Fairness and Redistribution: Experimental Insights on Inequality Awareness from a Large-Scale Study

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Abstract

This paper investigates how awareness of inequality influences preferences for taxation and redistribution. We conducted a large-scale randomized experiment with more than 20,000 participants in Italy, where individuals were asked about their preferred distribution of the tax burden across income groups before and after exposure to short videos on different dimensions of inequality (income, gender, education, and immigration). Our results show that exposure to inequality information, particularly on income disparities, significantly increases support for taxing the top 1% and reduces the burden assigned to the bottom 50% in the short run. The effects of other treatments are weaker and more heterogeneous across subgroups. However, a follow-up survey conducted several months later reveals that these effects largely vanish over time, indicating that inequality awareness shapes tax preferences temporarily rather than persistently. These findings underscore both the potential and the limitations of information campaigns: they can meaningfully shift redistribution preferences in the moment, but sustaining these changes may require repeated or more intensive interventions.

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1 Introduction

Public debates about inequality and taxation have intensified in recent years, raising questions about how citizens form preferences for redistribution. While economic self-interest is a central driver of tax attitudes, a growing body of research shows that perceptions of fairness and awareness of inequality also play a decisive role. Yet, evidence on how different dimensions of inequality—such as income, gender, education, and immigration—shape tax preferences remains limited, particularly outside of small-scale experiments.

This paper addresses this gap by presenting evidence from a large-scale randomized experiment with more than 20,000 individuals in Italy. Participants were first asked to allocate the tax burden across four income groups (the top 1%, the next 9%, the next 40%, and the bottom 50%). They were then randomly assigned to a control group or to one of four treatment groups, each exposed to a short video highlighting inequality in a specific domain (income, gender, education, or immigration). After treatment, all participants were asked again about their preferred tax distribution, enabling us to measure how exposure to inequality information influences redistribution preferences.

Our results show three main outcomes. First, exposure to inequality—especially income inequality—significantly increases support for taxing the top 1% while lowering the burden assigned to the bottom 50% in the short run. Second, the effects of gender, education, and immigration treatments are weaker and more heterogeneous across groups, suggesting that the salience of income inequality is particularly powerful. Third, a follow-up survey several months later indicates that these effects dissipate over time, pointing to the short-lived nature of information-driven changes in tax preferences.

The central research question of this study is therefore: *To what extent does raising awareness of different forms of inequality shape preferences for taxation, and are these effects persistent or transitory?* By combining a large sample size with randomized treatments across multiple inequality domains, this study contributes new evidence on the role of information in shaping redistribution preferences. It also highlights the challenges of sustaining such effects over time, underscoring the limits of one-shot interventions for influencing public support for taxation.

Recent research has highlighted the role of information in shaping attitudes toward taxation and redistribution. Studies have shown that when individuals are made aware of economic disparities, they may be more likely to support progressive tax policies (Stantcheva, 2021; Kuziemko et al., 2015a). However, others argue that tax preferences are deeply rooted in ideological and cultural factors, making them less responsive to informational interventions (Alesina et al., 2018a). Our study builds on this literature by examining how information about different dimensions of inequality—income, gender, education, and immigration—shapes preferences for taxation. While previous studies have mostly focused on income disparities, we broaden the scope to multiple domains of inequality and assess their relative effectiveness. Moreover, our contribution lies not only in the breadth of treatments but also in the scale and setting of the experiment: we rely on a sample of more than 20,000 individuals in Italy, making this one of the largest randomized studies on redistribution preferences to date. In line with prior work, we find that exposure to information about inequality can increase support for progressive taxation, particularly when income disparities are highlighted. However, we also show that the effects are short-lived, with preferences largely reverting in the months following treatment. This suggests that while information matters, its impact may be temporary and context-dependent, pointing to both the potential and the limits of informational interventions.

2 Literature Review

A growing body of literature explores the determinants of taxation preferences and redistribution attitudes. One strand of research emphasizes economic self-interest, suggesting that lower-income individuals favor higher taxation on the wealthy due to direct financial benefits (Piketty, 1995; Meltzer and Richard, 1981). Another line of inquiry highlights the importance of fairness perceptions, where individuals' beliefs about economic mobility and deservingness shape their policy preferences (Bénabou and Tirole, 2005; Fong, 2001).

Experimental studies have further shown that information can play a critical role in shaping tax attitudes. For instance, Kuziemko et al. (2015a) found that when individuals were informed about wealth inequality, they became more supportive of progressive taxation. Similarly, Ferrari and Pellegrino (2023) demonstrated that exposure to inequality statistics significantly altered perceptions of fairness in taxation. However, the durability of these effects remains contested, as some research suggests that informational treatments may only have temporary impacts (Cappelen et al., 2020).

Our study contributes to this literature in several ways. First, rather than focusing exclusively on income inequality, we introduce treatments across multiple domains—income, gender, education, and immigration—allowing us to assess their relative salience within a single experimental framework. Second, by conducting a large-scale randomized experiment with more than 20,000 participants in Italy, we provide robust evidence on how inequality awareness shapes redistribution preferences in a nationally representative setting. Finally, we go beyond short-run effects by incorporating a follow-up survey, which enables us to evaluate whether the shifts in taxation preferences induced by information persist over time.

3 Large-Scale Experiment and Randomization

3.1 Survey Overview and Objectives

This survey is part of a broader initiative funded under the PE09-GRINS program, aimed at establishing a permanent observatory on the channels of territorial inequality at the individual and household level. The project is jointly developed by the Department of Economics and the Department of Statistical Sciences at the University of Bologna. Within the framework of Spoke 8, the core objective is to explore, from a multidimensional perspective, the main drivers of inequality across Italian regions, and to monitor how these factors shape local disparities and social mobility over time.

Specifically, the observatory is designed to map territorial inequalities at the provincial and regional levels, while also providing insights into individualsâ perceptions of disparity and deprivation, particularly in relation to economic, educational, migratory, and gender-related dimensions. In addition to measuring inequality, the survey investigates social preferences, examining how individualsâ life trajectories and socio-economic backgrounds influence their prosocial attitudes, such as solidarity, reciprocity, and support for redistribution.

3.2 Survey Design and Implementation

To achieve these goals, we developed large-scale survey instrument to identify the multidimensional nature of inequality and to assess both objective indicators and subjective perceptions of disadvantage through the entire territory of Italy. The questionnaire includes modules designed to capture socio-demographic characteristics of respondents, attitudes toward inequality and fairness, perceptions of mobility and deprivation, and experimental behavioral tasks assessing prosocial preferences (e.g., how participants allocate resources between themselves and others). The survey was administered as a panel over three waves, with each respondent being recontacted at intervals of 6 to 9 months. The first wave contains a maximum of 70 multiple-choice questions and is conducted entirely online.

3.3 Sampling and Panel Structure

To ensure statistical reliability, the survey targets a representative sample of 20,000 individuals aged 18 to 69 residing in Italy. The sample is stratified by gender, age group, and province (NUTS-3 level), using population distributions from ISTAT as of January 1st, 2023.

The resulting grid includes 642 demographic cells. A pilot phase involving a small number of respondents in Northern and Southern regions was conducted to validate the questionnaire and test operational procedures. Participants were contacted three times over the course of the study. In case of attrition, respondents were not replaced; instead, reweighting techniques is used to maintain representativeness across waves.

4 Data Collection and Administration

Survey administration is handled by a professional polling agency with experience in large-scale online fieldwork. The firm was responsible for recruiting the sample, programming and hosting the online questionnaire, monitoring response rates, distributing participant incentives, and providing technical support during the survey period. At the conclusion of each wave, anonymized microdata was returned to the research team in formats agreed upon in advance. Informed consent protocols are developed in collaboration with the Data Protection Officers of the participating departments, ensuring compliance with ethical and legal standards.

4.1 Descriptive statistics

We begin by presenting the descriptive statistics of our Baseline Sample 2024, comprising 20,078 individuals residing across all Italian regions. The survey captures a rich set of demographic and socioeconomic characteristics, allowing us to document substantial heterogeneity in age, gender, income, education, civil status, and perceptions of inequality.

Table 3 reports the main individual-level statistics. The average age of respondents is 45.5 years (SD = 13.8), with a balanced gender composition (50% female). A large share of respondents (76%) report being income earners within the household. The vast majority are Italian-born (95%), and 71% report owning their home. Over half of the sample (53%) have children. Subjective well-being indicators show an average life satisfaction score of 6.5 out of 10, while self-assessed health averages 7.0 out of 10.

In terms of educational attainment (Table 4), 42.8% of respondents report completing an upper secondary diploma, while 14.6% and 13.9% hold two-year and three-year university degrees, respectively. A smaller portion have completed postgraduate education (7.5%). Nearly 10% report middle school as their highest level of education, while 0.8% have no formal education. Table 5 describes the distribution of annual household income across predefined brackets[1]. The most common income range is €30,001–48,000 (19.1%), followed by €24,001–30,000 (15.8%) and €18,001–24,000 (13.6%). About 12% of respondents report household income below €9,000, whereas only 0.8% report earnings above €150,000, highlighting the left-skewed nature of income distribution in the sample.

5 Empirical Exercise

5.1 Empirical Setting and Identification

Our empirical strategy follows a difference-in-differences design. Each respondent is asked about their preferred tax distribution both before and after treatment, which allows us to con-

[1]The income ranges were taken from ISTAT 2024

trol for individual baseline preferences and to identify how exposure to the videos shifts attitudes relative to the control group. This setup ensures that our estimated coefficients capture the causal effect of the informational treatments on changes in taxation preferences, rather than reflecting pre-existing differences across individuals. The specification should therefore be interpreted as estimating the *intention-to-treat* (ITT) effect: we compare all individuals assigned to a given treatment with those in the control group, regardless of the intensity of exposure. To improve the precision of our estimates, we include a set of individual-level covariates (e.g., gender, age, education, income), but the identifying variation comes from random assignment. Standard errors are clustered at the individual level to account for the panel structure of the data, since each person contributes both a pre- and post-treatment observation. For the long-term follow-up survey, we apply the same specification, while also checking for selective attrition across treatment and control groups. This ensures that any differences we observe in persistence are not simply due to differential dropout. Together, these steps provide a robust framework for estimating both the short-run and long-run effects of inequality awareness on taxation preferences.

We study the causal effect of information about inequality on preferred tax rates for different income groups using a two-wave panel, in Wave 1 (short-run horizon) and Wave 2 (long-run horizon), individuals report their preferred tax rates for four groups—Top 1%, Next 9%, Next 40%, and Bottom 50%—both before and after randomized interventions (e.g., a short video on different inequality). Randomization guarantees that, absent treatment, treated and control respondents would have evolved along parallel trends; panel structure with unit fixed effects further absorbs time-invariant individual heterogeneity (e.g., ideology, baseline knowledge). Common shocks across waves (e.g., macro news) are absorbed by time fixed effects. We estimate difference-in-differences (DiD) models with individual fixed effects, allowing treatment effects to differ across income groups and across horizons (Wave 1 (post) vs. Wave 2 (post)).

5.2 Fixed Effect DiD Model (Baseline Specification for Short Run)

$$Y_{it} = \alpha_i + \lambda \cdot \text{Post}_t + \delta \cdot (\text{Treated}_i \times \text{Post}_t) + \varepsilon_{it} \tag{1}$$

- Y_{it}: the outcome of interest for unit i at time t (e.g., taxing the top 1%).
- α_i: unit fixed effect, capturing time-invariant differences across units (e.g., persistent characteristics of an individual, region, or group).
- Post_t: an indicator variable equal to 1 in the post-treatment period(s) and 0 in the pre-treatment period.
- λ: the common time effect, i.e., factors that change after the intervention and affect both treated and control groups equally.

- $\text{Treated}_i \times \text{Post}_t$: the DiD interaction term, equal to 1 only for treated units in the post-treatment period.

- δ: the DiD estimator, capturing the average treatment effect on the treated (ATT).

- ε_{it}: the idiosyncratic error term.

$$Y_{it} = \alpha_i + \lambda \cdot \text{Post}_t + \sum_{g=2}^{4} \delta_g \cdot \left(\text{Treat}_i^{(g)} \times \text{Post}_t \right) + \varepsilon_{it} \tag{2}$$

- Y_{it}: the outcome of interest for unit i at time t.

- α_i: unit fixed effect, controlling for time-invariant heterogeneity across units.

- Post_t: an indicator equal to 1 in the post-treatment period and 0 otherwise.

- λ: the common time effect, capturing shocks that affect all units after treatment.

- $\text{Treat}_i^{(g)}$: indicator equal to 1 if unit i belongs to treatment group g, with one group omitted as the reference.

- $\sum_{g=2}^{4} \delta_g \cdot (\text{Treat}_i^{(g)} \times \text{Post}_t)$: interaction terms allowing the treatment effect to differ by group.

- δ_g: treatment effect for group g, relative to the omitted baseline group.

- ε_{it}: the idiosyncratic error term.

5.3 General Model For Event Study

Let $Y_{it}^{(g)}$ denote respondent i's preferred tax rate for group $g \in \{\text{Top 1\%, Next 9\%, Next 40\%, Bottom 50\%}\}$ at time t. Let Treat_i be an indicator for assignment to the information intervention, and let $\text{Post}_t^{(w)}$ indicate the post period of Wave $w \in \{1, 2\}$. We estimate:

$$Y_{it}^{(g)} = \alpha_i + \sum_{w=1}^{2} \lambda_w \, \text{Post}_t^{(w)} + \sum_{w=1}^{2} \delta_{g,w} \left(\text{Treat}_i \times \text{Post}_t^{(w)} \right) + \varepsilon_{it}, \tag{3}$$

where α_i are individual fixed effects. The coefficients $\delta_{g,1}$ and $\delta_{g,2}$ capture the average treatment effect on the treated (ATT) for group g in the short run (Wave 1 post) and in the long run (Wave 2 post), respectively. For a compact specification pooling groups, replace $Y_{it}^{(g)}$ by Y_{it} and interact treatment timing with group dummies:

$$Y_{it} = \alpha_i + \sum_{w=1}^{2} \lambda_w \, \text{Post}_t^{(w)} + \sum_{g \in \mathcal{G}} \sum_{w=1}^{2} \delta_{g,w} \left(\text{Treat}_i^{(g)} \times \text{Post}_t^{(w)} \right) + \varepsilon_{it}, \tag{4}$$

with one g omitted as the reference group. In all specifications we report standard errors clustered at the individual level to account for within-person serial correlation. The identifying assumption is parallel trends within treatment status, conditional on fixed effects and wave-time effects; balance checks and pre-trend tests (using pre-treatment measurements in Wave 1) support this assumption.

6 Results: Short and Long Run Effects

6.1 Short-run effects of inequality awareness

Table 1: Effect of Global Treatment on Tax Preferences (Pooled DiD FE)

	(1) Top 1%	(2) Next 9%	(3) Middle 40%	(4) Bottom 50%
Treated group (baseline)	0.501	0.163	-0.182	-0.482
	(0.373)	(0.184)	(0.206)	(0.317)
Post-treatment	0.810***	0.457***	-0.337*	-0.929***
	(0.199)	(0.123)	(0.148)	(0.188)
Treated x Post	0.519*	0.00948	-0.334*	-0.194
	(0.228)	(0.144)	(0.168)	(0.214)
Constant	37.72***	23.65***	20.28***	18.35***
	(0.333)	(0.163)	(0.184)	(0.284)
Observations	40156	40156	40156	40156

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Tables 1 and 2 present the estimated short-run effects of the informational treatments on preferences for the distribution of the tax burden across income groups. Several clear patterns emerge.

First, exposure to the *income inequality* video produces the most consistent and substantial effects. Respondents in this treatment group assign a significantly higher share of the tax burden to the top 1% and a correspondingly lower share to the bottom 50%. The magnitude of the effect is economically meaningful: support for taxing the top 1% increases by about 1.3 percentage points relative to the control group, while the share assigned to the bottom half decreases by 0.8 points. These findings confirm that highlighting stark income disparities raises the salience of progressive taxation.

Second, the other treatments—focusing on gender, education, and immigration—yield smaller and more heterogeneous effects. For gender and education inequality, the coefficients are generally in the expected direction, with modest increases in support for taxing higher-income groups, but most estimates are not statistically significant at conventional levels. The immigration treatment shows the weakest impact overall, with virtually no systematic change in tax preferences. This suggests that, at least in the short run, information about income

Table 2: Effect of each Treatment on Tax Preferences (DID FE)

	(1)	(2)	(3)	(4)
	Top 1%	Next 9%	Middle 40%	Bottom 50%
Post Treatment	0.810***	0.457***	-0.337*	-0.929***
	(0.199)	(0.123)	(0.148)	(0.188)
Video Gender× post	0.489	0.106	-0.260	-0.334
	(0.294)	(0.195)	(0.213)	(0.274)
Video Education× post	0.172	-0.238	-0.230	0.296
	(0.306)	(0.194)	(0.222)	(0.277)
Video Immigration × post	0.120	-0.0585	-0.157	0.0963
	(0.290)	(0.188)	(0.215)	(0.283)
Video Income × post	1.294***	0.229	-0.690**	-0.834**
	(0.309)	(0.195)	(0.212)	(0.278)
Constant	38.12***	23.78***	20.14***	17.97***
	(0.0490)	(0.0322)	(0.0346)	(0.0451)
Observations	40156	40156	40156	40156

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

inequality is far more powerful in shaping redistribution preferences than information about other forms of inequality.

Third, the results are robust across specifications and consistent when focusing on both increases for the top 1% and decreases for the bottom 50%. Taken together, these findings highlight the responsiveness of tax preferences to salient information about economic disparities, but also point to the limits of informational interventions when inequality is framed in domains other than income.

6.2 Long Run Effects of inequality awareness

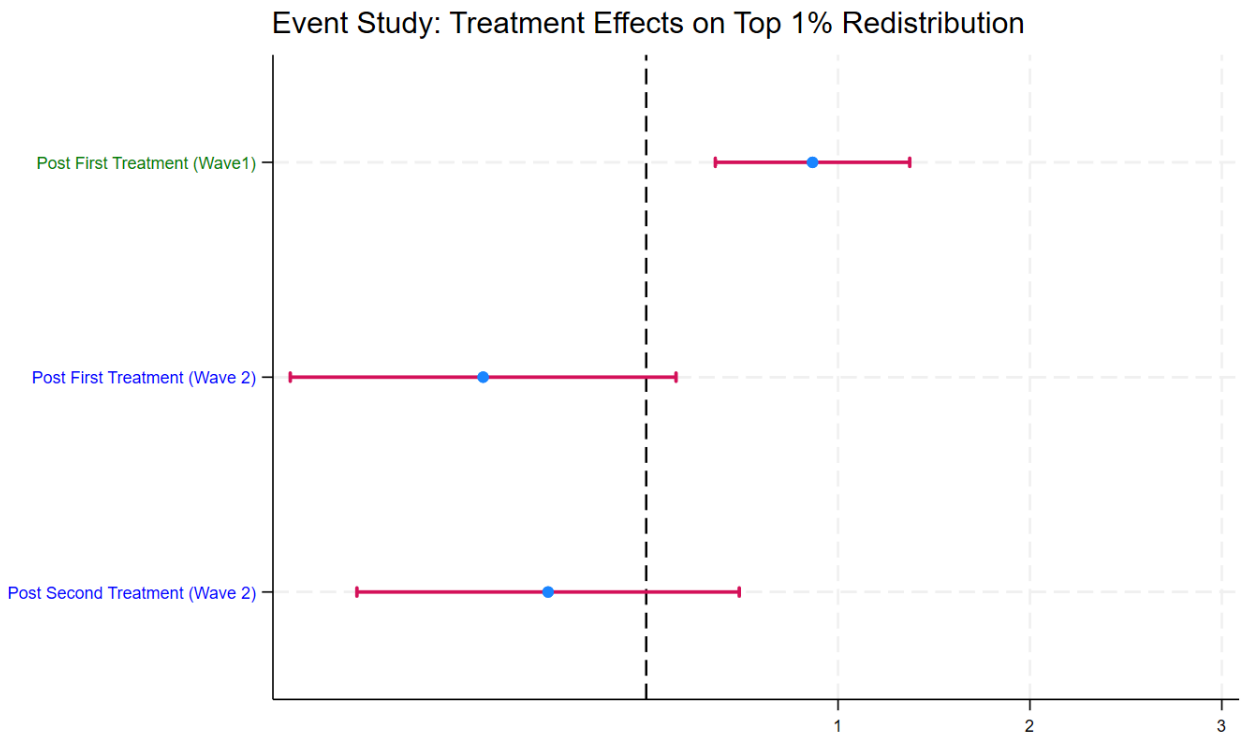

Figure 1: Event Study (2 Waves) for Global Treatment on taxing top 1%

Figure 1 presents event-study estimates of the treatment effects on preferred taxation of the Top 1%. We find a clear and statistically significant increase in support for taxing the Top$\tilde{1}$% immediately after the first intervention in Wave$\tilde{1}$. However, this effect does not persist in Wave$\tilde{2}$: the estimated coefficients for both the long-run follow-up to the first treatment and the second intervention in Wave$\tilde{2}$ are small. These findings suggest that the information treatment induced a short-run shift in attitudes, but that its effect decayed over time and was not reinforced by repeated exposure. This pattern is consistent with recent evidence showing that information shocks often have temporary impacts on preferences for redistribution and taxation (e.g., Alesina et al., 2018b; Kuziemko et al., 2015b).

Whereas, figure 2 reports event-study estimates of the treatment effects on preferred taxation across the income distribution. The results show a clear and statistically significant short-run effect of the first intervention in Wave$\tilde{1}$: respondents increased their support for taxing the Top 1%, while preferences regarding the taxation of the Next 9%, the Next 40%, and the Bottom 50% remained largely unchanged. In contrast, the estimated effects in Wave 2 are small across all groups, both when examining the persistence of the first treatment and the response to the second treatment. This pattern suggests that the intervention triggered an immediate attitudinal shift targeted specifically at the very rich, but that the effect quickly faded

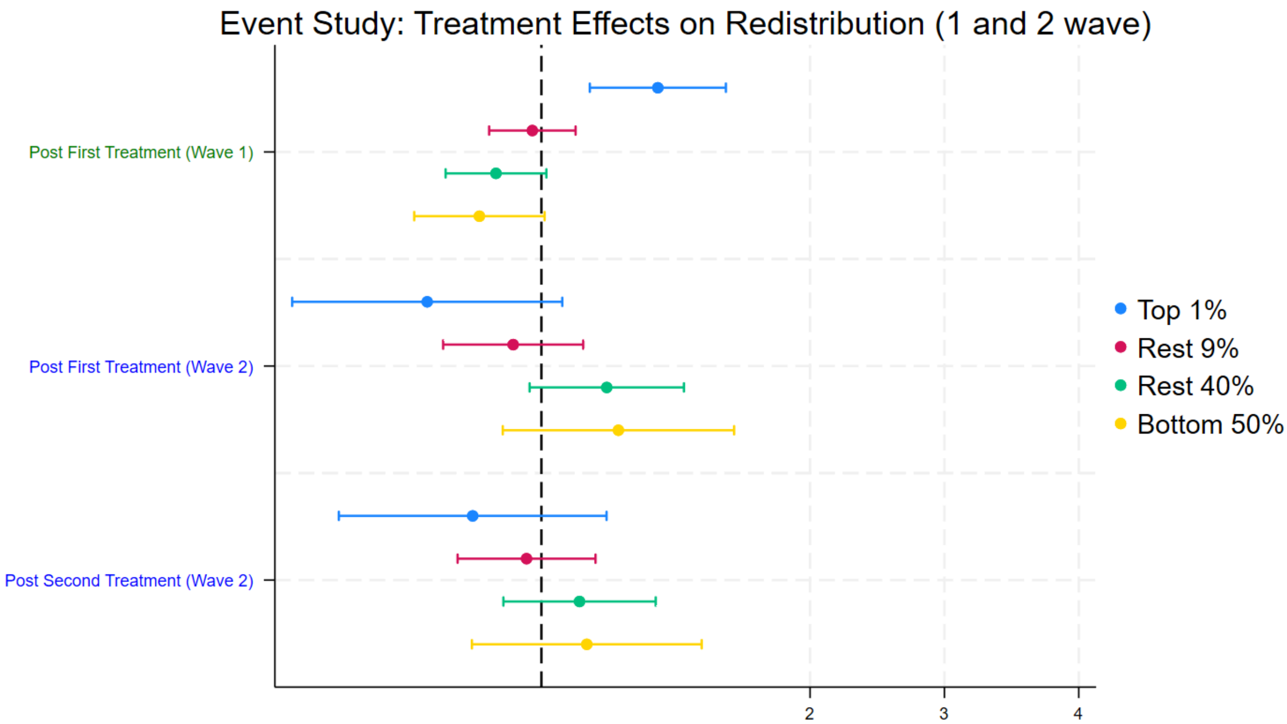

Figure 2: Event Study (2 Waves) for 1 and Second Global Treatment for different outcomes

over time. A natural interpretation is that information treatments act as salient reminders, temporarily reshaping perceptions of fairness and inequality. However, as time passes, competing information, daily concerns, and prior beliefs reassert themselves, so that the initial impact dissipates. The absence of effects for the repeated intervention in Wave$\tilde{2}$ further indicates that repeated exposure may not be sufficient to reinforce or sustain attitudinal change, as individuals either discount the information once it is no longer novel or revert to their entrenched preferences.

Figure 3 instead, examines heterogeneity by the type of information treatment given at the respondents, focusing on preferences for taxing the Top 1%. The results reveal that only the income inequality video produced a strong and statistically significant short-run effect: immediately after the first exposure in Wave 1, respondents expressed substantially higher support for increasing taxes on the richest group. However, the impact of the income inequality treatment faded over time, as neither the long-run follow-up in Wave 2 nor the repeated treatment in Wave 2 displayed robust effects. This pattern suggests that informational content must be both salient and directly related to income distribution to influence tax preferences, and that such effects are inherently short-lived, with limited reinforcement from repeated exposure. The heterogeneity across treatment types points to meaningful differences in how individuals connect inequality information to redistribution. The education inequality video appears to reduce support for taxing the Top$\tilde{1}$%, especially in Wave$\tilde{2}$. A plausible interpretation is that

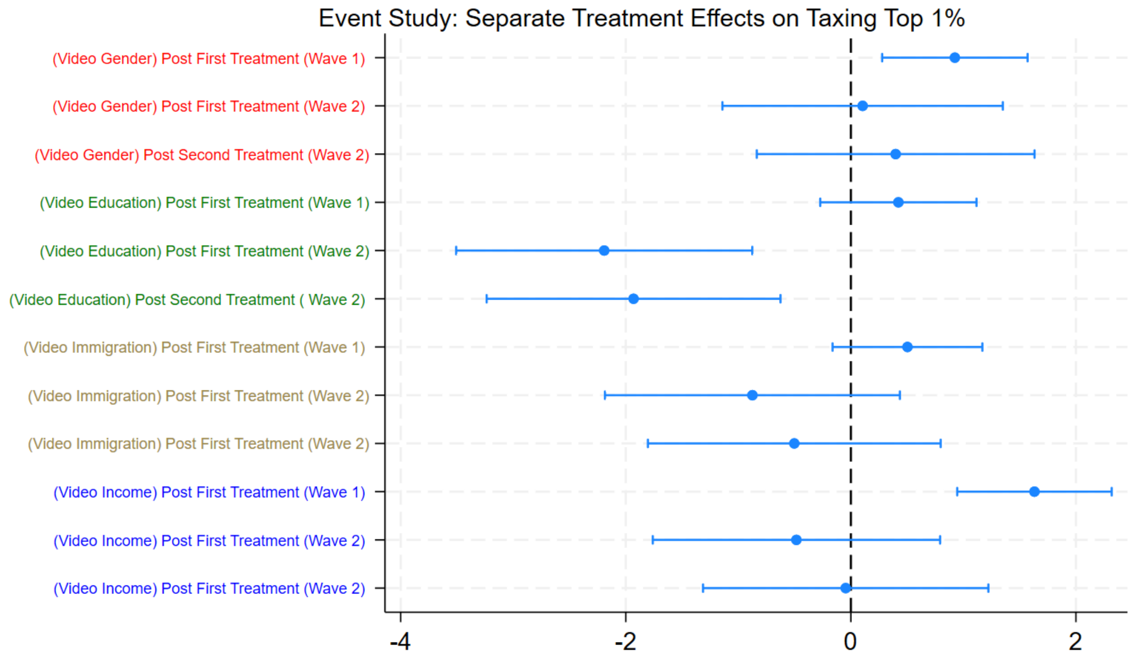

Figure 3: Event Study (2 Waves) for each Treatment on Taxing top 1%

exposure to education-related disparities shifts attention away from taxation of the rich and toward alternative policies, such as improving access to schooling or enhancing opportunities. In this sense, respondents may perceive education inequality as a problem best addressed through targeted investment rather than redistribution. By contrast, the gender inequality video produces a short-run positive effect on taxing the Top 1%. One possible mechanism is that information about gender gaps strengthens fairness concerns and heightens sensitivity to inequality more broadly, which temporarily translates into higher support for taxing the richest. Yet, as with the income inequality video, this effect does not persist, suggesting that salience and fairness considerations fade quickly once the treatment is no longer fresh.

Interestingly, the education inequality treatment produces a positive shift in preferences for taxing the Bottom 50%, particularly in Wave 2. At face value, this finding is puzzling, as one might expect such information to increase sympathy for the poorest. A possible interpretation is that respondents perceive education inequality not primarily as a problem of income redistribution, but rather as a challenge of financing collective goods. In this view, raising taxes even on lower-income groups may be seen as a way to fund better educational opportunities, reflecting a sense of shared responsibility rather than targeted relief. Another explanation is that exposure to education-related disparities redirects concerns from distributive fairness to equality of opportunity, reducing the link between inequality awareness and progressive taxation. Given the wide confidence intervals, part of this pattern may also reflect imprecision in the estimates rather than a systematic effect.

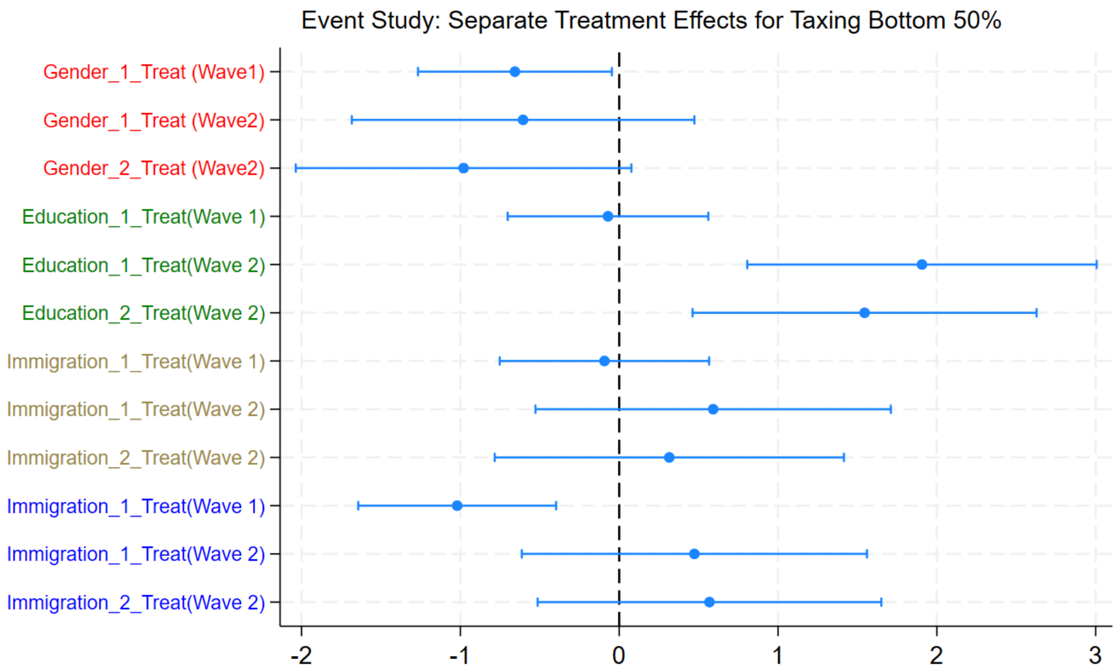

Figure 4: Event Study (2 Waves) for each Treatment on Taxing Bottom 50%

The income inequality video generates the clearest and most intuitive pattern. Immediately after exposure, respondents increase their support for taxing the Top 1% while simultaneously decreasing their support for taxing the Bottom 50%. This combination points to a stronger demand for progressivity in the tax system, consistent with the idea that income inequality information makes both the very rich and the very poor more salient as relevant reference groups. In this framing, the richest are viewed as those who should contribute more, while the poorest are seen as those who should contribute less. The effect, however, is short-run and fades in Wave 2, suggesting that while income-based information is highly salient in the moment, it does not translate into a persistent shift in redistributive preferences.

7 Discussion and Conclusion

Our analysis provides new evidence on how inequality awareness affects preferences for taxation. Using a large-scale randomized experiment with more than 20,000 respondents in Italy, we find that exposure to short videos highlighting inequality has measurable but heterogeneous effects on redistribution attitudes.

In the short run, information about *income inequality* proves to be the most powerful driver of change. Respondents exposed to the income inequality treatment significantly increase the share of the tax burden assigned to the top 1% while reducing the share attributed to the bottom 50%. The magnitude of these shifts is non-trivial, suggesting that highlighting stark disparities in income distribution makes progressive taxation more salient and desirable. By contrast, treatments focused on gender, education, and immigration inequality produce weaker and less consistent effects, with most coefficients close to zero or statistically insignificant. These findings align with prior studies emphasizing that income inequality is the most salient dimension shaping redistribution preferences (Kuziemko et al., 2015a; Ferrari and Pellegrino, 2023).

The follow-up survey conducted several months later reveals, however, that these effects are not persistent. The increases in support for taxing the top 1% largely dissipate, and preferences for the bottom 50% revert toward their baseline levels. This pattern is consistent with recent research showing that informational treatments often generate temporary rather than lasting effects (Cappelen et al., 2020). Our results therefore suggest that while information can shift redistribution preferences in the moment, sustaining these changes requires repeated or more intensive interventions.

Taken together, our findings highlight both the potential and the limits of inequality awareness campaigns. On the one hand, they demonstrate that citizensâ tax preferences are not fixed: they respond to salient information about economic disparities, especially when framed in terms of income. On the other hand, the transitory nature of these effects underscores the difficulty of producing durable attitudinal change through one-shot interventions. From a policy perspective, this suggests that governments and institutions aiming to build public support for progressive taxation may need to invest in sustained communication strategies, integrating evidence on inequality into broader narratives about fairness and social cohesion.

In conclusion, our study contributes to the growing literature on the determinants of redistribution preferences by providing robust experimental evidence on both the short-run responsiveness and the long-run fragility of information effects. By extending the scope beyond income to multiple dimensions of inequality and by relying on a large representative sample, we shed new light on how information shapes public support for taxation. Future research should explore alternative forms of information provision and examine whether repeated exposure or interactive formats can generate more persistent effects on redistribution attitudes.

8 Tables

Table 3: Baseline Summary Statistics

Variable	Mean	SD	Min	Median (p50)	Max	Count	CV
Age	45.47	13.84	18.00	47.00	70.00	20,078	0.30
Female	0.50	0.50	0.00	1.00	1.00	20,078	0.99
Income Receiver	0.76	0.43	0.00	1.00	1.00	20,078	0.57
Italian Born	0.95	0.23	0.00	1.00	1.00	20,078	0.24
Has Children	0.53	0.50	0.00	1.00	1.00	20,078	0.94
Home Owner	0.71	0.45	0.00	1.00	1.00	20,078	0.63
Life Satisfaction (0-10)	6.53	2.04	0.00	7.00	10.00	20,078	0.31
Health Status (0-10)	6.96	1.73	0.00	7.00	10.00	20,078	0.25

Notes: All variables refer to the 2024 Baseline survey (Wave 1, Italy). CV = Coefficient of Variation.

Table 4: What is the Highest Level of Education You Have Completed? (Sorted by Frequency)

Education Level	Frequency (b)	%	Cumulative %
Upper secondary education diploma	8,585	42.76	42.76
Two-year postgraduate degree	2,932	14.60	57.36
Three-year undergraduate degree	2,786	13.88	71.24
Middle school diploma	1,984	9.88	81.12
Upper secondary school diploma	1,740	8.67	89.78
Postgraduate education (Master/PhD)	1,512	7.53	97.32
Primary school diploma	333	1.66	98.97
No formal education	158	0.79	99.76
Doesn’t know	48	0.24	100.00
Total	20,078	100.00	

Notes: Baseline Sample 2024. Education level refers to the highest qualification completed by the respondent.

Table 5: Household Income Range (Annual, Euros)

Income Range	Frequency (b)	%	Cumulative %
€30,001 - €48,000	3,838	19.12	19.12
€24,001 - €30,000	3,175	15.81	34.93
€18,001 - €24,000	2,729	13.59	48.52
Under €9,000	2,335	11.63	60.15
€48,001 - €72,000	2,184	10.88	71.03
€15,001 - €18,000	1,635	8.14	79.17
€9,001 - €12,000	1,551	7.72	86.90
€12,001 - €15,000	1,539	7.67	94.56
€72,001 - €100,000	678	3.38	97.94
€100,001 - €150,000	259	1.29	99.23
Over €150,000	155	0.77	100.00
Total	20,078	100.00	

Notes:Baseline Sample 2024. Question asked: In which of these intervals does your households annual income fall?

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A Alternative Econometric Specifications

A.1 Pooled DID model with no Fixed Effect

$$Y_{itk} = \alpha + \sum_{g=1}^{G-1} \gamma_g \cdot \mathrm{TREAT}_{ig} + \lambda \cdot \mathrm{POST}_t + \sum_{g=1}^{G-1} \delta_g \cdot (\mathrm{TREAT}_{ig} \times \mathrm{POST}_t) + \boldsymbol{\beta}' \mathbf{X}_i + \varepsilon_{it} \tag{5}$$

- Y_{itk}: Outcome variable â the tax amount assigned by individual i at time t to income group k (e.g., top 1%).
- TREAT_{ig}: A dummy variable equal to 1 if individual i belongs to treatment group g ($g = 1, 2, 3, 4$), with group G (e.g., Cell 5) as the omitted reference.
- POST_t: A time dummy equal to 1 for the post-treatment wave, and 0 for the pre-treatment wave.
- $\mathrm{TREAT}_{ig} \times \mathrm{POST}_t$: The interaction term capturing the Difference-in-Differences effect â how much more (or less) the treated group changed relative to the control group.
- $\mathbf{X}_i$: A vector of individual covariates (e.g., age, gender, education, risk aversion, altruism).
- α: Constant term.
- γ_g: Treatment group fixed effects (pre-treatment differences).
- λ: Overall post-treatment time effect.
- δ_g: DiD coefficient for treatment group g relative to control.
- ε_{it}: Error term.

We estimate a pooled DiD model with covariates and clustered standard errors to assess the effect of informational treatments on support for taxing the top 1%.
Among the treatment groups, only Cell 4 exhibited a statistically significant treatment effect, with respondents increasing their allocation to the top 1% by 1.29 more than the control group. The control group itself increased their allocation by 0.81, yielding a total post-treatment shift of 2.10 for the Cell 4 group. Female, older, and more highly educated respondents were significantly more supportive of taxing the top 1%, while higher risk aversion and altruism scores

were associated with less support. These findings underscore the efficacy of specific informational interventions in shifting public attitudes toward progressive taxation.

A.2 Alternative: First Difference Model

$$\Delta Y_i = \delta \cdot \text{Treated}_i + \boldsymbol{\beta}' \mathbf{X}_i + \varepsilon_i \tag{6}$$

- ΔY_i: the change in the outcome variable for individual i, defined as the difference between the post-treatment and pre-treatment responses (e.g., change in support for taxing the top 1%).
- Treated_i: a binary indicator equal to 1 if individual i was assigned to any of the treatment groups (i.e., exposed to a video), and 0 if assigned to the control group.
- $\mathbf{X}_i$: a vector of individual-level covariates, including time-invariant characteristics such as gender, education, marital status, and risk aversion.
- $\boldsymbol{\beta}$: the vector of coefficients associated with the covariates $\mathbf{X}_i$.
- δ: the average treatment effect on the treated, capturing the additional change in outcome attributable to the treatment.
- ε_i: the individual-specific error term.

B Alternative Specification

Table 6: Effect of Treatment on Tax Preferences (DID with no Fixed Effect

	(1)	(2)	(3)	(4)
	Top 1%	Next 9%	Middle 40%	Bottom 50%
Cell 1	0.383	0.107	-0.252	-0.238
	(0.462)	(0.229)	(0.255)	(0.391)
Cell 2	1.036*	0.262	-0.243	-1.055**
	(0.472)	(0.238)	(0.262)	(0.384)
Cell 3	0.0456	0.135	-0.138	-0.0423
	(0.468)	(0.233)	(0.261)	(0.397)
Cell 4	0.401	0.122	-0.0560	-0.467
	(0.467)	(0.230)	(0.258)	(0.390)
Post=1	0.810***	0.457***	-0.337*	-0.929***
	(0.199)	(0.123)	(0.148)	(0.188)
Cell 1 × post=1	0.489	0.106	-0.260	-0.334
	(0.294)	(0.195)	(0.213)	(0.274)
Cell 2 × post=1	0.172	-0.238	-0.230	0.296
	(0.306)	(0.194)	(0.222)	(0.277)
Cell 3 × post=1	0.120	-0.0585	-0.157	0.0963
	(0.290)	(0.188)	(0.215)	(0.284)
Cell 4 × post=1	1.294***	0.229	-0.690**	-0.834**
	(0.309)	(0.195)	(0.212)	(0.278)
Constant	24.45***	15.95***	28.51***	31.09***
	(4.025)	(1.640)	(2.088)	(3.163)
Observations	40156	40156	40156	40156

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Household income ranges, education and marital status added as additional controls.

OLS Results for all treatments together

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Difference-top1%	Difference-top1%	Difference-top9%	Difference-top9%	Difference-rest40%	Difference-rest40%	Difference-bottom50%	Difference-bottom50%
Treat	0.519**	0.499**	0.00948	0.0180	-0.334*	-0.326*	-0.194	-0.191
	(0.245)	(0.229)	(0.144)	(0.144)	(0.173)	(0.168)	(0.226)	(0.214)
Age		-0.00554		-0.00106		0.00430		-0.00879
		(0.00754)		(0.00538)		(0.00574)		(0.00704)
Female		-0.133		0.119		0.0423		-0.294
		(0.199)		(0.132)		(0.141)		(0.182)
Risk-Lover		-0.0676		-0.0423		0.0247		-0.0499
		(0.0421)		(0.0269)		(0.0297)		(0.0385)
Altruist		0.0412		0.0371		-0.0188		0.0229
		(0.0433)		(0.0287)		(0.0298)		(0.0398)
Constant	0.810***	0.307	0.457***	0.716	-0.337**	-1.304	-0.929***	0.895
	(0.219)	(3.686)	(0.123)	(1.928)	(0.155)	(3.252)	(0.202)	(2.456)
Observations	20,078	20,078	20,078	20,078	20,078	20,078	20,078	20,078
R-squared	0.000	0.002	0.000	0.001	0.000	0.002	0.000	0.002

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Household income ranges, education and marital status added as additional controls.