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EMPIRICAL PROPERTIES OF AN EXTENDED CES UTILITY FUNCTION IN REPRESENTING DISTRIBUTIONAL PREFERENCES

Keigo Inukai
Yuta Shimodaira
Kohei Shiozawa

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The Institute of Social and Economic Research
Osaka University
6-1 Mihogaoka, Ibaraki, Osaka 567-0047, Japan

Empirical properties of an extended CES utility function in representing distributional preferences*

Keigo Inukai[†] Yuta Shimodaira[‡] Kohei Shiozawa[§]

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Abstract

In previous work, we proposed a method to address mathematical inconvenience by extending the constant elasticity of substitution (CES) utility function in Inukai, Shimodaira, and Shiozawa (2022, ISER DP No.1195). However, the relationships between the extended CES parameters and the external measurements are yet unrevealed. To explore these empirical properties of the extended CES utility function, in this paper we construct an online experiment of Amazon Mechanical Turk workers using a modified dictator game, a public goods game, and a questionnaire. We then compare the parameters of the utility function according to the modified dictator game to behavior in the public goods game and the responses to the questionnaire. This provides evidence that the distribution parameter of the extended CES utility function measures the preference for equality or selfishness. However, we do not find any positive evidence that the substitution parameter measures the preference for efficiency.

Keywords: CES, Distributional preferences, Equality, Efficiency, Amazon Mechanical Turk

JEL codes: C91, D63, D64, D90

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[†]Department of Economics, Meiji Gakuin University. E-mail: inukai@eco.meijigakuin.ac.jp

[‡]Graduate School of Economics, Osaka University. E-mail: u064674i@ecs.osaka-u.ac.jp

[§]Department of Economics, Takasaki City University of Economics. E-mail: shiozawa@tcue.ac.jp

1 Introduction

Debate about the trade-off between societal efficiency and fairness has prevailed throughout human history, from early hunter-gatherers to the modern day. Some argue that while inequality may indeed arise, as society becomes richer, the poor will also become richer. Others contend that it is more desirable to achieve equality, even at the expense of social efficiency. This efficiency–fairness trade-off continues to divide society. However, the question of distributive justice is not only a core question in the social sciences. In recent years, the allocation problem among individuals has also been pointed out as an essential adaptive issue in other organisms. For this reason, we need to know more about the mechanisms that create the values of efficiency and fairness among people.

The pivotal element in studying individual attitudes toward efficiency and fairness begins by modeling and measuring individual preferences for efficiency and fairness. The outcome-based model addresses the concerns of individual participants in the distribution of rewards between the individual and others (Fehr and Schmidt, 2006, Section 3.1; Cooper and Kagel, 2016, Section II). A method was proposed by Andreoni and Miller (2002) to model the distributional preferences elicited using the modified dictator game (henceforth MDG) using the constant elasticity of substitution (CES) utility function (Arrow et al., 1961), which has a flexible and helpful specification in modeling behaviors. Andreoni and Miller (2002) employed the CES utility function to encompass the three typical preference models—Rawlsian inequality aversion, altruistic, and selfish preferences—continuously. Further, Fisman et al. (2007) studied individual heterogeneity of preferences with a two-dimensional measure—selfishness and the elasticity of substitution—supposing that the parameter controlling elasticity also measures the preference for a trade-off between equality and efficiency. Subsequent studies following Fisman et al.'s (2007) paradigm have been ongoing to this day (Fisman et al., 2014, 2015a,b, 2022; Li et al., 2017, 2022).

Although this procedure has been adopted in several applications, the standard CES utility function is also known to have a theoretical difficulty in that the limit of parameters corresponding to the Rawlsian maximin form, the parameter quantifying selfishness becomes meaningless for identifying variations, and consequently, we may obtain biased results. We have already addressed this in Inukai et al. (2022) and proposed an extension of the CES utility function, which allows us to interpret the selfishness parameter without bias.

Given the mathematical properties, the two parameters—the distribution and the substitution parameter—of our extended CES utility function were expected to measure the preference for equality or selfishness and the preference for efficiency, respectively, at orthogonal scales to each other. However, the relationship between the extended CES parameters and individual behavior or thought has not yet been clarified. For this paper, we conducted an MDG experiment, an experiment on public goods games, and questionnaires on demographics, socioeconomics, and political attitudes/behaviors among participants of the Amazon Mechanical Turk (`https://www.mturk.com/`, henceforth MTurk).[1] We conducted the survey within the framework of previous studies—concerning elite (Fisman et al., 2015b), political behavior (Fisman et al., 2017), and demographic measures (Fisman et al., 2014)—among the US population. Note that our study is not a direct replication of these studies. However, the accumulation of findings from a variety of samples is useful for obtaining robust results in research on (experimental) economics as a whole (Mullinix et al., 2015; Kohler, 2019; Snowberg and Yariv, 2021).

We examined the correlation of the parameters of the extended CES utility by performing regressions with variables obtained from the public goods game experiment and questionnaire responses. The results of an online experiment with

[1]Evidence already exists that it is possible to obtain reliable results from the experiments using the sample of MTurk participants (Mason and Suri, 2012; Rand, 2012; Höglinger and Wehrli, 2017).

an MTurk sample showed that the parameter expected to measure selfishness is negatively correlated with cooperative behavior in public goods games, supporting the interpretation that the parameter measures selfishness. However, we could not obtain positive results indicating that the parameter controlling the substitution elasticity measures the preference for efficiency.

The remainder of the paper is organized as follows. Section 2 describes the extended CES utility model and the MDG experiment. Section 3 provides details on the public goods game and the questionnaires conducted following the MDG. Section 4 describes the statistical procedures for multiple comparisons and Section 5 describes the experimental implementation. Section 6 presents the results, and Section 7 concludes.

2 Modified dictator game

2.1 Utility model and parameter estimation

To elicit individual distributional preferences, we used an MDG. We now consider the decision problems associated with distributing the initial endowment between the decision makers themselves and their opponents. When an individual decides on a percentage of the endowment distributed to themselves as s and to the opponent as $1-s$, their own reward is $x_s = s/p_s$, and the opponent's reward is $x_o = (1-s)/p_o$. The ratio p_s/p_o represents the relative price of the distribution, which is manipulated by experimenters to measure individual distributional preferences. Here, the budget constraint is represented as $p_s x_s + p_o x_o = 1$.[2]

In Inukai et al. (2022), we documented an extended CES utility model that addresses the mathematical inconvenience of the standard CES utility function used to

[2] For simplicity, the amount of endowment is normalized to one.

model behaviors in MDGs. In this analysis, we characterize individual distributional preferences using our extended CES utility function, which has the form

$$U(x_s, x_o) = \begin{cases} \left[\alpha^{1+\rho} x_s^{-\rho} + (1-\alpha)^{1+\rho} x_o^{-\rho}\right]^{-\frac{1}{\rho}} & \text{if } \rho > 0 \\ \alpha \ln(x_s) + (1-\alpha)\ln(x_o) & \text{if } \rho = 0 \\ \left[\alpha x_s^{-\rho} + (1-\alpha) x_o^{-\rho}\right]^{-\frac{1}{\rho}} & \text{if } -1 \leq \rho < 0 \end{cases} \tag{1}$$

where $\alpha \in [0,1]$, $\rho \in [-1,\infty)$. Let α and ρ be the *distribution parameter* and the *substitution parameter*, respectively.[3]

By solving the utility maximization problem subject to the budget constraint, we obtain the demand function, which determines a decision maker's own expenditure share,

$$s(p_s/p_o \mid \alpha, \sigma) = \begin{cases} \dfrac{\alpha/(1-\alpha)}{\alpha/(1-\alpha) + (p_s/p_o)^{-(1-\sigma)}} & \text{if } 0 \leq \sigma \leq 1 \\ \dfrac{\big(\alpha/(1-\alpha)\big)^{\sigma}}{\big(\alpha/(1-\alpha)\big)^{\sigma} + (p_s/p_o)^{-(1-\sigma)}} & \text{if } \sigma > 1 \end{cases} \tag{2}$$

where $\sigma = 1/(\rho+1) \in (0,\infty)$ is the elasticity of substitution. Note that the value of the function $s(\bullet)$ corresponds to a percentage of the budget, that is, $s = p_s x_s$, and thus $s(\bullet) \in [0,1]$.

In this study, as in Inukai et al. (2022), a Bayesian statistical model was formulated to estimate the two parameters of the extended CES utility function, α and ρ. Each observation of the expenditure share s was assumed to be distributed on a unit interval in proportion to the normal distribution with location $s(\bullet)$ and scale σ_s. For the error term scale, σ_s, the exponential distribution with the rate parameter $\lambda = 0.5$ was adopted as a prior distribution. For the distribution parameter α, the uniform distribution on the unit interval is used as a noninformative prior

[3] The naming of the parameters has been carefully selected to be neutral.

distribution. For the substitution parameter σ, the prior distribution was specified in logarithmic form, $\ln \sigma$, and set to Student's t-distribution with degrees of freedom $\nu = 4$. To treat $\ln \sigma$ as a parameter with a unit interval scale, we converted it to the *rescaled substitution parameter* τ; that is, the value of the cumulative distribution function of the Student's t-distribution with $\nu = 4$, i.e.,

$$\tau = \frac{1}{2} + \frac{\ln \sigma \big((\ln \sigma)^2 + 6 \big)}{2 \big((\ln \sigma)^2 + 4 \big)^{\frac{3}{2}}}. \tag{3}$$

2.2 Possible interpretations of the utility parameters

Based on the following mathematical discussion, the distribution parameter α is expected to represent a preference for (selfless–) equality–selfishness. Here, we discuss the behavior of the function s at typical values of α. For $\alpha = 1$ ($\alpha = 0$), for any σ, we obtain $s = 1$ ($s = 0$) and observe a completely selfish (selfless) distribution, independent of price. Alternatively, for $\alpha = 1/2$, we obtain equation $s/(1-s) = (p_s/p_o)^{1-\sigma}$ and find that the behavior changes depending on σ. If $\sigma = 0$, we obtain an equation $s/p_s = (1-s)/p_o$ or $x_s = x_o$ which means that the payoffs received by both the decision maker and the opponent are equal. If $\sigma = 1$, we obtain $s = 1/2$, which corresponds to the Nash bargaining solution (Nash, 1950) for an allocation problem when the bargaining power is identical for the decision maker and the opponent. If $\sigma \longrightarrow \infty$, s becomes a step function where $p_s/p_o = 1$ is a switching point: $s = 1$ for $p_s < p_o$, $s = 0$ otherwise. Given that the price ratio facing the decision maker is a random variable following a symmetric distribution where the mean is 1, the expected s is 1/2 because $s = 0$ and $s = 1$ are realized with the same probability.[4] In this way, the decision maker distributes equitably with respect to the opportunity

[4]From this reasoning, the experimenter should instruct the participants in the MDG experiment to avoid forming the belief that the prices are drawn from a distribution that only one of themselves or their opponent has advantages.

to obtain a payoff.[5] In the three cases of $\alpha = 1/2$, although the implementation differs depending on the elasticity of substitution σ, an equality-oriented distribution is observed in any case. Eventually, we expect that the parameter α measures the preference for equality in the range between equality oriented and selfishness, or selfless and equality oriented.

Next, let us discuss the interpretation of the substitution parameter ρ. A neutral interpretation of the parameter ρ, which controls the elasticity of substitution σ, is a measure of the reactivity of the decision maker to prices, given the definition of elasticity.

We consider three typical cases in general $\alpha \in (0, 1)$. Note that σ is interpretable only if α is not 0 or 1. For $\sigma = 0$, we obtain an equation $x_s/x_o = \alpha/(1-\alpha)$: a decision maker determines the distribution so that the ratio of the payoffs matches the odds of α. For $\sigma = 1$, we obtain an equation $s/(1-s) = \alpha/(1-\alpha)$: a decision maker determines the distribution according to the Nash bargaining solution, taking the odds of α as the odds of bargaining power. For $\sigma \longrightarrow \infty$, s is a step function, where $p_s/p_o = \alpha/(1-\alpha)$ is a switching point: a decision maker more frequently gets a whole payoff according to the odds of α—although the frequency depends on the distribution of price the experimenter designs.

In the third case, s maximizes the α-weighted joint payoff among the decision maker and the opponent $\alpha x_s + (1-\alpha)x_o$. Given the weighted joint payoff for any decision is always lower than the case of $\sigma \longrightarrow \infty$, it may (partially) be possible to interpret that individuals with larger σ are efficiency oriented.[6]

[5]Note that the expected payoff amounts are not necessarily equal for both the decision maker and their opponent.

[6]Note that an individual with $\sigma = 0$ is not a minimizer of the weighted joint payoff, as they do not choose corners unless α is 0 or 1. Furthermore, the magnitude relationship between the weighted joint payoff at $\sigma = 0$ and at $\sigma = 1$ depends on the parameter α and the offered price. For example, we consider a situation where an individual whose α is 0.8 faces a budget constraint $4^{-1}x_s + 8^{-1}x_o = 1$. The weighted joint payoff $0.8x_s + 0.2x_o$ is ~ 3.02 if $\sigma = 0$ and is ~ 2.88 if $\sigma = 1$. In this example, the weighted joint payoff decreases as σ increases from 0 to 1. This

2.3 Experimental design

We follow Fisman et al.'s (2007) protocol for the MDG experiment. The instructions presented to the participants are provided in Appendix A.

Participants are required to distribute their initial endowment between themselves and an anonymous opponent so that they exhaust their budget. Following the protocol, participants are then presented with a screen displaying budget constraint lines in a two-dimensional plane and make decisions by clicking on the lines. The graphical interface allows participants to avoid the burden of calculating the rewards from the prices.

The participants were instructed that the axes of the graph measure the payoffs. Participants were also provided with a numerical value that indicated the amount that corresponded to the coordinates on the graph on which they clicked. Note that the payoffs were presented in experimental tokens and that the maximum payoff for one side in a single decision problem was less than 100 tokens.

The experiment consisted of 50 independent decision problems (i.e., budget constraints) corresponding to Fisman et al. (2007). However, rather than randomly generating problems for each participant as their procedure, a predetermined problem set was commonly offered to all participants. Table 1 shows the set of problems used. The columns "Max self" and "Max opp" are the intercepts of the budget constraint line, which correspond to ${p_s}^{-1}$ and ${p_o}^{-1}$, respectively. Because of the visual presentation of the budget constraint lines to the participants, we generated the problems so that the angles of the lines were uniformly distributed to ensure that the lines were visually unbiased. Therefore, the price ratios were distributed in symmetry with a center of 1.[7] The "Angle" column in Table 1 represents the

reversal is more likely to occur on average when the price ratios that comprise a problem set are distributed unevenly in favorable regions for the opponent.

[7]Efficient methods of generating decision problems for parameter estimation are open to discussion. Baader et al. (2021) are working on simplifying the methodology and have suggested that

angle ϕ between each line and the axis that measures the payoff to the decision maker. Note that $\tan\phi = p_s/p_o$. Figure 1 shows the budget constraint line in a two-dimensional plane, where a decision maker's own payoff in experimental tokens is measured on the horizontal axis and the opponent's payoff is measured on the vertical axis.[8] Figure 2 shows demand curves $s = s(p_s/p_o \mid \alpha = 1/2, \sigma)$ for several values of σ and price ratios associated with budget constraints.

One unit of the experimental token was 0.02 USD. Each participant was paid for realizing 5 of the 50 decision problems as dictator and 5 as recipient, while Fisman et al. (2007) realized one each as dictator and recipient. Given our decision problem set included some budget constraints with intercepts less than 50 tokens, if we followed their method, we expected too much volatility in the participants' rewards. Therefore, to control the volatility of rewards, the number of decisions to be realized was increased. To assign participant roles, either dictator or recipient, the "ring" matching algorithm was used, as documented in Crosetto et al. (2019).

Grech and Nax (2020) reported that when participants believe the dictator game to be interactive, reciprocal motivation also drives them to transfer to their opponent in the dictator game. To account for this, we did not explicitly instruct participants that the frequency of their becoming dictators is half of the 10 decisions to be realized. Thus, we expect to mitigate their reciprocal motives.

parameter estimation can be done with sufficient accuracy with fewer decision problems by devising price sampling. Imai and Camerer (2018) proposed an optimal adaptive method to generate decision problems for the convex time budget experiment, which has a structure similar to the MDG experiment.

[8] In the experiment, the correspondence between both axes of the graphs presented to the participants and self/opponent was randomly determined for each participant.

Table 1: Set of decision problems

	Max self	Max opp	Price	Angle		Max self	Max opp	Price	Angle
1	70.00	7.36	0.105	6.0	26	76.38	78.00	1.021	45.6
2	75.00	10.01	0.133	7.6	27	46.00	49.67	1.080	47.2
3	80.00	12.96	0.162	9.2	28	66.53	76.00	1.142	48.8
4	85.00	16.21	0.191	10.8	29	48.00	58.02	1.209	50.4
5	40.00	8.79	0.220	12.4	30	57.81	74.00	1.280	52.0
6	96.26	24.00	0.249	14.0	31	25.20	34.18	1.356	53.6
7	41.00	11.45	0.279	15.6	32	68.81	99.00	1.439	55.2
8	75.92	23.50	0.310	17.2	33	26.40	40.34	1.528	56.8
9	42.00	14.30	0.340	18.8	34	60.29	98.00	1.625	58.4
10	61.84	23.00	0.372	20.4	35	27.60	47.80	1.732	60.0
11	95.00	38.38	0.404	22.0	36	52.45	97.00	1.849	61.6
12	68.67	30.00	0.437	23.6	37	28.80	57.01	1.980	63.2
13	96.00	45.17	0.471	25.2	38	45.17	96.00	2.125	64.8
14	57.01	28.80	0.505	26.8	39	30.00	68.67	2.289	66.4
15	97.00	52.45	0.541	28.4	40	38.38	95.00	2.475	68.0
16	47.80	27.60	0.577	30.0	41	23.00	61.84	2.689	69.6
17	98.00	60.29	0.615	31.6	42	14.30	42.00	2.937	71.2
18	40.34	26.40	0.654	33.2	43	23.50	75.92	3.230	72.8
19	99.00	68.81	0.695	34.8	44	11.45	41.00	3.582	74.4
20	34.18	25.20	0.737	36.4	45	24.00	96.26	4.011	76.0
21	40.00	31.25	0.781	38.0	46	8.79	40.00	4.548	77.6
22	99.12	82.00	0.827	39.6	47	16.21	85.00	5.242	79.2
23	42.00	36.77	0.875	41.2	48	12.96	80.00	6.174	80.8
24	86.39	80.00	0.926	42.8	49	10.01	75.00	7.495	82.4
25	44.00	43.09	0.979	44.4	50	7.36	70.00	9.515	84.0

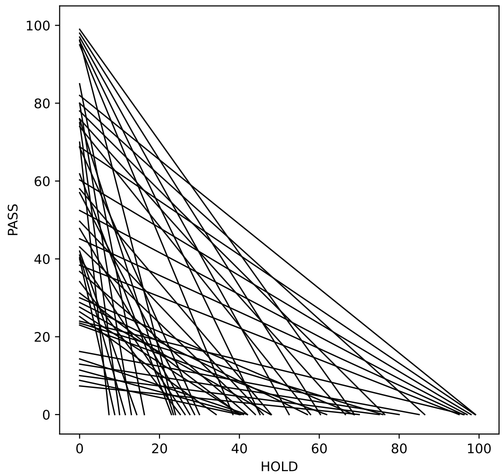


Figure 1: Budget constraint lines offered to participants

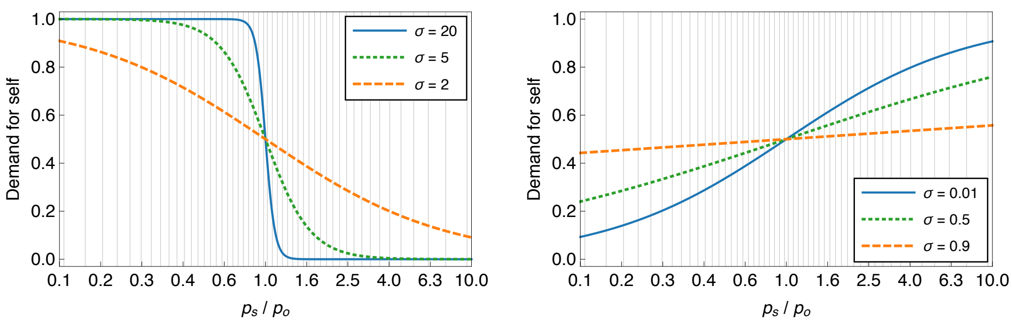


Figure 2: Demand curves and offered prices

Note: The vertical axis measures the expenditure share s for the decision makers themselves, and the horizontal axis measures the price ratio p_s/p_o on a logarithmic scale. For all demand curves, we fixed $\alpha = 1/2$. The vertical lines represent the price ratios of each decision problem.

3 Measures and hypotheses

We implemented the public goods game experiment and the questionnaire survey following the MDG and obtained the 26 variables listed in the following subsection. We performed ordinal least squares regression to examine the relationship between the collected variables (serving as independent variables) and the estimated utility parameters ($\widehat{\alpha}$ and $\widehat{\tau}$) and the logarithmic scale of error terms ($\ln \widehat{\sigma_s}$).[9]

3.1 Public goods game

The extended CES parameters were compared with behavior in a public goods game. As with dictator games, public goods games are experimental games used in many economics and social psychology studies. There are many observations of cooperative behaviors in public goods game experiments, which are not supported by the Nash equilibrium. Unlike the dictator game, the public goods game does not necessarily require pure altruistic preferences as a motive for cooperative behavior because they may also receive some payoffs from the opponents.[10] However, Galizzi and Navarro-Martinez (2019) have reported a correlation between altruistic behavior in dictator games and cooperative behavior in public goods games. Given the distribution parameter α of the extended CES utility is believed to represent a preference for equality–selfishness (the larger α, the more selfishness), we conjecture that α is negatively correlated with cooperative behavior in the public goods game. Following Galizzi and Navarro-Martinez's (2019) findings, we conduct statistical analysis and test the following hypotheses.

[9] We only attempt to find a relationship between the variables and parameters, with no intention of obtaining causality. Following the analysis in Fisman et al. (2014), we performed a regression with the estimated utility parameters as the dependent variable.

[10] Public goods games are frequently used to investigate the nature of reciprocally motivated behavior rather than to elicit altruistic preferences (Dhami, 2016; Drouvelis, 2021).

Hypothesis 1. *The distribution parameter α of the extended CES utility is negatively correlated with the contribution in the public goods game.*

The public goods game was played in groups of four players. The initial endowment was 20 tokens, each of which was exchanged for 0.06 USD. The marginal per capita return was 0.4. The participants responded with their contribution to the group as an integer from 0 to 20. We standardized each participant's decision and used the scores `R_public` obtained in the regression analysis. Randomly chosen participants with a 10% chance were paid for the dictator game.[11]

3.2 Socioeconomic status of eliteness

To reveal the relationship between eliteness and distributional preferences, we obtained measures predicted to be correlated with eliteness and compared them with the extended CES utility parameters. Fisman et al.'s (2015b) main finding is that the elite—authors defined as Yale Law School students—valued efficiency over equality, which was measured by the curvature parameter of the standard CES utility function. As noted above, by the extended CES utility function, the preference for efficiency can be measured as a component independent of the preference for equality. Following Fisman et al. (2015b), we focus on the rescaled substitution parameter τ, which is expected to represent a preference for efficiency, and hypothesize the following.

Hypothesis 2. *The rescaled substitution parameter τ of the extended CES utility is higher when socioeconomic status, which represents high eliteness, is high.*

We collected the seven variables listed below as socioeconomic status measures to

[11] The experiment followed the protocol of Fischbacher et al. (2001), where the experiment is designed to elicit the propensity for conditional cooperation. Therefore, the payoffs were calculated using the decisions of three unconditional contributions and one conditional contribution for each group.

test the hypothesis. See Appendix B for the original survey questions and detailed variable definitions.

`R_educational*`: education level

- `R_educational1`: dummy equal to 1 if respondent received a bachelor's or associate degree in college
- `R_educational2`: dummy equal to 1 if respondent received a master's, doctoral, or professional degree

`R_income*`: income level

- `R_income1`: dummy equal to 1 if respondent's annual income is less than \$30,000
- `R_income2`: dummy equal to 1 if respondent's annual income is not less than \$90,000

`R_employment`: dummy equal to 1 if respondent is employee or business owner

`R_occupational*`: Occupational prestige

- `R_occupational1`: dummy equal to 1 if `R_employment` = 1 and the respondent belongs to professional and technical occupations
- `R_occupational2`: dummy equal to 1 if `R_employment` = 1 and the respondent belongs to higher administrative occupations

3.3 Political attitudes and behaviors

We reveal the relationship between political attitudes or behaviors and distributional preferences. Fisman et al. (2017) reported that the curvature parameter of the standard CES utility function could predict Americans' political decisions: equality-oriented individuals were more likely to vote for Barack Obama in the 2012 presidential election or be affiliated with the Democratic Party. For equality-oriented individuals, the distribution parameter α of the extended CES utility function is believed to be close to 0.5, but close to 1 for selfish individuals. Following Fisman et al.'s (2017) conclusion, we focus on the distribution parameter α and hypothesize the following.

Hypothesis 3. *The distribution parameter α of the extended CES utility is lower for those who support the Democratic Party or the redistributive policies that Democrats mostly favor.*

We collected the six variables listed below as measures of political attitudes and behaviors to test the hypothesis. See Appendix B for the original survey questions and detailed variable definitions.

`R_political`: dummy equal to 1 if respondent thinks of self as liberal

`R_partisanship`: dummy equal to 1 if respondent thinks of self as closer to the Democratic party

`R_trump`: dummy equal to 1 if respondent approves Trump's job as President

`R_voting`: dummy equal to 1 if respondent voted for Biden in the 2020 presidential election

`R_redistribution`: dummy equal to 1 if respondent agrees for redistributive policies

`R_basicincome`: dummy equal to 1 if respondent agrees for basic income policies

3.4 Demographic characteristics

We collected the 12 variables listed below as demographic measures. See Appendix B for the original survey questions and detailed variable definitions.

`R_age`: standardized respondent's age

`R_gender`: dummy equal to 1 if respondent is female

`R_race*`: ethno-racial identity

- `R_race1`: dummy equal to 1 if respondent is Black or African American
- `R_race2`: dummy equal to 1 if respondent is Hispanic or Latino
- `R_race3`: dummy equal to 1 if respondent is Asian

`R_religious*`: religious identity

- `R_religious1`: dummy equal to 1 if respondent is Protestant
- `R_religious2`: dummy equal to 1 if respondent is Roman Catholic

`R_religious3`: dummy equal to 1 if respondent does not belong to a religion

`R_marital*`: marital status

`R_marital1`: dummy equal to 1 if respondent is married

`R_marital2`: dummy equal to 1 if respondent is widowed, divorced, or separated

`R_children`: dummy equal to 1 if respondent has children

`R_metro`: dummy equal to 1 if respondent lives in the metro area

4 Multiple comparison procedure

We collected 26 variables `R_*` and performed 26 statistical tests of the null hypothesis for the regression coefficients for each parameter of the extended CES utility α and τ, and the scale of error terms $\ln \sigma_s$. Each test is a two-sided t test. To account for the multiple comparison problem over these 26 tests, we adjusted the p values using the Benjamini–Hochberg procedure (Benjamini and Hochberg, 1995) and controlled for the false discovery rate.

Furthermore, we conducted 26 equivalence tests to explicitly clarify the absence of effects using the two-sided test procedure (TOST) (Lakens et al., 2018). We detected ineffective variables using one-sided t tests that were smaller than the symmetric smallest effect size of interest (SESOI). Following Lakens et al.'s (2018) suggestion, we set the SESOI based on a priori statistical power simulation for the null hypothesis multiple testing.[12] We searched for SESOI with a mean individual power (see Porter, 2018) of about 0.8 and determined for $\widehat{\alpha}$, $\widehat{\tau}$, and $\ln \widehat{\sigma_s}$ to be 0.105, 0.62, and 0.39, respectively. The p values for each TOST were also adjusted according to the Benjamini–Hochberg procedure.

[12] Simulations were performed using data collected in a pilot experiment conducted in September 2020. Because some questionnaires were added after conducting the pilot experiment, we ran the simulation using known data to supplement the missing variables.

We set the upper limit of the false discovery rate at 0.005. Setting the false discovery rate at 0.005, even if all null hypotheses were rejected, less than one hypothesis would be falsely detected because of a Type I error. We rejected the null hypothesis when the adjusted p value was less than 0.005. This conservative criterion results in decisive results.[13]

We preregistered the procedure for multiple comparisons and the SESOI values in Open Science Framework (`https://osf.io/68rn2`).[14]

5 Implementation

The experiments were conducted in April 2021. The experimental software for the MDG was developed from scratch using JavaScript and hosted on Firebase (`https://firebase.google.com`), and the public goods game and other questionnaires were implemented using the platform provided by Qualtrics (`https://www.qualtrics.com`).

We recruited participants via MTurk using the CloudResearch MTurk Toolkit (`https://www.cloudresearch.com`, Litman et al., 2017). By using CloudResearch's tool, we restricted the participants to US residents and tried to block workers based on suspicious locations or duplicate IP addresses.

Arechar et al. (2017) have reported that participants' decisions vary depending on the time at which they respond. To avoid biasing the results over time, we divided the experiment into the following seven waves starting at 1:00 AM, 7:00 AM, 9:00 AM, 1:00 PM, 3:00 PM, 7:00 PM, and 9:00 PM EDT. In each wave, we stopped

[13] As commented by Grech and Nax (2020), the relationships between distributional preferences and demographic measures delicate matters that warrant careful consideration.

[14] After starting the first experimental wave, we found a mistake in the simulation code, so we reran the simulation and modified the SESOI in the registration. This modification was done independently of the data collected in the first wave. See `https://osf.io/pn6ke` for the registration before modification.

recruiting when the number of participants that had completed all tasks reached 75 (50 in the first wave).

A total of 500 MTurk workers participated in our study. The average age of the participants was 38.0 years (SD: 10.2, range: 21–74) and 33.7% of the participants were female. Participants spent an average of 45.8 minutes (SD: 26.5, range: 3.6–119.4) completing all tasks. They received a fixed completion fee of 2.50 USD at the end of each wave and a variable bonus from the MDG for all participants and the public goods game for participants that won a lottery with a 10% chance after the completion of all waves. The average payment in the MDG was 4.99 USD (SD: 1.45, range: 1.22–9.81). In the public goods game, 52 lottery winners were paid an additional 1.55 USD on average (SD: 0.36, range: 0.77–2.49). The average total payment was 7.65 USD (SD: 1.52, range: 3.72–12.31) including the fixed fee.

6 Results

Figure 3 depicts a scatter plot of the parameter estimates α–τ for each participant. Inspection of Figure 3 reveals that there are three principal clusters: the first is a cluster with $\widehat{\alpha} = 1$ and $\widehat{\tau}$ that is widely distributed; the second is a cluster centered at $\widehat{\alpha} = 0.5$ and $\widehat{\tau} = 0$, and the third is a more widely distributed cluster centered at $\widehat{\alpha} = 0.5$ and $\widehat{\tau} = 0.2$.

As we discussed in Inukai et al. (2022), if the α estimate is close to 0 or 1, the τ estimate has little credibility. In the analysis of the τ estimate we report in the following sections, we omit participants that are purely selfless (5 participants) or purely selfish (58 participants) using a one-sided test at the 10% level as in Li et al. (2022). Participants excluded in the analysis of τ estimate are plotted with a cross in Figure 3.

Table 2 provides summary statistics for the measures of the public goods game and the questionnaires. For some variables, statistics for the raw data before coding to dummy variables or standardization are also provided.

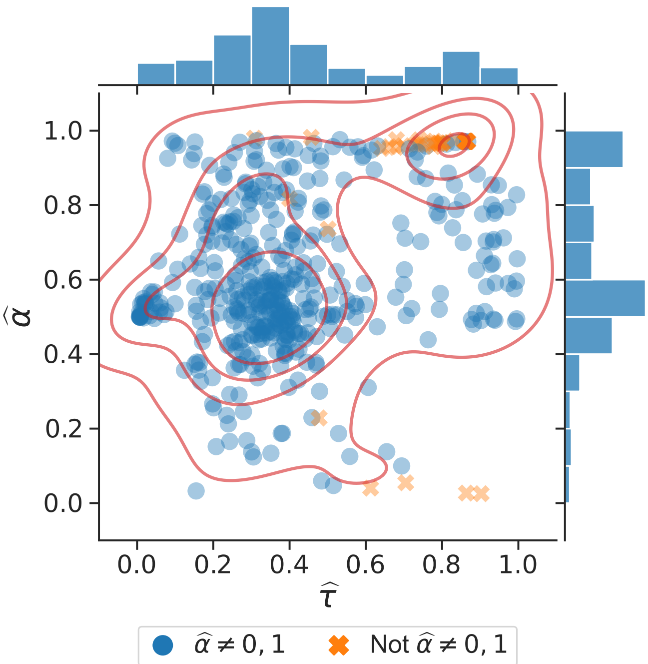


Figure 3: Scatter plot of the extended CES utility parameter estimates α and τ

Note: Individuals for whom the null hypothesis that their α estimate is equal to 0 or 1 cannot be rejected by a one-tailed test at the 10% significance level are identified by a cross. The contour lines represent kernel density estimates.

Table 2: Summary statistics

Variables	Type	Mean	Std	Obs
R_age (raw)	Integer	38.018	10.182	500
R_gender	Boolean	0.337	0.473	498
R_race1	Boolean	0.130	0.337	500
R_race2	Boolean	0.040	0.196	500
R_race3	Boolean	0.076	0.265	500
R_religious1	Boolean	0.128	0.335	491
R_religious2	Boolean	0.468	0.500	491
R_religious3	Boolean	0.238	0.426	491
R_marital1	Boolean	0.660	0.474	500
R_marital2	Boolean	0.056	0.230	500
R_children	Boolean	0.556	0.497	500
R_metro	Boolean	0.862	0.346	484
R_metro (raw)	$1, 2, \ldots, 9$	1.986	1.738	484
R_public (raw)	$0, 1, \ldots, 20$	8.794	6.517	500
R_educational1	Boolean	0.584	0.493	500
R_educational2	Boolean	0.224	0.417	500
R_income1	Boolean	0.176	0.381	500
R_income2	Boolean	0.176	0.381	500
R_employment	Boolean	0.948	0.222	500
R_occupational1	Boolean	0.290	0.454	500
R_occupational2	Boolean	0.082	0.275	500
R_political	Boolean	0.374	0.484	500
R_political (raw)	$1, 2, \ldots, 7$	4.298	2.032	500
R_partisanship	Boolean	0.590	0.492	500
R_trump	Boolean	0.490	0.500	500
R_trump (raw)	$1, 2, \ldots, 7$	3.828	2.161	500
R_voting	Boolean	0.724	0.447	500
R_redistribution	Boolean	0.742	0.438	500
R_redistribution (raw)	$1, 2, \ldots, 7$	5.046	1.589	500
R_basicincome	Boolean	0.752	0.432	500
R_basicincome (raw)	$1, 2, \ldots, 7$	5.236	1.538	500

6.1 Relationships with the demographic characteristics

Figure 4 illustrates the scatter plots for each continuum variable versus each parameter estimate. Figures 5 and 6 show the cumulative distribution of parameter estimates by category. Tables 3–5 report the regressions that analyze the relationships between the demographic variables and the estimated parameters.

For age (`R_age`), see the upper row of Figure 4. Only for $\widehat{\alpha}$, is a positive correlation observed at the 5% significance level. The results are consistent with Fisman et al.'s (2014) reported larger α for the group of participants over 60 years of age.

For gender (`R_gender`), see the first row of Figure 5. For the distribution of $\widehat{\alpha}$, females stochastically dominate males. Taking α as a measure of selfishness, females are more selfish, which is inconsistent with the reports of previous studies (Fisman et al., 2014; Andreoni and Vesterlund, 2001; Kamas and Preston, 2015; Balafoutas et al., 2012).

For ethno-racial identity (`R_race1`–`R_race3`), see the third row of Figure 5. Only for $\ln\widehat{\sigma_s}$, is there a 5% significant difference between the four groups, with Asian respondents displaying less noise. Fisman et al. (2014) reported African Americans to have a smaller $\widehat{\alpha}$, and we obtained results consistent with this at the 10% significance level in a two-sided t test between groups using the dummy variable `R_race1`. However, a regression considering the three variables did not reveal this effect (see column (3) in Table 3).

For religious identity (`R_religious1`–`R_religious3`), see the third row of Figure 5. For respondents identified as Catholic, $\widehat{\alpha}$ is small, while $\ln\widehat{\sigma_s}$ is large among the three groups. The $\widehat{\tau}$ is large for respondents indicating no religion. These results are inconsistent because Fisman et al. (2014) reported that religion does not have a strong effect.

For marital status (`R_marital1` and `R_marital2`), see the first row of Figure 6. For respondents identified as married, both $\widehat{\alpha}$ and $\widehat{\tau}$ are small among the three groups. The result for $\widehat{\alpha}$ lies opposite to the results reported by Fisman et al. (2014), whereas the result for $\widehat{\tau}$ is consistent.

For parenthood (`R_children`), see the second row of Figure 6. Respondents that live with their children have lower $\widehat{\alpha}$ and $\widehat{\tau}$.

For metro and non-metro residents (`R_metro`), see the lower row of Figure 4 and the third row of Figure 6. There is no difference between metro and non-metro residents. In the questionnaire on the place of residence, 417 (86.2%) participants responded that they lived in a county classified as a metro area, suggesting that the variable `R_metro` may be less informative.

Tables 3–5 provide the results of the regression analysis of the 12 variables observed in this subsection. Whereas the regression of the estimated α in Fisman et al. (2014, Table 4) resulted in a coefficient of determination R^2 of 0.041, in our results the (adjusted) R^2 is 0.116, indicating that the regression is not worsened. In the regression analysis, we rejected the hypothesis that `R_gender` (female), `R_religious1` (Protestant), and `R_religious3` (no religion) have no effect on the distribution parameter $\widehat{\alpha}$, respectively, at a level higher than 5% (see column (8) in Table 3). For the rescaled substitution parameter $\widehat{\tau}$, only `R_children` was found to be effective at the 5% significant level (see column (8) in Table 4). On the error term scale $\ln \widehat{\sigma_s}$, `R_race3` (Hispanic or Latino), `R_religious1` (Protestant), and `R_religious3` (no religion) were found to be effective at more than the 5% significant level (see column (8) in Table 5).

In the regressions of behavior in the public goods game experiment, the socioeconomic measures, and the political attitudes/behaviors presented in the following subsections, we also detail the results controlling for the 12 variables listed in this subsection.

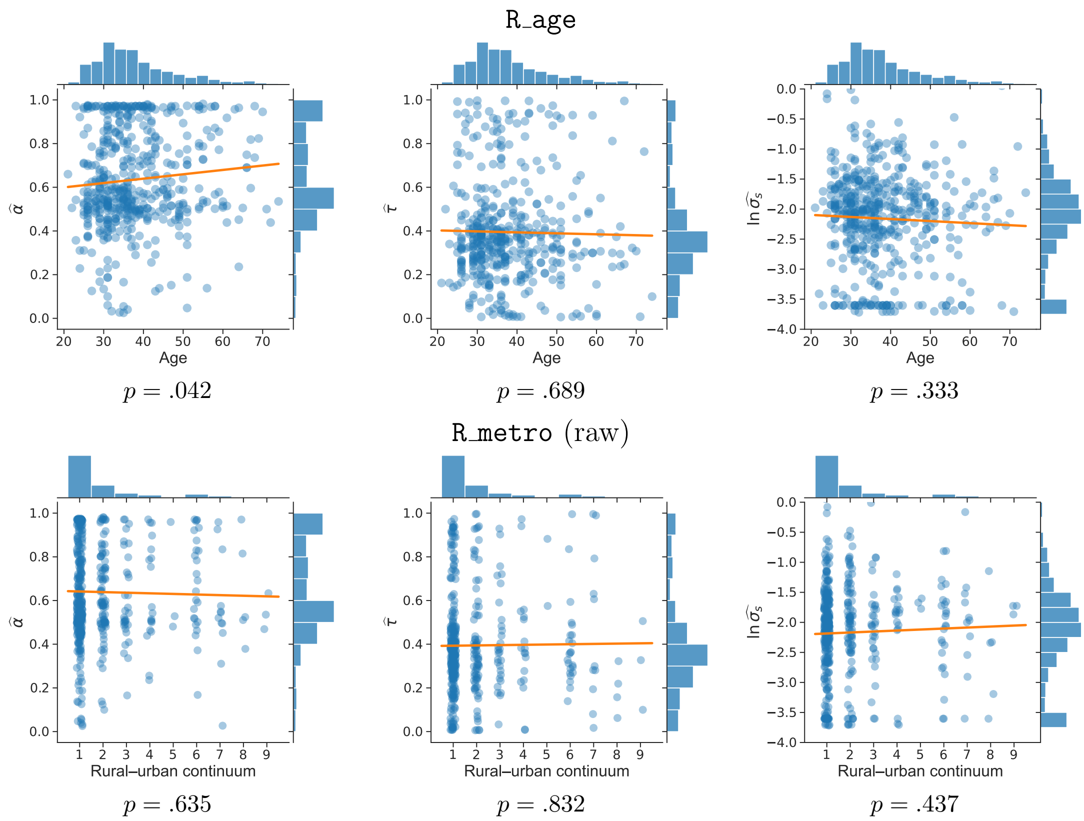


Figure 4: Scatter plots for `R_age` and raw `R_metro`

Note: **Left**: against estimated α. **Center**: against estimated τ. **Right**: against estimated $\ln \sigma_s$. Simple regression lines are drawn. p values are for each slope of regression lines. Each plotted point is jittered in the horizontal direction for raw `R_metro`.

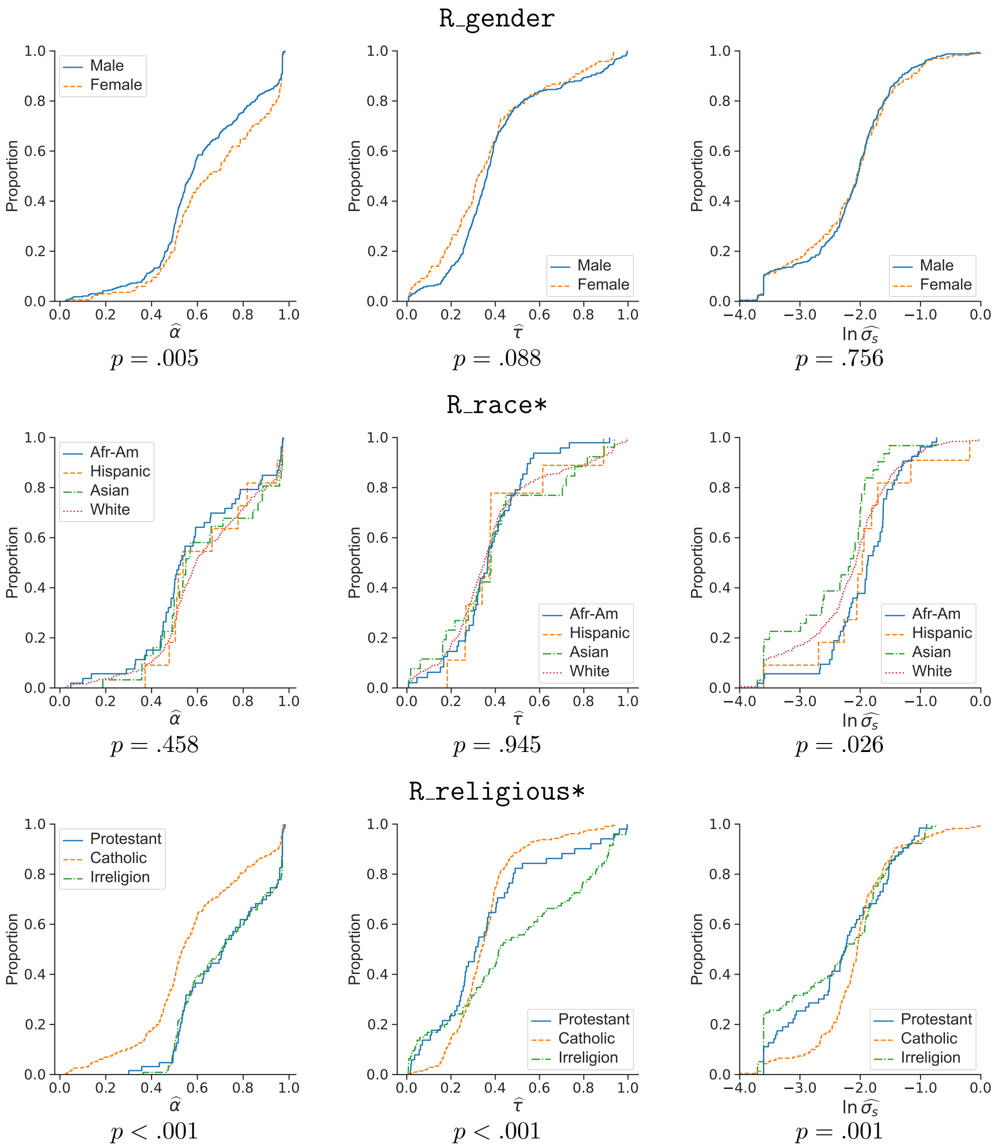


Figure 5: Distribution of estimates grouped by `R_gender`, `R_race*`, and `R_religious*`

Note: **Left**: CDF of estimated α. **Center**: CDF of estimated τ. **Right**: CDF of estimated $\ln \sigma_s$. p values are based on the one-way ANOVA.

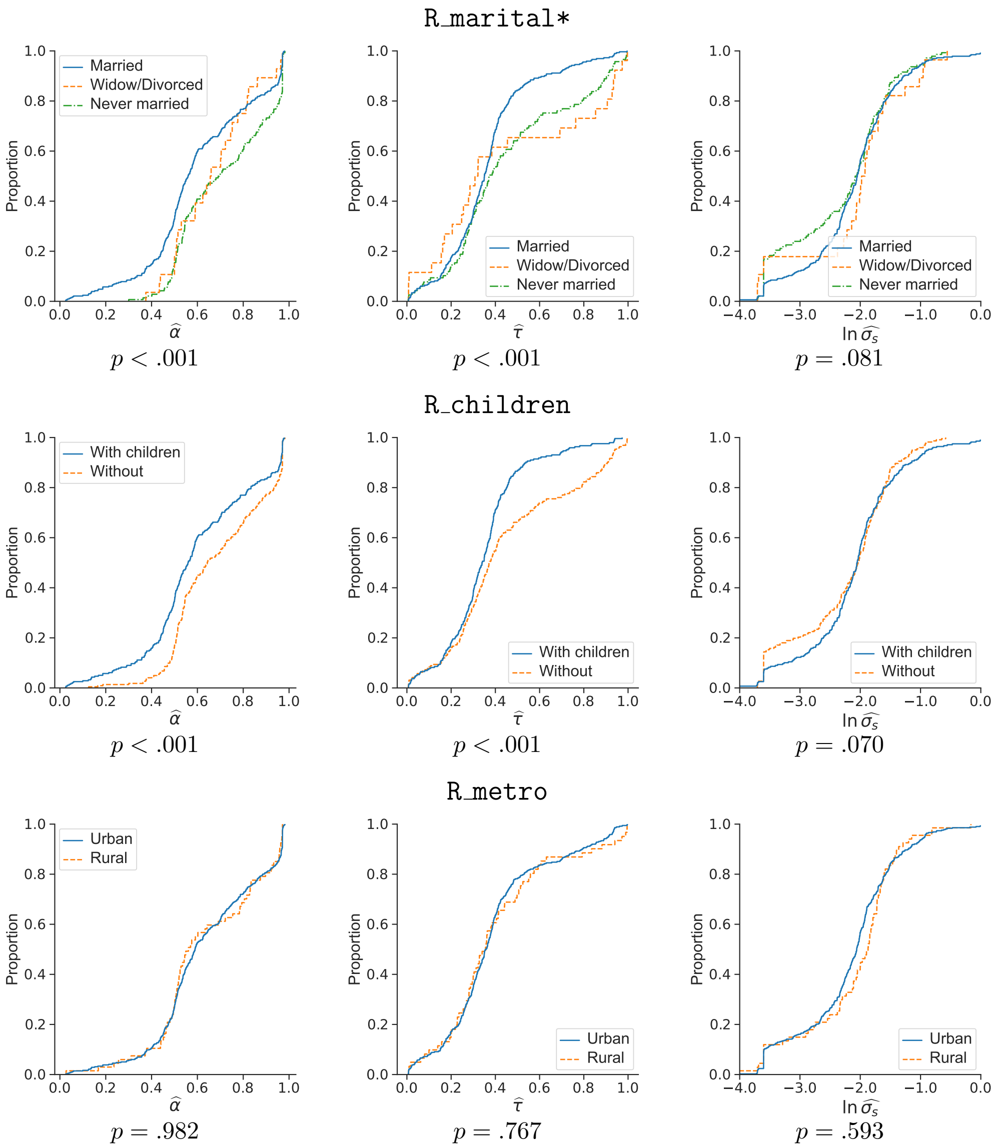


Figure 6: Distribution of estimates grouped by `R_marital*`, `R_children`, and `R_metro`

Note: **Left**: CDF of estimated α. **Center**: CDF of estimated τ. **Right**: CDF of estimated $\ln \sigma_s$. p values are based on the one-way ANOVA.

Table 3: Regressions of estimated α on demographic characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_age	0.041^{**}							0.039^{*}
	(0.020)							(0.022)
R_gender		0.059^{***}						0.055^{**}
		(0.021)						(0.021)
R_race1			−0.049					−0.045
			(0.030)					(0.030)
R_race2			0.007					0.028
			(0.051)					(0.049)
R_race3			−0.002					0.017
			(0.038)					(0.038)
R_religious1				0.106^{***}				0.103^{***}
				(0.036)				(0.036)
R_religious2				−0.043				−0.024
				(0.028)				(0.029)
R_religious3				0.108^{***}				0.081^{**}
				(0.031)				(0.033)
R_marital1					-0.112^{***}			-0.059^{*}
					(0.022)			(0.032)
R_marital2					−0.045			−0.063
					(0.045)			(0.051)
R_children						-0.091^{***}		−0.030
						(0.020)		(0.029)
R_metro							0.001	0.019
							(0.030)	(0.029)
Const.	0.635^{***}	0.615^{***}	0.642^{***}	0.615^{***}	0.712^{***}	0.686^{***}	0.635^{***}	0.641^{***}
	(0.010)	(0.012)	(0.011)	(0.024)	(0.018)	(0.015)	(0.027)	(0.041)
Observations	500	498	500	491	500	500	484	474
Adjusted R^2	0.006	0.014	−0.001	0.088	0.047	0.039	−0.002	0.116
F Statistic	4.141^{**}	7.887^{***}	0.888	16.739^{***}	13.355^{***}	21.289^{***}	0.001	6.157^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4: Regressions of estimated τ on demographic characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
`R_age`	-0.009							-0.012
	(0.023)							(0.026)
`R_gender`		-0.041^{*}						-0.030
		(0.024)						(0.025)
`R_race1`			-0.030					-0.006
			(0.033)					(0.033)
`R_race2`			0.012					0.017
			(0.056)					(0.055)
`R_race3`			0.028					0.023
			(0.042)					(0.044)
`R_religious1`				-0.046				-0.055
				(0.041)				(0.042)
`R_religious2`				-0.054^{*}				-0.045
				(0.031)				(0.033)
`R_religious3`				0.077^{**}				0.043
				(0.035)				(0.038)
`R_marital1`					-0.094^{***}			0.001
					(0.025)			(0.037)
`R_marital2`					-0.009			0.073
					(0.050)			(0.058)
`R_children`						-0.101^{***}		-0.065^{**}
						(0.022)		(0.033)
`R_metro`							-0.010	-0.007
							(0.032)	(0.032)
Const.	0.395^{***}	0.407^{***}	0.396^{***}	0.406^{***}	0.458^{***}	0.451^{***}	0.404^{***}	0.458^{***}
	(0.011)	(0.014)	(0.013)	(0.026)	(0.021)	(0.016)	(0.030)	(0.046)
Observations	437	435	437	429	437	437	423	414
Adjusted R^2	-0.002	0.004	-0.004	0.045	0.030	0.045	-0.002	0.051
F Statistic	0.160	2.928^{*}	0.444	7.775^{***}	7.783^{***}	21.374^{***}	0.088	2.848^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5: Regressions of estimated $\ln \sigma_s$ on demographic characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_age	−0.070							−0.102
	(0.072)							(0.081)
R_gender		−0.024						−0.013
		(0.076)						(0.080)
R_race1			0.194*					0.164
			(0.107)					(0.110)
R_race2			0.287					0.237
			(0.183)					(0.182)
R_race3			−0.256*					−0.293**
			(0.135)					(0.141)
R_religious1				−0.341***				−0.387***
				(0.132)				(0.135)
R_religious2				−0.107				−0.133
				(0.102)				(0.109)
R_religious3				−0.422***				−0.415***
				(0.114)				(0.122)
R_marital1					0.176**			0.094
					(0.080)			(0.119)
R_marital2					0.209			0.254
					(0.166)			(0.190)
R_children						0.131*		−0.042
						(0.072)		(0.106)
R_metro							−0.057	−0.043
							(0.107)	(0.107)
Const.	−2.158***	−2.150***	−2.175***	−1.968***	−2.286***	−2.231***	−2.103***	−1.963***
	(0.036)	(0.044)	(0.040)	(0.087)	(0.067)	(0.054)	(0.099)	(0.151)
Observations	500	498	500	491	500	500	484	474
Adjusted R^2	−0.000	−0.002	0.014	0.033	0.006	0.005	−0.001	0.043
F Statistic	0.940	0.096	3.355**	6.594***	2.532*	3.290*	0.287	2.753***

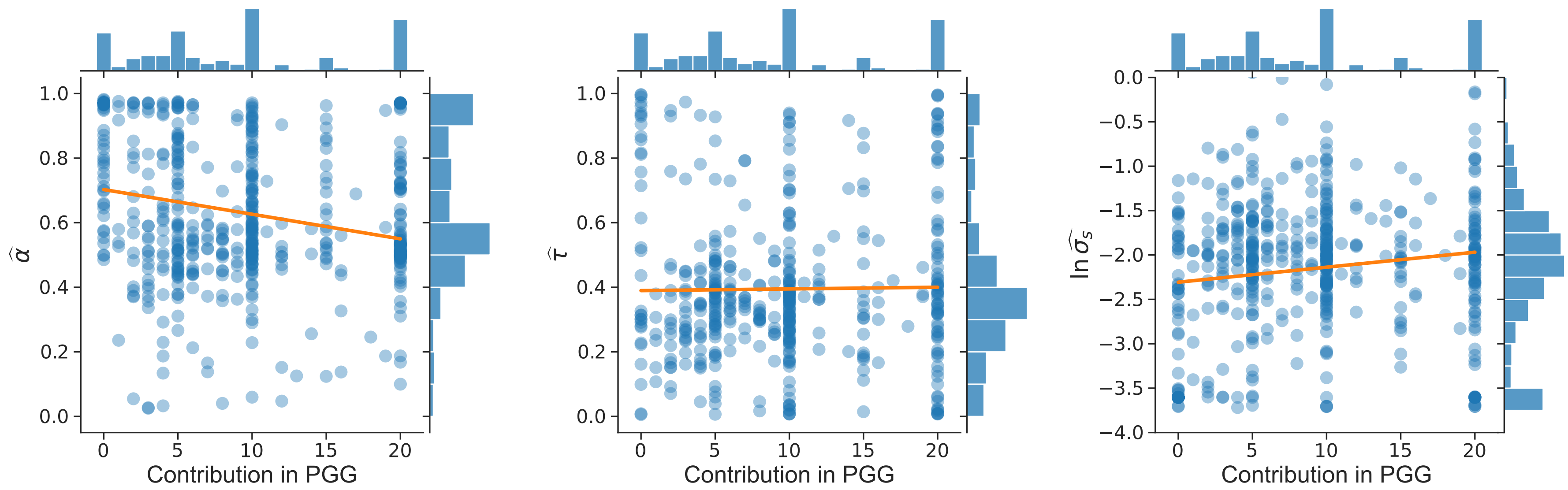
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6.2 Relationships with the public goods game

Figure 7 presents the scatter plots for `R_public` against each parameter estimate. Table 6 reports regressions that analyze the relationship between `R_public` and the estimated parameters. The results of the regression analysis also include a model in which the demographic variables are added to the independent variables.

We find a negative correlation between the contributions in the public goods game and the distribution parameter $\widehat{\alpha}$. Our results support Hypothesis 1.

Furthermore, we find a positive correlation between contributions and the error term scale $\ln \widehat{\sigma_s}$.



$p < .001$ $\qquad$ $p = .770$ $\qquad$ $p = .002$

Figure 7: Scatter plots for contributions in the public goods game

Note: **Left**: against estimated α. **Center**: against estimated τ. **Right**: against estimated $\ln \sigma_s$. Simple regression lines are drawn. p values are for each slope of the regression lines.

Table 6: Regressions on behavior in the public goods game

	α estimate	
	(1)	(2)
`R_public`	-0.100^{***}	-0.117^{***}
	(0.020)	(0.019)
Const.	0.635^{***}	0.643^{***}
	(0.010)	(0.039)
Demogr. Controls	No	Yes
Observations	500	474
Adjusted R^2	0.047	0.179
F Statistic	25.816^{***}	8.924^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	τ estimate	
	(1)	(2)
`R_public`	0.007	-0.010
	(0.023)	(0.024)
Const.	0.394^{***}	0.459^{***}
	(0.011)	(0.046)
Demogr. Controls	No	Yes
Observations	437	414
Adjusted R^2	-0.002	0.049
F Statistic	0.086	2.636^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	$\ln \sigma_s$ estimate	
	(1)	(2)
`R_public`	0.220^{***}	0.257^{***}
	(0.071)	(0.074)
Const.	-2.158^{***}	-1.969^{***}
	(0.036)	(0.149)
Demogr. Controls	No	Yes
Observations	500	474
Adjusted R^2	0.017	0.065
F Statistic	9.513^{***}	3.537^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6.3 Relationships with the socioeconomic status of eliteness

Figure 8 shows the cumulative distribution of the parameter estimates by category. Tables 7–9 report regressions that analyze the relationship between the socioeconomic status variables and estimated parameters.

For education level (`R_educational1` and `R_educational2`), see the first row of Figure 8. We observe that the higher the level of education, the lower the value of $\widehat{\alpha}$, i.e., the more equality oriented they tend to be. This may be inconsistent with Fisman et al.'s (2015b) finding that Yale law students defined as the elite have a greater $\widehat{\alpha}$ and are not equality oriented.

For income level (`R_income1` and `R_income2`), see the second row of Figure 8. There are no differences among the three groups for α and τ, which is inconsistent with Fisman et al.'s (2014) finding that being in a low-income group had a negative effect on $\widehat{\alpha}$ and a positive effect on $\widehat{\tau}$. We find that $\ln \widehat{\sigma_s}$ for respondents classified in the high-income group is smaller at the 5% significance level.

For employment status (`R_employment`), see the third row of Figure 8. For $\widehat{\alpha}$ alone, there is a significant difference at the 5% level. However, the result that $\widehat{\alpha}$ is lower for the employed than for the unemployed is in the opposite direction of the effect reported by Fisman et al. (2014).

For occupation (`R_occupationnal1` and `R_occupationnal2`), see the fourth row of Figure 8. There are no differences among the three groups. The absence of differences between respondents belonging to privileged occupations and others may not be consistent with Fisman et al.'s (2015b) findings.

In the regression analysis, for the distribution parameter $\widehat{\alpha}$, we find that only `R_educational2` (master and above) has a negative effect at the 5% significant level (see column (10) in Table 7). For the rescaled substitution parameter $\widehat{\tau}$, we find that `R_educational1` (bachelor) has an effect at the 5% significance level (see column (10) in Table 8). Given the sign of the coefficient is negative, it appears that at least those participants that completed their bachelor's degree are not efficiency oriented. Ultimately, we obtain no evidence to positively support Hypothesis 2.

Only the effect of `R_income2` is significant based on the regression analysis (see column (10) in Table 9).

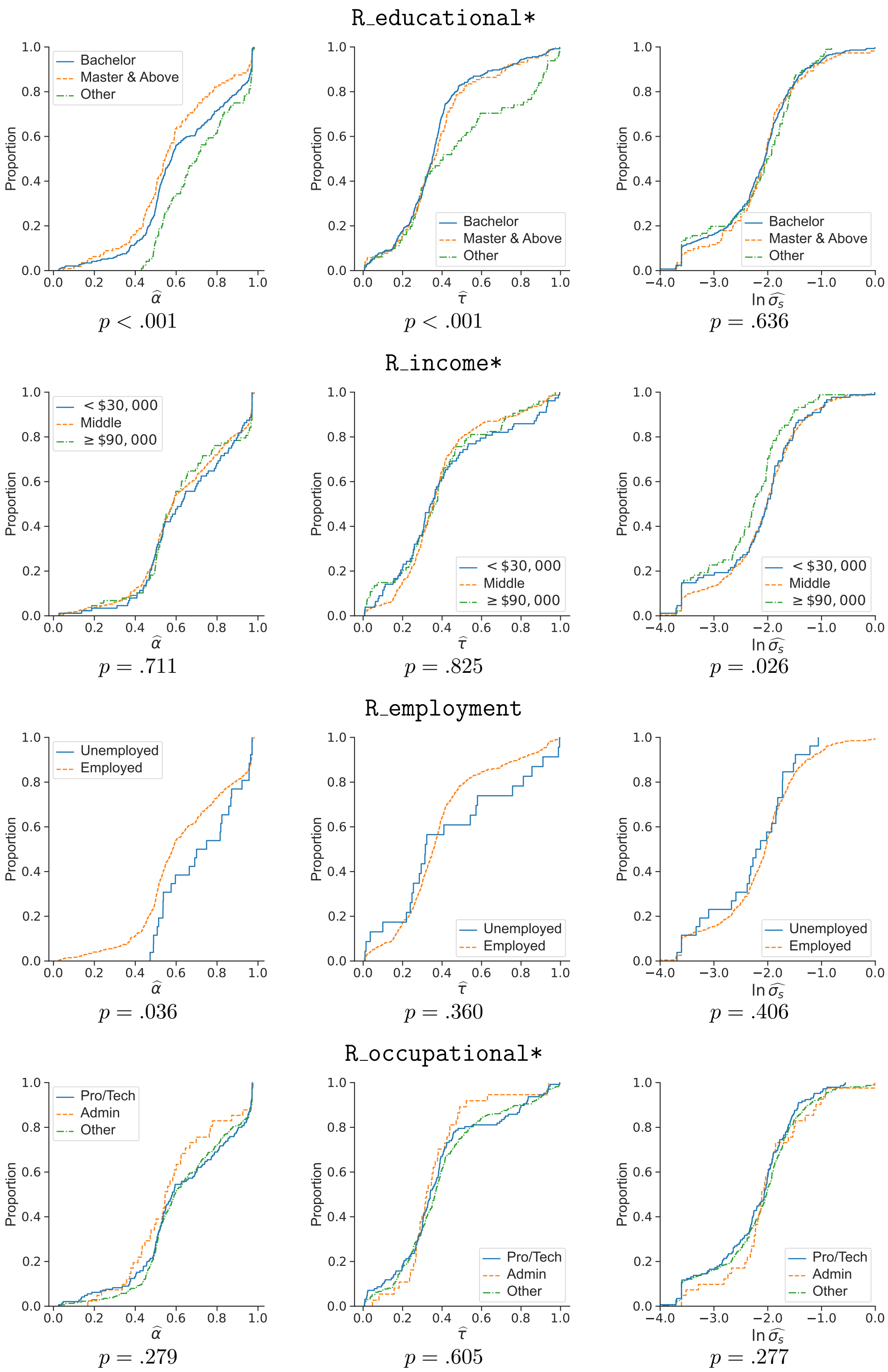


Figure 8: Distribution of estimates grouped by `R_educational*`, `R_income*`, `R_employment`, and `R_occupational*`

Note: **Left**: CDF of estimated α. **Center**: CDF of estimated τ. **Right**: CDF of estimated $\ln \sigma_s$. p values are based on the one-way ANOVA.

Table 7: Regressions of estimated α on socioeconomic status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
`R_educational1`	-0.087^{***}	-0.022							-0.081^{***}	-0.023
	(0.026)	(0.028)							(0.027)	(0.030)
`R_educational2`	-0.141^{***}	-0.065^{**}							-0.140^{***}	-0.070^{**}
	(0.031)	(0.033)							(0.033)	(0.035)
`R_income1`			0.022	-0.015					0.001	-0.021
			(0.027)	(0.027)					(0.027)	(0.028)
`R_income2`			-0.000	0.001					0.012	0.010
			(0.027)	(0.028)					(0.027)	(0.028)
`R_employment`					-0.094^{**}	-0.011			-0.055	-0.006
					(0.045)	(0.047)			(0.047)	(0.049)
`R_occupational1`							-0.010	-0.004	0.020	0.005
							(0.022)	(0.022)	(0.023)	(0.023)
`R_occupational2`							-0.059	-0.019	-0.035	-0.015
							(0.037)	(0.037)	(0.037)	(0.037)
Const.	0.718^{***}	0.659^{***}	0.632^{***}	0.648^{***}	0.725^{***}	0.650^{***}	0.643^{***}	0.643^{***}	0.762^{***}	0.674^{***}
	(0.022)	(0.044)	(0.012)	(0.042)	(0.044)	(0.057)	(0.013)	(0.041)	(0.047)	(0.061)
Demogr. Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	500	474	500	474	500	474	500	474	500	474
Adjusted R^2	0.038	0.121	-0.003	0.112	0.007	0.114	0.001	0.112	0.035	0.113
F Statistic	10.730^{***}	5.635^{***}	0.341	5.281^{***}	4.404^{**}	5.676^{***}	1.280	5.278^{***}	3.589^{***}	4.173^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8: Regressions of estimated τ on socioeconomic status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
`R_educational1`	-0.116^{***}	-0.072^{**}							-0.118^{***}	-0.082^{**}
	(0.029)	(0.033)							(0.031)	(0.035)
`R_educational2`	-0.101^{***}	-0.037							-0.104^{***}	-0.048
	(0.034)	(0.038)							(0.037)	(0.040)
`R_income1`			0.015	-0.011					0.004	-0.010
			(0.030)	(0.031)					(0.030)	(0.031)
`R_income2`			-0.008	0.011					0.002	0.013
			(0.030)	(0.032)					(0.031)	(0.033)
`R_employment`					-0.046	0.040			0.011	0.065
					(0.050)	(0.053)			(0.053)	(0.056)
`R_occupational1`							-0.011	-0.003	0.008	-0.004
							(0.025)	(0.025)	(0.026)	(0.027)
`R_occupational2`							-0.040	-0.013	-0.021	-0.012
							(0.041)	(0.042)	(0.041)	(0.042)
Const.	0.486^{***}	0.500^{***}	0.393^{***}	0.463^{***}	0.438^{***}	0.425^{***}	0.401^{***}	0.460^{***}	0.475^{***}	0.457^{***}
	(0.025)	(0.050)	(0.014)	(0.048)	(0.049)	(0.064)	(0.014)	(0.046)	(0.052)	(0.069)
Demogr. Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	437	414	437	414	437	414	437	414	437	414
Adjusted R^2	0.031	0.059	-0.004	0.047	-0.000	0.050	-0.002	0.046	0.021	0.051
F Statistic	8.006^{***}	2.845^{***}	0.193	2.452^{***}	0.841	2.668^{***}	0.503	2.437^{***}	2.338^{**}	2.177^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9: Regressions of estimated $\ln \sigma_s$ on socioeconomic status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R_educational1	−0.010	−0.107							−0.007	−0.098
	(0.095)	(0.106)							(0.098)	(0.109)
R_educational2	0.074	−0.021							0.131	0.035
	(0.112)	(0.123)							(0.119)	(0.129)
R_income1			−0.058	0.005					−0.037	0.013
			(0.096)	(0.101)					(0.099)	(0.103)
R_income2			-0.261^{***}	-0.238^{**}					-0.268^{***}	-0.244^{**}
			(0.096)	(0.102)					(0.098)	(0.104)
R_employment					0.135	0.073			0.166	0.140
					(0.162)	(0.175)			(0.170)	(0.181)
R_occupational1							−0.103	−0.088	−0.113	−0.080
							(0.081)	(0.082)	(0.085)	(0.086)
R_occupational2							0.094	0.062	0.075	0.061
							(0.133)	(0.137)	(0.135)	(0.138)
Const.	-2.169^{***}	-1.907^{***}	-2.102^{***}	-1.977^{***}	-2.286^{***}	-2.025^{***}	-2.136^{***}	-1.948^{***}	-2.260^{***}	-2.039^{***}
	(0.082)	(0.163)	(0.044)	(0.157)	(0.158)	(0.212)	(0.045)	(0.152)	(0.170)	(0.224)
Demogr. Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	500	474	500	474	500	474	500	474	500	474
Adjusted R^2	−0.002	0.042	0.011	0.050	−0.001	0.041	0.001	0.042	0.011	0.048
F Statistic	0.453	2.469^{***}	3.695^{**}	2.783^{***}	0.691	2.550^{***}	1.287	2.473^{***}	1.798^{*}	2.252^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6.4 Relationships with political attitudes and behaviors

Figure 9 depicts scatter plots for each continuum variable against each parameter estimate. Figures 10 and 11 plot the cumulative distribution of parameter estimates by category. Tables 10–12 report regressions that analyze the relationship between the political attitudes and behaviors variables and the estimated parameters.

For ideological identity (`R_political`), see the first row of Figure 9 and the first row of Figure 10. The finding that respondents that self-identify as liberal have a large $\widehat{\alpha}$, indicating selfishness, may not be consistent with Fisman et al.'s (2017) finding that Democrats have a small $\widehat{\alpha}$ and value equality.[15] We also find that $\ln \widehat{\sigma_s}$ is larger for respondents self-identifying as conservative.

For partisanship (`R_partisanship`), see the second row of Figure 10. For the distribution of $\widehat{\alpha}$, Democrats stochastically dominate Republicans at the 5% significance level. This result is inconsistent with Fisman et al.'s (2017) finding that Democrats have a small $\widehat{\alpha}$ and value equality. We also find that $\ln \widehat{\sigma_s}$ is larger for Republican respondents at the 5% significance level.

Regarding approval of Trump's job (`R_trump`), see the second row of Figure 9 and the third row of Figure 10. We observe effects in the same direction as the results of ideological self-identification and partisanship for $\widehat{\alpha}$, $\widehat{\tau}$, and $\ln \widehat{\sigma_s}$. In contrast to the observation of no significant differences in $\widehat{\tau}$ in ideological self-identification and partisanship, $\widehat{\tau}$ is significantly smaller—but not stochastically dominated—for Trump approvers.

For voting behavior for Biden, see the fourth row of Figure 10. There are no differences between Biden and Trump voters for $\widehat{\alpha}$, $\widehat{\tau}$, and $\ln \widehat{\sigma_s}$. Our results may then be inconsistent with Fisman et al.'s (2017) finding that voters for Democratic candidate Obama in the 2012 election were equality oriented. Interestingly, however,

[15] According to the Pew Research Center, Democrats are more likely to self-identify as liberal (Oliphant, 2019).

44.9% of Republican respondents responded that they voted for Biden, although 95.0% of the Democrats responded that they voted for Biden.[16] It seems impossible to compare behavior in the 2012 and 2020 elections according to partisanship.

For agreement with redistributive policies, see the third row of Figure 9 and the upper row of Figure 11. We observe that the higher the degree of agreement for redistributive policy, the lower the value of $\widehat{\alpha}$ and $\widehat{\tau}$ at the 5% significance level with uncoded data. Under the assumption that α measures the preference for equality–selfishness, it is consistent that supporters of redistributive policies have smaller $\widehat{\alpha}$, indicating an equality orientation.

For agreement with basic income policies, see the fourth row of Figure 9 and the lower row of Figure 11. Compared with the figures for the approval of redistributive policies, the approval of basic income policies has an effect in the same direction, but the results are not significant.

In the regression analysis, we find that only `R_political` (liberal) has a positive effect on the distribution parameter $\widehat{\alpha}$ at the 1% significance level (see column (14) in Table 10). For the rescaled substitution parameter $\widehat{\tau}$ and the error term scale $\ln \widehat{\sigma_s}$, we find that no variable has a significant effect (see column (14) in Tables 11 and 12). Given the only variable with a significant effect, `R_political`, did not display the expected direction of the effect, we obtain no evidence to support Hypothesis 3.

[16]The Pew Research Center reported that some Republicans voted for Biden (Igielnik et al., 2021).

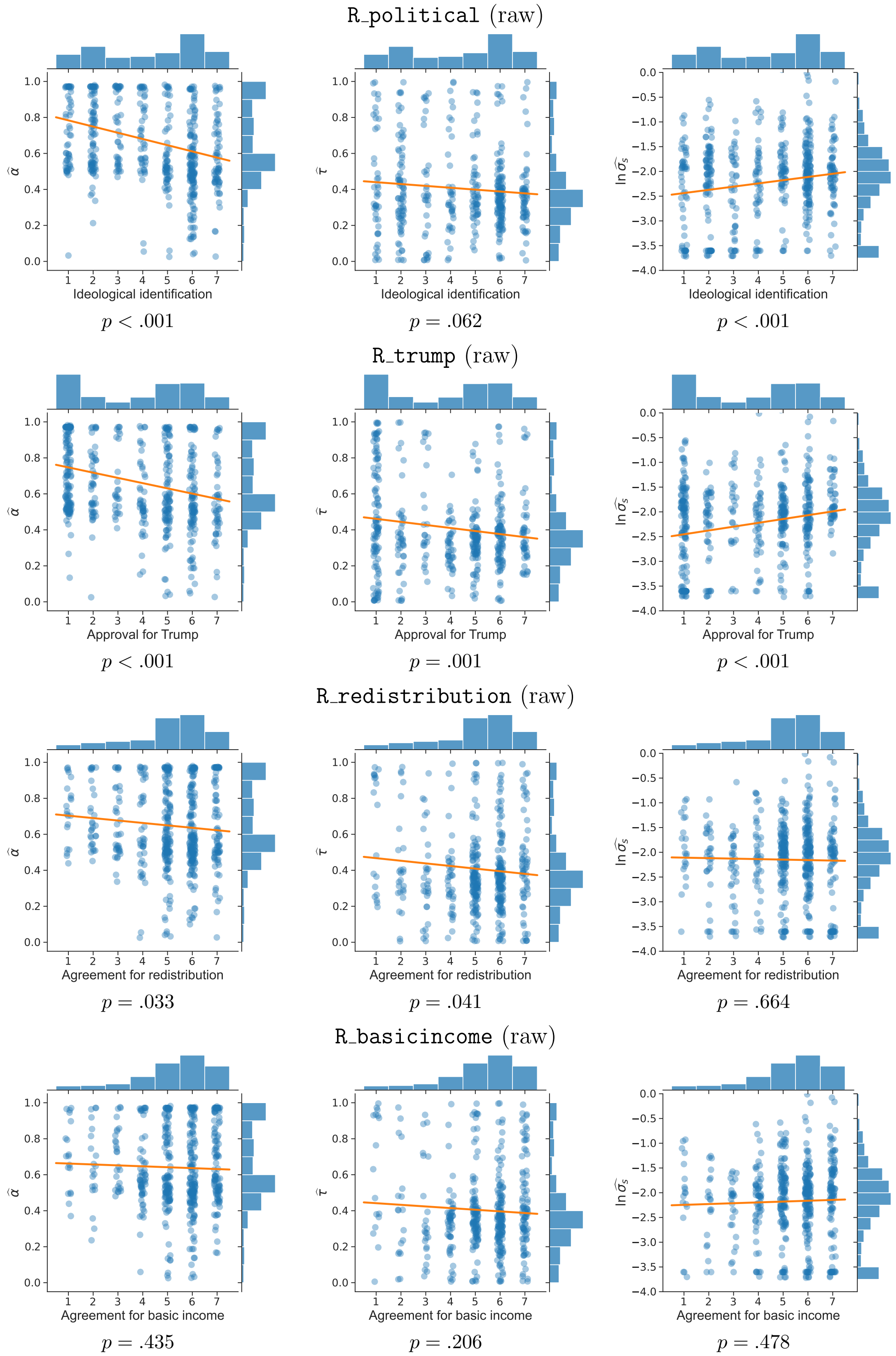


Figure 9: Scatter plots for raw `R_political`, `R_trump`, `R_redistribution`, and `R_basicincome`

Note: **Left**: against estimated α. **Center**: against estimated τ. **Right**: against estimated $\ln \sigma_s$. Simple regression lines are drawn. p values are for each slope of regression lines. Each plotted point is jittered in the horizontal direction.

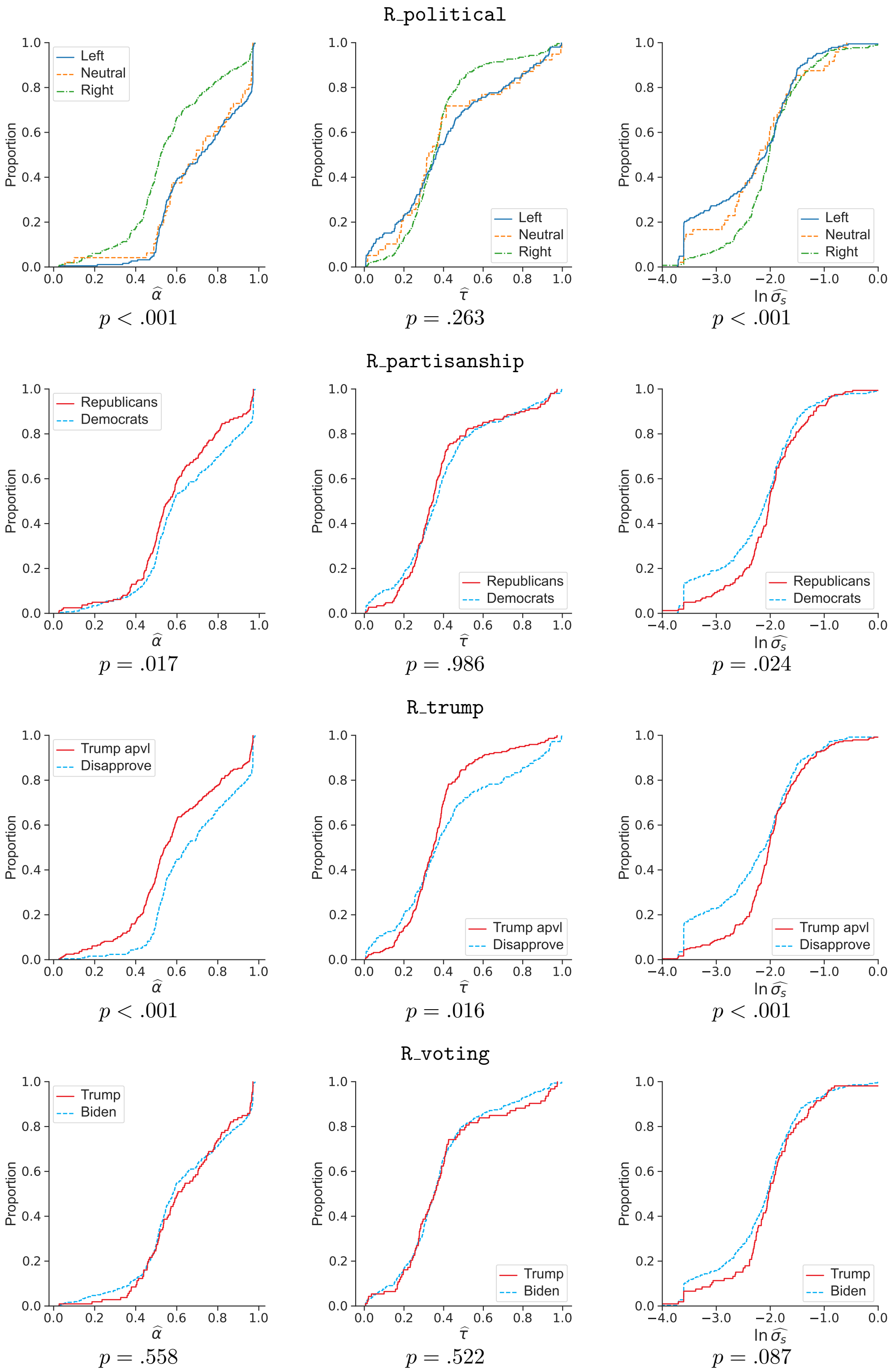


Figure 10: Distribution of estimates grouped by `R_political`, `R_partisanship`, `R_trump`, and `R_voting`

Note: **Left**: CDF of estimated α. **Center**: CDF of estimated τ. **Right**: CDF of estimated $\ln \sigma_s$. p values are based on the one-way ANOVA.

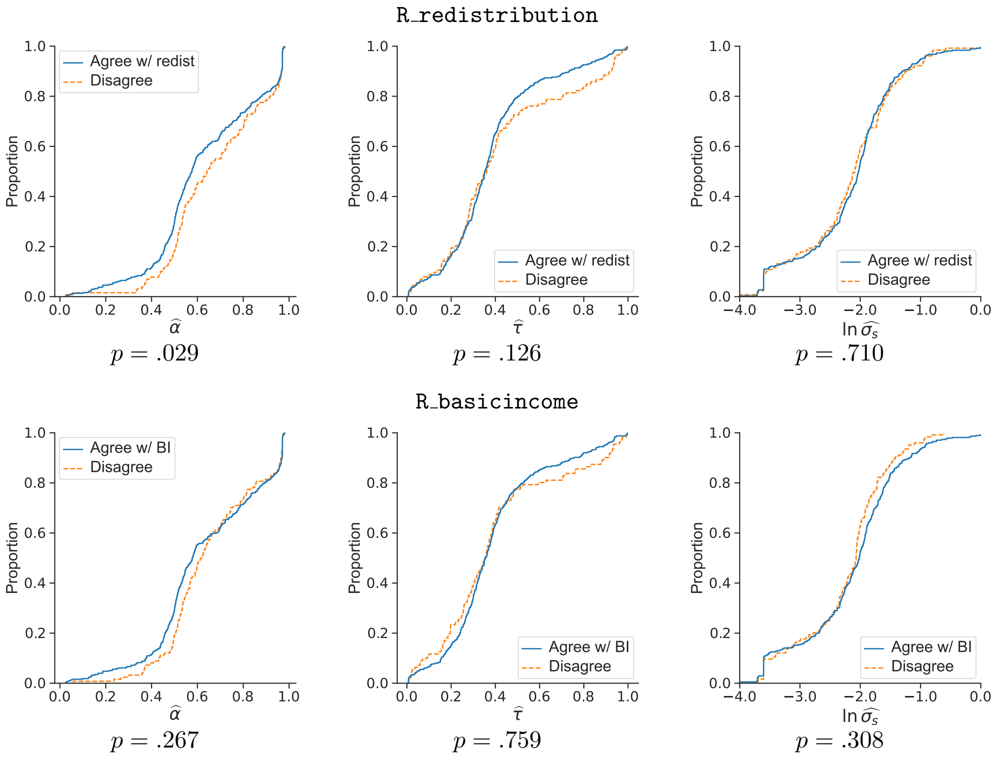


Figure 11: Distribution of estimates grouped by R_redistribution and R_basicincome

Note: **Left**: CDF of estimated α. **Center**: CDF of estimated τ. **Right**: CDF of estimated $\ln \sigma_s$. p values are based on the one-way ANOVA.

Table 10: Regressions of estimated α on political attitudes and behaviors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
`R_political`	0.138***	0.098***						
	(0.020)	(0.023)						
`R_partisanship`			0.023	0.009				
			(0.020)	(0.021)				
`R_trump`					−0.100***	−0.052**		
					(0.020)	(0.023)		
`R_voting`							−0.020	−0.014
							(0.022)	(0.023)
`R_redistribution`								
`R_basicincome`								
Const.	0.584***	0.623***	0.622***	0.637***	0.685***	0.672***	0.650***	0.647***
	(0.012)	(0.040)	(0.016)	(0.041)	(0.014)	(0.043)	(0.019)	(0.042)
Demogr. Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	500	474	500	474	500	474	500	474
Adjusted R^2	0.087	0.146	0.001	0.114	0.048	0.123	−0.000	0.115
F Statistic	48.794***	7.240***	1.280	5.688***	26.350***	6.120***	0.824	5.705***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 10: Regressions of estimated α on political attitudes and behaviors (cont'd)

	(9)	(10)	(11)	(12)	(13)	(14)
`R_political`					0.148^{***}	0.116^{***}
					(0.025)	(0.027)
`R_partisanship`					-0.034	-0.018
					(0.025)	(0.026)
`R_trump`					-0.052^{**}	-0.037
					(0.023)	(0.025)
`R_voting`					-0.056^{**}	-0.048^{*}
					(0.026)	(0.027)
`R_redistribution`	-0.050^{**}	-0.030			-0.035	-0.034
	(0.023)	(0.024)			(0.026)	(0.027)
`R_basicincome`			-0.026	-0.007	-0.005	0.008
			(0.023)	(0.024)	(0.027)	(0.028)
Const.	0.672^{***}	0.656^{***}	0.655^{***}	0.645^{***}	0.696^{***}	0.684^{***}
	(0.020)	(0.042)	(0.020)	(0.043)	(0.028)	(0.046)
Demogr. Controls	No	Yes	No	Yes	No	Yes
Observations	500	474	500	474	500	474
Adjusted R^2	0.008	0.117	0.000	0.114	0.119	0.155
F Statistic	4.771^{**}	5.815^{***}	1.236	5.679^{***}	12.229^{***}	5.833^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11: Regressions of estimated τ on political attitudes and behaviors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
`R_political`	0.032	−0.026						
	(0.023)	(0.028)						
`R_partisanship`			−0.001	−0.036				
			(0.023)	(0.024)				
`R_trump`					-0.053^{**}	−0.004		
					(0.022)	(0.027)		
`R_voting`							-0.044^{*}	−0.034
							(0.025)	(0.026)
`R_redistribution`								
`R_basicincome`								
Const.	0.384^{***}	0.464^{***}	0.395^{***}	0.474^{***}	0.422^{***}	0.461^{***}	0.427^{***}	0.475^{***}
	(0.014)	(0.046)	(0.017)	(0.047)	(0.016)	(0.048)	(0.021)	(0.047)
Demogr. Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	437	414	437	414	437	414	437	414
Adjusted R^2	0.002	0.051	−0.002	0.054	0.011	0.049	0.005	0.053
F Statistic	1.821	2.694^{***}	0.004	2.807^{***}	5.816^{**}	2.624^{***}	3.057^{*}	2.764^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11: Regressions of estimated τ on political attitudes and behaviors (cont'd)

	(9)	(10)	(11)	(12)	(13)	(14)
R_political					0.017	-0.013
					(0.029)	(0.032)
R_partisanship					-0.003	-0.030
					(0.029)	(0.030)
R_trump					-0.061^{**}	-0.025
					(0.026)	(0.030)
R_voting					-0.067^{**}	-0.028
					(0.030)	(0.032)
R_redistribution	-0.039	-0.023			-0.026	-0.017
	(0.025)	(0.027)			(0.031)	(0.032)
R_basicincome			-0.008	0.004	0.028	0.033
			(0.026)	(0.027)	(0.031)	(0.032)
Const.	0.423^{***}	0.469^{***}	0.400^{***}	0.456^{***}	0.468^{***}	0.493^{***}
	(0.022)	(0.048)	(0.022)	(0.048)	(0.032)	(0.053)
Demogr. Controls	No	Yes	No	Yes	No	Yes
Observations	437	414	437	414	437	414
Adjusted R^2	0.003	0.050	-0.002	0.049	0.017	0.047
F Statistic	2.356	2.682^{***}	0.095	2.623^{***}	2.281^{**}	2.139^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12: Regressions of estimated $\ln \sigma_s$ on political attitudes and behaviors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_political	-0.279^{***}	-0.139						
	(0.073)	(0.088)						
R_partisanship			-0.142^{*}	-0.056				
			(0.073)	(0.078)				
R_trump					0.276^{***}	0.149^{*}		
					(0.071)	(0.086)		
R_voting							-0.069	-0.048
							(0.080)	(0.084)
R_redistribution								
R_basicincome								
Const.	-2.054^{***}	-1.939^{***}	-2.074^{***}	-1.941^{***}	-2.293^{***}	-2.053^{***}	-2.108^{***}	-1.941^{***}
	(0.045)	(0.151)	(0.056)	(0.154)	(0.050)	(0.159)	(0.068)	(0.155)
Demogr. Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	500	474	500	474	500	474	500	474
Adjusted R^2	0.026	0.046	0.006	0.042	0.027	0.047	-0.001	0.041
F Statistic	14.428^{***}	2.742^{***}	3.801^{*}	2.578^{***}	15.104^{***}	2.784^{***}	0.726	2.563^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12: Regressions of estimated $\ln \sigma_s$ on political attitudes and behaviors (cont'd)

	(9)	(10)	(11)	(12)	(13)	(14)
`R_political`					-0.197^{**}	-0.111
					(0.093)	(0.103)
`R_partisanship`					-0.023	-0.002
					(0.093)	(0.098)
`R_trump`					0.183^{**}	0.121
					(0.085)	(0.096)
`R_voting`					0.032	0.011
					(0.096)	(0.104)
`R_redistribution`	0.031	0.005			-0.027	-0.015
	(0.082)	(0.088)			(0.099)	(0.103)
`R_basicincome`			0.085	0.052	0.142	0.088
			(0.083)	(0.089)	(0.100)	(0.106)
Const.	-2.181^{***}	-1.966^{***}	-2.222^{***}	-1.991^{***}	-2.270^{***}	-2.060^{***}
	(0.071)	(0.157)	(0.072)	(0.158)	(0.104)	(0.176)
Demogr. Controls	No	Yes	No	Yes	No	Yes
Observations	500	474	500	474	500	474
Adjusted R^2	-0.002	0.041	0.000	0.041	0.031	0.040
F Statistic	0.138	2.536^{***}	1.042	2.564^{***}	3.703^{***}	2.104^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6.5 Effective and ineffective variables

We conducted multiple comparisons according to the procedure described in Section 4 and conservatively identified variables with and without effect.

Tables 13–15 provide the regression results for all variables on the distribution parameter $\widehat{\alpha}$, the rescaled substitution parameter $\widehat{\tau}$, and the error term scale $\ln \widehat{\sigma_s}$. The adjusted R^2 of the regression is 0.208 for $\widehat{\alpha}$, 0.045 for $\widehat{\tau}$, and 0.064 for $\ln \widehat{\sigma_s}$. Column "p" in each table provides the p values and column "q" the adjusted p values (q values) using the Benjamini–Hochberg procedure. Column "TOST p" in each table reports the p values of the equivalence test and column "TOST q" adjusts these p values (q values) using the Benjamini–Hochberg procedure. The rows for variables for which the q value of the t test is below 0.005, the upper limit of the false discovery rate we set are highlighted in red, and the rows for variables for which the q value of the equivalence test are less than this value are highlighted in blue. Figures 12–14 provide a visual comparison of the effect size of each variable. The thick and thin lines indicate confidence intervals of 95% and 99.5%, respectively. The dot-dashed vertical line represents the SESOI set so that the mean individual power is 0.8 for the upper limit of the false discovery rate is 0.005, and the dashed vertical line represents the SESOI set for the upper limit of the false discovery rate is 0.05.[17]

After selecting the variables, only `R_public` and `R_political` on the distribution parameter $\widehat{\alpha}$ were found to be effective. On $\widehat{\alpha}$, `R_religious2`, `R_children`, `R_metro`, `R_educational1`, `R_income2`, `R_occupational1`, `R_partisanship`, and `R_basicincome` were found to be ineffective. On the rescaled substitution parameter $\widehat{\tau}$, `R_age`, `R_gender`, `R_race1`, `R_marital1`, `R_metro`, `R_public`, `R_income1`, `R_income2`, `R_occupational1`, `R_occupational2`, `R_political`, `R_partisanship`,

[17]Determined for $\widehat{\alpha}$, $\widehat{\tau}$, and $\ln \widehat{\sigma_s}$ to be 0.08, 0.1, and 0.3, respectively.

R_voting, R_trump, R_redistribution, and R_basicincome were found to be ineffective. On the error term scale $\ln \widehat{\sigma_s}$, R_age, R_gender, R_children, R_metro, R_income1, R_occupational1, R_political, R_partisanship, R_voting, R_redistribution, and R_basicincome were found to be ineffective.

It is noteworthy that for $\widehat{\tau}$, all measures of political attitude and behavior are shown to be ineffectual. While conclusive findings cannot be made on the rescaled substitution parameter τ, particularly regarding whether it truly reflects preferences for efficiency, it appears reasonable to conjecture that the correlations between parameter τ and political attitudes/behavior are not robust. Further precision in measurement or additional data is necessary to scrutinize relationships between parameters and other variables in greater depth.

Table 13: Regressions of estimated α

	Coef	Std. Err.	95% Conf. Interval	p	q	TOST p	TOST q
R_age	0.0529	0.0219	[0.0099 , 0.0959]	0.0160	0.1239	0.0088	0.0164
R_gender	0.0475	0.0209	[0.0063 , 0.0886]	0.0238	0.1239	0.0031	0.0073
R_race1	−0.0548	0.0288	[−0.1115 , 0.0018]	0.0578	0.2147	0.0413	0.0512
R_race2	0.0290	0.0473	[−0.0640 , 0.1220]	0.5407	0.7698	0.0544	0.0643
R_race3	−0.0019	0.0373	[−0.0752 , 0.0715]	0.9602	0.9602	0.0030	0.0073
R_religious1	0.0825	0.0354	[0.0130 , 0.1520]	0.0201	0.1239	0.2622	0.2840
R_religious2	−0.0044	0.0286	[−0.0607 , 0.0518]	0.8766	0.9602	0.0002	0.0013
R_religious3	0.0345	0.0347	[−0.0337 , 0.1027]	0.3208	0.5957	0.0214	0.0327
R_marital1	−0.0434	0.0316	[−0.1056 , 0.0187]	0.1705	0.4926	0.0260	0.0376
R_marital2	−0.0581	0.0488	[−0.1539 , 0.0378]	0.2345	0.5082	0.1682	0.1901
R_children	−0.0179	0.0274	[−0.0717 , 0.0360]	0.5148	0.7698	0.0008	0.0028
R_metro	0.0019	0.0279	[−0.0530 , 0.0567]	0.9465	0.9602	0.0001	0.0011
R_public	−0.1115	0.0194	[−0.1496 , −0.0733]	0.0000	0.0000	0.6303	0.6303
R_educational1	−0.0095	0.0287	[−0.0659 , 0.0470]	0.7413	0.9602	0.0005	0.0021
R_educational2	−0.0405	0.0338	[−0.1069 , 0.0259]	0.2314	0.5082	0.0285	0.0390
R_income1	−0.0296	0.0264	[−0.0815 , 0.0223]	0.2634	0.5268	0.0022	0.0065
R_income2	−0.0027	0.0268	[−0.0553 , 0.0500]	0.9207	0.9602	0.0001	0.0010
R_employment	0.0028	0.0464	[−0.0884 , 0.0941]	0.9511	0.9602	0.0142	0.0246
R_occupational1	−0.0053	0.0223	[−0.0492 , 0.0385]	0.8111	0.9602	0.0000	0.0001
R_occupational2	−0.0324	0.0356	[−0.1024 , 0.0377]	0.3641	0.6310	0.0211	0.0327
R_political	0.0999	0.0265	[0.0478 , 0.1520]	0.0002	0.0024	0.4238	0.4407
R_partisanship	−0.0146	0.0252	[−0.0640 , 0.0349]	0.5625	0.7698	0.0002	0.0012
R_voting	−0.0545	0.0269	[−0.1074 , −0.0016]	0.0434	0.1882	0.0307	0.0398
R_trump	−0.0433	0.0250	[−0.0925 , 0.0059]	0.0844	0.2743	0.0070	0.0141
R_redistribution	−0.0345	0.0267	[−0.0870 , 0.0180]	0.1969	0.5082	0.0043	0.0093
R_basicincome	0.0200	0.0270	[−0.0330 , 0.0731]	0.4582	0.7446	0.0009	0.0028
Const.	0.7120	0.0611	[0.5919 , 0.8322]	0.0000			

Note: Observations: 474, Adjusted $R^2 = 0.208$, $F(26, 447) = 5.777$ ($p < .001$).

Table 14: Regressions of estimated τ

	Coef	Std. Err.	95% Conf. Interval	p	q	TOST p	TOST q
R_age	−0.0133	0.0270	[−0.0664 , 0.0398]	0.6229	0.8524	0.0000	0.0000
R_gender	−0.0257	0.0260	[−0.0769 , 0.0255]	0.3248	0.7565	0.0000	0.0001
R_race1	−0.0227	0.0344	[−0.0904 , 0.0450]	0.5097	0.8283	0.0006	0.0012
R_race2	−0.0009	0.0569	[−0.1127 , 0.1109]	0.9870	0.9870	0.0094	0.0136
R_race3	0.0358	0.0459	[−0.0545 , 0.1261]	0.4364	0.7565	0.0157	0.0204
R_religious1	−0.0623	0.0438	[−0.1484 , 0.0238]	0.1557	0.7565	0.0487	0.0551
R_religious2	−0.0460	0.0341	[−0.1130 , 0.0209]	0.1774	0.7565	0.0046	0.0071
R_religious3	0.0359	0.0431	[−0.0489 , 0.1206]	0.4058	0.7565	0.0109	0.0150
R_marital1	0.0127	0.0383	[−0.0625 , 0.0879]	0.7399	0.9597	0.0007	0.0014
R_marital2	0.0705	0.0583	[−0.0441 , 0.1850]	0.2273	0.7565	0.1343	0.1343
R_children	−0.0683	0.0333	[−0.1337 , −0.0028]	0.0409	0.5319	0.0228	0.0270
R_metro	−0.0058	0.0330	[−0.0707 , 0.0591]	0.8601	0.9870	0.0001	0.0002
R_public	−0.0207	0.0245	[−0.0689 , 0.0275]	0.3992	0.7565	0.0000	0.0000
R_educational1	−0.0800	0.0360	[−0.1508 , −0.0091]	0.0271	0.5319	0.0637	0.0690
R_educational2	−0.0459	0.0417	[−0.1278 , 0.0360]	0.2713	0.7565	0.0165	0.0204
R_income1	−0.0171	0.0318	[−0.0796 , 0.0454]	0.5905	0.8524	0.0001	0.0004
R_income2	0.0033	0.0333	[−0.0622 , 0.0689]	0.9209	0.9870	0.0000	0.0002
R_employment	0.0667	0.0561	[−0.0436 , 0.1769]	0.2351	0.7565	0.1118	0.1162
R_occupational1	−0.0007	0.0270	[−0.0538 , 0.0523]	0.9779	0.9870	0.0000	0.0000
R_occupational2	−0.0122	0.0427	[−0.0963 , 0.0718]	0.7751	0.9597	0.0021	0.0035
R_political	−0.0190	0.0322	[−0.0823 , 0.0442]	0.5543	0.8477	0.0002	0.0005
R_partisanship	−0.0279	0.0303	[−0.0876 , 0.0317]	0.3580	0.7565	0.0002	0.0005
R_voting	−0.0267	0.0324	[−0.0905 , 0.0370]	0.4102	0.7565	0.0005	0.0010
R_trump	−0.0274	0.0303	[−0.0871 , 0.0322]	0.3668	0.7565	0.0002	0.0005
R_redistribution	−0.0042	0.0327	[−0.0686 , 0.0601]	0.8971	0.9870	0.0000	0.0002
R_basicincome	0.0379	0.0326	[−0.0261 , 0.1019]	0.2452	0.7565	0.0015	0.0026
Const.	0.4850	0.0737	[0.3400 , 0.6300]	0.0000			

Note: Observations: 414, Adjusted $R^2 = 0.045$, $F(26, 387) = 1.750$ ($p = .014$).

Table 15: Regressions of estimated $\ln \sigma_s$

	Coef	Std. Err.	95% Conf. Interval		p	q	TOST p	TOST q
R_age	−0.1271	0.0849	[−0.2939 ,	0.0397]	0.1350	0.5205	0.0010	0.0034
R_gender	−0.0023	0.0812	[−0.1620 ,	0.1573]	0.9773	0.9773	0.0000	0.0000
R_race1	0.1467	0.1119	[−0.0732 ,	0.3667]	0.1905	0.5205	0.0151	0.0262
R_race2	0.2296	0.1836	[−0.1313 ,	0.5905]	0.2118	0.5205	0.1915	0.2164
R_race3	−0.1778	0.1448	[−0.4623 ,	0.1068]	0.2202	0.5205	0.0717	0.0887
R_religious1	−0.3387	0.1372	[−0.6083 ,	−0.0691]	0.0139	0.1208	0.3543	0.3685
R_religious2	−0.1807	0.1111	[−0.3991 ,	0.0377]	0.1046	0.5205	0.0301	0.0412
R_religious3	−0.3578	0.1347	[−0.6224 ,	−0.0931]	0.0082	0.1063	0.4055	0.4055
R_marital1	0.1375	0.1227	[−0.1037 ,	0.3786]	0.2633	0.5704	0.0201	0.0307
R_marital2	0.2523	0.1893	[−0.1197 ,	0.6243]	0.1833	0.5205	0.2336	0.2531
R_children	−0.0732	0.1063	[−0.2822 ,	0.1357]	0.4914	0.6725	0.0015	0.0036
R_metro	0.0162	0.1083	[−0.1966 ,	0.2289]	0.8813	0.9166	0.0003	0.0013
R_public	0.2406	0.0753	[0.0927 ,	0.3885]	0.0015	0.0387	0.0238	0.0344
R_educational1	−0.1069	0.1115	[−0.3259 ,	0.1122]	0.3382	0.6725	0.0057	0.0106
R_educational2	−0.0223	0.1312	[−0.2801 ,	0.2355]	0.8651	0.9166	0.0026	0.0057
R_income1	0.0287	0.1025	[−0.1727 ,	0.2302]	0.7792	0.9166	0.0002	0.0012
R_income2	−0.2156	0.1039	[−0.4199 ,	−0.0113]	0.0386	0.2509	0.0470	0.0611
R_employment	0.1387	0.1802	[−0.2155 ,	0.4929]	0.4420	0.6725	0.0820	0.0969
R_occupational1	−0.0634	0.0865	[−0.2334 ,	0.1067]	0.4646	0.6725	0.0001	0.0009
R_occupational2	0.1016	0.1383	[−0.1703 ,	0.3735]	0.4632	0.6725	0.0188	0.0306
R_political	−0.0810	0.1030	[−0.2834 ,	0.1213]	0.4317	0.6725	0.0014	0.0036
R_partisanship	−0.0248	0.0976	[−0.2167 ,	0.1670]	0.7994	0.9166	0.0001	0.0009
R_voting	0.0497	0.1045	[−0.1556 ,	0.2550]	0.6345	0.8248	0.0006	0.0022
R_trump	0.1279	0.0972	[−0.0631 ,	0.3188]	0.1888	0.5205	0.0036	0.0072
R_redistribution	−0.0202	0.1037	[−0.2240 ,	0.1835]	0.8454	0.9166	0.0002	0.0012
R_basicincome	0.0753	0.1047	[−0.1305 ,	0.2810]	0.4726	0.6725	0.0014	0.0036
Const.	−2.1505	0.2373	[−2.6169 ,	−1.6842]	0.0000			

Note: Observations: 474, Adjusted $R^2 = 0.064$, $F(26, 447) = 2.244$ ($p = .001$).

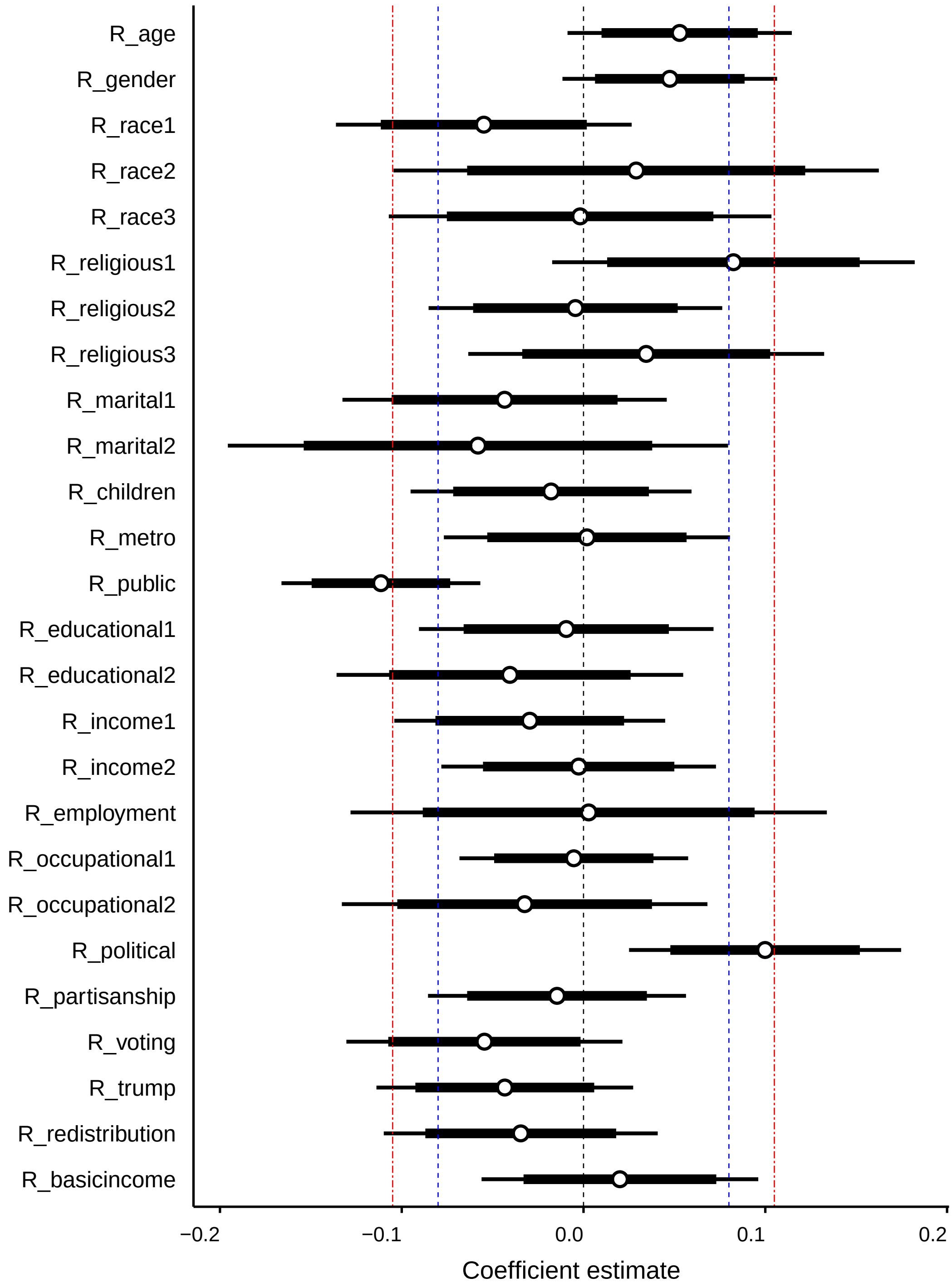


Figure 12: Confidence intervals for α estimate

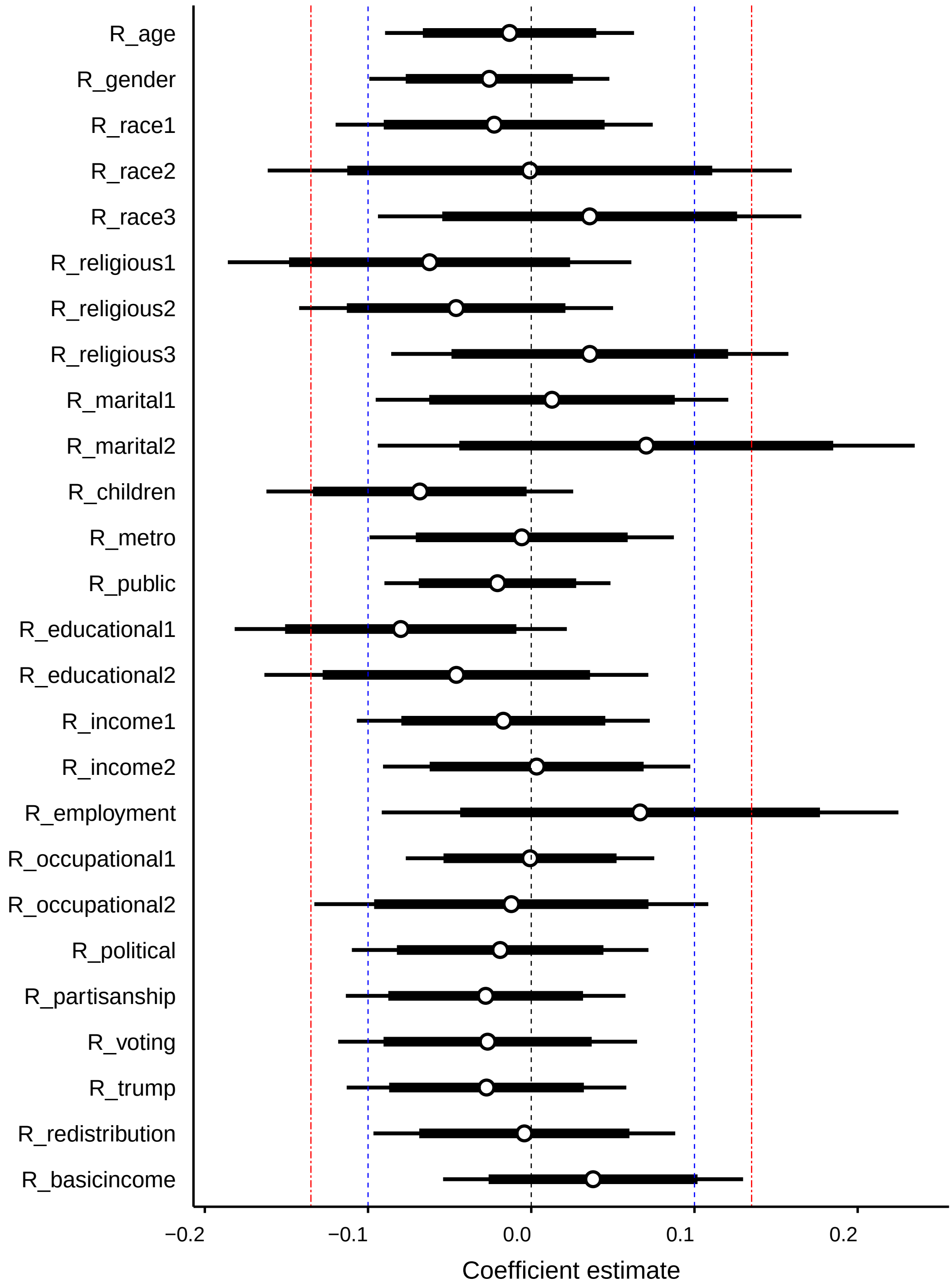


Figure 13: Confidence intervals for τ estimate

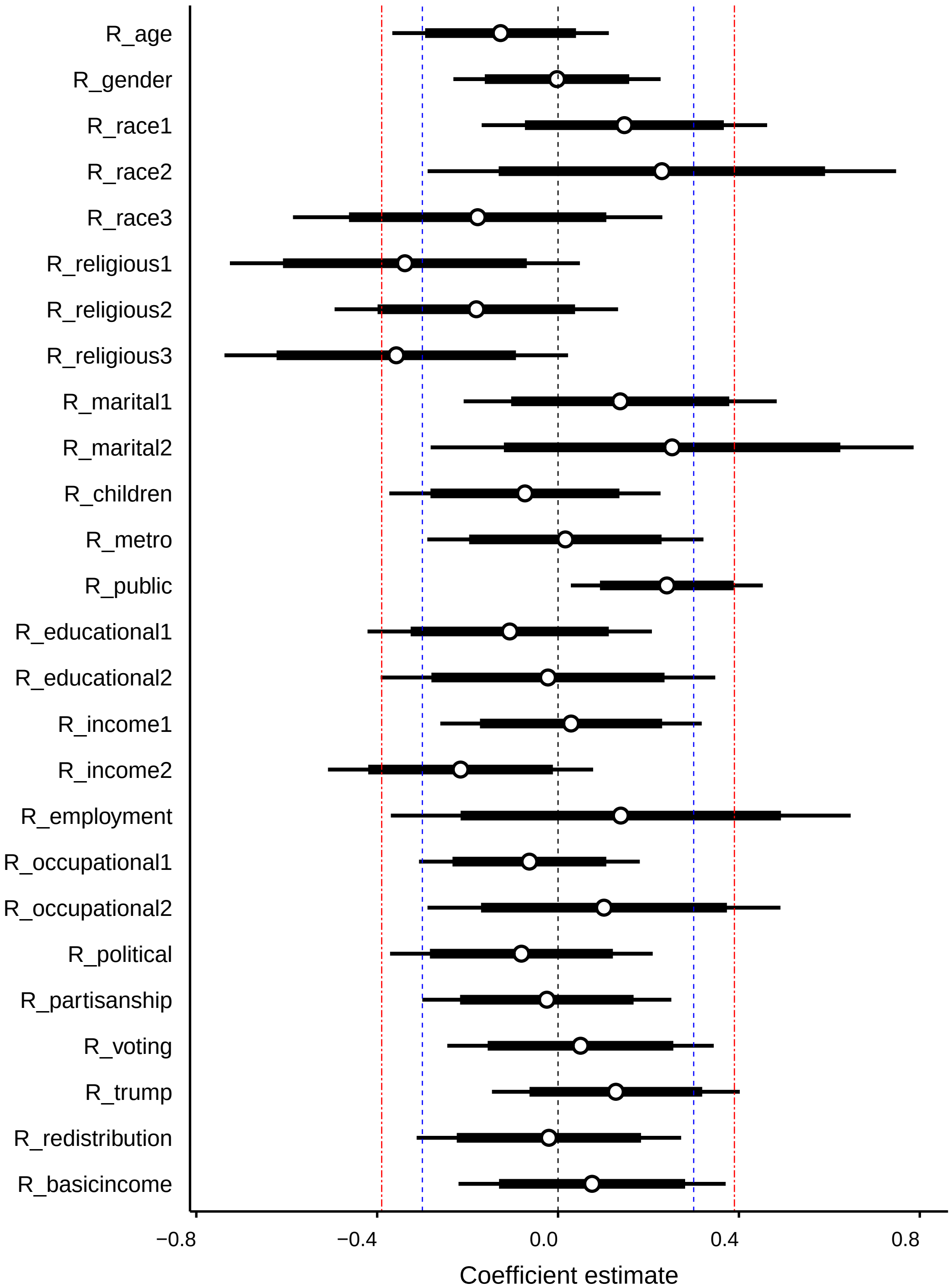


Figure 14: Confidence intervals for $\ln \sigma_s$ estimate

6.6 Correlations between error term scale and utility parameters

Table 16 shows the correlation coefficients for the full sample and for the sample excluding participants classified as purely selfless or selfish. We obtain a negative correlation between the error term scale $\ln \widehat{\sigma_s}$ and $\widehat{\alpha}$ in the population, which includes purely selfless/selfish participants. Furthermore, in the population excluding participants purely selfless/selfish, we find a positive correlation between $\ln \widehat{\sigma_s}$ and $\widehat{\tau}$, while the negative correlation against $\widehat{\alpha}$ disappears. A careful inspection of the scatter plot between $\widehat{\alpha}$ and $\ln \widehat{\sigma_s}$ shown in the left panel of Figure 15 reveals that there is a cluster around $\widehat{\alpha} = 1$ and $\ln \widehat{\sigma_s} = -3.5$, and that this cluster brings a negative correlation between $\widehat{\alpha}$ and $\ln \widehat{\sigma_s}$.

These observations suggest that it is necessary to control the estimates of utility parameters and the existence of purely selfless/selfish participants to analyze the relationship between $\ln \widehat{\sigma_s}$ and the variables. Comparing columns (1) and (2) in Table 17, we can see that controlling for $\widehat{\alpha}$ improves the explanatory power of the model in terms of adjusted R^2. Comparing columns (3) and (4) in Table 17, which are the analyses for the sample excluding purely selfless/selfish participants, we can see that controlling for $\widehat{\tau}$ improves the adjusted R^2. Comparing columns (1) and (5) in Table 17, we can see that controlling for the indicator of participants purely selfless ($I_{selfless}$) and selfish ($I_{selfish}$) also improves the adjusted R^2.

The negative correlation between `R_public` and $\ln \widehat{\sigma_s}$ is reduced by controlling for $\widehat{\alpha}$ or $I_{selfish}$, or by excluding purely selfless/selfish participants. Similarly, the negative correlation between `R_religious1` and $\ln \widehat{\sigma_s}$ weakens (but is not wholly diminished) through adding control variables. Conversely, for `R_religious3` and `R_income2`, the coefficients increase in magnitude through the addition of control variables. These two variables then provide relatively more explanatory power for the error term scale $\ln \widehat{\sigma_s}$ than the other variables.

Table 16: Correlation coefficients between estimates

	$\widehat{\alpha}$	$\widehat{\tau}$	$\ln \widehat{\sigma}_s$
$\widehat{\alpha}$		*.19*	*−.02*
$\widehat{\tau}$	.36		*.31*
$\ln \widehat{\sigma}_s$	−.21	−.04	

Note: The lower triangular part of the matrix is for all participants, and the upper triangular part (italicized) is for only participants that reject the null hypothesis $\widehat{\alpha} = 0, 1$.

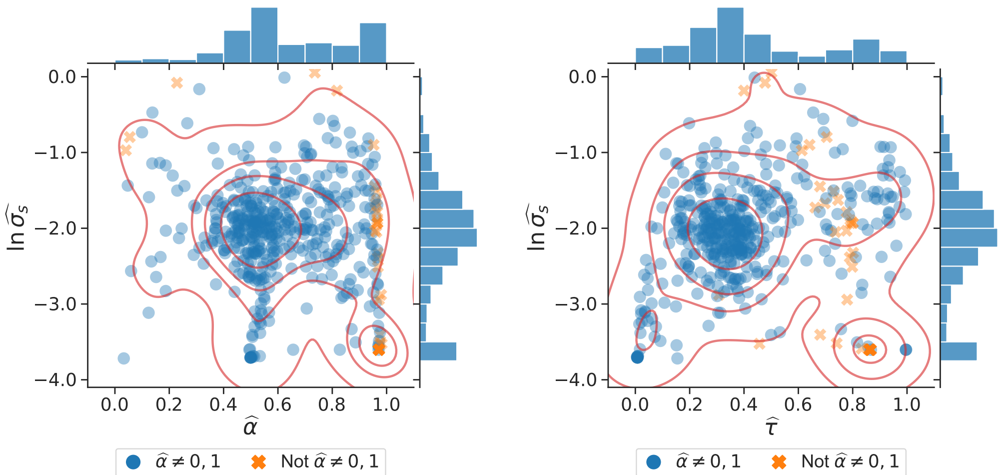


Figure 15: Scatter plots between error term scale and estimated utility parameters

Note: **Left**: against estimated α. **Right**: against estimated τ. Individuals for whom the null hypothesis that their α estimate is equal to 0 or 1 cannot be rejected by a one-tailed test at the 10% significance level are identified by a cross. The contour lines represent kernel density estimates.

Table 17: Regression of estimated $\ln \sigma_s$ controlling for utility parameter estimates

	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\alpha}$		-0.388^{**}				0.015
		(0.183)				(0.206)
$\widehat{\tau}$				0.941^{***}		0.687^{***}
				(0.144)		(0.162)
$I_{selfless}$					-0.408	-0.638^{*}
					(0.343)	(0.360)
$I_{selfish}$					-0.759^{***}	-1.024^{***}
					(0.114)	(0.138)
R_age	-0.127	-0.107	-0.079	-0.067	-0.098	-0.083
	(0.085)	(0.085)	(0.080)	(0.076)	(0.081)	(0.080)
R_gender	-0.002	0.016	0.006	0.030	0.002	0.016
	(0.081)	(0.081)	(0.078)	(0.074)	(0.078)	(0.077)
R_race1	0.147	0.125	0.131	0.152	0.106	0.119
	(0.112)	(0.112)	(0.102)	(0.097)	(0.107)	(0.106)
R_race2	0.230	0.241	0.103	0.104	0.215	0.218
	(0.184)	(0.183)	(0.169)	(0.161)	(0.176)	(0.172)
R_race3	-0.178	-0.178	-0.205	-0.239^{*}	-0.180	-0.206
	(0.145)	(0.144)	(0.137)	(0.130)	(0.138)	(0.136)
R_religious1	-0.339^{**}	-0.307^{**}	-0.300^{**}	-0.242^{*}	-0.269^{**}	-0.234^{*}
	(0.137)	(0.137)	(0.130)	(0.124)	(0.131)	(0.130)
R_religious2	-0.181	-0.182	-0.190^{*}	-0.146	-0.199^{*}	-0.177^{*}
	(0.111)	(0.111)	(0.101)	(0.097)	(0.106)	(0.104)
R_religious3	-0.358^{***}	-0.344^{**}	-0.338^{***}	-0.372^{***}	-0.312^{**}	-0.337^{***}
	(0.135)	(0.134)	(0.128)	(0.122)	(0.129)	(0.127)
R_marital1	0.137	0.121	0.068	0.056	0.085	0.076
	(0.123)	(0.122)	(0.114)	(0.108)	(0.117)	(0.115)
R_marital2	0.252	0.230	0.095	0.029	0.163	0.111
	(0.189)	(0.189)	(0.173)	(0.165)	(0.181)	(0.178)
R_children	-0.073	-0.080	-0.054	0.010	-0.021	0.022
	(0.106)	(0.106)	(0.099)	(0.095)	(0.102)	(0.101)
R_metro	0.016	0.017	0.012	0.018	0.037	0.044
	(0.108)	(0.108)	(0.098)	(0.093)	(0.104)	(0.102)
R_public	0.241^{***}	0.197^{**}	0.073	0.093	0.116	0.129^{*}
	(0.075)	(0.078)	(0.073)	(0.069)	(0.074)	(0.074)
R_educational1	-0.107	-0.111	-0.061	0.014	-0.106	-0.068
	(0.111)	(0.111)	(0.107)	(0.103)	(0.106)	(0.105)
R_educational2	-0.022	-0.038	-0.024	0.019	-0.045	-0.026
	(0.131)	(0.131)	(0.124)	(0.118)	(0.125)	(0.123)
R_income1	0.029	0.017	0.073	0.089	0.002	0.005
	(0.102)	(0.102)	(0.095)	(0.090)	(0.098)	(0.096)
R_income2	-0.216^{**}	-0.217^{**}	-0.207^{**}	-0.210^{**}	-0.198^{**}	-0.204^{**}
	(0.104)	(0.104)	(0.099)	(0.094)	(0.099)	(0.098)
R_employment	0.139	0.140	0.243	0.180	0.164	0.128
	(0.180)	(0.180)	(0.167)	(0.159)	(0.172)	(0.169)
R_occupational1	-0.063	-0.065	-0.064	-0.063	-0.074	-0.077
	(0.087)	(0.086)	(0.080)	(0.076)	(0.083)	(0.081)
R_occupational2	0.102	0.089	0.140	0.152	0.088	0.092
	(0.138)	(0.138)	(0.127)	(0.121)	(0.132)	(0.130)
R_political	-0.081	-0.042	0.014	0.032	-0.025	-0.024
	(0.103)	(0.104)	(0.096)	(0.091)	(0.099)	(0.098)
R_partisanship	-0.025	-0.030	-0.061	-0.034	-0.050	-0.037
	(0.098)	(0.097)	(0.090)	(0.086)	(0.094)	(0.092)
R_voting	0.050	0.029	-0.048	-0.023	-0.011	0.009
	(0.104)	(0.105)	(0.097)	(0.092)	(0.100)	(0.099)
R_trump	0.128	0.111	-0.044	-0.018	0.113	0.134
	(0.097)	(0.097)	(0.090)	(0.086)	(0.093)	(0.091)
R_redistribution	-0.020	-0.034	-0.041	-0.037	-0.010	0.003
	(0.104)	(0.103)	(0.097)	(0.093)	(0.099)	(0.098)
R_basicincome	0.075	0.083	0.138	0.102	0.121	0.101
	(0.105)	(0.104)	(0.097)	(0.092)	(0.101)	(0.099)
Const.	-2.151^{***}	-1.874^{***}	-2.033^{***}	-2.490^{***}	-2.083^{***}	-2.418^{***}
	(0.237)	(0.270)	(0.219)	(0.220)	(0.227)	(0.270)
Excluded	No	No	Yes	Yes	No	No
Observations	474	474	414	414	474	474
Adjusted R^2	0.064	0.071	0.018	0.114	0.147	0.177
F Statistic	2.244^{***}	2.345^{***}	1.296	2.969^{***}	3.901^{***}	4.396^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Participants who classified purely selfless or selfish are excluded if "Excluded" is Yes.

7 Concluding remarks

Using theoretical arguments, we have previously believed that the extended CES utility function, proposed by Inukai et al. (2022), measures preferences for equality–selfishness in the distribution parameter α, and efficiency in the substitution parameter ρ (or τ). In this paper, we studied empirical implications of the parameters by conducting a modified dictator game followed by a public goods game and a survey among participants in Amazon Mechanical Turk.

Upon comparing the results for 26 variables with conservative criteria, we found that only two variables, behavior in the public goods game, `R_public`, and ideological self-identity, `R_political`, exhibit a statistically significant effect on the distribution parameter $\widehat{\alpha}$. Based on the observation that a smaller the value of $\widehat{\alpha}$ corresponds to a larger contribution to the public goods game, we conclude that the supposition that α reflects selfishness is reasonable. For the self-identification of ideology, `R_political`, we observed a greater $\widehat{\alpha}$ for the liberal respondents. However, this observation contradicts the findings of Fisman et al. (2017). This suggests that the results of previous studies on the relationship between the parameters of the utility function and other variables may not be generalizable, even if this discrepancy is attributed to differences between subject pools (Kohler, 2019).

Furthermore, the equivalence tests revealed that the measures of political attitudes and behavior are irrelevant for the rescaled substitution parameter $\widehat{\tau}$. To conclude from the results of our regression analysis, it would be premature to suggest that τ has nothing to do with behavior in public goods games, socioeconomic measures, and political attitudes/behavior. As noted in Inukai et al. (2022), τ estimation tends to involve greater inferential uncertainty than α, even though both parameters are measured on the same scale. This property inevitably makes it difficult to identify effects in the regression analysis of $\widehat{\tau}$. To more thoroughly examine the relationship between $\widehat{\tau}$ and various variables, it is necessary to attempt to reduce the inferential uncertainty by increasing the sample size. Additionally, for the MDG experimental tasks that each participant takes, it may be beneficial to increase the number of tasks or to redesign them with a more efficient composition for estimation.

A Instruction for the modified dictator game

INSTRUCTION

Introduction

This HIT is an academic experiment about decision-making.

You will be paid a fixed fee for completing tasks and a bonus.

When you complete the HIT, you will receive **2.50 USD**.

And you will receive a bonus after the other workers in our experiment have completed the tasks.

The bonus you will earn depends partly on your decisions and the other participants' decisions, and partly on chance.

The HIT consists of two experiments (Part I and II) and several questionnaire surveys.

The entire HIT may be complete within 40 minutes.

At the end of the HIT, you will receive a completion SECRET KEY and input it on your MTurk screen.

Details of how to make decisions and receive payments will be provided below.

Part I

Decision Problems

In part I, you will repeatedly participate in 50 independent decision problems in the same form.

You will decide how to allocate your tokens to others.

The tokens in part I will be exchanged for USD at the following rate:
1 token = 2¢.

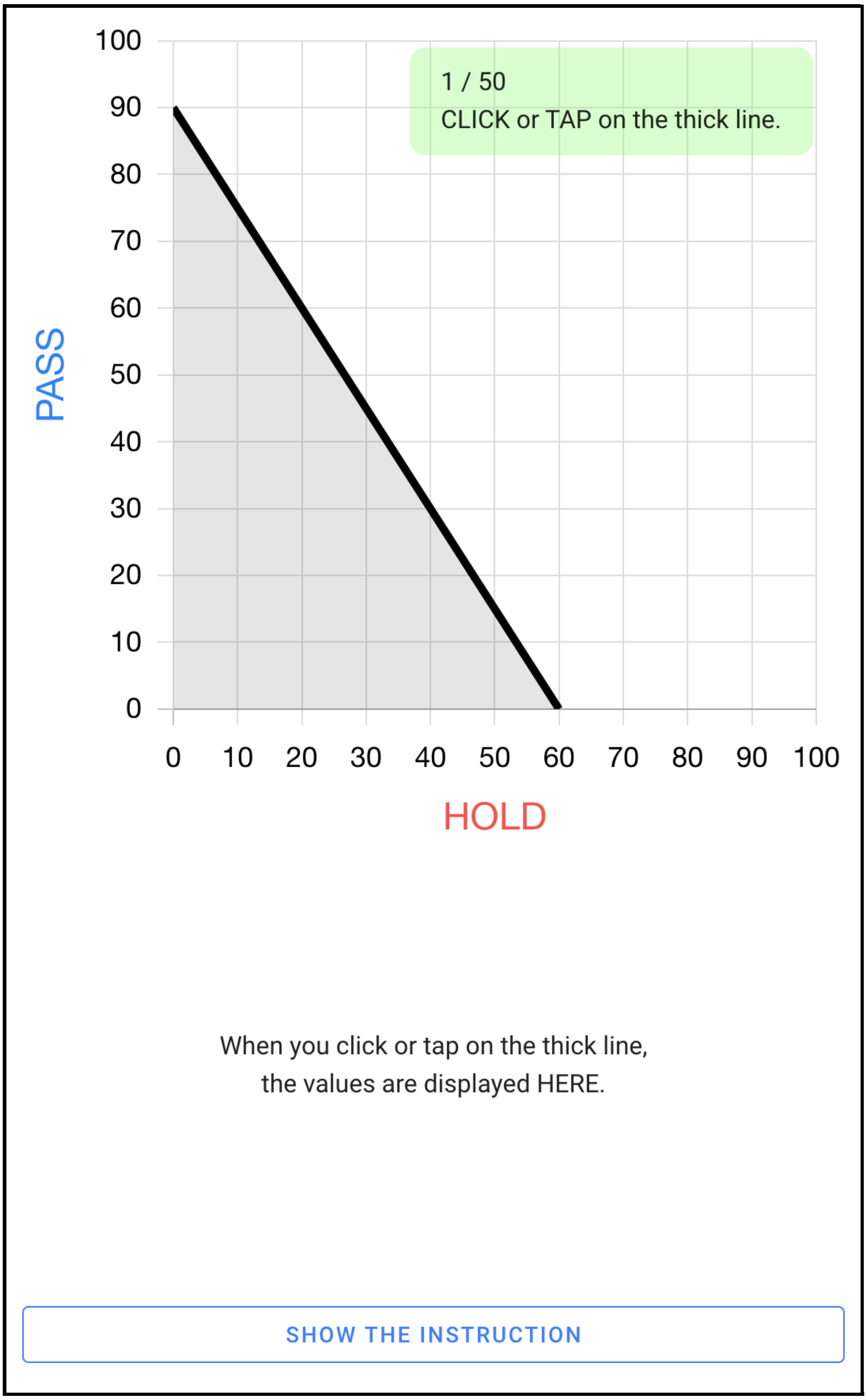
In each decision problem, you will be in a pair with another person chosen randomly from the other workers in this experiment.

You will then be asked to allocate tokens between yourself and the other.

Note that the person who will be paired with you may differ in each problem.

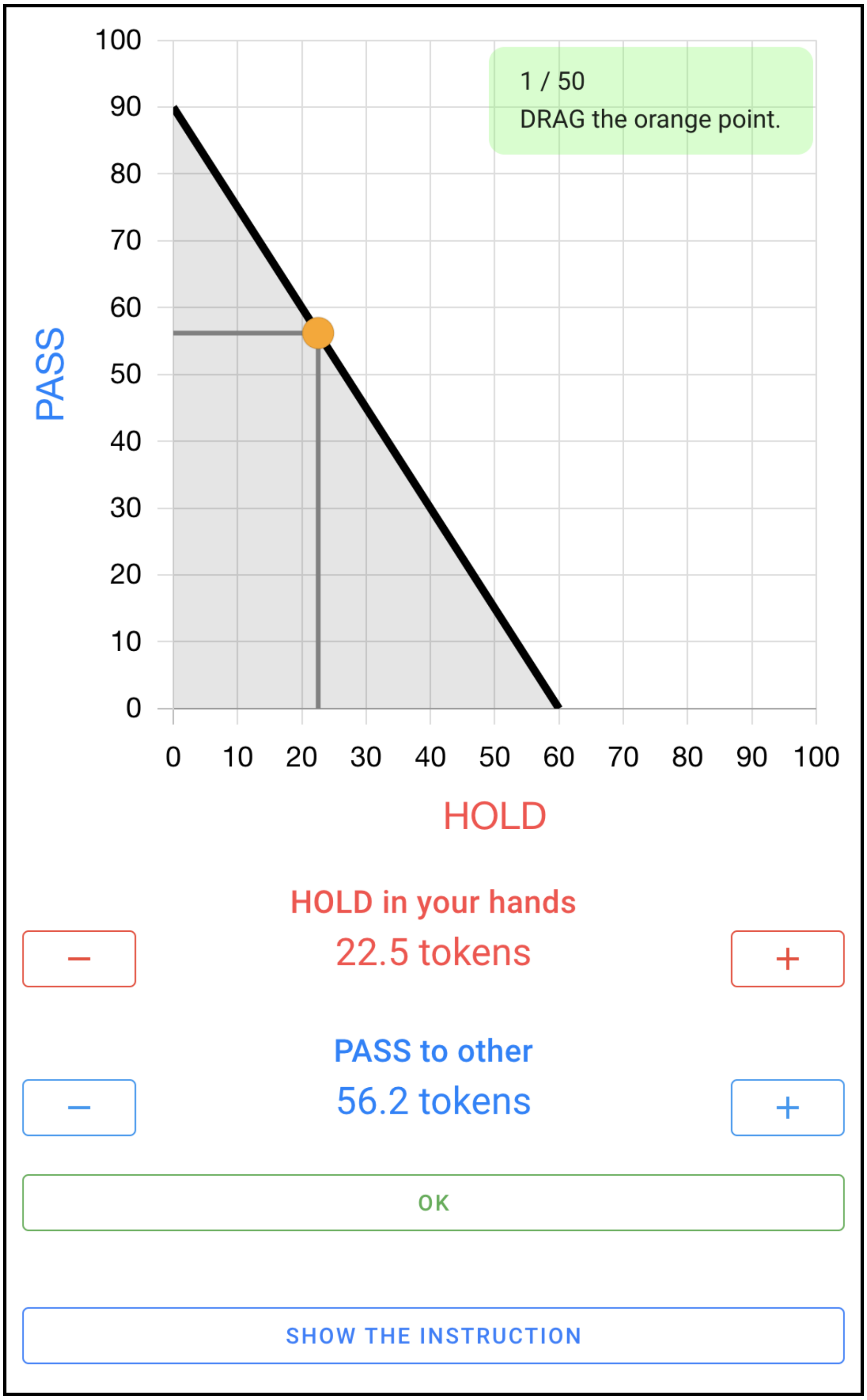
How to Operate

See the figure below.



When the experiment begins, a graph with a thick black line is displayed, as shown in the figure.

Clicking or tapping anywhere on the line makes an orange point (●) appear.



This orange point on the line represents a token allocation.

The horizontal axis of the graph measures the amount you HOLD, and the vertical axis measures the amount you PASS to the other.

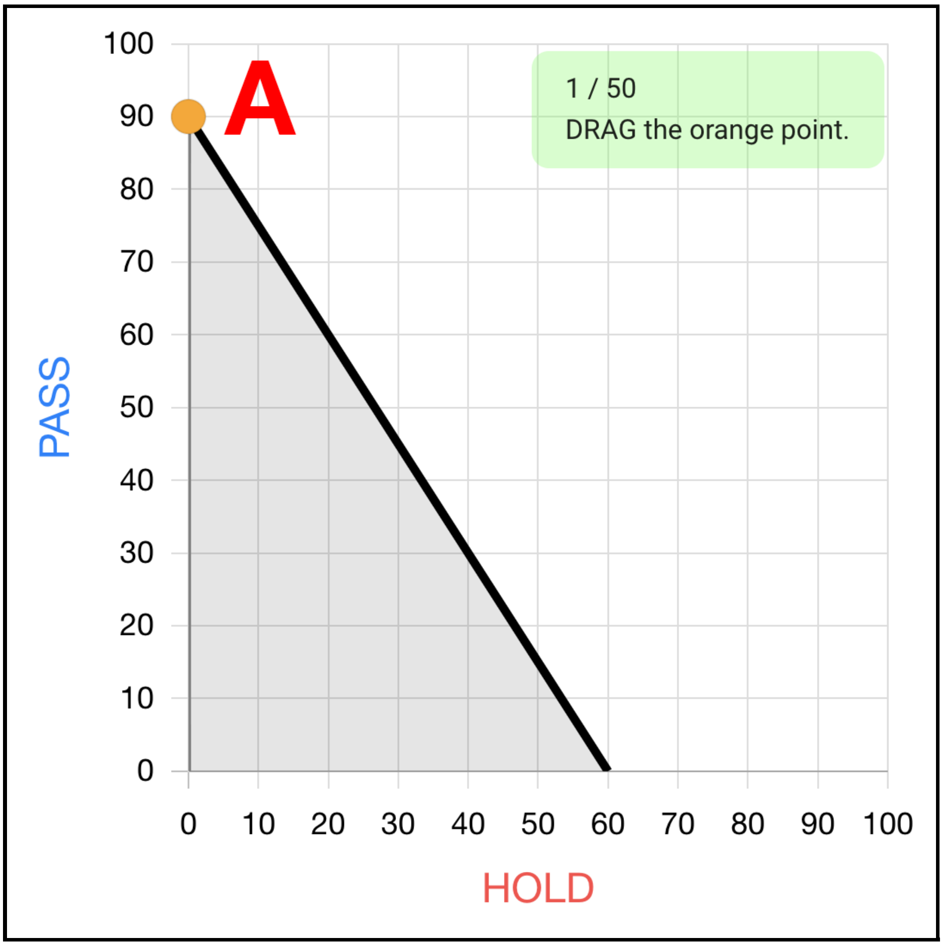
For example, as illustrated in the figure above, the point represents an allocation in which you HOLD 22.5 tokens and PASS 56.2 tokens.

Thus, if you choose this allocation, you will receive 22.5 tokens, and the other will receive 56.2 tokens.

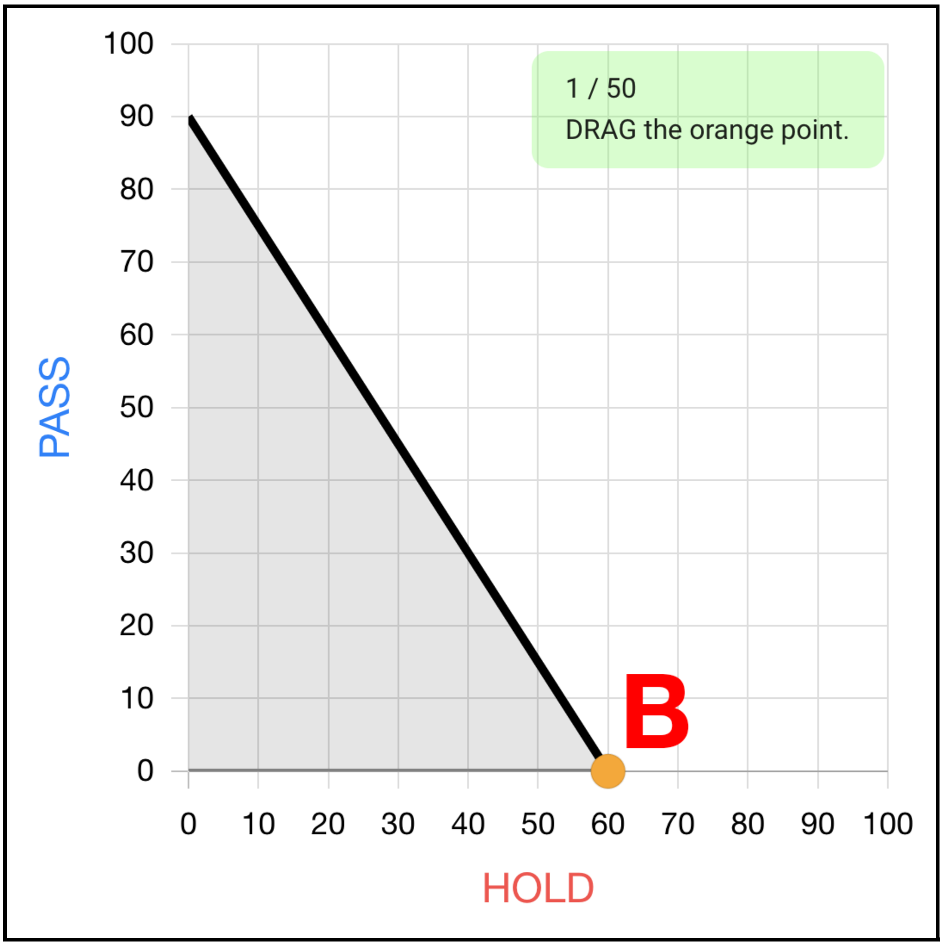
You can see the actual numbers: the amount you HOLD and the amount you PASS at the bottom of the graph.

Points A, B, and C in the figures below show an example.

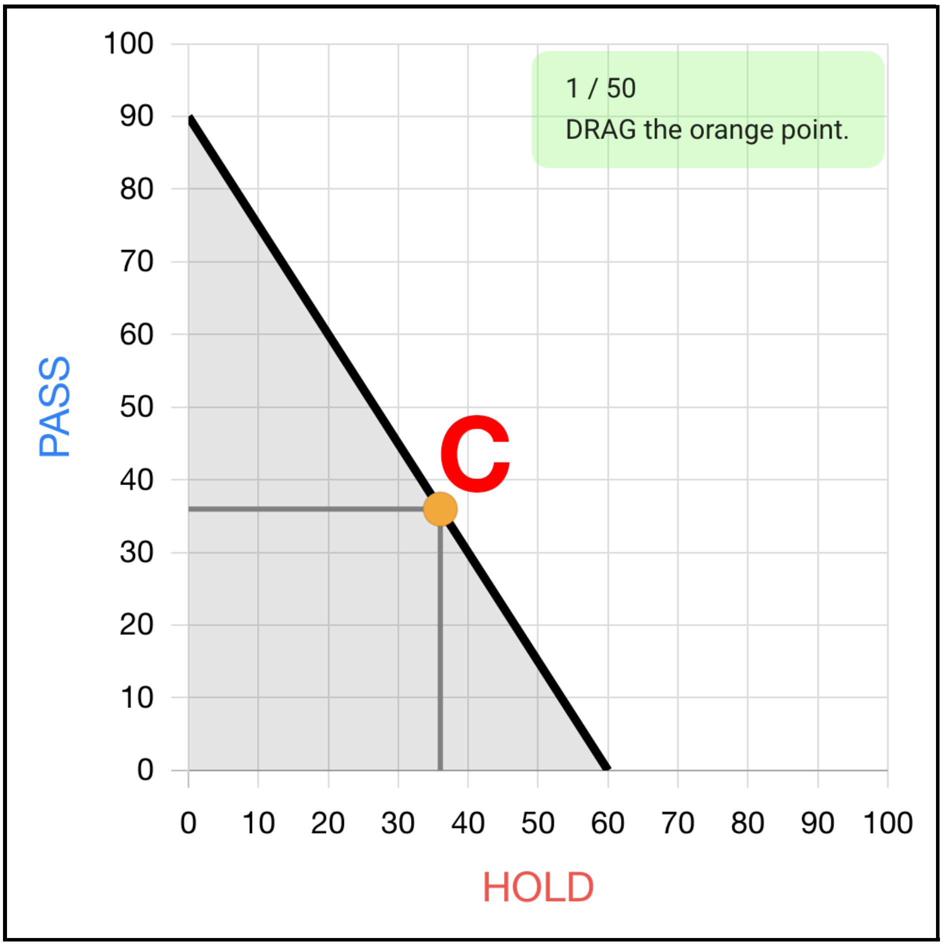
Point A means you will receive nothing, and the other will receive 90 tokens.



Point B means you will receive 60 tokens, and the other will receive nothing.



Point C means you and the other will receive equally 36 tokens.



In each problem, you will be asked to decide a HOLD/PASS combination by dragging the orange point with a mouse.

You can adjust the allocation by pressing + and − buttons at the bottom of the graph.

To move on to the next problem, press the OK button.

Next, a new graph with a different line will be displayed.

Then you will be asked to allocate with a new person in another independent problem.

You will need to complete this process 50 times.

Payments for You

The following describes how the amount of your bonus in part I is calculated.

The computer randomly chooses 10 of the 50 problems.

For each problem chosen, the computer randomly selects a worker to be paired with you and randomly chooses whether to adopt your decision or the paired person's decision.

If the decision you made is adopted, you receive tokens that you answer to HOLD.

If, on the other hand, the paired person's decision is adopted, you receive tokens that they answer to PASS.

As we have already explained, each token will be worth two cents, and less than a cent will be rounded up.

Trying Operation

You can manipulate the graph in the box below.

Practice the operation here.

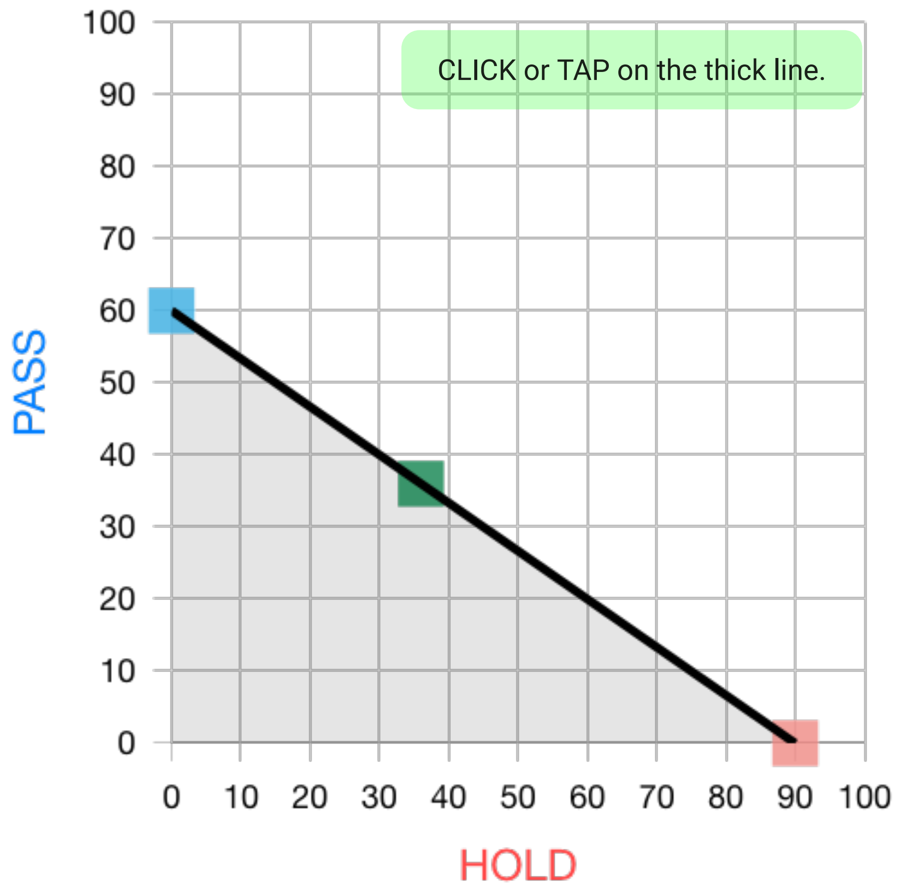
In the graph below, three points are displayed as examples:

- ■: HOLD nothing and PASS 60 tokens;
- ■: HOLD 36 tokens and PASS 36 tokens;
- ■: HOLD 90 tokens and PASS nothing.

In the experiment, these points will not be displayed.

When you want to start the experiment after practice, move to the bottom of this page, enter your Amazon Mechanical Turk Worker ID, and press the BEGIN button.

[Move to the bottom of this page]



When you click or tap on the thick line,
the values are displayed HERE.

Begin the Part I

Please make sure that your Amazon Mechanical Turk Worker ID is filled in the box below.

It is NOT your E-mail address.

If we do not have your correct Worker ID, we will not be able to pay you.

↓

Input your MTurk Worker ID

XXX

BEGIN

B Questions and variable definitions

B.1 Socioeconomic status of eliteness

Education level Participants answered the question "What is the highest level of school you have completed or the highest degree you have received?" by choosing one of these options: "Less than high school degree," "High school graduate (high school diploma or equivalent including GED)," "Some college but no degree," "Associate degree in college (2-year)," "Bachelor's degree in college (4-year)," "Master's degree," "Doctoral degree," and "Professional degree (JD, MD)." All participants were forced to answer this question. We defined two dummy variables, `R_educational1` and `R_educational2`, representing the choice of 1) "Associate degree in college" or "Bachelor's degree in college," and 2) "Master's degree," "Doctoral degree," or "Professional degree," respectively.

Income level Which category represents the total combined income of all members of your family (living here) during the past 12 months before taxes?" by choosing one of these options: "Less than \$10,000," "\$10,000 to \$19,999," "\$20,000 to \$29,999," ..., "\$90,000 to \$99,999," "\$100,000 to \$149,999," and "\$150,000 or more." All participants were forced to answer this question. We defined two dummy variables, `R_income1` and `R_income2`, representing 1) the annual income is less than \$30,000 and 2) not less than \$90,000, respectively.

Employment status Participants answered the question "What is your current employment status?" by choosing one of these options: "Full-time employee," "Part-time employee," "Self-employed or business owner," "Unemployed and looking for work," "Student," and "Not in labor force (for example: retired, or full-time parent)." All participants were forced to answer this question. We defined a dummy variable `R_employment` representing the choice of "Full-time employee," "Part-time employee," or "Self-employed or business owner."

Occupational prestige Participants who indicated that they were employed (i.e., `R_employment` = 1) answered the "To which of the following occupational groups do you belong?" by choosing one of these options: "Professional and technical (for example doctor, teacher, engineer, artist, accountant, nurse)," "Farm worker (for example farm laborer, tractor driver)," "Higher administrative (for example banker, executive in big business, high government official, union official)," "Service (for example restaurant owner, police officer, waitress, barber, caretaker)," "Sales (for example sales manager, shop owner, shop assistant, insurance agent, buyer)," "Skilled worker (for example foreman, motor mechanic, printer, seamstress, tool and die maker, electrician)," "Clerical (for example secretary, clerk, office manager, civil servant, bookkeeper)," "Unskilled worker (for example laborer, porter, unskilled factory worker, cleaner)," "Semi-skilled worker (for example bricklayer, bus driver, cannery worker, carpenter, sheet metal worker, baker)," and "Other." These options presented to the participants were randomly ordered for each participant. All participants were forced to answer this question. We defined two dummy variables, `R_occupational1` and `R_occupational2`, representing the choice of 1) "Professional and technical," and 2) "Higher administrative," respectively.

B.2 Political attitudes and behaviors

Think of self as liberal Participants answered the question "Here is a 7-point scale on which the political views that people might hold are arranged from very liberal (left) to very conservative (right). Where would you place yourself on this scale?" by choosing between 1 and 7. All participants were forced to answer this question. We defined a dummy variable `R_political` that is an indicator for liberal individuals whose answer is less than 4 on the 7-point scale.

Democrats Participants answered the question "Do you think of yourself as closer to the Republican or Democratic party?" by choosing one of these options: "Democrats," "Democratic leaners," "Equally close to Democrats and Republicans," "Republican leaners," and "Republicans." All participants were forced to answer this question. We defined a dummy variable `R_partisanship` that is an indicator for Democrats whose answer is "Democrats" or "Democratic leaners."

Trump job approval Participants answered the question "Looking back on Donald Trump's four years (2017–2021) in office, in general, do you approve or disapprove of his job as President?" on a 7-point scale: "Strongly disapprove (1)," "Disapprove," "Somewhat disapprove," "Neutral," "Somewhat approve," "Approve," and "Strongly approve (7)." All participants were forced to answer this question. We defined a dummy variable `R_trump` that is an indicator for individuals whose answer is "Somewhat approve," "Approve," or "Strongly approve."

Voting for Biden in 2020 Participants answered the question "In the 2020 presidential election, for which candidate would you have voted?" by choosing one of these options: "Donald Trump," "Joe Biden," and "Vote for neither/Other." Options for Trump and Biden were randomly ordered by participants. All participants were forced to answer this question. We defined a dummy variable `R_voting` that is an indicator for individuals whose answer is "Joe Biden."

Favor for redistributive policies Participants answered the question "Do you agree or disagree that the government in Washington should redistribute wealth from the rich to the poor?" on a 7-point scale: "Strongly disagree (1)," "Disagree," "Somewhat disagree," "Neutral," "Somewhat agree," "Agree," and "Strongly agree (7)." All participants were forced to answer this question. We defined a dummy variable `R_redistribution` that is an indicator for individuals whose answers are

"Somewhat agree," "Agree," or "Strongly agree."

Favor for basic income policies Participants answered the question "Do you agree or disagree about such a system that would automatically guarantee a certain basic income to all permanent residents? (Andersson and Kangas, 2007)" on a 7-point scale: "Strongly disagree (1)," "Disagree," "Somewhat disagree," "Neutral," "Somewhat agree," "Agree," and "Strongly agree (7)." All participants were forced to answer this question. We defined a dummy variable `R_basicincome` that is an indicator for individuals whose answer is "Somewhat agree," "Agree," or "Strongly agree."

B.3 Demographic characteristics

Age Participants chose their year of birth using a dropdown menu. We calculated age from the responses and conducted a regression analysis with standardized values `R_age`. All participants were forced to answer this question.

Gender Participants answered the question "With respect to gender, how do you self-identify?" by choosing one of these options: "Female," "Male," "Other," and "Choose not to answer." All participants were forced to answer this question. We defined a dummy variable `R_gender` representing female identity for all participants except those who chose not to answer.

Ethno-racial identity In response to the question "With respect to race or ethnicity, how do you self-identify?", participants were asked to choose from the following options: "American Indian or Alaska Native," "Native Hawaiian or Pacific Islander," "Black or African American," "White," "Hispanic or Latino," "Asian," and "Other." These options presented to participants were randomly ordered for each participant. Participants were allowed to choose more than one applicable option. They could also move on to the next question without selecting one, i.e., without answering the question. We defined three dummy variables, `R_race1`, `R_race2`, and `R_race3`, representing the unique choice of 1) "Black or African American," 2) "Hispanic or Latino," and 3) "Asian," respectively, for all participants except those who did not choose any of the options.

Religious identity Participants answered the question "What religion do you belong to or identify yourself most close to?" by choosing one of these options: "Jew," "Hindu," "Protestant," "Roman Catholic," "Orthodox (Russian/Greek/etc.)," "Muslim," "Buddhist," "Other Christian (Evangelical/Pentecostal/Free church/etc.)," "Other," "Do not belong to a religion," and "Choose not to answer." These options presented to the participants were randomly ordered for each participant. All participants were forced to answer this question. We defined three dummy variables, `R_religious1`, `R_religious2`, and `R_religious3`, representing the choice of 1) "Protestant," 2) "Roman Catholic," and 3) "Do not belong to a religion," respectively, for all participants except those who chose not to answer.

Marital status Participants answered the question "With respect to gender, how do you self-identify?" by choosing one of these options: "Married," "Widowed," "Divorced," "Separated," and "Never Married." All participants were forced to answer this question. We defined three dummy variables, `R_marital1` and `R_marital2`, representing the choice of 1) "Married" and 2) "Widowed," "Divorced," or "Separated," respectively.

Parenthood Participants answered the question "Do you have children living with you?" by choosing yes or no. All participants were forced to answer this question. We defined a dummy variable `R_children` representing those who answered yes.

Metro residents We asked participants for their ZIP code or Federal Information Processing System (FIPS) county code to obtain information on whether they lived in a metro area.[18] Participants could choose not to answer both the ZIP and FIPS codes. We converted the ZIP codes into FIPS codes and then obtained the United States Department of Agriculture (USDA) rural–urban continuum code corresponding to each participant's FIPS code. We defined participants with a USDA rural–urban continuum in the range of 1–3 as residents of the metro area, represented by a dummy variable `R_metro`.[19]

[18] In the early wave of the experiment, we only asked for the ZIP code. We received a message from one respondent that they did not want to answer the question because they believe that the ZIP code is personally identifiable information. In response to this request, we decided to add the option of answering with the FIPS code, which is more difficult to identify, instead of answering with the ZIP code.

[19] We retrieved the USDA rural–urban continuum code at https://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx. Our procedure to identify metro residents was followed Huff and Tingley (2015).

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