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Misperceptions of income distributions: Cross-country evidence from a randomized survey experiment

Elisabeth Bublitz

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Misperceptions of income distributions: Cross-country evidence from a randomized survey experiment

Elisabeth Bublitz ♠*

♠*Hamburg Institute of International Economics, Germany (HWWI)*

Abstract

This paper investigates whether the individual misperception of income distributions helps explain why, opposite to Meltzer and Richard (1981), higher initial inequality levels do not correlate positively with redistribution. I conduct a representative survey experiment in Brazil, France, Germany, Russia, Spain, and the United States, providing a personalized information treatment on the income distribution to a randomly chosen subsample. Most respondents misperceive their own position in the income distribution. These biases differ by country and the true income position. Misperceptions of the median income relate negatively to misperceived income positions, showing evidence for biased reference points. Correcting misperceptions slightly shifts the demand towards less redistribution in Germany and Russia which appears to be driven by respondents with a negative position bias. Apart from Spain and the US, treatment reactions lead to a convergence of the demand for redistribution across countries. The treatment also alters trust levels in government and beliefs about the importance of luck but not equally across bias types.

JEL classifications: D31, D63, H20

Keywords: Income distribution, biased perceptions, inequality, survey experiment

*Corresponding author: Elisabeth Bublitz, Baumwall 7, 20459 Hamburg, Germany, +49-(0)40-340576-366, E-mail: bublitz@hwwi.org.
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1 Introduction

Personal perceptions regularly differ from fact-based descriptions of the state of the world. Regardless of their origin, misperceptions can exert an important influence e.g. on personal decision making (Tversky and Kahneman, 1974). Taking this into account, it would not be enough to include standard (objective) indicators of inequality or of redistribution when analyzing existing social policies. Instead, both variables would also needed to be measured on the individual level to identify how individuals (mis-)perceive inequality and how that influences their opinions on related policy issues. The potential of such an approach becomes visible when standard Gini coefficients are replaced with subjective measures of inequality that incorporate potential misperceptions (Gimpelson and Treisman, 2015; Kuhn, 2015; Niehues, 2014; Engelhardt and Wagener, 2014): While previously the empirical support had been mixed, these new cross-country analyses confirm a positive relationship between the demand for redistribution and perceived inequality, as predicted in the seminal work by Meltzer and Richard (1981). However, due to data constraints, identifying misperceptions in existing data sources is only possible with indirect measures. Using a different methodological approach, reseachers have thus also gathered their own empirical evidence in tailor-made survey experiments, allowing them to estimate the causal effect of misperceptions of income distributions and of inequality on the demand for redistribution (e.g., Kuziemko et al., 2015; Karadja et al., 2016; Cruces et al., 2013). While significant treatment effects appear for certain groups, there is no consistent evidence for changing demand for redistribution for all respondents.

Yet, there have been no survey experiments on this topic involving more than one country, using the same survey design. This leaves the questions open to what degree misperceptions and their influence systematically differ not only within but also between countries or whether certain patterns on the group level can be extended from one country to another. For instance, important differences between countries regarding their degree of income inequality and demand for redistribution persist (Luttmer and Singhal, 2011; Alesina and Angeletos, 2005; Kuklinski et al., 2000) and could help explain why misperceptions and treatment reactions differ by country. Hence, this paper investigates the causes and consequences of misperceptions of the income distribution in the context of redistribution, on the individual and the country level, to identify within- and between-country differences.

The data were collected in a survey experiment in the following six countries that differ in their degree of actual inequality and redistribution: Brazil, France, Germany, Russia, Spain, and the United States. Sample quotas were implemented, ensuring that the complete country samples are representative on the variables sex, age, education, and region for the treatment and control group. After the initial questions on potential causes that may explain misperceptions, half of the participants in each country were randomly chosen to receive information on the shape of the income distribution, including data on the average income of selected groups, and on their own position in the distribution. Both treatment and control group then answered questions regarding their views on inequality and redistribution, allowing comparisons between both experimental groups.

The descriptive results confirm that, with the exception of Brazil, the average respondent has a negative income position bias, implying that he or she holds a lower rank than originally estimated. Within the negative bias group, Germany and Russia show, on average, the largest gap between the estimated and the true income position. In all countries, respondents' estimates move towards the middle, implying that lower income groups assess their position to be higher and higher income groups to be lower than is truly the case. There is no robust evidence that any of the other variables such as education levels or the polarization of the social network consistently predict the estimated position or the position bias in all countries.

As regards the experimental results, the information treatment barely alters the degree to which inequality is perceived as a problem when comparing treatment and control group, suggesting that the neutral intervention did not significantly change inequality concerns. In Germany and Russia, individuals in the treatment group prefer slightly more personal responsibility when compared to the control group where individuals demand more government responsibility. Due to different country movements in the treatment group, differences between Germany, Russia, Brazil, and France become insignificant, indicating a convergence when compared to the control group. Spain and the US significantly distance themselves from the rest towards less or more personal responsibility, respectively. The overall direction of the movements appears to be related to the type of income position bias that dominates in the country. For instance, a negative bias leads to a lower demand for redistribution in the treatment group. That is, after learning about a better than estimated position, the respondents in the treatment group want government to intervene less than in the control group. Note that German and Russian respondents who, on average, significantly reduce their demand for redistribution also show the largest negative position bias.

If misperceptions play a role for the median voter model by Meltzer and Richard (1981), it could show in a negative relationship between the income position bias and the perceived median income. This is confirmed by the data. Further indicative support for how misperceptions may distort the logic of the median voter model is provided by the fact that countries that, on average, overestimate the median income demand less redistribution in the treatment than in the control group.

Most other outcome variables do not change significantly between control and treatment group after the intervention. This holds, among others, for the demand for higher income differentials and the assessment of drivers for inequality. However, respondents with a positive income bias report significantly lower trust in government. As there are no noteworthy changes in other trust measures, such as general trust or trust in the media, these respondents appear to explicitly relate their income situation negatively to whether governments can be trusted. A significant increase in the importance attributed to luck in life for individuals with no bias leads to the disappearance of significant differences among bias types within the treatment group, as compared to the control group. This implies that all respondents in the treatment group share the same beliefs about luck.

Previous research has already successfully documented misperceptions of wealth and income inequality with survey data (Norton and Ariely, 2011, 2013; Eriksson and Simpson, 2012; Chambers et al., 2014), but there is also a small and rapidly increasing number of randomized survey experiments that can estimate internally valid effects of misperceived income distributions on policy preferences. Regarding potential causes of misperceived income positions, Cruces et al. (2013) show in a survey experiment in Argentina that poorer people overestimate and richer people underestimate their ranks in the income distribution. This may be due to the fact that respondents are likely to use their locality instead of the country as a reference group; however, having friends from more diverse social backgrounds reduces the biases. For Sweden, Karadja et al. (2016) provide evidence for a negative bias for the majority of the population; however, the degree to which individuals hold faulty beliefs decreases when age, wealth, education, and cognitive ability increase. My study confirms the bias trend towards the middle of the income distribution but clearly shows that the respondents' shares with no, a positive, or negative bias differ across countries. Hence, on a country level the average bias clearly differs. Overall, there is no evidence that common explanatory variables, such as education or a polarization of the social network, significantly correlate with the estimated income position bias in each country. However, on the aggregate country-level a misperceived median income relates negatively to the income position bias.

As regards consequences of misperceptions for policy preferences, respondents in Argentina who learn that they are worse off than expected demand more redistribution (Cruces et al., 2013). In Sweden, providing individuals with the good news of an actually better position in the income distribution decreases their demand for redistribution (Karadja et al., 2016); this effect is driven by the subgroup of respondents with right-of-center political preferences, while individuals on the left do not react to the information treatment. An important difference between these two groups is, among others, their assessment of whether effort or luck determines individuals' economic success. Engelhardt and Wagener (2016) provide evidence that in Germany only respondents who learn that they are losing from redistribution reduce their support of such policies. Regarding tax preferences, Fernández-Albertos and Kuo (2015) show that only people (1) with priors that or (2) who are informed that they are poor change their preferences. For the US, Kuziemko et al. (2015) find that informing individuals about income inequality and taxes increases the share of respondents who view inequality as a serious problem but triggers only small and often insignificant changes as regards the demand for different redistribution mechanisms. Distrust in government and a problem with relating social issues to public policies can partially explain the lack of statistically significant relationships. Zilinsky (2014) also finds that informing respondents in the US about income inequality increases the support for government to fight against inequality but redistribution is considered as an unacceptable measure. My analysis confirms the same varying treatment reactions by income position bias when investigating the demand for redistribution even though inequality concerns barely increase in the treatment group. Due to the cross-country sample, it now seems safe to conclude that these reactions can be regarded as a universal finding that holds across populations. In addition, the treatment effect carries over to trust in government and beliefs about luck but not for all bias types and never for a whole country. Since in the majority of cases treatment reactions among bias types go into different directions, they are likely to cancel each other out on the country level. It is, however, interesting to note that, probably driven by which income bias type holds the majority, the direction of the aggregate treatment reaction of countries varies.Such different country reaction's lead to different country rankings within the treatment group when compared to the control group, hinting at a potential bias of survey data that ranks countries as regards their overall demand for redistribution.

In line with the studies discussed above, only selected groups in my sample show a significant reaction. Analyzing different contexts, Balcells et al. (2015) find that the demand for inter-regional redistribution only changes with an underestimation of a region's ranking or when the region has a higher income than the median region. Lergetporer et al. (2016) show that informing about current spending levels reduces the support of the respective policies which is mostly driven by respondents who underestimate the spending levels. Taken together, previous studies confirm the existence of heterogeneous treatment reactions that depend on variables related to over- or underestimation of the true values. My paper provides some evidence that the size of the bias may play a role in whether the overall reaction turns out to be significant. Indeed, the power of the tests is too low to interpret a lack of significant treatment coefficients; only a much larger sample would allow reliably analyzing the insignificant results. Also, when manipulating the perceived status with false information Brown-Iannuzzi et al. (2015) find that by only feeling higher in status or believing to perform better than others, individuals already reduce support for redistribution. These results rule out that perceptions lack enough importance to yield significant reactions.

The remainder of this paper is organized as follows. Section 2 introduces the country samples, the data collection process, and the information treatment. Section 3 presents within- and between-country differences in income misperceptions. Section 4 contains the experimental results on the effects of misperceptions, sorted by inequality perception, demand for redistribution, and views on issues related to inequality. Section 5 concludes.

2 Data

My study departs from the questions (1) to what degree misperceptions differ between and within countries and (2) how misperceptions effect views on policy and other issues related to inequality. Using a survey experiment specifically designed to answer these research questions, I collected cross-country data on income and perceptions. The following section presents information on the country selection as well as a description of the design and implementation of the survey. Finally, I explain the informational treatment and analyze the randomization process into control and treatment group.

2.1 Country sample

Existing studies on biased perceptions of inequality have focused on one country each, hence, due to their data construction holding country-specific characteristics such as the cultural or institutional environment constant. Nonetheless, research comparing preferences for distribution has identified important differences between countries. For instance, differences in welfare states play an important role for how inequality is addressed (e.g., for US versus Europe see Ashok et al., 2015; Alesina et al., 2004; Alesina et al., 2001) and there are also studies on differences in the general influence of culture on the taste for redistribution (Luttmer and Singhal, 2011). Since the important variables in this context — namely, indicators for inequality, like the Gini coefficient, or, for public policy, social expenditures — vary on a national level, a cross-country comparison is a suitable method to understand (the mechanisms behind) misperceptions of inequality. So far, no comprehensive data source has been available to address this (as pointed out by e.g., Gimpelson and Treisman, 2015) which is why I conduct an own randomized survey experiment. The data are collected in the following six countries: Brazil, France, Germany, Russia, Spain, and the United States. Table 1 shows how these countries differ notably on various variables of interest, allowing, among others, to compare countries with varying levels of inequality and redistribution. For instance, the sample includes countries from North and Latin America as well as Europe and Central Asia. The GDP per capita is on average high but also covers lower values in the cases of Brazil and Russia. In terms of the economy, I hence include (major) developed and developing economies as well as economies in transition. Brazil and Russia are the countries with the largest inequality (measured with the Gini coefficient) and the lowest degree of redistribution (measured with public social expenditure as % of GDP). In general, since the Gini rarely takes on value below 0.25 or above 0.65, the sample covers important examples of inequality levels. The unemployment rate serves as an indicator for the ease with which one can generate own income from labor. With the exception of the high Spanish unemployment rate, the remaining countries show values between 4.7 and 10 %. Hence, the sample allows investigating how individuals behave in countries with different degrees of inequality and of redistribution.

Table 1: Country indicators

Country	Abbr.	Region	GDP per capita (US$ 2014)	Inequality (Gini)	Redistribution (Public social expenditure as % of GDP)	Unemployment rate (% of total labor force, 2014)	Economy
Brazil	BRA	Latin America	11612.5	0.55	14.4	7.1	Developing
France	FRA	Europe	42736.2	0.3	33	10	(Major) Developed
Germany	GER	Europe	47627.4	0.29	26.2	4.7	(Major) Developed
Russia	RUS	Central Asia	12735.9	0.4	15.7	5.3	In transition
Spain	SPA	Europe	30262.2	0.34	27.4	23.6	Developed
US	USA	North America	54629.5	0.38	20	5.9	(Major) Developed

Notes: Data source is the World Bank. Unemployment rates refer to the ILO definition.

2.2 Data collection

The data were collected via an online platform in August 2015, using the sampling variables sex, age, education, and region which ensure representativeness for the complete country samples by experimental groups. Put differently, both control and treatment group had to match the overall country distribution for these variables. The survey organization YouGov programmed the survey and administered the data collection, including the randomization.[1] A comparison of all individuals who had already completed the survey and those who were invited to start the questionnaire towards the end of the survey period (when quotas were almost reached and hence only selected individuals were still allowed to enter the sample) shows that without quotas the sample would not have been representative on the variables age (older) and education level (more educated). The initial sample per country consists of around 1000 observations, returning a total sample of around 6000 observations. Since, individuals were allowed to skip questions (with the exception of the sampling variables), the sample is smaller in the analysis due to missing values. The survey was translated into the official language of each country and referred to the national currency. Note that although the necessary sampling quotas were reached in most countries, in the analysis I include survey weights for all countries.[2]

The questionnaire was designed to last on average seven minutes. The survey started with the questions on the sampling variables and followed up with a module on social orientation and circles. Next, respondents answered several questions regarding income. At the end of this module, 50 percent of a country's sample were randomly chosen to receive information on the true income distribution in

[1] YouGov is a renowned market research institution that provides panels for online research (see www.yougov.com). Respondents register and receive regular invitations to surveys that match their characteristics. They are rewarded via vouchers. To avoid having the structure of the database bias the results, each country sample had to match representative quotas for the selected variables.

[2] The results hardly change when excluding survey weights.

their country (for details on the treatment, see Section 2.3). The randomization procedure ensured that both groups still matched the sampling quotas. Then all respondents were directed to a module on the assessment and drivers of inequality as well as on policy and other preferences. The survey closed with two more questions on the respondents' background.[3]

Since the focus is on income inequality and redistribution across countries, much effort was put in choosing a suitable income definition. Questions regarding income referred to gross household market income because this variable does not include any public redistribution such as subsidies or transfers (see Karadja et al., 2016). Asking for the household income takes into account that preferences are more likely to be shaped by the financial resources available on the household and not the personal level. To ensure that all respondents had the same working definition of income they read the following information repeatedly: "All of the following questions refer to total yearly market income which is defined as total yearly income before taxes from all household members (as you listed them above), such as income from labor (including paid and self-employment income) and income from capital (including interest and dividends; voluntary individual pensions; rental income; royalties). Please leave out any transfer income or subsidies (including work-related insurance transfers, universal benefits, assistance benefits)." In what follows, gross household market income will be abbreviated to income.[4]

Not all participants reported their income; nevertheless the response rate in all countries was on average relatively high with 70% when compared to other surveys implemented on online platforms. There are significant differences between individuals who chose and those who chose not to report their income (see Table A.2). Hence, in the analysis I include controls for additional individual characteristics.

2.3 Information treatment

The design of the survey experiment builds on previous work that uses randomized (field) experiments, aiming to achieve full knowledge on a selected topic for a subgroup of the sample via an informational treatment (Kuziemko et al., 2015; Cruces et al., 2013; Karadja et al., 2016).

The implementation of the randomized treatment required comparable information on the income distribution of each country. Due to difficulties in obtaining data access via national statistical agencies, I chose two harmonized income data sets that included as many countries as possible for the most recent years. For the European countries I rely on the European Union Survey on Income and Living Conditions (EU-SILC: France, Germany, Spain) and for the remaining countries on the Luxembourg Income Study (LIS: Brazil, Russia, US; Luxembourg Income Study , LIS). Income data were available for 2013 with the exception of Brazil in which case data from 2011 were deflated. The calculation of the income

[3]The questionnaire can be made available upon request.

[4]Although replacing income with wealth appeared an interesting alternative, it was not possible due to a lack of (comparable) data for the countries in the sample.

variable was based on the variable suggestions from the LIS for factor income and then mirrored in the EU-SILC data. Since selected country data were top- or bottom-coded, I uniformly implemented across all countries the identical bottom-coding (no negative incomes) and top-coding (maximum value of 10 times the median) to facilitate the interpretation of cross-country differences in the results.

Respondents in the treatment group saw a figure displaying the country's income distribution with income groups on the x-axis and the percentage of the population on the y-axis (see Figure A.1 for an example of the treatment). There was a short introduction on how to read the figure and on what inequality is in relation to the figure. Below the graph, respondents were confronted with their answers to the questions on the income of different groups as well as on what percentage of individuals have an income lower than their own. Next to their guesses they saw the true values as calculated from the LIS and EU-SILC. When no personal information on the income variables was provided or nobody earned less than the participant, the cells were left blank (in the latter case for technical reasons). Due to missing values for some participants, I cannot calculate the size of the bias for all respondents; however, I do not lose additional observations in the treatment group because everyone could be informed about the true values. As mentioned above, the treatment was designed to be neutral, allowing participants to make their own normative judgments, which allows to explicitly test whether individuals are content with the status quo. For this reason, the treatment did not present any statements on the degree to which the income distribution could be considered (un-)equal but instead provided participants with the tools to reach their own conclusions. In addition, the intervention did not inform individuals about whether, in sum, their perceptions were (in-)correct, particularly, because I elicited different perceptions which could be true for one and false for another variable.

Note that the treatment combines and extends two interventions from previous studies. First, respondents in the treatment group are informed about the income distribution and thereby about income inequality in general, following Kuziemko et al. (2015), Norton and Ariely (2011), and Eriksson and Simpson (2012). Second, the size of the bias regarding the position in the income distribution is measured similar to Cruces et al. (2013) but using more detailed information on the percentages as done by Karadja et al. (2016).

To estimate reliable treatment effects, control and treatment group may not differ significantly from each other in terms of the sample composition due to selection into the sample or due to attrition. To this end I first regress on the likelihood to belong to the treatment group a set of covariates, each in an individual estimation (for this and the following estimations, see Table A.1) and next simultaneously (for a F-test on joint significance), with no significant results. This underlines that the randomization was successfully implemented. Next, I investigate attrition by looking at whether individuals finished the survey and the number of missing values by individuals. Around 94% of all respondents arrived at the last question. 44% of the sample have a maximum of 1 missing value for variables following the treatment (13 potential questions) and 72% a maximum of 3 missing values. This already suggests that only a minority discontinued the survey before the last question and that the majority answered most questions. I see that the likelihood to stop the survey before the official end and skip over questions significantly correlates with several covariates but not with treatment status. Considering the small share in the attrition group, the significant correlations are a minor concern. Nonetheless, I always include a set of control variables in the regressions.

3 Differences in misperceptions

The analysis starts with an overview of the perception biases of the own rank in the income distribution by country and other group characteristics. While the previous literature has already confirmed systematic biases, for instance, between education levels, I focus on the role of countries and social circles, which have received less attention. I start by providing an descriptive overview of the bias by country, income quintiles, education levels, and social classes. Next, I investigate in a regression framework to what degree these variables explain the estimated position in the income distribution.

A misperception is labeled as bias in the following way (cf. Cruces et al., 2013): Respondents who place themselves in a higher income position than is truly the case are subject to overestimation and, hence, categorized as having a positive bias. Contrary, respondents who believe their income position to be lower than is actually the case are regarded to suffer from an underestimation or negative bias (see Figure 1). As such an estimated placement is a difficult task, a measurement or perception error (up to 10 percentage points) is accepted, yielding a corridor of 20 percentage points in which individuals' perceptions are considered as unbiased (see Cruces et al., 2013; Karadja et al., 2016).

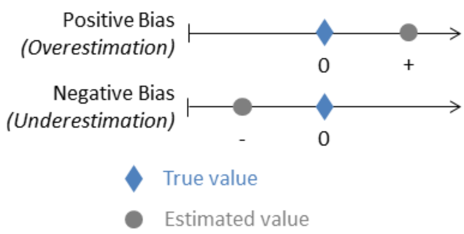


Figure 1: Definition of biases

3.1 Distributions of income position biases

Figure 2 provides an overview of the average income rank bias for all countries. The 45-degree line shows the case of no bias. A country above the 45-degree line has on average a positive bias while a country below the line has on average a negative bias. The average income rank bias across all countries is negative and amounts to -10.

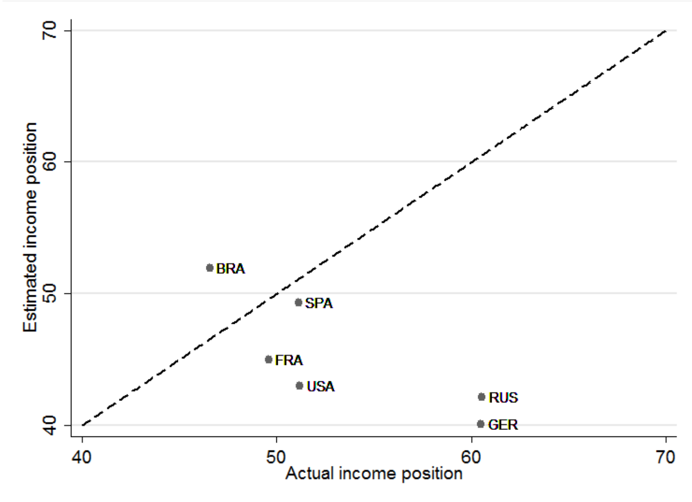


Figure 2: Average income position bias

Brazil is the only country with a positive value. Germany and Russia display the largest negative position biases. Spain has the smallest income rank bias, followed by France and the US. For a better understanding, Figure 3 shows the position bias of all observations by countries where the distribution of points in each panel illustrates how widespread biases are. For instance, in Spain there are misperceptions above and below the 45-degree line, indicating that although the country displays on average the smallest bias, this results from taking the average across negative and positive biases. In Brazil, observations seem most widespread across the complete diagram, indicating that the respondents with positive biases outweigh the rest when taking the average. Germany shows most observations below the 45-degree line, suggesting that the majority of individuals actually has a negative position bias.

Differences in the misperceptions may result from various sources, as already shown by Karadja et al. (2016). Figure 4 shows the average position bias by different characteristics across all countries (for individual countries, see Figures A.2 to A.7). The first panel for income quintiles illustrates that as income increases the bias moves from positive to negative values with the highest values at either end. The smallest bias is found for respondents in the second and third income quintile. A similar linear relationship can be identified across education levels. With the exception of education levels in Germany, these relationships hold for each country although there are obviously differences in the average size of the position biases in income quintiles or education levels. The picture looks different for the five social classes to which individuals assigned themselves. Across the complete sample, all classes have on average a negative position bias but it seems to be u-shaped with the largest biases in the middle and upper-middle class. Looking at each country individually, Brazil and France show a negative trend while it seems u-shaped for Russia, Spain, and the US. Germany stands out with very similar bias levels across

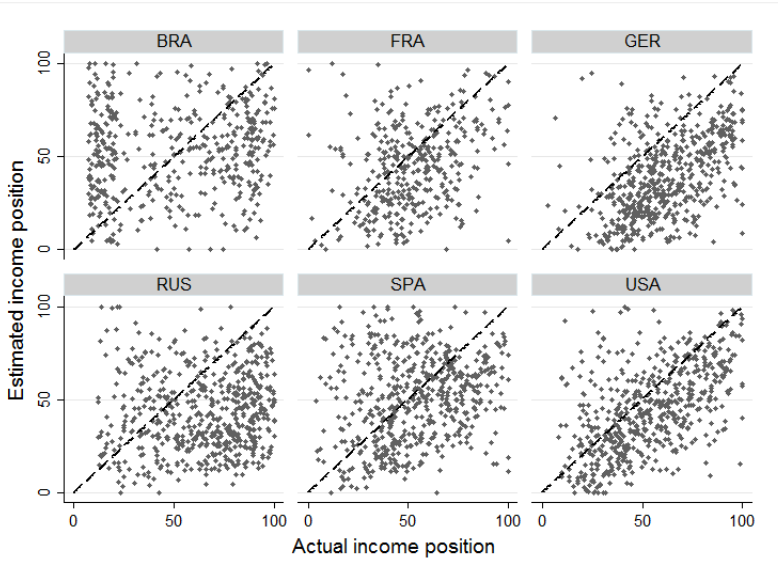


Figure 3: Average income position bias by countries

all social classes.

The results for income quintiles confirm the idea put forward in previous work, according to which individuals tend to move towards the middle. Hence, the closer the true income position comes to the median income, the nearer the estimated rank is to the true rank, explaining also the direction of the rank bias. The positive correlation between education levels and income may explain the similar distribution of position biases across both groups. The classification by social classes, which may be understood as a categorization based on subjective views, differs from the rest and shall therefore be investigated in more details.

It is important to consider that, conceptually, social classes group together individuals that resemble each other on variables such as wealth, influence, and status– not only income. Individuals decide for themselves where they see themselves, hence, using their subjective understanding of social class. To better understand the specific relationship between income and social classes I compare how social classes are distributed across income quintiles (see Table A.3). As it turns out, individuals from all income quintiles are found across all classes. Naturally, this may result from the personal assessment of other variables that are typical for the social class which we do not measure. However, misperceived rankings of the own income position could lead to difficulties in identifying a suitable social class.

As discussed for instance by Cruces et al. (2013), reference groups may play an important role in explaining biases. In other words, individuals observe their direct environment and use this information to infer where they stand in the income distribution. For instance, in a heterogeneous setting the respondents are more likely to have a more accurate perception of reality. Cruces et al. (2013) use information on the income distribution of the neighborhood and the distribution of friends across social classes, find-

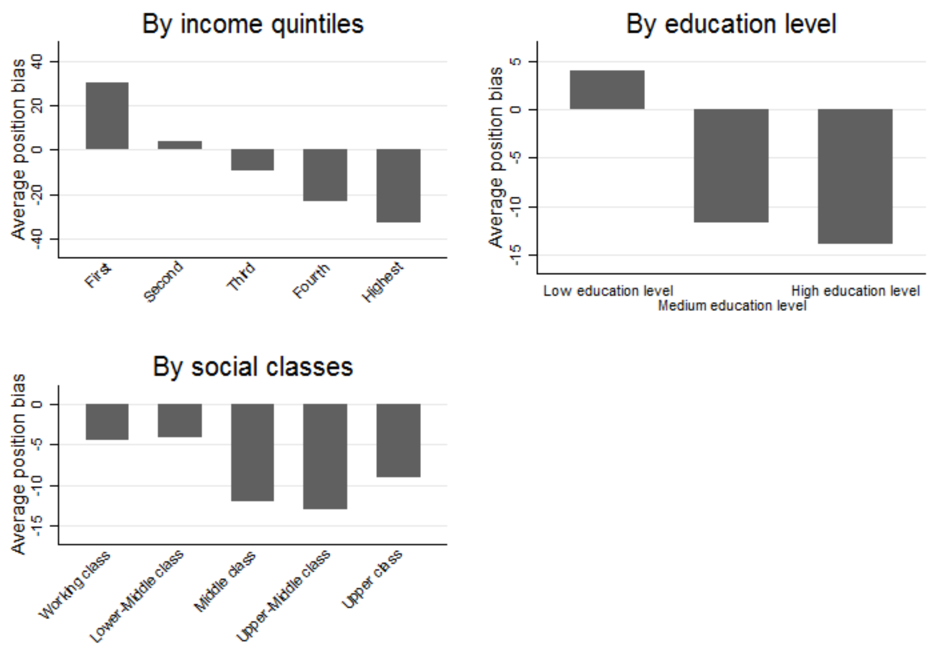


Figure 4: Average income position bias by group characteristics

ing that both significantly contribute to explaining the position bias. In my survey, respondents gave information on how their social contacts are distributed across the five social classes: working (w), lower middle (lm), middle, upper middle (um), and upper (u) class (c). From this, I construct an indicator for the polarization of the social network that measures how (un)equally distributed social contacts are. To this end, contacts at the working class are given twice the negative weight than contacts in the lower middle class. Correspondingly, contacts in the upper class are given twice the positive weight than contacts in the upper middle class.[5] The sum of weighted contacts is then divided by 200 resulting in a value of -1 (1) which implies that more contacts are found in the lowest (highest) classes. The regressions later include a categorical variable that indicates whether the social network is shifted towards lower or upper social classes, or whether it is equally distributed.

$$Polarization_i = \frac{-2 * c_{w^i} - c_{lm^i} + c_{um^i} + 2 * c_{u^i}}{200} \tag{1}$$

The results in Figure 5 show how the polarization of the network differs by self-assigned social classes. Across all respondents I see that most individuals report to have a network that consists mostly of social contacts in lower classes. The distribution is very similar across all countries.[6] Note that similar to the average negative position bias across all countries the perceived income distribution for all countries

[5] Contacts in the middle can be disregarded as they are split in half and each group is given a weight of either 0.5 or -0.5.

[6] Results are available upon request.

is also shifted towards the left. When looking at the social network by social classes, the peak of the distribution corresponds with the own social class for all but the upper classes. This is also shown by a high significant correlation of 0.68 between the variables. These results suggest that the own social network is perceived to hold on average the same social position as the respondent and is rarely equally distributed. In terms of a reference group, it thus may distort perceptions and explain an income position bias. This implies that the social network is not heterogeneous enough; hence, for lower classes the reference incomes are shifted too far to the left, leaving individuals with the expression of holding a better relative position, while the opposite holds for upper classes.

Figure 5: Polarization of the social network

3.2 Explaining the estimated income position and bias

To test the combined relevance of these variables for the estimated income position, I follow two strategies: (1) Building on previous work I run OLS regressions, taking into account the relationship between the estimated income position (as dependent variable) and the actual income position. (2) Explanations for income biases differ by the type of bias. I therefore extend my analysis with a multinomial logit model, using the income position as dependent variable.[7] Previous research has allowed for a measuring mistake of up to ten percentage points below or above the true value, where an estimated position within this range is regarded as no bias. I construct a categorical variable that indicates whether respondents

[7] I refrain from using the position bias as a continuous dependent variable. As the position bias can take on values between -1 (negative bias) and 1 (positive bias) where 0 implies no bias, the variable cannot be easily interpreted in a standard regression framework where the changes are measured along a continuum from -1 to 1, implying an incremental change towards a either high or low value but not towards zero. See also Cruces et al. (2013) for a discussion on the estimation strategy. Using an ordered logit model, instead of a multinomial logit model, does not change the main results.

have no, a positive, or a negative bias. In addition to information on income,the estimated models include variables for (the polarization of) the social network and education levels in a stepwise fashion. The control variables comprise dummies for countries, job type, and sex as well as continuous variables for age and household members. The different models are estimated using ordinary least squares or multinomial logit with robust standard errors. In separate estimations, I investigate whether the group differences differ between country by using interactions for the OLS estimations.[8] The country-specific results are discussed below.

Column (1) in Table 2 shows that the estimated income position correlates positively with the actual income position. On average, medium education levels report lower estimated income positions than lower education levels. It turns out that significant coefficients are only found in Russia where higher education levels lead to lower reported income positions. In the other countries there are no significant differences. The polarization of the network shows no significant correlations. Column (2) indicates that the higher the social class is, the higher the estimated position becomes. These coefficients are driven by Germany and the US. Looking at country differences, positively biased respondents in the US show a highly significant coefficient, suggesting that with more friends from higher classes the estimated position increases for this group, which is opposite to what the reference group hypothesis would predict. Nonetheless, according to my measure the distribution of social contacts plays in most cases no significant role while the self-assigned own social class significantly correlates with the estimated income position. As regards the country dummies, compared to Germany, respondents in the US, Spain, and Brazil report significantly higher income positions. There are no significant differences in the full model between Germany, Russia, and France.

By replacing the dependent variable "estimated income position" in the OLS estimation with the "actual income position", I can test whether the central variables continue to show the expected relationships. Conceptually, this approach resembles a standard wage regression. Table A.4 in the Annex confirms that respondents with higher education levels also hold higher positions in the income distribution. The results for social class are very similar to the previous estimation, suggesting that the true and estimated position relate on average in similar ways to social classes. However, this may be driven by the wide dispersion of classes across income quintiles. There are also general country differences which show that, compared to Germany, the US, France, and Brazil have significantly lower and Russia has significantly higher actual income positions. Due to the existence of biases, in all cases the significant country coefficients show opposite signs compared to before. This implies that, for instance, against the German baseline, respondents in the US, France, and Brazil tend to report higher estimated positions than they actually have. This underlines again the on average very large negative income position bias

[8] The complete results are not reported here but are available upon request.

Table 2: Group differences of the estimated position in the income distribution

	(1)	(2)
Actual income position	0.250***	0.193***
	(0.0225)	(0.0239)
Ref: Low education level		
Medium education level	-4.439***	-4.748***
	(1.401)	(1.386)
High education level	-1.723	-4.068***
	(1.398)	(1.424)
Ref: Working class		
Lower-Middle class		1.990
		(1.468)
Middle class		6.774***
		(1.425)
Upper-Middle class		17.72***
		(1.983)
Upper class		16.94***
		(6.359)
Ref: Polarization zero		
Neg. polar.	-1.840	0.902
	(1.465)	(1.494)
Pos. polar.	2.419	-0.0830
	(1.718)	(1.732)
Ref: Germany		
USA	7.883***	8.494***
	(1.234)	(1.191)
Russia	5.959***	7.614***
	(1.567)	(1.559)
France	6.818***	6.467***
	(1.412)	(1.377)
Spain	12.87***	13.28***
	(1.395)	(1.370)
Brazil	16.94***	17.19***
	(1.803)	(1.762)
Constant	24.69***	19.54***
	(5.794)	(5.782)
Observations	3044	3044
R^2	0.128	0.160

Notes: OLS regressions with robust standard errors in parentheses. The dependent variables is the estimated income position. Control variables and survey weights are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Group differences in the income position bias

	(1a) Neg Bias	(1b) Pos Bias	(2a) Neg Bias	(2b) Pos Bias
Actual income position	0.00921***	-0.00653***	0.0101***	-0.00675***
	(0.000288)	(0.000280)	(0.000326)	(0.000285)
Ref: Low education level				
Medium education level	0.0401*	-0.0147	0.0467**	-0.0173
	(0.0232)	(0.0194)	(0.0238)	(0.0199)
High education level	-0.000113	-0.0239	0.0290	-0.0356*
	(0.0246)	(0.0205)	(0.0256)	(0.0213)
Ref: Working class				
Lower-Middle class			0.00418	0.0186
			(0.0234)	(0.0180)
Middle class			-0.0843***	0.0298
			(0.0232)	(0.0194)
Upper-Middle class			-0.196***	0.102***
			(0.0351)	(0.0357)
Upper class			-0.276***	0.0468
			(0.0980)	(0.103)
Ref: Polarization zero				
Neg. polar.	0.0415	-0.0480*	0.000728	-0.0337
	(0.0272)	(0.0286)	(0.0277)	(0.0281)
Pos. polar.	-0.00930	-0.0380	0.0173	-0.0459
	(0.0329)	(0.0327)	(0.0333)	(0.0310)
Ref: Germany				
USA	-0.178***	0.0290	-0.182***	0.0307
	(0.0277)	(0.0212)	(0.0268)	(0.0212)
Russia	-0.157***	0.127***	-0.166***	0.132***
	(0.0316)	(0.0296)	(0.0320)	(0.0301)
France	-0.179***	0.0730***	-0.166***	0.0703***
	(0.0292)	(0.0232)	(0.0285)	(0.0229)
Spain	-0.260***	0.163***	-0.259***	0.162***
	(0.0276)	(0.0256)	(0.0275)	(0.0257)
Brazil	-0.272***	0.223***	-0.277***	0.221***
	(0.0309)	(0.0295)	(0.0312)	(0.0302)
Observations	3044	3044	3044	3044

Notes: Marginal effects from two multinomial logit regressions with robust standard errors in parentheses. The dependent variable is the income position bias (Ref: No bias). Control variables and survey weights are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in Germany, suggesting that, in reality, in my data German respondents hold on average higher income positions. Note that this does not mean that they earn more than respondents in other countries but that this refers to the position in the country-specific income distribution.

The results from the multinomial logit regressions with the position bias as dependent variable confirm that the signs of the explanatory variables differ between individuals with a positive and a negative position bias when compared to individuals with no bias (see Table 3). Both specifications show that an increase in the actual income position leads the multinomial log odds for having a negative bias, instead of no bias, to increase and for showing a positive bias to decrease. This also holds in each country individually.[9] The relative odds of having a negative instead of no bias decrease when living in any country that is not Germany, confirming again the large negative bias in this country. While there are no significant differences between the US and France in relation to Germany, the relative odds of having a positive instead of no bias increase in Russia, Spain, and Brazil. Education level and polarization are insignificant. The control variables for social classes show a significant decrease in the relative odds of having a negative bias against having no bias when the social class is higher. This is not found with respect to a positive bias.

In sum, the OLS results for the estimated income position confirm the importance of the actual income position, education levels, and social classes in a pooled country sample. However, notable country differences exist in the significance of the explanatory variables when looking at each country individually, suggesting that these factors may in most cases be disregarded. The hypothesized relationship regarding the influence of reference groups — measured with the polarization of the social network — cannot be confirmed. Although the own social class and the polarization are closely related, one would have expected the network to hold additional explanatory value. However, as respondents with similar incomes show already such different perceptions of their own social classes, it is likely that similar mechanisms distort the polarization index. The only way to overcome this problem is via a more objective measure of the social class structure which is unfortunately not available here. The multinomial analyses of differences between bias types confirm what the descriptive analyses already showed with regard to country differences or the actual income position. The results for social networks are again not robust. Taken together, how individuals arrive at their estimated income position is part of a process that cannot be fully captured with this data.

4 Effects of misperceptions

Considering the differences in (mis-)perceptions across countries, the question arises whether views or attitudes that build on these perceptions might simultaneously suffer from a 'bias'. If that is the case,

[9]Results are available upon request.

informing about the true underlying values can be expected to effect personal views and opinions of respondents in the treatment group regarding related (policy) issues. The following section presents the corresponding experimental results. The outcome variables consist of an assessment of inequality (Section 4.1) and demand for redistribution (Section 4.2). In addition, I look at views on issues that are related to inequality (Section 4.3). In the analysis I investigate the treatment effect by comparing within and between group differences on the country and on the position bias type level.

By design, my treatment allows investigating not only the effect of correcting an income position bias but of providing the complete picture as regards the shape of the income distribution. However, to identify heterogeneous treatment responses the more detailed analysis focuses on the personalized part of the intervention which informed about the personal position in the income distribution. Out of all the information provided, this one is likely to have had the largest impact on the participants as it relates most directly to their own situation while the other information provided the respective context.

I take advantage of the cross-country data set by looking at treatment effects within countries (differences between experimental groups by countries) and changes in rankings within experimental groups (differences between countries by experimental group). The latter do not measure the effect of providing information (against lacking it) but show differences within the group of all informed individuals in a country. All country results are drawn from the basic regression equation (2) but later I vary the display of the coefficients for an easier interpretation. If the country averages move into different directions, this also implies that some countries may move towards or away from each other which is of additional interest. In the next step, I investigate whether the treatment varies by the type of income bias (see equation (3), differences between experimental groups by bias types).[10] Conceptually, it is very likely that learning about a better position than initially expected should yield different responses from being informed about a worse position. Again, I also consider differences within each experimental group (differences between bias types by experimental group) to see to what degree differences between bias groups changed.

$$y_i = \beta_o + \beta_1 Treatment_i + \beta_2 Country_i + \beta_3 Treatment_i * Country_i + \gamma X_i + \varepsilon_i \tag{2}$$

$$y_i = \beta_o + \beta_1 Treatment_i + \beta_2 Bias_i + \beta_3 Treatment_i * Bias_i + \gamma X_i + \varepsilon_i \tag{3}$$

where y_i is the outcome variable for individual i, $Treatment_i$ indicates whether the respondent belongs to the treatment group, $Country_i$ identifies the country and $Bias_i$ the type of position bias. X_i

[10] Looking at the perception bias by country is unfortunately not possible due to insufficient observations in the subgroups.

represents a vector of control variables and ε_i is the error term. Of particular interest are the interactions between the treatment status and country or bias type.

Note that if my results were driven by the reactions to being corrected through the information treatment I would expect the same reactions across all groups (countries and biases). For instance, respondents should react the same way regardless of whether they have a negative or positive bias. However, if correcting a bias leads to different reactions in different groups, it is unlikely that results are driven by the fact that individuals were told that their beliefs were initially false.

As mentioned before, there are slight differences in the group composition of the experimental groups which is why I run my regression with and without individual control variables or survey weights to test whether the results hold universally or only conditionally on other controls/weights, always using the identical sample of observations. Throughout my main results are robust to the choice of including or excluding controls/weights and thus, for the sake of brevity, I only report the regression results when survey weights and the following additional covariates were included: sex, age, number of household members, education levels, job categories, social network, and actual income position.

I always estimate OLS regressions with robust standard errors that include interactions between the experimental group and the variables of interest (country/income bias). Germany or individuals with no bias serve as reference groups. The interpretation of potential treatment effects within the no bias group is difficult because while all were informed about general income inequality there is a mix of individuals with a, although small, positive and negative bias. It is likely that different reactions cancel each other out if indeed there are any due to the small misperceptions. All regressions are alternatively estimated using as dependent variables binary variables. However, the main results hardly change. For the interpretation of rankings within experimental groups, the predictive margins of the continuous variables are most informative and, hence, this paper focuses on continuous dependent variables.

For the sake of completeness I also include outcome variables that were not significantly altered by the treatment because they provide an important context for the interpretation of the general results. However, due to the low power of the tests, the insignificant treatment effects cannot be reliably interpreted as the lack of a significant relationship.

The summary statistics for the dependent variables by experimental groups are found in Table A.5.

4.1 Assessment of inequality as a problem

The main goal of the intervention was to reveal to respondents the true degree of income inequality in their country. However, the intervention did not explicitly label the current state as (un)equal but only showed the overall income distributions. Respondents were asked to reach their own conclusions. A priori it is thus unclear how information on the income distribution may have affected the individuals' views on inequality as a problem. I take this variable as a starting point to understand the effect of the treatment. The outcome variable is constructed from the question whether inequality is a serious problem in the country.

The results of multivariate analyses for countries show that the treatment did not significantly alter views on the seriousness of inequality between control and treatment group in any country (see Table A.6). In addition, the country ordering within experimental groups remained the same. This indicates that despite the intensive but relatively neutral information in the treatment, on average individuals do not react differently to the status quo of inequality than they do without this information. One explanation could be that in both experimental groups the majority of respondents already considered inequality as a very serious problem, leaving no room for the majority of the respondents to select larger values.

However, respondents' reactions to the treatment differ depending on whether they display an upward or downward bias regarding their income position (see Table 4). Column (1) and (2) include interactions between the experimental group and the type of income bias. Based on the same regression equation, the varying display of coefficients allows interpreting differences within the bias groups (column (1)) or within the experimental groups (column (2)). This allows analyzing the treatment effect by bias group and the changes in the ordering of bias group within experimental groups. For an easier read, Figure 6 depicts the predictive margins of the interactions with their confidence intervals by income bias groups. The vertical lines connect different income bias groups within an experimental group to facilitate the comparison of rankings. The stars indicate whether the respective differences are significant.

The results show that within each bias group, although moving answers in different directions, none of the differences between treatment and control group are significant on conventional levels. The negative bias group views inequality of less than a problem when in the treatment group but only at the 10%-level. Within the control group, respondents with a negative and a positive bias perceive inequality to be significantly more of a problem than respondents with no bias. Due to a different movement within the bias groups, the ordering changes in the treatment group where respondents with no and a negative bias consider inequality to be less of a problem than those with a positive bias. I further find that there are no more significant differences in the assessment of inequality between the negative and no bias groups when being treated. Since the treatment leads to a different ranking of answers, it seems fruitful to check whether the direction of the reaction, although barely or even not significant, makes sense. Considering that the inequality perception serves as a "first stage", this is a useful step for the later analysis. After the treatment, individuals with a positive and no income bias perceive inequality to be more of a problem. When considering other information provided in the treatment as the context for the own position, this result makes sense because (1) finding out one is worse off and (2) receiving additional

Table 4: Treatment effect on whether inequality is perceived as a problem (by income bias)

	(1) (a)	(2) (b)
Treatment		0.116
		(0.0889)
Ref: See notes		
Treatment × Neg. income bias	-0.115*	-0.0178
	(0.0595)	(0.0772)
Treatment × No income bias	0.116	
	(0.0889)	
Treatment × Pos. income bias	0.0963	0.180**
	(0.0846)	(0.0891)
Ref: No income bias		
Neg. income bias	0.214***	
	(0.0792)	
Pos. income bias	0.199**	
	(0.0893)	
Ref: Control x no income bias		
Control × Neg. income bias		0.214***
		(0.0792)
Control × Pos. income bias		0.199**
		(0.0893)
Ref: Germany		
USA	-0.246***	-0.246***
	(0.0784)	(0.0784)
Russia	-0.166**	-0.166**
	(0.0820)	(0.0820)
France	0.0124	0.0124
	(0.0744)	(0.0744)
Spain	0.351***	0.351***
	(0.0689)	(0.0689)
Brazil	0.529***	0.529***
	(0.0761)	(0.0761)
Constant	3.147***	3.147***
	(0.258)	(0.258)
Observations	3091	3091
R^2	0.095	0.095

Notes: OLS regressions with robust standard errors in parentheses. The dependent variable is whether inequality is perceived as a serious problem (1=no problem at all, 5=a very serious problem). Control variables and survey weights are included. Using the same estimation, column (a) focuses on differences between control and treatment group by income bias (reference: control group x income bias), column (b) on differences within the experimental groups (reference: treatment group x no bias group). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

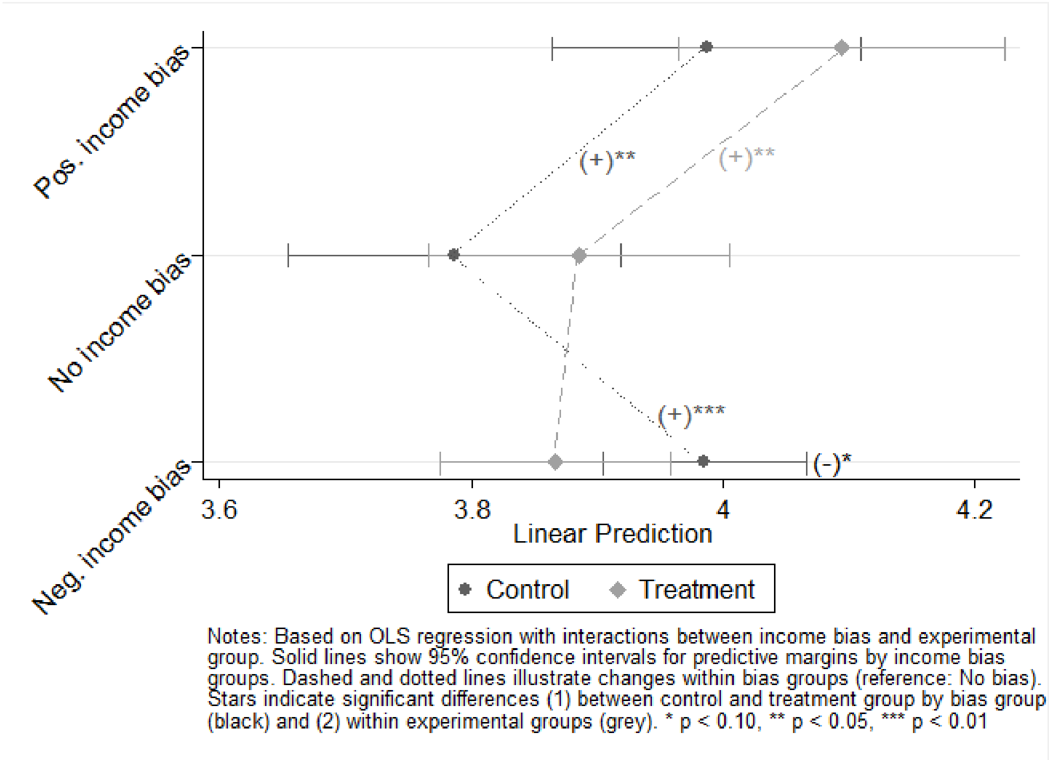


Figure 6: Predictive margins on whether inequality is perceived as a problem by income bias

information on the income distribution illustrating that income is not equally distributed should raise concerns. A decrease in the assessment of inequality is found for treated individuals with a negative income position bias. Since these respondents found out that they were actually better off than they thought, it seems only consistent that they tend to view inequality as a smaller problem than the control group.

From these findings I learn (1) that the treatment did not lead to higher inequality concerns among all individuals in the treatment group (compared to the control group) by country and (2) that the type of income position bias moderates how individual react to questions following the treatment. Since I find each bias type in each country and reactions go in opposite directions depending on the bias type, an insignificant overall treatment effect in a country appears plausible because reactions cancel each other out. In addition, I see that, although the reaction to the treatment is by and large insignificant, the direction of the movement is plausible, suggesting that my treatment fulfilled its purpose of correcting views on inequality.

4.2 Demand for redistribution

The next step of the analysis consists of the investigation of differences in the demand for redistribution between experimental groups. At first sight, such differences seem improbable because there are few changes in whether inequality is perceived as a problem. However, particularly in light of the seriousness with which inequality is already considered a problem without any intervention, it is plausible that changes may only be observed in other variables that actually tackle this problem. I first follow the introduced estimation strategy to identify potential treatment effects (Section 4.2.1). Then I broaden the scope of the analysis to explore the relation between the median voter model by Meltzer and Richard (1981) and misperceptions (Section 4.2.2).

4.2.1 Treatment effects

To measure the demand for redistribution I rely on the following two standard question from the World Values Survey 2012: Individuals were asked to place themselves on a scale between the two opposing statements (1) "Incomes should be made more equal" and (10) "We need larger income differences as incentives for individual effort". In addition, respondents could choose a number in between (1) "Government should take more responsibility to ensure that everyone is provided for" and (10) "People should take more responsibility to provide for themselves". In both cases a higher number implies a more liberal view with larger inequality or less government intervention. I assess each outcome variable individually.

First, I investigate the treatment effect for each country, using OLS regressions with interactions between treatment and country dummies (see Table 5). There are no significant changes in income preferences within countries between treatment and control groups (column 1). With the exception of Brazil that moves towards the bottom, the ranking of the other countries remains the same in the control and treatment group (column 2).[11]

Moving to my second outcome variable on redistribution, the treatment leads to a preference for less government responsibility in Germany and Russia but only at the 10%-level (column 3). In addition, I can check the ranking of countries within the treatment and control group by comparing the alignment of dots (control group) and diamonds (treatment group) in terms of the linear prediction (x-axis). Interestingly, there is a new clustering of countries in the treatment group because Germany and Russia move up while Brazil and France move down the scale (column 4). Against the baseline of Germany, there are no more significant differences between these countries. However, the treatment group in Spain demands significantly more and in the US less government responsibility than in Germany, both countries were already at the tails of the variable distribution.

Second, I look at heterogeneous responses to the treatment by the type of income position bias (see Figure 8, based on Table A.7). Again, there are no significant changes for the question on income differentials. However, as regards preferences for individual responsibility, individuals with a negative bias show a significantly lower demand for government responsibility in the treatment group when compared

[11] This result builds on the regression in column 2 but becomes more visible when looking at the predictive margins (available upon request).

Table 5: Treatment effect on demand for redistribution (by countries)

	(1) Diff. (a)	(2) Diff. (b)	(3) Resp. (a)	(4) Resp. (b)
Treatment		0.0793		0.413*
		(0.203)		(0.221)
Ref: See notes#				
Treatment × Germany	0.0793		0.413*	
	(0.203)		(0.221)	
Treatment × USA	0.136	0.925***	0.220	1.074***
	(0.250)	(0.233)	(0.276)	(0.254)
Treatment × Russia	0.291	0.309	0.556*	-0.245
	(0.301)	(0.246)	(0.297)	(0.277)
Treatment × France	-0.0801	0.467*	-0.0870	0.237
	(0.286)	(0.252)	(0.288)	(0.264)
Treatment × Spain	0.0543	0.437*	-0.238	-1.023***
	(0.229)	(0.234)	(0.233)	(0.242)
Treatment × Brazil	-0.362	0.0237	-0.217	0.421
	(0.400)	(0.315)	(0.396)	(0.314)
Ref: Germany				
USA	0.869***		1.266***	
	(0.233)		(0.254)	
Russia	0.0966		-0.388	
	(0.281)		(0.267)	
France	0.627**		0.736***	
	(0.252)		(0.257)	
Spain	0.462**		-0.373	
	(0.223)		(0.238)	
Brazil	0.465		1.051***	
	(0.324)		(0.336)	
Ref: Control x Germany				
Control × USA		0.869***		1.266***
		(0.233)		(0.254)
Control × Russia		0.0966		-0.388
		(0.281)		(0.267)
Control × France		0.627**		0.736***
		(0.252)		(0.257)
Control × Spain		0.462**		-0.373
		(0.223)		(0.238)
Control × Brazil		0.465		1.051***
		(0.324)		(0.336)
Ref: No bias				
Neg. income bias	-0.138	-0.138	-0.129	-0.129
	(0.139)	(0.139)	(0.148)	(0.148)
Pos. income bias	0.150	0.150	0.0586	0.0586
	(0.189)	(0.189)	(0.188)	(0.188)
Constant	4.830***	4.830***	4.530***	4.530***
	(0.675)	(0.675)	(0.708)	(0.708)
Observations	3076	3076	3080	3080
R^2	0.033	0.033	0.070	0.070

Notes: OLS regressions with robust standard errors in parentheses. The dependent variables are preferences for larger income differentials (Columns 1-2; (1) Incomes should be made more equal and (10) We need larger income differences as incentives for individual effort) and preferences for less government responsiblity (Columns 3-4, (1) Government should take more responsibility to ensure that everyone is provided for and (10) People should take more responsibility to provide for themselves). Control variables and survey weights are included. Using the same estimation, columns (a) focus on differences between control and treatment group by country reference: control group x country), columns (b) on differences within the experimental groups (reference: treatment group x Germany). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

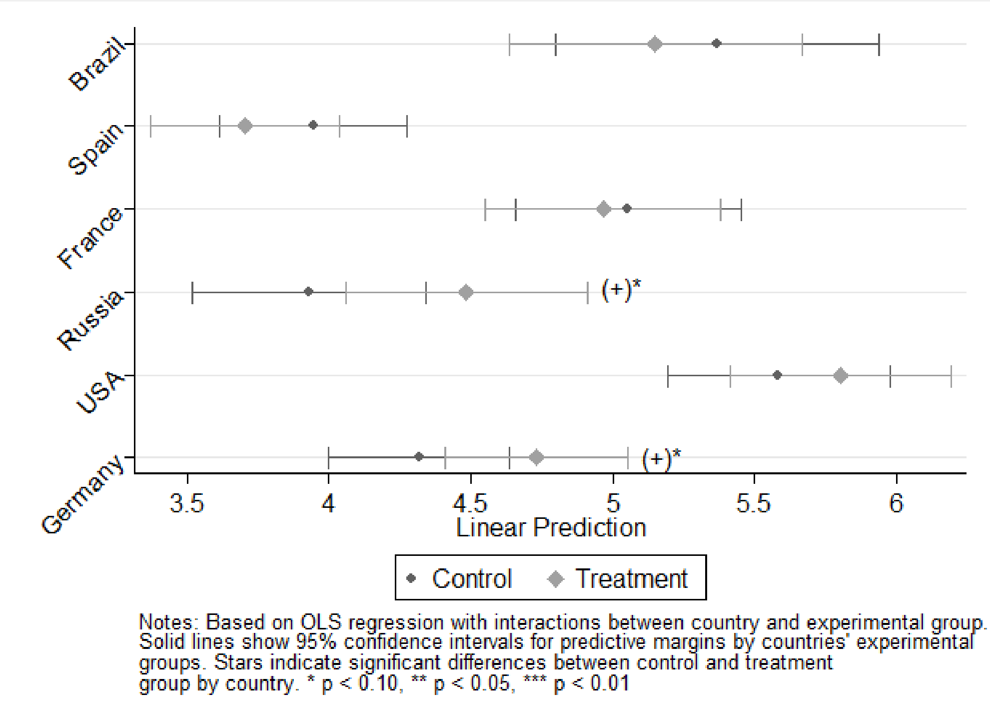


Figure 7: Predictive margins on whether people should take on more responsibility (countries)

to the control group. This implies that learning about a better standing than expected moves preferences towards more individual responsibility, potentially because the favorable own position is attributed to reasons under the own control, reducing the need for the help of others for instance through government intervention. Although insignificant, the positive bias shows the expected opposite relationship. Going back to the country-specific characteristics, remember that Germany and Russia display on average the largest negative position biases which may explain the average positive treatment effect found in each country. As regards the ranking, within the treatment group there are no more significant differences (compared to the control group) in terms of the preferences for responsibility, meaning that the treatment brought about a consensus because the groups moved towards each other.

4.2.2 The role of a misperceived median income

Whether a country displays on average an over- or underestimation of the income position does not seem to relate to the actual degree of inequality or redistribution. For instance, Brazil and Russia show high Gini coefficients and low redistribution but stand opposed to each other with an overestimation and an underestimation of the income position, respectively. As the importance of individuals with a median income is highlighted by Meltzer and Richard (1981), this section empirically explores alternative relationships between biases and redistribution on the country level, namely potential connections between misperceived median income and the demand for redistribution. For instance, a potential reference point for estimating the own income position can be the perceived median income; that is, conceptually,

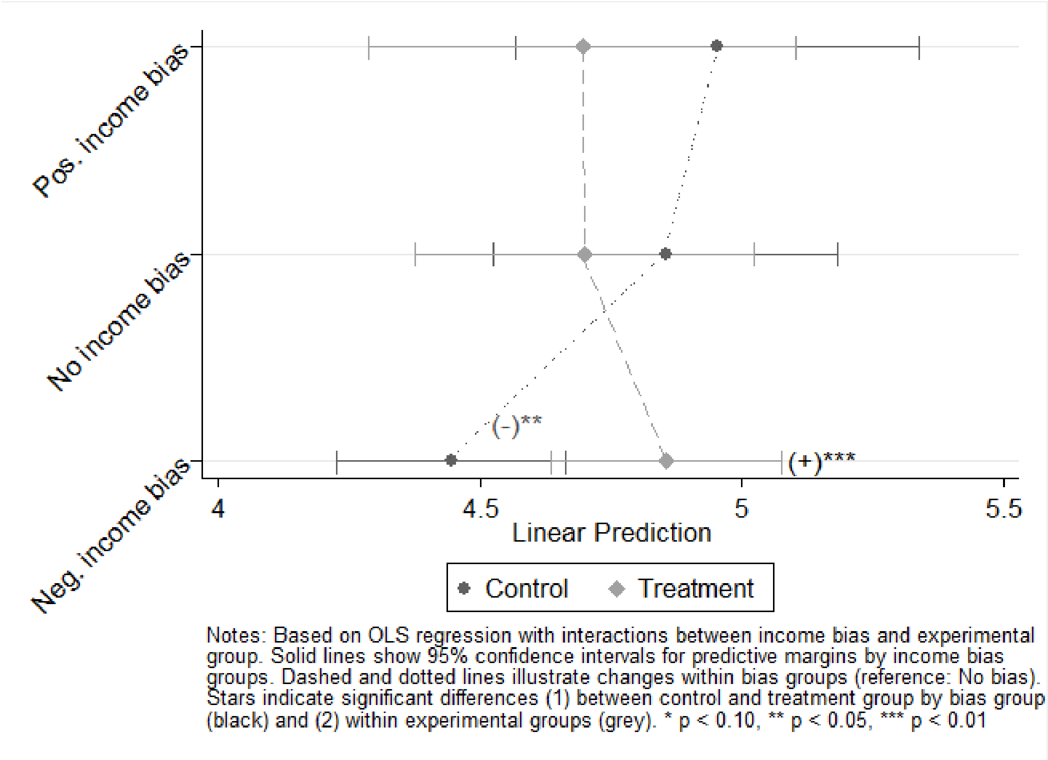


Figure 8: Predictive margins on whether people should take on more responsibility (income bias)

individuals may arrive at their own position in relation to where the median income is located. By estimating the median income to be higher than the true median, individuals automatically underestimate their own position (see Figure 9). This relies on the assumption that the shape of the distribution is identical in the estimated and the true scenario. In the case of an underestimation of the median income, I would expect an overestimation of the own position. Taking averages by countries, I plot the degree of misperception of the median income (in percent) against the income position bias (see Figure 10). Both variables can take on positive (overestimation) or negative (negative) values. If the conjecture was confirmed there should be a downward sloping line that crosses the point of origin. The results provide first evidence that the median income may be an important reference point as there is a clear negative relationship between misperceptions of the median income and of the own income position. Note that France and Spain, both countries with small negative income position biases, show a negative median income bias. While this goes against the strict interpretation of what was argued above, their location within the coordinate system still suggests that the main story regarding the distorting consequences of misperceptions of median income holds.

In a next step, one may investigate how the degree of misperception of the median income relates to the demand for redistribution. Meltzer and Richard (1981) suggest that individuals with a median income are decisive for the degree of redistribution because anyone below the median will demand more and anyone above will demand less redistribution. According to Figure 9, in countries where the median

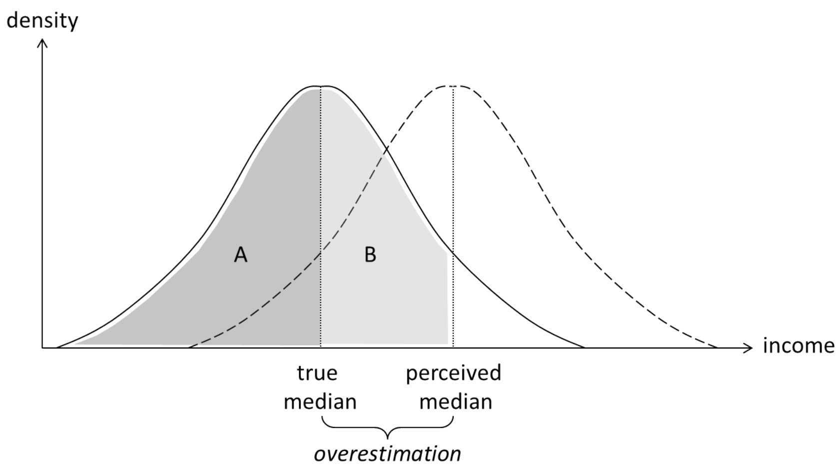


Figure 9: The role of misperceptions in relation to median voter model by Meltzer and Richard (1981)

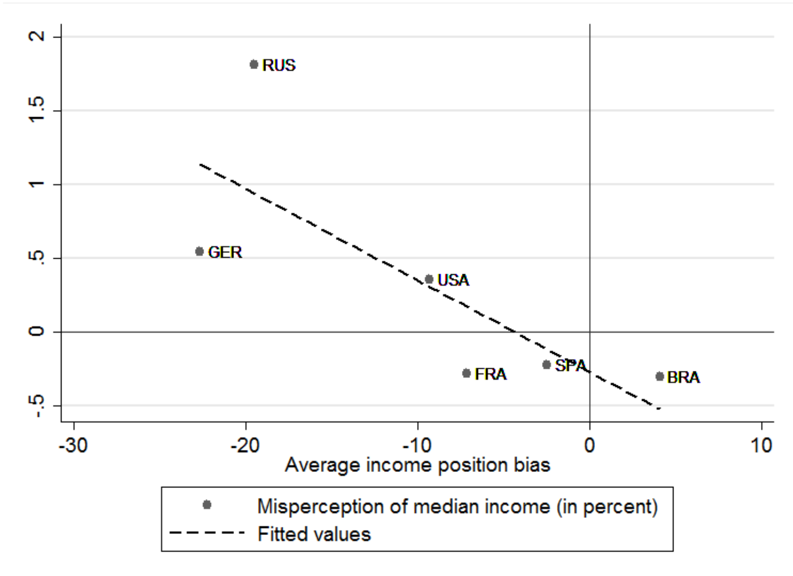


Figure 10: The relationship between misperceptions of the median income and of the income position

is on average overestimated, a share of individuals falsely believes to be located below the median income, leading them to demand more redistribution than they would if they knew that they were located above median income (area B). They can be added to those individuals who are truly located below the median income (area A) and therefore have an actual reason to demand more redistribution. Hence, in countries with an overestimation of the median income, I would expect to see a lower demand of redistribution after the treatment as group B updates their preferences. The opposite reaction would be expected for an underestimation of the median. While most changes between treatment and control group in the demand for redistribution turn out to be insignificant, the direction of the coefficients remains of interest for this idea (see Table 5). Indeed, for countries that overestimate the median (Russia, Germany, USA) there is an increase in the demand for higher income differentials and more personal responsibility. For countries that underestimate the median income (France, Spain, Brazil) there is, with one exception, the opposite treatment reaction, implying a higher demand for lower income differentials and more government responsibility.

For more definite conclusions it would be necessary to construct a larger country sample. Nonetheless, these first results suggest that including misperceptions of the median income in the analysis is a promising avenue for further research.

4.3 Views on issues related to inequality

Although the focus of this study is on the relationship between redistribution and misperceptions, it is of interest to understand whether the treatment group displays different personal views on matters connected to inequality than the control group. This helps to better interpret the nature of the treatment and its resulting influence on the main variables by providing more context. The following sections thus present the results based on the same regression equations as above for different outcome variables.

It is likely that country averages of these variables differ but the focus of the following analysis remains on differences between bias groups as this is where I observed more interesting changes in the previous section. Furthermore, there is no discussion of the direction the (insignificant) effects or the changes in the ordering of groups when there is no significant treatment effect.[12]

Trust and political interest

The questionnaire elicited general trust levels in people and specific trust level in (1) the government/parliament/political parties, (2) the courts/legal institutions, and (3) the press/media. The clustering of different organizations follows Rothstein and Stolle (2008) who find that when summarizing confidence in institutions the following dimensions emerge (numbering mirrors list above): (1) political/biased institutions, (2) neutral and order institutions and (3) power checking institutions. Respondents also answered whether they are interested in politics. The results are found in Table A.8 and A.9.

As regards general trust, the treatment group shows lower trust levels on the 10%-level. I further observe a significant lower trust in governments for the positive bias (treatment) group (see Figure 11). This implies that by learning that they are worse off than assumed, respondents see less reason to trust governments. There are no significant changes in political interest.

Luck and charity

As known from previous research, individuals in the treatment group tend to update their beliefs about the importance of luck (Karadja et al., 2016). In addition, they may change their opinion about charity organizations that (privately) redistribute on a voluntary basis (Kuziemko et al., 2015). Participants

[12] As a robustness check all regressions were also run for countries, showing, however, no significant treatment effects within countries.

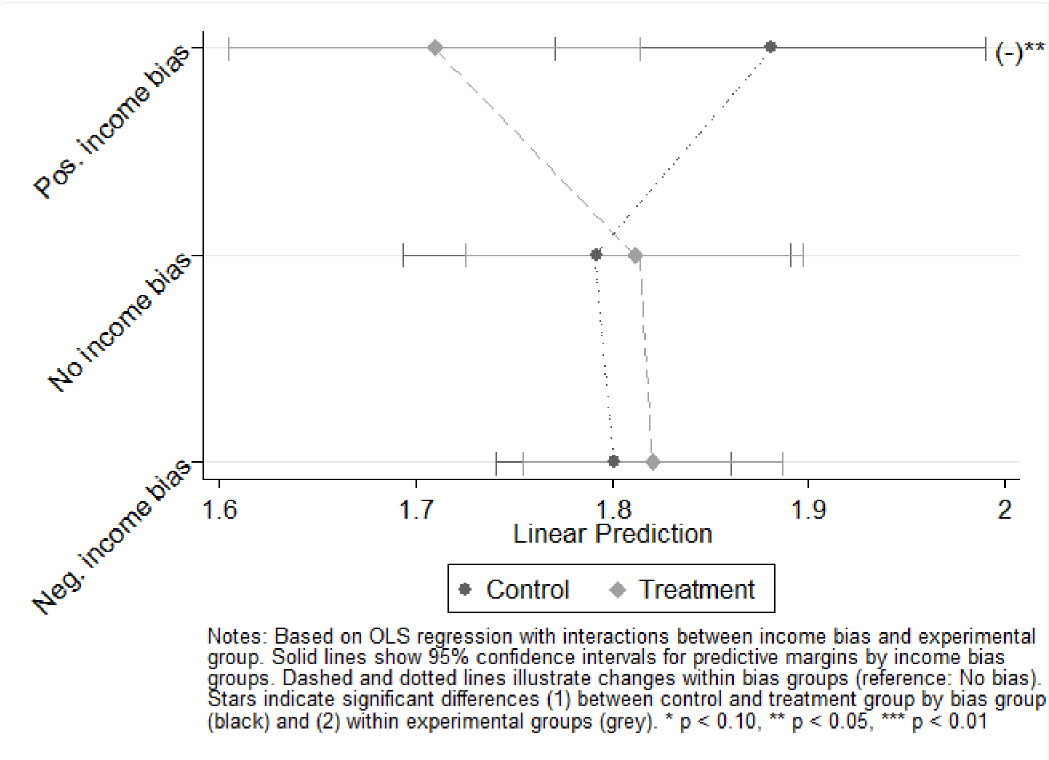


Figure 11: Predictive margins on trust in government (by income bias)

were thus asked to place themselves between the two statements "In the long run, hard work usually brings a better life" and "Hard work doesn't generally bring success - it's more a matter of luck and connections". Then they responded to whether private charities should play a role in redistributing income. The complete results are found in Table A.10.

The treatment group without a bias considers luck to be significantly more important than the control group (see Figure 12). As mentioned above, since this group consists of a bias mix, this result is difficult to interpret. However, it indicates that my treatment cannot only be interpreted in terms of the position bias but, as proposed earlier, needs to be understood in the context of all income-related information provided. In addition, any significant differences within the control group disappear within the treatment group. Regarding the redistributive function of charities, there are no reactions significant at levels below 10%.

Drivers of inequality

When respondents learn that they were misinformed about the income distribution they may also change their opinion on potential explanations for reaching a higher income position. To this end I investigate the following five drivers that are included in the International Social Survey Programme when inquiring about what is important for getting ahead in life: (1) coming from a wealthy/well-educate family, (2) having a good education yourself, (3) having ambition, (4) knowing the right people,

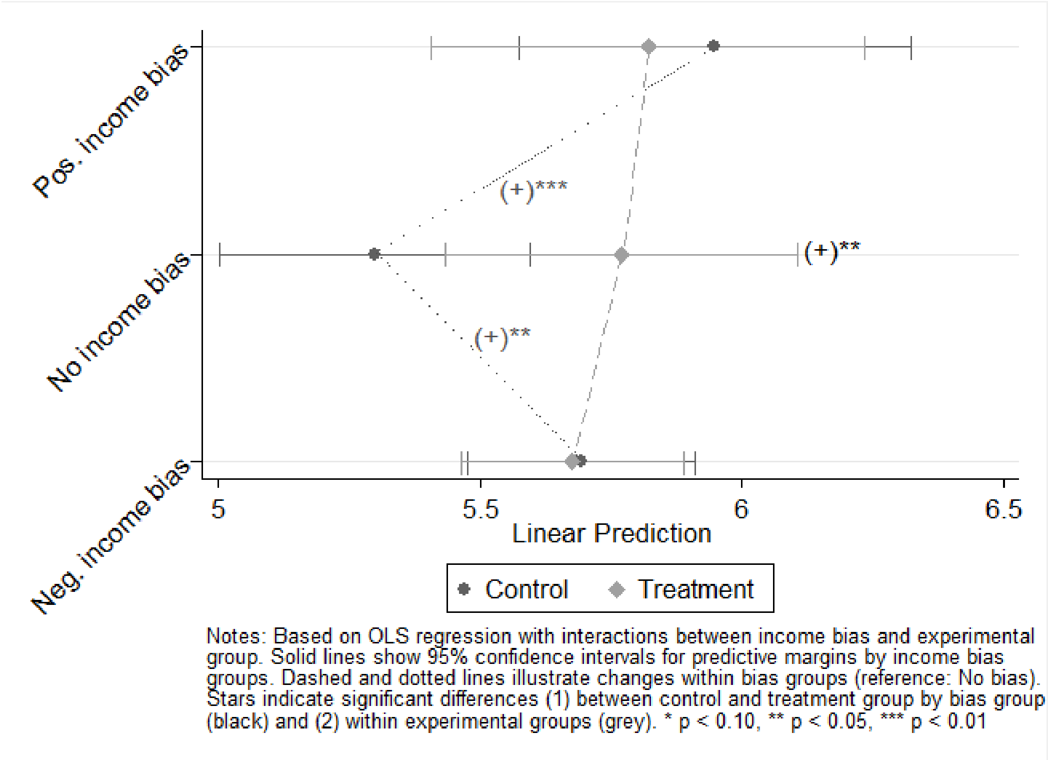


Figure 12: Predictive margins on the importance of luck (by income bias)

and (5) being born a man or a woman. The results are found in Table A.11.

The specification shows no treatment effect by bias groups for any of the variables. This is of particular interest because I see a change for the previous questions on luck and connections which appear closely related to having ambition and knowing the right people. For the treatment group without a bias a higher importance of ambition and a lower importance of networks would have been plausible because they previously considered luck to be of higher importance. For the treatment group with a negative bias, I would have expected a higher assessment of the importance of ambition. My results suggest that individuals may not relate the proposed drivers to the inequality situation or that it is a combination of different aspects (see question on government versus personal responsibility) that is able to yield a significant reaction. It would also take further analysis to better understand to what degree different drivers are considered to relate to luck or effort.

5 Conclusion

Research has shown that misperceptions of income distributions can matter for the demand for redistribution. Previous studies focus on within-country differences in misperceptions, their reasons and consequences, finding that the bias level of perceptions differs systematically within a population. Treatment effects of correcting false beliefs are regularly insignificant, although in some cases this can be explained by divergent responses within population groups. In a common survey framework I thus collect representative cross-country data for Brazil, France, Germany, Russia, Spain, and the United States, allowing to analyze both the individual and the country level to identify within- and between-country differences. Comparing countries is of particular interest because welfare policies such as redistribution decisions differ primarily on a national level. A randomly chosen subsample of the population is informed about the true shape of the income distribution and the own position in it.

My analysis finds systematic differences in misperceptions between countries. For instance, while there are individuals with all types of incomes biases in each country, Germany shows on average the largest underestimation while Brazil displays, on average, the largest (and only) overestimation of the own position in the income distribution. As their true income position increases, individuals move from a positive towards a negative position bias. Hence, the largest biases are found at the lower and upper tail of the income distribution and individuals tend to place themselves closer to the middle. This holds universally across all countries. There is no robust evidence for the influence of the social network as reference group. The treatment effects differ between and within countries. For instance, while within countries inequality is not perceived to be more of a problem in the treatment group, there are divergent responses for individuals with different biases which nullify significant differences in the inequality assessment between individuals with no and a negative bias. While only significant at the 10%-level, treated individuals from Germany and Russia demand moving responsibility from governments towards people, suggesting less redistribution. This appears to be driven by respondents with a negative bias because this is the largest group in both countries. Also, the average level of the demand for government responsibility changes within countries, leading to a different ranking of countries within the treatment group when compared to the control group. Combining the median voter model (Meltzer and Richard, 1981) with the influence of misperceptions I find the hypothesized negative relationship between the income position bias and the misperceived median income. In addition, there is indicative evidence that the direction of changes in the demand for redistribution is related to the average median income bias. There are very few other treatment effects for variables that are considered to relate to inequality more generally. Respondents with a positive income bias show significant less trust in government but there are no significant differences within experimental groups. There are no significant changes in other trust variables. A significant increase in the importance attributed to luck for individuals with no bias makes significant differences within the treatment group disappear. The assessment of potential drivers of inequality does not differ between treatment and control group.

In sum, the results show a new ranking and clustering of countries as regards the demand for individual responsibility after the treatment. Accordingly, country differences identified in standard questionnaires are at a high risk to be biased and some countries may be more, others less similar than previously assumed. The treatment reaction also differs by the income position bias in such a way that often respondents' answers go into opposite directions, not only on variables related to the demand for redistribution. This underlines that, in further research, analyzing treatment responses by the income position bias may provide promising insights. Also, including larger country samples would allow to analyze treatment reactions by bias types within countries. Regarding the survey design, informing individuals about income inequality in a neutral way and correcting several potential biases in this context continues to influence individuals' opinions. For instance, although the treatment did not significantly change views on whether inequality is a serious problem, it directly altered the demand for redistribution in Germany and Russia between experimental groups. Note that if the goal is to inform individuals about the true income distribution, the ideal communication channels still need to be identified. In a similar vein, the information in the treatment was presented neutrally but in a complex way which may have posed challenges to the respondents. It would thus be helpful to find a easily communicable format that can be made accessible to a broader audience. Pellicer et al. (2016) show for South Africa that informing about inequality and giving comparison values for other countries changes the demand for redistribution compared to when no reference values are given. Including such data in a cross-country survey would give important insights on the context given in treatments.

References

Alesina, Alberto and George-Marios Angeletos, "Fairness and Redistribution," *American Economic Review*, 2005, *95* (4), 960–980.

__ , Edward Glaeser, and Bruce Sacerdote, "Why Doesn't the United States Have a European-Style Welfare State?," *Brookings Papers on Economic Activity*, 2001, *2*, 187–278.

__ , Rafael Di Tella, and Robert MacCulloch, "Inequality and happiness: are Europeans and Americans different?," *Journal of Public Economics*, 2004, *88* (9-10), 2009–2042.

Ashok, Vivekinan, Ilyana Kuziemko, and Ebonya Washington, "Support for Redistribution in an Age of Rising Inequality: New stylized facts and some tentative explanations," *NBER Working Paper*, 2015, *No. 21529, September 2015, National Bureau of Economic Research, Cambridge.*

Balcells, Laia, José Fernández-Albertos, and Alexander Kuo, "Preferences for Inter-Regional Redistribution," *Comparative Political Studies*, 2015, *48* (10), 1318–1351.

Brown-Iannuzzi, Jazmin L., Kristjen B. Lundberg, Aaron C. Kay, and B. Keith Payne, "Subjective status shapes political preferences," *Psychological Science*, 2015, *26* (1), 15–26.

Chambers, John R., Lawton K. Swan, and Martin Heesacker, "Better off than we know: distorted perceptions of incomes and income inequality in America," *Psychological Science*, 2014, *25* (2), 613–618.

Cruces, Guillermo, Ricardo Perez-Truglia, and Martin Tetaz, "Biased perceptions of income distribution and preferences for redistribution: Evidence from a survey experiment," *Journal of Public Economics*, 2013, *98*, 100–112.

Engelhardt, Carina and Andreas Wagener, "Biased Perceptions of Income Inequality and Redistribution," *CESIFO Working Paper*, 2014, *No. 4838, June 2014, Center for Economic Studies & ifo Institute.*

__ and __ , "What do Germans Think and Know about Income Inequality? A Survey Experiment," *Working Paper*, 2016, *January 2016, Leibniz University of Hannover.*

Eriksson, Kimmo and Brent Simpson, "What do Americans know about inequality? It depends on how you ask them," *Judgement and Decision Making*, 2012, *7* (6), 741–745.

Fernández-Albertos, José and Alexander Kuo, "Income Perception, Information, and Progressive Taxation: Evidence from a Survey Experiment," *Political Science Research and Methods*, 2015, pp. 1–28.

Gimpelson, Vladimir and Daniel Treisman, "Misperceiving Inequality," *NBER Working Paper* , 2015, *No. 21174, May 2015, National Bureau of Economic Research, Cambridge.*

Karadja, Mounir, Johanna Möllerström, and David Seim, "Richer (and Holier) Than Thou? The Effect of Relative Income Improvements on Demand for Redistribution," *Review of Economics & Statistics*, 2016, *forthcoming.*

Kuhn, Andreas, "The Individual Perception of Wage Inequality: A Measurement Framework and Some Empirical Evidence," *IZA Discussion Paper*, 2015, *No. 9579, December 2015, Institute for the Study of Labor, Bonn.*

Kuklinski, James H., Paul J. Quirk, Jennifer Jerit, David Schwieder, and Robert F. Rich, "Misinformation and the Currency of Democratic Citizenship," *The Journal of Politics*, 2000, *62* (3), 790–816.

Kuziemko, Ilyana, Michael I. Norton, Emmanuel Saez, and Stefanie Stantcheva, "How elastic are preferences for redistribution? Evidence from randomized survey experiments," *American Economic Review*, 2015, *105* (4), 1478–1508.

Lergetporer, Philipp, Guido Schwerdt, Katharina Werner, and Ludger Woessmann, "Information and Preferences for Public Spending: Evidence from Representative Survey Experiments," *IZA Discussion Paper*, 2016, *No. 9968, Institute for the Study of Labor, Bonn* (May 2016).

Luttmer, Erzo F. P and Monica Singhal, "Culture, Context, and the Taste for Redistribution," *American Economic Journal: Economic Policy*, 2011, *3* (1), 157–179.

Luxembourg Income Study (LIS) Database, *http://www.lisdatacenter.org (multiple countries; 2015/03/06-2015/12/31)*, Luxembourg: LIS, 2015.

Meltzer, Allan H. and Scott F. Richard, "A Rational Theory of the Size of Government," *The Journal of Political Economy*, 1981, *89* (5), 914–927.

Niehues, Judith, "Subjective Perceptions of Inequality and Redistributive Preferences: An International Comparison," *Discussion Paper*, 2014, *August 2014, Cologne Institute for Economic Research.*

Norton, Michael I. and Dan Ariely, "Building a Better America-One Wealth Quintile at a Time," *Perspectives on Psychological Science*, 2011, *6* (1), 9–12.

_ **and** _ , "American's desire for less wealth inequality does not depend on how you ask them," *Judgement and Decision Making*, 2013, *8* (3), 393–394.

Pellicer, Miquel, Patrizio Piraino, and Eva Wegner, "Is Inequality Inevitable? A Survey Experiment on Demand for Redistribution in South Africa," *mimeo*, 2016.

Rothstein, Bo and Dietlind Stolle, "The State and Social Capital: An Institutional Theory of Generalized Trust," *Comparative Politics*, 2008, *40* (4), 441–459.

Tversky, Amos and Daniel Kahneman, "Judgment under Uncertainty: Heuristics and Biases," *Science (New York, N.Y.)*, 1974, *185* (4157), 1124–1131.

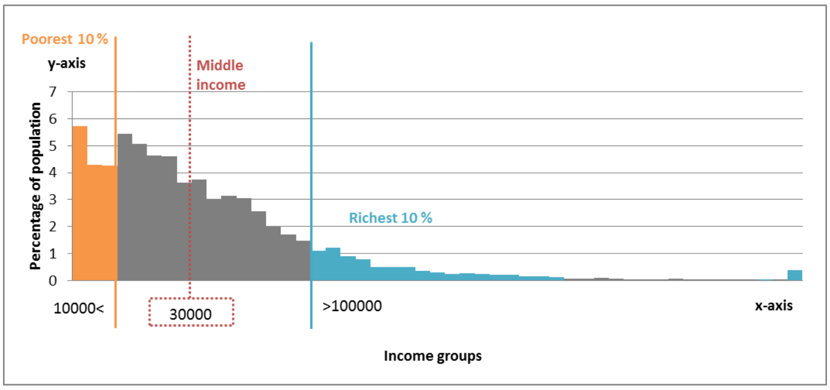
Zilinsky, Jan, "Learning About Income Inequality: What is the Impact of Information on Perceptions of Fairness and Preferences for Redistribution?," *mimeo*, 2014.

Annex

The figure below shows the income distribution of <COUNTRY> for total yearly market income.

<u>How to read the figure:</u> The horizontal x-axis reflects income levels for different groups. The more you go to the right, the higher is the income. The length of the bars indicates the share of the population for an income level (vertical y-axis). The longer the bar is, the larger is the share of the population that earns a particular income.

<u>What is inequality:</u> If income was equally distributed, we would have only one bar for one unique income level. For instance, 100% of the population could earn the middle income. Income inequality exists when different numbers of people earn different incomes. For instance, high income inequality can be reflected by a large number of income bars. In addition, longer bars in lower income groups and shorter bars in high income groups imply that a large share of the population earns a low income and a small share of the population earns a high income.



Please take some time and carefully compare the answers you gave before and the true values for <COUNTRY>.

	You answers were	**True values**
income of household in the *middle of the population*	ANSWER TO < >	**NUMBER**
average income of *10% poorest* households	ANSWER TO < >	**NUMBER**
average income of *10% richest* households	ANSWER TO < >	**NUMBER**
percentage of individuals with a lower income than yours	ANSWER TO < >	**NUMBER**

Notes: The research group collected with great care information on the income distribution from official sources. To calculate income distributions we used harmonized microdata from the cross-national data center of the Luxembourg Income Study (LIS) and the European Union statistics on income and living conditions (EU-SILC) for the year 2013. For illustrative purposes the lowest percentiles, including individuals with negative income before taxes, are excluded from the figure.

Figure A.1: Example of treatment information (not country-specific)

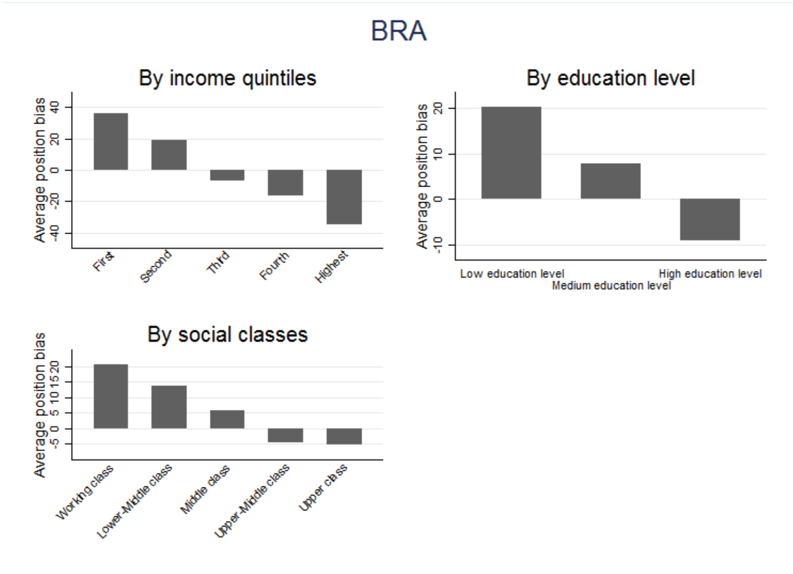


Figure A.2: Average income position bias by group characteristics in BRAZIL

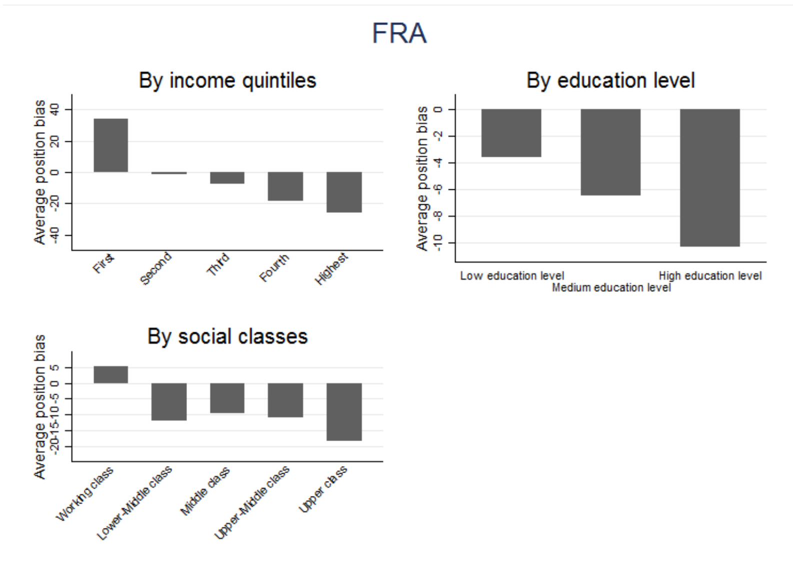


Figure A.3: Average income position bias by group characteristics in FRANCE

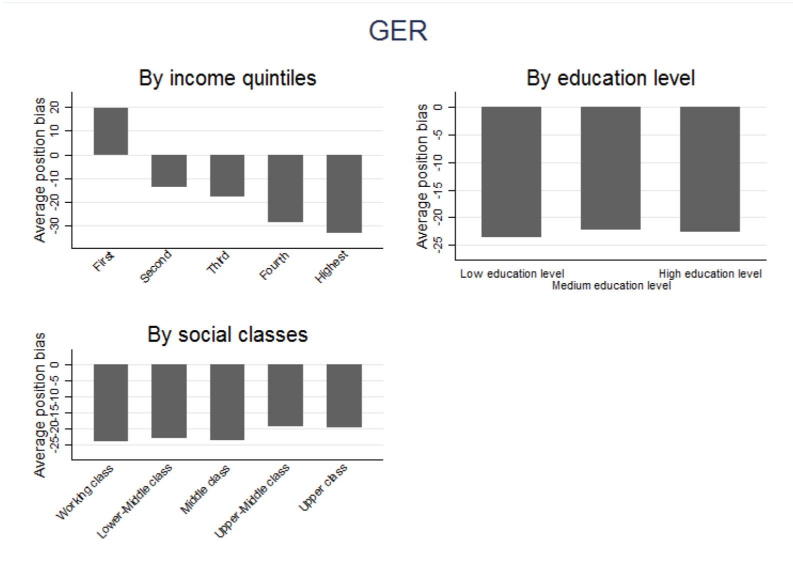


Figure A.4: Average income position bias by group characteristics in GERMANY

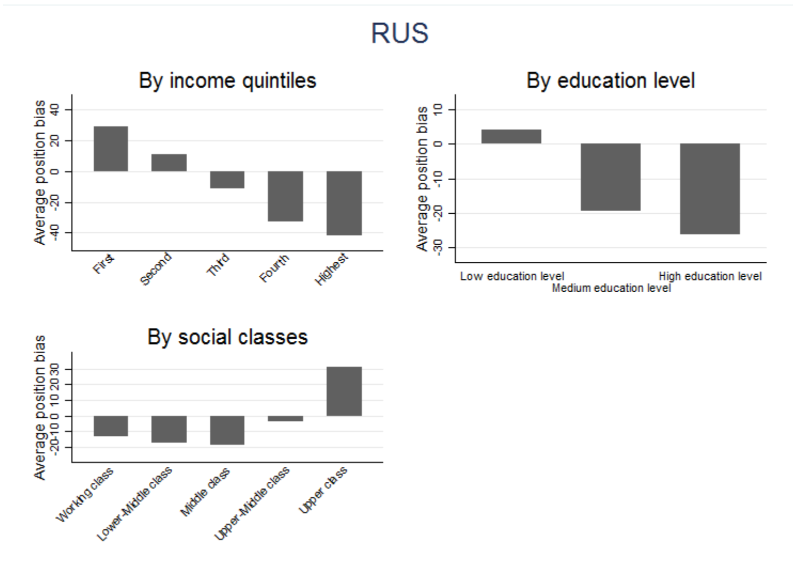


Figure A.5: Average income position bias by group characteristics in RUSSIA

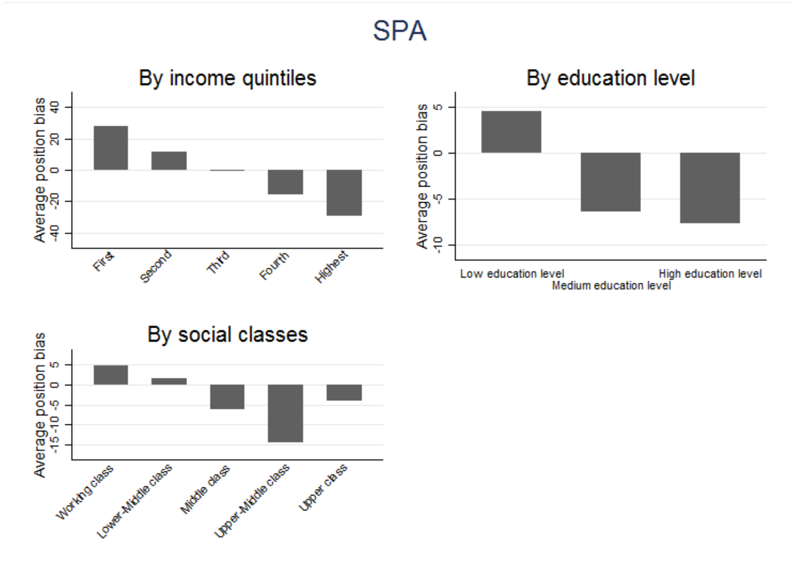


Figure A.6: Average income position bias by group characteristics in SPAIN

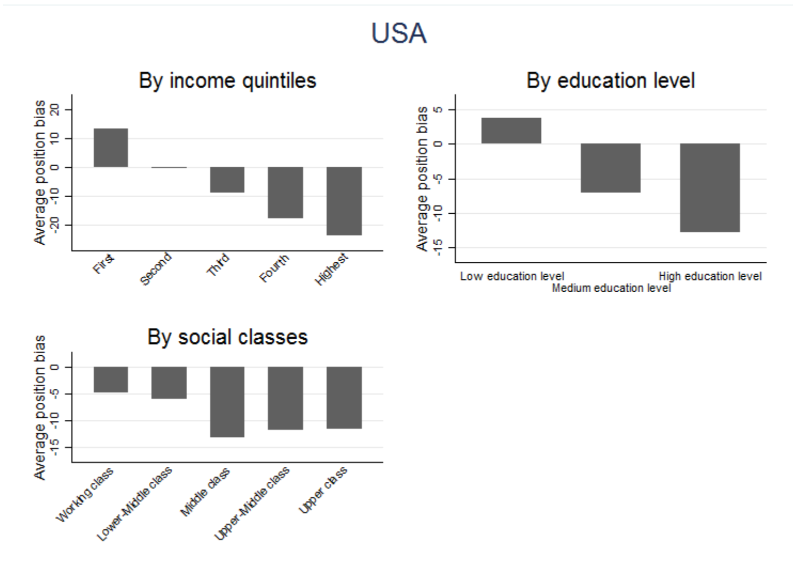


Figure A.7: Average income position bias by group characteristics in US

Table A.1: Randomization and attrition tests

Covariate	*Treatment status* Coefficient	P-value	*Survey end* Coefficient	P-value	*No. missing values* Coefficient	P-value
Treatment group			0.000	0.896	0.147	0.079
Female	-0.001	0.942	-0.007	0.221	0.430	0.000
Age	-0.000	0.890	0.001	0.000	-0.020	0.000
Education						
Medium education level	-0.018	0.260	0.023	0.003	-0.850	0.000
High education level	-0.010	0.570	0.063	0.000	-1.639	0.000
Actual income position	-0.000	0.961	0.000	0.015	-0.012	0.000
Political affiliation	0.003	0.178	-0.003	0.010	0.064	0.000
Number of household members	-0.000	0.890	-0.004	0.000	0.073	0.000
Social polarization						
Neg. polar.	0.013	0.532	0.024	0.008	-0.812	0.000
Pos. polar.	0.005	0.829	0.032	0.004	-0.996	0.000
Job						
Private employed	0.016	0.450	0.016	0.074	-0.670	0.000
Own business	-0.028	0.340	0.017	0.199	-0.919	0.000
Student	-0.013	0.629	-0.023	0.062	-0.019	0.911
Unemployed	0.016	0.504	-0.017	0.114	0.379	0.008
Not in labor force	0.000	0.979	0.015	0.147	-0.359	0.008
I never had a job	-0.072	0.235	-0.124	0.000	2.779	0.000
Other	-0.022	0.473	-0.046	0.001	0.605	0.001

Notes: For each covariate the coefficient and p-value from single regressions are shown. Around 94% finished the survey and 90% have no more than 5 missing values, in most cases less than that. Regressing the dependent variables jointly on all covariates yields a p-value of joint significance of 0.53 for treatment status and significant differences at 1%-level for for reaching the end of the survey and the number of missing values.

Table A.2: Likelihood that respondents report their income

	(1)
Female (1=Yes)	-0.0687***
	(0.0144)
Age	0.00245***
	(0.000640)
Number of all household members	-0.00566*
	(0.00310)
Ref: Low education level	
Medium education level	0.0816***
	(0.0207)
High education level	0.134***
	(0.0213)
Ref: Polarization zero	
Neg. polar.	0.0439*
	(0.0249)
Pos. polar.	0.0540*
	(0.0287)
Ref: Public employed	
Private employed	0.0610***
	(0.0227)
Own business	0.0711**
	(0.0334)
Student	-0.133***
	(0.0378)
Unemployed	-0.110***
	(0.0305)
Not in labor force	0.00998
	(0.0282)
I never had a job	-0.0250
	(0.103)
Other	-0.0703*
	(0.0388)
Political affiliation	-0.00584**
	(0.00291)
Ref: Germany	
USA	0.0697***
	(0.0229)
Russia	0.0783***
	(0.0298)
France	-0.0280
	(0.0240)
Spain	0.128***
	(0.0223)
Brazil	-0.0460*
	(0.0278)
Observations	4738

Notes: Marginal effects from logit regressions with robust standard errors in parentheses. The dependent variable is whether respondents reported their income. Survey weights are included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Distribution of social classes across actual income quintiles

	First	Second	Third	Fourth	Fifth	TOTAL
Working class	114	170	194	93	34	605
Lower-middle class	116	146	225	143	46	676
Middle class	120	136	357	447	318	1378
Upper-middle class	18	14	56	85	171	344
Upper class	6	4	3	4	24	41
TOTAL	374	470	835	772	593	3044

Source: Own calculations for all countries.

Table A.4: Group differences of the actual position in the income distribution

	(1)	(2)
Position in income distribution	0.236***	0.177***
	(0.0220)	(0.0221)
Ref: Low education level		
Medium education level	8.348***	6.952***
	(1.379)	(1.368)
High education level	15.04***	10.93***
	(1.391)	(1.428)
Ref: Working class		
Lower-Middle class		4.351***
		(1.271)
Middle class		12.48***
		(1.271)
Upper-Middle class		21.60***
		(1.861)
Upper class		17.53***
		(5.809)
Ref: Polarization zero		
Neg. polar.	-3.153**	1.461
	(1.493)	(1.501)
Pos. polar.	1.973	0.269
	(1.761)	(1.777)
Ref: Germany		
USA	-9.151***	-7.324***
	(1.122)	(1.060)
Russia	0.295	2.835*
	(1.656)	(1.628)
France	-8.995***	-8.363***
	(1.201)	(1.148)
Spain	-6.265***	-4.910***
	(1.263)	(1.213)
Brazil	-16.14***	-14.39***
	(1.895)	(1.882)
Constant	19.57***	9.367*
	(5.008)	(4.867)
Observations	3044	3044
R^2	0.290	0.337

Notes: OLS regressions with robust standard errors in parentheses. The dependent variable is the actual income position. Control variables and survey weights are included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Summary statistics of dependent variables by experimental group

Variable	Group	Obs	Mean	Std. Dev.	Min	Max
Inequality problem	Treatment	1521	3.972	1.121	1	5
	Control	1551	3.953	1.122	1	5
Pref. Income differentials	Treatment	1516	4.482	2.754	1	10
	Control	1550	4.450	2.736	1	10
Pref. Government responsibility	Treatment	1524	4.784	2.945	1	10
	Control	1556	4.623	2.952	1	10
General trust	Treatment	1492	0.279	0.449	0	1
	Control	1536	0.298	0.457	0	1
Trust press/media	Treatment	1513	2.201	0.783	1	4
	Control	1548	2.209	0.798	1	4
Trust courts/legal institutions	Treatment	1513	2.426	0.809	1	4
	Control	1545	2.392	0.801	1	4
Trust government/parliament/political parties	Treatment	1511	1.802	0.827	1	4
	Control	1546	1.798	0.819	1	4
Interest in politics	Treatment	1521	6.986	2.491	1	10
	Control	1546	6.833	2.497	1	10
Importance of luck	Treatment	1517	5.709	2.867	1	10
	Control	1549	5.644	2.882	1	10
Importance of charities	Treatment	1403	5.004	2.753	1	10
	Control	1435	5.086	2.721	1	10
Driver wealth/well-educated family	Treatment	1516	3.408	1.098	1	5
	Control	1544	3.442	1.138	1	5
Driver own good education	Treatment	1521	4.099	0.842	1	5
	Control	1554	4.053	0.882	1	5
Driver having ambition	Treatment	1516	3.771	0.978	1	5
	Control	1551	3.716	0.984	1	5
Driver knowing people	Treatment	1519	3.885	0.906	1	5
	Control	1550	3.874	0.942	1	5
Driver gender	Treatment	1497	2.558	1.231	1	5
	Control	1527	2.525	1.184	1	5

Table A.6: Treatment effect on whether inequality is perceived as a serious problem (by countries)

	(1) (a)	(2) (b)
Treatment		-0.0416
		(0.0954)
Ref: See notes		
Treatment × Germany	-0.0416	
	(0.0954)	
Treatment × USA	0.0179	-0.211*
	(0.117)	(0.109)
Treatment × Russia	-0.0124	-0.148
	(0.123)	(0.120)
Treatment × France	-0.0193	0.0248
	(0.108)	(0.106)
Treatment × Spain	-0.0820	0.331***
	(0.0783)	(0.0946)
Treatment × Brazil	0.0822	0.597***
	(0.101)	(0.102)
Ref: Germany		
USA	-0.270**	
	(0.108)	
Russia	-0.177*	
	(0.106)	
France	0.00244	
	(0.102)	
Spain	0.372***	
	(0.0904)	
Brazil	0.473***	
	(0.104)	
Ref: Control x Germany		
Control × USA		-0.270**
		(0.108)
Control × Russia		-0.177*
		(0.106)
Control × France		0.00244
		(0.102)
Control × Spain		0.372***
		(0.0904)
Control × Brazil		0.473***
		(0.104)
Ref: No bias		
Neg. income bias	0.0984*	0.0984*
	(0.0573)	(0.0573)
Pos. income bias	0.183***	0.183***
	(0.0648)	(0.0648)
Constant	3.214***	3.214***
	(0.260)	(0.260)
Observations	3091	3091
R^2	0.094	0.094

Notes: OLS regressions with robust standard errors in parentheses. The dependent variable is whether inequality is perceived as a serious problem (1=no problem at all, 5=a very serious problem). Control variables and survey weights are included. Using the same estimation, column (a) focuses on differences between control and treatment group by country (reference: control group x country), column (b) on differences within the experimental groups (reference: treatment group x Germany).
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A.7: Treatment effect on demand for redistribution (by bias groups)

	(1) Diff. (a)	(2) Diff. (b)	(3) Pref. (a)	(4) Pref. (b)
Treatment		0.164		-0.154
		(0.216)		(0.234)
Ref: See notes				
Treatment × Neg. income bias	0.154	-0.140	0.411***	0.156
	(0.140)	(0.194)	(0.147)	(0.202)
Treatment × No income bias	0.164		-0.154	
	(0.216)		(0.234)	
Treatment × Pos. income bias	-0.360	-0.117	-0.260	-0.00476
	(0.288)	(0.266)	(0.276)	(0.265)
Ref: No income bias				
Neg. income bias	-0.131		-0.409**	
	(0.185)		(0.203)	
Pos. income bias	0.407		0.100	
	(0.255)		(0.257)	
Ref: Control x no income bias				
Control × Neg. income bias		-0.131		-0.409**
		(0.185)		(0.203)
Control × Pos. income bias		0.407		0.100
		(0.255)		(0.257)
Ref: Germany				
USA	0.899***	0.899***	1.183***	1.183***
	(0.168)	(0.168)	(0.183)	(0.183)
Russia	0.209	0.209	-0.300	-0.300
	(0.191)	(0.191)	(0.201)	(0.201)
France	0.553***	0.553***	0.493***	0.493***
	(0.181)	(0.181)	(0.187)	(0.187)
Spain	0.454***	0.454***	-0.671***	-0.671***
	(0.170)	(0.170)	(0.179)	(0.179)
Brazil	0.246	0.246	0.749***	0.749***
	(0.226)	(0.226)	(0.232)	(0.232)
Constant	4.767***	4.767***	4.750***	4.750***
	(0.674)	(0.674)	(0.708)	(0.708)
Observations	3076	3076	3080	3080
R^2	0.034	0.034	0.070	0.070

Notes: OLS regressions with robust standard errors in parentheses. The dependent variables are preferences for larger income differentials (Columns 1-2; ; (1) Incomes should be made more equal and (10) We need larger income differences as incentives for individual effort) and preferences for less government responsiblity (Columns 3-4; (1) Government should take more responsibility to ensure that everyone is provided for and (10) People should take more responsibility to provide for themselves). Control variables and survey weights are included. Using the same estimation, columns (a) focus on differences between control and treatment group by income bias (reference: control group x income bias), columns (b) on differences within the experimental groups (reference: treatment group x no bias group).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Treatment effect on trust and political interest (by bias group, part 1)

	(1) General	(2) Media	(3) Courts	(4) Government	(5) Pol. interest
Treatment × Neg. income bias	-0.00838	-0.00221	0.0285	0.0203	0.0654
	(0.0252)	(0.0405)	(0.0409)	(0.0432)	(0.120)
Treatment × No income bias	-0.0274	0.00584	0.0199	0.0197	0.0673
	(0.0345)	(0.0634)	(0.0645)	(0.0660)	(0.185)
Treatment × Pos. income bias	-0.0568*	-0.0699	-0.108	-0.171**	0.137
	(0.0334)	(0.0724)	(0.0775)	(0.0729)	(0.239)
Ref: No bias					
Neg. income bias	0.0183	0.0665	-0.00253	0.00895	-0.0651
	(0.0314)	(0.0539)	(0.0542)	(0.0590)	(0.155)
Pos. income bias	-0.00196	0.0917	0.00209	0.0891	-0.0175
	(0.0368)	(0.0705)	(0.0721)	(0.0753)	(0.222)
Ref: Germany					
USA	0.0246	-0.188***	-0.130***	-0.139***	0.137
	(0.0306)	(0.0492)	(0.0459)	(0.0487)	(0.138)
Russia	0.0450	-0.00154	-0.287***	0.269***	-0.712***
	(0.0359)	(0.0581)	(0.0608)	(0.0674)	(0.170)
France	-0.168***	-0.0631	-0.234***	-0.373***	-0.773***
	(0.0300)	(0.0548)	(0.0549)	(0.0539)	(0.161)
Spain	-0.0248	0.0500	-0.474***	-0.422***	-0.924***
	(0.0312)	(0.0510)	(0.0501)	(0.0512)	(0.150)
Brazil	-0.106***	0.339***	-0.0573	-0.449***	-0.492***
	(0.0319)	(0.0606)	(0.0637)	(0.0616)	(0.188)
Constant	0.210**	2.420***	3.395***	2.489***	6.511***
	(0.0991)	(0.190)	(0.186)	(0.220)	(0.562)
Observations	3005	3005	3005	3005	3082
R^2	0.083	0.056	0.069	0.120	0.128

Notes: OLS regressions with robust standard errors in parentheses. The dependent variables are (1) general trust (1=most people can be trusted or 0=Need to careful) and trust (4=trust completely to 1=Do not trust at all) in (2) press/media, (3) courts/legal institutions, and (4) government/parliament/political parties. Results for political interest are found in column (5). Control variables and survey weights are included.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A.9: Treatment effect on trust and political interest (by bias group, part 2)

	(1) General	(2) Media	(3) Courts	(4) Government	(5) Pol. interest
Treatment	-0.0274	0.00584	0.0199	0.0197	0.0673
	(0.0345)	(0.0634)	(0.0645)	(0.0660)	(0.185)
Ref: Treatment x no bias income bias					
Treatment × Neg. income bias	0.0373	0.0585	0.00608	0.00951	-0.0670
	(0.0311)	(0.0558)	(0.0559)	(0.0554)	(0.165)
Treatment × Pos. income bias	-0.0314	0.0160	-0.126	-0.102	0.0521
	(0.0348)	(0.0712)	(0.0773)	(0.0686)	(0.227)
Ref: Control x no income bias					
Control × Neg. income bias	0.0183	0.0665	-0.00253	0.00895	-0.0651
	(0.0314)	(0.0539)	(0.0542)	(0.0590)	(0.155)
Control × Pos. income bias	-0.00196	0.0917	0.00209	0.0891	-0.0175
	(0.0368)	(0.0705)	(0.0721)	(0.0753)	(0.222)
Constant	0.210**	2.420***	3.395***	2.489***	6.511***
	(0.0991)	(0.190)	(0.186)	(0.220)	(0.562)
Observations	3005	3005	3005	3005	3082
R^2	0.083	0.056	0.069	0.120	0.128

Notes: OLS regressions with robust standard errors in parentheses. The dependent variables are (1) general trust (1=most people can be trusted or 0=Need to careful) and trust (4=trust completely to 1=Do not trust at all) in (2) press/media, (3) courts/legal institutions, and (4) government/parliament/political parties. Results for political interest are found in (5). Control variables and survey weights are included. For country coefficients check Table A.8. * p < 0.10, ** p < 0.05, *** p < 0.01

Table A.10: Treatment effect on the importance of luck and charities

	(1) Luck	(2) Luck	(3) Charities	(4) Charities
Treatment		0.471**		0.167
		(0.225)		(0.213)
Ref: See notes#				
Treatment × Neg. income bias	-0.0172	-0.0948	0.0333	0.0726
	(0.146)	(0.201)	(0.144)	(0.196)
Treatment × No income bias	0.471**		0.167	
	(0.225)		(0.213)	
Treatment × Pos. income bias	-0.128	0.0501	-0.519*	-0.341
	(0.265)	(0.274)	(0.282)	(0.269)
Ref: No income bias				
Neg. income bias	0.393**		0.206	
	(0.189)		(0.179)	
Pos. income bias	0.649***		0.345	
	(0.242)		(0.249)	
Ref: Control x no income bias				
Control × Neg. income bias		0.393**		0.206
		(0.189)		(0.179)
Control × Pos. income bias		0.649***		0.345
		(0.242)		(0.249)
Ref: Germany				
USA	-1.740***	-1.740***	0.785***	0.785***
	(0.168)	(0.168)	(0.174)	(0.174)
Russia	-1.720***	-1.720***	0.775***	0.775***
	(0.209)	(0.209)	(0.209)	(0.209)
France	-1.415***	-1.415***	0.681***	0.681***
	(0.178)	(0.178)	(0.180)	(0.180)
Spain	-0.661***	-0.661***	1.292***	1.292***
	(0.171)	(0.171)	(0.174)	(0.174)
Brazil	-1.119***	-1.119***	1.417***	1.417***
	(0.217)	(0.217)	(0.217)	(0.217)
Constant	5.992***	5.992***	5.513***	5.513***
	(0.675)	(0.675)	(0.659)	(0.659)
Observations	3075	3075	2847	2847
R^2	0.091	0.091	0.077	0.077

Notes: OLS regressions with robust standard errors in parentheses. The dependent variables are the importance of luck (Columns 1-2; (1) In the long run, hard work usually brings a better life and (10) Hard work doesn't generally bring success - it's more a matter of luck and connections) and of charities (Columns 3-4; Private charities should play a role in redistributing income with (1)=Disagree completely to (10)=Agree completely). Control variables and survey weights are included. Using the same estimation, columns (a) focus on differences between control and treatment group by income bias (reference: control group x income bias), columns (b) on differences within the experimental groups (reference: treatment group x no bias group). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Treatment effect on drivers for a higher income position (by bias group)

	(1) Wealth	(2) Education	(3) Ambition	(4) Network	(5) Gender
Treatment × Neg. income bias	-0.0839	0.0158	0.0502	0.0194	0.0259
	(0.0594)	(0.0429)	(0.0474)	(0.0497)	(0.0617)
Treatment × No income bias	0.0949	0.0461	-0.0160	0.0252	0.0985
	(0.0906)	(0.0687)	(0.0802)	(0.0701)	(0.0888)
Treatment × Pos. income bias	-0.0769	-0.0796	0.0605	-0.0497	0.0533
	(0.106)	(0.0756)	(0.0968)	(0.0859)	(0.130)
Ref: No bias					
Neg. income bias	0.167**	0.0401	0.0404	0.0161	0.0899
	(0.0790)	(0.0609)	(0.0720)	(0.0655)	(0.0771)
Pos. income bias	0.112	0.142*	0.00635	0.0498	0.173
	(0.100)	(0.0744)	(0.0907)	(0.0774)	(0.107)
Ref: Germany					
USA	-0.101	-0.257***	0.307***	-0.124**	-0.156**
	(0.0696)	(0.0514)	(0.0540)	(0.0589)	(0.0718)
Russia	-0.267***	-0.199***	-0.150**	-0.116	-0.777***
	(0.0876)	(0.0616)	(0.0660)	(0.0713)	(0.0862)
France	-0.286***	-0.349***	0.0361	-0.0996	-0.183**
	(0.0797)	(0.0529)	(0.0599)	(0.0627)	(0.0788)
Spain	0.146**	-0.345***	-0.497***	0.0272	-0.370***
	(0.0724)	(0.0533)	(0.0602)	(0.0604)	(0.0764)
Brazil	-0.233***	0.157***	-0.553***	0.156**	-0.405***
	(0.0843)	(0.0570)	(0.0813)	(0.0688)	(0.104)
Constant	2.870***	3.652***	3.861***	3.638***	2.830***
	(0.263)	(0.201)	(0.242)	(0.214)	(0.292)
Observations	3015	3015	3015	3015	3015
R^2	0.039	0.067	0.109	0.023	0.057

Notes: OLS regressions with robust standard errors in parentheses. The dependent variables are the following drivers (1) wealth, (2) education, (3) ambition, (4) network, and (5) gender (5=essential to 1=not important at all). Control variables and survey weights are included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$