The Psychological Values Underlying Redistributive Behavior

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Abstract

Economic inequality is an urgent issue which many societies are becoming increasingly confronted with. In spite of the dire consequences of allowing inequality persist unabated, efforts to mitigate inequality via redistribution typically fail, often because economically disadvantaged people oppose the very redistributive policies which would improve their lives. This counterintuitive finding has posed challenges to existing theories of human behavior, leading many to speculate that it is fairness, not material interest, which underlies redistributive choice. In the current study, we propose a novel experimental paradigm to assess how both fairness and self-interest impact redistributive choice. In an online sample of 231 participants, we demonstrate that the choice of redistributive tax rate was impacted by both factors. However, employing a computational modeling approach, we also find evidence that strategic norms underlie redistributive choice, both in choices observed in the laboratory and the policy views that participants hold.

Introduction

One of the most urgent threats to political stability is that of economic inequality. Inequality has been consistently associated with increases in crime (Blau & Blau, 1982; Kang, 2016; Coccia, 2018), decreases in public health (Kawachi, 1997; Pickett & Williamson, 2011; Pickett & Williamson, 2015 Vega & Sribney, 2017), limitations in social mobility (Grusky & Hauser, 1984; Haveman & Smeeding, 2006; Chetty et al., 2017), and degradation of civil society (Solt, 2008; Karakoç, 2012; Cole, 2018). However, these problems are not simply symptoms of inequality – they also *exacerbate* the problem, leading to a vicious cycle wherein existing disparity produces greater and greater inequality over time (Birdsall, 2006; Cingano, 2014). In the absence of direct intervention via redistribution, this can lead to rampant inequality with its attendant negative effects worsening in kind.

Considering the aforementioned negative consequences, there is often surprisingly little public support for redistribution as a potential solution to inequality (Gallup, 2018; Gelman et al., 2010; Page & Jacobs, 2009; Saad, 2011; Shapiro & Young, 1989). Redistribution as defined here encompasses all policies that transfer money from the more wealthy to the less wealthy, and given the skewed distribution of wealth, the majority of people would stand to benefit from redistribution. Therefore, the lack of popular support for such policies is at odds with the notion that people act rationally in their own self-interest. While wealthier individuals do behave consistently with this picture of self-interest, typically seeking to maintain what they have (Page, Bartels, & Seawright, 2013), in contrast, individuals on the lower end of the socioeconomic ladder often oppose the redistributive efforts which could help them (Jost et al., 2003; Solt et al., 2016; Buchel, Luijkx, & Achterburg, 2021; Morris et al., 2022). Explanations abound for this paradoxical finding, though no direct causal evidence outlines when, and why, people oppose redistribution. Here we explore this question, adopting an experimental and computational approach to clarify the role of several important factors in redistribution decisions, namely fairness and self-interest.

While examining self-interest in a redistributive setting is straightforward, the role of fairness is more nuanced, as there are several concepts of fairness that can underlie these judgments. For example, people may consider how objectively unequal wealth distribution is, they may assess who benefits from how resources are distributed, or they can factor in the criteria for initial resource distribution. Here we focus on the latter, as previous research suggests that the most important factor in these judgments is the rationale for underlying inequality (i.e. van den Bos, Lind, & Wilke, 2001; Tyler, 2015). That is, when people perceive that a distribution was determined ‘unjustly’, they judge that distribution to be unfair irrespective of whether it is equal or unequal. This *perceived cause of inequality* has also been shown to correspondingly change distributive preferences in laboratory experiments (Hoffman et al., 1994; Oxoby & Spraggon, 2008; Engel, 2011; Dreber et al., 2013; Ku & Salmon, 2013; Dreoni, Mentzakis, & Schaafsma, 2022). Building on Smith’s (2010) work, here we examine the role of four particular causes of underlying inequality on redistribution decisions. These four causes of inequality – namely merit, luck, entitlement, and corruption – are outlined in Table 1.

Table 1

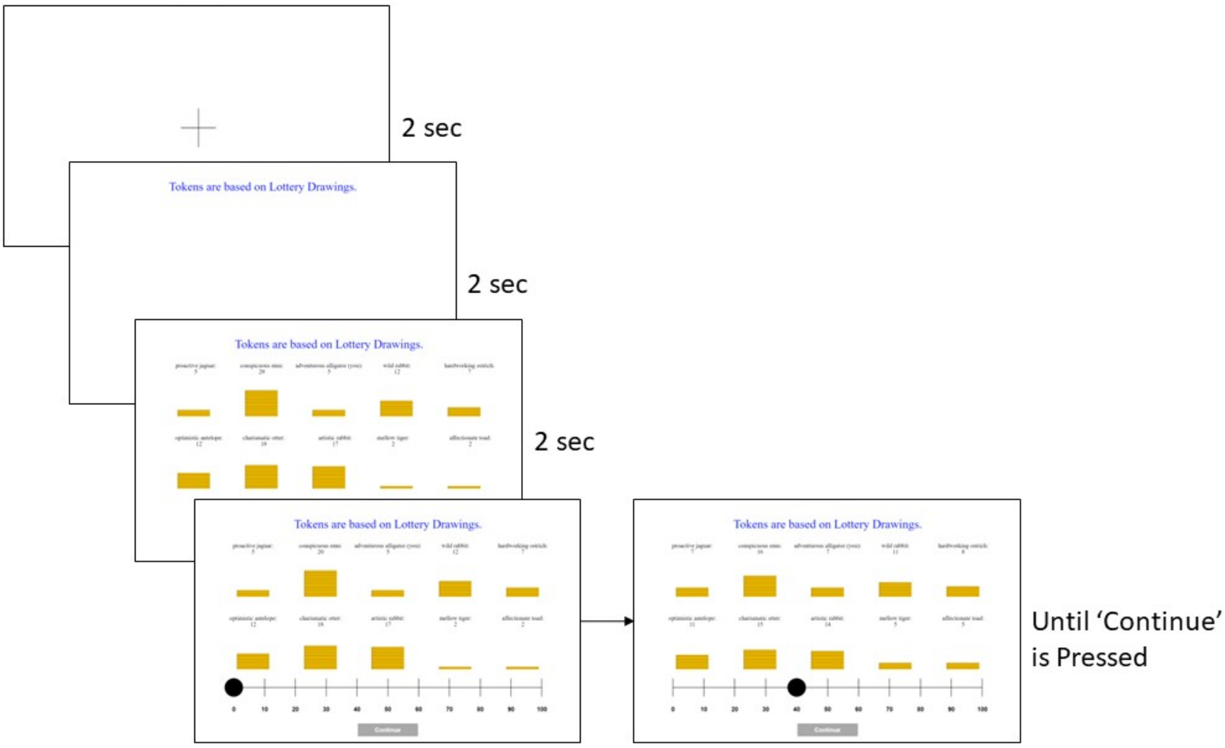
Causes of Inequality

Cause of Inequality	Attribution of Financial Success	Experimental Manipulation
Merit	Hard work, talent, skill, etc.	Analytical Reasoning Test
Luck	Randomness	Lottery Drawings
Entitlement	Inheritance, Discrimination	Life Advantage Score
Corruption	Illegal or immoral conduct	Machiavellianism Score

In order to experimentally investigate how self-interest and the perceived cause of inequality affect redistributive decision-making, we developed a novel socio-economic task termed the Redistribution Game. In the Redistribution Game, 10 anonymous players are complete a one-shot interaction together. As depicted in Figure 1, 100 tokens are initially allocated between these 10 players. These tokens are based on the players’ ranking on one of four previously completed tasks, which were constructed to operationalize either merit, luck, entitlement, or corruption (Table 1). Then, one of the 10 players (the participant) has the opportunity to set a ‘tax rate’ to be applied to the entire group. This tax rate determines the percentage of tokens that all players must contribute to a community pot, which is then equally dispersed among the 10 players irrespective of each player's contribution. Each player's final payout is the amount retained after being taxed, plus whatever was received from the community pot. We predict that both self-interest (i.e. the amount initially allocated to the participant) and fairness (i.e. the criteria that tokens are originally allocated by) will have effects on subsequent redistributive decisions. However, we also expand these findings to advance and test a psychological theory of *why* this happens.

Figure 1

Redistribution Game



Note. After an initial 2 second fixation cross, players see the distributive condition for that trial (i.e. the source of the inequality) for another 2 seconds. Then, the participant sees all player's names and their respective token amounts based on this initial allocation. After 2 seconds a slider is added, initially set to a tax rate of 0 (indicating unchanged payouts). Changes in tax rate via the slider immediately change the token amounts for each player. Once they have decided on a specific tax rate, participants click on the 'Continue' button to confirm their choice and proceed to the next trial. Colors assigned to each condition are randomized over participants. Conditions vary over blocks of 20 trials.

In this psychological theory of redistributive choice, we propose that decision-makers first assess the cause of the underlying inequality, and that this judgment then leads people to adopt one of three qualitatively distinct redistributive norms to govern their decision-making. The first of these redistributive norms is *Payout-Maximization* which draws on rational choice theory (Scott, 2000; Green, 2002). When redistributing according to Payout-Maximization, people will consider what is in their self-interest and redistribute accordingly, leading to decisions to support redistribution when it is economically advantageous and decisions to oppose it when it is not. The second redistributive norm is *Equity-seeking*, which draws on Equity theory (Adams, 1965). Equity-seeking involves unconditionally opposing redistribution irrespective of self-interest, and people often adopt this norm when they believe that a particular distribution is fair, even if it is unequal. For example, allocations as a function of effort are often deemed fair, even if it leads to inequality. Inversely, the third and final norm, *Equality-seeking*, prescribes unconditionally supporting redistribution and typically follows from a belief that inequality is inherently unfair, irrespective of the cause. In the context of the Redistribution Game, these three redistributive norms make predictions which are differentiated across the levels of self-interest.

In general, we predict that Equity-seeking will be most prevalent in the Merit condition since it will be judged as the fairest, while Equality-seeking will be most prevalent in the Entitlement condition since it will be judged as the least fair. However, and importantly, individual differences in norm preferences are often found to play a substantial role in social decision-making (van Baar, Chang & Sanfey, 2019; van Baar et al., 2020; Huijsmans, 2022, Li et al., 2022, Gao et al., 2024)., and thus we propose that norm preferences function as something akin to a stable trait across people. Consequently, in our theory of redistribution we propose that both context-dependent and context-invariant processes govern the choice of redistributive norm in a given scenario.

To test this, we implement this theory as a computational model, as this approach allows us to systematically capture individual preferences for each norm (Konolov, Hu, & Ruff, 2018; Vahed, Galván, & Sanfey, 2024). Computational modeling is an ideal approach to theory-building as it demands that theories are grounded and that they are rigorously falsifiable (van Rooij, 2008; Guest & Martin, 2021). Using competitive model testing provides a formal means by which to verify the claims made by our theory of redistributive choice (Wilson & Collins, 2019; Galván & Sanfey, Under Review).

Methods

Open Science

The hypotheses, sampling procedure, confirmatory analyses, and exclusion criteria for this study were registered prior to data collection on the Open Science Framework (https://osf.io/3gzq2). The most notable exception to this was the Linear Mixed Effects Modeling analysis, as our analyses were intended to focus on our computational modeling approach: other deviations from the preregistration will be explicitly stated. This project on the Open Science Framework also contains a report on the pilot data which is freely accessible to view. All research activities were carried out in accordance with the Declaration of Helsinki, approved by the local ethics committee (Ethical Reviewing Board CMO/METC [Institutional Research Review Board] Arnhem-Nijmegen, CMO 2014/288), and conducted according to these guidelines and regulations. Data and code will be made freely and openly accessible via the Radboud Data Repository after the peer-review process.

Sample

An a priori power analysis for the current study was conducted based on a generic small effect size estimate of d = 0.2, with 0.8 power and a 0.95 confidence interval, Bonferroni-corrected for 6 tests. This resulted in a recommended sample size of 265 participants. 265 participants were collected via Prolific. Since only completed submissions were saved on Pavlovia and a completion code was given only once the study was completed and the data was saved, no exclusion criteria were preregistered. Our sample was comprised only of English-speaking Pavlovia workers currently residing in the Netherlands, and was balanced on the basis of gender (1455 such workers were active on Prolific in the 90 days prior to data collection). Data collection begun on 15 July 2023 and ended 27 July 2023. Data for 22 participants was lost due to errors with GitLab and Pavlovia which prevented the data from being written. Varying from pre-registration, we excluded participants who previously participated in the pilot version of study (n = 12): we intended to prohibit these individuals from participating in the current study but mistakenly did not do so. Thus, the final sample for analysis was 231 participants. Demographic data for these 231 participants is given in Appendix A.

Procedure

Participants were recruited for the experiment, advertised as ‘Decision-Making with Others’, via Prolific. Consistent with Prolific’s guidelines, the reimbursement rate of £9/hour but not the bonus rate was shown in the study description. The experiment was advertised as taking 75 minutes to complete, and participants completed the study with the median completion time of 64 minutes. Upon choosing to participate in the experiment in Prolific, participants were redirected to a plain webpage where they were informed about the benefits and risks of the study. Consent was obtained by participants clicking a hyperlink saying “BEGIN” at the bottom of the webpage which redirected them to the actual experiment link.

Upon being redirected to the experiment link, participants were asked for their Prolific ID and to choose a screen name using 1 of 50 adjectives and 1 of 50 animals. In the Redistribution Game, they would be identified by “[Chosen Adjective] [Chosen Animal] (you)”. This was done to enhance the believability of our cover story, which is that participants are playing with real partners. Participants then completed four tasks: they chose a lottery number, completed a Machiavellianism questionnaire (Appendix B), Demographic questionnaire (Appendix C), and an Analytical Reasoning test (Appendix D). We incentivized effort on the Analytical Reasoning test by offering a 2 GBP bonus to participants based on their accuracy on this test. After this, participants played 4 blocks of 20 trials of the Redistribution Game, which we referred to as the “Community Game” to reduce awareness that the study was intending to study redistribution: the “Tax Rate” was also referred to as the “Contribution Rate” for the same reason. Prior to each block, the scoring criteria was explained to participants. After each block, participants were given a mandatory, paid 2 minute break to improve their engagement in the task. Each block of the experiment contained the exact same 20 trials to maximize experimental control, though the arrangement on screen and the screen names varied from block to block which made the trials unrecognizable to participants.

After completing all four blocks of the Redistribution Game, participants completed several questionnaires before they were informed of their bonus and the completion code which would allow them to finish the experiment on Prolific.

Measures

We collected participants' responses on several questionnaire items. These included the novel Perceived Importance of Success Defining Attributes Scale (PISDAS; Appendix E), Redistributive Policy Attitudes Questionnaire (RPAQ; Appendix F), and Redistributive Policy Importance Questionnaire (RPIQ; Appendix G). We also asked participants to report their Current Income as well as both Current and Future Believed Net Benefit from Redistribution (Appendix H), which was explained to participants as the difference between the benefits received from the government and the amount paid in taxes to help fund redistribution schemes.

Results

Linear Mixed Effects Modeling

In order to assess how both Self-Interest and the Cause of Inequality affects Redistributive Choices in the Redistribution Game, we estimated a Linear Mixed Effects Model using the *lme4* package (Bates et al., 2015) in R (R Core Team, 2022). Herein, Tax Rate was predicted by participants' Initial Allocation, the Condition, and interaction between these variables. Thus, we included these three terms as fixed effects in the model and we included a random intercept and random effect of Initial Allocation per participant. Initial Allocation was binned into three levels: since participants' payouts are completely unaffected by the Tax Rate at exactly 10 tokens, these bins were Disadvantaged (0-7 tokens), Neither (8-12 tokens), or Advantaged (13-21 tokens). The model was respecified using the *afex* package (Singmann et al., 2022) with degrees of freedom estimate using the Satterwhite method. A Type 3 ANOVA revealed that all three terms in the model were highly significant, as shown in Table 2. Using the *MuMIn* package (Bartón, 2023) we found that the model was found to 58.7% of the variance in redistribution decisions though only 14.2% of this variance was identified at the whole-group level: the remaining 44.5% was attributed to individual differences (Marginal R^2 = 0.142, Conditional R^2 = 0.587).

Table **2**

ANOVA Results

	df	F	p
Initial Allocation	2, 230	94.296	<0.001
Condition	3, 17778	73.845	<0.001
Initial Allocation * Condition	6, 17778	10.401	<0.001

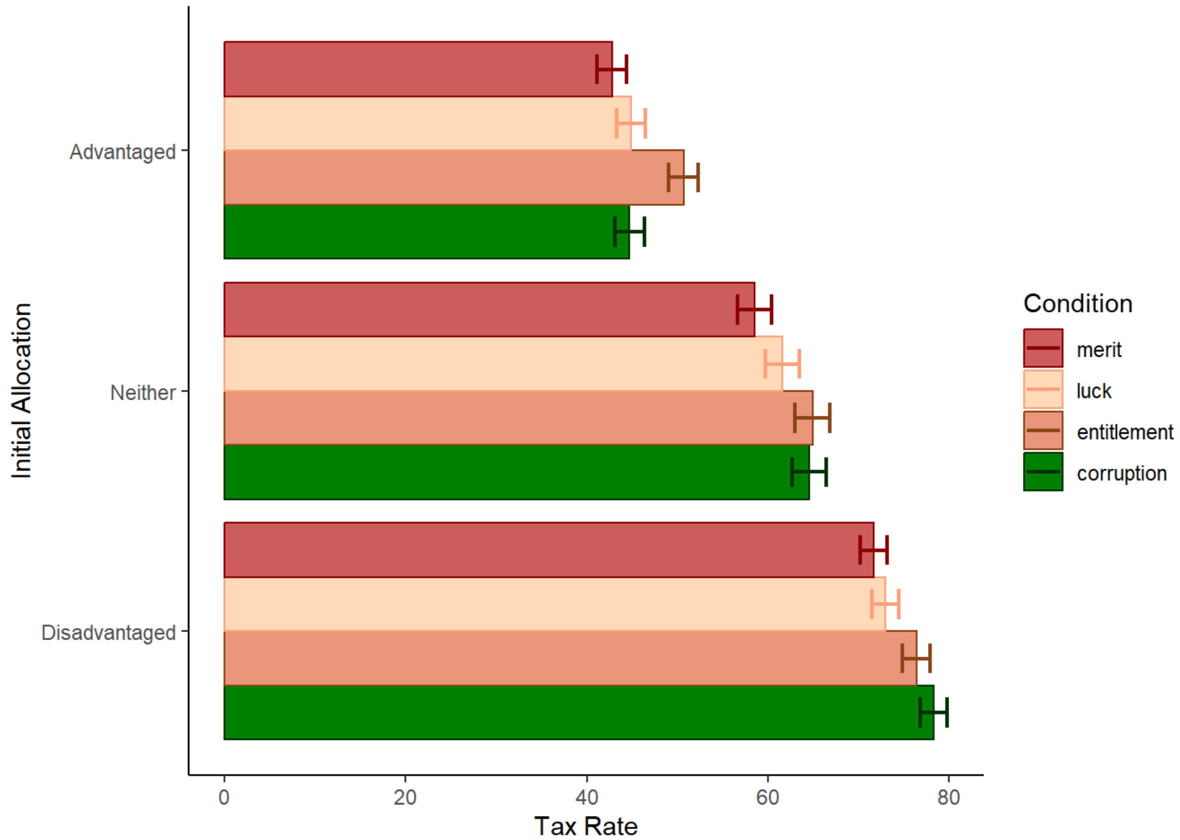
Note. The results of our Omnibus ANOVA reveal that all three terms in our model have a significant effect on Tax Rate decisions.

Since we found that all three terms in our model had a significant effect on redistribution decisions, we then sought to examine exactly how this occurs. To this end, we conducted two sets of post-hoc comparisons. The first set of post-hoc comparisons assessed the effect of Initial Allocation on Tax Rate: here we found that Tax Rate was significantly different between the three levels of Initial Allocation across all four conditions (Appendix I). Participants always redistributed the most when they were Disadvantaged and always redistributed the least when they were Advantaged, as shown in Figure 2.

After demonstrating that Self-Interest influenced Redistributive Choice, we then sought to assess how these Self-Interest effects differed depending on the Cause of Inequality. To this end we conducted a second set of post-hoc comparisons which assessed the effect of Condition on Tax Rate across all three levels of Initial Allocation. This analysis revealed a more complex set of results (Figure 2; Appendix J). In the Corruption condition participants demonstrated the strongest self-interest effect, setting the significantly highest tax rate of all when Disadvantaged and among the lowest tax rates when Advantaged. Across all three levels of Initial Allocation, participants always redistributed more in the Entitlement condition compared to the Merit or Luck conditions. Finally, participants redistributed less in the Merit condition compared to the Luck condition.

Figure 2

Effect of Self-Interest and the Cause of Inequality on Redistribution Decisions



Note. Tax Rate decisions significantly differ across all three levels of Initial Allocation, in line with a self-interest effect. However, this effect further contingent upon the cause of inequality. All results are visualized with *ggplot2* (Wickham, 2016).

Computational Modeling

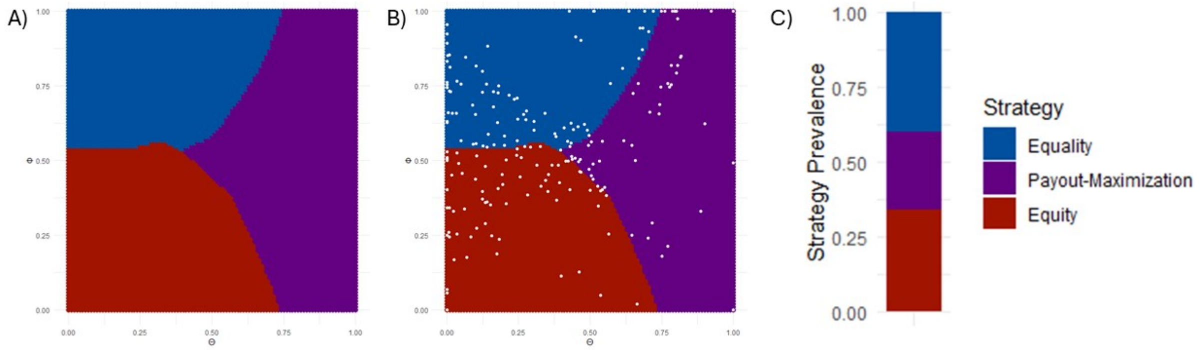
While these results demonstrate that redistributive choices are indeed affected by both self-interest and the cause of inequality; individual differences were an overwhelming source of variance in redistributive choice. To try to explain these individual differences, we adopted a computational modeling approach, developing a novel utility model we termed the Redistributive Norms Model (RNM). Herein, we propose that participants derive Utility from selecting a Tax Rate (U_{tr}) which adheres to one of three norms: maximizing payout, maximizing equity, or maximizing equality (Appendix K).

We first sought to determine which norms were utilized within each condition: specifically, if only a single norm was influential within a given condition, two norms, or all three norms. To test this question, we compared the RNM to derivatives of the RNM which were comprised of only one or two of the three norms in the RNM. We computed model performance per participant in the form of Akaike Information Criterion (AIC; AIC rewards parsimony and accuracy) and conducted paired t-tests between the RNM and the simpler models. We found that the RNM had a significantly lower AIC than the best performing derivative model in the Merit ($t(203) = -3.289$, $p < 0.001$), Luck ($t(186) = -11.166$, $p < 0.001$), Entitlement ($t(197) = -3.427$, $p < 0.001$), and Corruption ($t(203) = -9.409$, $p < 0.001$) conditions (all tests are shown in Appendix L). Thus, all three norms were used when making redistributive choices in the Redistribution Game: it was never justified to ignore any single strategy. Across all four conditions, we found that the RNM explained 70% of the variance in Tax Rate decisions and that it also explained 89% of the variance in participants' own payouts. Thus, the three norms of Equity, Equality, and Payout very accurately characterized how people decide to redistribute resources in the Redistribution Game.

After demonstrating that redistributive norms aptly characterize the Tax Rate decisions observed in the Redistribution Game, we then sought to assess how norm use changed depending on the cause of inequality. To this end, we employed a model-based classification approach wherein we created "borders" in our parameter space by clustering our model's predictions. This a priori clustering approach allowing us to classify the redistributive norm employed by participants in a given condition in a non-arbitrary manner which was not biased by the range of behavioral patterns in the data (van Baar, Chang & Sanfey, 2019; van Baar et al., 2020; Huijsmans et al., 2024). The logic of this classification approach is visualized in Figure 3. With these strategies assigned to participants on a condition-by-condition basis, we then sought to assess two possible explanations for the effect of condition on redistributive choice.

Figure 3

Strategy Classification

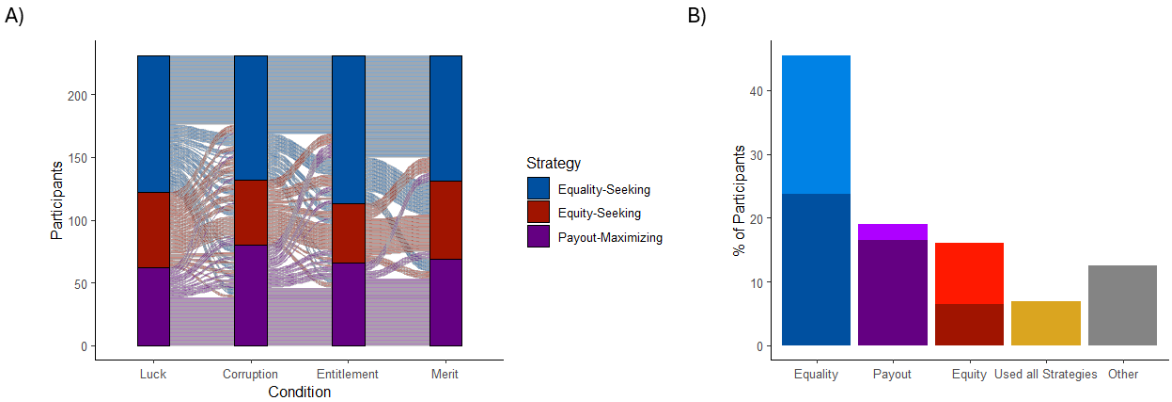


Note. In Figure 3a, the A Priori Clustering of the Parameter Space is shown. Model predictions were simulated for the Social Utility Model shown in Equation 1, and these simulations were then clustered. The optimal solution for the model predictions was found to be a 3-cluster solution, which results in the delineation of the Parameter Space as shown. In Figure 3b, participants' recovered parameters in the merit condition are shown as an example. Points within the red area are classified as Equity-seeking, points within the blue area are Equality-seeking, and in the purple area are Payout-Maximizing. In Figure 3c, the prevalence of the three strategies in the merit condition is shown, based on this classification approach.

One explanation is that the Cause of Inequality changes the norm that people employ to make redistribution decisions. To explore this possibility, we estimated logistic regression models where we predicted the Strategy participants would use based on the Cause of Inequality. An omnibus Type 3 ANOVA revealed a significant effect of Condition on Strategy used ($\chi^2(3) = 9.091$, $p = 0.028$). To further probe these differences, we conducted post-hoc analyses which revealed that Equality-seeking was significantly more likely to be used in the Entitlement condition compared to the Corruption condition (Estimate = 0.636, SE = 0.241, $z = 2.634$, $p = 0.042$) and that Payout-Maximization was significantly more likely to be used in the Corruption condition than the Luck condition (Estimate = 0.990, SE = 0.343, $z = 2.885$, $p = 0.021$): no other pairwise differences were significant (Appendix M). Importantly, we noted that across conditions the most common trend was strategy invariance: as Figure 4 illustrates, 47% of participants never changed the strategy they employed while another 34% of participants changed the strategy used only once. Further, even among participants who changed strategies from condition-to-condition, there was not a dominant systematic trend which characterized how this occurs.

Figure 4

Trends in Strategy Selection Over Conditions

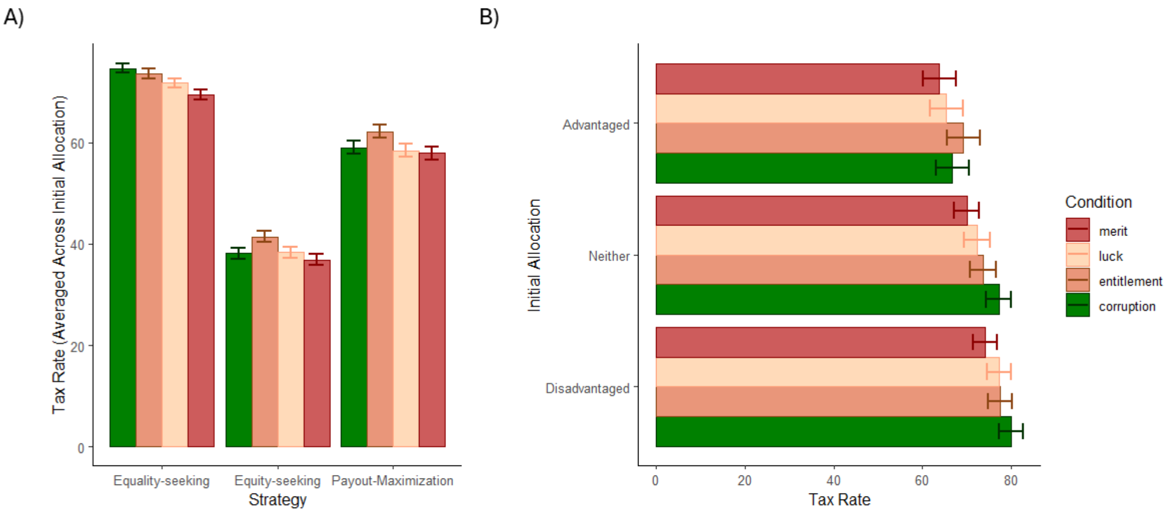


Note. Figure 4a illustrates how strategies changed between conditions. Participants' changes in strategy from condition-to-condition are shown via an alluvial plot created using the *ggalluvial* package (Brunson, 2023). The most noticeable trend in strategy selection is a high degree of context-invariance, suggesting that redistributive strategy often functions as something akin to a stable trait. Figure 4b complements this graph by demonstrated the overall strategy switching prevalence. Darker shades represent participants who used the same strategy in all four conditions, lighter shades indicate those who used one strategy in all-but-one condition.

An alternative explanation could be that the Cause of Inequality shifts the redistributive decisions that people make, rather than changing the norm that guides these decisions. To assess this explanation, we conducted the initial Linear Mixed Effects model within Strategy groups. An omnibus ANOVA revealed that Condition exerted a significant effect on Tax Rate decisions for Equality-seekers ($F(3, 8062) = 33.793$, $p < 0.001$), Equity-seekers ($F(3, 4145) = 7.6237$, $p < 0.001$), and Payout-Maximizers ($F(3, 5297) = 7.8808$, $p < 0.001$). Further, among Equality-seekers there was a significant interaction between Starting Allocation and Condition ($F(6, 7102) = 4.559$, $p < 0.001$), though this interaction was not significant for Payout-Maximizers ($F(6, 4956) = 1.355$, $p = 0.229$) or Equity-seekers ($F(6, 2773) = 1.281$, $p = 0.263$). Post-hoc analyses revealed that Payout-Maximizers and Equity-seekers alike redistributed significantly more in the Entitlement condition compared to other conditions which did not significantly differ from each other (Figure 5; Appendices N & O). We also conducted post-hoc analyses on Equality-seekers which assessed the interaction between Self-Interest and the Cause of Inequality. These suggested that, across all levels of Initial Allocation, Equality-seekers redistributed significantly less in the Merit condition, followed by the Luck condition (Figure 5; Appendix P). Among Equality-seekers in the corruption condition, redistributive behavior was most strongly influenced by Self-Interest.

Figure 5

Within-Strategy Condition Effects



Note. Figure 5a shows the effects of Condition on Tax Rate across all three strategies. These effects are averaged across all levels of Initial Allocation since the interaction was non-significant for Equity-seekers and Payout-Maximizers. Figure 5b shows the interaction between Initial Allocation and the Cause of Inequality for Equality-seekers, since this interaction was found to be statistically significant.

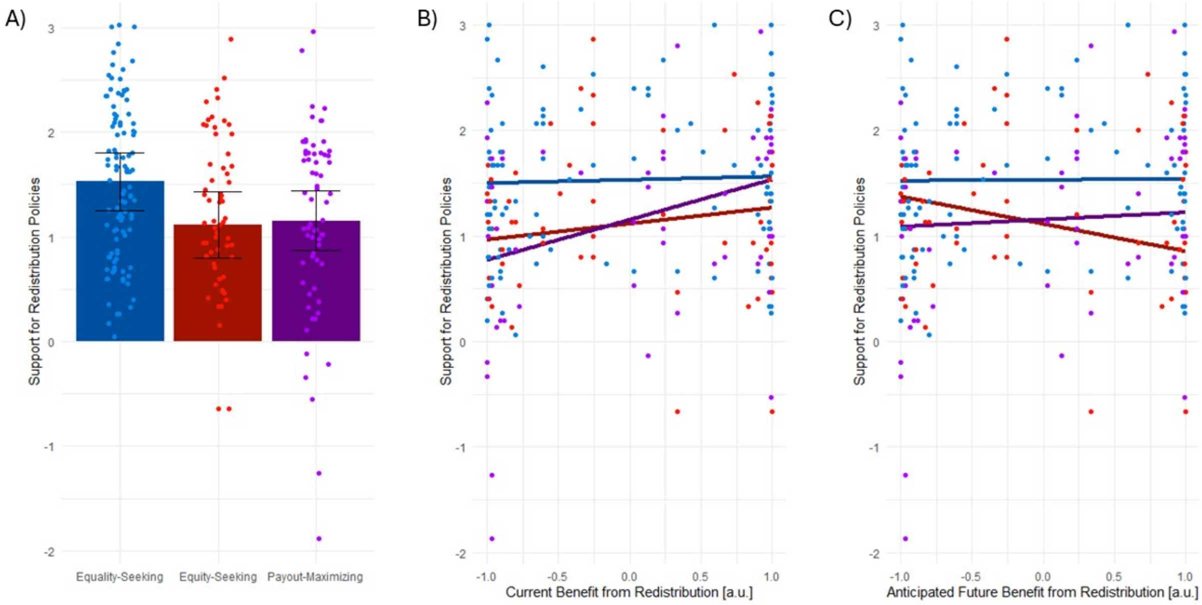
Policy Views

If individual differences in preferences for redistributive norms indeed shape redistributive decisions, then the strategies observed in the Redistribution Game may reflect the motives responsible for the views people have towards redistributive policies. To assess this possibility, we used a Multiple Regression where we evaluated how the relationship between Self-Interest and Policy Views differed between Strategy groups. For each participant, we distilled a single strategy using a pre-registered algorithm (see Supplementary Information). We operationalized Self-Interest using three metrics for Net Benefit from Redistribution (NBR): Objective NBR was calculated based on Current Income (see Appendix Q), Perceived NBR was self-reported, and Believed Future NBR was self-reported. All three NBR terms were transformed to reflect the psychophysics of value – that the difference in subjective between \$0 and \$5000 is larger than the difference between \$5000 and \$10,000 (Tversky & Kahneman, 1992; Appendix R). The final regression model predicted Support for Redistribution Policies using a main effect of Strategy, the interactions between Strategy and these three NBR terms, and meritocratic perceptions as a potential covariate of interest. This deviated from the preregistered analysis which only included Strategy and the interaction between Strategy Believed Future NBR. Policy Views were created using a simple average of the RPAQ which was validated using SEM (Appendix S)

This multiple regression model was found to be significant ($F(12, 218) = 3.682$, $p < 0.001$) and explain a substantial amount of variance in redistribution policy views ($R^2 = 0.205$). We found a significant negative effect of meritocratic perceptions: participants who indicated that they perceived merit as being more important to societal success supported redistribution significantly less (Standardized β = -0.308, SE = 0.062, $t(230) = 4.951$, $p < 0.001$). In line with predictions of the RNM, we found that Equality-seekers supported redistribution significantly more on average (Standardized β = 0.241, SE = 0.083, $t(103) = 2.906$, $p = 0.004$). Also in line with the RNM, we found that Payout-Maximizers' support for redistribution increased as a function of how much they benefitted from it (Standardized β = 0.403, SE = 0.122, $t(65) = 3.312$, $p = 0.001$). Interestingly, we also found that Equity-seekers' support for redistribution decreased as a function of how much they believed they would benefit from it in the future (Standardized β = -0.242, SE = 0.119, $t(61) = -2.042$, $p = 0.042$).

Figure 6

Policy Views on Redistribution are Shaped by Norms



Note. Figure 6a shows that when neither advantaged nor disadvantaged and controlling for meritocratic perceptions, Equality-seekers support redistribution significantly more than either Equity-seekers or Payout-Maximizers. Figure 6b shows that Payout-Maximizers support redistribution policies when personally beneficial and oppose them when personally harmful. Figure 6c shows that Equity-seekers who perceive that they have poor long-term financial prospects oppose redistribution policies more than their more optimistic counterparts.

Discussion

In the current study, we developed a novel experimental paradigm – the Redistribution Game – to assess the role of two highly influential factors in redistributive choice: self-interest and fairness. Across our sample of 231 participants, the role of self-interest was found to be a much stronger determinant of the redistributive tax rate participants chose, as compared to the source of the inequality itself. Participants redistributed significantly more when they benefitted from it and significantly less when they were harmed by it. Crucially, while there was a significant interaction between fairness and self-interest, there was no overlap between levels of self-interest. That is, even when participants were advantaged by unfair inequality, they still redistributed significantly less compared when they had no advantage or disadvantage with fair inequality. Inversely, when participants were disadvantaged by fair inequality, they still redistributed significantly more compared to a neutral state with unfair inequality.

While the effect of fairness was comparatively smaller as compared to self-interest, we nonetheless did find a significant effect of fairness on the tax rate participants chose. Across all levels of self-interest, we found that participants consistently redistributed the least in the merit condition. Similar to the merit condition, which is often normatively assumed to represent the most fair cause of inequality (Hoffman et al., 1994; Oxoby & Spraggon, 2008; Engel, 2011; Dreber et al., 2013; Ku & Salmon, 2013; Dreoni, Mentzakis, & Schaafsma, 2022; Vavra, Galván, & Sanfey 2024), we also found that participants consistently redistributed less in the luck condition. This is in contrast to previous research which has proposed that inequality attributed to luck results in greater equality-seeking (Fong, 2001; Alesina, Glaeser, & Sacerdote, 2001; Alesina & Angeletos, 2005). Our data show that inequality attributed to entitlement produced significantly greater redistribution across all levels of self-interest, with one exception, when participants were disadvantaged by inequality due to corruption. Inequality due to corruption seemed to elicit the strongest effect of self-interest: when advantaged, tax rates did not differ between corruption and merit but when disadvantaged by corruption, the tax rate was the highest observed across all situations.

Although these group-level findings do offer straightforward and informative insight into the psychology of redistribution, our data shows that individual differences play a comparatively larger role. Consequently, we sought to assess redistributive choice at an individual level. To this end, we employed a computational modeling approach, which allowed us to demonstrate that a heterogeneous and qualitatively distinct set of redistributive norms govern how people make redistribution decisions. The data provided evidence suggesting that individuals' preferences for these redistributive norms functioned as something akin to a stable moral trait: that is, most people utilized one particular redistributive to inform decision-making in this redistributive context.

Examining the data in greater detail through the lens of these redistributive norms allows for greater clarification as to how fairness influences redistributive norms. Firstly, we found that preferences for norms did shift from condition-to-condition: Equality-seeking was most prevalent in the Entitlement condition, Equity-seeking was most prevalent in the Merit and Luck conditions, and Payout-Maximization was most prevalent in the Corruption condition. However, the data suggest that the shifts we observe in redistributive choice at the group-level are generally not due to participants changing the norm that they use to guide their decision-making. Instead, we find that these effects are mostly due to subtle shifts in redistributive behavior: participants apply the same strategy, but tend to redistribute slightly less or more depending on how fair the inequality is. Secondly, and crucially, we also found that real-life attitudes towards various redistributive polices were intuitively and uniquely predicted by the strategy that participants employed in the Redistribution Game. Demonstrating this link between experimental behavior and real-world attitudes is important, as it empirically underscores the ecological validity of the Redistribution Game: that is, it is a valid means by which to study the psychology of redistribution.

While the current study offers compelling insights into the psychological study of redistribution, there are naturally certain limitations to the conclusions drawn here. As with much experimental research, particularly research which relies on the assumption that experimental inequality can produce psychological phenomena that occur in the real world, the findings of the current study have limited external validity. However, by demonstrating the link between redistributive norms and policy views, the current study represents an important step towards external validating these findings. Another notable limitation is that our sample is on a WEIRD population: in non-weird contexts, redistributive preferences are strongly impacted by a myriad of factors that may limit the extent to which norm preferences play a role in redistributive choice (Willis et al., 2022; Sánchez-Rodríguez et al., 2024). While this is undeniably an important limitation of the current research which future research must address, we believe that the current work represents an important step towards understanding the psychological preferences underlying redistributive choice.

Economic inequality is a very relevant issue in modern society and the lack of consensus for reducing inequality via redistribution poses many interesting questions for the social sciences. How do people evaluate inequality? How does this affect their redistributive preferences? Are they capable of discerning what is good for them? And do people truly intentionally act against their own self-interest? In the current study, we show that people’s redistributive choices are largely due to trait-like values, but that redistributive choices can be altered based on the fairness of the inequality.

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Appendices

Appendix A

Demographic Data of Participants Included in Analyses

Age

	Number of Participants	Number of Students Only
18-25	84	68
25-35	110	21
35-50	31	3
50-65	6	0

Race

	Number of Participants
White	175
Asian	12
Black	11
Mixed	19
Other	14

Sex

	Number of Participants
Male	110
Female	121

Nationality

	Number of Participants
Dutch	159
Other	72

Employment Status

	Number of Participants	Number Excluding Students

Full-Time	71	60
Part-Time	58	24
Not Paid in Work	13	8
Unemployed, Job-Seeking	35	14
Data Unavailable	39	29
Other	15	4

Appendix B

Machiavellianism Scale Items

Item Number	Item
1	I am willing to be unethical if I believe it will help me succeed
2	I am willing to sabotage other people if they threaten my own goals
3	I would cheat if there was a low chance of getting caught
4	I believe that lying is necessary to maintain a competitive advantage over others
5	The only good reason to talk to others is to get information that I can use to my own benefit
6	I would stop at nothing to achieve an important goal
7	Using connections to powerful people in order to get ahead is acceptable
8	I would stop at nothing to achieve a goal if I set my mind to it

Appendix C

Demographic Questionare

Item Number	Item	Options
1	What is your age?	[18-100]
2	What is your gender?	Male Female Non-binary
3	What is your race?	White/European

		Sub-Saharan African North African or Middle Eastern Indian Central or East Asian Pacific Islander North or South American
4	What was your socioeconomic class growing up?	Poor, Lower Middle Class Middle Class Upper Middle Class Upper Class Ultra Wealthy
5	What was your parents’ highest education level?	VMBO HAVO VWO MBO HBO WO Master Doctorate or Equivalent

Appendix D

Analytical Reasoning Test Questions

Questions 1-8 use the following prompt:

An organization will hold its first six annual meetings in exactly six cities - Leiden, Maastricht, Amsterdam, Rotterdam, Eindhoven, and Utrecht - using each city only once. The following conditions govern the order in which the cities are used:

- Leiden must be used in some year after Rotterdam is used
- Eindhoven must be used either immediately before or immediately after Utrecht
- The meeting in Rotterdam must be separated from the meeting in Maastricht by exactly meetings in exactly 2 other cities

- The meeting in Eindhoven must be separated from the meeting in Leiden by meetings in exactly 2 other cities.

Question 1

Which one of the following lists the cities in an order in which they could be used for the meetings, from the first year through the sixth?

a) Rotterdam, Eindhoven, Utrecht, Maastricht, Leiden, Amsterdam

b) Eindhoven, Utrecht, Maastricht, Leiden, Amsterdam, Rotterdam

c) Eindhoven, Utrecht, Rotterdam, Amsterdam, Leiden, Maastricht

d) Utrecht, Maastricht, Eindhoven, Amsterdam, Rotterdam, Leiden

e) Utrecht, Eindhoven, Amsterdam , Rotterdam, Leiden, Maastricht

Question 2

Which one of the following must be true?

a) Rotterdam is used in the first year

b) Maastricht is used in the fourth year

c) Rotterdam is used at some time before Maastricht is used

d) Amsterdam is used either immediately before or immediately after Eindhoven

e) The meeting in Amsterdam is separated from the meeting in Utrecht by meetings in exactly two other cities

Question 3

There is exactly one possible order in which the cities are used if which one of the following is true?

a) Leiden is used in the fifth year

b) Maastricht is used in the sixth year

c) Amsterdam is used in the fifth year

d) Eindhoven is used in the first year

e) Utrecht is used in the second year

Question 4

Which one of the following is a complete and accurate list of the years in which Utrecht could be used?

a) 1, 3, 5

b) 2, 3, 4, 5

c) 2, 3, 4, 6

d) 1, 2, 4, 6

- **e) 1, 2, 3, 4, 5, 6**

Question 5

If Maastricht is used in the first year, which one of the following CANNOT be true?

- a) Utrecht is used in the third year
- b) Eindhoven is used in the third year
- c) Rotterdam is used in the fourth year
- d) Amsterdam is used in the fifth year
- **e) Leiden is used in the third year**

Question 6

Which one of the following could be true?

- a) Leiden is used in the first year
- **b) Amsterdam is used in the second year**
- c) Maastricht is used in the third year
- d) Eindhoven is used in the fourth year
- e) Rotterdam is used in the sixth year

Question 7

Which one of the following must be false?

- a) Leiden is used either immediately before or immediately after Amsterdam
- **b) Leiden is used either immediately before or immediately after Utrecht**
- c) Amsterdam is used either immediately before or immediately after Rotterdam
- d) Rotterdam is used either immediately before or immediately after Eindhoven
- e) Rotterdam is used either immediately before or immediately after Utrecht

Question 8

If Utrecht is used at some time before Rotterdam, then which one of the following could be true?

- a) Leiden is used at some time before Rotterdam
- b) Leiden is used at some time before Eindhoven
- c) Leiden is used at some time before Utrecht
- **d) Maastricht is used at some time before Eindhoven**
- e) Rotterdam is used some before Eindhoven

Question 9

In the state of Dougland, most universities offer science courses, and most of those that offer science courses also offer business courses. However, any university that offers business courses but not science courses does offer evening classes; and no privately-owned university in Dougland offers evening classes.

If the statements above are true, which one of the following must be true?

a) **No privately-owned university in Dougland offers business courses but not science courses**

b) Any privately-owned university in Dougland that does not offer business courses offers science courses

c) Some universities in Dougland that offer evening classes also offer science courses

d) Most universities in Dougland that are not privately-owned do not offer science courses

e) No universities in Dougland that offer science courses and business courses offer evening classes

Question 10

Most experts agree that strict adherence to the hurricane preparedness protocol by states that are prone to hurricanes reduces the death toll from hurricanes. However, in the state of Scalex, the death toll from a hurricane that came in 2010, when the state did not adhere to this protocol, was only 25, while the death toll from a hurricane that came in 2018, when the state strictly adhered to this protocol, was 53.

Which one of the following, if true, most helps to reconcile the experts' belief with the apparently contradictory evidence described above?

a) The death toll in the state of Scalex from a hurricane in the year 2012, when the state had partially adhered to the hurricane preparedness protocol, was 40

b) The death toll from hurricanes is directly proportional to the intensity of the hurricanes, and the intensity of the 2018 hurricane was 5x greater than the hurricane that came in the state in 2010

c) Implementation of the hurricane preparedness protocol ensures the rapid evacuation of people from areas that are likely to be affected by the hurricane

d) The adoption of the hurricane preparedness protocol by a state lulls many residents into a false sense of security causing lower adherence to the protocol

e) The population of the state of Scalex increased by 10 percent between the years 2010 and 2018

Question 11

A test that examines people on their memory capacity for spatial layouts has placed Jason in the top 1 percentile of all test-takers. We can conclude from this that his memory capacity for things that do not involve spatial layouts will be below average.

The conclusion follows logically if which one of the following is assumed?

a) Jason tried hard to remember spatial layouts

b) Jason has a greater proclivity to remember spatial layouts than most people

c) It is possible for Jason to improve, through practice and effort, his memory capacity for things that do not involve spatial layouts

d) The total memory capacity of the human brain is fixed and equal for all people

e) Some people have a greater memory capacity than others

Question 12

Henry: An average American car driver drives a thousand miles per month. If all American car drivers drove only five miles less daily, their monthly mileage would reduce by 15 percent. Five miles is ten thousand steps, the amount of daily walking recommended by doctors for good health. Therefore, if the government could persuade car drivers to drive five miles less daily and walk that distance instead, the total transport-related carbon emissions in the United States would reduce by 15 percent.

Bill: Cars are responsible for 30 percent of all transport-related carbon emissions in the United States."

Bill's response to Henry proceeds by:

a) refuting an assumption on which Henry's argument relies

b) discrediting Henry's argument by giving of erroneous information

c) arguing that the benefit of Henry's hypothetical measure might also be achieved in another way

d) citing seemingly irrefutable evidence that contradicts one of the stated premises on which Henry's argument depends

e) providing additional information in support of Henry's argument

Appendix E

Perceived Importance of Success Defining Attributes Scale

How important do you believe each of these attributes is in determining who becomes successful or not in your country? (all answers must add up to 100)

a) Merit - success is earned through hard work, intelligence, and ambition

b) Entitlement - success is obtained through inherited and discriminatory advantages

c) Corruption - success is obtained by committing illegal and immoral acts

d) Luck - success is merely a consequence of happenstance

Appendix F

Redistributive Policy Attitudes Questionnaire

What is your stance on this issue?

Issue	**Explanation**
Food subsidies	Includes food stamps and price control on food
Housing subsidies	Programs include rent controlled housing
Universal healthcare	Programs include single payer government insurance or a public option
Universal retirement	Programs include social security and mandatory pension contributions
Unemployment Benefit	Programs include unemployment insurance
Universal Basic Income	Programs give a fixed amount of cash to all citizens, usually monthly
Paid Family Leave	Programs include paid maternity/paternity leave, bereavement leave, and caretaking leave
Conditional Cash Transfers	Programs give money to families if children remain enrolled in school and receive regular medical inspection
Free University	Government pays tuition of university and other post-secondary education such as trade schools
Interest-free government loans	Includes small business loans and subsidized student loans
Estate Taxes	When someone dies, their estate is taxed before inheritance is given
Property Taxes	Private individuals pay a fixed percentage of the listed value of their property annually
Corporate Income Taxes	Companies pay taxes on their annual earnings
Progressive Private Income Taxes	Private individuals pay taxes on their annual income which is a higher percentage if they earn more
Capital Gains Taxes	Private individuals pay a percentage of the appreciate of their invested assets such as stocks or bonds

Appendix G

Redistributive Policy Importance Questionnaire

How import is this issue to your voting decisions?

Issue	**Explanation**
Food subsidies	Includes food stamps and price control on food
Housing subsidies	Programs include rent controlled housing
Universal healthcare	Programs include single payer government insurance or a public option
Universal retirement	Programs include social security and mandatory pension contributions
Unemployment Benefit	Programs include unemployment insurance
Universal Basic Income	Programs give a fixed amount of cash to all citizens, usually monthly
Paid Family Leave	Programs include paid maternity/paternity leave, bereavement leave, and caretaking leave
Conditional Cash Transfers	Programs give money to families if children remain enrolled in school and receive regular medical inspection
Free University	Government pays tuition of university and other post-secondary education such as trade schools
Interest-free government loans	Includes small business loans and subsidized student loans
Estate Taxes	When someone dies, their estate is taxed before inheritance is given
Property Taxes	Private individuals pay a fixed percentage of the listed value of their property annually
Corporate Income Taxes	Companies pay taxes on their annual earnings
Progressive Private Income Taxes	Private individuals pay taxes on their annual income which is a higher percentage if they earn more
Capital Gains Taxes	Private individuals pay a percentage of the appreciate of their invested assets such as stocks or bonds

Appendix H

Net Benefit Question Items

Question	**Explanation**
What is your current income, in	

thousands of euros	
How much do you think you currently lose or gain from income taxes, in thousands of euros?	This means how much you receive from the government minus how much you pay in taxes
In 10 years, how much do you think you will lose or gain from income taxes, in thousands of euros of today's money?	This means how much you will receive from the government minus how much you will pay in taxes in 10 years time, adjusting for inflation

Appendix I

Effect of Initial Allocation Per Condition

Corruption

Contrast	Estimate	SE	*z*	*p*
Disadvantaged - Neither	13.733	1.296	10.600	<0.001
Disadvantaged - Advantaged	33.595	2.214	15.175	<0.001
Neither - Advantaged	19.863	1.538	12.918	<0.001

Entitlement

Contrast	Estimate	SE	*z*	*p*
Disadvantaged - Neither	11.468	1.296	8.851	<0.001
Disadvantaged - Advantaged	25.705	2.214	11.611	<0.001
Neither - Advantaged	14.237	1.538	9.260	<0.001

Luck

Contrast	Estimate	SE	*z*	*p*
Disadvantaged - Neither	11.442	1.296	8.831	<0.001
Disadvantaged - Advantaged	28.086	2.214	12.687	<0.001
Neither - Advantaged	16.644	1.538	10.825	<0.001

Merit

Contrast	Estimate	SE	*z*	*p*
Disadvantaged - Neither	13.186	1.296	10.17	<0.00

			8	1
Disadvantaged - Advantaged	28.918	2.214	13.06 2	<0.00 1
Neither - Advantaged	15.732	1.538	10.23 2	<0.00 1

Appendix J

Effect of Condition Per Initial Allocation Level

Disadvantaged

Contrast	Estimate	SE	*z*	*p*
Corruption – Entitlement	1.953	0.721	2.708	0.034
Corruption – Luck	5.330	0.721	7.389	<0.001
Corruption – Merit	6.650	0.721	9.220	<0.001
Entitlement – Luck	3.377	0.721	4.681	<0.001
Entitlement – Merit	4.697	0.721	6.512	<0.001
Luck – Merit	1.320	0.721	1.830	0.259

Neutral

Contrast	Estimate	SE	*z*	*p*
Corruption – Entitlement	-0.312	0.912	-0.341	0.986
Corruption – Luck	3.039	0.912	3.331	0.005
Corruption – Merit	6.104	0.912	6.690	<0.001
Entitlement – Luck	3.351	0.912	3.672	0.001
Entitlement – Merit	6.416	0.912	7.031	<0.001
Luck – Merit	3.065	0.912	3.359	0.004

Advantaged

Contrast	Estimate	SE	*z*	*p*
Corruption – Entitlement	-5.937	0.771	-7.699	<0.001
Corruption – Luck	-0.178	0.771	-0.233	0.996
Corruption – Merit	1.973	0.771	2.558	0.051
Entitlement – Luck	5.758	0.771	7.466	<0.001
Entitlement – Merit	7.910	0.771	10.257	<0.001
Luck – Merit	2.152	0.771	2.791	0.027

Appendix K

Redistributive Norms Model

Model Specification

The RNM was specified according the following utility equation:

Here, X_{tr} refers to value of X under a given tax rate tr. Thus, the utility under a given tax rate is a function of Payout, Equality, and Equity produced by that tax rate, as weighted by the free parameters Θ and Φ which both range from 0 to 1 and are estimated based on participants' decisions. Where $tr = 100$ reflects perfect Equality, $tr = 0$ reflects perfect Equity, and $Payouts_{tr}$ is a vector of values reflecting all 10 players' payouts under a given tax rate:

Additionally, where $Payout_{tr}$ is the participants own initial allocation and 10 reflects the highest payout unless $Payout_{tr}$ is greater than 10, in which case $Payout_{tr}$ is the highest possible payout:

Parameter Recovery

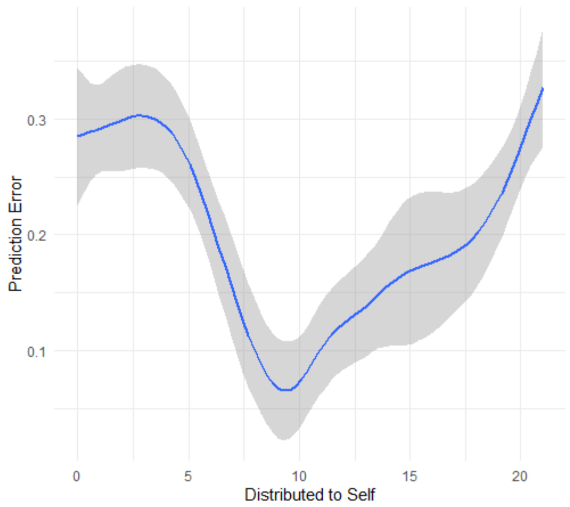
Parameters were recovered using OLS using the fmincon function from the *pracma* package in R (Borchers, 2022). The initial guess supplied for all values was Θ = 0 and Φ = 1. No additional arguments were supplied to the optimizer.

Model Fit

We inspected the model fit of the RNM using several metrics. RNM was found to explain a high degree of variance in both Outcomes (R^2 = 0.894) and Redistribution Behavior (R^2 = 0.704). With regard to Outcomes – which is theoretically what the model aims to predict, predicted and observed values were similarly correlated across conditions (r = [0.939 – 0.948]) and across blocks (r = [0.925 – 0.960]).

Model Performance

Model performance was quantified as AIC, which encapsulates a tradeoff between model fit and model complexity: AIC is superior to BIC if the true data-generating model is not in the model set which we believe is true of the current data (Akaike, 1974; Hurvich & Tsai, 1989; Wagenmakers & Farrell, 2004). Model performance was highly accurate – the average prediction error of outcomes for the self was much less than the minimum unit of 1 token as shown below. Here the model is slightly more accurate when the participant is allocated close to 10 tokens – this is unsurprising because the task design dictates that allocations close to 10 tokens will have a smaller range of potential outcomes for oneself.

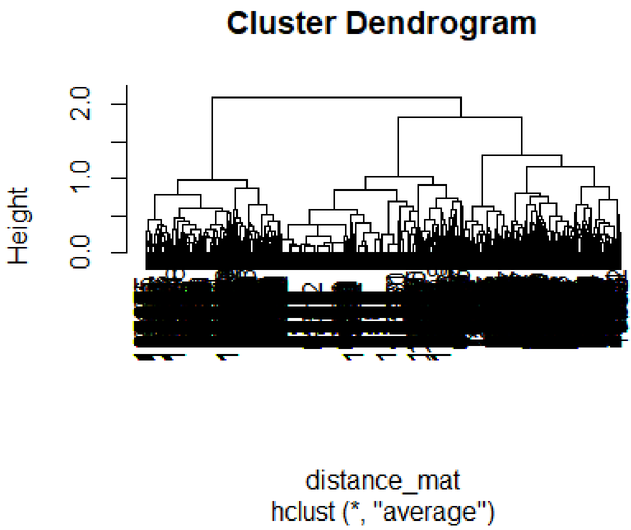


Model Validation

The RNM was validated using a fivefold validation approach wherein the trials are split into fifths where for each fifth the trials in the fifth are withheld and the model is trained on the remaining four fifths and sum of squares are calculated for each of the withheld fifths. Here, the root mean squared error per trial increased minimally for each condition on average (ΔRMSE = [0.173 – 0.204]). Average cosine similarity for each condition were high for both Theta (cosine = [0.978, 0.985]) and Phi (cosine = [0.970, 0.975]). Thus, we are highly confident that valid conclusions can be drawn from the RNM.

A Priori Clustering

Model predictions were generated using the same trial set of 20 trials that participants were exposed to for values from 0 to 1 in increments of 0.01 for all possible combinations of Θ and Φ. For these 10201 points, we clustered the simulations across the 20 trials. This resulted in the dendrogram shown below which suggests that the best solution for the data is 3 clusters.



When plotting the Θ and Φ values according to the clusters identified in the simulations, the parameter space shown in Figure 3a is produced.

Appendix L

Model Testing

Model Specifications

Equity

Equality

Payout

Equity-Payout

Equity-Equality

Equality-Payout

RNM Performance Against Derivative Models

Condition	Model	df	*t*	*p*
Merit	Equity-Equality	203	-4.733	<0.001
	PM-Equity	203	-4.222	<0.001
	PM-Equality	203	-3.289	<0.001
	PM	203	-4.168	<0.001
	Equity	202	-6.100	<0.001
	Equality	203	-5.314	<0.001
Entitlement	Equity-Equality	196	-5.563	<0.001
	PM-Equity	197	-5.318	<0.001
	PM-Equality	197	-3.427	<0.001
	PM	197	-5.397	<0.001
	Equity	197	-8.773	<0.001
	Equality	196	-6.406	<0.001
Corruption	Equity-Equality	187	-16.860	<0.001
	PM-Equity	187	-12.607	<0.001
	PM-Equality	187	-9.409	<0.001
	PM	187	-12.289	<0.001
	Equity	187	-28.124	<0.001

	Equality	187	-17.959	<0.001
Luck	Equity-Equality	186	-19.287	<0.001
	PM-Equity	186	-14.476	<0.001
	PM-Equality	186	-11.166	<0.001
	PM	186	-13.712	<0.001
	Equity	186	-24.220	<0.001
	Equality	186	-21.667	<0.001

Appendix M

Norm Use Across Conditions

Payout-Maximizers

IsPayout ~ Condition + (1 | Subject)

Where IsPayout is a logical pertaining to whether Payout-Maximization was the strategy employed (Yes/No).

Omnibus Type III Anova: $\chi^2(3) = 9.310$, $p = 0.025$

Contrast	Estimate	SE	*z*	*p*
Corruption - Entitlement	0.752	0.334	2.249	0.11
Corruption - Merit	0.581	0.329	1.766	0.29
Corruption - Luck	0.99	0.343	2.885	0.02
Entitlement - Merit	-0.171	0.338	-0.506	0.958
Entitlement - Luck	0.238	0.346	0.689	0.901
Merit - Luck	0.409	0.344	1.189	0.634

Equity-Seekers

IsEquity ~ Condition + (1 | Subject)

Where IsEquity is a logical pertaining to whether Equity-seeking was the strategy employed (Yes/No).

Omnibus Type III Anova: $\chi^2(3) = 5.725$, $p = 0.126$

Equality-Seekers

IsEquality ~ Condition + (1 | Subject)

Where IsEquality is a logical pertaining to whether Equality-seeking was the strategy employed (Yes/No).

Omnibus Type III Anova: $\chi^2(3) = 9.091$, $p = 0.028$

Contrast	Estimate	SE	*z*	*p*
Corruption - Entitlement	-0.636	0.241	-2.634	0.042
Corruption - Merit	-0.034	0.241	-0.141	0.999
Corruption - Luck	-0.336	0.24	-1.398	0.501
Entitlement - Merit	0.602	0.241	2.497	0.06
Entitlement - Luck	0.3	0.239	1.255	0.592
Merit - Luck	-0.302	0.24	-1.258	0.59

Appendix N

Effect of Condition Among Payout-Maximizers

Contrast	Estimate	SE	*z*	*p*
Corruption – Entitlement	-3.194	0.951	-3.359	0.004
Corruption – Luck	0.513	0.979	0.525	0.953
Corruption – Merit	1.087	0.962	1.130	0.671
Entitlement – Luck	3.707	0.982	3.774	<0.001
Entitlement – Merit	4.280	0.963	4.446	<0.001
Luck – Merit	0.573	0.975	0.588	0.936

Appendix O

Effect of Condition Among Equity-Seekers

Contrast	Estimate	SE	*z*	*p*
Corruption – Entitlement	-3.267	0.999	-3.270	0.006
Corruption – Luck	-0.168	0.968	-0.174	0.998
Corruption – Merit	1.247	0.970	1.285	0.573
Entitlement – Luck	3.099	0.946	3.276	0.005

Entitlement – Merit	4.514	0.976	4.623	<0.001
Luck – Merit	1.415	0.929	1.523	0.424

Appendix P

Effect of Condition Per Initial Allocation Level Among Equality-Seekers

Disadvantaged

Contrast	Estimate	SE	*z*	*p*
corruption - entitlement	2.478	0.83	2.984	0.015
corruption - luck	2.674	0.856	3.125	0.010
corruption - merit	5.823	0.868	6.711	<0.001
entitlement - luck	0.197	0.809	0.243	0.995
entitlement - merit	3.346	0.826	4.048	<0.001
luck - merit	3.149	0.852	3.697	0.001

Neutral

Contrast	Estimate	SE	*z*	*p*
corruption - entitlement	3.425	1.016	3.37	0.004
corruption - luck	4.88	1.041	4.689	<0.001
corruption - merit	7.185	1.059	6.782	<0.001
entitlement - luck	1.455	0.99	1.47	0.456
entitlement - merit	3.76	1.012	3.714	0.001
luck - merit	2.305	1.037	2.222	0.117

Advantaged

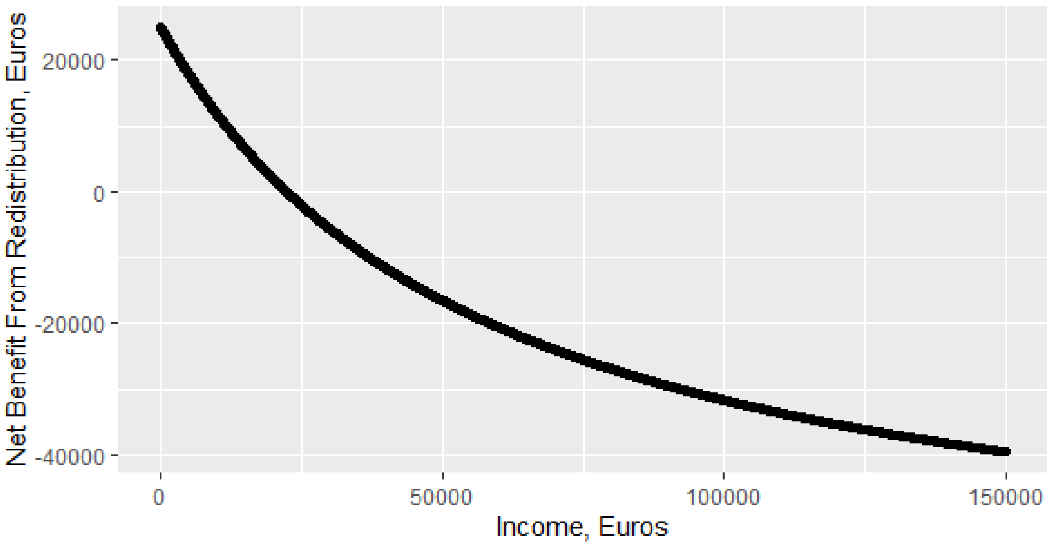
Contrast	Estimate	SE	*z*	*p*
corruption -	-2.462	0.899	-2.738	0.031

entitlement				
corruption - luck	1.287	0.929	1.385	0.509
corruption - merit	2.929	0.941	3.115	0.010
entitlement - luck	3.749	0.877	4.276	<0.001
entitlement - merit	5.392	0.895	6.027	<0.001
luck - merit	1.643	0.924	1.777	0.284

Appendix Q

Transforming Income to Net Benefit from Redistribution

In order to estimate participants' actual net benefit from redistribution, we first needed to identify a means by which to transform income to Net Benefit from Redistribution. Data from a recent CPB report reported three values of interest for the population of the Netherlands: 1) average share of income per decile, 2) income for the top decile, and 3) average net benefit from redistribution per decile (Bruil et al., 2022). With this information, we were able to relate income to net benefit from redistribution for each income decile. These estimates were not infallible since they were ascertained visually and were not preregistered, but these were only estimated once: therefore, the estimations were not tailored to achieve a specific result. Then, an equation was fitted to relate income (in thousands of Euros) to objective net benefit from redistribution which is plotted below.

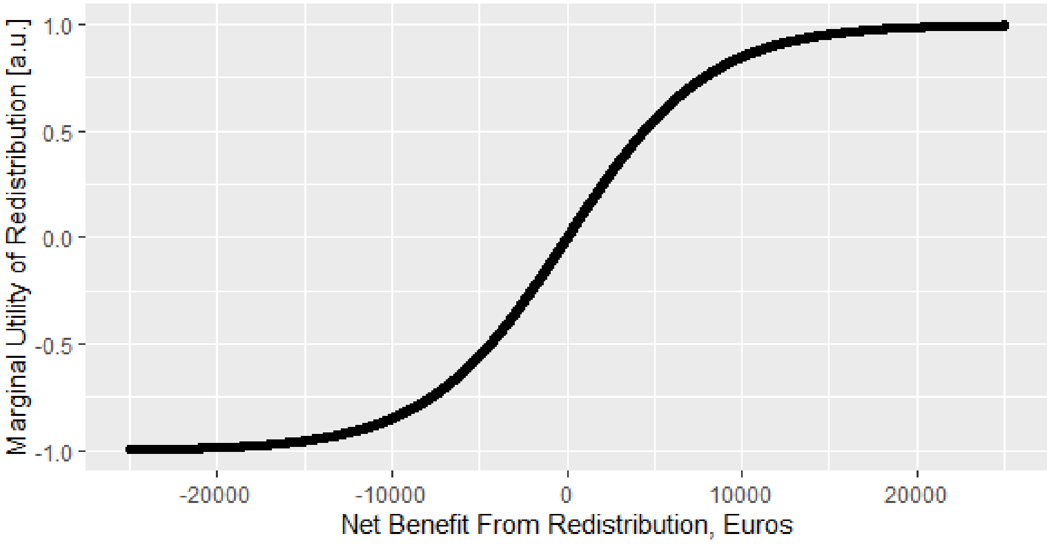


Appendix R

Marginal Utility Transformation

The marginal utility transformation of net benefit from redistribution was preregistered (in thousands of Euros).

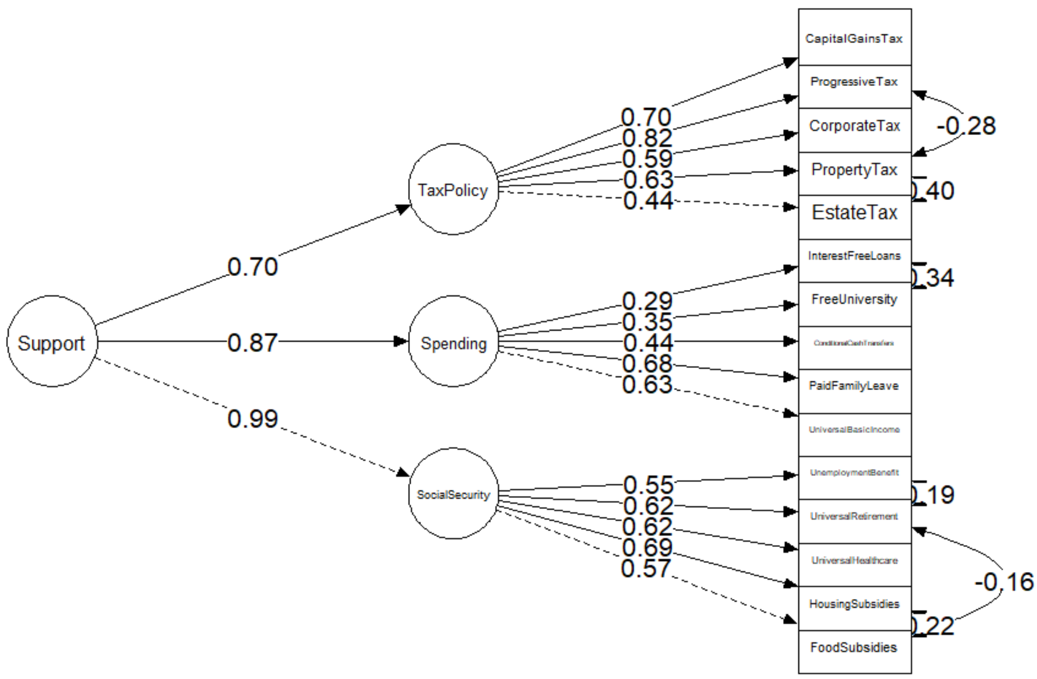
This transformation is used because it encapsulates the important fact that changes in net benefit from redistribution are more meaningful closer to 0 and less meaningful further from 0. This is visualized below.



Appendix S

Structural Equation Modeling

In order to assess the validity of using simple averaging of the 15-item redistribution policy stance questionnaire to assess Support for Redistribution, a structural equation modeling (SEM) analysis was conducted using the *lavaan* package (Rosseel, 2012) using Maximum Likelihood Estimation. We used Chi-Square, CFI, SRMR, and RMSEA to assess the model fit, as recommended by Kline (2005) The initial model was specified where support was predicted by three latent variables: Tax Policy, Social Spending, and Social Security which were each measured via 5 items in the questionnaire. This initial model specification was found to be inadequate and was re-estimated after adding the term with the highest modification index. This process was repeated 5 times: importantly the covariance terms which were recommended were only found *amongst* indicators of the same latent variables. The resulting model is shown in below using the *semPlot* package (Epskamp, 2022; $\chi^2(81) = 106.98$, $p = 0.03$; CFI = 0.972, SRMR = 0.43, RMSEA = 0.037). The latent variable Support was found to be highly correlated with the simple average used to test H3 ($r = 0.948$).



Support
TaxPolicy
Spending
SocialSecurity
0.70
0.87
0.99
CapitalGainsTax
ProgressiveTax
CorporateTax
PropertyTax
EstateTax
InterestFreeLoans
FreeUniversity
PaidFamilyLeave
UniversalBasicIncome
UnemploymentBenefit
UniversalRetirement
UniversalHealthcare
HousingSubsidies
FoodSubsidies
0.70
0.82
0.59
0.63
0.44
0.29
0.35
0.44
0.68
0.63
0.55
0.62
0.62
0.69
0.57
-0.28
0.40
0.34
0.19
-0.16
0.22