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Inequality and cooperation: meta-analytical evidence from Public Good Experiments.

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Abstract: We build a dataset based on 23 experiments that introduce heterogeneous endowments into linear public good games. We use it to measure the effect of inequality on cooperation. This method allows an investigation of a large panel of inequality scenarios, with maximum representativeness in terms of the strength of inequality and design features. It offers the possibility to study the effect of the *strength* of inequality, a distinctive feature of our paper compared to the past experimental literature which has focused mainly on the *existence* of inequality. We also explore the contribution gaps between the relatively rich and relatively poor in heterogeneous groups. We discuss the interaction of time (dynamics) and punishment with inequality. We find that not only the presence, but also the strength of inequality has a negative impact on cooperation, but that the marginal effect becomes less negative as the level of inequality increases. We find that the rich contribute more than the poor in absolute amounts, while the poor contribute more as a proportion of their endowment. Both these gaps increase with the strength of inequality. Finally, punishment strongly attenuates the effect of inequality on aggregate cooperation, but has contrasted effects on the contribution gaps between the rich and the poor. There is no significant effect of inequality on the dynamics of contributions.

JEL codes: C92, H41, D91

Keywords : Public good game, cooperation, inequality, meta-analysis.

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I. Introduction

Cooperation is at the root of a great many economic activities. At the level of a country, social capital, the ease with which strangers trust each other and cooperate, has a sizable economic payoff (Knack and Keefer 1997). At the micro level, cooperation is often necessary to achieve economic efficiency: team members must cooperate to achieve a common goal, neighbors must cooperate to preserve a peaceful and clean neighborhood and communities must cooperate to avoid the exhaustion of common resources. Determining whether and under what circumstances non-kin individuals cooperate is thus an important line of research in economics as well as in the social and natural sciences. Given the well-documented recent increase in within-country inequalities across the world (e.g., Piketty 2014; Chancel and Piketty 2021), a pressing question is whether cooperation can be sustained between agents with unequal resources. The effect of inequality on cooperation is theoretically uncertain, empirically hard to identify with observational data, and has important policy implications.[3] If inequality is very detrimental to cooperation, then it is all the more important to avoid excessive levels of inequalities or to find behavioral mechanisms that can alleviate this effect.

To contribute to this question, we collect original data from past public good experiments in which participants within a group have unequal endowments. We use this dataset to explore the effect of inequality on cooperation. Compared to single experiments, our database provides substantial

[3] Some previous works have used observational data to study the effect of inequality on cooperation. For instance, Alesina and La Ferrara (2000) find that cooperation, measured as participation in social activities, is less frequent in more unequal localities.

power and a wide range of parameters. We take advantage of these specific features to assess the effect of inequality on cooperation at the intensive margin (i.e., the impact of going from *some* inequality to a *higher* level of inequality), which is hardly done with a single experiment. We also study the dynamic impact of inequality on cooperation, the interaction with a mechanism aimed at sustaining cooperation (punishment) and the individual contribution patterns of the relatively rich and relatively poor.

We focus on the linear public good game because it has been used extensively to study cooperation. In public good experiments, participants in a group must decide how to split an endowment between a personal and a group account. The group account yields a lower private return than the personal account, but a greater social one. Consequently, it is in each member's selfish interest not to contribute any of their endowment to the group account, but in the group's best interest for every member to contribute their full endowment. Contributions to the group account constitute a measure of cooperation, and the strength of the experimental approach is to allow the researcher to vary exogenously some features of the game (institutions, social return to cooperation, size of the group, etc.) to identify their causal effects on cooperation. The external validity of such lab measures of cooperation has been debated (Levitt and List 2007; Falk and Heckman 2009; Stoop, Noussair, and van Soest 2012), but it has been shown to be predictive of several real-life cooperative behaviors such as resource conservation (Rustagi, Stefanie, and Kosfeld 2010; Fehr and Leibbrandt 2011), charitable giving (de Oliveira, Croson, and Eckel 2011), the choice of cooperative work arrangement (Carpenter and Seki 2011) and, more recently, Covid-19 vaccine take-up (Reddinger, Charness, and Levine 2022).

Several stylized facts emerge from the literature on public goods games (Ledyard 1994; Zelmer 2003; Chaudhuri 2011). First, participants contribute positive amounts, in contrast to their selfish best-response of null contributions. Second, when the game is repeated, contributions tend to decrease over time. Third, the existence of sanctioning/rewarding institutions helps sustain cooperation. A widely accepted explanation is that most people are conditional cooperators: they want to contribute if they feel that others are contributing their fair share. Nonetheless, a minority of individuals are free-riders, which leads to a decay in cooperation (Fischbacher, Gächter, and Fehr 2001; Kurzban and Houser 2005; Burlando and Guala 2005; Fischbacher and Gächter 2010).[4] Social preferences (such as reciprocity) and contribution norms are underpinnings of conditional cooperation.

Introducing inequality into public good games has uncertain effects in theory. If people are particularly fair minded, introducing inequality might not hurt cooperation because the increased contributions of the rich – the participants with a relatively high endowment – may offset the decreased contributions of the poor – the participants with a relatively low endowment. That being said, when inequality is introduced, what constitutes a fair share may become ambiguous, and contribution norms may become blurry. By combining surveys and experimental data, Reuben and Riedl (2013) find evidence of what they term "normative conflicts": in groups with unequal endowments, the rich, the poor and the "neutral spectators" disagree on what a fair contribution

[4] Thöni and Volk (2018) apply a homogeneous methodology to identify conditional cooperators and free-riders using the data of 17 past experiments. They find that about 60% of participants can be classified as conditional cooperators, and about 20% can be classified as free-riders. These figures are relatively stable across studies.

is.[5] In addition, the rich and the poor may self-servingly hold different beliefs about what constitutes a fair share. In light of this, the logic of conditional cooperation predicts that inequality in endowments is detrimental to cooperation. Most experiments have found results consistent with this prediction. There are nonetheless some exceptions (Isaac and Walker 1988; Hofmeyr, Burns, and Visser 2007; Reuben and Riedl 2013). While this literature has grown to a decent size, there is no systematic, rigorous and quantitative analysis of the literature. In a meta-analysis of public good games, Zelmer (2003) tests, among other things, the effect of heterogeneous endowments on cooperation and finds a negative effect. However, the focus of her meta-analysis is not on heterogeneous endowments, and consequently has limitations as regards the question at hand. First, the most recent study included was published in 2000. Second, she does not have individual-level data and cannot run an analysis at the individual level. Third and most importantly, only 1 study out of 27 considers heterogeneous endowments (about 3% of her observations).[6]

To bridge this gap, we identify, to the best of our knowledge, all the published papers in which heterogeneous endowments are introduced into a linear public good game. We include both experiments in which a baseline with homogeneous endowments is introduced and experiments in

[5] Related to this, Nikiforakis, Noussair, and Wilkening (2012); Gangadharan, Nikiforakis, and Villeval (2017) study the normative conflicts that arise when participants derive heterogeneous returns from the public good.

[6] While working on this paper, we became aware of an important initiative, the Cooperation Databank (Spadaro et al. 2022). The Cooperation Databank is a freely accessible database that allows one to explore quantitatively the past experimental literature on cooperation. In particular, one can explore the effect of endowment inequality on contributions in public good games, and observe a negative effect of endowment inequality on contributions. Note that, while the scope of the Cooperation Databank is much broader than the scope of our paper, our database allows for a much more detailed analysis. For instance, the Cooperation Databank consists of effect sizes at the treatment level, while we retrieved individual contribution decisions. In addition, the Cooperation Databank cannot be used to explore the effect of the *strength* of inequality.

which there is no such baseline. While this forbids the use of regular meta-analytical technics, it allows for a more a comprehensive inclusion of papers with maximum representativeness in terms of the strength of inequality and of design features that might interact with inequality. We collected the original dataset from most of these studies to build a meta-dataset. Our final dataset includes 23 papers, 116 treatments, more than 17,000 observations at the group*period-level and 57,102 observations at the individual level. We coded a wealth of relevant variables at the paper, treatment and group level. Notably, for each observation, we computed the Gini index of endowments in the respective group. The Gini index is a well-known measure of inequality. It is continuous, allowing us to measure not only the effect of the presence of inequality, but also of the strength of inequality. Consequently, a key interest of our dataset is to allow cooperation levels to be related to a wide range of levels of inequality. Doing this with a single experiment would be practically impossible given the costs of collecting a sufficient number of observations.

We run two complementary analyses. First, we investigate the effect of inequality on contributions at the group level, i.e., we relate the measure of inequality to a measure of efficiency of contributions, which is equal to the share of the sum of endowments contributed within a group. While in principle this analysis could be done with individual decisions, focusing on groups is (i) an intuitive way to avoid complications due to Simpson's paradox (aggregating relative contributions of the rich and the poor) and (ii) is also economically relevant from the perspective of efficiency.[7] The following results emerge from this analysis. First, we confirm the negative

[7] To provide an illustration of the Simpson paradox in our analysis, if we focus on relative contributions (in order to get rid of differences in calibrations), we would need to be careful in our conclusion. Indeed, a decrease in relative contributions in heterogeneous groups with respect to homogeneous groups would not imply a lower efficiency if this

effect of inequality on cooperation. Second, and in a complementary approach with the past literature based on individual studies, we identify that the negative effect exists at the intensive margin: it is not only a matter of the presence of inequality but also of its *strength*. In addition, the effect of inequality is non-linear: an increase in inequality is less detrimental to cooperation when a high level of inequality already exists. We also find that the decay in contributions is not affected by inequality. However, the negative effect of inequality is significantly smaller when punishment is available. As a consequence, punishment helps close the efficiency gap between equal and unequal groups.

We then turn to the analysis of individual contribution decisions. We identify contribution gaps between the rich and the poor: the rich contribute higher absolute amounts than the poor, while the poor contribute a higher share of their endowments. Both these gaps widen as inequality increases. The effects of time and punishment on these gaps are more nuanced. The gap in absolute contributions decreases marginally over periods, as the absolute contributions of the rich decrease faster than the absolute contributions of the poor. On the other hand, the gap in relative terms does not change over time. Regarding punishment, it increases the contribution gap in absolute terms (as the rich increase their absolute contribution more than the poor), but does not reduce the gap in relative terms.

The rest of the paper is structured as follows. Section II presents the methods and the dataset. Section III introduces our results. Finally, section IV discusses the results and concludes.

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decrease in relative contributions came from poor participants and if rich participants offset the decrease by contributing a larger absolute amount.

II. Dataset and Methods

a. Data collection

To build our database, we started by identifying studies introducing heterogeneity into public good games. We first searched every working paper and article in Research Paper in Economics (repec.org) and in Google Scholar that included in their title or abstract the keywords "Heterogeneity + VCM", "Heterogeneity + PGG", "Inequality + VCM", "Inequality + PGG" "Heterogeneity + Voluntary Contribution Mechanism" "Heterogeneity + Public Good Game" "Inequality + Voluntary Contribution Mechanism" or "Inequality + Public Good Game". After having identified a first set of articles to be included, we sent an e-mail to the Economic Science Association (the main professional association of experimental economists) mailing list asking for references that we might have missed. Altogether, we had 108 references.

We then screened all the studies identified with the following inclusion criteria. We first excluded all articles that did not include an experiment, and those that did not follow the method of experimental economics (in particular, incentives and no deception rules). We then selected papers that use linear public good games with more than two players and with a Marginal Per Capita Return (hereafter MPCR) lower than 1 and higher than $\frac{1}{n}$.[8] Finally, we only considered published articles. While this might be an issue for the representativeness of the final sample, we deemed it difficult to obtain the raw data from the authors of manuscripts that are yet to be published. We

[8] We left out linear public good games with privileged agents (MPCR > 1) because we want cooperation to be costly for every agent.

ended up with a list of 28 articles published between 1988 and 2021. We aimed at collecting the original raw dataset for every paper included. We began the collection of the primary data in June 2020.[9] Two methods were used. When possible, we collected the data directly from online open repositories and publishers' websites. Otherwise, we retrieved the email address of corresponding authors, and sent them an e-mail presenting our study and asking for the original raw dataset of their experiment. When we did not get a response to the initial e-mail, we sent up to 4 reminders. Most authors kindly answered and provided the data. Out of 28 articles, we finally retrieved the data of 23 articles. The list of the articles included is in Appendix A. Our dataset is made up of individual decisions.[10,11]

b. Variables in the meta-dataset

We combined the datasets from the 23 articles included to create our meta-dataset. It includes a number of control variables that were either present in the original dataset, extracted from the corresponding paper or retrieved from public databanks. These variables are listed below.

[9] We also collected some data for non-linear games. Given the difference between non-linear and linear public good games, we decided to run separate analyses, and the effect of inequality of endowment in non-linear public good games will be done in a separate paper.
[10] Unfortunately, individual data were unavailable for one article. This dataset was consequently excluded from the individual analyses.
[11] In some cases, some treatments in a study matched our inclusion criteria, while other did not. In this case, we included only the treatments that matched our criteria.

i. Variables at the level of the participant

Contribution: this variable represents the amount contributed by the participant to the public good during the decision period.

Endowment: this variable represents the number of tokens available by the participant during the decision period.

Period: the decision period.

Observed Contribution: this variable is equal to 1 when participants were able to observe the contributions made by other group members, and 0 otherwise.

Observed Endowment: this variable is equal to 1 when participants were able to observe the endowment of other group members, and 0 otherwise.

ii. Variables at the level of the group

Sum Endowment: this variable is equal to the sum of endowments of the members of a given group at the time of the decision.

Gini Endowment: this variable measures the level of inequality (discussed in Section c below) within the group at the time of the decision.

Inequality Dummy: this variable is equal to 1 when there is inequality in endowments within the group during the decision period, and 0 otherwise.

Size of the group: this variable indicates the number of members in a contribution group during the decision period.

Mean Mpcr: this variable indicates the average number of tokens earned by group members for each token contributed to the public good during the decision period.

Inequal Mpcr: this variable is equal to 1 when at least two members of the same group have a different Mpcr during the decision period.

Communication: this variable is equal to 1 when communication is possible between members of a contribution group during the decision period, and 0 otherwise.

Punishment: this variable is equal to 1 when punishment is available for members of a contribution group during the decision period, and 0 otherwise.

Stakes: this variable presents a harmonized value of the incentives at stake.[12]

Communication: this variable is equal to 1 if a communication mechanism is implemented at the time of the decision, and 0 otherwise.

Other mechanism: this variable is equal to 1 if a mechanism different from punishment and communication is implemented, and 0 otherwise.

iii. Variables at the level of the session/treatment

Nb period: this variable indicates the number of periods in the game for a given session.

[12] To compute this value, we converted the value of a unit of endowment, in a given experiment, into 1998 US dollars, correcting for the purchasing power difference across countries and inflation. We then multiply the sum of endowments by this value to obtain a variable that is comparable between studies: stakes.

Endogenous group: this variable is equal to 1 when the composition of the group is not random but depends on earlier stages, and 0 otherwise.

Endogenous Endowment: this variable is equal to 1 when the endowment depends on actions in earlier stages of the experiment, and 0 otherwise.

iv. Variables at the level of the study

Year: this variable takes the value of the year of publication of the study.

Equal baseline: this variable is equal to 1 when there is a baseline without endowments inequality for the given study, and 0 otherwise.

Gini Country: This variable indicates the value of the Gini index of the country for the year in which the experiment was run (in case of missing value, the value for the closest year available is used), retrieved from the World Bank data.[13]

Weird: this variable is equal to 1 if the country in which the experiment was run is "western, educated, industrialized, rich and democratic" (see e.g., Henrich, Heine, and Norenzayan (2010)), and 0 otherwise.

c. Method

We run two complementary analyses. The first one is done at the aggregate level, focusing on the cooperation of groups, while the second is done at the individual level, and considers individual contribution decisions, depending on whether one is relatively "rich" or relatively "poor".

[13] https://data.worldbank.org/indicator/SI.POV.GINI?view=chart

Our main explanatory variable is the Gini index of endowment in each group. The Gini index is a continuous measure of inequality commonly used both by macroeconomists (e.g., Ravallion 2012) and by policy makers (e.g., OECD Income and Wealth Distribution Databases). For a given distribution of endowments, the Gini index links the cumulated share of endowments to the cumulated share of the population that owns it. In our study, for a group of n subjects with endowment e_i ordered from the poorest to the richest ($e_1 \leq e_2 \leq \cdots \leq e_n$), the Gini index is computed as follows:

$$G = 2\frac{\sum i e_i}{n \sum e_i} - \frac{(n+1)}{n}$$

The Gini index of a group is equal to 0 when every group member has the same endowment, and is equal to $\frac{n-1}{n}$ if all the endowment in a group of size n is owned by a single individual.[14] For the aggregate analysis, our dependent variable is the *per* period group-level efficiency index. The efficiency index is computed for each group g and for each period t as the ratio between the sum of individual contributions $c_{i,g,t}$ and the potential maximum individual contributions $e_{i,g,t}$ (i.e., the sum of endowments).

$$EffIndex_{g,t} = \frac{\sum_{i \in g} c_{i,g,t}}{\sum_{i \in g} e_{i,g,t}} = \frac{C_{g,t}}{E_{g,t}}$$

[14] Other indexes of inequality could have been used: variance of endowments within a group, General Entropy Indexes, etc. A discussion about the advantages and disadvantages of these indexes is beyond the scope of this paper. In Appendix B.3, we reproduce our main result with a large set of alternate measures of inequality.

The aggregate analysis (i) considers a group as the unit of interest, and (ii) allows us to focus on the public good provision.[15] The efficiency index allows us to capture a dimension of aggregated efficiency that would have been left out if we had only considered individual relative contributions ($\frac{c_{it}}{e_{it}}$).[16]

Our second analysis is performed at the individual level. We consider two variables of interest: relative contributions and normalized absolute contributions. Relative contribution is the ratio between one's contribution and endowment ($\frac{c_{it}}{e_{it}}$). This variable allows us to study whether rich and poor participants contribute the same share of their endowments. The normalized absolute contribution is the contribution divided by the sum of endowments ($\frac{c_{it}}{E_{g,t}}$). As the sum of endowments is the same for rich and poor, this indicator allows us to focus on absolute contributions controlling for the difference in calibrations between studies. A difference in normalized absolute contributions between rich and poor can be interpreted as a difference in absolute contributions. To account for the potential change of meaning of the value of absolute normalized contributions that could stem from groups of different sizes, we also run separate analyses for groups of different size.

[15] While the aggregate analysis focuses on the total contributions of a group in a given period, we account for the fact that different groups in a session might influence each other, and we cluster standard errors at the session level in our analysis.

[16] From a perspective of efficiency, it is important to correct the relative contribution by endowment. However, it is not possible with different experiments that have been run at different times with different incentives and with different calibrations.

d. Description of the data

Table 1: descriptive statistics of our sample.

	mean	sd	min	max
ID study	-	-	-	23
ID treatment	-	-	-	116
ID sessions	-	-	-	506
ID Group	-	-	-	1842
ID participant	-	-	-	6762
Year	-	-	1988	2021
Gini Endowment	0.15	0.16	0.00	0.51
Inequality Dummy	0.65	0.48	0.00	1.00
Equal baseline	0.75	0.43	0.00	1.00
Efficiency index	0.51	0.29	0.00	1.00
Period	7.22	5.55	1.00	40.00
Nb period	12.86	7.21	1.00	40.00
Size of the group	4.07	0.61	3.00	5.00
Mean Mpcr	0.45	0.07	0.30	0.93
Inequal Mpcr	0.04	0.20	0.00	1.00
Punishment	0.32	0.47	0.00	1.00
Endogenous Endowment	0.18	0.39	0.00	1.00
Endogenous group	0.06	0.25	0.00	1.00
Observed Contribution	0.87	0.33	0.00	1.00
Observed Endowment	0.84	0.36	0.00	1.00
Communication	0.06	0.23	0.00	1.00
Other mechanism	0.17	0.38	0.00	1.00
Gini Country	40.19	10.37	28.10	63.60
Stakes	4.99	11.95	0.04	364.66
Weird	0.73	0.45	0.00	1.00
Individual Obs.	57102			

The meta-dataset is described in Table 1. The dataset combines 23 studies (the oldest was published in 1988 and the most recent was published in 2021), 116 treatments, 506 sessions, 1842 groups and 17,084 group-level Efficiency Indexes. We have 57,102 contribution decisions overall. Group size varies from 3 to 5 members (most groups have 4 members). The Gini index computed for the endowments of the group varies from 0 to 0.51.[17] The efficiency index varies from 0 to 1 indicating heterogeneity in behavior. In more than 80% of the decisions, contributions and endowments are public knowledge. For half of the observations, a mechanism is implemented (32% punishment, 6% communication, and 17% other mechanisms). Three quarters of the observations were collected in *WEIRD* (Western Educated Industrialized Rich and Democratic) countries.

III. Results

a. Aggregate results

i. Efficiency

We first establish the group level results. In this part, the level of observation is a group in a given period. The dependent variable is the efficiency index, defined as the share of the sum of the endowments in a group that is contributed by its members.

Figure 1 shows the distribution of the efficiency index, depending on whether inequality of endowment is introduced. The level of observation is the group in a given period.[18] Overall, the sum of contributions relative to the sum of endowments is 49.5%.[19] In equal groups, it is 58.4% (5932 obs.), while it is 45.4% in unequal groups (11,152 obs.). Null contributions rise from about

[17] To illustrate the value of a Gini index, consider a group of 4 participants with a sum of endowments of 100 tokens. In a situation with no inequality (i.e., a Gini index equal to 0), all of them have 25 tokens. A possible distribution that gives a Gini coefficient of 0.125 is (15,25,30,30). A possible distribution that gives a Gini coefficient of 0.51 is (8,8,8,76).

[18] Using a more aggregate measure – for instance, the average efficiency index for a group over every period – would have prevented us from observing full and null contributions.

[19] Note that the level of observation is different from Table 1, which explains why the efficiency index is slightly different.

2% of the observations in equal groups to 4% in unequal groups, while full contributions decrease from about 14% of the observations in equal groups to about 5% (both these differences are significant at the 1% level, see Table 12 in Appendix B.1 for more details).

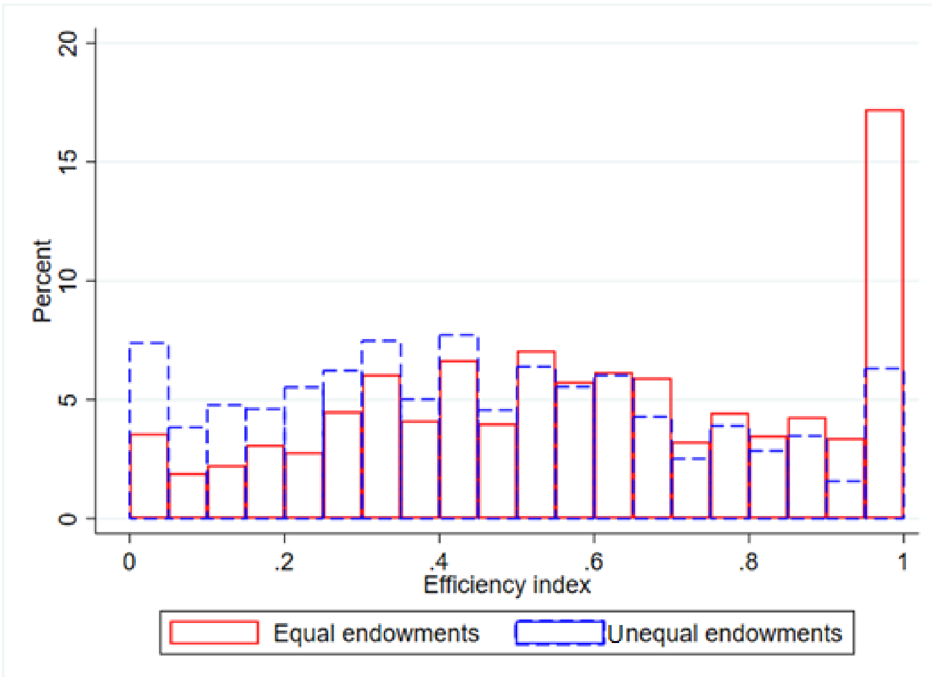

Figure 1: Distribution of efficiency indexes.

In our sample, there are 14 studies which include a baseline without inequality. For this subsample, we compute the treatment effect of inequality on contributions for each study separately in a homogeneous way: we regress the efficiency index on a dummy variable indicating inequality, with standard errors clustered at the group level. For 11 out of 14 studies, we find a negative and significant effect of inequality (3 at the 10% level, 8 at the 5% level), while we only find one positive and significant effect. We run an Egger test of small-study effect on this set of effects and do not find evidence of it (p=0.571). More details about this analysis are given in Appendix B.2.

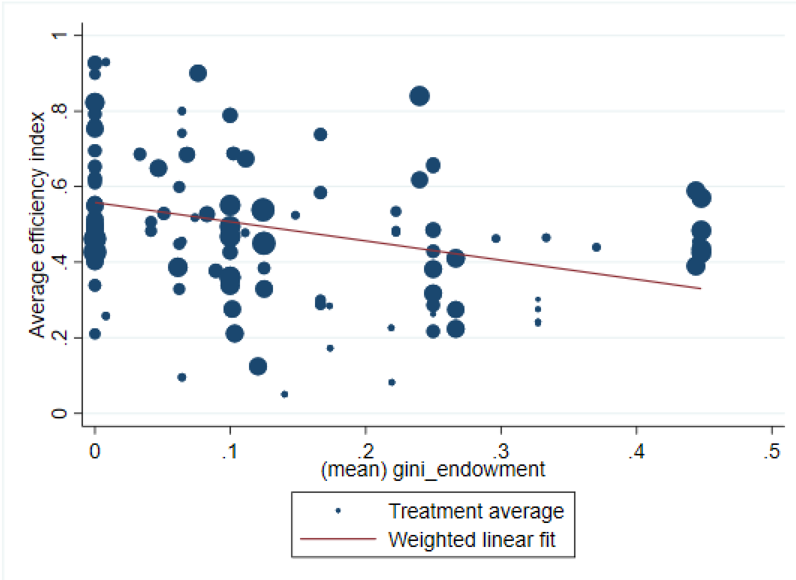

Figure 2: Correlation between the Gini index and contributions as a proportion of the sum of endowments.

Figure 2 plots the mean efficiency indexes against the levels of inequality measured by the mean Gini index of the distribution of endowments for each treatment (the size of the point represents the number of observations in each treatment). It shows a negative correlation between the strength of inequality and the efficiency index. To further explore this, we use standard econometric modeling. In Table 2, we report the results of random-effect linear regressions (with random effect at the group level). In every model, the explained variable is the Efficiency Index (i.e., the share of the sum of endowments contributed to the public good). The main explanatory variable is the Gini index of endowments within the group for the given period, our continuous measure of inequality (some robustness checks using different measures of inequality are reported in Appendix B.3, with consistent results). In models (1) to (3), we include all the observations at the group*period level. In models (4) to (6), we exclude groups with equal endowments. In specifications (2)-(3) and (5)-(6), we introduce standard control variables (see e.g., Zelmer, 2003) to control for observable heterogeneity between studies, and study fixed-effects (in (3) and (6)) to control for potential unobserved heterogeneity. Finally, we cluster standard errors at the session level to account for potential non-independence at this level.[20] Two meaningful results emerge from this analysis.

Result 1: There is a sizable negative effect of inequality on contributions. This is consistent with what is found in the literature. This effect holds when we exclude groups with equal endowments, suggesting that the strength, and not only the presence, of inequality is detrimental to cooperation.

Support: The coefficient of the Gini Endowment is negative, sizable and highly significant in every specification.

Result 2: The negative effect of inequality is non-linear: the marginal effect of inequality is "less negative" for high levels of inequality than for low levels of inequality.

Support: In Table 2, the coefficient of the quadratic term for the Gini Endowment is positive and significant in every model, meaning that the negative effect of inequality becomes smaller as the level of inequality increases. To complement this analysis, we computed the marginal effects of the Gini Endowment at its 25, 50 and 75 percentiles, using the models reported in Table 2.[21]

[20] Clustering at the study level does not change the results. However, it would lead to a low number of clusters, which might be problematic.

[21] Note that because we exclude groups with equal endowment in models (4)-(6), the values of the percentiles are different between models (1)-(3) and models (4)-(6). For models (1)-(3), p25=0; p50=.1 and p75=.24 For models (4)-(6), p25=.1, p50=.163, p75=.25.

Table 2: The effect of inequality on the efficiency index (random effect models).

	(1) Efficiency index	(2) Efficiency index	(3) Efficiency index	(4) Efficiency index	(5) Efficiency index	(6) Efficiency index
Gini Endowment	-0.395****	-0.850****	-0.777****	-0.212***	-0.840****	-0.850***
	(0.053)	(0.112)	(0.118)	(0.065)	(0.246)	(0.272)
Gini Endowment²		1.019****	0.966***		0.822*	0.963*
		(0.275)	(0.330)		(0.489)	(0.577)
Year		0.002	0.063**		0.007**	0.056**
		(0.003)	(0.027)		(0.003)	(0.027)
Period		-0.010****	-0.010****		-0.011****	-0.011****
		(0.001)	(0.001)		(0.001)	(0.001)
Nb period		0.010****	0.011		0.010****	0.013
		(0.002)	(0.011)		(0.003)	(0.011)
Size of the group		0.070****	0.051***		0.067***	0.064**
		(0.018)	(0.018)		(0.024)	(0.031)
Mean Mpcr		0.365*	0.310		0.361*	0.412*
		(0.193)	(0.236)		(0.205)	(0.246)
Inequal Mpcr		0.090*	0.991***		0.076*	1.020***
		(0.049)	(0.343)		(0.045)	(0.361)
Punishment		0.186****	0.189****		0.227****	0.232****
		(0.017)	(0.017)		(0.021)	(0.021)
Other mechanism		0.184****	0.232****		0.219****	0.275****
		(0.031)	(0.034)		(0.034)	(0.037)
Endogenous Endowment		-0.004	0.026		-0.066**	-0.017
		(0.028)	(0.021)		(0.033)	(0.028)
Endogenous group		0.000	0.982*		-0.014	0.924*
		(0.044)	(0.562)		(0.050)	(0.561)
Observed Contribution		-0.089***	0.036		-0.050	-0.077
		(0.028)	(0.213)		(0.040)	(0.219)
Observed Endowment		-0.013	0.051		0.030	0.095**
		(0.041)	(0.050)		(0.039)	(0.040)
Communication		0.257***	0.272***		0.351****	0.389****
		(0.093)	(0.101)		(0.093)	(0.087)
Gini Country		-0.001	0.052**		-0.001	0.057**
		(0.001)	(0.022)		(0.002)	(0.024)
Stakes		-0.001**	-0.001		-0.001****	-0.001****
		(0.000)	(0.000)		(0.000)	(0.000)
Weird		-0.081**	-0.253***		-0.123**	-0.227**
		(0.041)	(0.084)		(0.060)	(0.099)
Obs.	17084	17084	17084	11152	11152	11152
Study FE	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Groups	1,842	1,842	1,842	1,242	1,242	1,242
Sessions	506	506	506	400	400	400
R2	0.020	0.156	0.277	0.000	0.175	0.264
Wald-Chi2 p	0.000	0.000	0.000	0.001	0.000	0.000

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001

The results, reported in Table 3, are consistent: the higher the level of inequality, the smaller the negative impact of inequality.[22] [23]

Table 3: The marginal effect of inequality on contributions for different levels of inequality.

	(1) Efficiency index	(2) Efficiency index	(3) Efficiency index	(4) Efficiency index	(5) Efficiency index	(6) Efficiency index
Dydx Gini Endowment						
P25	-0.996****	-0.850****	-0.777****	-0.511***	-0.676****	-0.658****
	(0.139)	(0.112)	(0.118)	(0.161)	(0.158)	(0.167)
P50	-0.666****	-0.646****	-0.584****	-0.373****	-0.574****	-0.539****
	(0.083)	(0.070)	(0.069)	(0.110)	(0.113)	(0.115)
P75	-0.205****	-0.361****	-0.313****	-0.176***	-0.429****	-0.369****
	(0.045)	(0.067)	(0.081)	(0.060)	(0.087)	(0.097)
Study FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Obs.	17084	17084	17084	11152	11152	11152

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001 - The models used are those from Table 2.

ii. Dynamic / sustainability

A robust finding from the experimental literature on public good games is that contributions decrease over time. This is apparent in our data given that the time trend is always negative and significant in the models reported in Table 2. We now examine the dynamic of the efficiency index depending on the presence of inequality.

Result 3: The dynamic of contributions is not significantly different in equal and unequal groups.

[22] One may worry that the result is mechanical: for high levels of inequality, efficiency may be so low that increasing inequality cannot further reduce efficiency. We can reject this possibility: the average efficiency index for the observations in the p75 is 0.41, meaning that there is ample room for efficiency to decrease further.

[23] An inspection of Figure 2 may suggest that the non-linearity is driven by a fistful of outlying observations with very high inequality. To test for this, in Table 14 in Appendix B.4, we reproduce the regressions (4)-(6) from Table 3 excluding the groups with very high levels of inequality, with largely consistent results.

Support: First, in Appendix B.5 we show that the negative effect of inequality is already found in the first period (note that the effect is somewhat smaller). Second, Table 4 presents the marginal effect of the period (i.e., the time trend of the efficiency index), depending on whether there is inequality in endowments in the group.[24] There seems to be a *slightly more negative* trend in unequal groups, but the difference is never significant in our specifications.[25]

Table 4: Time trend, contrasted by the presence of inequality in endowment.

	(1) Efficiency index	(2) Efficiency index	(3) Efficiency index
Time trend for			
Inequality Dummy=0	-0.005**	-0.007****	-0.007****
	(0.002)	(0.002)	(0.002)
Inequality Dummy=1	-0.008****	-0.010****	-0.011****
	(0.002)	(0.001)	(0.001)
p-value diff.	0.166	0.155	0.115
Study FE	No	No	Yes
Controls	No	Yes	Yes
Obs.	17084	17084	17084

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001 - The models used are those from Table 2.

iii. The effect of punishment.

In general, contributions to public goods are higher than predicted by Nash Equilibrium, yet far from socially optimal. As seen earlier, the issue is even more stringent in unequal groups. Efficiency-enhancing mechanisms are often introduced with two aims: (i) identifying ways to improve public good contributions (i.e., sustaining high cooperation) and (ii) identifying underlying motives for contribution. We now check the effectiveness of punishment in our dataset

[24] For ease of interpretation, we do not use the continuous measure of inequality here. This is done in Appendix B.5 with consistent results overall.

[25] Here we use the whole dataset. Excluding one-shot experiments does not change the results.

and we compare the effectiveness of punishment between equal and unequal groups. Beyond its fundamental interest, we focus on punishment because it is the only mechanism introduced in a sufficient number of studies (6 studies, 4272 observations).[26]

Result 4: The availability of punishment significantly *reduces* the negative impact of inequality on contributions. Note that inequality is still harmful to cooperation when punishment is available, but to a smaller extent.

Support: Table 5 compares the effect of inequality on the efficiency index when punishment is available and when punishment is not available. The marginal effect of inequality is negative and significant even when punishment is possible, except for Model (3). In all models, the negative effect of inequality is significantly smaller in groups with punishment than in groups without punishment.

Table 5: The effect of inequality depending on the availability of punishment.

	(1) Efficiency Index	(2) Efficiency Index	(3) Efficiency Index
Dydx Gini index			
Punishment=0	-0.555****	-0.625****	-0.582****
	(0.067)	(0.077)	(0.073)
Punishment=1	-0.175**	-0.211**	-0.159
	(0.073)	(0.091)	(0.109)
p-value diff.	0.000	0.000	0.000
Obs.	17084	17084	17084
Study FE	No	No	Yes
Controls	No	Yes	Yes

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001. Controls are the same as in Table *2*.

[26] In contrast, we only have two experiments and very few observations with communication (360 observations), which is insufficient for a robust analysis.

b. Individual results

We now turn to the analysis of individual contributions to gain additional insights into the effect of inequality on cooperation. We use two definitions of contributions, namely relative contributions and (normalized) absolute contributions of an individual i in period t:

$$Relative\ contribution_{it} = \frac{contribution_{it}}{endowment_{it}}$$

$$Normalized\ absolute\ contributions_{it} = \frac{contribution_{it}}{sum\ endowment\ group_{it}}$$

We classify as "rich" a participant whose endowment is strictly above the median in his group in a given period. Roughly 43% of the decisions in unequal groups are made by "rich participants" (16,045 out of 37,242 decisions).[27]

Table 6: share of the endowment of the rich and poor, depending on the size of the group.

Size of the group		Obs.	Mean	SD
3	Poor	3137	0.243	0.086
	Rich	1486	0.525	0.055
4	Poor	11174	0.190	0.048
	Rich	10030	0.319	0.048
5	Poor	6886	0.098	0.047
	Rich	4529	0.355	0.151

Table 6 shows the share of the total endowment in a group that is held by the rich and the poor. For comparability, we separate by the size of the group. Figure 3 presents the average normalized

[27] Our results hold if we classify as rich participants whose endowments are at least equal to the median.

absolute and relative contributions of the members of equal groups, the rich and the poor.

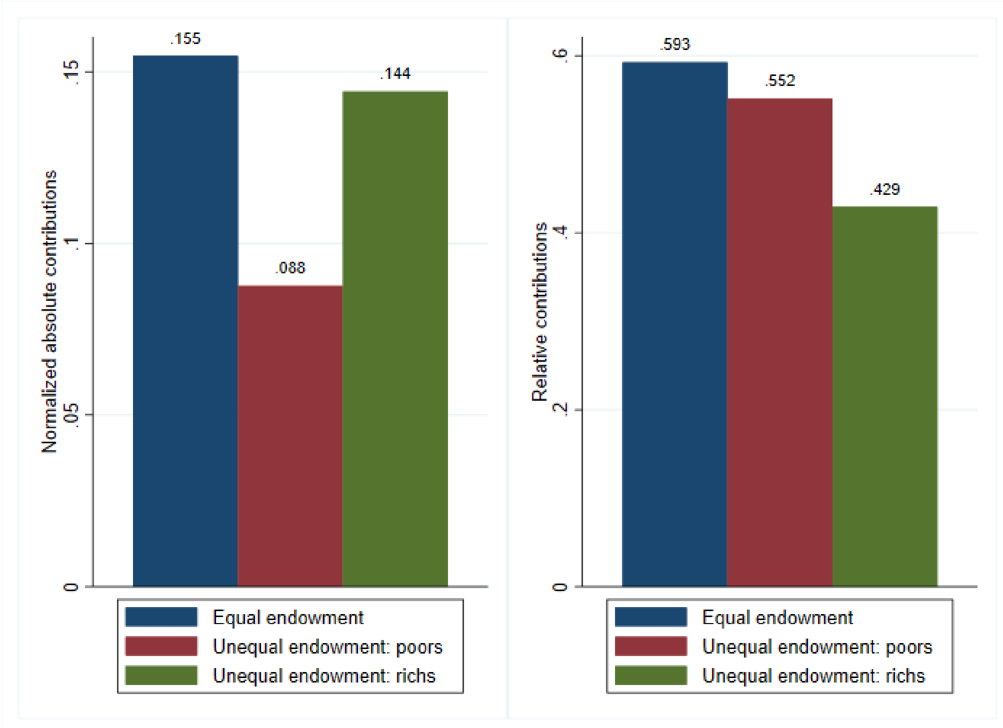

Figure 3: Normalized absolute (left panel) and relative (right panels) contributions of the members of equal groups, poor and rich.

i. The contribution gaps between the rich and the poor.

Result 5: Compared to members of equal groups, the rich contribute less in relative terms, and more in absolute terms. The poor contribute less than the members of equal groups in absolute terms but not a significantly different share in relative terms.

Table 7: Relative and Normalized absolute contributions of rich and poor with respect to a member of a homogeneous group.

	(1) Norm. Abs. Cont.	(2) Norm. Abs. Cont.	(3) Norm. Abs. Cont.	(4) Norm. Abs. Cont.	(5) Rel. Cont.	(6) Rel. Cont.	(7) Rel. Cont.	(8) Rel. Cont.
Rich	0.032****	0.021*	0.011*	0.008	-0.124****	-0.133****	-0.055***	-0.030
	(0.005)	(0.011)	(0.006)	(0.008)	(0.017)	(0.030)	(0.020)	(0.037)
Poor	-0.034****	-0.025**	-0.020****	-0.009	-0.012	-0.050**	-0.026	0.023
	(0.005)	(0.011)	(0.005)	(0.007)	(0.017)	(0.024)	(0.021)	(0.035)
Obs.	57102	8643	35619	12840	57102	8643	35619	12840
Group size	-	3	4	5	-	3	4	5
Study FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	6,762	800	4,712	1,435	6,762	800	4,712	1,435
Sessions	496	70	246	212	496	70	246	212
R2	0.207	0.154	0.202	0.370	0.184	0.169	0.189	0.177
Wald-Chi2 p	0.000	.	.	.	0.000	.	.	.

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001. Controls are the same as in Table 2.

Support: Figure 3 presents the first evidence in support of this result. We run random-effect regressions explaining contributions by dummy variables indicating that one is rich or poor (the reference category is thus being member of an equal group). The outcomes of these regressions are reported in Table 7. In columns (1) and (4), we pool all the observations. In the other columns, we separate by group size. The coefficient of the dummy "rich" is positive and significant for normalized absolute contributions, while it is negative, large (around 10 percentage points) and significant for relative contributions. On the other hand, the dummy "poor" is not significant overall for relative contributions (except of for groups of 3), while it is negative and significant for normalized absolute contributions (except for groups of 5).[28] Note that in Figure 3, the absolute contributions of the rich seem to be equal to those of the members of equal groups. This can be

[28] We run a study-by-study analysis to complement this analysis, with consistent results. More details are given in Appendix B.6.

explained by the fact that, contrary to our regressions in Table 7, this figure does not account for heterogeneity between experiments.

From now on, our main focus will be on the gap in absolute and relative contributions between the rich and the poor in groups with inequality. Consequently, unless stated otherwise, the data from the baseline without inequality will be excluded from the analysis.

<u>Result 6:</u> The rich contribute more in absolute terms than the poor. Conversely, the rich contribute less than the poor in relative terms.

Table 8: Relative and Normalized absolute contributions of the rich and the poor.

	(1) Norm. Abs. Cont.	(2) Norm. Abs. Cont.	(3) Norm. Abs. Cont.	(4) Norm. Abs. Cont.	(5) Rel. Cont.	(6) Rel. Cont.	(7) Rel. Cont.	(8) Rel. Cont.
Rich	0.065****	0.033*	0.028****	0.016***	-0.118****	-0.067****	-0.037****	-0.053**
	(0.004)	(0.018)	(0.003)	(0.006)	(0.011)	(0.016)	(0.008)	(0.027)
Obs.	37242	4623	21204	11415	37242	4623	21204	11415
Group size	-	3	4	5	-	3	4	5
Study FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	4,652	496	2,948	1,320	4,652	496	2,948	1,320
Sessions	393	44	159	206	393	44	159	206
R2	0.203	0.154	0.206	0.360	0.184	0.190	0.188	0.152
Wald-Chi2 p	0.000	.	.	.	0.000	.	.	.

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001 - Controls are the same as in Table 2.

Support: Figure 3 presents the first strong evidence in support of this result. We run random-effect regressions explaining contributions by a dummy variable indicating that one is rich. The outcomes of these regressions are reported in Table 8. We use only data from groups with unequal endowments, so the reference category is “poor” in an unequal group. We pool all the data in columns (1) and (4) and separate by group size in the remaining columns. The outcomes of these regressions are reported in Table 8. The coefficient for "Rich" is positive in every specification for absolute contributions, and negative in every specification for relative contributions.[29]

Table 9: The effect of the strength of inequality on the contribution gaps.

	(1) Norm. Abs. Cont.	(2) Norm. Abs. Cont.	(3) Norm. Abs. Cont.	(4) Norm. Abs. Cont.	(5) Rel. Cont.	(6) Rel. Cont.	(7) Rel. Cont.	(8) Rel. Cont.
Dydx Gini Endowment								
Poor	-0.232****	-0.157****	-0.336****	0.000	-0.064	0.038	-0.560****	0.000
	(0.027)	(0.036)	(0.037)	(.)	(0.070)	(0.073)	(0.145)	(.)
Rich	0.000	0.058	-0.110***	1.384****	-0.537****	-0.105	-0.889****	1.161**
	(0.032)	(0.055)	(0.040)	(0.186)	(0.068)	(0.099)	(0.118)	(0.506)
p-value diff.	0.000	0.010	0.000	0.000	0.000	0.262	0.000	0.022
Obs.	37242	4623	21204	11415	37242	4623	21204	11415
Group size	-	3	4	5	-	3	4	5
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$ – Controls are the same as in Table 2.

We now investigate how the gap in contributions between the rich and the poor is impacted by the strength of inequality.

Result 7: Larger inequalities lead to larger gaps in contributions between the rich and the poor.

Support: We focus on data from unequal groups and run random-effect models explaining individual contributions. We interact a dummy variable indicating that one is rich with our continuous measure of inequality, the Gini index. In Table 9, we report the marginal effect of the level of inequality, contrasted by whether one is rich or poor. In columns (1) and (4), we pool all

[29] In Appendix B.6, we report the results of a study-by-study analysis. In 19 out of 22 studies, the rich contribute more than the poor in absolute terms (significantly so in 17 studies). In all 22 studies the poor contribute more than the rich in relative terms (with significant differences in all but 3 studies).

the data, irrespective of the group size. In the other columns, we separate by group size. The effect of an increase in inequality depends on endowments and on group size. For the rich, more inequality does not impact absolute contributions (except for groups of 5 participants). For the poor, more inequality leads to lower absolute contributions. As a consequence, the gap in absolute contributions between the rich and the poor increases as inequality increases. Further analyses are provided in Appendix B.7.

The relative contributions of the rich decrease when inequality increases (except for groups of 5 participants). Overall, the relative contribution of the poor is not impacted by an increase in inequality. Note, however, that the effect of inequality on the relative contributions of the rich is always more negative than the effect on the relative contributions of the poor. As a consequence, the gap in relative contributions increases as inequality increases.

ii. Dynamic of the gaps

We now turn to the dynamic of the contribution gaps between the rich and the poor.

Result 8: There is a negative time trend of contributions for both the rich and the poor. The gap in absolute contributions decreases in time, i.e., the poor catch up in absolute terms.

Table 10: The time trend of contributions, contrasting the contributions of the rich and the poor.

	(1) Norm. Abs. Cont	(2) Norm. Abs. Cont	(3) Norm. Abs. Cont	(4) Norm. Abs. Cont	(5) Rel. Cont.	(6) Rel. Cont.	(7) Rel. Cont.	(8) Rel. Cont..
Period								
Poor	-0.001****	-0.003****	-0.001***	0.000	-0.005****	-0.012****	-0.006***	0.010****
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)
Rich	-0.002****	-0.005****	-0.002***	0.001	-0.004***	-0.009****	-0.005***	0.005*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
p-value diff.	0.016	0.003	0.067	0.315	0.468	0.007	0.717	0.110
Obs.	37242	4623	21204	11415	37242	4623	21204	11415
Group size	-	3	4	5	-	3	4	5
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses are clustered at the session level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$, **** $p<0.001$ - Controls are the same as in Table 2.

Support: Here we focus on groups with inequality. First, we establish that the gaps already exist in the first period (See Table 18 in Appendix B.8). Second, we examine the comparative time trends of contributions of the rich and the poor. To do so, we interact a dummy variable indicating that one is rich with a continuous variable for period. We find that the gap in absolute terms decreases over time, since the time trend of the rich is more negative, while we find no difference for relative contributions. Table 10 presents the marginal effects of the period, separating rich and poor. We note that the magnitude of the coefficients is, at most, small.

iii. The effect of punishment on the contribution gaps.

The last question we ask is whether the availability of punishment reduces the contribution gaps between the rich and the poor.

Result 9: Punishment increases the contribution gap in absolute terms, but does not reduce the gap in relative terms.

Table 11: The contribution gaps, depending on the availability of punishment.

	(1) Norm. Abs. Cont.	(2) Norm. Abs. Cont.	(3) Norm. Abs. Cont.	(4) Norm. Abs. Cont.	(5) Rel. Cont.	(6) Rel. Cont.	(7) Rel. Cont.	(8) Rel. Cont.
Dydx Rich								
Punishment=0	0.055****	0.034*	0.025****	-0.001	-0.113****	-0.056****	-0.038****	-0.079**
	(0.005)	(0.018)	(0.003)	(0.008)	(0.013)	(0.013)	(0.008)	(0.034)
Punishment=1	0.085****	0.024	0.036****	0.029****	-0.126****	-0.172***	-0.034***	-0.033
	(0.006)	(0.035)	(0.005)	(0.007)	(0.015)	(0.066)	(0.013)	(0.027)
p-value diff.	0.000	0.755	0.022	0.003	0.433	0.074	0.732	0.125
Obs.	37242	4623	21204	11415	37242	4623	21204	11415
Group size	-	3	4	5	-	3	4	5
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses are clustered at the session level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$ - Controls are the same as in Table 2.

Support: In Table 11, we report the marginal effects of "being rich", contrasting by whether punishment is available. We pool all the data in columns (1) and (4) and separate by group size in the other columns. For absolute contributions, the overall effect of being rich is significantly greater when there is punishment (the effect is driven by groups of 4 and 5 participants). For relative contributions, there is no significant difference between groups with and without punishment opportunities.

IV. Discussion and Conclusion

In this paper, we build a dataset comprising most past public good experiments with unequal endowments. We confirm the negative effect of inequality on cooperation. We also identify an effect of the *strength* of inequality: *more inequality* (measured by the Gini index of endowments within a group) *leads to less cooperation.* This extends the experimental literature, which mainly focuses on the effect of the *presence* of inequality. In addition, we find that an increase in inequality is less negative for higher levels of inequality. To our knowledge, these results are new, and important for the modeling of public goods and cooperation more broadly. In terms of individual contribution patterns, we find that inequality generates contribution gaps between the rich and the poor: the rich contribute more in absolute terms, but less in relative terms. In addition, we find that, while punishment largely cancels out the effect of inequality on aggregate contributions, it does not cancel the contribution gaps at the individual level. Finally, we find that the dynamics of cooperation are not significantly impacted by inequality (or its strength).

Of course, our meta-analysis suffers from some limitations. First, we include only published studies. Studies with inconvenient results are less likely to be published or written at all (the file drawer problem), which may weaken the reliability of our results. We cannot totally rule out the possibility that the studies stuck in the file drawer have very different conclusions to the ones we included, but we provide tests in Appendix B.2 that should ease this concern. Second, we do not observe participants' beliefs, which prevents us from digging into the motivations of the participants when they are confronted with inequality. For instance, we are unable to classify participants into conditional cooperators and selfish types, and cannot study how / whether the composition in terms of types changes when inequality increases. Nor can we test whether inequalities lead to more pessimistic beliefs about the contributions of others (as suggested in Fischbacher, Schudy, and Teyssier (2014)for heterogeneity in returns). Finally, we cannot observe what participants consider to be a fair contribution, below which negative reciprocity is triggered. Nonetheless, given the richness of our dataset and the knowledge accumulated on public good experiments, our results call for discussions and extensions.

The negative impact of inequality on aggregate contributions is consistent with conditional cooperation based on a mix of reciprocal agents and free-riders. In such a situation, sustaining cooperation typically requires that a norm of “fair contribution” be shared between the participants. The introduction of inequality may impair the emergence and sharing of such a norm, triggering more negative reciprocity. Rich and poor may not share the same definition of a fair contribution, as they do not contribute the same amount neither in absolute (normalized) terms nor in relative terms, even in the very first round of the game. It is possible that what the rich and the poor consider to be a fair contribution is determined by their level of endowment, which might lead to yet stronger normative conflicts.[30] We can speculate that the discrepancy between what the rich and the poor consider to be fair contributions widens as inequality increases. This is an open question that may warrant further investigation.

However, some results are not easily explained in the light of conditional cooperation and call for further research, both theoretical and experimental. At first glance, the effect of punishment on the efficiency gap between equal and unequal groups is consistent with conditional cooperation: punishment has an expressive value, used by the punisher to signal to others that they judge their contributions “unfair”. Alternatively, punishment deters free-riding, deescalating negative reciprocity. However, punishment leaves the relative contribution gap unchanged. This might be because punishment is not effective at making the rich contribute as much as the poor in relative terms. Another possibility is that equality in relative contributions is not a widespread rule of contribution, even though it is fairly salient and easy to follow.

[30] For instance, Babcock et al. (1995) show that what participants hold as fair in a bargaining experiment depends on the (random) role they were assigned.

The apparent breakdown of cooperation as inequality increases is associated with a reduction in the relative contributions of the rich. At first glance, this casts doubts on the sustainability of the social contract based on redistribution in the absence of (centralized) institutions to make the rich contribute their fair share, especially given that the contributions of the rich set the tone for the contributions of the poor (Martinangeli 2021). However, in our dataset, ex-post inequality is on average *lower* than ex-ante inequality: the average Gini index of endowment is .130 and the average Gini index of per-round payoffs is .116 (treatment average, treatments with inequality only, sign-rank test: $p<0.001$). This suggests that public good contributions have a redistributive effect, even if the rich contribute a smaller share of their endowment. Beyond the mechanical effect of contribution in a public good, it might be that participants, and especially the rich, account for the ex-post inequality resulting from their contributions as much as for their contributions. This is consistent with the observation that the rich contribute more in absolute terms as inequality increases, despite the fact that the contributions of the poor decrease.

In addition, we find no effect of inequality on the dynamics of cooperation. The decay of cooperation in public good games is generally explained by "frustrated attempts at kindness" (Andreoni 1995), i.e., participants who start contributing a relatively high amount to foster cooperation but are confronted with contributions that they do not deem fair, leading them to reduce their contributions (negative reciprocity). One could expect inequality to strengthen this effect, because of the normative conflicts generated by inequality, with faster unravelling as a result.

Last, the non-linear effect of inequality is intriguing. Why would inequality be less harmful to cooperation when the level of inequality is already high? It would be interesting to study the conditional cooperation of the rich and the poor for extreme levels of inequality. Is there a level of inequality beyond which the rich do not take into account the contributions of the poor to decide on their contributions?

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A. Studies included

Study	N Treatments	N Sessions	N Subjects	N Groups	N Periods	Gini endowment	Equal baseline?
Levati, Sutter, and Van Der Heijden (2007)	9	10	-[31]	124	24	0.0745	1
De Geest and Kingsley (2019)	3	18	350	70	18	.24	1
Hargreaves-Heap, Ramalingam, and Stoddard (2016)	6	15	210	70	20	.26	1
Balafoutas et al. (2013)	1	8	72	24	15	.22	0
Visser and Burns (2015)	4	17	567	144	6	.12	1
Cadigan et al. (2011)	3	9	136	34	10	.09	1
Charness, Cobo-Reyes, and Jiménez (2014)	6	22	176	92	24	.15	1
Cherry, Kroll, and Shogren (2005)	4	4	124	31	1	.25	1
Corazzini, Faravelli, and Stanca (2010)	1	3	48	12	20	.103	0
Dickinson (2001)	5	10	40	10	40	.054	0
Fung and Au (2014)	10	4	96	32	10	.246	1
Gächter et al. (2017)	8	22	656	164	11.22	.112	1
Hauser et al. (2021)	6	180	900	180	9.725	.446	0
Hofmeyr, Burns, and Visser (2007)	2	1	80	20	10	.125	1

Isaac and Walker (1988)	10	7	92	23	20	.047	1
Kamei (2018)	4	14	185	37	1	.327	0
Kesternich, Lange, and Sturm (2018)	2	4	96	24	10	.25	0
Koukoumelis, Levati, and Weisser (2012)	2	2	128	32	10	.1	0
Markussen et al. (2021)	2	112	1344	336	1	.25	1
Martinangeli (2021)	4	6	360	90	10	.25	1
Oxoby and Spraggon (2013)	5	16	316	79	1	.187	0
Reuben and Riedl (2013)	8	11	210	70	10	.166	1
Weng and Carlsson (2015)	11	11	576	144	10	.25	1

[31] We do not have the individual data for this experiment.

B. Appendix: Robustness checks and additional results

1. Null and full contributions at the group level.

We run random effect logit models explaining null (models (1)-(3)) and full (models (4)-(6)) contributions at the group level. The main variable of interest is a dummy variable indicating that there is inequality in endowments. Marginal effects are reported in Table 12.

Table 12: The effect of inequality on the likelihood of null and full contributions at the group level.

	(1) Eff index=0	(2) Eff index=0	(3) Eff index=0	(4) Eff index=1	(5) Eff index=1	(6) Eff index=1
Dummy Inequality	0.018**	0.012*	0.012*	-0.054****	-0.060****	-0.062****
	(0.009)	(0.007)	(0.007)	(0.008)	(0.011)	(0.013)
Obs.	17084	17084	17084	17084	17084	13887
Controls	No	Yes	Yes	No	Yes	Yes
Study FE	No	No	Yes	No	No	Yes

Standard errors in parentheses are clustered at the session level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$. Controls are similar to those which are in Table 2.

2. Meta-analytical results on the subsample of studies with a baseline.

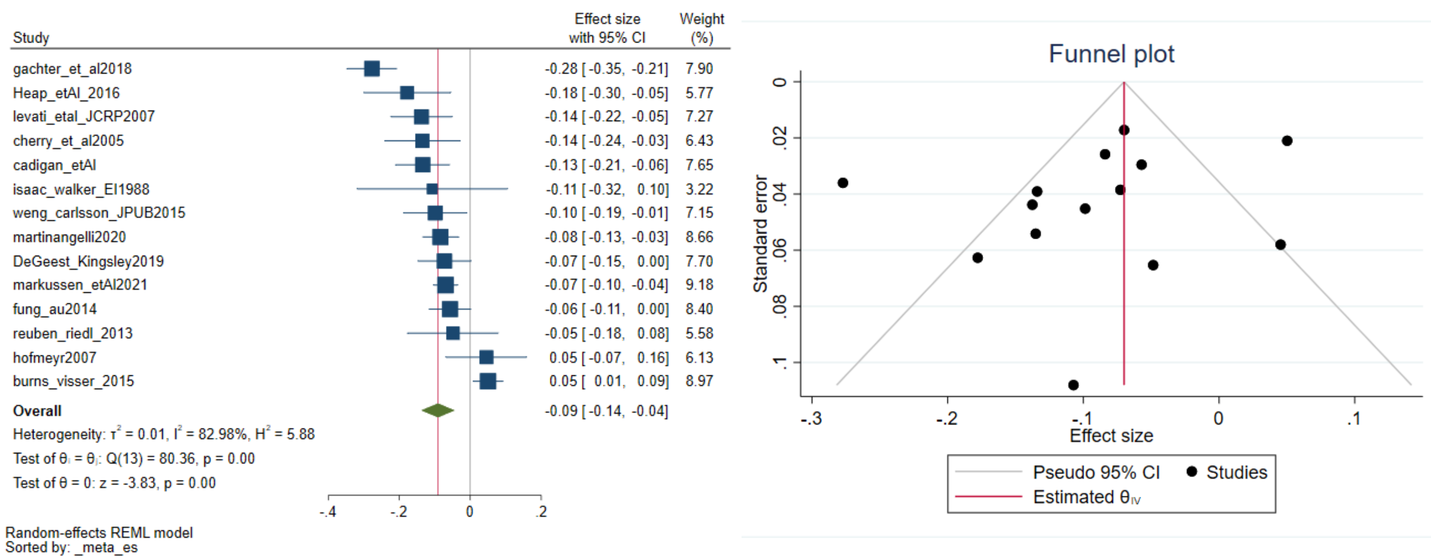

Figure 4: Left panel: forest plot investigating the effect of inequality by study. Right panel: Funnel plot to investigate a potential publication bias.

We focus here on the subsample of studies which include a baseline without inequality (14 out 23). We regress the efficiency index on a dummy variable indicating inequality separately for each study in this subsample. We clustered standard errors at the group level. We end up with 14 effect sizes that are plotted in the left panel of Figure 4. 12 effect sizes are negative, 8 are significantly negative (with $p < 0.05$) and one is significantly positive. The average effect is -0.09 (CI [-0.14, -0.04]). The right panel of Figure 4 is the funnel plot of the effects. It can be used to detect a "small-study bias" that can be indicative of publication bias. A visual inspection of the funnel plot does not reveal small study bias, nor does the Egger test (p=0.571).

3. Different measures of inequality.

Table 13: The Effect of inequality using different measures.

	(1) Efficiency index	(2) Efficiency index	(3) Efficiency index	(4) Efficiency index	(5) Efficiency index	(6) Efficiency index	(7) Efficiency index	(8) Efficiency index
cov_endowment	-0.154**** (0.023)							
GEI-1		-0.175**** (0.040)						
GEI0			-0.458**** (0.096)					
GEI1				-0.587**** (0.128)				
GEI2					-0.559**** (0.131)			
Atkinson_0p5						-1.153**** (0.241)		
Atkinson_1							-0.584**** (0.114)	
Atkinson_2								-0.344**** (0.059)
Obs.	17084	16124	16124	16124	16124	16124	16124	16124
Study FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Groups	1,842	1,802	1,802	1,802	1,802	1,802	1,802	1,802
Sessions	506	502	502	502	502	502	502	502
R2	0.194	0.194	0.201	0.202	0.201	0.203	0.203	0.205
Wald-Chi2 p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001. Controls are in the same as in Table 2

We reproduced Model (3) in Table 2, using alternative measures of inequality. These measures are: the covariance of endowment, four values of the General Entropy Index (GEI-1, GEI0, GEI1, GEI2), and three values of the Atkinson Index (Atkinson -0.5, Atkinson 1, and Atkinson 2).

The results are presented in Table 13. Altogether, these results suggest that the effect of inequality that we identify in this meta-analysis does not come from our measure of inequality (Gini Index).

4. Non-linear effect of inequality excluding the most unequal groups.

In Table 14, we report a robustness check for the result presented in Table 3: we run the same models as models (4)-(6) of the aforementioned Table, dropping the most unequal groups (those with a Gini index of endowment above the 90th percentile). The results are largely unchanged.

Table 14: The non-linear effect of inequality, dropping the most unequal groups.

	(1) Efficiency index	(2) Efficiency index	(3) Efficiency index
Dydx Gini Endowment			
P25	-0.497***	-0.765****	-0.687****
	(0.164)	(0.168)	(0.170)
P50	-0.452***	-0.692****	-0.628****
	(0.141)	(0.144)	(0.145)
P75	-0.229****	-0.325****	-0.334****
	(0.070)	(0.086)	(0.094)
Study FE	No	No	Yes
Controls	No	Yes	Yes
Obs.	9948	9948	9948

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001 - The models used are those from Table 2.

5. Additional results on the dynamics of the Efficiency index.

We analyze the effect of inequality on the Efficiency Index in period 1. The models used are those from Table 2. In models (1) to (3), we pool the data of every group. In models (4) to (6), we run our analyses only on unequal groups.

The outcomes of the regressions are available in Table 15. We find that the Efficiency Index is already lower in the first period.

Table 15: The effect of inequality in the first period.

	(1) Efficiency index	(2) Efficiency index	(3) Efficiency index	(4) Efficiency index	(5) Efficiency index	(6) Efficiency index
Gini Endowment	-1.002****	-0.594****	0.146	-2.159****	-0.616	0.847
	(0.139)	(0.141)	(0.161)	(0.397)	(0.736)	(0.853)
Gini Endowment²	1.943****	0.864**	-2.075****	3.848****	1.258	-3.008*
	(0.339)	(0.439)	(0.609)	(0.657)	(1.347)	(1.688)
Obs.	1772	1772	1772	1002	1002	1002
Study FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Sessions	500	500	500	366	366	366
R2	0	0	0	0	0	0
Wald-Chi2 p	0.000	0.000	.	0.000	0.000	.

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001. Controls are the same as in Table 2

In Table 16, we interact the time trend with a continuous variable of inequality. We replicate Result 3, namely, there is no difference in time trend for different levels of inequality.

Table 16: Time trend with a continuous measure of inequality.

	(1) Efficiency index	(2) Efficiency index	(3) Efficiency index
Gini Endowment	-0.433****	-0.519****	-0.514****
	(0.060)	(0.071)	(0.073)
Period	-0.00732****	-0.00973****	-0.00988****
	(0.002)	(0.001)	(0.001)
Gini Endowment # Period	0.00168	0.00219	0.00227
	(0.008)	(0.007)	(0.007)
Obs.	17084	17084	17084
Study FE	No	Yes	Yes
Controls	No	No	Yes
Groups	1,842	1,842	1,842
Sessions	506	506	506
R2	0.025	0.153	0.277
Wald-Chi2 p	0.000	0.000	0.000

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001.
Controls are in the same as in Table 2

6. Analyses study-by-study of the contribution gaps.

i. Comparison of the contributions of the rich / poor with the contributions of the members of equal groups.

We focus first on the subsample of studies which include a baseline without inequality (14 studies out of 23). We regress the normalized absolute contributions and relative contributions on a dummy variable indicating that a participant is rich, study by study. We exclude poor participants from these regressions. We cluster standard errors at the group level. In Figure, we plot the coefficients of “being rich” on the absolute contributions (left panel) and on the relative contributions (right panel) obtained in these regressions. Regarding normalized absolute contributions, we find 2 negative and significant effects, 4 positive and significant effects and 8 non-significant effects. The overall effect of “being rich” on normalized absolute contributions is not significant (-0.01; CI [-0.02, 0.03]). Regarding relative contributions, we find 11 negative and significant effects, and 3 non-significant effects. The overall effect is negative, relatively large and significant (-0.14; CI [-0.21, -0.07]).

We do the same analysis for poor participants. In Figure, we plot the coefficient of “being poor” on absolute contributions (left panel) and on relative contributions (right panel) Regarding normalized absolute contributions, we find 10 negative and significant effects, and 4 non-significant effects. The overall effect is negative and significant: -0.05 (CI [-0.06, -0.04]). Regarding relative contributions, we find 1 negative and significant effect, 2 positive and significant effects and 11 non-significant effects. The overall effect of “being poor” on relative contributions is not significant: -0.01 (CI [-0.07, 0.04]).

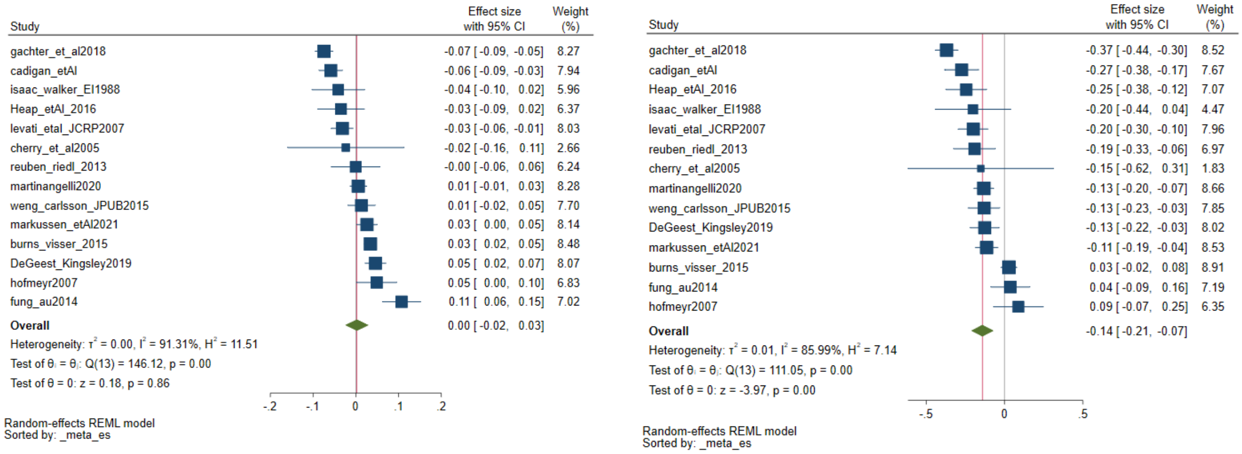

Figure 5: Study-by-study analysis of the contribution of rich vs members of equal groups. Left panel: normalized absolute contributions. Right panel: Relative contributions.

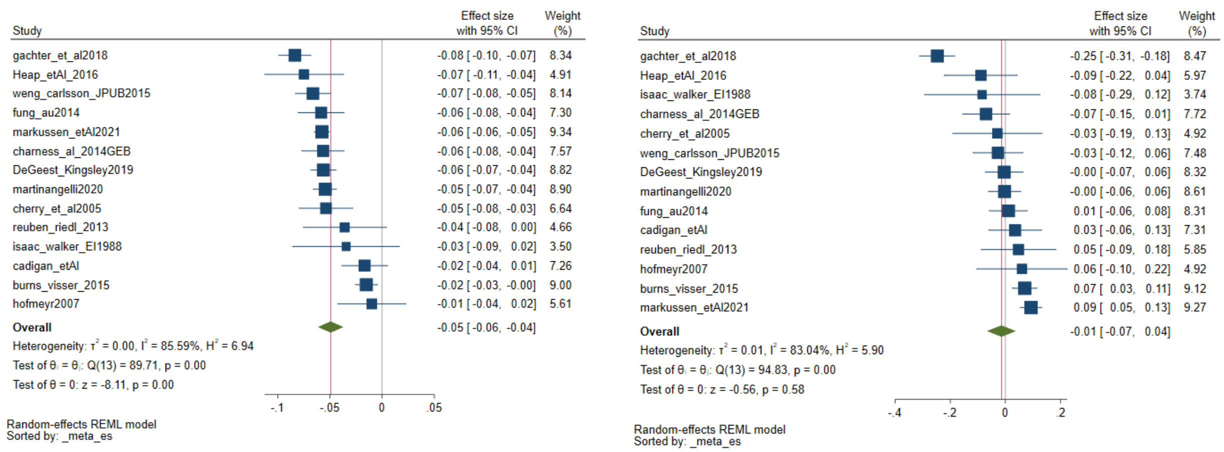

Figure 6:Study-by-study analysis of the contribution of poor vs members of equal groups. Left panel: absolute contributions. Right panel: Relative contributions.

ii. Comparison of the contributions of the rich with the contributions of the poor.

We use the data from the treatments with inequality only.[32] We regress contributions on a dummy variable indicating that one is "rich" for each study separately. We use standard errors clustered at the group level. In Figure 5, we plot the effects of "being rich" on normalized absolute (left panel) and relative (right panel) contributions. Regarding normalized absolute contributions, we find 17 positive and significant effects, 2 negative and significant effects and 3 non-significant effects. The overall effect is positive and significant 0.05 (CI [0.03, 0.06]). Regarding relative contributions, we find 18 effect size that are negative and significant and 4 non-significant effects. The average effect is -0.12 (CI [-0.16, -0.09]).

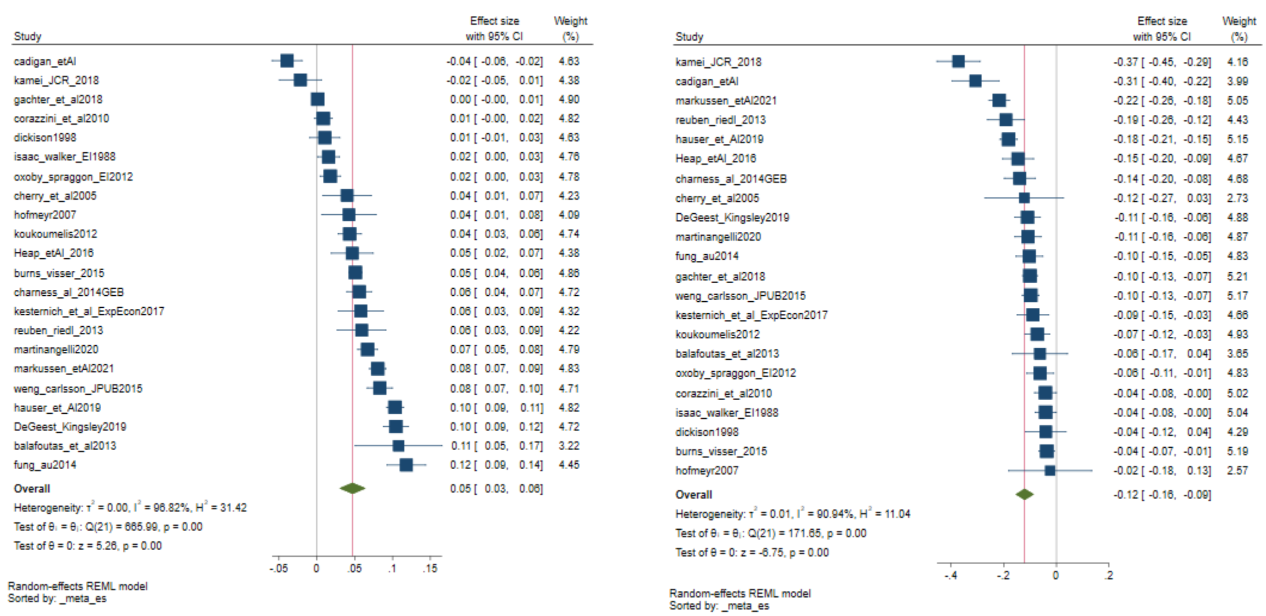

Figure 5: Contribution gaps between the rich and the poor: absolute (left) and relative (right) contributions.

[32] Note that we do not have the individual data for (Levati, Sutter, and Van Der Heijden 2007) so this study is excluded from this analysis.

7. Contribution gaps and the strength of inequality

To rule out a censoring effect (when inequality increases, some individuals may have a very low endowment, preventing contributions), we run the same regressions as in Table 9*Table 8*, dropping the individuals whose endowment share was within the 10% smallest.

Results are presented in Table 17. Censoring does not drive our results, as the results presented in Table 17 are very similar to those in Table 9.

Table 17:The effect of the strength of inequality on the contribution gap, dropping individuals with a share of endowment below the 10th percentile.

	(1) Abs. Cont.	(2) Abs. Cont.	(3) Abs. Cont.	(4) Rel. Cont.	(5) Rel. Cont.	(6) Rel. Cont.
Dydx Gini endowment						
Poor	-0.126****	-0.157****	-0.213****	0.191**	-0.111	-0.138
	(0.017)	(0.022)	(0.027)	(0.080)	(0.094)	(0.093)
Rich	0.051**	0.035	-0.010	-0.162**	-0.579****	-0.562****
	(0.023)	(0.026)	(0.034)	(0.072)	(0.084)	(0.084)
P diff.	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Study FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Obs.	33549	33549	33549	33549	33549	33549

Standard errors in parentheses are clustered at the session level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001

8. Contribution gaps in the first period

We run random effect models explaining the differences in relative and absolute contributions in period 1 between the rich and the poor (models (1)-(3) focus on relative contributions and models (4)-(6) focus on normalized absolute contributions). The outcomes of the regressions are available in Table 18. We show that a contribution gap exists in the first period. Rich individuals contribute less than the poor in relative terms and more in absolute terms.

Table 18: Contribution gaps in the first period.

	(1) Rel. Cont.	(2) Rel. Cont.	(3) Rel. Cont.	(4) Norm. Abs. Cont.	(5) Norm. Abs. Cont.	(6) Norm. Abs. Cont.
Rich	-0.090****	-0.096****	-0.085****	0.081****	0.076****	0.079****
	(0.011)	(0.012)	(0.012)	(0.004)	(0.004)	(0.004)
Controls	No	Yes	Yes	No	Yes	Yes
Study FE	No	No	Yes	No	No	Yes
Obs.	3841	3841	3841	3841	3841	3841
Sessions	359	359	359	359	359	359
R2	0.034	0.115	0.134	0.095	0.170	0.191
Wald-Chi2 p	0.000	0.000	.	0.000	0.000	.

Standard errors in parentheses are clustered at the session level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$, **** $p<0.001$.