences for the conditions taken individually.

4.4. Robustness checks

Appendix 2 contains a range of further robustness checks. Because tax rates, our outcome variable, are bounded at 0 and 100, we show that the results hold when using Tobit instead of OLS (Tables A1 to A3). In Table A4, we show that the results hold when on top of actual and expected rank, we also control for the actual and expected individual marginal cost of taxation (see Section 3.1 for details). That is, we calculate the net cost to each individual of raising the tax by 10 percentage points given their rank (actual or expected), as well as their tax cost and efficiency loss. This approach also takes into account the quite different income distributions in the two studies.

In Table A5, we show results from regressions that control for actual rank, risk aversion and overconfidence non-parametrically by using a separate dummy variable for each possible level of the variables. While this technique controls more completely for these factors (see Gillen et al., 2019), it makes it impossible to present all the coefficients, which is why we chose to present linear controls in the main tables.

Finally, in Table A6 we show results from regressions where we interact the controls for actual rank, risk aversion and overconfidence with a dummy for the data source to take into account that the different designs and the scaling of variables

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[18] See Gillen et al. (2019) for a discussion of measurement error in experimentally elicited controls.

[19] The DPW experiment did not measure subjective rank (and therefore overconfidence) in the Random condition.
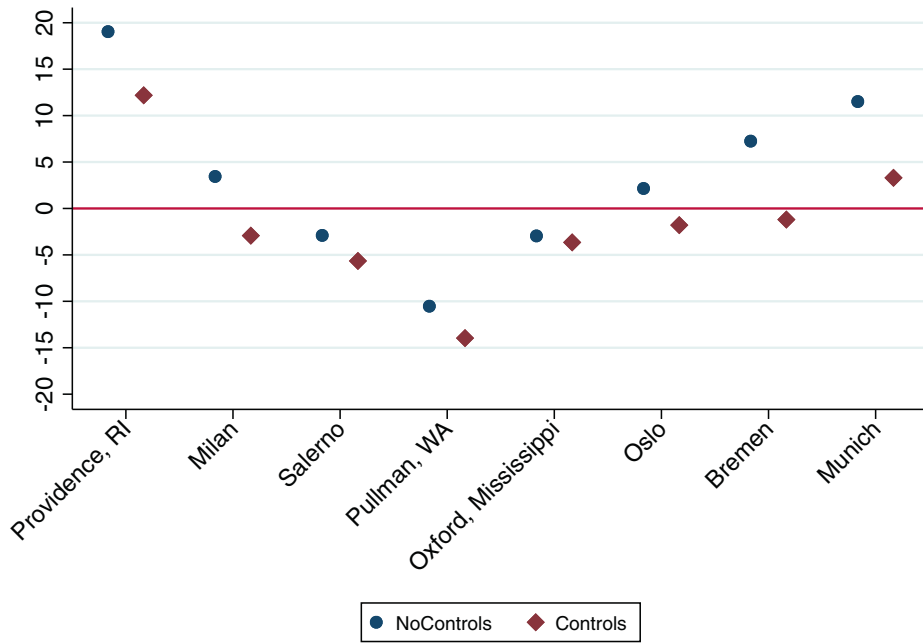
Fig. 4. Gender coefficient in the Performance condition without and with added controls for risk attitudes and overconfidence (Part 2: behind the veil of ignorance). Note: The dots show the gender coefficient in regressions which are equivalent to columns 7 and 10 in Table A3.

Table 4
Gender differences in tax rates (Part 3: known rank).

	(1) All	(2) Random	(3) Origin	(4) Performance
Female	-1.681	-4.166	2.077	-2.108
	(1.763)	(3.069)	(3.297)	(2.329)
p-val vs. (2)			0.296	0.505
Observations	1813	456	440	917
R^2	0.372	0.413	0.330	0.388

Note: The table shows coefficients from OLS regressions. All regressions control for site fixed effects. Standard errors in parentheses are clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

may lead to different effects on tax rates in the two datasets (note that throughout the paper, we control for the data source through site dummies). The results do not change but actual and expected rank tend to have a stronger negative effect on chosen tax rates in the DPW experiment, possibly reflecting the higher income inequality between top and bottom ranked subjects in the DPW design.

4.5. Redistribution without uncertainty

As our results show, gender differences in redistribution behind the veil of ignorance are driven by differences in both risk aversion and confidence. One would therefore expect that eliminating income uncertainty should lead to an elimination or at least reduction in gender differences. Our experimental design allows us to evaluate that hypothesis. In Table 4, we analyze gender differences in Part 3 where subjects are fully informed about their earnings before tax and redistribution. Conditional on actual rank, women choose slightly *lower* tax rates in all conditions except the Origins condition, but none of the coefficients are statistically significant. As the Wald tests reported in the table show, there are also no statistically significant differences in the gender coefficient across conditions, confirming that uncertainty about (pre-tax) income is a main driver of gender differences in redistribution.

Table 5
Gender differences in tax rates (Part 1: disinterested decision maker).

	(1) All	(2) Random	(3) Origin	(4) Performance
Female	6.433***	1.868	4.923*	9.891***
	(1.810)	(2.744)	(2.841)	(2.038)
p-val vs. (2)			0.310	0.005
Observations	2565	644	628	1293
R^2	0.030	0.054	0.025	0.037

Note: Coefficients are from OLS regressions. All regressions control for site fixed effects. p-values for the difference in the Female coefficient between regressions stem from OLS regressions interacting the female dummy with a condition dummy. Standard errors in parentheses are clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

4.6. Disinterested redistribution choices

Our experimental design also allows us to see what happens when we eliminate the element of self-interest from redistributive choices, as we did in Part 1 ("impartial observer") where subjects made redistributive choices for others without affecting their own income. Based on the attitudinal differences (see Fig. 1) and the literature on gender differences in social preferences surveyed above, a reasonable conjecture is that women redistribute more than men do in the "impartial observer" condition. In fact, gender differences in favored tax rates in the "impartial observer" condition are remarkably similar to those in Part 2, i.e. "behind the veil of ignorance". In particular, women and men choose very similar tax rates when income is randomly allocated (49 percent for men vs. 51 percent for women; $p=0.547$, *t*-test), but women redistribute significantly more than men when income depends on performance in the cognitive/effort tasks, which is mainly due to men favoring substantially lower tax rates in this case (33 percent vs. 43 percent; $p=0.000$). Table 5 shows that the difference in the gender effect between the Random and Performance conditions is statistically significant.

Comparing the results between the "impartial observer" and the "veil of ignorance" conditions, we thus observe very similar patterns in both conditions. One interpretation of this result is that men see performance as a stronger justification to reduce redistribution. Note however that the lack of gender differences in Part 3 of the experiment indicates that this difference is not strong enough to influence choices where own income is at stake.[20] An alternative interpretation is that participants' judgements in the disinterested observer condition are guided by their personal valuation of social insurance, which would imply that choices in Part 1 (the disinterested observer condition) could be explained by overconfidence and risk attitudes too. That is, a participant in the role of a disinterested observer might ask herself what she would want others to choose for her, were she the affected party. A more confident subject might answer that she would wish for her achievement to stand, and not be rescinded by redistribution. In this way, confidence and risk aversion could affect even a disinterested choice.[21]

In Table A7 in Appendix 3, we investigate this second explanation by regressing choices in Part 1 on our measure of risk attitudes and our measure of overconfidence obtained from Part 2. The patterns we observe are very similar to those we find behind the veil of ignorance. Gender difference in overconfidence and, to a lesser extent, risk aversion can explain a large part of the gender difference in redistribution choices when pre-tax income is due to performance in a task. This indicates that the outcome that subjects would prefer for themselves may very well influence their choice for others.

5. Discussion and conclusion

We investigate gender patterns in redistributive choices, using experimental data from multiple locations in the U.S. and Europe. Behind a "veil of ignorance", men tend to be more sensitive to the origin of inequality and decrease their desired tax rates when initial inequality is "earned" by performance on a task, rather than being determined randomly or on the basis of socioeconomic background. Conversely, women do not decrease their demand for redistribution as much as men across the two conditions. As a result, the average gender gap in chosen tax rates is more than 10 percentage points when income is due to relative performance, and is close to zero when income is determined randomly.

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[20] In most sessions of DPW, modest charges for redistribution put the decision maker's income at stake even in Part 1 (see Appendix 4 for more details). However, even in DPW, earners in the highest ranks faced much larger costs to redistribute in Part 3 than in Part 1.

[21] Note that we can rule out confusion about the payoff scheme among participants as an explanation. Participants were not aware of the payoffs in the second part of the experiment when the first part was played. In a more recent lab experiment, Ng and Semenov (2018) find that subjects, although not themselves affected, choose to redistribute more among others when overconfidence raises their perception of the likelihood that earnings are determined by effort rather than luck. These are choices also open to interpretation as 'placing oneself in the other's shoes' or 'do unto others'. A large literature in psychology and neuroscience (for example, Singer, 2006) discusses the neural basis of inferring others' wishes and motivations from own brain states.

We can explain this difference in large part by the fact that women are less (over)confident and more risk averse than men, where (over)confidence plays the largest role. While absolute gender differences vary considerably across locations, we find robust evidence that confidence mediates gender effects across all locations in our study. Consistent with the relevance of confidence and risk aversion in accounting for gender differences, such gender differences disappear when uncertainty over one's income is lifted and therefore neither overconfidence nor risk can play a role. However, when subjects make redistribution decisions affecting only others they act much as when the decisions also affect their own payoff. This pattern is consistent with the idea that subjects are "doing for others what they would have others do for them", a novel finding in need of confirmation by future research.

While we view any direct extrapolations of our data to a political context as conjectures that require testing by other methods, our results have important parallels outside the lab. Overall, the tax rate chosen in the experiment is a strongly significant predictor of our measure of political orientation (p=0.000).[22] Thus, subjects demanding more (less) redistribution in the experiment are more likely to declare left-leaning (right-leaning) political orientation, suggesting our results are externally valid.

Furthermore, there is indirect evidence for a link between gender differences in confidence and political attitudes outside the laboratory. First, field evidence shows that men are more (over)confident than women concerning their current or future rank in the income distribution. Dawson (2017) finds that men are overly optimistic about their labor market prospects, while women are overly pessimistic. Smith and Powell (1990) find that male college students overestimate their future income more than female students. This is not the case when they estimate others' income, showing clearly that men "self-enhance", in the terminology of the authors. Reuben et al. (2017) experimentally measure overconfidence on a computational task, and find that it explains a substantial part of the gender gap in earnings expectations. Second, there is evidence linking (mis)perception of relative income to redistributive attitudes. Clarke et al. (2005) show that men tend to be more optimistic about the economy (and in particular their personal prospects) and that this difference in economic evaluations accounts for a substantial proportion of gender differences in presidential approval. Cruces et al. (2013), Kuziemko et al. (2015) and Karadja et al. (2017) find common misperceptions in US, Argentine and Swedish data respectively, and show that support for redistribution changes in predictable ways when people's misperceptions are corrected.

Our study organizes these findings by providing a direct link between gender differences in confidence and redistributive attitudes. Our results also complement structural explanations of the observed shifts in voting patterns, with women voting increasingly to the left of the political spectrum in Europe and the U.S. compared to 40 years ago. Specifically, women have faced increased income uncertainty due to rising divorce rates, decreasing rates of (early) marriage and increased labor market participation (Edlund and Pande, 2002). Again using cautious extrapolation, our results suggest that increased uncertainty may have driven women to vote for parties that advocated higher redistribution. They also suggests that women put in place more redistributive policies when given the opportunity to do so. This conjecture is confirmed in Ranehill and Weber (2017), who compare voting for redistribution in groups with a majority of men and groups with a majority of women, and find that women-dominated groups vote for and implement more redistributive policies.

Finally, our proposed explanation for real-life gender differences in voting patterns and attitudes toward redistribution generates new testable implications, especially when going beyond student samples in the laboratory. For instance, our findings suggest that measures to reduce voter misperception could be targeted at male voters with lower income, who are most prone to overestimate their income. Furthermore, our explanation is valid only if people see real-life income differences as being mainly driven by differences in performance. By contrast, if people see real-life income differences as the result of the position of their family in the socio-economic ladder, or other sources of luck, the overconfidence channel will be less relevant. Future research can elicit such beliefs and their interactions with confidence, thus further informing the empirical debate in political science and economics about gender differences in voting patterns and redistributive attitudes.

Declaration of Competing Interest

To whom this may concern:

On behalf of myself and my co-authors of the paper "Overconfidence and Gender Gaps in Redistributive Preferences," I hereby state that we have no relevant interests to declare.

Acknowlgedgments

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[22] This is the p-value from OLS regression of political orientation on chosen tax rates in Part 2, controlling for gender and location dummies (standard error clustered at the individual level).

Appendix A. Disaggregated data

Main results by location

Fig. A1. Gender difference in chosen tax rates by condition (Part 2: behind the veil of ignorance). Note: The bars show gender differences in average chosen tax rates whereby a positive value means a higher average tax rate for women. Error bars represent 90% confidence intervals.

Main results by country

Fig. A2. Gender difference in chosen tax rates by condition (Part 2: behind the veil of ignorance). Note: The bars show the difference in the gender difference (women - men) in average chosen tax rates between the random and performance conditions whereby a positive value means that the gender difference is more positive in the performance condition compared to the random condition. Error bars represent 90% confidence intervals.
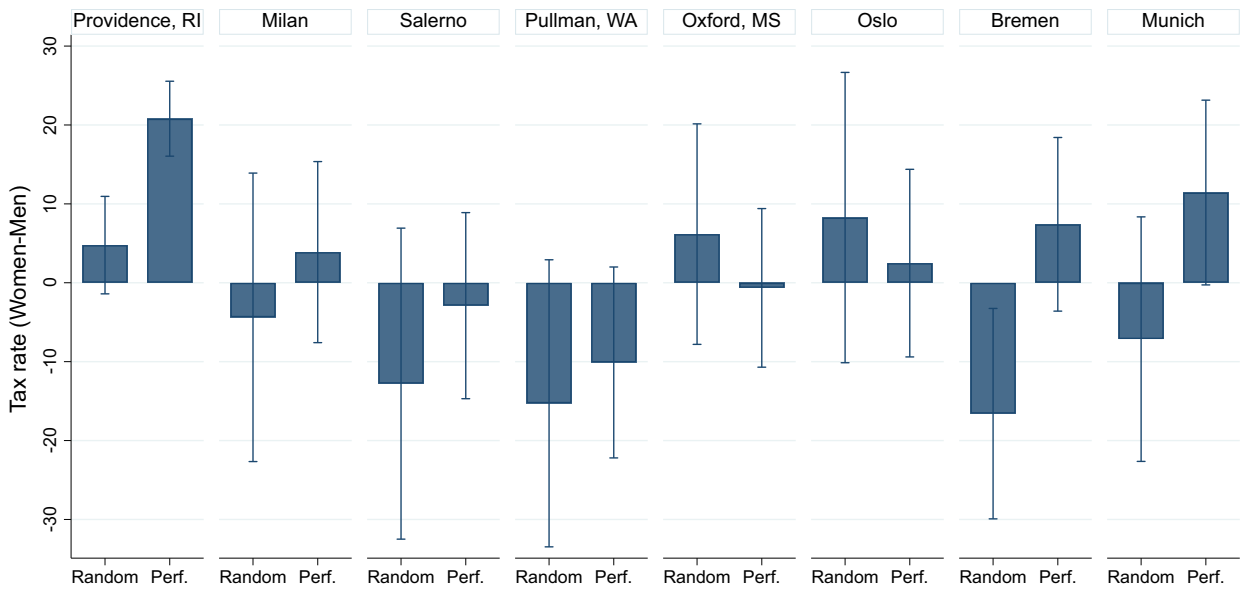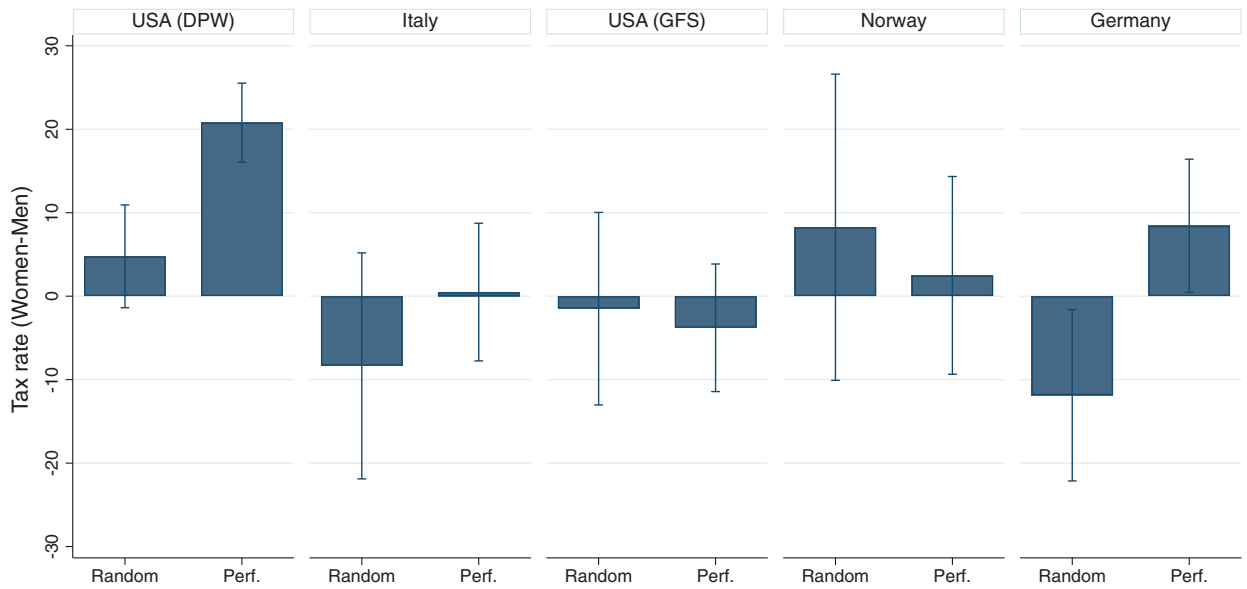
Fig. A3. Gender difference in chosen tax rates by condition (Part 2: behind the veil of ignorance). Note: The bars show gender differences in average chosen tax rates whereby a positive value means a higher average tax rate for women. Error bars represent 90% confidence intervals.

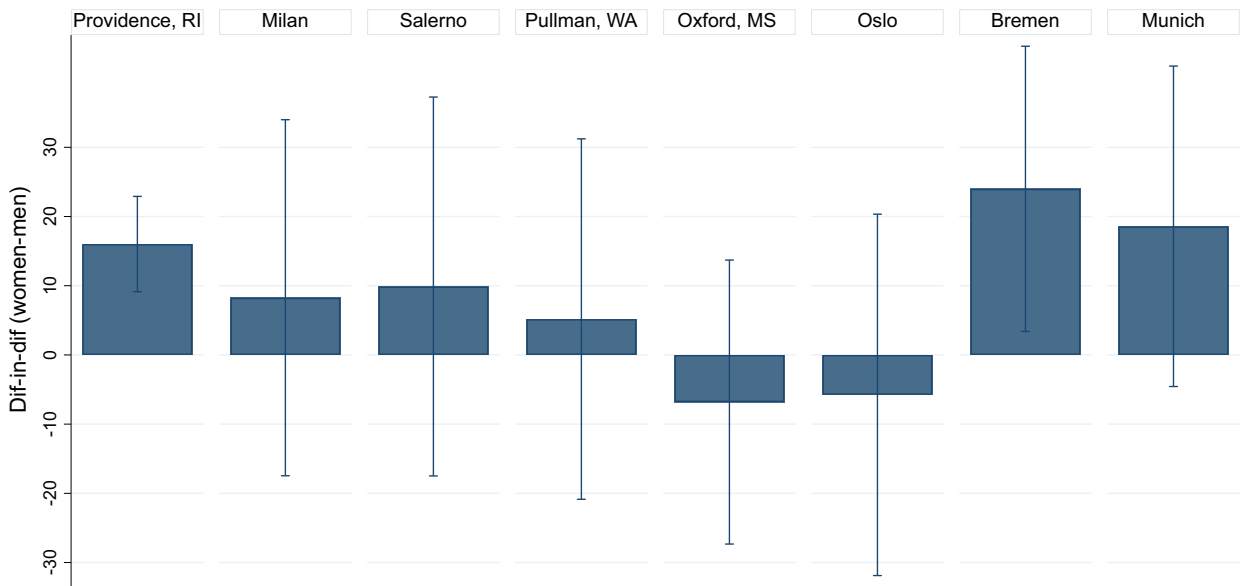**Fig. A4.** Gender difference in chosen tax rates by condition (Part 2: behind the veil of ignorance). Note: The bars show the difference in the gender difference (women - men) in average chosen tax rates between the random and performance conditions whereby a positive value means that the gender difference is more positive in the performance condition compared to the random condition. Error bars represent 90% confidence intervals.
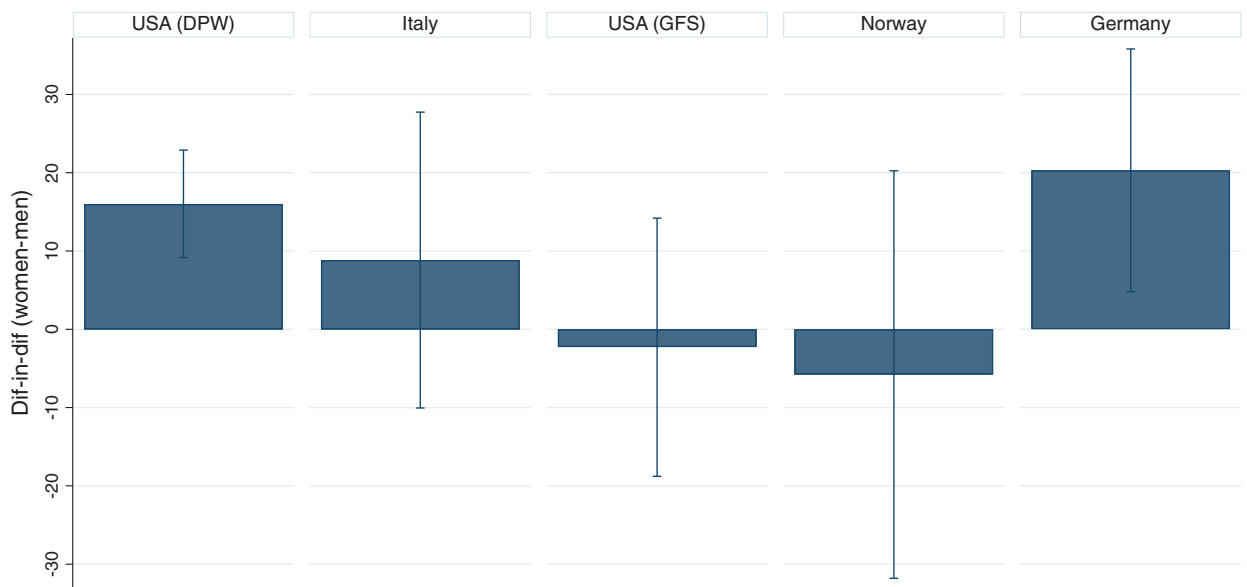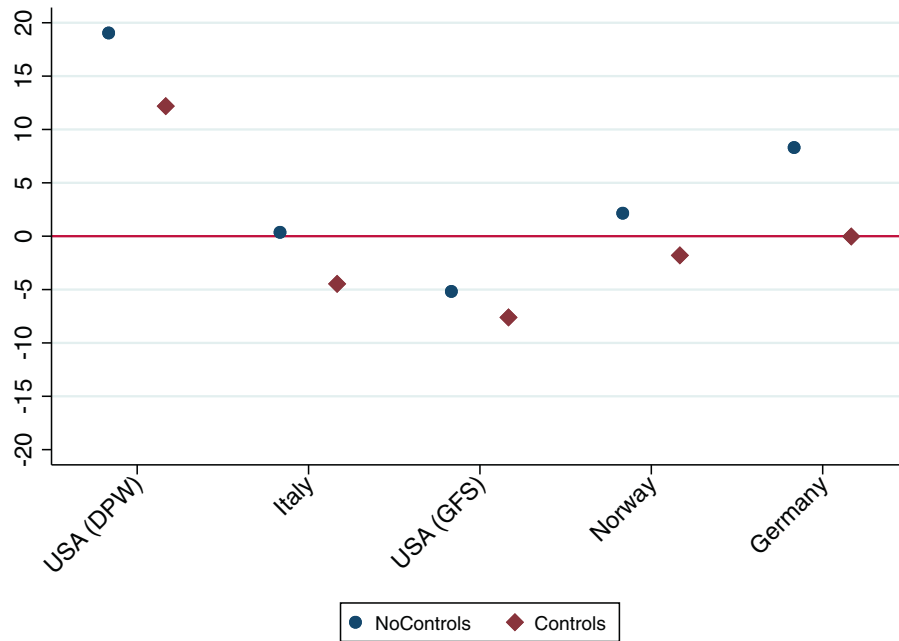
Fig. A5. Gender coefficient in the Performance condition without and with added controls for risk attitudes and overconfidence (Part 2: behind the veil of ignorance). Note: The dots show the gender coefficient in regressions which are equivalent to columns 7 and 10 in Table.

Appendix B. Robustness checks

Tobit regressions

Table A1
Gender differences in tax rates (Part 1: disinterested dictator).

	(1) All	(2) Random	(3) Origin	(4) Performance
Female	10.70***	4.484	7.826*	15.36***
	(2.705)	(4.195)	(4.306)	(2.924)
p-val vs. (2)			0.466	0.005
Observations	2565	644	628	1293

Note: The table shows coefficients from tobit regressions. All regressions control for site fixed effects. Standard errors in parentheses are clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01

Table A2
Gender differences in tax rates (Part 2: behind the veil of ignorance).

	(1) All	(2) Random	(3) Origin	(4) Performance
Female	10.80***	1.166	6.850	17.31***
	(2.487)	(3.996)	(4.489)	(2.797)
p-val vs. (2)			0.277	0.000
Observations	2565	644	628	1293

Note: The table shows coefficients from tobit regressions. All regressions control for site fixed effects. Standard errors in parentheses are clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01

Table A3
The effect of confidence and risk aversion on the gender difference in Part 2 (Tobit).

	(1) Random	(2) Random	(3) Origin	(4) Origin	(5) Origin	(6) Origin	(7) Perform.	(8) Perform.	(9) Perform.	(10) Perform.
Female	1.111	-0.508	6.156	4.028	2.443	0.651	15.62***	13.78***	8.264***	7.099**
	(4.006)	(3.998)	(4.374)	(4.395)	(3.933)	(3.927)	(2.776)	(2.760)	(2.874)	(2.853)
Actual Rank	-0.146	-0.142	-1.981***	-1.869***	-5.822***	-5.691***	-1.172***	-1.126***	-3.840***	-3.703***
	(0.328)	(0.327)	(0.371)	(0.369)	(0.484)	(0.484)	(0.213)	(0.213)	(0.402)	(0.405)
Risk aversion		1.111**		1.562***		1.324***		1.313***		1.023***
		(0.518)		(0.532)		(0.490)		(0.344)		(0.343)
Overconfidence					-5.112***	-5.067***			-3.103***	-2.987***
					(0.460)	(0.457)			(0.385)	(0.386)
p-value (Δ Female)		0.052		0.021	0.067	0.011		0.001	0.000	0.000
Observations	644	644	628	628	628	628	1293	1292	1293	1292

Note: The table shows coefficients from tobit regressions. All regressions control for site fixed effects. The p-values for the change in the female coefficient are bootstrapped (10,000 repetitions, stratified by gender and site). The p-value in column 2 refers to the change in the female coefficient relative to column 1, the p-values in columns 4–6 are relative to column 3, and the p-values in columns 8–10 are relative to column 7. Standard errors in parentheses are clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01

Controlling for individual cost of redistribution

Table A4
The effect of confidence and risk aversion on the gender difference in Part 2.

	(1) Random	(2) Random	(3) Origin	(4) Origin	(5) Origin	(6) Origin	(7) Perform.	(8) Perform.	(9) Perform.	(10) Perform.
Female	-0.228	-1.295	3.758	2.309	1.248	0.0109	10.26***	8.976***	4.649**	3.918*
	(2.711)	(2.726)	(2.806)	(2.833)	(2.537)	(2.548)	(1.982)	(1.989)	(2.061)	(2.058)
Actual cost	-1.214	-1.192	-3.915***	-4.027***	-0.662	-0.781	-0.0465	-0.187	0.776	0.640
	(1.218)	(1.216)	(1.151)	(1.164)	(0.944)	(0.966)	(0.873)	(0.849)	(0.806)	(0.794)
Actual Rank	0.135	0.131	-0.413	-0.315	-2.291***	-2.185***	-0.829***	-0.770***	-1.696***	-1.632***
	(0.342)	(0.341)	(0.346)	(0.346)	(0.462)	(0.462)	(0.224)	(0.223)	(0.380)	(0.381)
Risk aversion		0.705**		1.047***		0.908***		0.911***		0.647***
		(0.338)		(0.337)		(0.312)		(0.246)		(0.247)
Expected cost					-5.165***	-5.145***			-6.253***	-5.990***
					(0.966)	(0.982)			(0.916)	(0.906)
Overconfidence					-2.125***	-2.102***			-0.993***	-0.971***
					(0.409)	(0.406)			(0.355)	(0.353)
p-value (Δ Female)		0.054		0.016	0.049	0.006		0.001	0.000	0.000
Observations	644	644	628	628	628	628	1293	1292	1293	1292
R^2	0.036	0.043	0.067	0.081	0.262	0.272	0.067	0.082	0.154	0.162

Note: The table shows coefficients from OLS regressions. Actual cost means the net cost to an individual of raising the tax rate by 10 percent given rank, tax cost and efficiency loss. Expected cost means the net cost to an individual of raising the tax rate by 10 percent given their expected rank. All regressions control for site fixed effects. The p-values for the change in the female coefficient are bootstrapped (10,000 repetitions, stratified by gender and site). The p-value in column 2 refers to the change in the female coefficient relative to column 1, the p-values in columns 4–6 are relative to column 3, and the p-values in columns 8–10 are relative to column 7. Standard errors in parentheses are clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01

Non-parametric controls

Table A5
The effect of confidence and risk aversion on the gender difference in Part 2.

	(1) Random	(2) Random	(3) Origin	(4) Origin	(5) Origin	(6) Origin	(7) Perform.	(8) Perform.	(9) Perform.	(10) Perform.
Female	-0.445	-0.582	3.585	2.486	1.290	0.00621	10.55***	9.289***	4.949**	4.353**
	(2.741)	(2.800)	(2.854)	(2.933)	(2.598)	(2.657)	(1.984)	(2.014)	(2.107)	(2.120)
Rank dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Risk dummies		✓		✓		✓		✓		✓
Expected rank dummies					✓	✓			✓	✓
p-value (Δ Female)		0.804		0.104	0.128	0.025		0.011	0.000	0.000
Observations	644	644	628	628	628	628	1293	1292	1293	1292
R^2	0.076	0.102	0.076	0.104	0.311	0.328	0.077	0.099	0.185	0.201

Note: The table shows coefficients from OLS regressions. All regressions control for site fixed effects. The p-values for the change in the female coefficient are bootstrapped (10,000 repetitions, stratified by gender and site). The p-value in column 2 refers to the change in the female coefficient relative to column 1, the p-values in columns 4–6 are relative to column 3, and the p-values in columns 8–10 are relative to column 7. Standard errors in parentheses are clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01

Controlling for data source (DPW vs GFS)

Table A6
The effect of confidence and risk aversion on the gender difference in Part 2.

	(1) Random	(2) Random	(3) Origin	(4) Origin	(5) Origin	(6) Origin	(7) Perform.	(8) Perform.	(9) Perform.	(10) Perform.
Female	-0.163	-1.114	3.161	1.909	1.740	0.691	10.27***	9.011***	4.798**	4.068*
	(2.741)	(2.767)	(2.767)	(2.775)	(2.534)	(2.544)	(1.980)	(1.992)	(2.104)	(2.093)
Source	10.42*	11.25*	29.53***	33.15***	31.64***	36.12***	6.836*	5.193	22.59***	21.76***
	(5.763)	(6.438)	(5.634)	(6.521)	(8.172)	(8.993)	(3.891)	(4.624)	(6.820)	(7.769)
Actual rank	0.126	0.159	0.228	0.415	-1.833***	-1.553***	-0.699***	-0.663***	-2.032***	-1.958***
	(0.320)	(0.320)	(0.320)	(0.313)	(0.559)	(0.557)	(0.209)	(0.210)	(0.355)	(0.358)
Actual rank x source	-0.509	-0.559	-2.769***	-2.936***	-2.712***	-2.969***	-0.274	-0.289	-1.566***	-1.549***
	(0.451)	(0.453)	(0.448)	(0.443)	(0.629)	(0.629)	(0.294)	(0.296)	(0.489)	(0.502)
Risk aversion		0.868*		1.598***		1.389***		0.830***		0.712**
		(0.484)		(0.466)		(0.466)		(0.313)		(0.309)
Risk aversion x source		-0.345		-0.904		-0.773		0.104		-0.0932
		(0.687)		(0.650)		(0.620)		(0.490)		(0.494)
Overconfidence					-2.003***	-1.888***			-1.610***	-1.561***
					(0.449)	(0.445)			(0.342)	(0.342)
Overconfidence x source					-2.048***	-2.151***			-1.360***	-1.322***
					(0.609)	(0.606)			(0.473)	(0.481)
p-value (Δ Female)		0.139		0.085	0.224	0.066		0.003	0.000	0.000
Observations	644	644	628	628	628	628	1293	1292	1293	1292
R^2	0.007	0.015	0.100	0.118	0.261	0.275	0.061	0.074	0.142	0.150

Note: The table shows coefficients from OLS regressions. "Source" is binary indicator of data origin (DPW vs GFS). All regressions control for site fixed effects. The p-values for the change in the female coefficient are bootstrapped (10,000 repetitions, stratified by gender and site). The p-value in column 2 refers to the change in the female coefficient relative to column 1, the p-values in columns 4–6 are relative to column 3, and the p-values in columns 8–10 are relative to column 7. Standard errors in parentheses are clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Appendix C. Explaining choices in Part 1 (disinterested observer)

Table A7
The effect of confidence and risk aversion on the gender difference in Part 1.

	(1) Random	(2) Random	(3) Origin	(4) Origin	(5) Origin	(6) Origin	(7) Perform.	(8) Perform.	(9) Perform.	(10) Perform.
Female	1.817	0.643	4.630	3.859	3.163	2.505	9.415***	8.334***	5.497**	4.786**
	(2.750)	(2.772)	(2.825)	(2.874)	(2.741)	(2.775)	(2.064)	(2.073)	(2.144)	(2.143)
Actual Rank (Part 2)	-0.164	-0.162	-0.648***	-0.609**	-2.197***	-2.153***	-0.325**	-0.299*	-1.748***	-1.667***
	(0.226)	(0.225)	(0.238)	(0.239)	(0.328)	(0.330)	(0.157)	(0.157)	(0.282)	(0.286)
Risk aversion		0.775**		0.560		0.484		0.766***		0.613**
		(0.331)		(0.346)		(0.343)		(0.250)		(0.253)
Overconfidence (Part 2)					-2.080***	-2.067***			-1.659***	-1.590***
					(0.301)	(0.300)			(0.265)	(0.268)
p-value (Δ Female)		0.041		0.141	0.073	0.023		0.003	0.000	0.000
Observations	644	644	628	628	628	628	1293	1292	1293	1292
R^2	0.055	0.063	0.037	0.041	0.113	0.116	0.041	0.051	0.080	0.086

Note: The table shows coefficients from OLS regressions. The dependent variable is the chosen tax rate in Part 1. All regressions control for site fixed effects. The p-values for the change in the female coefficient are bootstrapped (10,000 repetitions, stratified by gender and site). The p-value in column 2 refers to the change in the female coefficient relative to column 1, the p-values in columns 4–6 are relative to column 3, and the p-values in columns 8–10 are relative to column 7. Standard errors in parentheses are clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Appendix D. Additional methodological aspects of DPW and GFS studies

Further procedural aspects of the two studies

We here report other aspects of the DPW and GFS design, with an eye to further highlight their methodological differences in addition to those illustrated in Section 3.

While in DPW the tasks determining performance were a knowledge quiz and the Tetris game, the two tasks used in the Performance conditions in GFS were a tedious real-effort task taken from Azar (2019) and a Raven progressive matrices task used to measure fluid intelligence. The choice to replace the DPW tasks was motivated mostly by the impossibility of running comparable general knowledge quizzes in the four countries that were part of the experiment. Moreover, GFS believed that differences in the reward of effort vis-à-vis natural abilities could end up being a relevant explanation of cross-country differences in attitudes toward redistribution.

In GFS subjects performed a new task in each round before they chose their favored tax rate, while in DPW all tasks were performed only once after the second tax choice. Moreover, GFS featured an additional round between Parts 2 and 3, where people learned their pre-tax earnings from Part 1 and Part 2, but not yet the actual pre-tax earnings in that round, which was determined on the basis of a new performance on the task. This decision was introduced to test specifically the so-called Prospect of Upward Mobility hypothesis (Bénabou and Ok, 2001), i.e. the idea that more or less optimistic expectations over one's future earnings may affect current demand for redistribution. This required individuals to receive some "signals" about their relative earning capability (which was possible in all treatments except Random) and about the uncertainty over their future earnings. We excluded this decision from the data, as it is not comparable to any condition in DPW. Moreover, the Decisive Individual was paid the average earnings of 11 tokens in GFS (equal to e.g. $14.30 in Washington State), rather than their income being randomly chosen over a restricted interval of possible payments. Since subjects took part in three tasks, and since only one decision was randomly implemented, it was extremely unlikely that subjects could make out whether they had been selected as Decisive Individuals. Moreover, all subjects in GFS made the decision in Part 3, rather than this being the result of a random draw as in DPW.

Another difference in the experimental design is that while subjects in DPW were faced with costs of the tax rate (if chosen as Decisive Individual) ranging from zero up to $1.00 (per 10% increment of selected tax rate), costs were always equal to zero in GFS. Likewise, no efficiency loss from redistribution was applied in GFS, contrary to DPW (see Section 3.1). The econometric analysis controls for all such differences in the design.

Finally, there are some subtle differences in the risk aversion test and the phrasing of the questionnaire items on determinants of income mobility and political orientation in the two studies, which are detailed below.

Risk aversion

In DPW, risk attitudes were measured in an incentivized way using the "multiple price list" method introduced by Harrison and Rutström (2008). This consists of five choices between a certain payment of $1 and a lottery that pays zero or a positive amount x (x=1.8, 2, 2.33, 2.67, 3 for choices 1–5) with equal probability. Our risk aversion control is equal to the sum of the numbers of the choices where a subject picked the safe option, yielding a variable that ranges from 0 to 15 (e.g. if a subject picks the safe option for choices 1–3 and the risky option for choices 4–5, risk aversion is equal to 1+2+3=6).

In GFS, risk aversion was measured through three choices between a certain amount and a lottery. The lottery always pays 0 or 5 with equal probability while the certain amount is equal to 2.5 for choice 1, 2.1 for choice 2 and 1.7 for choice 3. Our risk aversion control is again equal to the sum of the numbers of the choices where a subject picked the safe option, yielding a variable that ranges from 0 to 6. To make the two measures comparable, in the GFS data we multiply the measure by 15/6. This means that in both cases, subjects with the highest risk aversion score of 15 rejected a gamble that in expectation pays roughly 1.5 times the certain amount.

Attitudes

In DPW, attitudes towards redistribution are measured by the question "In general, do you think there is too little income redistribution". Answers are on a scale from 1 (disagree strongly) to 7 (agree strongly). In GFS, it is based on the question "Do you think gov't should reduce income differences?". Answers are on a scale from 1 (disagree strongly) to 5 (agree strongly). For the GFS data, we rescale the variable by multiplying it by 7/5. In DPW, political philosophy is measured by the question "Which of the following best describes your political philosophy (ideology)?" Answers are on a scale from 1 (very conservative) to 7 (very liberal). In GFS, it is based on the question "In political issues people often refer to positions of 'left' and 'right'. Where would you locate your opinions in the following scale, where 1 means 'Left' and 10 means 'Right'?". For the GFS data, we rescale the variable by multiplying it by 7/10.

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