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Lifting the Veil of Ignorance – Survey Experiments on Preferences for Wealth Redistribution

Abstract

We study beliefs about wealth inequality and preferences for wealth redistribution. For this, we conduct a large-scale online survey in Germany. First, we analyze how well participants are informed about the German wealth distribution and their position in it. Second, we investigate how preferences for wealth redistribution are affected by an information experiment. One treatment group receives information about the shape of the German wealth distribution, while another treatment group receives information about their position in this distribution. Using a multidimensional approach to measure preferences for wealth redistribution, we find no significant average treatment effect for either treatment in the full sample, although those who overestimate their position reduce their aversion to inequality after learning their position, while those who underestimate their position are more likely to agree that anyone can become successful through hard work. We employ a data-driven approach to further investigate heterogeneity in treatment effects and present evidence that younger participants decrease their support for redistribution after learning about the shape of the wealth distribution. In contrast, older participants decrease their support after learning their position in the distribution.

JEL-Codes: C900, D310, D630, D830.

Keywords: wealth distribution, preferences for redistribution, inequality, survey experiment, information provision.

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1 Introduction

Over the past 30 years, wealth inequality in Germany has steadily increased. As reported by Albers et al. (2022, p.29), the top 10% now own about 60% of the country's wealth, up from 52% in 1988. In contrast, the bottom 50% have experienced a decrease in their share from 5% to less than 3% over the same period. According to the Meltzer-Richard model, an increase in inequality should lead to an increased demand for redistribution (Meltzer and Richard, 1981). However, this assumes that individuals are perfectly informed about their position in the distribution. A growing body of literature has shown that individuals across countries have biased beliefs about the shape of their country's *income* distribution and their position in it (Cruces et al., 2013; Kuziemko et al., 2015; Engelhardt and Wagener, 2018; Gimpelson and Treisman, 2018; Hoy and Mager, 2021; Bublitz, 2022; Gassmann and Timár, 2024). Biased beliefs can affect individuals' preferences for redistribution. This is supported by the existent, but not always conclusive, effect of information treatments in the above studies. Given that *wealth* is much more unequally distributed than *income*,[1] it is even more likely that beliefs about the *wealth* distribution are biased, with important consequences for preferences for wealth redistribution.

Our research aims to explore the relationship between (biased) beliefs about the *wealth* distribution in Germany and preferences for *wealth* redistribution. Based on a survey containing an information experiment, we want to shed light on belief formation and how correcting biased beliefs affects preferences for wealth redistribution. To capture beliefs about the wealth distribution, we consider two perspectives. The first concerns beliefs about the aggregate shape of the German wealth distribution. The second is about the perceived individual position in the German wealth distribution. This dual approach allows us to gain a deeper understanding of how the German public perceives wealth inequality, the mechanisms behind preference formation, and the role of information. This is highly relevant for policymakers, especially in the context of the often controversial public debate about wealth inequality.

So far, individual beliefs about wealth inequality and preferences for wealth redistribution have received little attention in the economic literature. Fisman et al. (2020) use an online survey to examine preferences for *joint* taxation of wealth and income in the U.S. by implementing a vignette study. Their findings indicate that participants generally demand that wealth be taxed, but they differentiate between different sources of wealth (e.g., wealth from inheritance vs. wealth from savings). Bastani and Waldenström (2021) provide participants in Sweden with information about the importance of inherited wealth and test the impact of this information on participants' support for inheritance taxation. There is evidence of increased support for inheritance taxation, which is likely due to the low salience of the size of inherited wealth.

Closest to our study is Albacete et al. (2022) who aim at measuring the effect of information about wealth inequality on preferences for wealth redistribution. Their study was conducted in Austria and implemented in the Household Finance and Consumption Survey. After a comprehensive elicitation of the participant's net household wealth, participants receive information about their household's position in the Austrian wealth distribution. While they find insignificant average

[1] In 2020 the top 10% *income* share was about 38% of Germany's income (Chancel and Piketty, 2021).

treatment effects, overestimators are more supportive of wealth taxation and underestimators decrease their support for wealth taxation after being informed about their household's position in the Austrian wealth distribution.

We contribute to the literature on the causal impact of information on preferences for wealth redistribution. To this end, we investigate, first, how well individuals in Germany are informed about the shape of the wealth distribution and their position in it, and, second, whether the correction of biased beliefs affects preferences for wealth redistribution. To answer these questions, we conduct a large-scale, quota-representative online survey in Germany. About 2,600 participants answer questions about their wealth and their beliefs about the shape of the German wealth distribution as well as their position in it and preferences for wealth redistribution. In contrast to Albacete et al. (2022), we focus on individual wealth. We consider individual wealth to be better suited than household wealth to identify the effect of information on preferences for wealth redistribution for two reasons. First, given the complex nature of wealth, accurately measuring household wealth can be even more difficult than measuring individual wealth. Second, the distribution within and contribution to total household wealth becomes invisible when wealth is aggregated at the household level. As a further contribution, we want to improve on survey item design from the International Social Survey Project (ISSP) used in studies on perceptions of inequality (e.g., Gimpelson and Treisman, 2018; Knell and Stix, 2020), where it is not always clear if questions refer to distributions of income or wealth. We come back to these issues in the following section.

As part of our information experiment, we randomly assign participants to two treatment groups and one control group. The first treatment group receives information about the shape of the German wealth distribution using histograms, while the second treatment group receives information about their position in the wealth distribution. The control group does not receive any information. We then elicit different dimensions of preferences for redistribution from all three experimental groups and finally ask all participants again about their beliefs about the shape of the wealth distribution and their position in it. To elicit preferences for wealth redistribution, we use a multidimensional approach. Following the literature, we distinguish between inequality aversion, i.e. aversion to wealth inequality, and support for redistributive policies (see, e.g., Choi, 2021; Hoy and Mager, 2021). Our third outcome is related to equality of opportunity and our fourth outcome asks about preferences for the introduction of a wealth tax in Germany. With these four outcome questions, we aim to capture the complex nature of preferences for redistribution.

Based on this unique dataset, we first analyze participants' beliefs about wealth inequality and their position in the distribution descriptively using simple correlational probit regressions. Our descriptive analysis shows that about 40% of the participants correctly select the histogram representing the German wealth distribution. In addition, our regression analysis on the determinants of prior beliefs shows that men, left-wing participants, and participants with higher financial literacy scores are more likely to select the correct histogram. In contrast, participants are mostly unaware of their own position in the wealth distribution. As often observed in the literature on income inequality (Cruces et al., 2013; Engelhardt and Wagener, 2018; Hoy and Mager, 2021; Bublitz, 2022; Gassmann and Timár, 2024), prior beliefs exhibit a strong bias toward the center of the distribution. Participants with higher financial literacy scores are more likely to underestimate and less likely to overestimate their position. Additionally, we find that participants with left-wing attitudes are less likely to underestimate their position.

Looking at treatment effects in a second step, we find no average treatment effects (ATE) of either treatment for the full sample. We also distinguish between the bottom 40% and the top 40% of the wealth distribution. This differentiation aligns with the theoretical expectation that the relatively poor would exhibit stronger support for wealth redistribution if driven by self-interest (Meltzer and Richard, 1981). We find that once individuals know their position, the relatively poor reduce their inequality aversion, while the relatively rich become more convinced that hard work leads to success. The latter finding aligns with theoretical predictions, while the former does not. Instead, it replicates findings in the context of income inequality. Hoy and Mager (2021) coin the term "benchmarking" to explain this phenomenon, noting that participants in the bottom 40% of the income distribution who overestimate their position become less concerned about inequality when they realize their lower position, possibly because they perceive their standard of living as average given that most of them overestimated their position. A similar mechanism may be at work in our study.

Finally, we analyze the heterogeneity of treatment effects using a causal forest approach (see Athey and Imbens, 2016; Wager and Athey, 2018; Athey et al., 2019). This data-driven approach was developed to overcome ad hoc assumptions about relevant covariates and to identify non-linear heterogeneities. We find that several of our covariates are important for treatment effect heterogeneity. We provide detailed insights into the role of age, trust in official statistics and institutions as well as individual wealth levels. We show that younger and older participants respond similarly to both treatments with respect to inequality aversion, but have opposing reactions in the support for redistribution. In addition, we find that getting informed about the shape of the German wealth distribution leads to less support for redistribution among those with low trust in institutions and statistics and to stronger inequality aversion among those with higher levels of trust in statistics. Lastly, we find some non-linear heterogeneities related to wealth. While relatively poor participants tend to increase their support for a wealth tax as a response to the personalized treatment, richer participants tend to decrease their support for a wealth tax. Interestingly, the richest 20% show less negative reactions than their slightly poorer counterparts, with a significant share of this group even increasing their support for a wealth tax.

Our paper is structured as follows: In Section 2, we describe the setup of our survey and the experimental design, and derive our hypotheses. In Section 3, we present descriptive results on the distribution of wealth in our sample, prior beliefs about wealth inequality, and preferences for wealth redistribution. Section 4 explains our empirical strategy. Section 5 presents our results on the determinants of (biased) prior beliefs and treatment effects, while the heterogeneity of the treatment effects is analyzed in Section 6. Finally, Section 7 concludes.

2 Data and Experimental Design

2.1 Survey Data

We conducted an online survey with approximately 2,600 participants in which we implemented our information provision experiment. The survey is quota representative of the German population in terms of age, gender, residence in East/West Germany, and educational attainment (secondary level). Participants were recruited in March 2023 through GapFish GmbH, a professional survey provider. Our questionnaire collects information about participants' wealth. A detailed explanation of how we do this using a step-by-step process is provided below.

In addition, we ask about participants' beliefs about wealth inequality, i.e., the distribution of wealth and their position in the wealth distribution, their preferences for wealth redistribution along various dimensions, political attitudes, and sociodemographic characteristics. At the beginning of the survey, participants had to pass a standard attention screener (Chandler et al., 2019; Haaland et al., 2023).

Our covariates include age, gender, residence in East/West Germany, employment status, migration background, education (school/university), financial literacy, income, and wealth as elicited in the survey. We also control for political orientation on a left-right spectrum, trust in public institutions, trust in official statistics, and participants' beliefs about their wealth position. Table 1 presents summary statistics for all of our covariates (see Appendix A for detailed descriptions of the variables). Information on our outcome variables is provided later in this section.

2.2 Elicitation of Individual Wealth

Unlike the approach of Albacete et al. (2022), who measure net wealth at the household level, we measure individual net wealth. We argue that individual wealth is better suited to identify the effect of information on preferences for wealth redistribution for two reasons. First, given the complex nature of wealth, accurately measuring household wealth may be even more difficult than measuring individual wealth. As the number of household members increases, the potential biases due to someone not knowing their (or their partner's) wealth quickly add up. Second, in hetero-normative families, the implications of the gender wealth gap become invisible when wealth is aggregated at the household level. In Austria, the average net wealth of male single households is about twice the average net wealth of female single households (Schneebaum et al., 2018, p. 307). However, this pattern does not seem to be limited to single households. Sierminska et al. (2010) find that the gender wealth gap in Germany is particularly large among married couples.[2] This is not surprising as the majority of unpaid care work is still done by women, leading to lower labor market participation and fewer opportunities to accumulate wealth (Sierminska et al., 2010). In addition, access to household wealth may not be equally distributed between spouses (Sierminska et al., 2010; Schneebaum et al., 2018). Therefore, we argue that beliefs about wealth inequality, and especially perceptions of one's own wealth position, should be measured at the individual level, as beliefs may vary within the household based on one's

[2] Note that when the study of Sierminska et al. (2010) was published, same-sex marriage was not yet legal in Germany. Therefore, "married couples" refers only to marriages between a man and a woman.

Variable	N	Mean	Std. Dev.	Min	Max
Covariates					
Age	2,175	50.322	15.959	18	93
Female	2,175	0.509	0.500	0	1
East	2,175	0.139	0.346	0	1
Employed^R	2,175	0.495	0.500	0	1
Civil servant	2,175	0.025	0.156	0	1
Self-employed	2,175	0.046	0.209	0	1
Unemployed	2,175	0.154	0.361	0	1
Retired	2,175	0.280	0.449	0	1
Migration background	2,175	0.320	0.467	0	1
Married	2,175	0.439	0.496	0	1
Low education	2,175	0.334	0.472	0	1
Mid education^R	2,175	0.435	0.496	0	1
University	2,175	0.242	0.428	0	1
University parent	2,175	0.210	0.407	0	1
Financial literacy	2,175	2.186	0.912	0	3
Low income	2,175	0.095	0.293	0	1
Mid Income^R	2,175	0.704	0.457	0	1
High income	2,175	0.201	0.401	0	1
Net wealth (in 1000s)	2,175	144.005	262.064	−48	2,057
Left	2,175	0.134	0.341	0	1
Centrist^R	2,175	0.782	0.413	0	1
Right	2,175	0.084	0.277	0	1
Trust institutions	2,175	5.319	2.809	0	10
Trust statistics	2,175	5.048	2.740	0	10
Prior Beliefs					
Histogram correct	2,175	0.404	0.491	0	1
Own position	2,175	2.833	1.037	1	5
Position under	2,175	0.450	0.498	0	1
Position over	2,175	0.303	0.460	0	1
Outcome Variables					
Inequality aversion	2,175	8.200	2.213	0	10
Support for redistribution	2,175	6.616	2.820	0	10
Equality of opportunity	2,175	5.619	2.675	0	10
Support for tax	2,175	0.491	0.500	0	1

Table 1: Summary Statistics

Notes: This table presents the summary statistics of our control variables, prior beliefs, and outcome variables. R marks the reference categories in our regressions.

own contribution to the household's wealth and the distribution of wealth within the household. To still account for variation in perceptions due to being married, we control for marital status in all of our analyses.

Eliciting individual wealth is relatively uncommon in online surveys, most likely due to the sensitive nature of disclosing this information. Despite some potential advantages of face-to-face or telephone interviews, the key advantage of online surveys for collecting wealth data is anonymity. Online surveys not only increase participants' willingness to answer more sensitive questions (see, e.g., Čehovin et al., 2023), they also mitigate concerns about experimenter demand effects (Haaland et al., 2023).

To ensure comparability with existing data, which we use as a baseline for the distribution of wealth in Germany, our questions on individual wealth are closely related to the questionnaire of the German Socioeconomic Panel (SOEP). Our only modification was to merge some wealth categories to reduce the total number of questions on this topic. The categories we used to elicit net individual wealth are the following: Real estate, financial assets, life insurance/private pension insurance, vehicles, tangibles, commercial business, and debt.[3] We ask about each category in a step-by-step manner, starting with a yes/no question about owning that category of asset, followed by one or more questions about its value. We do the same with debt. The wording of all questions used to elicit individual net wealth is presented in Appendix B.

One of the key concerns when collecting data on individual wealth is the reliability of participants' responses. We take several steps to ensure that we obtain an accurate picture of our participants' wealth. First, we elicit individual net wealth in a step-by-step process to help participants become aware of the different categories relevant to the calculation of their net wealth. Second, we give participants the option of not answering questions. This leaves us with a higher number of observations we have to exclude due to incomplete responses but it is still preferable to having complete observations with inaccurate or dishonest responses. Third, we let participants go back and forth throughout the wealth elicitation process. If they realized that they gave inaccurate answers because they misunderstood what we included in a particular wealth category, they could simply go back and change their answer.

Finally, we manually review each observation for suspicious response patterns. Since total wealth was elicited through various wealth categories, participants were identified who, for example, made identical odd-number statements across multiple wealth categories or claimed ownership of 150 housing units worth a total of 1,000 EUR. These participants, who made up about 2% of our sample, were flagged as having given suspicious and potentially false responses to the wealth questions. As to the related concern of incomplete responses, we find a high willingness of participants to disclose highly sensitive information about their wealth. Only about 8.7% of respondents chose "Do not know/Do not want to answer" for at least one of the wealth questions.

[3] We are aware that public pension entitlements are not included here. In the case of Germany, the inclusion of these entitlements would change the distribution significantly, as many employees rely on the statutory pension insurance for their retirement. Bartels et al. (2023) have shown that including public pension entitlements increases the share of wealth held by the bottom 50% and decreases the share of wealth held by the top 1%, i.e., it reduces wealth inequality. However, public pension entitlements cannot be sold or divested, so the money accumulated in them is not accessible under any circumstances other than retirement. Therefore, we follow the convention of the international economic literature and include only marketable wealth (Albers et al., 2022). In our regressions, we include employment status as a control, considering that self-employed individuals may accumulate more marketable wealth compared to employed ones, while civil servants may accumulate less. Self-employed individuals typically do not contribute to the statutory pension insurance, while civil servants benefit from superior pension plans, which may affect their measured wealth. Furthermore, we conduct a robustness check as seen in Table D.3 where we exclude civil servants and self-employed participants from our sample. Our findings, including the heterogeneity analysis, are robust to this exclusion.

If this response was given, we assigned a value of 0 to the respective wealth category during the survey so that the participant could continue with the survey.

Table C.1 tests for balance between participants with complete responses and those with suspicious or incomplete responses. In particular, the incomplete group appears to be significantly different from our full sample on several covariates. However, there is no clear pattern regarding their characteristics. On the one hand, they seem to have significantly lower financial literacy scores, but on the other hand, they are significantly more likely to report high incomes. It appears that this group does not represent a specific social group, but rather includes participants who were probably less attentive in responding to our survey.

For our main analysis, we omit both participants who gave a “Do not know/Do not want to answer” reply to at least one of the wealth questions and those with suspicious patterns in their wealth responses. We expect the gain in data quality to outweigh the loss in sample size, especially given the sensitive nature of the topic.[4] To address the issue of outliers, we top and bottom code at 1% to exclude extreme outliers. In addition, we exclude a small number of participants who did not respond to all of our relevant covariates. Our final sample size for the main analysis is then 2,175 participants.

2.3 Experimental Design

We conduct an information provision experiment to identify the causal effect of correcting biased beliefs about wealth inequality on preferences for wealth redistribution. We randomly assign participants to two treatment groups and one control group. The first treatment group receives information about the shape of the German wealth distribution using histograms, while the second treatment group receives information about their position in the wealth distribution. As expected, our sample is balanced across our covariates (see Table C.2). Since randomization between experimental groups was successful, our information treatment presents an exogenous intervention that allows us to estimate causal effects. This section describes the details of our pre-registered experimental design (see Figure 1 for a visualization of the timeline).

2.3.1 Prior Beliefs

We elicit prior beliefs about wealth inequality from two perspectives: First, we show participants four simple histograms and ask them to choose the one representing the German distribution of net individual wealth. This allows us to gain insights into how our participants perceive wealth inequality at the aggregate level. Second, we ask participants where they think they are in the German wealth distribution. For this, we provide them with their net wealth calculated from their responses to the individual wealth questions. They are then asked to choose the quintile of the wealth distribution to which they believe they belong, which gives us insights into where participants see themselves *relative* to the rest of the German population.

Since both of the methods we use to elicit prior beliefs require some understanding of basic economic concepts, we have tried to keep our questions as simple as possible including visualizations

[4]As a robustness check, we present results of our estimates including these omitted participants (see Table D.2). Our findings are robust to this inclusion.

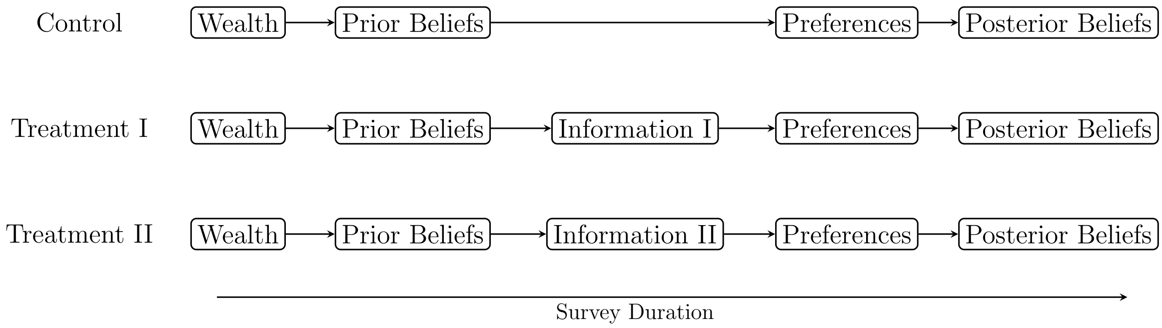


Figure 1: Timeline of Survey

Notes: This figure visualizes our experimental design and the order in which different components appeared in the survey.

and explicit explanations. The issue of designing survey items that are too technical for the average layperson has been the subject of some debate in the literature. Heiserman and Simpson (2021) have specifically tested different measures for capturing beliefs about aggregate inequality and conclude that stratification belief diagrams, as used in the International Social Survey Project (ISSP), are one of the best measures for accurately capturing beliefs about aggregate inequality. The diagrams in the ISSP questionnaire are histograms that visualize different distributions of resources in a society. However, the details of the wording in the ISSP questionnaire have some shortcomings. Participants are asked to choose a histogram that "best" represents their country's "type of society" (Gimpelson and Treisman, 2018, p. 31), without even specifying whether the diagrams represent income or wealth distributions before or after taxes and transfers. To address these shortcomings, our experiment provides participants with a clear explanation of what our histograms represent. As shown in Figure 2, we designed the histograms specifically for our needs so that one of the histograms exactly represents the German wealth distribution. This approach allows us to avoid any ambiguity and ensures that we only provide completely accurate information to participants in the first treatment group. Participants are also given a brief explanation of how to read the graphs and are then asked to choose which graph represents the German wealth distribution.[5]

To elicit beliefs about the individual position in the wealth distribution, we rely on the well-established approach of combining a graphical cue with aggregation of possible responses into quintiles (Hoy and Mager, 2021). Figure 3 shows how we structured this survey item. To help participants understand the task, we remind them of the definition of net wealth and that we have just calculated their net wealth. The answer options are sorted vertically such that the richest group is at the top.

Combining these two perspectives on beliefs about wealth inequality allows us to gain a deeper understanding of beliefs and mitigates the weaknesses of using only a single measure (Heiserman and Simpson, 2021).

[5]The German wealth distribution is shown in graph (A), based on the 2017 SOEP data. Graph (B) shows the Belgian wealth distribution and graphs (C) and (D) are fictional.

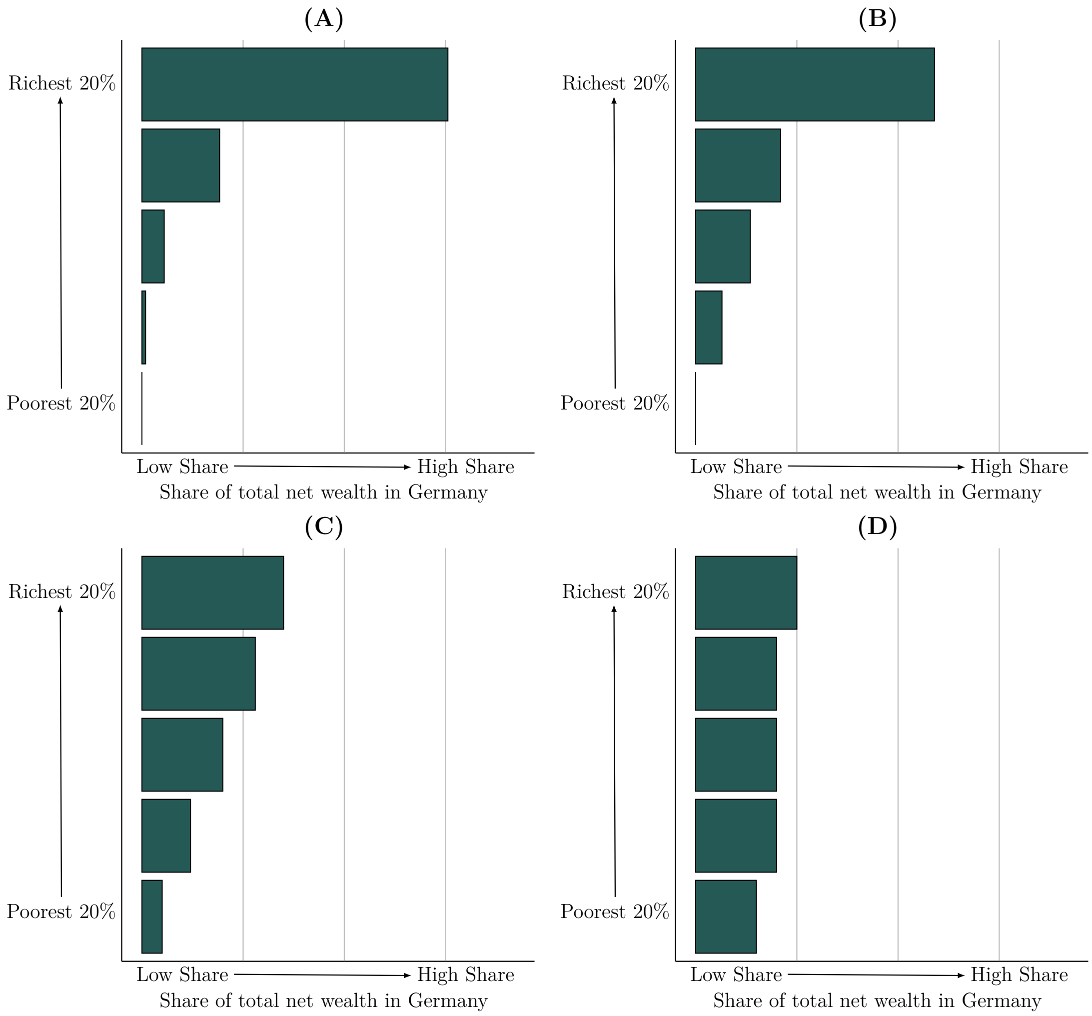


Figure 2: Survey Item: Prior Beliefs (German Wealth Distribution)

Notes: This figure shows the histograms presented to our survey participants. Additionally, participants were provided with a short explanation of how to read these diagrams: "The following graphs show 4 different wealth distributions, one of which shows the German wealth distribution. A wider bar indicates that this group of society owns a larger share of total wealth."

2.3.2 Information Treatments

After eliciting prior beliefs, the two treatment groups receive one piece of information while the control group goes straight to the questions about their preferences for redistribution. The two treatments relate directly to our two perspectives of wealth inequality for which we elicited prior beliefs. The first treatment group is told which histogram represents the German wealth distribution (*aggregate treatment*). The second treatment group is informed about their actual position in the wealth distribution (*personalized treatment*). In addition, participants in this group are informed whether they underestimated, correctly estimated, or overestimated their position to help them understand the implications of the information for their estimates. Our baseline wealth distribution from the 2017 SOEP data was used to determine each participant's


Think about the distribution of wealth in Germany. What do you think, which percentage of adults in Germany has a **lower net wealth than yourself**?

Your net wealth is your total wealth minus all debt. Please note that we have just calculated your wealth based on the most important wealth categories.

almost everyone
80%-100%
60%-79%
40%-59%
20%-39%
0%-19%
almost nobody

Figure 3: Survey Item: Prior Beliefs (Individual Wealth Position)

Notes: This figure shows our survey item to elicit beliefs about the participants' individual position in the wealth distribution.

position.[6]

2.3.3 Preferences for Redistribution

Our outcome variables capture different dimensions of preferences for wealth redistribution. First, we use two literature-based survey items to separately capture aversion to wealth inequality and support for wealth redistribution. Although these preferences are likely related (for *income* inequality see, e.g., Choi, 2021; Hoy and Mager, 2021), research suggests that the relationship between inequality aversion and support for redistribution may not be linear (Kuziemko et al., 2015). In the international sample of Hoy and Mager (2021, p. 316), 11% to 23% of participants across countries indicate that they think *income* inequality is too high, but that they do not see it as the role of the government to reduce it. Kuziemko et al. (2015) suggest that low trust in the government may explain the divergence between inequality aversion and support for redistribution for some individuals again referring to *income*. While the literature has focused primarily on *income* in these survey questions, we believe it is also reasonable to differentiate between inequality aversion and support for redistribution in the context of *wealth*.

Second, we measure the effect of our treatment on perceptions of equality of opportunity. Economic inequality and equality of opportunity are often thought to be closely related (Alesina et al., 2018): If equality of opportunity is high, higher levels of economic inequality may be tolerated; if economic inequality is high, equality of opportunity may be perceived as low. The exact wording of our outcome variables is given in the following.

Please indicate whether you agree or disagree with the following statements:

[6]The SOEP includes the wealth questionnaire only every 5 years. Therefore, we used the most recent data set available at the time of our survey.

- **Inequality aversion**: "The difference in wealth between the rich and the poor in Germany is too large" (as in Hoy and Mager (2021) for income); answer options ranging from "I do not agree" (0) to "I fully agree" (10).
- **Support for redistribution**: "It is the responsibility of the German government to reduce the wealth difference between the rich and the poor in Germany. / *Please note that to reduce the wealth difference, the government either has to reduce spending in other areas (such as infrastructure or defense), increase public debt, or increase taxes for certain groups.*" (based on Hoy and Mager (2021) with the note on the trade-off added by us); answer options ranging from "I do not agree" (0) to "I fully agree" (10).

Furthermore, we ask:

- **Equality of opportunity**: "Some people think that anybody can become successful if they work hard enough. Others think that the success of a person is determined by other factors (e.g. ancestry, luck, health). What do you think?" (based on Alesina et al., 2018, we combined multiple survey items); answer options ranging from "Anybody can become successful if they work hard enougj" (0) to "Other factors determine success" (10).

Finally, we ask participants about a specific policy measure, namely the (re-)introduction of the wealth tax in Germany. After being declared unconstitutional in 1995, the German government stopped collecting the wealth tax (Albers et al., 2022, p. 8).[7] On the same page, participants are given the opportunity to indicate their preferred tax rate and exemption. We made sure that these follow-up questions were salient to all participants in order to reduce the noise in the preferences for the introduction of a tax.

The wording is as follows (loosely based on the 2017 Austrian Household Finance and Consumption Survey, HFCS):

- **Support for tax**: "Are you in favor or opposed to the introduction of an annual wealth tax in Germany?"; answer options on a 5-point Likert scale ranging from "I am opposed" (1) to "I am in favor" (5).
- **Tax rate**: "If you are in favor of the introduction of a wealth tax, what should be the tax rate for an annual tax on individual net wealth?"; answer options from "Less than 0.5%", "Between 0.5% and below 1%", "Between 1% and below 2%", "Between 2% and below 5%" to "5% or higher" including "I do not know".
- **Tax exemption**: "If you are in favor of the introduction of a wealth tax, what should be the tax exemption (amount of wealth below which no tax is paid) for an annual wealth tax?"; answer options from "Up to 50,000 Euro", "Between 50,000 Euro and below 250,000

[7] Specifically, it was ruled unconstitutional for different forms of wealth to be taxed differently. Under the German wealth tax, real estate was protected from this taxation, which made other forms of wealth less favorable compared to real estate. So technically, it was not the wealth tax itself that was found unconstitutional, but rather the specific design of the tax. However, the Wealth Tax Act still exists today and provides that private assets are taxed annually at 1% of taxable assets, while business assets are taxed at 0.5% (§10 Absatz 1 VStG). We believe that most individuals in Germany are unaware that this law is technically still in effect. Therefore, we ask whether participants support or oppose the *introduction* of an annual wealth tax.

Euro", "Between 250,000 Euro and below 1 million Euro" to "1 million Euro or more" including "I do not know".

By using these different dimensions of preferences for redistribution, we account for the complex nature of such preferences in order to capture them as accurately and comprehensively as possible.

2.4 Hypotheses

While theoretical models assume that individuals are perfectly informed and form selfish preferences (Meltzer and Richard, 1981), empirical studies of *income* inequality have shown that individuals have biased beliefs about the shape of their country's income distribution and their position in it (see, e.g., Cruces et al., 2013; Kuziemko et al., 2015; Hoy and Mager, 2021). Our pre-registered hypotheses are based on these theoretical predictions, but take into account recent empirical evidence.

For prior beliefs, our hypotheses are as follows:

Hypothesis I: Participants underestimate aggregate wealth inequality. On average, they choose histograms (B) or (C) instead of (A). Yet, they are aware that wealth in Germany is not distributed (nearly) equally, which would correspond to histogram (D).

Hypothesis II: Participants are unaware of their position in the wealth distribution. In the aggregate, the beliefs suggest a bias towards the center of the wealth distribution.

Hypothesis IIa: Participants with relatively little wealth overestimate their position in the wealth distribution.

Hypothesis IIb: Participants with relatively high wealth underestimate their position in the wealth distribution.

For the treatment effects, we have the following hypotheses:

Hypothesis III: Providing information about the aggregate shape of the wealth distribution, on average, increases support for redistribution when participants learn that wealth is distributed more unequally than they thought.

Hypothesis IV: Providing information about the own wealth position leads participants to change their support for redistribution, varying with their actual position in the wealth distribution.

Hypothesis IVa: Providing information about the own wealth position leads those in the bottom two quintiles to increase their support for redistribution. These participants become aware that they belong to the poorer half of the population and expect to benefit from redistribution rather than contribute to it.

Hypothesis IVb: Providing information about the own wealth position leads those in the top two quintiles to decrease their support for redistribution. These participants become aware that they belong to the richer half of the population and expect to have to contribute to redistribution rather than benefit from it.

3 Wealth Inequality and Policy Preferences

In this section, we present an overview of our data using descriptives. The structure of this section follows that of our questionnaire: We begin by comparing the wealth distribution of our sample with our baseline distribution from the SOEP. We then present data on participants' prior beliefs about their own position in the distribution and how these beliefs compare to their actual positions. Finally, we present the responses to our outcome questions.

3.1 Distribution of Wealth

Table 2 reports some key statistics of our sample relative to the SOEP baseline wealth distribution. The data show that our distribution is very similar to the SOEP distribution for most of the measures shown, especially the Gini coefficient and the median. However, our mean and 90% quantile are slightly higher than in the SOEP, suggesting an over-representation of relatively rich participants, while at the same time, the 25% quantile is lower. Figure 4 provides a visualization of the comparison of the distributions of wealth as derived from our sample and from the SOEP.

Measure	SOEP	Our Data
Gini Coefficient	0.759	0.754
Mean (in EUR)	108,449	144,005
Median (in EUR)	26,260	27,000
P90 (in EUR)	419,766	440,000
P25 (in EUR)	1590	1000

Table 2: Data Comparison

Notes: This table compares the wealth distribution according to our baseline SOEP data with the distribution in our survey. The SOEP statistics on net wealth are obtained from Grabka and Halbmeier (2019).

We offer some possible explanations for the slight deviations: On the one hand, it is possible that the wealth distribution changed to some extent between 2017 (the most recent SOEP wealth data at the time of our survey) and 2023 (the year of our survey). As seen in IAW (2015, p. 119), the wealth distribution usually does not fluctuate much, even over 10 years and more. However, given the events that occurred between 2017 and 2023, particularly the COVID-19 pandemic and the energy crisis, and their potential impact on individual wealth, the distribution may have shifted slightly. Participants with low wealth may have been forced to dissave either because of the financial hardship they experienced during the pandemic, or because of rising energy prices and (near) double-digit inflation rates, while real wage growth lagged behind. The inflation rate is also likely to have directly affected the savings of the bottom 50%, most of which are held in low-interest savings accounts (Bundesbank, 2022). On the contrary, participants with high wealth may have seen their wealth appreciate, e.g. due to rising real estate prices (Bundesbank, 2022).

On the other hand, it is possible that participants at the upper end of the distribution rounded their responses quite generously. When asked about the current value of their assets, most participants would only be able to give an approximate estimate. This is sufficient for our

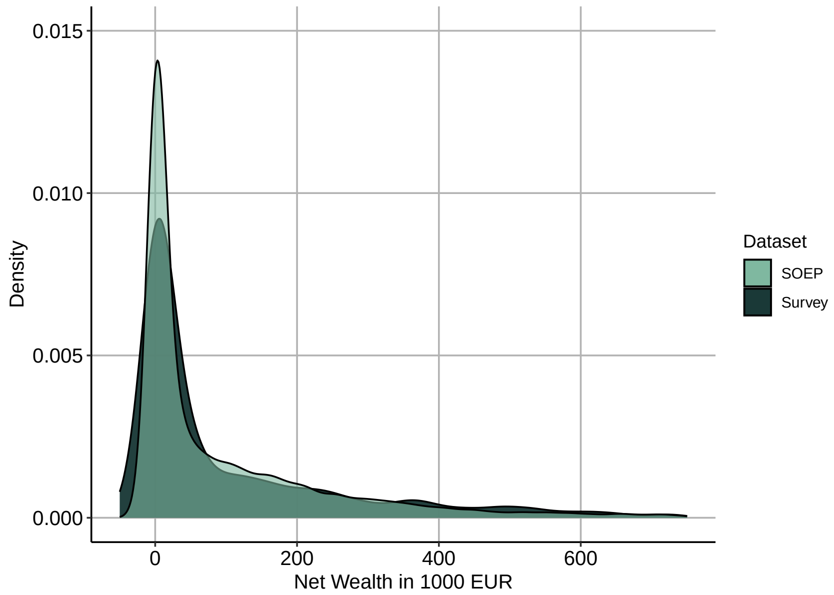


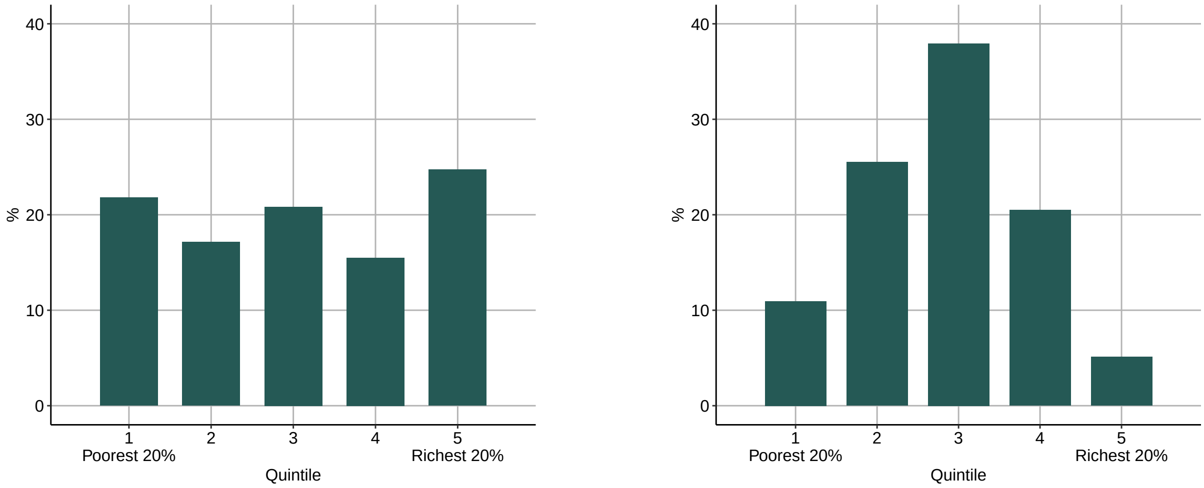
Figure 4: Comparison of the distribution of wealth derived from our survey and from the SOEP

Notes: This figure shows the wealth distribution we obtained from our sample (excluding incomplete and suspicious responses) in comparison to our baseline distribution from the SOEP.

experiment since we only divide participants into quintiles, which are quite broad. However, this may have slightly skewed our distribution.

The latter explanation for the differences between the SOEP distribution and our distribution is further supported in Figure 5a. This figure visualizes the distribution of quintiles of our participants based on the SOEP distribution. If we had a perfectly representative sample of the German population, each quintile should contain close to 20% of our sample. However, we observe some over-representation especially in the fifth quintile, while the second and fourth quintiles are underrepresented. If the distribution had simply shifted upward compared to 2017, we would not expect to see the under-representation of the fourth quintile. Instead, it seems more plausible that rounded estimates can explain the small imbalances in our distribution. The threshold for a participant to be placed in the second quintile instead of the first was a net wealth of > 0 EUR. Thus, participants who did not report the 50 EUR in their savings account because they considered it negligible would be placed in the first quintile despite being in the second quintile. As explained in the previous paragraph, a similar mechanism could have caused the slight over-representation of the fifth quintile. The threshold between the fourth and fifth quintiles was 182,000 EUR. Given this rather odd number, it seems plausible that participants with net wealth close to this level would round up to a more even number.[8] Overall, however, these imbalances are minor and we do not expect them to affect the results of our information experiment.

[8]The wealth thresholds are as follows. First quintile: ≤ 0 EUR, second quintile: > 0 EUR and $\leq 9{,}700$ EUR, third quintile: $> 9{,}700$ EUR and $\leq 59{,}034$ EUR, fourth quintile: $> 59{,}034$ EUR and $\leq 182{,}000$ EUR, fifth quintile: $> 182{,}000$ EUR.



(a) Wealth Position (Actual)

(b) Wealth Position (Beliefs)

Figure 5: Summary of Individual Wealth Position (Actual and Beliefs)

Notes: These figures visualize our participants' actual wealth positions (a) and their beliefs about their positions (b).

3.2 Prior Beliefs

While Figure 5a shows the frequency of our participants' actual quintiles, Figure 5b visualizes their beliefs about their position in the wealth distribution. We observe a strong bias toward the center of the distribution, with nearly 40% of participants thinking that they belong to the third quintile and only 11% and 5% of respondents believing they are in the first and fifth quintiles, respectively. The literature consistently finds this as a recurring pattern regarding beliefs about *income* inequality (Cruces et al., 2013; Engelhardt and Wagener, 2018; Hoy and Mager, 2021; Bublitz, 2022). Based on Hypothesis II, we expected a similar pattern to emerge in the context of wealth, and our evidence supports this.

To gain further insights into the biases in beliefs, Table 3 shows the mean of the average perceived quintile, the average bias, and the share of participants who correctly estimated their position. These means are reported for the full sample and for each quintile of individual wealth separately. We find that the average perceived quintile ranges from 2.52 for participants in the first quintile to 3.31 for those in the fifth quintile. This range is quite narrow. Accordingly, the average biases at both ends of the distribution are substantial, i.e. participants at both ends of the wealth distribution significantly misperceive their position in the wealth distribution. Consistent with the bias toward the center of the distribution in Figure 5, most participants in the poorer quintiles overestimate their position, while most participants in the richer quintiles underestimate their position. These results support Hypotheses IIa and IIb. Potential explanations for biased perceptions about *income* inequality have been identified in the literature. Cruces et al. (2013) note that people tend to compare themselves with others of similar backgrounds, which can distort their views of reality. Their study finds a negative correlation between having a diverse social background and the extent of perception biases. Building on this, Hoy and Mager (2021) introduce the term "benchmarking" to explain that the majority of participants perceive themselves as being in the center of the income distribution. They argue that individuals often consider their own standard of living to be average – because it is about average within their peer group – which can lead to systematic misperceptions.

The last column of Table 3 reports the share of participants who selected the correct histogram when asked about the German wealth distribution. 40% of participants chose the correct histogram, while 60% chose one of the histograms showing a more equal wealth distribution. The share of correct answers is slightly lower for poorer participants and slightly higher for richer participants. Overall, these numbers support our Hypothesis I, which states that (the majority of) participants underestimate wealth inequality in Germany.

Individual net wealth				German distribution
Actual quintile (1)	Avg. perceived quintile (2)	Avg. bias (3)	Position correct (4)	Histogram correct
1	2.52	1.52	0.22	0.34
2	2.60	0.61	0.29	0.33
3	2.72	-0.28	0.46	0.41
4	2.93	-1.07	0.21	0.46
5	3.31	-1.70	0.08	0.47
Total	2.83	-0.21	0.25	0.40

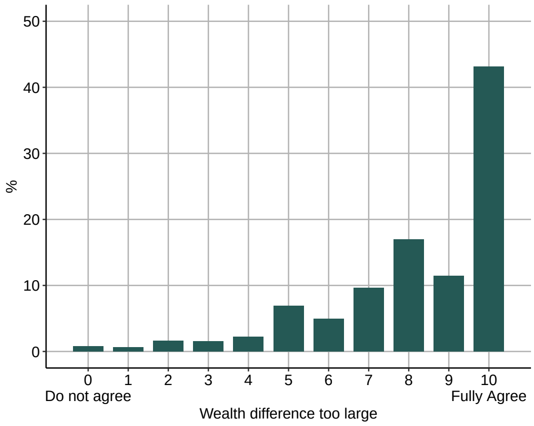
Table 3: Descriptive Statistics by Quintiles

Notes: This table shows the mean of the average perceived quintile, the average bias (caculated as (2)-(1)), the share of participants who correctly estimated their position, and the share of participants who correctly identified the histogram with the German wealth distribution.

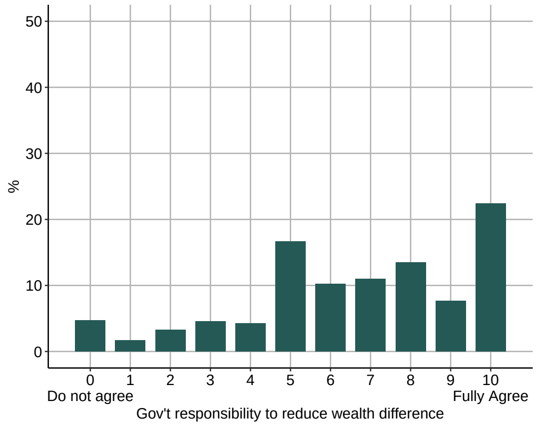
3.3 Preferences for Redistribution

In Section 2.3.3 we introduced our outcome variables, which are designed to capture different dimensions of preferences for wealth redistribution. While we use the term "preferences for redistribution" to talk about our outcomes in general, we specifically distinguish between inequality aversion, support for redistribution, perception of equality of opportunity, and support for the introduction of a wealth tax.

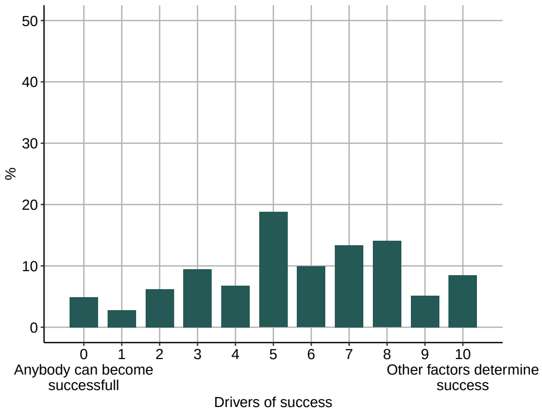
Figures 6a and 6b show participants' responses to our questions about inequality aversion and support for redistribution. We observe that inequality aversion is remarkably high, with more than 40% of participants fully agreeing that the wealth differences in Germany are too large. However, when explicitly asked about their support of redistributive policies, preferences for redistribution drop significantly. Now, only just over 20% of participants fully agree that the government should reduce wealth differences, while moderate support along answer options 5 and 6 is much more common. These results suggest that while participants may be averse to inequality, the costs of redistribution are not salient to them in the absence of some cues. A very similar mechanism was observed by Engelhardt and Wagener (2018), who first provided survey participants with information about their actual *income* position, with no significant effect on the demand for redistribution. The participants were then informed whether they were



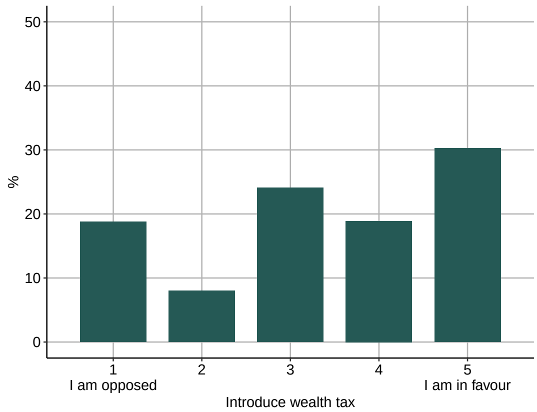
(a) Inequality Aversion



(b) Support for Redistribution



(c) Equality of Opportunity



(d) Support for Wealth Tax

Figure 6: Preferences for Redistribution

Notes: These figures show the distribution of responses for our outcome variables inequality aversion (a), support for redistribution (b), equality of opportunity (c) and support for a wealth tax (d).

net-beneficiaries or net-contributors to the tax-transfer system. The response to the second treatment was that relatively rich participants (i.e. net-contributors) reduced their demand for redistribution. In our case, the difference in answers between the two questions may also be due to a lack of trust in the German government to redistribute efficiently, as proposed by Kuziemko et al. (2015) to explain similar observations related to *income* inequality. To account for this, we use both inequality aversion and support for redistribution as regression outcomes. In addition, we control for participants' trust in public institutions and official statistics.

Furthermore, we use a third outcome to assess the perception of equality of opportunity and a fourth outcome to elicit support for the introduction of a wealth tax in Germany. As shown in Figure 6c, some participants believe that success in Germany is based solely on hard work, while others believe that factors such as ancestry, luck, and health play a key role. However, the majority of participants believe that the reality lies somewhere in between these two extremes. Regarding the introduction of a wealth tax, we find that almost 50% of participants are in favor of introducing such a tax (see Figure 6d). Less than 30% of participants are clearly against a wealth tax. It is important to note that participants were given the opportunity to specify various features of a potential wealth tax. However, for our study, we only consider the responses about the introduction of a wealth tax. We code this as a binary variable that takes the value of one for participants who rated their support for a tax as either 4 or 5, and zero otherwise.

We aim to capture a variety of dimensions of preferences for redistribution through our pre-registered outcome questions. The descriptive results suggest that participants were indeed attentive to our questions and were able to express their opinions in a nuanced way.

4 Empirical Strategy

4.1 Determinants of Prior Beliefs

Due to the ordinal nature of our two belief questions (4 categories for the aggregate beliefs about the German wealth distribution and 5 categories (quintiles) for the personalized beliefs about one's own position), we use probit models to examine factors contributing to prior beliefs.

For the aggregate beliefs we estimate the following equation:

$$CorrectA_i = \alpha_0 + \alpha \mathbf{X_i} + \varepsilon_i \tag{1}$$

where $CorrectA_i$ is a binary indicator of whether a participant correctly identifies the histogram with the German wealth distribution. $\mathbf{X_i}$ is our vector of socio-economic variables such as age, gender, residence in East/West Germany, education (school/university), employment status, income, and wealth, as well as the financial literacy score, political attitudes, and trust variables. ε_i is the error term.

For the personalized beliefs we estimate the following equations:

$$Under_i = \beta_0^u + \beta^u \mathbf{X_i} + \varepsilon_i^u \tag{2}$$

$$CorrectP_i = \beta_0 + \beta \mathbf{X_i} + \varepsilon_i \tag{3}$$

$$Over_i = \beta_0^o + \beta^o \mathbf{X_i} + \varepsilon_i^o \tag{4}$$

where $CorrectP_i$, $Over_i$ and $Under_i$ are binary indicators of whether a participant correctly estimated their position or over-/underestimated their position by at least one quintile. $\mathbf{X_i}$ is the same vector as in equation 1, and ε_i is the error term.

4.2 Preferences for Redistribution

To identify the effect of our treatments on our outcome variables we estimate the following equation:

$$y_i = \gamma_0 + \gamma_1 T1_i + \gamma_2 T2_i + \gamma \mathbf{X_i} + \varepsilon_i \tag{5}$$

where y_i is one of our outcome variables as explained in Section 2.3.3, $\mathbf{X_i}$ is the vector of explanatory variables as above, and $T1_i$ and $T2_i$ are our treatment indicators for the aggregate treatment and the personalized treatment, respectively. ε_i is the error term.

5 Main Results

5.1 Determinants of Prior Beliefs

In the first step of our analysis, we examine determinants of prior beliefs. We aim to distinguish between participants with biased and unbiased views on wealth inequality. Table 4 presents the average marginal effects for Equations 1 to 4 from probit regressions. Column (1) examines whether a participant selected the correct histogram for the German wealth distribution. 878 participants out of our 2,175 participants chose the correct histogram. For columns (2) to (4), the outcome variables indicate whether participants underestimated, correctly estimated, or overestimated their position in the wealth distribution. Out of our 2,175 participants, 979 underestimated their position, 537 correctly estimated it and 659 participants overestimated it.

We present several explanatory variables that are of particular interest in explaining (un)biased beliefs. These variables include age, gender, financial literacy, net wealth, marital status, political leaning, trust in institutions and statistics, and prior beliefs about one's own position. The financial literacy literature has shown that younger and older adults, on average, have lower financial literacy than middle-aged adults (Lusardi and Mitchell, 2011) and that women, on average, have lower financial literacy than men (Lusardi et al., 2017). Since we expect a positive correlation between financial literacy and the ability to understand and process our questions about wealth inequality, we consider age, gender and financial literacy to be relevant. In their study in the income context, Engelhardt and Wagener (2018) show that the actual position in the income distribution and ideology (measured on a left-right scale) are highly relevant in explaining prior beliefs. We therefore expect that participants' net wealth, as well as political leaning and trust in institutions will also be relevant. As beliefs might also vary with a participant's household wealth and the individual contribution to their household wealth, we include marital status as a binary variable.

Our results for beliefs about the German wealth distribution show that, on average, older participants are generally more likely to select the correct histogram while women are 8.9% less likely to do so and thus tend to underestimate wealth inequality more often than men. Both effects are highly significant. In addition, we observe that a one-point increase in the financial literacy score correlates with a 7.8% higher probability of selecting the correct histogram. This effect is particularly interesting because we control for education, income, and wealth, i.e., variables that are expected to be highly correlated with financial literacy. One possible explanation for this finding may be that participants with higher levels of financial literacy are better able to interpret diagrams. Although we attempted to design simple histograms, participants with advanced financial literacy may still have an advantage in understanding the histograms, making them more likely to correctly identify the wealth distribution.

In contrast to participants with centrist attitudes, participants with left-wing attitudes are 9.6% more likely to select the correct histogram. This effect is substantial and statistically significant. On the contrary, participants with right-wing attitudes have no significant difference in their likelihood of selecting the correct histogram. Since inequality and social issues are more

	German distribution	Individual net wealth		
	Histogram correct	Position under	Position correct	Position over
	(1)	(2)	(3)	(4)
Age	0.003***	0.002***	-0.001	0.0004
	(0.001)	(0.001)	(0.001)	(0.0005)
Female	-0.089***	-0.019	-0.020	0.011
	(0.021)	(0.018)	(0.019)	(0.011)
Financial Literacy	0.078***	0.056***	0.013	-0.018***
	(0.012)	(0.010)	(0.011)	(0.006)
Net Wealth (in 1000s)	0.00005	0.001***	-0.0002***	-0.005***
	(0.00004)	(0.0001)	(0.0001)	(0.0002)
Married	0.011	0.109***	-0.022	-0.027**
	(0.022)	(0.019)	(0.020)	(0.012)
Left	0.096***	-0.055**	0.017	0.003
	(0.031)	(0.024)	(0.027)	(0.015)
Right	-0.001	0.0001	-0.052	-0.003
	(0.037)	(0.032)	(0.032)	(0.022)
Trust Institutions	-0.001	0.004	0.003	-0.002
	(0.006)	(0.005)	(0.005)	(0.003)
Trust Statistics	-0.011**	-0.001	0.0005	-0.001
	(0.006)	(0.005)	(0.005)	(0.003)
Prior Belief: Position	0.001	-0.208***	-0.012	0.199***
	(0.010)	(0.008)	(0.009)	(0.003)
Controls	Yes	Yes	Yes	Yes
Observations	2,175	2,175	2,175	2,175
McFadden R^2	0.0606	0.3692	0.0287	0.6960

Notes: This table presents the average marginal effects from our probit estimations. The outcome variables are the prior beliefs about aggregate inequality and the (biases of the) position in the wealth distribution. Control variables include residence in East Germany, employment status, migration background, education (school), university, university education of parents, and net household income. Detailed variable descriptions can be found in Appendix A. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Determinants of Prior Beliefs

fundamental to the left-wing political agenda, participants with such attitudes may be more aware and better informed about the prevalence and extent of inequality.

Regarding biased beliefs about one's position in the distribution, we find that very few of our variables can effectively explain the probability of correctly estimating one's position. There are no factors among our displayed variables that systematically affect correct estimation except for net wealth, which is also reflected in the low McFadden R^2 of less than 3%. However, we can better explain underestimation and overestimation of the individual position with McFadden R^2 values close to 37% and 70%, respectively. A higher financial literacy score is associated with a significantly higher probability of underestimating one's own position and a significantly lower probability of overestimating it. In addition, Table 4 shows that a higher amount of net wealth is significantly associated with an increased probability of underestimating one's own position and a decreased probability of overestimating it. These results are consistent with the descriptive results presented in Table 3. Our observations for financial literacy and wealth may be due to the hypothesized positive correlation between the two. However, since we control for both, financial literacy seems to capture additional relevant dimensions beyond wealth.

With respect to marital status, we find that married participants are significantly more likely to underestimate their position and less likely to overestimate it. This may indicate that married participants have more difficulty than unmarried individuals in distinguishing between their household's wealth and their individual contribution to it. In addition, column (2) shows that those with left-wing attitudes are significantly less likely to underestimate their position. We also see that higher prior beliefs about one's own position make one significantly less likely to underestimate one's own position and more likely to overestimate it. However, this is more of a technical relationship.

5.2 Preferences for Redistribution

Table 5 shows our main regression results for our four outcomes (based on equation 5). Columns (1) - (3) are estimated using OLS regressions, while we use a probit regression for the binary outcome in column (4). Panel A presents the results for the full sample. Panels B and C differentiate between relatively poor (bottom two quintiles) and relatively rich (top two quintiles) participants to test our Hypotheses IVa and IVb.

For the full sample (Panel A of Table 5), we find no statistically significant average treatment effects (ATE). This may point towards heterogeneity in treatment effects that cannot be captured by ATE. As indicated in our pre-registered hypotheses, we expect that a relevant dimension of heterogeneity may be the wealth level. More specifically, we expect that participants who learn that they are richer than they thought might respond differently than participants who learn that they are poorer. Assuming purely selfish preferences, the former group should decrease their support for redistribution, while the latter group should increase it.

To investigate this potential mechanism, Panel B of Table 5 focuses on the bottom 40% of the wealth distribution, while Panel C focuses on the top 40%. We find that the bottom 40% significantly reduce their inequality aversion after learning about their position in the distribution. This effect challenges our Hypothesis IVa, as we expected poorer participants to increase their inequality aversion after learning that they are relatively poor. Interestingly, a similar effect was found by Hoy and Mager (2021) in the context of income inequality, which the authors explain with "benchmarking". This phenomenon may also be at work in our data on wealth inequality.

Furthermore, we find that the top 40% are more convinced that anyone can become successful after being informed about their position.[9] This effect is consistent with Hypothesis IVb, suggesting that richer respondents become aware of their position and decrease their support for redistribution (or, as measured by this outcome, perceive a higher level of equality of opportunity).

[9]Remember that the variable is defined such that 0 indicates "Anybody can become successful if they work hard enough" to 10 "Other factors determine success".

	Inequality Aversion (1)	Support for Redistribution (2)	Equality of Opportunity (3)	Support for Tax (4)
Panel A: Full Sample				
Treat: Aggregate	0.092	-0.017	0.107	-0.009
	(0.113)	(0.147)	(0.140)	(0.069)
Treat: Personalized	-0.143	-0.125	-0.141	-0.049
	(0.112)	(0.146)	(0.139)	(0.068)
Observations	2,175	2,175	2,175	2,175
Adjusted R^2	0.076	0.040	0.034	
Panel B: Bottom 40%				
Treat: Aggregate	-0.110	-0.090	0.194	0.113
	(0.172)	(0.226)	(0.214)	(0.112)
Treat: Personalized	-0.286*	-0.102	-0.190	0.051
	(0.171)	(0.225)	(0.212)	(0.110)
Observations	847	847	847	847
Adjusted R^2	0.081	0.027	0.045	
Panel C: Top 40%				
Treat: Aggregate	0.145	-0.059	0.015	-0.053
	(0.194)	(0.245)	(0.227)	(0.111)
Treat: Personalized	-0.111	-0.125	-0.380*	-0.115
	(0.192)	(0.243)	(0.225)	(0.109)
Observations	875	875	875	875
Adjusted R^2	0.099	0.070	0.058	

Notes: This table presents the average treatment effects (ATE) from our OLS (columns (1) to (3)) and probit (column (4)) estimations. The outcome variables are our different dimensions of preferences for redistribution. Control variables include age, female, living in East Germany, employment status, migration background, marital status, education (school), university, university education of parents, financial literacy score, net household income, individual net wealth, left- and right-wing political attitudes, trust in institutions and trust in statistics. Detailed variable descriptions can be found in Appendix A. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Treatment Effects

Based on Table 5, we find no evidence in favor of Hypothesis III, which refers to the aggregate treatment.

As a first robustness check, we re-run Panels B and C in Table 5, but instead of subsetting the sample to the bottom 40% and top 40%, we follow Hoy and Mager (2021) and use overestimators and underestimators as a subsample. The results can be found in Table D.1. The effect of the personalized treatment on inequality aversion for overestimators is now significant at the 5% level (as opposed to the 10% level for the bottom 40% subgroup). The same is true for the effect of the personalized treatment on beliefs about equality of opportunity for underestimators. This suggests that the two initially identified effects are robust.

As a second robustness check, we include participants with suspicious and incomplete responses in our regression analysis. Table D.2 shows the results. Our results are generally robust to the inclusion of suspicious/incomplete responses. As a further robustness check, we exclude civil servants and the self-employed from our sample in Table D.3) (see also Footnote 3). Also, in this case, our findings are largely robust.

However, we do not want to overemphasize these results. The two initially identified effects are only significant at the 10%-level and only affect two of our four outcomes for one of our two treatments. Overall, we find quite large standard errors for many of our treatment effects which could indicate undetected heterogeneity.

Recent advances in computing power and software engineering have developed systematic data-driven approaches to facilitate the identification of heterogeneity in treatment effects. The following section presents such a data-driven method.

6 Heterogeneity in Treatment Effects

In this section, we briefly introduce the technical background of machine learning and its application in economics and then apply the causal forest approach developed by Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) to our data.

6.1 Method

The advantages of machine learning (ML) for identifying heterogeneities in treatment effects are becoming increasingly apparent in the economic literature. The primary application of ML algorithms in economics is to predict outcomes more accurately than traditional econometric methods due to the higher flexibility of ML algorithms for the functional form of the regressions. While traditional econometrics often assumes linear relationships and requires careful construction of regression models to identify non-linear relationships, ML algorithms are generally nonlinear and highly flexible (Lechner, 2023).

One common underlying mechanism of ML for making predictions is recursive partitioning. This describes the process of dividing the data into subgroups with similar outcomes. These subgroups can be defined across many covariates and split points thereof, allowing for a more complex but more accurate prediction of the outcome (Athey et al., 2019). As the name suggests, the process of recursive partitioning is performed many times on random samples of the original data set to estimate the optimal split points, i.e., the values of the covariates that distinguish between different outcomes as accurately as possible (Lechner, 2023). A round of recursive partitioning produces a decision tree. Through repetition, the average of many trees then produces a random forest (Wager and Athey, 2018).

To address our research questions, we are not interested in predicting the outcome, i.e., predicting preferences for redistribution based on our covariates, but in identifying heterogeneity in treatment effects. Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) have developed the causal forest approach for precisely this purpose. Instead of maximizing the predictive power of the decision trees, the algorithm[10] is slightly adjusted to split the dataset based on differences in treatment effects (Athey and Imbens, 2016). In practice, however, individual treatment effects

[10]The algorithm is implemented in R in the “grf” package (Tibshirani et al., 2023).

are unobservable. As defined by Rubin (1974), the individual treatment effect is given by

$$\delta_i = Y_i(1) - Y_i(0) \tag{6}$$

where $Y_i(1)$ refers to the outcome Y of individual i after treatment and $Y_i(0)$ refers to the outcome Y of individual i in the absence of treatment. However, it is impossible to measure both $Y_i(1)$ and $Y_i(0)$ for the same i. To circumvent this "fundamental problem of causal inference" (Holland, 1986, p. 947), Athey and Imbens (2016) proposed the concept of conditional average treatment effects (CATEs). Under the assumption of unconfoundedness, i.e. random treatment assignment, CATE calculates a counterfactual treatment effect for each individual conditional on the covariates given by

$$\tau(x) = E[Y_i(1) - Y_i(0)|X_i = x]. \tag{7}$$

Again, $Y_i(1)$ and $Y_i(0)$ represent the outcome of individual i in the presence and absence of treatment, respectively (Athey and Imbens, 2016, p. 7354). The main difference from Equation 6 is that the CATE $\tau(x)$ is equal to the expected value of the treatment effect $(Y_i(1) - Y_i(0))$ conditional on the covariates X_i (Athey and Imbens, 2016). The outcome Y can be transformed to Y_i^* as

$$Y_i^* = \frac{Y_i(W_i - p)}{p(1-p)} \tag{8}$$

where $W_i \in [0,1]$ is a binary treatment indicator and p is the marginal treatment probability (Athey and Imbens, 2016, p. 7357). Individual treatment effects can then be predicted with

$$\tau(x) = E[Y_i^*|X_i = x]. \tag{9}$$

using regression trees (Athey and Imbens, 2016, p. 7357). To ensure consistent estimators, one subsample is used to "grow the trees" (Wager and Athey, 2018, p. 1229), that is, to identify relevant covariates and determine split points, while another subsample is used to estimate the CATE (Wager and Athey, 2018). This process is randomized and has been called "honest" by Wager and Athey (2018). Recall that the underlying mechanism for causal forests is recursive partitioning, which means that the described process is repeated many times and CATE estimates the result from the aggregation of all causal trees by local maximum likelihood estimation (Lechner, 2023). As this method is relatively novel and the literature is still emerging, there is little experience yet on the optimal settings of parameters. In their application, Athey and Wager (2019) mostly use the default settings of the *causal_forest()* command in the "grf" package (Tibshirani et al., 2023), which we follow in our estimation with one exception: The default number of trees is set at 2000, which we increase to 5000. This can only increase the stability of our results. However, we find that the results are qualitatively the same as with 2000 trees.

6.2 Results

Figure 7 visualizes the distribution of our CATEs by treatment and outcome. The distributions show that there is some underlying heterogeneity in treatment effects, although this varies by treatment and outcome. For example, for the inequality aversion outcome, the majority of the CATEs for the aggregate treatment are positive while most (but not all) of the CATEs for the personalized treatment are negative. This tells us two things: First, the two treatments have different effects on inequality aversion. Second, there is heterogeneity within the treatments. A similar picture emerges for equality of opportunity. Participants tend to react positively to the aggregate treatment and negatively to the personalized treatment. By estimating the CATEs, it is now possible to examine whether there are systematic differences between those with a positive and negative CATE. For support for redistribution, we observe that both distributions have similar shapes, although the distribution of the aggregate treatment is shifted slightly to the right. The distributions for the support for a wealth tax also look very similar and are quite centered around zero, suggesting that participants did not react very strongly and that both treatments had similar effects on the outcome.

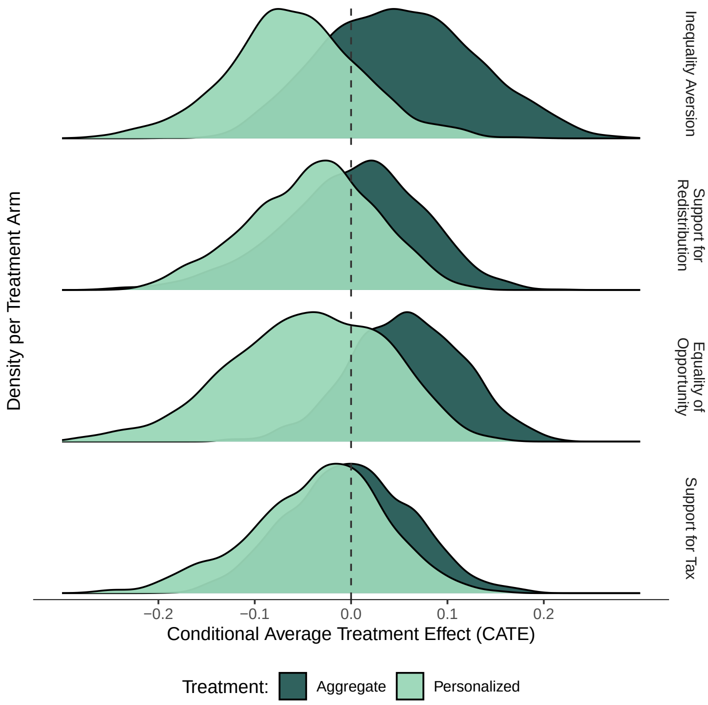


Figure 7: Distribution of CATE

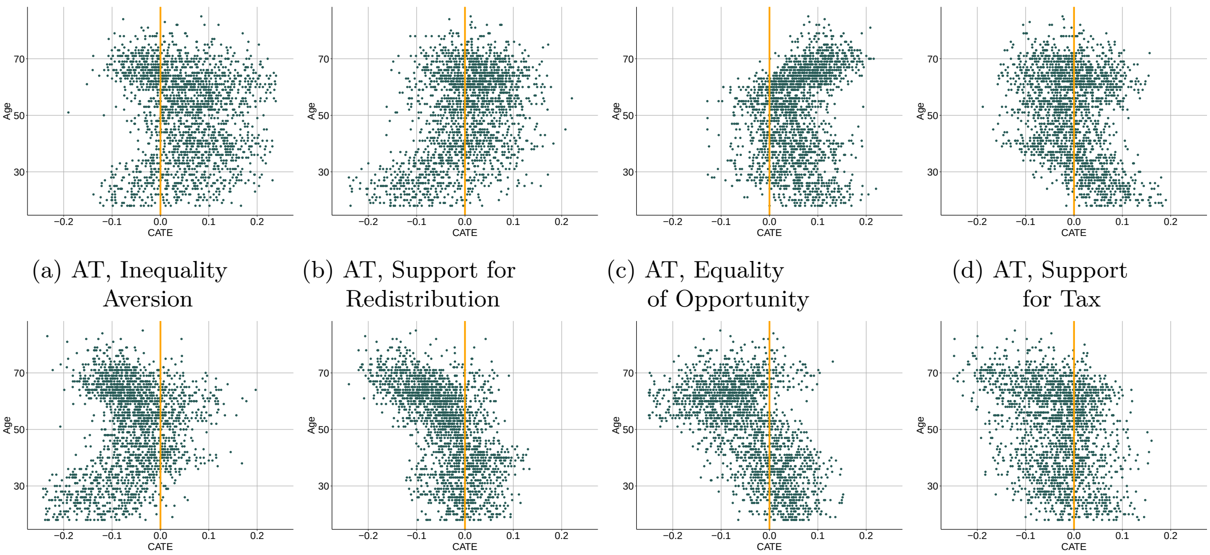
Notes: This figure shows the density of conditional average treatment effects (CATEs) for both treatments and each outcome.

To further explore covariates related to heterogeneity in CATE, we regress a binary indicator for having a CATE above the median CATE on our covariates. We determine the median CATE for each treatment-outcome combination and then code a binary variable equal to one for participants with a CATE above the median and zero otherwise. We then use linear probability models to identify covariates associated with above and below median CATE. Our covariates are standardized for better comparability.

The results are presented in the appendix in Figures E.1 and E.2 for the aggregate treatment and the personalized treatment, respectively. Both figures show the regression coefficients as well as the corresponding 95% confidence intervals. We find that several covariates are significantly related to having an above-median CATE and that there are large differences between treatments and outcomes.

Since we cannot provide detailed insights into all significant variables, we focus on those covariates that we have already considered in the determinants of prior beliefs (see Table 4) and that have a coefficient of at least 0.1 (in absolute terms) in Figures E.1 and E.2.

As age is an important determinant in several outcomes across our two treatments, we provide detailed insights for all outcomes and both treatments. The results can be found in Figure 8, where we plot the estimated CATE of our participants against their age.



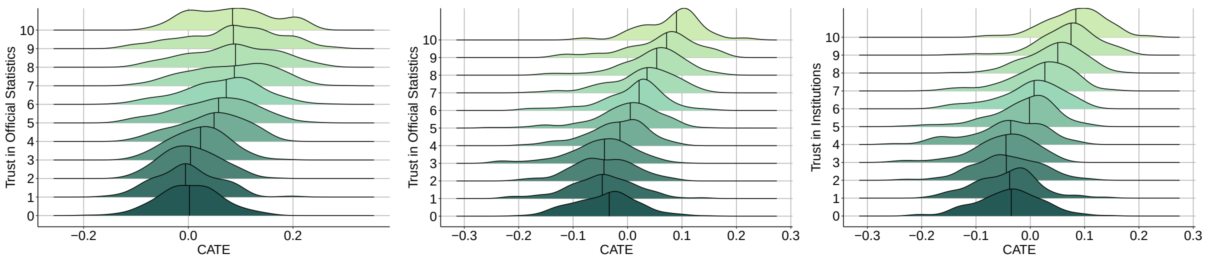
(a) AT, Inequality Aversion
(b) AT, Support for Redistribution
(c) AT, Equality of Opportunity
(d) AT, Support for Tax
(e) PT, Inequality Aversion
(f) PT, Support for Redistribution
(g) PT, Equality of Opportunity
(h) PT, Support for Tax

Figure 8: CATE Distributions by Age

Notes: This figure visualizes the correlation between age and CATE. AT: aggregate treatment; PT: personalised treatment

Based on Figure 8a and 8e, we find a decrease in inequality aversion for both particularly young and old participants as a reaction to both treatments. A smaller decrease in inequality aversion (personalized treatment) and even an increase in inequality aversion (aggregate treatment) can be observed for middle-aged participants.

Yet, for other treatment-outcome combinations the relationship between the estimated CATE and age is more linear. Figure 8b shows that a decrease in their support for redistribution can be found for *younger* participants after learning about aggregate inequality, whereas *older* participants tend to increase their support, while Figure 8f shows that a decrease in their support for redistribution can be found for *older* participants after learning about their position in the



(a) AT, Inequality Aversion (Trust in Statistics)

(b) AT, Support for Redistribution (Trust in Statistics)

(c) AT, Support for Redistribution (Trust in Institutions)

Figure 9: CATE Distributions by Trust

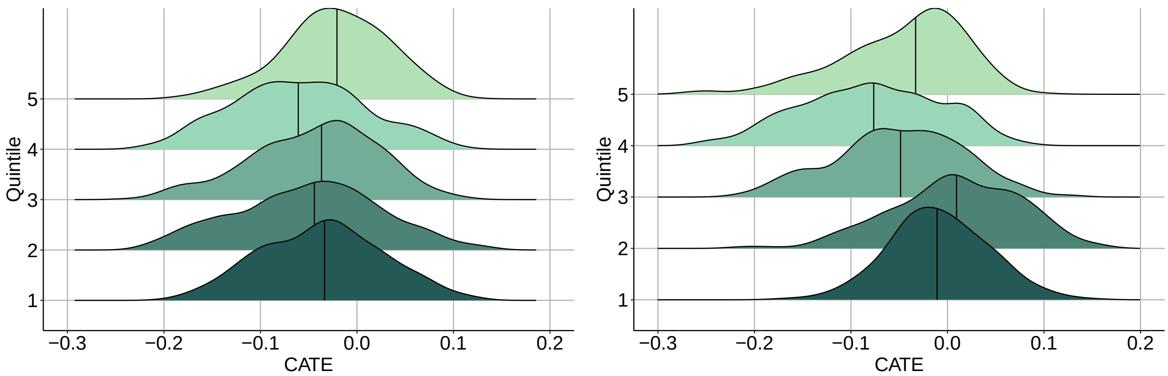
Notes: This figure visualizes the density of CATE for the aggregate treatment on support for redistribution at different levels of trust in official statistics in (a) and (b) and trust in institutions in (c). AT: aggregate treatment; PT: personalised treatment

wealth distribution. Figure 8g is then consistent with Figure 8f and shows that older participants are also more convinced that anyone can become successful after learning about their position. Analogously, Figure 8c shows a pattern similar to Figure 8b – at least for the *older* participants. The most similar relation across the two treatments can be found for age and support for a wealth tax (see Figures 8d and h). These results are interesting because of the different responses to the aggregate and personalized treatment between different age groups. While information about the level of inequality in Germany leads younger participants to be less supportive of redistribution, information about the individual position leads older participants to be less supportive of redistribution. This may suggest generational differences in whether support for redistribution is based on beliefs about society as a whole or on beliefs about one's own position in the wealth distribution. However, this issue requires further research to identify potential mechanisms.

With respect to our trust variables, we see in Figures E.1 and E.2 that higher trust in official statistics and institutions is associated with a higher likelihood of having an above-median CATE for inequality aversion and support for redistribution in the aggregate treatment. To gain further insights into this relationship, Figure 9 plots the distributions of estimated CATE for different levels of trust in official statistics (Figure 9a and 9b) and institutions (Figure 9c). Since the trust variables are measured on an 11-point Likert scale (0 = cannot be careful enough; 10 = most statistics/institutions can be trusted), we can obtain CATE distributions for each of these levels to see how treatment effects differ with the level of trust. The vertical lines in the CATE distributions represent the median CATE for that level of trust.

Figure 9a shows that those with lower levels of trust in statistics do not react much to the aggregate treatment when considering the inequality aversion outcome. However, as trust in statistics increases, so does inequality aversion as a response to the aggregate treatment. This relationship becomes even clearer in Figures 9b and 9c. It can be seen that those with relatively low levels of trust in official statistics and institutions even have overwhelmingly negative CATE. Receiving information about the shape of the German wealth distribution leads them to reduce their demand for redistribution. Since the outcome "support for redistribution" refers specifically to the role of the government in redistribution, this is not so surprising. They may interpret our information as biased or manipulated to support a particular narrative, reinforcing their skepticism and reducing their support for redistribution. In addition, they may suspect that redistributive efforts are driven by political agendas rather than genuine concern for addressing inequality, which could again reduce their support for redistribution. As trust increases, so do the CATEs – initially becoming less negative and eventually becoming positive for most of the distribution when trust in statistics and institutions is particularly high.

Lastly, we look closer at the relationship between the CATE and individual net wealth as shown in Figure 10. For a more intuitive visualization, we present the CATE distributions for each quintile of the wealth distribution. We do not find much variation for the support for redistribution. However, the CATE for the richest quintile are slightly less negative, i.e. the richest 20% of our sample tend to decrease their support for redistribution less than poorer participants when learning about their position (Figure 10a). Figure 10b shows more complex, non-linear heterogeneities in the effect of the personalized treatment on support for a wealth tax. Participants in the second quintile tend to increase their support for the tax while those in the third and fourth quintile tend to decrease their support. Interestingly, participants in the fifth quintile, i.e. the richest 20%, react less negatively with a median CATE just below zero, suggesting a positive reaction among almost half of this group.



(a) Personalized Treatment, Support for Redistribution

(b) Personalized Treatment, Support for Tax

Figure 10: CATE Distributions by Wealth

Notes: This figure visualizes the density of CATE for the personalized treatment on support for redistribution and a wealth tax for the wealth quintiles. As before, "1" refers to the poorest 20% of our participants based on the SOEP data while "5" refers to the richest 20%.

7 Conclusion

Wealth redistribution is a highly controversial topic in public debates and political positions vary greatly across the political spectrum. To make informed voting choices, individuals must have access to accurate information. However, a growing body of economic literature shows that individuals are poorly informed about many socioeconomic indicators. These studies have highlighted that individuals hold biased beliefs about migration (see, e.g., Haaland and Roth, 2020; Grigorieff et al., 2020; Dylong and Uebelmesser, 2024), macroeconomic indicators such as inflation (see, e.g., Armantier et al., 2016; Cavallo et al., 2017), and many more. For income inequality, Cruces et al. (2013), Engelhardt and Wagener (2018), Hoy and Mager (2021), and Bublitz (2022) have found that beliefs about one's own income position are strongly biased toward the center of the distribution – for both relatively poor as well as relatively rich individuals. This has important implications for the formation of policy preferences since traditional economic theories do not account for the possibility that there may be discrepancies between individuals' perceived and actual positions. These theories, based on the Meltzer-Richard model (Meltzer and Richard, 1981), propose that preferences for redistribution are based solely on selfishness, i.e., someone who would benefit from redistribution is in favor of it and vice versa.

Our study is among the first to analyze beliefs about wealth inequality and preferences for wealth redistribution. By conducting a large-scale online survey with information treatments, we were able to gain an understanding of beliefs about wealth inequality and determine the effect of correcting biased beliefs on preferences for redistribution. Similar to previous studies on income inequality, we found that most participants are unaware of the shape of the wealth distribution and their position in it. Participants with relatively low wealth tend to overestimate their position, and participants with relatively high wealth tend to underestimate their position. This creates precisely the bias toward the center of the distribution that is often observed in the income context. As part of our treatments, we then provided information to help participants correct their biased beliefs concerning the shape of the wealth distribution or their own position in it. We estimated the effects on preferences for redistribution measured in four different outcomes to capture a variety of dimensions of redistribution.

Our full sample regressions showed no significant average treatment effects. However, a simple pre-registered subsample analysis indicated heterogeneities in treatment effects by individual net wealth level. In particular, those who are relatively poor decrease their inequality aversion after learning about their position, while the relatively rich become more convinced that anybody can be successful if they work hard enough. This evidence was substantiated by a robustness check following the results of Hoy and Mager (2021).

Using a systematic data-driven approach, we find evidence that treatment effect heterogeneity with respect to participants' age varies between treatments and outcomes. Both younger and older participants exhibit similar responses to both treatments regarding inequality aversion, but their reactions in the support for redistribution differ between treatments. Younger participants reduce their support for redistribution after learning about the wealth distribution's shape, whereas older participants decrease support after learning their position in the distribution. Additionally, we find that those with high trust in official statistics increase their inequality aversion, while those participants with particularly low trust in statistics and institutions decrease their support for redistribution when they learn about the shape of the wealth distribution. Since our question to capture support for redistribution explicitly emphasized the role of the government in redistribution, this result is not surprising. These participants may well be averse to inequality but simply do not trust the government and its institutions to address it. Lastly, we find non-linear heterogeneities related to wealth. While relatively rich participants (quintiles

3 and 4) tend to decrease their support for a wealth tax after learning about their position, the richest 20% show a less negative reaction.

Overall, we have presented novel insights into the relationship between biased beliefs about wealth inequality and preferences for wealth redistribution based on a new dataset. We provide evidence that preference formation does not follow simple theoretical predictions. Instead, preferences appear to be driven by non-selfish motives. We find that support for wealth redistribution is generally high across the sample. However, correcting biased beliefs about wealth inequality seems to affect preferences only for selected groups. For Germany, other national surveys have also shown that support for wealth redistribution is strong (see, e.g., Baarck et al., 2020), but the currently governing political parties do not seem to intend to explicitly address wealth redistribution. This issue certainly requires further research, e.g., with a multi-country sample, improved or alternative approaches to the elicitation of wealth, and possible follow-up surveys. Our study can be seen as a first step in the field of wealth inequality and redistribution, a topic that has hardly been analyzed so far.

References

Albacete, Nicolas, Pirmin Fessler, and Peter Lindner (2022). *The Wealth Distribution and Redistributive Preferences: Evidence from a Randomized Survey Experiment.* Working Paper 239. Oesterreichische Nationalbank (Austrian Central Bank).

Albers, Thilo, Charlotte Bartels, and Moritz Schularick (2022). *Wealth and its Distribution in Germany, 1895-2018.* CEPR Discussion Paper No. DP17269.

Alesina, Alberto, Stefanie Stantcheva, and Edoardo Teso (2018). "Intergenerational mobility and preferences for redistribution". *American Economic Review* 108 (2), 521–554.

Armantier, Olivier, Scott Nelson, Giorgio Topa, Wilbert Van der Klaauw, and Basit Zafar (2016). "The price is right: Updating inflation expectations in a randomized price information experiment". *Review of Economics and Statistics* 98 (3), 503–523.

Athey, Susan and Guido Imbens (2016). "Recursive partitioning for heterogeneous causal effects". *Proceedings of the National Academy of Sciences* 113 (27), 7353–7360.

Athey, Susan, Julie Tibshirani, and Stefan Wager (2019). "Generalized Random Forests". *The Annals of Statistics* 47 (2), 1148–1178.

Athey, Susan and Stefan Wager (2019). "Estimating treatment effects with causal forests: An application". *Observational studies* 5 (2), 37–51.

Baarck, Julia, Mathias Dolls, Kai Unzicker, and Lisa Windsteiger (2020). *Gerechtigkeitsempfinden in Deutschland.* `https://www.bertelsmann-stiftung.de/fileadmin/files/BSt/Publikationen/GrauePublikationen/DZ_Studie_Gerechtigkeitsempfinden_2022.pdf`.

Bartels, Charlotte, Timm Bönke, Rick Glaubitz, Markus M. Grabka, and Carsten Schröder (2023). "Accounting for pension wealth, the missing rich and under-coverage: A comprehensive wealth distribution for Germany". *Economics Letters* 231, p. 111299.

Bastani, Spencer and Daniel Waldenström (2021). "Perceptions of inherited wealth and the support for inheritance taxation". *Economica* 88 (350), 532–569.

Bublitz, Elisabeth (2022). "Misperceptions of income distributions: Cross-country evidence from a randomized survey experiment". *Socio-Economic Review* 20 (2), 435–462.

Bundesbank, Deutsche (2022). "Eine verteilungsbasierte Vermögensbilanz der privaten Haushalte in Deutschland–Ergebnisse und Anwendungen". *Monatsbericht der Deutschen Bundesbank* July/2022, 15–40.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia (2017). "Inflation expectations, learning, and supermarket prices: Evidence from survey experiments". *American Economic Journal: Macroeconomics* 9 (3), 1–35.

Čehovin, Gregor, Michael Bosnjak, and Katja Lozar Manfreda (2023). "Item nonresponse in web versus other survey modes: a systematic review and meta-analysis". *Social Science Computer Review* 41 (3), 926–945.

Chancel, Lucas and Thomas Piketty (2021). "Global Income Inequality, 1820–2020: the Persistence and Mutation of Extreme Inequality". *Journal of the European Economic Association* 19 (6), 3025–3062.

Chandler, Jesse, Cheskie Rosenzweig, Aaron J. Moss, Jonathan Robinson, and Leib Litman (2019). "Online Panels in Social Science Research: Expanding Sampling Methods beyond Mechanical Turk". *Behavior Research Methods* 51 (5), 2022–2038.

Choi, Gwangeun (2021). "Individuals' socioeconomic position, inequality perceptions, and redistributive preferences in OECD countries". *The Journal of Economic Inequality* 19 (2), 239–264.

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

Dylong, Patrick and Silke Uebelmesser (2024). "Biased Beliefs About Immigration and Economic Concerns: Evidence from Representative Experiments". *Journal of Economic Behavior & Organization* 217, 453–482.

Engelhardt, Carina and Andreas Wagener (2018). "What do Germans think and know about income inequality? A survey experiment". *Socio-Economic Review* 16 (4), 743–767.

Fisman, Raymond, Keith Gladstone, Ilyana Kuziemko, and Suresh Naidu (2020). "Do Americans want to tax wealth? Evidence from online surveys". *Journal of Public Economics* 188, p. 104207.

Gassmann, Franziska and Eszter Timár (2024). "Perceived position on the social ladder and redistributive preferences – A survey experiment from the Kyrgyz Republic". *European Journal of Political Economy* 81, p. 102496.

Gimpelson, Vladimir and Daniel Treisman (2018). "Misperceiving inequality". *Economics & Politics* 30 (1), 27–54.

Grabka, Markus M. and Christoph Halbmeier (2019). *Vermögensungleichheit in Deutschland bleibt trotz deutlich steigender Nettovermögen anhaltend hoch.* DIW Wochenbericht No. 40.

Grigorieff, Alexis, Christopher Roth, and Diego Ubfal (2020). "Does information change attitudes toward immigrants?" *Demography* 57 (3), 1117–1143.

Haaland, Ingar and Christopher Roth (2020). "Labor market concerns and support for immigration". *Journal of Public Economics* 191, p. 104256.

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart (2023). “Designing information provision experiments”. *Journal of Economic Literature* 61 (1), 3–40.

Heiserman, Nicholas and Brent Simpson (2021). “Measuring perceptions of economic inequality and justice: An empirical assessment”. *Social Justice Research* 34 (2), 119–145.

Holland, Paul W (1986). “Statistics and causal inference”. *Journal of the American Statistical Association* 81 (396), 945–960.

Hoy, Christopher and Franziska Mager (2021). “Why Are Relatively Poor People Not More Supportive of Redistribution? Evidence from a Randomized Survey Experiment across Ten Countries”. *American Economic Journal: Economic Policy* 13 (4), 299–328.

IAW (2015). *Analyse der Verteilung von Einkommen und Vermögen in Deutschland.* Armuts- und Reichtumsberichterstattung der Bundesregierung (zusammen mit ZEW GmbH and IZA and Martin Biewen), Tübingen.

Knell, Markus and Helmut Stix (2020). “Perceptions of inequality”. *European Journal of Political Economy* 65, p. 101927.

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

Lechner, Michael (2023). “Causal Machine Learning and its use for public policy”. *Swiss Journal of Economics and Statistics* 159 (1), 1–15.

Lusardi, Annamaria and Olivia S Mitchell (2011). “Financial literacy around the world: an overview”. *Journal of pension economics & finance* 10 (4), 497–508.

Lusardi, Annamaria, Anya Samek, Arie Kapteyn, Lewis Glinert, Angela Hung, and Aileen Heinberg (2017). “Visual tools and narratives: New ways to improve financial literacy”. *Journal of Pension Economics & Finance* 16 (3), 297–323.

Meltzer, Allan H and Scott F Richard (1981). “A rational theory of the size of government”. *Journal of Political Economy* 89 (5), 914–927.

Rubin, Donald B (1974). “Estimating causal effects of treatments in randomized and nonrandomized studies”. *Journal of Educational Psychology* 66 (5), 688–701.

Schneebaum, Alyssa, Miriam Rehm, Katharina Mader, and Katarina Hollan (2018). “The gender wealth gap across European countries”. *Review of Income and Wealth* 64 (2), 295–331.

Sierminska, Eva M, Joachim R Frick, and Markus M Grabka (2010). “Examining the gender wealth gap”. *Oxford Economic Papers* 62 (4), 669–690.

Socio-Economic Panel (SOEP) (2019). *Data for years 1984-2017, Version 34.* doi:10.5684/soep.v34.

Tibshirani, Julie, Susan Athey, Erik Sverdrup, and Stefan Wager (2023). "grf: Generalized Random Forests (R package)". *https://CRAN.R-project.org/package=grf*.

Wager, Stefan and Susan Athey (2018). "Estimation and inference of heterogeneous treatment effects using random forests". *Journal of the American Statistical Association* 113 (523), 1228–1242.

A Variable Descriptions

Variable name	Type	Description
Covariates		
Age	Continuous	
Female	Binary	= 1, if gender is female
East	Binary	= 1, if participant lives in East Germany
Civil servant	Binary	= 1, if participant is a civil servant
Employed	Binary	= 1, if participant is employed (reference category for all variables related to employment status and retirement)
Self-employed	Binary	= 1, if participant is self-employed
Unemployed	Binary	= 1, if participant is not in employment (includes students and those unemployed participants who are not seeking a job)
Retired	Binary	= 1, if participant is retired
Migration background	Binary	= 1, if participant or at least on of their parents was born with non-German citizenship
Married	Binary	= 1, if participant is married or in a registered same-sex partnership
Low education	Binary	= 1, if participant has completed lower secondary education or no secondary education
Mid education	Binary	= 1, if participants has completed upper secondary education but has not gone to university (reference category)
University	Binary	= 1, if participant has completed tertiary education (this may include individuals with only lower secondary education who still report a university degree)
University parent	Binary	= 1, if at least one parent of the participant has obtained a tertiary education degree
Financial literacy	Numerical (0–3)	Number of questions on financial literacy answered correctly
Low income	Binary	= 1, if net household income $<$ 1000 EUR / month
Mid income	Binary	= 1, if net household income $\geq$ 1000 EUR and $<$ 5000 EUR / month (reference category)
High income	Binary	= 1, if net household income $\geq$ 5000 EUR / month
Net wealth (in 1000s)	Continuous	Individual net wealth in 1000s EUR
Left	Binary	= 1, if political orientation <3 on a $0-10$ (left–right) scale
Centrist	Binary	= 1, if participant is neither left nor right (reference category)
Right	Binary	= 1, if political orientation >7 on a $0-10$ (left–right) scale
Trust institutions	Numerical (0–10)	Trust in institutions with 0 = "One cannot be careful enough" to 10 = "Most institutions can be trusted"
Trust statistics	Numerical (0–10)	Trust in official statistics with 0 = "One cannot be careful enough" to 10 = "Most statistics can be trusted"
Prior Beliefs		
Histogram correct	Binary	= 1, if participant selected the correct histogram
Prior belief: position	Numerical (1–5)	Perceived position in the wealth distribution in quintiles (1 = poorest 20%, 5 = richest 20%)
Position under	Binary	= 1, if participant underestimated their position
Position over	Binary	= 1, if participant overestimated their position
Outcome Variables		
Inequality aversion	Numerical (0–10)	*"The difference in wealth between the rich and the poor in Germany is too large"* Answer options range from 0 "I do not agree" to 10 "I fully agree"
Support for redistribution	Numerical (0–10)	*"It is the responsibility of the German government to reduce the wealth difference between the rich and the poor in Germany. / Please note that to reduce the wealth differences, the government either has to reduce spending in other areas (such as infrastructure or defense), increase public debt, or increase taxes for certain groups."* Answer options range from 0 "I do not agree" to 10 "I fully agree"
Equality of opportunity	Numerical (0–10)	*"Some people think that anybody can become successful if they work hard enough. Others think that the success of a person is determined by other factors (e.g. ancestry, luck, health). What do you think?""* Answer options range from 0 "Anybody can become successful if they work hard enough" to 10 "Other factors determine success"
Support for tax	Binary	= 1, if *"Are you in favour or opposed to the introduction of an annual wealth tax in Germany?"* was answered with "4" or "5". Original answer options range from 1 "I am opposed" to 5 "I am in favour"

Table A.1: Overview of variables.

B Wealth Questions

Wealth Category	Wording
Introduction of topic	Wealth accumulation in all social classes is an important topic today, especially with regard to old-age provision. That is why we try to get a reliable overall picture of your wealth situation. We would like to invite and ask you to participate in this project. To this end, we would like to create your personal ”balance sheet”, which will also help you to gain an overview. You can be absolutely sure that your information will be anonymous, will be treated confidentially, and will only be used for scientific evaluation.
Real estate	(1) Do you own any properties, i.e. self-occupied or rented housing or leased premises? [IF (1) == YES] (2) What is the current market value of all your properties? The market value is the amount of money you could obtain from selling your properties right now. [IF (1) == YES] (3) Do you still have a mortgage on any of your properties? [IF (3) == YES] (4) To estimate the total value of your properties, we need to take into account the remaining mortgages (without interest). How high is the remaining mortgage for all of your properties? [IF (1) == YES] (5) Are you the sole owner of your properties or do you have co-owners? [IF (5) == CO-OWNER] (6) To what share do you own your mentioned properties?
Financial assets	(1) Do you have any financial assets, i.e. savings (on checking or savings accounts), stocks, funds, building loan contracts, bonds or investment shares? [IF (1) == YES] (2) What is the value of these financial assets?
Life insurance	(1) Do you have any life insurance or private pension insurance plans (including ”Riester- and Rürup- Rente”)? [IF (1) == YES] (2) What is the repurchase value/balance for these contracts?
Vehicles	(1) Do you own any vehicles, i.e. cars, motorbikes, campervans, or privately used motortrucks? [IF (1) == YES] (2) What is the current market value of your vehicle(s)? The market value is the amount of money you could obtain from selling your vehicle(s) right now.
Tangible assets	(1) Do you own any considerable tangible assets, i.e. gold, jewelry, coins, or valuable collections? [IF (1) == YES] (2) Assuming you could sell these tangible assets, what is your estimate of the total value of the assets?
Businesses	(1) Do you own any commercial businesses, i.e. a company, shop, law office, doctor's office, or an agricultural enterprise, or do you have a share in a commercial business like that? [IF (1) == YES] (2) What is the net worth of your commercial businesses / your share in the commercial businesses? The net worth is the value before taxes you could obtain through selling your commercial businesses / your share in the commercial businesses, taking into account possible loans.
Debt	(1) Apart from possible property mortgages, do you owe money to any bank, institution, or private individual? Please also consider debt for education such as student loans. [IF (1) == YES] (2) What is the remaining debt you still have to pay off for these loans?

Table B.1: Wording of wealth questions. Based on the Socio-Economic Panel (SOEP) (2019) questionnaire and translated to English.

C Balance Tests

Variable	Complete	Suspicious	Incomplete
Age	50.322	42.783***	43.567***
Female	0.509	0.457	0.590**
East	0.139	0.130	0.175
Civil servant	0.025	0.109*	0.014
Self-employed	0.046	0.022	0.028
Unemployed	0.154	0.239	0.263***
Retired	0.280	0.196	0.212**
Migration background	0.320	0.609***	0.341
Married	0.439	0.435	0.429
Low education	0.334	0.239	0.382
Uni	0.242	0.370*	0.198
Uni parent	0.210	0.326	0.281**
Financial literacy	2.186	1.783**	1.548***
Low income	0.201	0.239	0.171
High income	0.095	0.109	0.152**
Net wealth (in 1000s)	144.005	125.940	73.870***
Left	0.134	0.109	0.074***
Right	0.084	0.152	0.055*
Trust institutions	5.319	6.087*	4.811***
Trust statistics	5.048	5.413	4.774
Prior belief: position	2.833	3.087	2.811
Inequality aversion	8.200	7.609*	7.774**
Support for redistribution	6.616	6.826	6.304*
Equality of opportunity	5.619	5.935	5.521
Support for tax	0.491	0.500	0.346***
Observations	2,175	59	217

Notes: This table tests for balance between participants with complete responses and those with suspicious or incomplete responses in the wealth questions. Stars indicate significant differences in means between the respective suspicious/incomplete group and the complete group. The complete group constitutes our cleaned sample. A total of 13 participants have given both suspicious and incomplete responses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.1: Sample Balance for Suspicious and Incomplete Responses

Variable	Control	Aggregate Treatment	Personalized Treatment
Age	50.575	50.374	50.021
Female	0.510	0.498	0.521
East	0.134	0.141	0.142
Civil servant	0.024	0.019	0.032
Self-employed	0.051	0.045	0.042
Unemployed	0.152	0.152	0.160
Retired	0.287	0.274	0.278
Migration background	0.302	0.333	0.325
Married	0.442	0.410	0.467
Low education	0.344	0.330	0.328
Uni	0.234	0.242	0.515
Uni parent	0.230	0.197	0.203
Financial literacy	2.178	2.194	2.186
Low income	0.200	0.201	0.203
High income	0.097	0.080	0.108
Net wealth (in 1000s)	145.287	140.446	146.463
Left	0.139	0.134	0.129
Right	0.077	0.099	0.075
Trust institutions	5.281	5.397	5.275
Trust statistics	4.976	5.149	5.013
Prior belief: position	2.876	2.774*	2.853
Inequality aversion	8.214	8.096	8.296
Support for redistribution	6.659	6.566	6.625
Equality of opportunity	5.621	5.513	5.728
Support for tax	0.497	0.487	0.490
Observations	704	720	751

Notes: This table tests for balance between experimental groups across our covariates and outcome variables. Stars indicate significant differences in means between the respective treatment and the control group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Sample Balance

D Robustness Checks

	Inequality Aversion (1)	Support for Redistribution (2)	Equality of Opportunity (3)	Support for Tax (4)
Panel A: Overestimator				
Treat: Aggregate	-0.300	-0.244	0.159	0.043
	(0.205)	(0.265)	(0.255)	(0.047)
Treat: Personalized	-0.420**	-0.096	0.065	0.048
	(0.207)	(0.268)	(0.258)	(0.047)
Observations	659	659	659	659
Panel B: Underestimator				
Treat: Aggregate	0.218	-0.039	-0.035	-0.055
	(0.174)	(0.230)	(0.211)	(0.038)
Treat: Personalized	0.030	-0.042	-0.487**	-0.060
	(0.171)	(0.226)	(0.207)	(0.037)
Observations	979	979	979	979

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

Notes: This table presents the average treatment effects (ATE) from our OLS (columns (1) to (3)) and probit (column (4)) estimations for those participants who overestimate and underestimate their position in the wealth distribution. The outcome variables are our different dimensions of preferences for redistribution. Please refer to Table 5 and Appendix A for information on control variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.1: Treatment effects by overestimators and underestimators

	Inequality Aversion	Support for Redistribution	Equality of Opportunity	Support for Tax
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Treat: Aggregate	0.131	0.025	0.113	-0.006
	(0.108)	(0.138)	(0.131)	(0.065)
Treat: Personalized	-0.170	-0.084	-0.120	-0.054
	(0.107)	(0.136)	(0.130)	(0.064)
Observations	2,438	2,438	2,438	2,438
Panel B: Bottom 40%				
Treat: Aggregate	-0.070	-0.004	0.199	0.068
	(0.164)	(0.211)	(0.198)	(0.104)
Treat: Personalized	-0.293*	-0.015	-0.192	0.040
	(0.162)	(0.209)	(0.197)	(0.102)
Observations	980	980	980	980
Panel C: Top 40%				
Treat: Aggregate	0.219	-0.022	-0.073	-0.025
	(0.188)	(0.234)	(0.218)	(0.107)
Treat: Personalized	-0.092	-0.053	-0.404*	-0.106
	(0.184)	(0.230)	(0.214)	(0.105)
Observations	940	940	940	940
Panel D: Overestimator				
Treat: Aggregate	-0.194	-0.073	0.220	0.099
	(0.195)	(0.246)	(0.235)	(0.116)
Treat: Personalized	-0.385*	0.047	0.070	0.146
	(0.197)	(0.249)	(0.238)	(0.117)
Observations	765	765	765	765
Panel E: Underestimator				
Treat: Aggregate	0.257	-0.030	-0.042	-0.111
	(0.167)	(0.217)	(0.201)	(0.100)
Treat: Personalized	0.004	-0.017	-0.476**	-0.153
	(0.164)	(0.213)	(0.197)	(0.098)
Observations	1,061	1,061	1,061	1,061

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

Notes: This table presents the average treatment effects (ATE) from our OLS (columns (1) to (3)) and probit (column (4)) estimations including participants with incomplete and/or suspicious responses to the wealth questions. The outcome variables are our different dimensions of preferences for redistribution. Please refer to Table 5 and Appendix A for information on control variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.2: Treatment effects including incomplete/suspicious answers

	Inequality Aversion	Support for Redistribution	Equality of Opportunity	Support for Tax
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Treat: Aggregate	0.086	0.017	0.150	-0.015
	(0.117)	(0.152)	(0.145)	(0.071)
Treat: Personalized	-0.142	-0.085	-0.135	-0.061
	(0.116)	(0.150)	(0.144)	(0.071)
Observations	2,021	2,021	2,021	2,023
Panel B: Bottom 40%				
Treat: Aggregate	-0.113	-0.061	0.177	0.124
	(0.175)	(0.228)	(0.215)	(0.114)
Treat: Personalized	-0.307*	-0.136	-0.216	0.069
	(0.174)	(0.227)	(0.214)	(0.113)
Observations	819	819	819	819
Panel C: Top 40%				
Treat: Aggregate	0.146	-0.020	0.119	-0.063
	(0.204)	(0.259)	(0.242)	(0.117)
Treat: Personalized	-0.141	-0.077	-0.378	-0.136
	(0.201)	(0.255)	(0.237)	(0.115)
Observations	783	783	783	783
Panel D: Overestimator				
Treat: Aggregate	-0.308	-0.257	0.152	0.074
	(0.209)	(0.270)	(0.258)	(0.127)
Treat: Personalized	-0.446**	-0.093	0.067	0.110
	(0.213)	(0.274)	(0.262)	(0.129)
Observations	632	632	632	632
Panel E: Underestimator				
Treat: Aggregate	0.174	0.021	0.021	-0.150
	(0.185)	(0.242)	(0.223)	(0.111)
Treat: Personalized	-0.012	0.005	-0.514**	-0.172
	(0.181)	(0.237)	(0.218)	(0.108)
Observations	884	884	884	884

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

Notes: This table presents the average treatment effects (ATE) from our OLS (columns (1) to (3)) and probit (column (4)) estimations excluding self-employed participants and civil servants. The outcome variables are our different dimensions of preferences for redistribution. Please refer to Table 5 and Appendix A for information on control variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.3: Treatment effects without civil servants and self-employed participants

E Heterogeneity in Treatment Effects

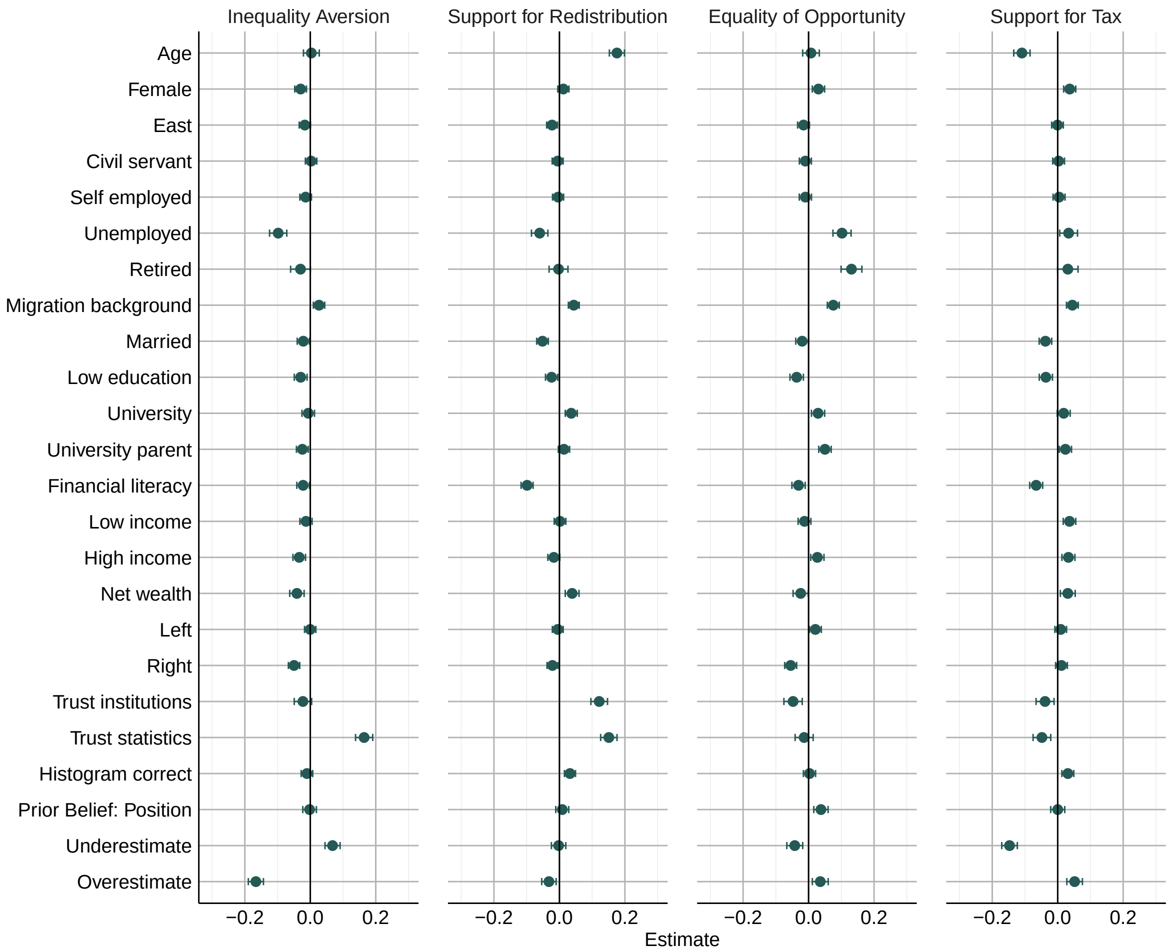


Figure E.1: Determinants of above-median CATE for aggregate treatment

Notes: This Figure shows coefficients and 95% confidence intervals from LPM regressions with a binary outcome indicating an above-median CATE in the aggregate treatment. The median CATE is determined separately for each outcome.

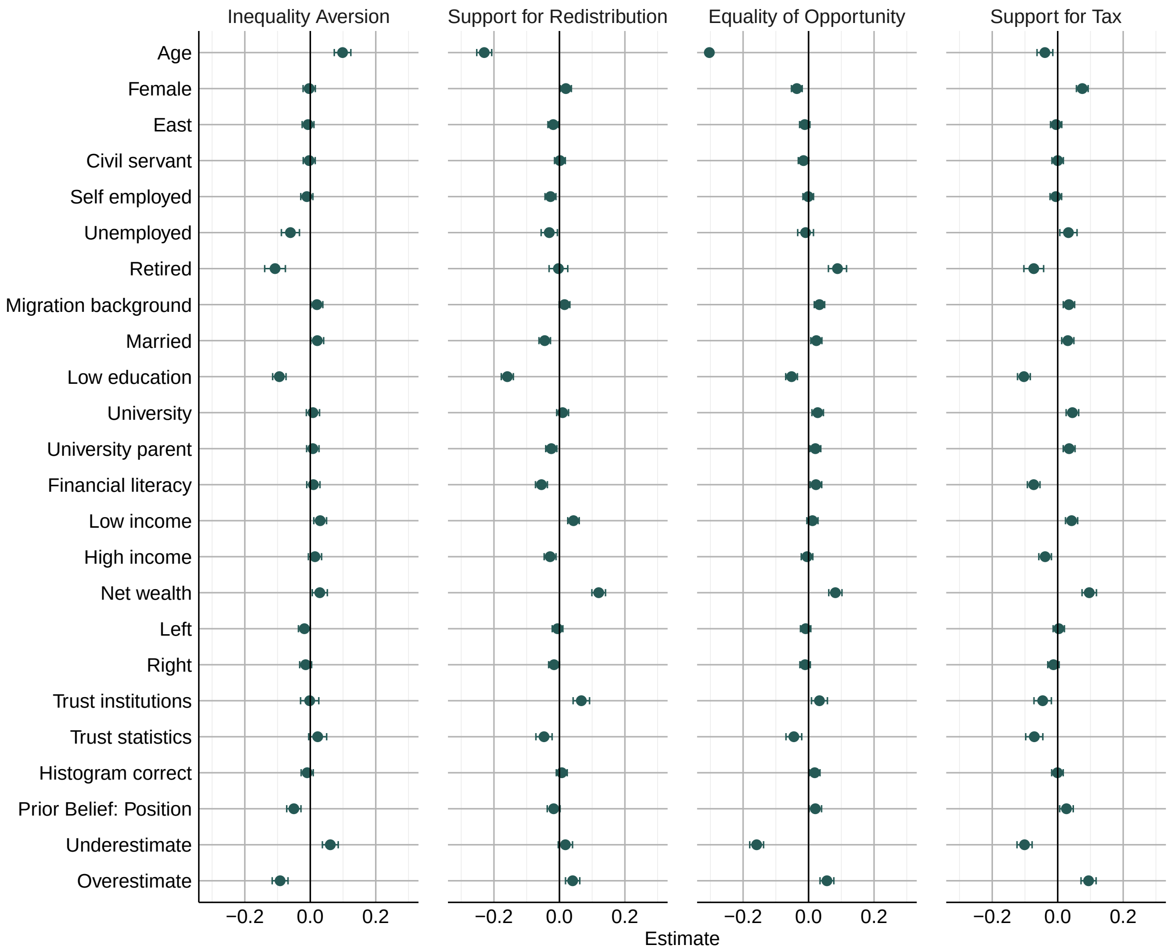


Figure E.2: Determinants of above-median CATE for personalized treatment

Notes: This Figure shows coefficients and 95% confidence intervals from LPM regressions with a binary outcome indicating an above-median CATE in the personalized treatment. The median CATE is determined separately for each outcome.