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Essays on cognition, prosociality, and distributive preferences

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Introduction

The first decades of the XXI century were marked by different economic, geopolitical, sanitary and environmental crisis. These episodes have exacerbated social inequality to concerning levels. If this trajectory persists, inequality may escalate to unprecedented heights. To ameliorate its effects, our societies need social actors, such as politicians, social leaders, and lobbies, to foster inclusive economic and social progress based on more cooperative social interactions and better conditions to levelling the playing field for all.

Certain individuals hold a more pivotal position. Decision making is not homogenously distributed in the population. Previous research shows that individuals with higher cognitive abilities tend to have better access to leadership positions, gain more influence, and become more involved in collective decisions (Dal Bó et al., 2017). Consequently, policies coming out of all sort of organizations, from small groups and companies up to the larger scale of government action, will tend to be skewed towards their preferences.

Encouraging them to advocate for equality does not necessarily require appealing to their personal interests. Human beings often act selfishly, but they also care about others in a genuine and disinterested manner (Dawes et al., 2007). That is, people have prosocial preferences and behave in accordance. Prosocial behavior promotes the basis of fairer, more caring, and sustainable societies. All of which are salient social features to successfully overcome major social shocks, such as current and future crisis. Prosociality enhances tax morale, and thus tax compliance (And, 1998), increases individuals' trust (Corgnet et al., 2016), which in turn is conducive to better governance and institutions, raises the likelihood of political participation in democratic life (Mueller, 2003), facilitates de delivery of public services (Gregg et al., 2011), and enhances pro-environmental action (Nolan and Schultz, 2014).

Given the social benefits of prosociality and the larger social influence of more cognitive able individuals, the relevant questions are whether the latter have more prosocial preferences and if they impact their behavior. This dissertation seeks to provide solid answers to these questions, by means of both observational and experimental data, and to investigate new mechanisms underlying the relationship between cognitive abilities and prosociality.

Chapter 1 explores support for redistribution among high-cognition individuals. To do so, I leverage two rich birth-cohort studies that have followed thousands of participants since birth into adulthood. I rely on test scores for measuring cognitive ability, which were administered closely before individuals entered high school. These measures are highly useful, as the timing of the tests aligns with the period in which cognitive ability development halts. I connect these measures with data for the same individuals in their 30s and 40s. The analysis is based on the stability of cognition within individuals. This feature proves highly useful, as it allows me to leverage an individual variable for which I can confidently claim there is no reverse causality from any adult condition. Moreover, by exploiting extensive information on individual upbringing context and early childhood schooling, I can isolate unrelated variations in cognition and closely approximate the true effect of cognition on support for redistribution.

I find that most cognitively able individuals tend to support more income redistribution. This result is consistent across different outcomes, such as support for public policies and voting behavior. This is particularly noteworthy because they are much richer than the mean. With little scope for self-interest in explaining this behavior, I explore whether concern for others plays a role. I leverage information on volunteering throughout different periods of participant's lives, a useful proxy for other-regarding preferences. I find that high-cognition individuals who drive the increased support for redistribution are those who volunteer. This result is significant as it suggests social preferences play a relevant role in the support for redistributive policies among cognitively able individuals.

Chapter 2 extends on the previous findings by testing its validity in a complementary domain. I take advantage of the unique setting provided by the rollout of the COVID-19 vaccines. I focus in preferences on how to distribute the vaccines within the population, which is a form of health distribution. The setting is not only useful to verify results generalizability, but is ideal to examine how social preferences impact support for distributive policies. COVID-19 was a salient issue which was very-much perceived to be determined by circumstances. This feature minimizes the incidence that merits can have on distributive support, allowing to scrutinize the role of social preferences.

I use longitudinal and high-frequency data from five European countries that include a set of questions about vaccine distribution preferences. These questions were designed to distinguish support between schemes based on circumstances from those based on efforts. They were asked in March 2021, a time when vaccines were scarce, policy-makers had to decide who to vaccine first, and news covered extensively this topic. I focus the analysis on the comparison between individuals with higher and lower cognitive abilities. I connect responses with cognition assessments and a wide variety of individual characteristics that precede the outcome and find that high-cognition individuals are 35% more likely to support vaccine-distribution schemes that emphasise circumstances rather than outcomes or efforts. These preferences are not driven by scheme convenience nor vaccine hesitancy, but appear to be caused by prosociality. The results confirm the key role of social preferences. I then leverage information to explore why this happens. Among many social attitudes, equality of opportunities emerges as the most relevant factor. High-cognition individuals have a more negative perception on this topic and this significantly explains their larger support for health distribution

Chapter 3 builds upon these results and directly tests differences in social preferences by cognitive abilities. For this puporse, I run a laboratory in the field experiment. In the experiment, participants are presented with scenarios marked by unequal opportunities and are tasked with deciding whether (and how) to redistribute earnings. These decisions are made from the perspective of third-party spectators, with no potential for personal gain influencing their choices. This design allows to isolate what each individual considers to be fair and to distinguish if they account or not for unequal opportunities. The main focus is to test for differences by cognitive abilities. To do so, I recruit children from a same school and aged between 10 and 15. This sample offers various advantages relevant to my objectives. On the one hand, children share similar socio-economic context and schooling, limiting confounders affecting both cognition and social preferences and leading to reliable results. On the other, the sample covers an age period marked by notable changes in the brain structure, which provides relevant variation in cognition.

I find that older children increasingly take into account the unequal opportunities in the situations they face and that cognitive maturity is part of the explanation. Doing this is not a trivial task. In fact, older and more able children are better at dealing with the complex procedures it implies: inferring counterfactual situations and incorporating them into their decisions. This leads to increased redistribution of earnings. I then provide evidence on the role of the information used in their decisions. I show that drawing attention to the unequal opportunities yields no overall effect, but disclosing counterfactual situations has a relevant impact.

The concluding remarks connect these key findings and research contributions. I recapitulate the main points discussed, highlight the original insights by shedding light on the novel findings and methodologies employed, and examine the broader implications of the research, discussing its relevance.

Chapter 1:

Support for Redistribution and Cognitive Ability*

Individuals with higher cognitive ability have been found to be more politically influential. But it is not clear how their political preferences regarding redistribution play out, as they tend to be richer and more pro-social. We asses empirically this question by exploiting two cohort studies from the United Kingdom that measure cognitive ability during childhood and preferences during adulthood. We find that the top 10% most able individuals are more supportive for redistribution, even without controlling for their higher income. By controlling for a rich set of variables, we unveil a partial positive effect of 10.7 p.p. that prevails over negative ones. This effect appears to be focused on individuals that have volunteered in organizations, suggesting that social motives may be a consequential factor for this pivotal group of individuals.

Keywords: preferences for redistribution, cognitive ability
JEL classification: D31, D72, D91, C23

1.1 Introduction

Political influence is unevenly distributed among the population. One of the groups that exert disproportionate influence is that of individuals with higher cognitive ability. They have larger knowledge about political discussion, involvement in collective decision, access to leadership positions, and participation in elections (Cassel and Lo, 1997; Dal Bó et al., 2017; Deary et al., 2008b). These make policies coming out of organizations to be more alligned to their interests. In a topic such as redistribution, which is mostly channeled through institutions, the support or opposition of this influential group may have significant implications. Yet, we know little about their preferences for redistribution.

A first intuition could be to think them to be less supportive for redistribution, as they tend

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to earn more income (Edin et al., 2022; Fé et al., 2022; Hanushek et al., 2015; Heckman et al., 2006). But there is increasing evidence that factors other than self-interest play a role in support for redistributive policies (Cappelen et al., 2021; Fehr et al., 2022; Fisman et al., 2017; Harrs and Sterba, 2023; Kerschbamer and Müller, 2020; Müller and Renes, 2021; Stantcheva, 2021). In particular, higher cognitive ability has been linked with more pro-social attitudes.[1] Pro-social attitudes are particularly relevant for support for redistribution among those with income above the median (Epper et al., 2020), a group where this influential individuals tend to concentrate. If pro-sociality is higher among those more cognitively able, could we expect its impact to prevail in their support for redistribution?

To answer this question, we leverage two rich birth-cohort studies that have followed thousands of participants since birth. Cognition measurements are much scarce on adult population, but more available for children.[2] We rely on scores from well established and age-appropiate tests to measure it just before individuals entered high school. Those measures prove useful, as cognition becomes relatively stable and resistant to attempts to change them through education and training (Carroll, 1993). We connect cognition data with preferences for redistribution collected for the same individuals in their 30s and 40s. We take advantage of the variability of cognition across individuals and its stability within individuals, which makes it precede preferences for redistribution and its most common determinants. This enables us to adress issues of reverse causality, as we can confidently claim that cognition is not affected by current support for redistribution nor income education and occupation. We also control for possible endogeneity in our specification by incorporating information on upbringing environment provided by parents at individual's birth and early childhood schooling, which could simultaneously explain the variation in both variables (Cornelissen and Dustmann, 2019; Cunha and Heckman, 2007; Cunha et al., 2010). Thus, our identification strategy exploits the plausibly exogenous differences between individual's cognition that are not explained by the socio-economic context of their upbringing. We further control for modeled individual heterogeneity to asses the impact of that variation on support for redistribution using panel data, and also provide consistent estimates

[1] In experiments these individuals have been found to contribute more in non-strategic games (Chen et al., 2013), and to cooperate more (Basic et al., 2021) and reach more efficient equilibria (Proto et al., 2019) in strategic games. Also, many factors relevant for pro-sociality such as impatience, risk-aversion (Dohmen et al., 2010; Shamosh and Gray, 2008), forecasting accuracy (Rydval, 2012) and complex strategy solving (Palacios-Huerta, 2003) appear to change alongside cognitive ability. For a review on existing empirical literature and experimental tests on the effect of cognitive ability over economic decision, consult Deck and Jahedi (2015).

[2] Adequate cognitive ability assessments demand much time. Ability assessment should rely on the correlation among performance of various tasks. In particular, cognition is the ability on tasks dependent on information processing (Carroll, 1993; Colom et al., 2002; Jensen, 1998). Generally, these data is measured in schooling-age children, for whom is less costly to undertake the various tasks necessary. However, childhood measurements are rarely linked with adult information.

with a more restrained model using each cross-section subsample.

We find that most cognitive able individuals tend to declare a higher support for redistribution. Even when not controlling for other observable characteristics, those in the top 10% of the cognitive ability distribution are 6.6 p.p. more supportive for redistribution (16% above the mean). The difference is noteworthy considering that those individuals earnings are 42% larger than the average in our sample and hints that non-monetary concerns might be at play. Including a wide set of controls we uncover the prevailing partial positive effect over support for redistribution to be of 10.7 p.p. (26% of the mean value). We further prove that the coefficient is positive and significant for distinct thresholds in the top of the cognitive ability distribution.

Our main results are consistent to considering more detailed information, such as declared intensity on preferences for redistribution and continuous variation of cognition. We also show that most able individual not only tend to support in greater extent income redistribution, but also public provision of health and education. Moreover, those in the top of the cognitive ability distribution are more likely to vote for parties that favor more the introduction, maintainance and expansion of public services and social security.

We find that the effect is mostly focused on people not in the bottom quintile of the income distribution, and that it is larger for the subgroups of men, university graduates and workers in non-manual occupations. It appears we are identifying a variation that is observed more strongly in individuals that probably have less economic gains from redistribution. Interestingly, the increased support for redistribution is entirely explained by most able individuals that also involve in voluntary organizations, which is a commonly used proxy for pro-sociality. This impact adds to the average effect among volunteers, suggesting the positive effect for high cognitive ability is channeling through higher pro-sociality.

Related literature. These results contribute at least to two branches of literature. First, to the one exploring the determinants of preferences for redistribution. The most similar study is Mollerstrom and Seim (2014), which to our knowledge is the only antecedent directly assessing the relationship between support for redistribution and cognitive ability. The authors find a negative relationship between both variables, partially mediated by income and beliefs about the role of effort on outcomes. However, the analysis is centered in the mean, for which individual's political leverage is not so prominent and connection with pro-sociality not strongly established. Our study puts the emphasis on those who are most able and finds a reversion of the negative relationship, prompted by enhanced concerns towards others. This result relates with recent studies accounting for increased support for redistribution among groups that *a priori* don't benefit directly from it (Epper et al., 2020; Häusermann et al., 2015; Piketty, 2018).[3] We identify an additional group whose support for redistribution is in contrast to the predictions that current theoretical models yield. The accumulation of these results signal the need to better comprehend what is being valued within redistribution to overturn an apparent immediate economic loss. Additionally, we provide underpinning for the presence of a group highly recognized in the modern and lesser class-based political alliances.[4]

Second, the research relates to the exploration of the effects of high cognitive ability on preferences. Among the numerous variables studied, this work connects more closely with the political science literature that analyzes participation and social attitudes. Previous studies center in general attitudes such as liberalism, conservatism, anti-racism and feminism (Deary et al., 2008a; Schoon et al., 2010; Lewis and Bates, 2018). We focus on an specific policy preference that involve expectations about the government's behavior and result from complex strategic optimization. We also incorporate to this literature a different empirical strategy that adds heterogeneity analysis and the exploration of pro-sociality as a possible mechanism accounting for the relationship found.

The paper is structured as follows. Section 1.2 describes the datasets used and provides basic descriptive statistics. Section 1.3 presents the empirical strategy to estimate the relationship. Sections 1.4 and 1.5 present and discuss the results obtained. Section 1.6 concludes the paper.

1.2 Data and Descriptive Statistics

1.2.1 Data

We use data from the 1958 National Child Development Survey (NCDS58) and the 1970 British Cohort Study (BCS70), conducted in the United Kingdom. Each of these cohort surveys track around 17,000 individuals born in England, Wales and Scotland in a single week.[5] The first data wave was collected at the birth of the participants, followed by several waves during childhood and adulthood. Survey participation has been high throughout recollection waves (see Table A.1).

The primary objective of the surveys is to follow individuals life and document information on

[3] A trend that mimicks the acknowledgment of *a priori* benefiting groups that opposed redistribution which fuelled earlier development in the literature (i.e. Benabou and Ok, 2001; Charité et al., 2015).

[4] Some of the many works referring to this trend are (Benedetto et al., 2020; Hooghe and Marks, 2018; Kuziemko and Washington, 2018; Piketty, 2018)

[5] Participation at time of birth amounted to 99% and 96% of all births registered. Subsequent data recolection waves included immigrants of the same cohort.

diverse aspects (e.g., health, cognitive and social development, education and employment, and home lives). Three waves collected information during school years, and more than five waves have been carried out during adulthood. Following, we describe key information we leverage for our study.

Cognitive ability. Participants completed a wide range of age appropriate cognitive tests during their childhood: NCDS58 members at 11, and BCS70 members at age 5 and 10.[6] These tests allow the identification of a single dimension accouting for cognitive ability, which have been proved to be significantly stable across time (Shepherd, 2012; Parsons, 2014). We leverage cognitive ability measurements centering in the age 11 (10) tests for NCDS58 (BCS70) cohort members.

Preferences for Redistribution. Participants were surveyed with a 5-point Likert scale for the following statement: *'Government should redistribute income from the better off to those who are less well off'*. This measure is commonly used in the empirical literature studying preferences for redistribution based on observational data and strongly correlated with effective voting (see Table C.2). Opinions on this subject were collected at age 33 (30) for NCDS58 (BCS70) and 42 for both cohorts. We base our main analysis on computed support for redistribution, which takes the value of 1 when individuals declare to 'Strongly Agree' or 'Agree' with redistribution and 0 otherwise.

Other variables. We leverage additional information on several individual and household characteristics recollected in the cohort studies.[7] In particular, we consider household characteristics (e.g., region of residence, marital status, presence of children, size of household), educational attainment, labor and income. We also incorporate upbringing information provided by parents at the time of the birth of survey participants. This includes basic individual characteristics such as sex and ethnicity, and parental educational attainments, father's occupation type and household income range. All these variables temporally precede and are correlated with cognitive ability and preferences for redistribution. We account for them to address possible ommited variable bias.

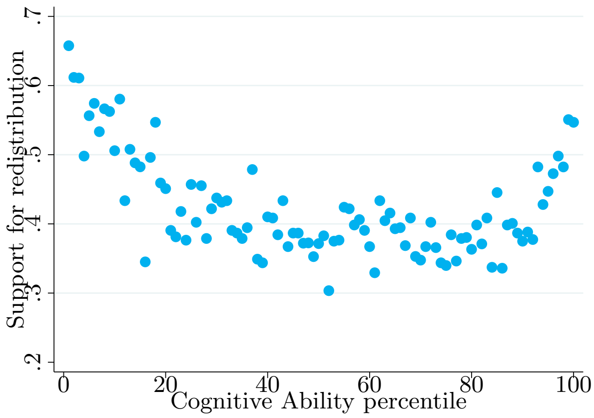
[6]NCDS58 also completed similar tests at age 7 and 16, which are not sufficient to asses cognition. BCS70 members completed additional cognition tests at age 16. The results from all childhood tests have been unevenly analyzed. Early test scores have been scrutinized extensively, as well as the scores at age 10 and 11, which have been used as predictors of adult outcomes, including educational attainment (Schoon et al., 2010), employment (Breen and Goldthorpe, 2001), health (Batty et al., 2007) and political participation (Deary et al., 2008b). There has, however, been relatively little research carried out using the age 16 test scores, mainly due to incompleteness for assesment of general ability for NCDS58, and incomplete coverage for BCS70 resulting from difficulties at the time of its administration (including a teachers' strike).

[7]Except when noted, these variables refer to the same time-period when support for redistribution was assessed.

1.2.2 Descriptive Statistics

Support for redistribution changes alongside various individual characteristics. It reduces steadily for richer individuals and for educational achievements before university, where the relationship inverts. Similarly, the changes alongside cognitive ability show a U-shaped form. Approval exceeds 50% of those in the lowest percentiles of cognitive ability, but drops towards around 30% in the median. The hike in upper levels of cognitive ability is much clear (see Figure 1.1). Support for redistribution climbs more than 20 p.p. in the top two deciles.

Figure 1.1: Support for Redistribution, by Cognitive Ability



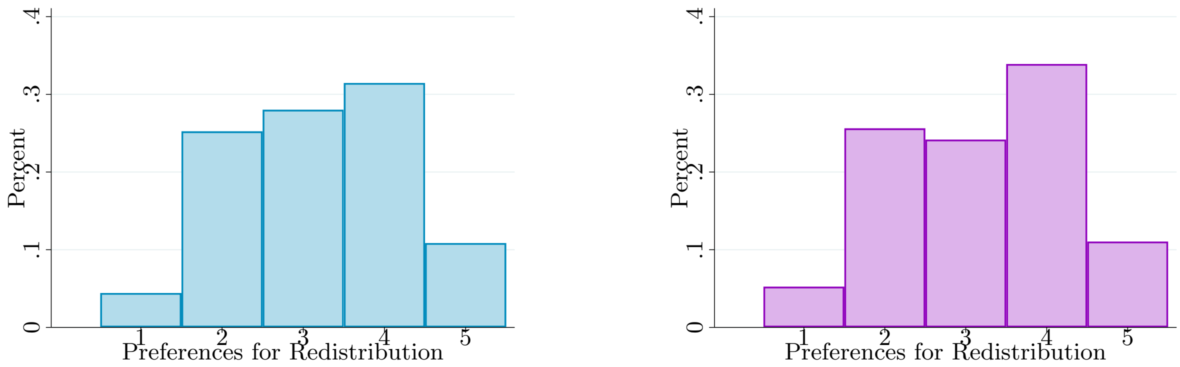
Notes: This figure plots mean support for redistribution by cognitive ability percentiles for the total sample. Cognitive ability was measured at age 10 (11) for BCS70 (NCDS58) cohort members. Preferences for redistribution were measured at age 30 (33) and 42 for BCS70 (NCDS58) cohort members. Support for redistribution corresponds to agree (4) and strongly agree (5) in the preferences for redistribution questions (coded as a 5-point Likert scale from strongly disagree to strongly agree). Sample size is 19,182.

The rise in support for redistribution for the highest deciles reaches elevated levels among the total distribution. In fact, demand for redistribution among the top decile is higher than the average population (see Figure 1.2), with a greater share of high-cognition people declaring to agree and strongly agree with redistribution and fewer being in disagree or uncertain.[8] In the remainder of the paper we use the top 10% of the cognitie ability distribution for our baseline analysis, providing robustness checks for the results afterwards.

[8]This observation is also confirmed with distinct partitions of the right tail of the cognitive ability distribution (such as top 1%, 5% and 25%).

Figure 1.2: Preferences for Redistribution

(a) **Total sample** (b) **Top 10% CA**



Notes: These figures plot preferences for redistribution shares of population for the total sample and individuals in the top 10% of cognitive ability distribution. Cognitive ability was measured at age 10 (11) for BCS70 (NCDS58) cohort members. Preferences for redistribution were measured at age 30 (33) and 42 for BCS70 (NCDS58) cohort members. PR are coded as follows: strongly disagree (1), disagree (2), uncertain (3), agree (4), strongly agree (5). Sample size is 19,182 for the total population and 1,918 for population in the top 10% of cognitive ability distribution.

1.3 Empirical strategy

We run a linear probability model on support for redistribution of individual i at time t, as in the following reduced-form model:

$$y_{it} = X_{it}\alpha + Z_i\omega + High\_CA_i\beta + \bar{X_i}^M\gamma + \nu_i + \lambda_t + \epsilon_{it} \tag{1}$$

for $(i = 1, \ldots, N)$ and $(t = 1, \ldots, T)$, being y_{it} support for redistribution; X_{it} a matrix of time-varying individual characteristics; Z_i a matrix of variables reflecting upbringing conditions; $High\_CA_i$ a vector of dummy variables taking value 1 for individual i with cognitive ability in top of distribution and value 0 otherwise; $\bar{X_i}^M$ a Mundlak term with the time-averaged value of the time-varying explanatory variables; ν_i the error from the modeled unobserved heterogeneity; λ_t the year fixed-effects; and ϵ_{it} an error term.

The main parameter from our specification (β) intends to capture correlations between being a high-cognition individual and support for redistribution. Our estimates collapse possible causal effects from high-cognition and from other variables correlated with belonging to that group. We exploit a relevant set of upbringing characteristics to discard that something other than cognitive ability explains the correlation. Given the rich information available, we come close to identify a true effect.

The inclusion of a Mundlak term ($\bar{X_i}^M$) aims to solve the problem in estimating the effect of a time-constant variable ($High\_CA_i$) over the dependent variable (y_{it}) when working with unobserved effects in panel regression (c_i). Our estimator is simultaneously able to capture the effect of $High\_CA_i$ and reduces the consistency assumption by modelling the unobserved heterogeneity as correlated with the group means of the explanatory variables ($c_i = \bar{X}_i^M + \nu_i$).

Our empirical strategy is based in constructed dummy variables for support for redistribution and high cognition. We include robustness checks for the analysis by exploiting the entire variation in both variables.

1.4 Results

1.4.1 Main results

Results of Equation 1 are presented in Table 1.1. Individuals in the upper part of the cognitive ability distribution have higher preferences for redistribution. With no controls included, those on the top 10% of the CA distribution are 6.6 p.p. more likely to support redistribution (almost 16% above the mean value). The result is particularly remarkable considering that those individuals earn incomes 42% larger than the average in our sample. This suggests that additional concerns might be at play.

Table 1.1: Support for Redistribution

	LPM				Probit	Margins
	(1)	(2)	(3)	(4)	(5)	(6)
$High\_CA$	.066***	.085***	.101***	.107***	.420***	.110***
	(.014)	(.014)	(.014)	(.015)	(.057)	(.015)
Upbringing		X	X	X	X	X
Individual and hh.			X	X	X	X
Education and labor				X	X	X
Mundlak term			X	X	X	X
N	19,182	19,182	19,182	19,182	19,182	19,182
R^2/pseudo-R^2	.016	.023	.045	.061	-	-

Notes: This table reports the coefficients for support for redistribution on a dummy for cognitive ability test score in the top 10%. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. Mean dependent variable is 0.417 in the estimation sample. Columns 1 to 4 report estimates from a linear probability model. Column 5 reports estimates from a probit model. Column 6 reports the marginal effect at the mean. Upbringing controls include sex, ethnicity, and parental education, occupation type and income range. Individual and household controls include locus of control, political cynicism, household size, region, share of immigrants, marital status and presence of children. Education and labor controls include include categorical values for educational attainment and occupation, net annual income, its quadratic term, and dummies for expectancy of better and of worse welfare on 10 years time. Robust standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

The positive association is robust to the inclusion of a wide set of controls. After controlling for upbringing conditions, current income and prospects, education level, region of residence and a wide set of individual characteristics the coefficient climbs up to 10.7 p.p. (representing 26% of the mean value). The observable variables included seem to capture conditions related to cognitive ability that lessen support for redistribution, further unveiling a partial possitive effect that prevails without controls.

The result is statistically significant and increasingly positive for individuals on the highest percentiles of the distribution, as shown in Table 1.2 and Figure C.1. With all controls included, the coefficient is not significant when considering the top half of the cognitive ability distribution, turning significant at 4.2 p.p. for the top 25% and at 14.9 p.p. for the top 5%.

Table 1.2: Support for Redistribution
Different $High\_CA$ thresholds

	(1)	(2)	(3)	(4)
$High\_CA$	.004	.042***	.107***	.149***
	(.009)	(.010)	(.015)	(.020)
CA threshold	Top 50%	Top 25%	Top 10%	Top 5%
N	19,182	19,182	19,182	19,182
R^2	.057	.058	.061	.061

Notes: This table reports the coefficients for support for redistribution on dummies for cognitive ability test score in the top 50%, 25%, 10%, and 5%. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. Mean dependent variable is 0.417 in the estimation sample. Columns 1 to 4 report estimates from a linear probability model. All controls used in Table 1.1 are included. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.4.2 Robustness checks

We further test the robustness of the results to different specifications of the model that exploit more information in the dataset.

Cross-section data. Our main specification exploits the information of panel data by incorporating a Mundlak term to model unobserved heterogeneity. To check if our results are conditioned on the assumptions implied in the procedure, we also estimate support for redistribution using cross-section data from each adult wave merged with childhood information. The coefficients for high-cognition are statistically significant in all subsamples and range from 9.2 p.p. to 16.0 p.p. (see Table C.2).

Non-binary dependent variable. While our main dependent variable only captures differences between individuals who support redistribution and others, we have information that reveals different intensities in opinions (from strong disagreement to strong agreement). We estimate preferences for redistribution (i) using standarized values for preferences for redistribution, and (ii) using an Ordered Probit model, with no assumptions regarding the distance in intensities between declared statements. High-cognition individuals prefer more redistribution in both estimations (see Table C.7 and Table C.8).

Alternative dependent variable. Transferring income is not the only redistributive policy in government's toolbox. We exploit two alternative policy preferences gathered simultaneously: provision of public health and education.[9] We compute support for each policy, taking the value 1 when indviduals declare to 'Strongly Agree' or 'Agree' and 0 otherwise, and estimate Equation 1 using each variable as dependent. Most able individuals have higher approval for both policies. With all controls included, they are 6.6 p.p. more supportive for health provision and 3.4 p.p. for education provision (see Table C.9).

Policy preferences can also translate into voting behavior. We merge individual declared vote for past general elections in England with political parties' stances towards public services and social security schemes gathered from Project Manifesto Database.[10] Individuals in the top decile of cognitive ability distribution are more likely to vote parties that favor the welfare state, resulting in 7.1 p.p. less votes for the Conservative party among those who voted in the 1987, 1997 and 2010 general elections (see Table C.10).

Continuous independent variable. Our main analysis unifies individuals in the top 10% of the cognitive ability distribution. Table 1.2 shows that the positive relationship found is present at least for the top 25% and Figure C.1 confirms that the effect is increasing as we consider upper percentiles of the distribution, but null below.

To further explore this, we firstly estimate an alternative to Equation 1 using the continous values of cognition as main independent variable. Table C.11 shows no effect when all controls included, which is consistent with an impact concentrated on the top of the distribution. Secondly, we asses which part drives the results by using as main independent variable a vector of splines for the cognitive ability measure (at the 50^{th}, 75^{th}, 90^{th} and 95^{th} percentiles). Table C.12 shows a positive effect over support for redistribution in the upper part of the cognitive ability distribution that is entirely captured above the 90^{th} percentile with all splines included.

[9]Both variables were asked through a 5-point Likert scale. Preferences for public health provision is assesed through agreement with: '*The time has come for everyone to arrange their own private health care and stop relying on the National Health Service (NHS)*', being NHS the British publicly funded healthcare system. Preferences for public education provision is assesed through agreement with: '*Private schools should be abolished*'

[10]We exclude Scotland and Wales voters due to lack of complete political stances for the regionalist parties.

Alternative independent variable. We test the robustness of the results to changes in the variable measuring cognition, which is possible in the BCS70 sample. We use a subcomponent of the tests administered at age 10 that can be used on its own to measure cognitive ability: the British Ability Scale (BAS). We also consider the results from a similar test taken at age 5. The relationship appears to be robust to measurement at two particularly significant moments of childhood: before and after entering school (see Table C.13). Nonetheless, results are stronger for the assessment at age 10, which could reflect that they are partly capturing the effect from learning on the outcome variable. In that sense, achievements may constitute a part of what is measured as cognitive ability and seem to be reinforcing the impact over support for redistribution. As a matter of fact, the correlation between cognitive measures at both ages is highly significant but stands at 0.53, implying that the learning process might be affecting what is measured as cognition.

1.4.3 Heterogeneity analysis

Table 1.3 examines the heterogeneity of the effect of high cognitive ability depending on different individual characteristics. A set of dummies identifying population subgroups interacts with the high-cognition coefficient. The associated coefficients represent the differential effect on support for redistribution that high cognitive ability exerts over those individuals in comparison with the excluded reference group.

The effect of high-cognition is significantly larger for those who are men, have an university degree and are employed in non-manual occupations (such as managers and professionals). All these subgroups could be expected *a priori* to benefit less from income redistribution. In a similar fashion, the increased support for redistribution is much subdued in the lowest income quintile, at similar levels than overall population in the reference group comprising Q2 to Q4 and indistinct to it in the highest quintile. Figure 1.3 show estimates for subsamples comprising individuals in the bottom 5%, 10% and 25% and upper 25%, 10% and 5% of the income distribution. The overall effect appears to be driven by those with highest incomes.

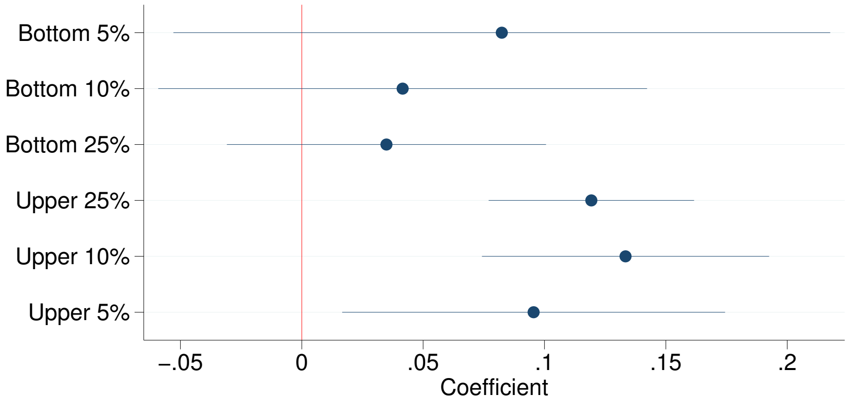
Table 1.3: Support for Redistribution
Heterogeneity across characteristics

	Baseline	Sex	Educ.	Occup.	Income
	(1)	(2)	(3)	(4)	(5)
High_CA	.107***	.077***	.042*	.059***	.119***
	(.015)	(.020)	(.023)	(.021)	(.018)
High_CA		.056**			
* Male		(.027)			
High_CA			.099***		
* Secondary			(.029)		
High_CA				.073***	
* Prof./Manag.				(.025)	
High_CA					-.078***
* Q1 Income					(.034)
High_CA					-.007
* Q5 Income					(.025)
Dummy	-	Male	Secondary	Prof./Manag.	Q5;Q1
N	19,182	19,182	19,182	19,182	19,182
R^2	.061	.061	.062	.061	.061

Notes: This table reports the coefficients for support for redistribution on a dummy for cognitive ability test score in the top 10% and its interaction with population subgroups. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. Mean dependent variable is 0.417 in the estimation sample. All columns report estimates from a linear probability model. Column 1 reports estimates from our main specification. Columns 2 to 5 report estimates adding interactions to the main independent variable to the main specification. Column 2 tests differences between males and females. Column 3 tests differences between those who completed secondary education and the rest. Column 4 tests differences between those occupied in proffesional and managerial roles and the rest. Column 5 tests independently differences between those with earnings in the first (Q1) and fifth (Q5) quintile and the rest (Q2, Q3, and Q4). All controls used in Table 1.1 are included. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results, and particularly the last ones, are in line with what found by Epper et al. (2020) and may follow similar reasons. Low-income individuals have already strong motives to support redistribution, as it entails direct economic gains. There is room for other motives to play an opposing role (i.e. income prospects, relative income perceptions), a topic largely explored in the literature. However, there is less room for other considerations to play an additional positive role, as economic self-interest may max out support for redistribution. The case is the opposite for high-income individuals, and in some extent is probably common also for men, university graduates and those occupied in non-manual occupations. They have direct economic motives to oppose redistribution, making it easier to identify among themselves features that prompt increased demand for redistribution. Higher cognitive ability could be channeling such.

Figure 1.3: High Cognitive Ability coefficient, by income group



Notes: This figure plots estimates for differences in support for redistribution between individuals with cognitive ability test score in the top 10% and the rest, by income groups. All estimates include controls used in Table 1.1. Income groups are constructed with data collected at the time of eliciting preferences for redistribution. Sample size is 19,182.

1.5 Mechanisms exploration

The positive effect over support for redistribution found for most able individuals is robust to the inclusion of a wide set of controls, but we still need explaining how does that relationship emerge. The effect appears to originate from high cognition, but is probably channeling through some socio-economic or psychological factors distinctive of that population. We know most able individuals tend to be more pro-social and to differ in other relevant features involved in decision-making (i.e. impatience, risk-averison, and strategy solving). We explore two possible mechanisms linked to them for which sufficient information is available.[11]

Organisational involvement. A possible proxy for pro-social attitudes is involvement in voluntary organizations. In most cases, it manifests utility yielding that is not mainly driven by monetary benefits. We exploit a set of questions that are contemporary to the assesment of preferences for redistribution to construct a dummy variable measuring past and present membership or participation in organizations.

People involved in organizations appear to be in average more supportive of redistribution (see column 2 in Table 1.4), which seems reasonable if the variable is capturing individual's pro-sociality. The effect for high-cognition appears to be robust to its inclusion, as the coefficient remains largely unchanged. However, it seems that the positive effect found on most able individuals is mostly driven by the interaction with those who involve in organizations (see column 3 in Table 1.4). If we consider that organizational involvement is correctly capturing by

[11]Results are robust to the selection of different high cognitive ability thresholds used throughout the paper.

pro-sociality, this result could be suggesting that the positive effect we find is due to increased concern for others.

Table 1.4: Support for Redistribution
Adding organizational involvement

	(1)	(2)	(3)
High_CA	.107***	.102***	.030
	(.015)	(.015)	(.025)
Org. involvement		.043***	.034***
		(.008)	(.009)
High_CA			.103***
* Org. involvement			(.029)
N	19,182	19,182	19,182
R^2	.061	.062	.063

Notes: This table reports the coefficients for support for redistribution on a dummy for cognitive ability test score in the top 10%. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. Mean dependent variable is 0.417 in the estimation sample. All columns report estimates from a linear probability model. All controls used in Table 1.1 are included. Column 1 reports estimates from our main specification. Column 2 adds organizational involvement as an additional control. Column 3 further tests differences in the effect of *High_CA* on support for redistribution between those with organizational involvement and the rest. Organisation involvement was measured at the time of measuring preferences for redistribution. It refers to membership and/or current participation in social organizations such as political parties, environmental groups, charities, women's group, guilds, parent school organizations and/or tenants-residents associations. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Changing preferences. Inflexibility to adapt preferences over time could be part of the explanation (as in Mullainathan and Washington, 2009). As a cognitive bias, it plausibly affect less the most able individuals. Higher flexibility may permit finding a more optimal equilibria, resulting in distinctive preferences for the most able. To explore this, we exploit the preference variation between the two waves of data for each cohort, which reflects changes between 30s and 40s. We find no evidence supporting the hypothesis. There are no significant difference for high cognition individuals in probability of change favoring redistribution, opposing it, or in the intensity of preferences for redistribution (see Table C.14).

1.6 Conclusions

Individuals with higher cognitive ability exert greater influence over political matters, but little we know regarding their political preferences about redistribution. We could expect that higher cognition reduces support for redistribution due to higher earning potential (Heckman et al., 2006) or to increase it through enhanced pro-sociality (Epper et al., 2020). Up to know, the empirical evidence on this relationship is still limited.

Building over the recent outburst of empirical findings on preferences for redistribution, we test the effect of high-cognition by taking advantage of two large-scale datasets from the United Kingdom. Linking cognitive ability tests taken by individuals during their childhood with repeated questionnaires on individual and household characteristics, educational attainment, labor outcomes, future prospects and support for redistribution in their 30s and 40s, we perform a panel regression. The results provide a novel insight complementing the sole study on the subject (Mollerstrom and Seim, 2014), adding a new context to the analysis and providing the first large-scale estimation of the relationship.

We find that cognitive ability is connected with preferences for redistribution. Most able individuals tend to support it more, particularly those that show signs of large pro-sociality. This suggests that social motives may be what tilts the balance for this relevant group. The results amount to the previous estimates, providing a further step on the understanding of a relationship that could be more complex than previously considered. Future research should exploit information from different contexts to help building over the limitations of this work. Moreover, the exploration of other possible channels driving the results (i.e. differential perceptions, risk-aversion, or strategic problem solving) should be taken to better elucidate this subject. Lastly, if most able individuals are confirmed to be socially pivotal and more supportive for redistribution, then we still need to understand how this translates into redistributive outcomes.

Chapter 2:

After you. Cognition and health-distribution preferences*

We analyse individuals' preferences for vaccine-distribution schemes in the World, the EU, and their country of residence that emphasise circumstances rather than outcomes or effort. We link preferences to previously-measured cognition, and find that high-cognition individuals are 35% more likely to always support such schemes. These preferences are not driven by scheme convenience nor vaccine hesitancy, but appear to be caused by prosociality. We argue that this latter is linked to the perception of less equality of opportunity in society: despite having similar ideals about the role that effort and luck should play in life, high-cognition individuals perceive outcomes to be more determined by luck.

Keywords: social preferences, redistribution, COVID-19, vaccines, cognition.
JEL classification: I14, D91, D71

2.1 Introduction

There is a large literature on the determinants of preferences for redistribution (Alesina and Giuliano, 2011), distinguishing these by individual characteristics. This literature has considered individual education, but rarely the role of cognitive abilities. On the one hand, Mollerstrom and Seim (2014) find, using Swedish data that higher cognition individuals show a lower propensity to redistribute, and argue that this is due to their higher income and assigning larger role to effort than luck. On the other hand, Chapter 1 shows that individuals with greater cognitive abilities are more supportive for income redistribution, which is argued to be related to pro-social preferences. We here contribute to this scarce literature, and analyse the preferences for health distribution of higher-ability individuals. Focusing on the latter is of interest, as they are better

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informed about the political discussions in society (Cassel and Lo, 1997), have greater access to leadership positions (Dal Bó et al., 2017), and vote more often in elections (Deary et al., 2008b). We show that other-regarding preferences can explain differences in preferred health distributions,[12] and provide estimates for high-cognition individuals that plausibly establish an upper bound for the impact of cognition on distributional preferences.[13]

Our work also contributes to the exploration of fairness views as determinants of redistributive-policy preferences (in the line with Piketty, 1995; Alesina and Angeletos, 2005; Bénabou and Tirole, 2006). We add to this literature showing that perceptions of equality of opportunity play a role in support for distributive policies (Alesina and Fuchs-Schuendeln, 2007; Durante et al., 2014; Almås et al., 2020), even when the role of effort in determining outcomes is similar across groups. These results stress the importance of perceived actual fairness in addition to normative fairness ideals.[14]

This paper contributes also to the inequality literature by documenting individuals' preferences for health redistribution in a context in which fairness and equality issues were very salient: the period when COVID-19 vaccines were developed and started to be commercialised. By the end of 2020, many pharmaceutical companies were requesting authorisations to start delivering vaccines to tackle the disease (see Figure 2.1a for a timeline of COVID-19 vaccine development). The imminent arrival of initially-limited vaccines sparked heated discussions about recipients who should have priority. Those discussions involved many concerns that are closely related to those that lie behind attitudes to income redistribution. The few papers that have examined the impact of the COVID-19 pandemic on social preferences find mixed results. While there are some positive effects in (Shachat et al., 2021; Grimalda et al., 2021; Alsharawy et al., 2021), on others they are negative (Buso et al., 2020), or zero (Casoria et al., 2023; Lohmann et al., 2023). None of this previous work, however, has considered how these preferences change by cognitive ability.

We use data from five European countries in which individuals were asked to report their preferences on how to distribute the COVID-19 vaccines across the World, the European Union

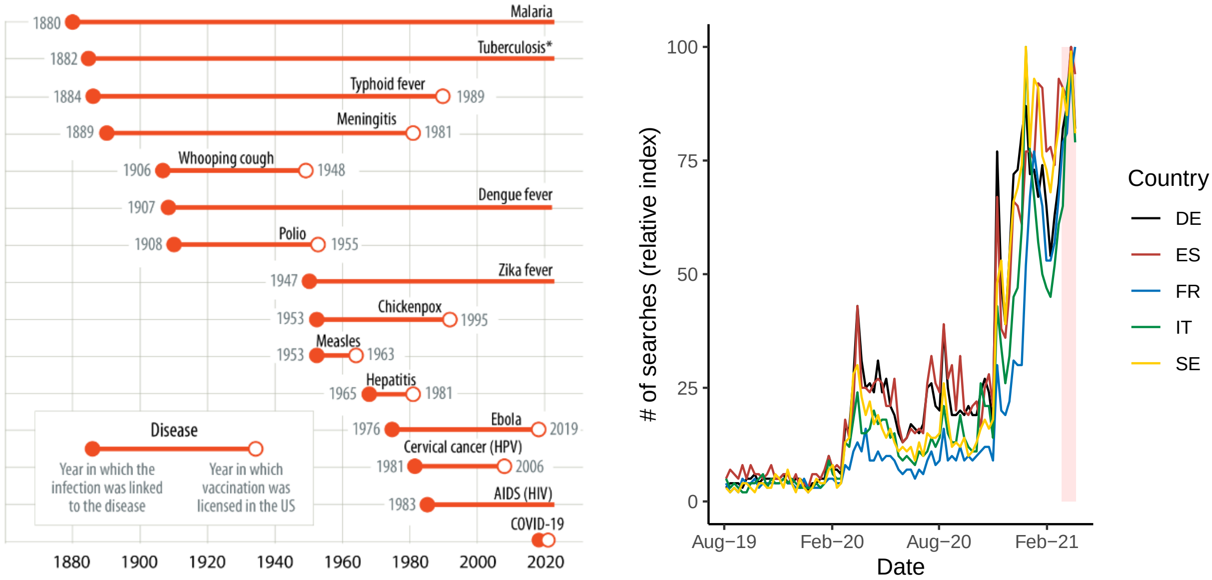
[12] In line with recent finding concerning income, such as Tyran and Sausgruber (2006); Durante et al. (2014); Almås et al. (2020); Kerschbamer and Müller (2020); Fehr et al. (2021)

[13] Our data was collected in a context where a salient health issue (COVID-19) was very-much perceived to be determined by circumstances (rather than effort). In that sense, our findings relate to the role of circumstances in a salient period of time and over a salient issue.

[14] Understanding whether perceptions of unfairness affect desired fairness has also been analysed in political science and social psychology, although the results remain inconclusive. García-Castro et al. (2020) and Kuhn (2019) find that perceived inequalities reduce tolerance to inequality. In turn, García-Sánchez et al. (2018) and Trump (2018) find that they affect ideal views about inequality, driving higher tolerance for inequality in more-unequal societies.

Figure 2.1: COVID-19 vaccines in context

(a) Development **(b) Interest**



Source: Stanley, A. (2021). The journey of the COVID-19 vaccine. International Monetary Fund. Based on data from Our World in Data. *Notes*: This figure plots years in which diseases were discovered and in which vaccination was licensed in the United States. The Hepatitis vaccine in the charts is for Hepatitis B. Vaccines for Tuberculosis and Dengue exist, but are not fully effective in adults.

Source: Google Trends. *Notes*: This figure plots relative interest in vaccines as proxied by Google searches for 'vaccine' in France, Germany, Italy, Spain, and Sweden between June 2019 and April 2021. The red bar indicates the days when the data on preferences for vaccine distribution were collected.

(EU) and within their own country of residence. The data was collected in March 2021, a time when vaccines were scarce and policy makers had to decide who to vaccine first when using their share of vaccines purchased centrally by the European Commission. This health-distribution decision was apparent to all, in particular in terms of the the discussion about how many vaccines each EU country would receive, and who should be vaccinated first. These subjects appeared every day in the news and were widely-debated among the general public. This debate offers a unique context in which to understand what drives individual preferences for the 'distribution of health'.

The COVID-19 vaccine distribution is in itself a form of redistribution: vaccines are freely distributed in the population, and are financed by the Government's budget (to which some individuals contribute more than others). The order of vaccination is also a form of redistribution. Vaccination provides valuable protection against illness and, later on, greater access to transport and services. COVID-19 vaccines not only reduced severe health complications, they also prevented deaths (Watson et al., 2022; Polack et al., 2020; Baden et al., 2020; Voysey et al., 2021; Sadoff et al., 2021). As such, similarly to preferences for income redistribution, attitudes to COVID-19 vaccination distribution reflect views about solidarity (Cappelen et al., 2021), fairness (Fehr et al., 2021), risk aversion (Rehm, 2009; Gärtner et al., 2017), and self-interest (Meltzer and Richard, 1981; Benabou and Ok, 2001; Alesina and Giuliano, 2011). The first of these was particularly relevant at the time, with widespread calls for solidarity from influential sources (e.g., Guterres, 2020).

The majority of individuals in our survey countries viewed vaccines as providing substantial protection against disease. Vaccines are thus a clear example of what researchers would define to be a *merit good*.[15] We consider that distributional preferences for this type of goods provide information about other situations of interest, such as economic crises in general and natural disasters. Most importantly, they provide an upper bound for distributional preferences determined by fairness considerations, as they are measured in a context where both the exogeneity of the situation and the perception of vaccines as a good is broadly shared.

Our empirical analysis focuses on the comparison of the preferences for vaccine distribution declared by individuals with higher and lower cognitive abilities. We take advantage of the unique longitudinal and high-frequency information from the COME-HERE survey covering five European countries (France, Germany, Italy, Spain, and Sweden: see below for details). The wide variety of information in the survey allows us to control for individual characteristics other than cognition that might lie behind the correlation.

Opinions on vaccine distribution for the World, the EU, and across individuals within their country of residence were collected in March 2021, when vaccine-distribution schemes were hotly debated (see Figure 2.1b).

The questions were designed to distinguish schemes based on circumstances from those based on efforts.[16] In particular, the questions allow us to evaluate the prevalence of preferences for distributional schemes that prioritize circumstances (i.e, the vulnerability of the population) versus those that value effort more (i.e., taking preventive measures to reduce the spread of the virus). Around 34% of individuals prioritized circumstances in all three vaccine questions, and for high-cognition individuals this figure is 10.4 percentage points (p.p.) higher.

Cognition was measured seven months before vaccine opinions, in August 2020, through a

[15] Merit goods are commodities that are judged to be deserved by individuals irrespective of their ability or willingness to pay for them. In Musgrave (1959, p. 13), merit goods satisfy needs '*considered so meritorious that their satisfaction is provided for through the public budget, over and above what is provided for through the market and paid for by private buyers'*. For a more recent conceptualisation of the term see Ver Eecke (2003).

[16] In line with the literature, we consider circumstances as the factors that are beyond individual's responsibility, and effort as those for which individuals are deemed responsible. For a review on these ideas and their application to perceptions of fairness in distribution, see Pignataro (2012); Roemer and Trannoy (2015); Ferreira and Peragine (2016); Ramos and Van de gaer (2016), and the references therein.

Cognitive Reflection Test (CRT) that assesses the type of cognitive ability that relies on deliberate and conscious thought (Frederick, 2005). The test consists of 3 questions, all of which have an intuitive, but incorrect, response. The correct responses require some judgement. CRT test results are consistently correlated with those from other more complete-tests of cognitive ability (Frederick, 2005; Brañas Garza et al., 2012), and are predictive of decision making, such as strategic sophistication (Besedeš et al., 2012; Carpenter et al., 2013) and behavioral biases (Oechssler et al., 2009; Hoppe and Kusterer, 2011).[17] Between 17.2% and 32.3% of the sample in each country answered at least 2 of the 3 cognitive questions correctly: we call these high-cognition individuals. We will also see whether our results are robust to considering as high-cognition only those individuals who answered all three questions correctly (between 6.6% and 13.2% in each country).

We find that high-cognition individuals favor vaccine distribution schemes within their country of residence that prioritize vulnerable populations over other schemes emphasising individual preventive behavior to avoid infection. These priorities are in line with their preferred distribution within the EU and across the World. Controlling for basic socio-demographic characteristics, the individual's COVID-19 history, reported concerns about COVID-19 infection, and confidence in the national health system to handle the pandemic, high-cognition individuals are 11.2 p.p. more likely to support schemes that favor circumstances in all scenarios, which figure is 35% above the mean.

These preferences are not driven by individual benefit (high-cognition individuals do not favor schemes that would grant them earlier vaccination) or vaccine-hesitancy. We instead suggest that they reflect pro-social preferences and behavior of high-cognition individuals, as well as their perceptions of lower equal opportunities in their country of residence.

The remainder of the paper is structured as follows. Section 2.2 describes the data and provides basic descriptive statistics. Section 2.3 presents the empirical strategy, and the results appear in Sections 2.4 and 2.5. Last, Section 2.6 concludes.

2.2 Data and Descriptive Statistics

[17] Measuring cognitive ability is not straightforward (Carroll, 1993; Jensen, 1998; Colom et al., 2002). There are a number of distinct traits to be measured, which are evaluated by different tests (e.g., Need For Cognition, Wonderlic Personnel Test, Raven Advanced Progressive Matrices). A common feature of these is their aim to capture a generalization of the skills needed to succeed in tasks that require information processing. These tests are usually long and time consuming, restricting their widespread use. One test that overcomes this drawback is the Cognitive Reflection Test, based on the dual-system theory of Kahneman and Frederick (2002). The CRT questions have an intuitive incorrect response that results from a rapidly-executed cognitive process. However, the correct response requires the individual to apply deliberative and conscious thought.

2.2.1 Data

We use data from the COME-HERE (COVID-19, MEntal HEalth, REsilience and Self-regulation) panel survey collected by the University of Luxembourg starting in April 2020. The survey is representative of adults in France, Germany, Italy, Spain, and Sweden.[18] Respondents completed on-line questionnaires lasting around 20 minutes each. The survey collects information at both the individual and household levels, and is longitudinal. Ten survey waves have been carried out at the time of writing. The first wave was conducted in April 2020, and the most-recent in December 2022. Under 15% of participants of our sample in the first wave failed to complete an additional wave, and over half have been surveyed at least five times (see Annex D for more details on respondents' participation rates). Ethics approval for the study was granted by the Ethics Review Panel of the University of Luxembourg.

The primary objective of the survey is to collect individual information on living and mental-health conditions during the COVID-19 pandemic. Besides information on standard socio-demographic characteristics (e.g., age, gender, educational attainment, employment status, and household income), the survey includes questions related to perceptions and well-being. In addition, specific modules were included in each wave to address a variety of topics. Notably, in March 2021 the questionnaire included questions on preferences for vaccine distribution, and in August 2020 questions to measure individual's cognitive ability. We describe the key variables for our study below.

Cognitive Ability. The third wave of COME-HERE, carried out in August 2020, includes the three standard questions of the Cognitive Reflection Test, as shown in Figure E.1 in the Annex. All of the questions have both a correct and an intuitive (but incorrect) answer. Following the usual procedure, we weight each question equally. We also account for possible errors-in-reporting driven by the units of measure used in question one, which have also been detected in previous studies (Sirota and Juanchich, 2018).[19]

Preferences for Vaccine Distribution. At the time of concern about limited vaccine availability in Europe, we introduced three questions about individual preferences for COVID-

[18]The data is collected by Qualtrics and fulfill many high standard criteria. The respondent's IP addresses and electronic fingerprints are checked to discard duplicated observations. Also, information from surveys that are completed abnormally quickly is dropped. The samples are nationally representative, stratified by age, gender, and region of residence. Particular efforts are made to contact hard-to-reach groups (via specialised recruitment campaigns through local networks).

[19]A common ambivalence in CRT tests is the response 0.05 cents in question 1, as participants mistake the unit of answer (cents) for dollars (Sirota and Juanchich, 2018). In our data, a non-negligible share of the answers for question 1 reflect this unit-of-answer mistake. See notes in Figure E.1 and Table E.1 for further details

19 vaccine distribution (Wave 5, in the field in March 2021).[20] These referred to vaccine distribution within the respondent's own country, between EU member states, and across the World. The questions were designed to capture the two main factors behind equality of opportunity: circumstances, factors beyond the individual's control, and efforts, those that result from individual's choices. There is more equality of opportunity in a society the larger the part of effort relative to circumstances in determining individual outcomes such as education or income. The survey question asks respondents to choose among options that give vaccination priority to population groups that differ in the effort they exert (taking more or less care in avoiding infection) or their circumstances (being more or less vulnerable, or front-line workers). The effort variable in the question on vaccine distribution between EU countries is the stringency of the country's lockdown measures, and the circumstance variable is the percentage of the population who are vulnerable. Last, the question on how vaccines should be distributed across the World allows respondents to choose the criteria that should be used to decide how to pay for the vaccines (as a percentage of the country's GDP, or otherwise) and how to distribute them across the World (according to their needs, or to their financial contribution to the purchase of the vaccines).

The exact wording of the questions appears in Figures F.1, F.2, and F.3 in the Annex. The labels for each response, used throughout the rest of the document, are described in Table F.1 in the Annex.

Other individual variables. The empirical analysis includes a number of other variables. Basic socio-demographic variables (country of residence, sex, age, educational attainment) were collected in the first wave, while questions on employment, occupation, and household income appear in each wave (see tables in Annex D for descriptive statistics of these variables in our sample). We also use regularly-collected information on COVID-19 history, perceptions of its consequences, and related behavior (e.g., testing and compliance with preventive measures). Finally, we complement our analysis with information collected in a variety of special modules.[21] The topics include individual risk preferences, patience, pro-social behaviors (e.g., trust in others and hypothetical donations), inequalities (e.g, perceptions regarding the income-generation process and the government's efficiency in redistributing, and income comparisons), politics (e.g, perceived and desired public budget allocations), social identity, and fairness.

[20] In early February 2021, the EU proposed allowing governments to block vaccine exports due to limited production capacity, and one large European producer reported production shortfalls. See, for instance, https://www.ft.com/content/1b2afe60-b5e6-456d-98e0-313fe664d0b9 for a journalistic account of the situation.

[21] The timing of the data collection in each module is different: some variable were collected before the main outcomes in our analysis, and others afterwards. We discuss this in the results section.

2.2.2 Descriptive Statistics

The descriptive statistics for the CRT test scores are presented in Table 2.1a. The percentage of correct answers ranged from 18.5% to 32.8% for each question. Over half of the respondents answered all questions incorrectly (56.0%), while 9.0% answered them all correctly. These values place our sample on the left tail of scores observed in this test.[22]

Table 2.1: Descriptive statistics

(a) Cognitive Reflection Test

	Share
Panel A. Individual questions	
Bat & Ball	18.5
Machines	32.8
Lily pads	30.3
Panel B. Aggregation	
Score = 0	56.0
Score = 1	21.0
Score = 2	13.9
Score = 3	9.0

Notes: Sample size is 5,541 for all rows.

(b) Vaccine distributions prioritizing circumstances

	Share (1)
Panel A. Individual questions	
World	51.7
EU	67.6
Country	82.6
Panel B. Aggregation	
Sum = 0	5.3
Sum = 1	21.4
Sum = 2	39.3
Sum = 3	34.0

Notes: This table lists the population shares for preferring vaccine-distribution schemes that prioritize circumstances. Panel A shows the responses to each individual question. Panel B shows the total number of responses to all three questions. The labels used in the rest of the document are explained alongside the question descriptions in Table F.1. The sample size is 4,950 for all rows.

These test scores convey useful information. They are positively correlated with educational attainment (Figure E.2b) and income (Figure E.3), in line with previous work (Heckman et al., 2006). Respondents with postgraduate qualifications scored 0.31 points higher than the average, while those whose with Secondary-school qualifications at most scored 0.20 points below (both differences are significant at the 95% confidence level). The scores also differ along other socio-demographic dimensions: men score significantly higher (see Figure E.2d), as is common for this type of test (Frederick, 2005; Zhang et al., 2016; Brañas Garza et al., 2019); and the Northern countries (Germany and Sweden) outperformed the rest (see Figure E.2a).

[22] Frederick (2005) collects test scores in different locations in the US and in one University in Spain, finding a mean percentage of respondents with no correct answers of 33% (ranging from 7% to 64%). The analogous figure for all correct answers is 17% (from 5% to 48%). The scores for Spain are similar to those for Spain in our sample. In a recent meta-study (Brañas Garza et al., 2019) of 118 CRT results covering 45,000 participants, and find that, 38% of respondents answer all questions incorrectly, and 18% answer all of them correctly.

Based on the CRT test results, we define individuals with scores of 2 and 3 (22.9% of respondents) as being high-cognition. Table E.4 in the Annex shows how basic socio-demographic characteristics and attitudes vary between individuals with low and high CRT scores. The cognitive-able are more risk-averse and more patient, but do not differ significantly in their trust towards others. This is consistent with earlier work showing that individuals with higher IQs are more patient and more risk-averse (Potrafke, 2019).[23] Table 2.2 shows that high-cognition individuals were equally likely to have had COVID-19 or to be close to someone who became ill or died during the pandemic. However, their perceptions about the pandemic and society differ. They are more prone to think inequality of opportunities restrict the possibility of economic success, and that luck matters for how well an individual does economically in life, despite having similar ideals on how much it should matter.

Table 2.2: Group comparison. COVID-19 variables

	Total sample	High CRT score	High vs. Low
Panel A. COVID-related history			
Tested for COVID-19	.334	.284	-.036
			(.023)
Had COVID-19	.085	.089	.006
			(.015)
Close to someone sick	.066	.070	.011
			(.012)
Close to someone dead	.100	.096	.003
			(.016)
Panel B. COVID perception			
Worried about getting COVID-19	.431	.360	-.072***
			(.016)
Worried about severe COVID-19	.386	.305	-.086***
			(.016)
Health system coping capacity	.628	.666	.040**
			(.014)
Panel C. COVID-related behaviors			
Following measures	.824	.835	.028**
			(0.013)

Notes: All responses are contemporary to those of vaccine distribution. Differences are controlled for basic socio-demographic characteristics. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[23] Other work, however, has found that cognitive ability is positively related to willingness to take risks and patience (e.g., see Frederick, 2005; Burks et al., 2009; Dohmen et al., 2010; Benjamin et al., 2013). However, more recently Andersson et al. (2016) shows that the relationship between cognitive ability and risk preferences may be spurious, due to bias from noisy decision making.

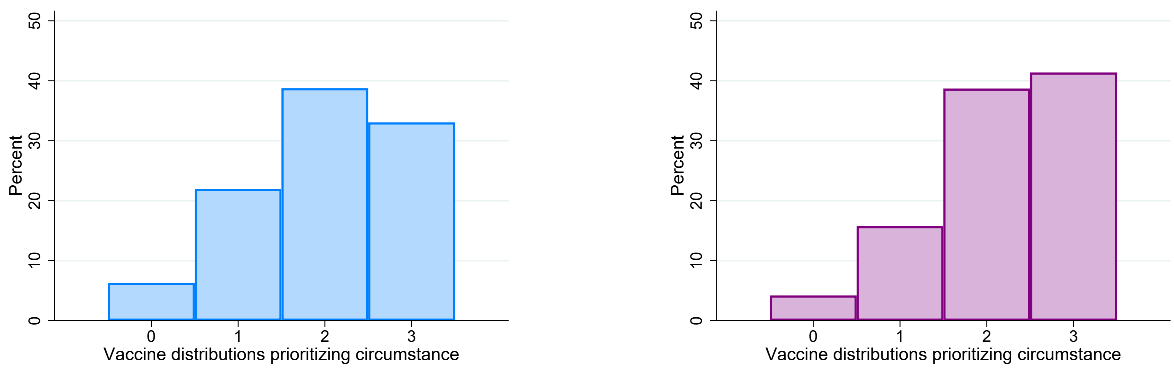
Table F.2 in the Annex lists population shares for each response in each of the three questions related to the COVID-19 vaccine distribution. The responses to these three questions can be categorized according to how individuals prioritize between circumstances and efforts. Individuals are classified as giving priority to circumstances (falling outside individuals or countries responsibility) if they answer: distribute vaccines according to 'Needs' in the case of distribution across the World, to 'Population' and 'Vulnerability' across the EU, and to 'Vulnerability' and 'Vulnerability and Carefulness' in the case of vaccine distribution within the country. Table 2.1b displays the population shares for these responses to each question, and the aggregate measure. Around 34% of the population preferred distribution schemes based on circumstances in all questions, while 5.3% always prioritized vaccine distribution based on country or individual effort.

These answers provide relevant information, not only for the particular case of vaccine distribution during the COVID-19 pandemic, but also in other situations. In our data, those who always put circumstances first for vaccine distribution tend to be more-active in non-governmental organizations that promote the common good, and are more supportive for income redistribution (see Figure F.5 in the Annex).

High-cognition individuals are more likely to favor these replies in all of the three questions. Figure 2.2 shows the distribution of the number of preferred vaccine-distribution schemes prioritizing circumstances in the total sample and for high-cognition individuals. The distribution for high-cognition individuals is slightly skewed to the right. The results for each individual question are shown in Figure F.4 in the Annex.

Figure 2.2: Vaccine distributions prioritizing circumstances

(a) Total sample **(b) High CRT score**



Notes: These figures plot the shares of the population preferring vaccine-distribution schemes that prioritize circumstances in the total sample and fo those individuals with CRT scores of 2 and 3 (high score). The CRT scores were measured in August 2020, and preferences for vaccine distribution in March 2021. The sample size is 4,317 for the total population and 989 for population with High CRT score.

2.3 Empirical Strategy

We estimate a linear-probability model for support for prioritizing circumstances in all vaccine-distribution schemes in the following model for $(i = 1, \ldots, N, j = 1, \ldots, M)$,:

$$y_{ij} = High\_CA_i\beta + X_i\gamma + \lambda_j + \epsilon_{ij} \tag{2}$$

Here y_{ij} is a dummy for the total support by individual i from country j for vaccine-distribution schemes prioritizing circumstances, $High\_CA_i$ a dummy variable for individual i scoring 2 or 3 in the CRT, X_i a vector of individual characteristics with one as the first element, λ_j the country of residence fixed-effects; and ϵ_{ij} the error term.

Preferences for vaccine distribution were assessed in March 2021, while cognition test scores were measured seven months earlier in August 2020. We control for time-invariant socio-demographic characteristics measured in April 2020 (sex, age group, and educational attainment) and time-variant characteristics collected at the same wave as vaccine-distribution preferences (employment status, occupation, and household income). We also include pandemic-related variables, such as the history of COVID-19 infection, concerns about getting it, and confidence in the national health system to cope with the pandemic. We will present robustness checks including fewer or no controls.

The main parameter in Equation 2, β, captures the correlation between being a high-cognition individual and vaccine-distribution preferences. This reflects both the causal effects of cognition and that of other variables correlated with cognition. As is usual in the literature, we cannot control for all of the potential confounders as some are unobserved in our data.[24] We do however check that the correlation is robust to a number of observable variables. Given the large number of observables available, we have some confidence that we have identified a real effect.

To check robustness to the functional form, we estimate a probit model of the probability of supporting all schemes prioritizing circumstances and an ordered probit model for the number of distribution schemes where circumstances are prioritized. We last estimate the support for each specific vaccine-distribution scheme K in $(k = 1, \ldots, K)$ referring to the World/EU/country $(q = 1, \ldots, Q)$ via separate multinomial logit models, which allow us to account for correlation between the answers to each question without imposing an order on the dependent variables.

[24] Despite the measurement of cognition preceding that of our outcome variables, it may well be determined by unobservable variables. Cognition measured during adulthood reflects early-life conditions and long socialization and learning processes. We cannot account for all of these.

These are based on the following:

$$P(y_{ijq} = k \mid High\_CA_i, X_i, c_j) = G(\cdot) \tag{3}$$

with k discrete responses for question q; and c_j being the country of residence. We derive the index models $G(\cdot)$ from the following underlying latent model:

$$y^*_{ij} = High\_CA_i\beta + X_i\gamma + \lambda_j + \epsilon_{ij}. \tag{4}$$

We define $G(\cdot)$ to reflect the three types of outcomes above. We present MLE coefficients of $High\_CA$ in each model and the marginal effect for the probability of each answer.

2.4 Results

2.4.1 Main results

We first discuss the estimates for the total support for vaccine distribution that prioritizes circumstances, where the latter reflects answering that (i) countries should contribute to vaccine purchase according to their wealth, (ii) EU countries should receive vaccines in proportion to their clinically-vulnerable population, and (iii) clinically-vulnerable individuals in a country should be vaccinated first. High-cognition individuals are 10.3 p.p. more likely to support these types of schemes (see Table 2.3). The coefficient is precisely estimated (s.e.0.026). Controlling for basic socio-demographic characteristics and the COVID-19 related variables (the history of COVID-19 infection, concern about getting COVID-19, and confidence in the national health system), slightly increases the estimate to 11.7 p.p. (s.e. 0.025). This estimated gap is sizable, being 35% above mean support.

Our initial results continue to hold in ordered probit regressions of the intensity of preferences (see Table G.1). High-cognition individuals are less likely to prefer 0 or 1 distributional schemes based on circumstances, with the former figure being 75% lower than the mean figure. As above, they are also more likely to prefer that all three schemes be focused on circumstances.

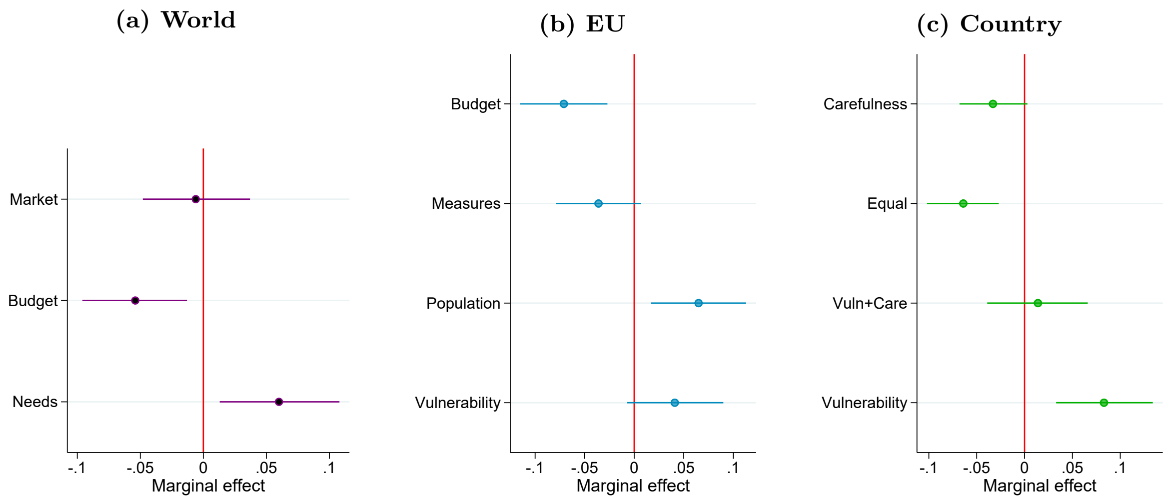
We obtain similar results considering each individual response. Figure 2.3 plots the marginal effects from the high-cognition dummy for each type of vaccine distribution, controlling for socio-demographic and COVID-19 variables. The tables underlying these figures appear in the Annex (Tables G.2, G.3, and G.4).

Table 2.3: Total support for distributional schemes prioritizing circumstances

	LPM			Probit	Margins
	(1)	(2)	(3)	(4)	(5)
$High\_CA$	.103***	.128***	.117***	.336***	.112***
	(.026)	(.025)	(.025)	(.071)	(.023)
Socio-demographic			X	X	X
COVID-19 related		X	X	X	X
N	2,511	2,511	2,511	2,511	2,511
R^2/pseudo-R^2	.009	.068	.077	.064	-

Notes: This table reports the coefficients for total support for vaccine-distribution schemes that focus on circumstances on a dummy for CRT scores of 2 or 3. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317 in the estimation sample. Columns 1 to 3 report estimates from a linear-probability model. Column 4 reports estimates from a probit model. Column 5 reports the marginal effect at the mean. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence; the COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2.3: High cognitive ability marginal effect



Notes: These figures plot the marginal effects for the $High\_CA$ dummy for each vaccine-distribution question. All regressions control for 'Socio-demographic' and 'COVID-19 related' variables, as defined in Table 2.3. The 95% confidence intervals are constructed with standard errors calculated via the Delta method.

The figure shows, for example, that high-cognition individuals are 8.4 p.p. more likely to give priority to vulnerable populations in the vaccine distribution in their own country (see Table G.4). These preferences are consistent across vaccine-distribution questions (see Tables G.2, G.3, and G.4). Similarly, high-cognition individuals are less likely to prefer vaccine-distribution schemes based on effort. For example, they are 3.3 p.p. less likely to prefer a vaccine distribution scheme in which those who were more careful during the pandemic receive vaccines first (Table G.4). They are between 5.4 p.p. and 7.4 p.p. less likely to favor the budget as a factor for vaccine distribution between countries in the World or the EU, as shown in Tables G.2 and Tables G.3).

2.4.2 Robustness checks

We further test the robustness of the results to different classifications and model specifications.

Alternative high-cognition group. We check that these results are robust to the definition of high cognition. Annex G includes estimates (i) defining as high cognition individuals those who answer all three questions correctly (9% of the population) and (ii) using CRT scores as a categorical independent variable. For (i), the coefficients remain fairly similar and precisely estimated: ranging from 0.098 (s.e. 0.035) to 0.118 (s.e. 0.038), depending on the controls included (see Tables G.6, and G.7). For (ii), with a categorical CRT variable from 0 to 3, the stylized facts above mostly continue to hold (see Tables G.8), with the estimated coefficients for CRT scores of 2 and 3 being very similar.

Alternative classification of vaccine-distribution preferences. We also consider a tighter criterion for classifying a response as 'prioritizing circumstances over effort'. We limit these to: 'vaccines should be distributed according to each country's needs' (Needs in Table C.1) and 'proportional to the member state's clinically vulnerable population' (Vulnerability in Table C.1). With this definition, the mean share of population always prioritizing circumstances drops from 34 to 8.4%. The high-cognition coefficient is now significantly smaller, but remains positive and significant. The coefficient on a high CRT score ranges from 0.032 to 0.39, depending on the controls. With all of the controls, this is 3.4 p.p. (see Table G.9), corresponding to support around 40% above the mean.

Additional controls and specifications. We check that our results are robust to adding additional controls related to individual: (i) COVID-19 related risk factors (see Table G.10) and (ii) perceptions about COVID-19 (see Table G.11). The first set covers whether the individual has pre-existing medical conditions (cancer, lung diseases, heart diseases, and diabetes), is a front-line worker, and follows recommendations to prevent the diffusion of the virus. The second set captures individuals' reported concerns about catching COVID-19 and their perceived probabilities of different outcomes if they do catch it. Our results are robust to including all, none or some of these two set of controls, as well as controlling for age as a continuous variable, and including additional controls for those aged 60 and over.

2.4.3 Heterogeneity analysis

We explore heterogeneity by socio-demographic characteristics (see Table G.5) by introducing interaction terms between high cognition and sex, age, employment status, household income, educational attainment, and country of residence. While the main coefficient remains positive, precisely estimated, and similar to that in the baseline specification, the interaction terms are very imprecisely estimated and relatively small for all variables except employed and income. We conclude that there is no significant heterogeneity in the high cognition coefficient for the support of distributional schemes prioritizing circumstances.

2.5 Mechanisms exploration

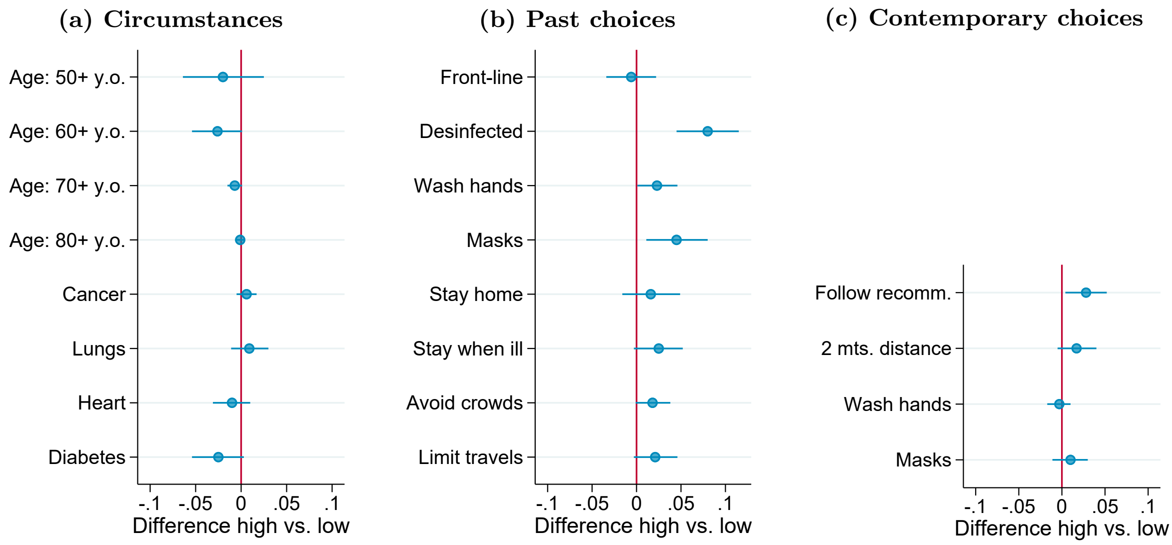
Preferences for vaccine distribution emphasizing circumstances over outcomes or effort can stem from a number of sources. In this section we provide evidence that high-cognition individuals' preferences over vaccine distribution are driven by their concerns about those who are more vulnerable, as opposed to self-interest. We lend weight to this reading by ruling out alternative causes related to self interest and that may yield similar responses: scheme convenience, differential eligibility status, early-adoption aversion, and differential cost perceptions. We also show that individuals favoring vaccine distribution according to circumstances report other-regarding preferences in other survey questions: the perception of equality of opportunities, social participation, and support for redistribution.

Table 2.6 lists the baseline results (column 1) and those including controls to test for each of the four mechanisms noted above (columns 2 to 5). Column 6 includes controls for all four mechanisms at the same time.

Scheme convenience. The proposed vaccination schemes favor groups with particular characteristics, for example front-line workers or those who took more care during the pandemic. Individual preferences may therefore take into account their own benefit. If these characteristics are positively correlated with cognition, our findings could be driven by self-interest. Our baseline regression includes a number of controls to address this concern. We further check for differences between high- and low-cognition individuals that could lie behind the responses with respect to the characteristics specifically mentioned in the vaccine questions: clinical vulnerability, front-line workers and care taken during the pandemic to avoid infection.

The high-cognition individuals in our sample are not much different in terms of medical vulnerability to COVID-19. Graph 2.4a plots the differences in age-groups and prevalence of medical conditions. The percentage aged over 60 is slightly lower in the high-cognition group, but the percentage over 80 is the same. There are no significant differences in the prevalence of cancer, lung, and heart diseases between the two groups, or in the share of front-line workers. COVID-19 avoidance behaviors do however differ slightly between groups (see Graph 2.4b). High-cognition individuals were slightly more careful at the beginning of the pandemic, with significant differences for disinfecting surfaces, washing hands, and acquiring masks. By the time the distribution preferences were elicited, these differences were smaller, although the cognitive-able remained slightly more likely to follow recommendations (see Graph 2.4c).

Figure 2.4: Differences in circumstances and choices



Notes: These figures plot the estimated differences between individuals with CRT scores of 2 and 3 (high score) and individuals who score 0 and 1 (low score) controlling for socio-demographic characteristics (see details in Table E.4). Circumstances refer to age and declared medical conditions in April 2020 (no age controls are added). Past choices refer to front-line occupation (health services) and COVID-19 related behaviors in April 2020. Contemporary choices refer to COVID-19 behaviors in March 2021. The bars refer to 95% confidence intervals with robust standard errors.

In short, high-cognition individuals are mostly not affected differently when vaccine distribution prioritizes the medically vulnerable and front-line workers, although they might have been somewhat favored if those who took less care were punished.[25] Table G.10 shows that our baseline results are unchanged when including these variables. The difference in the estimated coefficient is small and only statistically significant, at the 10% level, when controlling for adherence to recommendations to prevent COVID-19 spread. When including all three controls, the coefficient falls very slightly to 0.110 but remains very precisely estimated (s.e. 0.022).

[25] The same holds for vaccination orders across countries. Our sample subjects live in countries that are richer, have larger populations, and contribute more to the EU budget (see Table D.6). In 2019, Germany, France, Italy, and Spain were the top four countries in the EU in terms of GDP, population, and total population above 65, and budget contribution to the EU in the 2014-2020 period (excluding Great Britain). Sweden ranked 12th in total and old population, and 8th in EU-budget contribution. The five countries are in the top 25 wealthiest countries in the World in 2019, measured by total GDP in current USD.

Actual eligibility. We further check if responses are self-interested by exploring differences by vaccine accessibility. At the time the preferences were elicited, some people were already eligible for vaccination while others were not. These eligibility differences, which might be correlated with cognition, could affect responses. Those who were not eligible may have been in favor of schemes that accelerated their vaccination elegiblity.

We use information on pandemic policy responses from the Oxford COVID-19 Government Response Tracker (OxCGRT).

We exploit cross-country, -time, and -individual variations in vaccine eligibility, based on age group, medical condition, and front-line occupations. Merging individual information to government policies allows us to derive eligibility status at the time of the survey.[26]

Table 2.4: Vaccination eligibility

	Total sample	High CRT score	High vs. Low
	(1)	(2)	(3)
Contemporary: March 2021	.085	.077	-.009
			(.014)
3 months after: June 2021	.786	.835	.029
			(.021)
7 months after: October 2021	1.000	1.000	.

Notes: This table describes the declared COVID-19 vaccine eligibility of the analysis sample. Columns (1) and (2) show the means, and column (3) the differences between individuals with CRT scores of 2 and 3 (high score) and those who score 0 and 1 (low score) controlling for socio-demographic characteristics (see the details in Table **??**). Vaccine eligibility in March 2022 is excluded, as it is the same as that in October 2021: universal access. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

There was little eligibility at the time the vaccine-distribution questions were asked, and distributed similarly by cognition (see Table 2.4): 7.7% of high-cognition individuals were eligible, as compared to 8.5% of the others. These figures were respectively 83.5 and 78.6% three months after the survey took place (June 2021). We see in Table 2.6 that controlling for vaccines access (eligibility) does not affect the differential response of high-cognition individuals.

Early adoption aversion. If responses were not driven by the desire to get vaccinated first, they may have been driven by the desire to delay it. Vaccine hesitancy has been observed for different subpopulations throughout the pandemic (Troiano and Nardi, 2021), fueled by

[26]We consider people diagnosed with cancer as those medically at risk. Oncology patients were prioritized in all countries in our sample due to greater mortality risk if catching COVID-19. We consider workers in the health sector as front-line workers.

uncertainty (short and long-term effects, efficiency, and immunization status). Some people could have been more averse to being among the first to receive the COVID-19 vaccine. For each specific individual, however, delaying vaccination means prioritising circumstances or effort differently. Although there is no difference in circumstances across the two groups, high-cognition individuals took slightly more care during the pandemic. Therefore, if anything, high-cognition individuals would be in favor of prioritizing circumstances (and not effort) if they wished to delay their own vaccination. In order to rule out vaccination hesitancy as an explanation, we use information on concerns regarding vaccines and declared vaccination status 3, 7, and 12 months after vaccine-distribution responses.

We first analyze self-reported concerns for not taking the COVID-19 vaccine one year after the vaccine-distribution questions were asked. These include side effects from the vaccines, inefficiency, safety, needle phobia, and conspiracy theories, among others. The share of people expressing any of these concerns is small (under 5% for any motive). We find no statistical difference for high-cognition individuals (see Figure E.6 in the Annex). In addition, although the gap is not statistically significant, high-cognition individuals systematically express fewer concerns about COVID-19 vaccines.

We also explore vaccination rates 3, 7, and 12 months after the responses: these are higher for high-cognition individuals, especially in the first months (see Table 2.5). The cognitively-able are more vaccinated 3 months and 7 months later (3.6 and 2.8 p.p. above the mean, respectively). This gap reduces to 1.8 p.p. one year after and becomes insignificant. Thus, if anything, high-cognition individuals are more likely to be early adopters of the COVID-19 vaccine, so that vaccine reluctance is not a plausible explanation of our main findings. This difference is also not explained by differential access to vaccines, as there is no significant difference in this between groups (see Table 2.4).

The costs of infection. As shown above, the objective COVID-19 risk factors (measured by age, pre-existing medical conditions, and being a front-line worker) do not seem to explain the differences we find. However, individuals may differ in their beliefs about their health prospects in the pandemic. The most cognitive-able individuals perceived risks differently (see Table 2.2). They were less worried about catching COVID-19 and getting seriously ill from it, trusted more the health system's capacity to cope with demands from the pandemic more, and believed that other's probabilities of suffering severe COVID-19 were lower. In short, the cognitive-able were more confident about what could happen throughout the pandemic (see Figure E.4a, Figure E.5a, and Figure E.4b in the Annex). These perceptions do not seem to reflect over-confidence,

Table 2.5: Vaccination status

	Total sample (1)	High CRT score (2)	High vs. Low (3)
3 months after: June 2021	.859	.895	.036*
			(.019)
7 months after: October 2021	.927	.945	.028*
			(.015)
12 months after: March 2022	.922	.933	.018
			(.017)

Notes: This table describes the declared COVID-19 vaccination status in the analysis sample. Columns (1) and (2) show means, and column (3) the differences between individuals with CRT scores of 2 and 3 (high score) and those who score 0 and 1 (low score) controlling for socio-demographic characteristics (see the details in Table ??). Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

as they match the official statistics on the consequences of COVID-19.[27]

Including concerns and perceptions about COVID-19 slightly reduces our baseline coefficient at a 10% level: the high cognition coefficient with these controls ranges from 0.122 to 0.112 (see Table G.11).

Prosociality. Having ruled out other alternative explanations, we suggest that our findings show that high-cognition individuals have greater other-regarding preferences (concerns towards others). We appeal to different variables capturing social perceptions and behaviors: perceptions about the role of luck (as opposed to effort) in outcomes and equality of opportunities, hypothetical donations to a 'good cause', and trust in people, in other's fairness and in other's helpfulness. We find that the joint inclusion of these variables reduces the $High\_CA$ coefficient by 36% (from 0.117 to 0.075), a difference that is statistically significant at a 1% level (see Table 2.6).

In column 6 of Table 2.6 we include all of the individual controls that appeared singly in columns 2 to 5. The high-cognition coefficient in column 6 is statistically identical to that in column 5, which only controls for prosociality: 0.080 (s.e. 0.023) versus 0.075 (s.e. 0.022). These findings suggest that greater social concerns are a significant part of the explanation of why the most cognitively-able individuals prefer COVID-19 vaccine distribution schemes prioritizing circumstances.

[27]Estimates for the infection-hospitalization ratio (IHR) range between 2% and 3% (Salje et al., 2020; Lapidus et al., 2021; Le Vu et al., 2021; Menachemi et al., 2021). These results are based on registered hospitalizations and COVID-19 positive cases derived from antibodies prevalence in representative samples. The latter takes into account the underreporting of COVID-19 cases (mainly due to little testing of people with mild or no symptoms). The mean believed IHR for total population in our estimation sample is 11.6%; for high-cognition individualsthis drops to 7.3%.

We further explore which social attitudes are the main drivers. We find that perceptions of equal opportunities drive these findings (see Table G.12). In particular, perceptions of equality of opportunity capture 27% of the overall effect, and reduce the coefficient from 0.117 to 0.085. The other variables related to social perceptions and behaviors (importance of luck, hypothetical donations, and trust) only slightly alter the main coefficient. As such, the relationship between cognition and preferences for vaccine distribution favoring circumstances partly reflects perceptions about the equality of opportunities in society.

We use additional information from more recent COME-HERE waves, and find that the desired level of equality of opportunities does not differ by cognition (see Table E.4). In that sense, the vaccine-distribution preferences of the cognitively-able do not reflect preferences over equality, but rather that they are more negative about the prevalence of equal opportunities.

Table 2.6: Total support for distributional schemes prioritizing circumstances with additional controls

	(1)	(2)	(3)	(4)	(5)	(6)
$High\_CA$	.117***	.110***	.117***	.112***	.080***	.075***
	(.023)	(.022)	(.023)	(.023)	(.022)	(.022)
(+) Convenience		X				X
(+) Eligibility			X			X
(+) Cost perception				X		X
(+) Prosociality					X	X
Wald test	-	3.046	.260	2.987	25.622	18.873
p-value	-	.081	.610	.084	.000	.000
N	2,511	2,511	2,511	2,511	2,511	2,511
R^2	.077	.091	.077	.081	.115	.127

Notes: This table reports the coefficients for total support for vaccine distribution schemes that focus on circumstances on a dummy for CRT scores of 2 and 3. The dependent variable is valued 1 when all three vaccine distribution schemes favor circumstances, and 0 otherwise. Mean dependent variable is 0.317 in the estimation sample. All columns report estimates from a linear probability model. Column 1 reports estimates from our main specification. Columns 2 to 6 report estimates adding controls to the main specification. Main specification controls include sex, age group, educational attainment, occupational status, household income, country of residence, history of contracting COVID-19, concern about getting it, and confidence in the national health system to cope with the pandemic. Convenience controls include concern about catching COVID-19 (measured in March 2021) and assigned probabilities for COVID-19 outcomes (measured in August 2020). Eligibility is derived for March 2021 based on information on policy responses from OxCGRT and individual's age group, medical risk condition and front-line occupation (all of which were measured in April 2020). Cost perception controls include concern about catching COVID-19 (measured in March 2021) and assigned probabilities for COVID-19 outcomes (measured in August 2020). Prosociality controls include perceptions about role of luck (as opposed to effort), perceptions about equality of opportunity, hypothetical donation to 'a good cause', and trust in people, other's fairness and other's helpfulness, all of which were measured in March 2021. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wald test for equality of $High\_CA$ coefficient with main specification are reported, with its associated p-value.

2.6 Conclusions

Priorities in the order of vaccination are a clear example of distributional preferences. The COVID-19 pandemic context made the exogeneity of circumstances and the relevance of distribution even more salient, providing an upper-bound benchmark of the importance of the factors lying behind these preferences. This paper therefore provides a reference point for more-standard situations, as well as an approximation to the distributive preferences to be expected in future critical periods (e.g., economic crises or environmental disasters).

We focused on high-cognition subjects, who tend to have a larger say in distributional policies. We find that they support vaccine schemes that value circumstances over effort in determining who should receive vaccines first and who should pay for them. We show that our findings are largely driven by high-cognition individuals showing more concerns towards others, and provide a likely underpinning for this concern in terms of the perception of less equality of opportunity. The reasons why these individuals perceive fairness in society differently is a topic that deserves further exploration.

Our findings provide an explanation of distributional policies across societies. We show that a highly-influential group in collective decisions prioritizes those who are more vulnerable in critical moments. This could explain the ubiquitous success of policies such as safety net, food stamps, and housing assistance. While many central topics have been analyzed, others have remained largely unaddressed (e.g., environment). There are thus many open questions. Future research should explore how preferences change alongside the assessment of how critical the situation is, and what determines which situations are considered to be critical.

Chapter 3:

The complexity of being fair*

People adhere to distinct fairness views, but the understanding about the sources of such disagreement is still limited. In this paper, I focus on the complexity costs of implementing each view. I explore how fairness develops as children enter into adolescence, a period of relevant cognition change. I report from an experiment conducted with school students aged between 10 and 15. In the experiment, children decide how to distribute money between workers who completed tasks for different piece-rate payments. As children grow up, they increasingly take into account the unequal opportunities faced by the workers. I find that cognitive maturity is part of the explanation. Older and more able children are better at dealing with the complex procedures it implies: inferring counterfactual choices and incorporating them into their decisions. This leads to increased assignments for low-paid workers among meritocrats. I provide evidence on the role of the information used in their decisions. I show that drawing attention to the unequal opportunities yields no overall effect, but disclosing counterfactual choices helps closing the assignment gap across fairness views. These findings highlight the role of procedural choice on fairness adherence and introduce cognition as an additional determinant for fairness pluralism.

Keywords: fairness, children, cognition, inequality of opportunities
JEL classification: D91, D63, D83, D84

3.1 Introduction

Fairness plays a crucial role in shaping individuals' acceptance of inequality. The prevailing view in western societies is meritocratic (Alesina and La Ferrara, 2005; Almås et al., 2020; Cappelen et al., 2007; Stantcheva, 2021), by which inequalities arising from personal effort choices are fair, while those resulting from lucky circumstances are perceived as unjust (Cappelen et al.,

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2020; Konow, 2000).[28] However, effort choices are rarely detached from circumstances (Altmejd et al., 2021; Bursztyn et al., 2017; Falk et al., 2020; Glover et al., 2017; Parsons et al., 2011). Most people acknowledge the influence of unequal opportunities on effort exertion, but only part of them want to correct the resulting inequality (Andre, 2022; Bhattacharya and Mollerstrom, 2022; Cappelen et al., 2023; Preuss et al., 2022).

In this paper, I propose that procedural complexity is part of the explanation. I study how fairness develops as children grow up. I report results from an experiment on school students from ages 10 to 15, a period of intense cognitive changes (Steinberg, 2005).[29] Children decide how to distribute money between workers that completed tasks under unequal opportunities. The experiment consists of two phases. In the first phase, workers in a lab complete effort tasks for either a low or high piece-rate payment per task.After all work is done, I form pairs consisting of one unlucky worker (assigned to the low piece-rate) and one lucky worker (assigned to the high piece-rate). In the second phase, I elicit children fairness preferences using a spectator game (Cappelen et al., 2007, 2013). Spectators have to distribute earnings within worker pairs. I ask spectators to state and reveal their preferences separately. Stated preferences are directly asked. Revealed preferences are derived from the actual decisions and precede preference statements. This approach allows me to identify each spectator's fairness view and how they implement it.

Children in my sample adhere to diverse fairness views: 13% declare as egalitarians (who want to equalize income regardless of effort exerted), 11% as libertarians (who want to maintain the existing distribution), and the remaining 76% as meritocrats (who prioritize efforts for their decisions). Among the latter, two thirds focus on the efforts actually exerted, and the other third favor the efforts that would have been exerted for equal piece-rate payments. In line with recent literature, I label the first group as factual meritocrats and the second group as counterfactual meritocrats (Andre, 2022; Cappelen et al., 2023). To explore how fairness evolves, I leverage age and cognitive ability variations. The sampling plan was pre-registered. Participants comprise students in 5th to 9th grade from a private full-day school, with ages ranging from 10 to 15 years old. These children share similar schooling experiences and socio-economic background. Most entered the school at kindergarten, have received all their formal education there, live in the surrounding neighborhoods, and lack material deprivations. These features provide a clean

[28] This ideal is closely intertwined with the notion of equality of opportunity, which often contrasts with reality. Various empirical works show that individual's income, educational attainment, and overall life outcomes tend to be closely tied to their family background (Akee et al., 2019; Becker et al., 2018; Chetty et al., 2014; Chetty and Hendren, 2018; Corak, 2013).

[29] Brain develops throughout early adolescence, both in structure and function. White-to-gray matter ratio alters, multiple regions of the prefrontal cortex grow, and linkages on the whole brain expand rapidly (Paus, 2005). These changes focus on areas that are particularly relevant for executive functioning (Giedd et al., 1999), and result in marked improvements in reasoning and information processing (Keating, 2004).

group to explore how fairness preferences evolve with age and cognitive development, as there is limited scope for cofounding impact of different upbringing experiences.

I find that the share of meritocrats increases with age. Meritocrats climb from 71% among younger students (attending 5th to 7th grade) to 84% of the older students in my sample (8th and 9th grade). The increase is entirely explained by counterfactual meritocrats, who expand by 16.6 percentage points (p-value=.013). The share among older children almost doubles the one among younger ones. As a counterpart, the share of egalitarians decreases (-12.3 p.p., p-value=.005), while the share of libertarians remains stable. These results are in line with previous findings that suggest that children move towards more complex fairness views as they are more cognitively mature (Almås et al., 2010). Each fairness view is linked with a decision rule and these rules are increasingly more complex to implement. Egalitarianism prescribes an invariant decision: dividing equally. Implementing libertarianism implies maintaining the preexisting earnings in a case-by-case basis. Meritocracy is slightly more complex, as it additionally requires to assess efforts case by case and translate into earnings. And counterfactual meritocracy is even more complex, as individuals need first to infer what would have happened under equal opportunities.

I explore the role of cognitive maturity in explaining the age differences. After the spectator game, I apply a Raven's Standard Progressive Matrices (SPM) test (Raven, 1936, 2000). This test comprises 12 questions and is a commonly used assessment for measuring cognitive ability for children in this age range. Though older students score higher on average, scores are dispersed within age groups. I split the sample into two groups by the median. Differences in the prevalence of fairness views mimic the ones by age. I find that, even controlling for age group, more cognitive able children are less likely to be egalitarians (-8.6 p.p., p-value=.073) and more likely to be counterfactual meritocrats (11.2 p.p., p-value=.084). In fact, the increase in counterfactual meritocrats is mainly concentrated among older and more able children. These results suggest that cognition plays a role in the change in fairness views with age.

I show that these stated preferences are indicative of actual decisions. I exploit a strategy method (Selten, 1967; Brandts and Charness, 2011), and analyze decisions for contingent choice differences between the unlucky and lucky worker. Spectators face scenarios in which the unlucky worker completes less or (at most) as many tasks as the lucky worker and always has lower preexisting earnings. I find that spectators that declare as egalitarians assign the unlucky worker the largest share, approaching equality. Libertarians assign the lowest share, closest to the unequal preexisting distribution. Meritocrats are in between: they partially correct the unequal earnings, but do not fully equalize. Among them, counterfactual meritocrats assign a higher share to the unlucky worker. This difference is in line with expected, as this meritocratic view prescribes accounting for the increased effort provision under equal opportunities. I also show that spectators justify their decisions in line with their stated preferences. I ask participants to report the reasons behind their decisions and analyze the concepts they use. Explanations differ in key aspects. Egalitarians talk more about equality, libertarians emphasize earnings, and meritocrats favor tasks and efforts. Among meritocrats, counterfactual meritocrats are more likely to refer to luck.

Lastly, I shed light on plausible behavioral underpinnings for the change in fairness views prevalence by age. First, I focus on procedural complexity. I show that implementation consistency varies across fairness views –with counterfactual meritocracy being the hardest, but also that implementation capacity varies across individuals. Older and more able children have better implementation capacity, which facilitates their adherence to complex views, such as counterfactual meritocracy. Second, I concentrate on the additional information needed to implement counterfactual meritocracy. I show that more able children infer lower effort differences in equal opportunity scenarios, which makes that fairness view more relevant. I also find that information provision closes the assignment gap between decisions from counterfactual meritocrats and factual meritocrats. In turn, prompting children to think about counterfactual choices before making decisions has no impact, stressing how uncertainty prevents meritocrats to decide based on counterfactuals.

Related literature. My work builds and contribute to the vast literature of fairness and inequality acceptance (e.g., Almås et al., 2020; Cappelen et al., 2007, 2013; Konow, 2000; Stantcheva, 2021). These studies show that a significant share of people are sensitive to the source of inequalities. I focus on a recent extension that distinguishes within meritocrats and complement this literature by testing behavioral underpinnings for its existence. Considering counterfactual choices implies belief formation, which makes for a more complex decision strategy. My main finding shows that the prevalence of that fairness view increases alongside with age and cognitive maturity, as people find it less costly to implement.

Two strands of this literature are closest to my study. One of them finds that people partly account for unequal opportunities on moral decisions (Andre, 2022; Bhattacharya and Mollerstrom, 2022; Cappelen et al., 2023; Preuss et al., 2022). Proposed explanations include uncertainty aversion, belief biases, and lack of recognition that circumstance-dependent effort is morally relevant. My work contributes to this literature in several aspects. First, I explore how counterfactual meritocracy develops as children grow up and connect it to cognitive maturity and its implementation complexity. Second, I provide behavioral underpinnings for the (lack of) prevalence of counterfactual meritocrats. My findings suggest that procedural complexity deters some people from adhering to it, and that individual's cognition affects its adoption. I also underscore the role of uncertainty aversion, showing that while information provision is sufficient for impacting distribution decisions, counterfactual thinking is not. Third, I incorporate a measurement of stated fairness preferences into spectator games and show that it is consistent with preferences resulting from decisions. This allows to identify fairness views at an individual level and to assess its implementation.

The other strand of literature analyzes the development of social preferences in children (Almås et al., 2010; Fehr et al., 2008, 2013; Martinsson et al., 2011; Sutter et al., 2018). One important message from these studies is that fairness views evolve throughout childhood, partly due to cognitive maturity. I complement this literature by connecting these changes with age-appropriate and validated measurements of cognitive ability. I provide direct evidence that meritocrats increase alongside cognitive maturity, as proposed by Almås et al. (2010). My results also extend this literature by further disentangling meritocratic views in two types: factual meritocrats and counterfactual meritocrats. I show that the fairness view which is more complex to implement is more prevalent among older and more able children, drawing again attention to the role of cognition in fairness pluralism.

My work also relates to the automata literature in economics (Banovetz and Oprea, 2023; Enke et al., 2023; Gabaix and Graeber, 2023; Martínez-Marquina et al., 2019; Oprea, 2020). This literature shows that complexity costs determine procedural choices —i.e. the strategy that individuals adopt to implement. Importantly, these costs vary across individual cognitive ability and so does the strategy they select. For instance, this has been used to explain cooperative behavior (Jones, 2014; Rubinstein, 1986). I contribute by extending its application to explore the prevalence of fairness views. My findings that views that subscribe more complex strategies are more prevalent as individual mature both align with and add to results from this literature.

The remainder of the paper is structured as follows. Section 3.2 describes the experiment design and implementation. Section 3.3 presents the theoretical framework guiding my analysis. Section 3.4 and 3.5 show the main findings and explores plausible mechanisms. Section 3.6 concludes.

3.2 Experimental design and implementation

The experiment is designed to investigate fairness views on the distribution of income between individuals that faced unequal opportunities. I additionally collect data on belief formation concerning non-observed equal-opportunity situations, and willingness to inform about such situations. I also assign participants to different treatments to explore the effectiveness of information availability in shaping distributive decisions.

The experiment consists of two phases.[30] In the Workers phase, workers perform simple effort tasks and accumulate earnings. In the Spectator phase, spectators state their preferred distribution criteria and make decisions that can affect the income of paired workers. The analysis focuses mainly on the spectators. The workers are recruited to create realistic economic conditions.

3.2.1 Workers phase

I hire workers on *Prolific* to perform a simple effort task, based on letter-to-number encryption (Benndorf et al., 2019) and programmed in *oTree* (Chen et al., 2016).[31] Participants are paid a 2.00 British Pounds ($\sim$ 2.50 USD) base payment and can earn additional money for each succesfully completed encryption.[32]

Workers encrypt '*words*' formed by letters, based on an encryption table. They can only proceed to the next '*word*' if the encryption is done correctly. There is no limited time or opportunities to answer. Before they start working, I inform participants about two possible piece-rate for each encryption succesfully completed: low piece-rate (π^L) of 0.05 British Pounds ($\sim$ 0.06 USD), or high piece-rate (π^H) of 0.50 British Pounds ($\sim$ 0.60 USD). I ask participants to commit a number of tasks for each piece-rate. I inform participants their final payoff can be influenced by a third-party. To avoid effort decisions to be distorted in anticipation, I restrict information about when, how, why, and who is involved in the income allocation. The resulting piece-rate is randomly assigned, and participants follow-up on their commitment. Appendix I summarizes the main instrutions for the workers.

After the worker phase is completed, I form worker pairs. Each pair consists of an unlucky

[30]For summaries of the main instrutions for each phase, see Appendix H and I respectively.

[31]This word encryption task has many advantages that make it suitable for our experiment: (i) it is a simple and easy to explain task, (ii) it needs not any preexisting knowledge, (iii) it mostly eliminates the scope for guessing, and (iv) it minimizes learning after repetition.

[32]*Prolific* works with British Pounds. Participants with sufficient experience in the platform are used to it. On average, participants in my sample have previously completed 937 tasks on *Prolific*. Still, I display an approximation for United States Dollars (USD) for the sake of clarity.

worker (randomly assigned to the low piece-rate) and a lucky worker (randomly assigned to the high piece-rate).

3.2.2 Spectators phase

I invite school students to be spectators, in collaboration with a private full-day school in Montevideo, Uruguay. Students are between 10 and 15 years old. The project was granted ethical approval by the UAB Ethics Committee on Animal and Human Experimentation and the principal board of the school. Parents of involved students received a consent form asking approval for their children participation.[33] All parents gave their consent. Children were also instructed that their participation was voluntary. None refused to participate. Participants are offered prize baskets consisting of school canteen products worth 75 Uruguayan Pesos ($\sim$ 2.00 USD) and can earn additional prizes (worth up to 265 Uruguayan Pesos, $\sim$ 7.00 USD).[34]

This phase consists of two stages: distribution and belief elicitations, and surveys (see Figure 3.1). Both are taken individually on a computer through a software programmed in *oTree* (Chen et al., 2016). I start by laying out the workers phase setting and explaining the decisions that spectators will make. Instructions were read aloud previous to being provided on the computer screens. To verify that all spectators understood the setting and instructions, I ask a set of comprehension questions.[35] I only allow participation after all questions are correctly answered. Instructed teachers provide explanations if required at any part of the study. Appendix H summarizes the main instructions for the spectators.

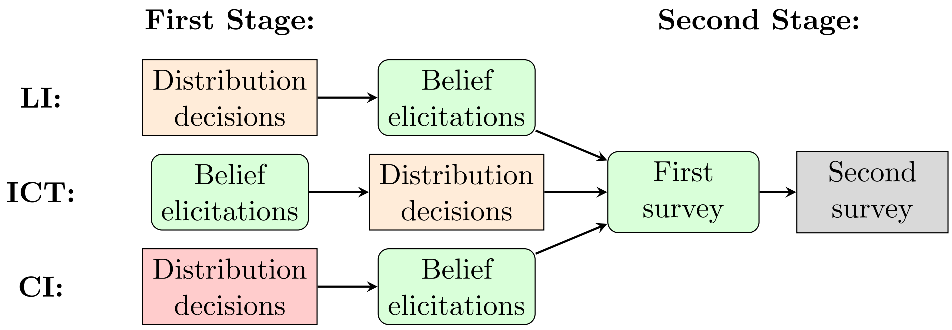
Treatment conditions. I randomly assign spectators to different treatment conditions in a 2x2 between-subject setting. Only the first stage of the spectator phase varies across treatments. Each condition consists of information provision, distribution decisions, and belief elicitations sections. Treatments differ on the information provided before the decisions and in the order in which the belief elicitation takes place. As the flow order is inconsequential under complete information, I merge the two possible treatments into one. As detailed in Figure 3.1, my design involves three treatment conditions: Limited Information (`LI`) is my control group; Incentivized Counterfactual

[33] The consent form contained information on the project and the rewards for the children, with an explicit school endorsement. No specific details on the tasks or aim of the research was communicated.

[34] The minimum (maximum) prize is worth more than 2 (8) days of average daily canteen expenditure in our sample. Average daily canteen expenditure within the sample is 32.5 Uruguayan Pesos ($\sim$ 0.87 USD), with low variance. Additional prizes are bundled together in different types of baskets, with each basket offering escalating rewards. See Appendix H for more details in the spectator phase payments.

[35] Afterwards, I also ask spectators to report how much they understood the instructions for that stage. None of the participants in my sample reported a lack of understanding of the instructions. Over 80% reported to mostly understand all of the task. I show results are robust to excluding those who failed to understand part of the instructions (see Section **??**).

Figure 3.1: Stages of the spectator phase



Notes: This figure depicts the experiment flow for the spectator phase. Each row shows different treatment conditions: Limited Information (`LI`), Incentivized Counterfactual Thinking (`ICT`), and Complete Information (`CI`). Treatment conditions differ in the first stage. Distribution decisions in yellow are with Limited Information. Distribution decision in red are with Complete Information. The boxes filled in green are parts of the experiment in which participants can increase their chances of earning additional prizes.

Thinking (`ICT`) has belief elicitations preceding distribution decisions; and Complete Information (`CI`) provides additional information on worker's performance in an equal-opportunity situation.

Distribution decisions. Spectators make distribution decisions for five scenarios with different worker pairs. Information provided for each spectator is the same for each scenario. I show all spectators the piece-rate, effort choice (i.e., tasks completed), and prexisting earnings of each worker in the pair.[36] All information is displayed using simple text, alongside graphical illustrations (see Figure 3.2).[37] For each worker pair, the total amount to redistribute is the sum of both worker's earnings. Spectators decide on the final payoff of the workers by selecting which share of the total earnings each worker would get. Decisions are made with a slider and aided by a dynamic graph.

I employ a strategy method (Selten, 1967; Brandts and Charness, 2011). Spectators are informed that their decisions can have real consequences. I announce that one of the five contingency scenarios involves a real worker pair and that decisions for the real pair can be implemented after a lottery. The last scenario refers to a real worker pair from the workers phase. The

[36]Depending on the treatment condition, spectators receive additional information. In the `LI` and `ICT` treatment, spectators are only provided with the aforementioned information. In the `CI` treatment, I complement that information by disclosing worker's task commitment for an equal piece-rate. For each scenario, I randomly choose the low or high piece-rate and show both worker's commitment for it. I maintain the same disclosure piece-rate when eliciting beliefs.

[37]The visual design was created with input from local teachers. The focus was on making the information easy to understand and the interface intuitive to use. Teachers were not on the staff of the school where the experiment occurred and they were not informed about the research's objectives. Spectators decide on a setting where money is shown as equivalent points. Point conversion rate is 0.05 GBP = 1 point. Low piece-rate is valued 1 point and High piece-rate is valued 10 points. I use points for the sole purpose of simplifying numbers for children. I explain that the points will be converted into money at the end of the experiment, but do not disclose the conversion rate.

preceding scenarios are hypothetical and displayed in random order. Spectators do not know which scenario is real and which are hypothetical.[38] The strategy method allows me to elicit merit judgements for various effort differences between the unlucky and lucky worker (see Table 3.1). I restrict the analysis to the hypothetical scenarios for consistent comparissons across spectators. Each spectator sees the same effort differences benchmarked to the real worker pair assigned.[39]

Table 3.1: Scenarios description

	Scenario			
	i	ii	iii	iv
Panel A. Effort differences				
Factual	0	5	10	15
Counterfactual	-10	-5	0	5
Panel B. Worker with higher share				
Factual	Equal	Lucky	Lucky	Lucky
Counterfactual	Unlucky	Unlucky	Equal	Lucky

Notes: This table shows characteristics of the hypothetical scenarios used in the spectator phase. Scenarios are presented to each spectator in random order. Numerical labels are used in this table only for reference. The real scenario is always presented after all the hypothetical scenarios. Panel A shows the observed and counterfactual effort difference. Differences are positive when favoring the lucky worker and negative when favoring the unlucky worker. The number of tasks presented to each spectator varies to accomodate with the reference point taken from the real workers. Panel B states the worker that exerts higher effort within the pair.

After deciding for the five scenarios, participants are randomly presented one of their decisions and asked to justify it in an open-ended form. Next, they are asked about their preferred distribution criteria for distributing within pairs. I present a close list, with simple statements, each adhering to (i) egalitarism, (ii) libertarianism, (iii) factual meritocracy, and (iv) counterfactual meritocracy. Responses are presented in random order.

Finally, spectators are offered the possibility of gaining additional information to remake decisions. Offered information is on worker's effort commitment under equal piece-rate payment. To access such information, spectators need to complete a counting-zeros task (Abeler et al., 2011). Spectators are able to take or not the opportunity. They can also give up the task in any point,

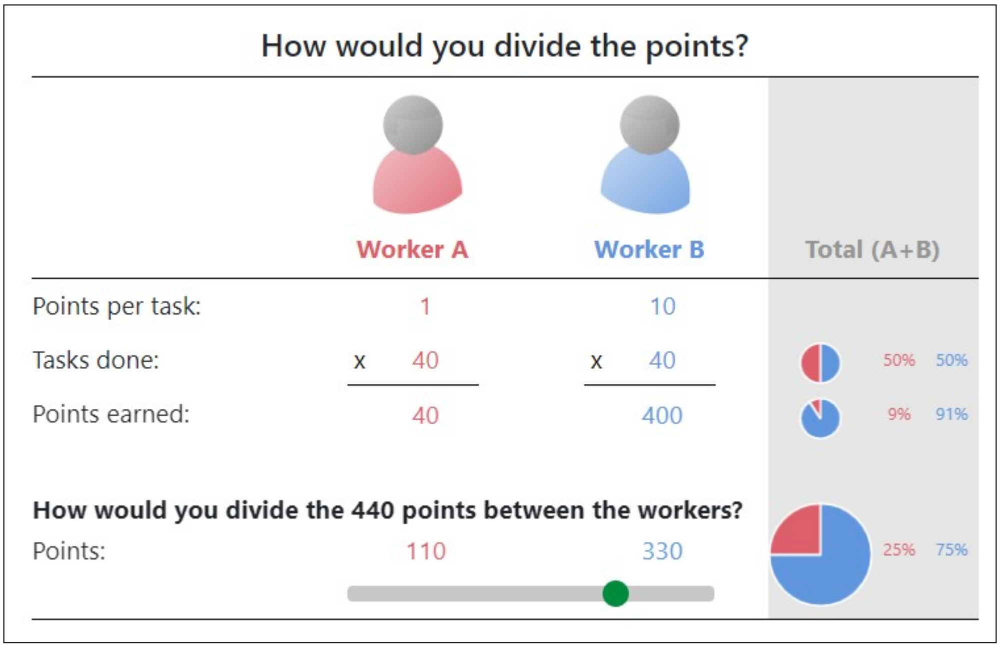
[38] I randomly select 20 spectator decisions. This implies that 1 in 10 spectators makes a decision with real consequences. I ask spectators to guess which of the scenario they are presented is real. Responses for each scenario are all around the share selected by chance (20%). The share for the correct guess is 12%.

[39] Hypothetical scenarios show effort differences between the lucky and unlucky worker of 0, 5, 10, and 15 tasks. Scenarios are constructed taking as reference point the effort of the unlucky worker in the real scenario. Efforts choices are constructed by adding multiples of 5 to the reference point. For example, if the unlucky worker in the real scenario completed 16 tasks, the hypothetical scenarios will show workers completing figures such as 16, 21, 26, or 31 tasks.

loosing access to the additional information.

Belief elicitations. Spectators elicit their beliefs on workers' task commitment for an equal piece-rate for each of the five scenarios.[40] See Figure H.4 for an example of the belief elicitation. Belief elicitation is incentivized. Spectators increase their chances of receiving additional prizes if their guess is approximately correct.

Figure 3.2: Distribution decision screen



Notes: This figures exemplifies the distribution decision screen. The figure shows a pair of workers. Piece-rate payment, tasks completed, and initial earnings for each worker are provided. Shares for tasks and earnings are automatically computed and displayed. Participants can modify the allocation by moving the slider. A dynamic graph updates with the spectator's decision. This figure correspond to the `LI`/`ICT` treatment conditions. In the `CI` treatment I additionally disclose the task commitment for a same piece-rate payment (randomly selected for each pair). See Figure H.2 for a comparisson between treatment conditions.

Surveys. Spectators answer two surveys. The first survey consists of the twelve items from Raven's Standard Progressive Matrices (SPM) test (Raven, 1936, 2000). The SPM is a non-verbal assessment used to measure cognitive ability, which has been used in various studies analyzing social behavior (e.g., Gill and Prowse, 2016; Proto et al., 2019; Lambrecht et al., 2021). Each item consists of a 3x3 matrix with a missing cell in the bottom right corner. Participants are asked to select the missing cell out of eight choices provided (see Figure H.5

[40] The equal piece-rate is randomly chosen between the low and high piece-rate for each scenario, and is the same as the one disclosed in the `CI` treatment. I ask spectators to estimate how much the worker not assigned to that piece-rate would have worked for it. Piece-rate, effort choice, and initial earnings for both workers (as previously provided) are shown. Depending on the treatment, spectators answer about their beliefs before or after the distribution decisions. In the `LI` and `CI` treatment, spectators are asked about their beliefs after the distribution decisions. In the `ICT` treatment, I elicit beliefs before the distribution decisions. I also ask participants their certainty about the estimate for each.

for an item example). Participants receive the test instructions before it begins.[41] Performance is incentivized. Participants increase their chances of earninig additional prizes if they answer correctly. The items in the test are presented in increasing difficulty order. Participants are able to navigate back and forth throughout the test to review and modify their answers as needed. The test lasts up to 6 minutes. All unanswered items are considered incorrect.

The second survey is non-incentivized and concernes age, gender, neighborhood of residence, and diverse socio-demographic questions. There is no time limit to answer this survey. After the surveys are completed, participants are thanked and dismissed. Participants pick-up their rewards when leaving. Rewards are delivered in sealed bags anonymously, based on computer's number.

3.2.3 Samples

Worker phase. I recruited 40 participants in *Prolific* on August 2023. Workers completed an average of 15.9 tasks (SD = 14.5) and earned an average of 7.13 British Pounds ($\sim$ 8.55 USD). Half of the workers were randomly assigned to the low piece-rate payment and the other half to the high piece-rate payment. Workers committed significantly more tasks for the high piece-rate (23.1 tasks vs. 11.8 tasks).[42] I form 20 pairs of workers. Each pair consists of one unlucky worker (assigned to the low piece-rate payment) and one lucky worker (assigned to the high piece-rate payment).

Spectator phase. I recruited 198 participants who attend a private full-day school in Montevideo, Uruguay. Spectators are between 10 and 15 years old and mostly live in high-class neighborhoods surrounding the school. The sampling plan was preregistered, as working with this sample allows me to hold constant many schooling and socio-economic factors that might otherwise confound the analysis.

Most students entered the school for kindergarten between ages 2 and 5, and had received their entire formal education at the school. Table H.2 in the Appendix compares characteristics of my sample with Montevidean population based on data from the 2022 Uruguayan Household Survey. Given the observed characteristics, it is reasonable to believe that spectators reside in households on the right part of the income distribution. Moreover, households are much homogenous in their lack of limitations to provide material conditions for appropiate cognitive development.

[41] I require participants to answer a small set of comprehension questions. These refer to time allocation, number of correct options per item and an illustrative item (previously used in the instructions). The test only begins after all comprehension questions are correctly answered.

[42] See Appendix I for detailed results of the worker phase.

The experiment was conducted throughout four days on September 2023. Sessions took place during regular school hours at the computer lab and lasted 40 minutes. Attendance was high for all groups (see Table H.1). With the experiment ran during regular school hours and all attending students participating, there is no self-selection. The average value of the prize basket reward was 113 Uruguayan Pesos ($\sim$ 3.00 USD).

3.3 Theoretical framework

I describe a short theoretical framework to illustrate the role of fairness views for distribution decisions in situations with limited information about the effect of circumstances over effort exertion. My framework follows Andre (2022) and Cappelen et al. (2023), which build over the distributive choice model introduced by Cappelen et al. (2007).

First, I model circumstance-dependent effort choices by workers. Then, I model spectators distributive decisions for a pair of workers under unequal opportunities.

3.3.1 Workers

Workers decide how much tasks to complete under different piece-rate payments. Total income results from the number of tasks completed and the piece-rate payment. Task completion implies effort, which I assume is increasingly costly for workers.[43] I model workers utility as dependent of total income and effort disutility. The worker i optimization problem is as follows:

$$\max_{p_i} \quad U(y_i, p_i) = y_i - C_i(p_i) \tag{5}$$

$$\text{s.t.} \quad y_i = \pi_i \times p_i \tag{6}$$

where $U_i(\cdot)$ is worker i utility; y_i is income derived from task completion; p_i is total number of tasks completed; π_i is piece-rate payment; and $C_i(p_i)$ is worker's disutility from work.

Workers utility is maximized when the marginal cost of completing an additional task equals the piece-rate payment received for an additional task. With basic assumptions, solutions are interior and workers complete less tasks for the low piece-rate than for the high piece-rate:[44]

[43] I assume all workers have equal disutility from effort for simplicity. As long as spectators don't consider this heterogeneity in their decisions, it has a neutral effect over our main results. I incorporate increasing effort disutility of task completion. This is easily met with increasing difficulty in the tasks.

[44] Piece-rate payment equals income utility as I normalize it to 1. Main results are not affected for considering each worker to have particular income utility. Incorporating concave income utility yields similar results as using convex cost function. I further assume that workers find: (i) optimal to complete at least one task when piece-rate is high ($\pi^H - C'(\underline{p}) > 0$), and (ii) sub-optimal to complete the maximum allow number of tasks when piece-rate is low ($\pi^L - C'(\overline{p}) < 0$). I test these assumptions in my sample and find they are met. Results are

$$\pi_i = \frac{\partial C_i}{\partial p_i} \tag{7}$$

$$p_i(\pi^L) < p_i(\pi^H) \tag{8}$$

3.3.2 Spectators

Spectators redistribute income between two workers for each situation. Worker A is the worker receiving the lower piece-rate payment. Worker B is the worker receiving the higher piece-rate payment. A situation is characterized by the actual tasks completed each worker ($p_A(\pi^L)$, $p_B(\pi^H)$), the counterfactual tasks each worker would have completed ($p_A(\pi^H)$, $p_B(\pi^L)$), and the pre-distribution incomes (y_A^{PRE}, y_B^{PRE}). The initial setting involves unequal piece-rate payments and pre-distribution incomes. I define worker A as the worker with lower pre-redistribution income.

The decision is on the costless redistribution. With total income and pre-redistribution incomes fixed, the redistributive transfer decision determines post-redistribution incomes. The spectator problem can be solved focusing in only one worker.[45] I assume spectator s utility depends on fairness concerns about worker A's income, as follows:

$$\max_{r_s} \quad U_s = -(y_A^{POST} - m_A)^2 \tag{9}$$

$$\text{s.t.} \quad y_A^{POST} = y_A^{PRE} + r_s \tag{10}$$

$$y_B^{POST} = y_B^{PRE} - r_s \tag{11}$$

$$y_A^{PRE} + y_B^{PRE} = y_A^{POST} + y_B^{POST} \tag{12}$$

where $U_s(\cdot)$ is spectator s utility; m_i is what the spectator considers to be the fair income for worker i; y_i^{POST} is post-redistribution income for worker i; y_i^{PRE} is pre-redistribution income for worker i; and r_s is spectator s decision for the redistributive transfers, such that $(y_A^{POST}, y_B^{POST}) = (y_A^{PRE} + r, y_A^{PRE} - r)$ and $r \in \{-y_A^{PRE}, \ldots, 0, \ldots, y_B^{PRE}\}$. I define X as total income, which is fixed and equal to the sum of pre- and post-redistribution incomes.

shown in Appendix I.

[45]Given only two workers, the redistributive transfer equals half the difference between the income difference in pre-redistribution and post-redistribution ($r = \frac{(y_B^{PRE} - y_A^{PRE}) - (y_B^{POST} - y_A^{POST})}{2}$). For instance, (i) closing post-redistribution income difference is achieved with a redistributive transfer of half the income difference in pre-redistribution; while (ii) making no redistributive transfers makes post-distribution income difference equal to that of pre-redistribution.

With no stakes in play and no costs nor relevant restrictions in redistribution, the spectators maximize their problem by implementing what they consider to be the fair income for each worker.

$$y_i^{POST} = m_i \tag{13}$$

Fairness views. I consider spectators adhere to one of the three most salient fairness views: libertarianism, egalitarianism, and meritocratic fairness views (Cappelen et al., 2007). Decisions following each view are as follows:

Libertarians: Each worker should get according to their earnings: $m_i = y_i^{PRE}$.
Egalitarians: Both workers should get the same: $m_i = X/2$.
Meritocrats: Each worker should get according to their choices: $m_i = p_i$.

Redistributive transfers for libertarians and egalitarians are independent of unequal opportunities, but not for meritocrats. The existence of unequal opportunities present a dilemma for assessing each worker's choices. Part of the meritocrats consider the impact of unequal opportunities on choices should be accounted for. This is the same as making comparissons in a counterfactual situation with equal opportunities (for example one where the actual choices were $p_A(\pi^H)$ and $p_B(\pi^H)$). I label those spectators as counterfactual meritocrats. Other meritocrats only consider the actual choices by each worker, even if they originated in unequal circumstances. I label them as factual meritocrats. Decisions for each group are as follows:

Factual Meritocrats: Each worker should get according to their factual choice: $m_i = p_i(\pi_i)$.
Counterfactual Meritocrats: Each worker should get according to their counterfactual choice in an equal-opportunity scenario: $m_i = p_i(\pi_s)$, with π_s equal $\forall\, i$.

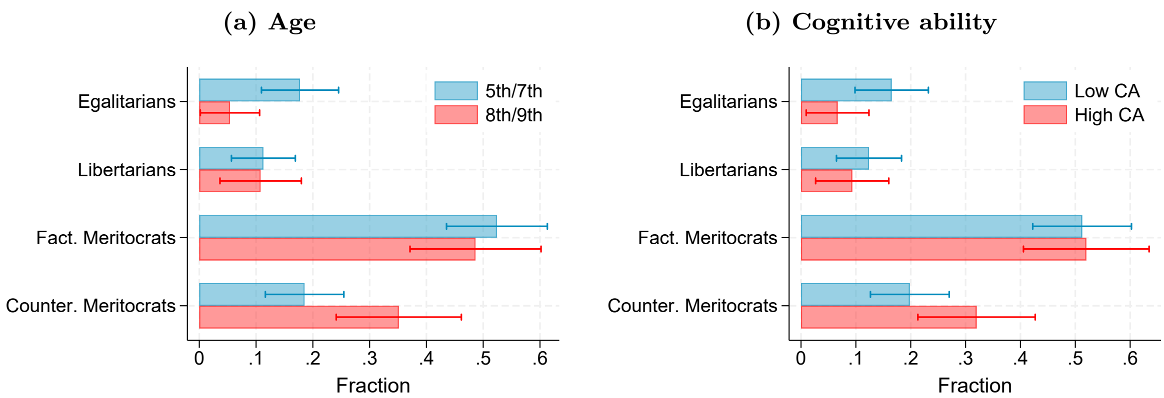
3.4 Results

3.4.1 Stated preferences

I start by analyzing spectator's stated preferences. Although there are diverse fairness views in my sample, meritocracy is by far the most common (see Table J.1 for complete details). Around three quarters of the spectators (75.7%) adhere to meritocracy. The remaining spectators are split between egalitarianism (13.1%) and libertarianism (11.1%). Meritocrats can be classified into two groups: factual meritocrats and counterfactual meritocrats. Factual meritocrats value the efforts actually exerted. They represent 51.0% of the sample. Counterfactual meritocrats place a higher value on the efforts that would have been exerted under equal circumstances. They account for 24.7% of the sample.

Figure 3.3 shows the main findings. Fairness preferences vary across age. I split the sample into two groups. The first group comprises the younger children, who attend from 5th to 7th grade. These are between 10 and 13 years old. The second group comprises the older children, who attend from 8th to 9th grade and are aged between 13 and 15 years old. Egalitarians are much less common among older children. Their share more than halves (-12.3 p.p., p-value=.005). Libertarians remain relatively stable across age groups. The share of factual meritocrats shows no statistically significant change. The only fairness view that increases with age is counterfactual meritocracy. The prevalence of counterfactual meritocrats almost doubles in size (16.6 p.p., p-value=.013).

Figure 3.3: Stated fairness preferences



Notes: These figures plot preferred criteria for distributing between workers, as declared by spectators. Figure (a) distinguishes between younger and older children. Differences in proportions are statistically significant at the 5% level using Fisher's exact test (p-value = .012), Pearson's chi-squared test (p-value = .014), and Likelihood-ratio chi-squared test (p-value = .010). Figure (b) distinguishes between children scoring above and below the median in the cognitive ability measurement. Differences in proportions are statistically significant at the 10% level using Fisher's exact test (p-value = .082), Pearson's chi-squared test (p-value = .081), and Likelihood-ratio chi-squared test (p-value = .072).

I leverage Raven's SPM test scores to explore the role of cognition in explaining the increase in counterfactual meritocracy. I split the sample by the median test score (8 out of 12) into two groups. There are children of all ages in both groups, but older ones are more likely to be in the group with higher cognitive ability (see Table J.2 and Figure J.1). Fairness views prevalence by cognitive ability mimics what observed by age groups. Egalitarians drop among children with higher cognitive ability (-9.9 p.p., p-value=.028), while counterfactual meritocrats increase (12.2 p.p., p-value=.064). I further explore changes by cognition within age groups. Table 3.2 shows differences on adherence to each fairness view by cognition, both without and including age group fixed effects. Even controlling for age group, more cognitive able children are less likely to be egalitarians and more likely to be counterfactual meritocrats. These results suggest that cognition is part of the explanation for the overall change in fairness views.

Table 3.2: Stated fairness preferences

	Egal.		Libe.		Fact. Merit		Counter. Merit.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High CA	-.109**	-.086*	-.022	-.022	-.013	-.004	.144**	.112*
	(.046)	(.048)	(.046)	(.051)	(.074)	(.077)	(.065)	(.065)
Age FE	No	Yes	No	Yes	No	Yes	No	Yes
Dep. var. mean	.131	.131	.111	.111	.510	.510	.247	.247
Effect magn.	-83%	-65%	-20%	-20%	-3%	-1%	58%	46%
Observations	196	196	196	196	196	196	196	196
R^2	.028	.047	.009	.009	.014	.015	.040	.061

Notes: This table reports the coefficients of dummies on cognitive ability groups on preferred distribution criteria. The independent variables are computed as dummy valued 1 for students scoring above the median (8 out of 12) on the cognitive ability measurement, and 0 otherwise. The dependent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for sex. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I also analyze the prevalence of each fairness view by cognitive ability group within each age group. With the sample twice split standard errors are large, but additional patterns arises (see Figure J.2). Younger children are not much different across cognitive ability groups, while older children are. In fact, older children scoring below the median in the cognitive ability test are similar to younger children in their stated preferences. The increase in counterfactual meritocracy appears on those who are both older and more cognitive able. Table 3.3 shows the estimates on the probability of adhering to the egalitarian and counterfactual meritocratic fairness view.[46] Older and more cognitive able children are 12.4 p.p. (95% of the sample mean) and 10.9 p.p. (83% of the sample mean) less likely to be egalitarians, respectively. Among older children, there are no statistically significant differences, but point estimates show those scoring above the median in the cognitive ability test to be less likely to be egalitarians. Conversely, older and more cognitive able children are 16.8 p.p. (68% of the sample mean) and 14.4 p.p. (58% of the sample mean) more likely to be counterfactual meritocrats, respectively. Older and high-cognition children are even more likely to be counterfactual meritocrats, 63% above the older group mean.

[46] Estimates in Table 3.3 control for sex and can yield marginally different values than those in Figure 3.3. In line with previous results, there are no significant differences for libertarians and factual meritocrats. See Table J.3 for estimates on all fairness views.

Table 3.3: Stated fairness preferences

	Egalitarian			Counter. Merit.		
	(1)	(2)	(3)	(4)	(5)	(6)
8th/9th	-.124***			.168**		
	(.044)			(.066)		
High CA		-.109**	-.067		.144**	.222**
		(.046)	(.054)		(.065)	(.110)
Sample	All	All	8th/9th	All	All	8th/9th
Dep. var. mean	.131	.131	.054	.247	.247	.351
Effect magn.	-95%	-83%	-124%	68%	58%	63%
Observations	198	196	73	198	196	73
R^2	.034	.028	.021	.051	.040	.058

Notes: This table reports the coefficients of dummies on age and cognitive ability groups on preferred distribution criteria. The independent variables are computed as dummy variables. Age groups are formed based on current school grade: valued 1 for students from 8th to 9th grade, and 0 otherwise. Cognitive ability groups are formed based on Raven's SPM test score: valued 1 for students scoring above the median (8 out of 12), and 0 otherwise. The dependent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for sex. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness checks. I test the robustness of the results to different analysis decisions.

Participant comprehension. One plausible explanation of the difference in stated preferences is that older and more cognitive able children have a better understanding of the instructions. I take several steps to ensure all participants understand the experiment instructions and to avoid that channel (see Appendix H for a detailed description of the procedures). To further check that lack of comprehension is not driving the results, I ask participants about their degree of understanding of the instructions after the spectator game. None of the participants report not understanding the instructions and most report almost complete understanding (over 80%). I replicate the main analysis excluding participants who failed to understand part of the instructions (see Table J.5). Results are robust to this exclusion.

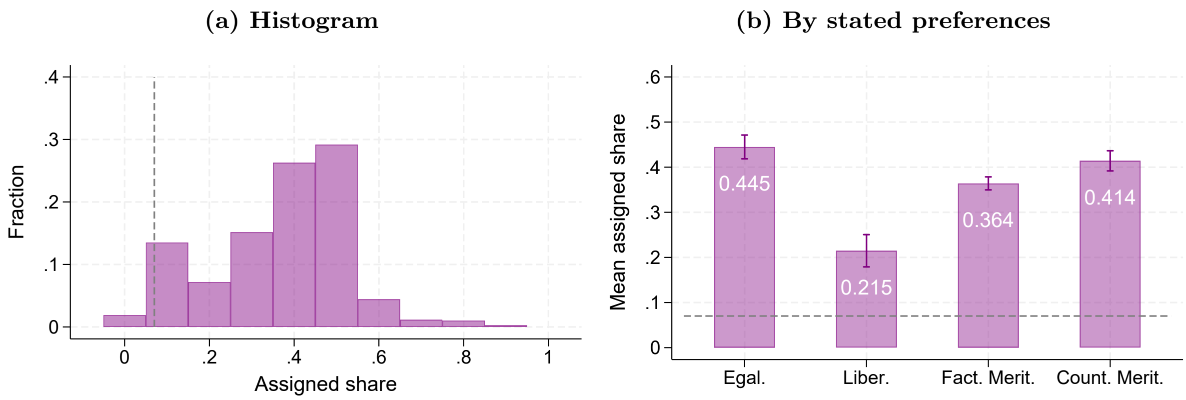
Age cutoff. Main results are based on splitting the sample into two groups by the median, both by grade (7th grade) and cognitive ability (score of 8 out of 12). To check the robustness of the results to this choice, I estimate differences for different cutoffs (see Table J.6). I split groups by age, using the 6th and 8th grade as the cutoff for older students. For both cutoffs, the share of counterfactual meritocrats is higher among older students. I split groups by cognitive ability, using scores of 7 and 9 as the cutoff for high cognitive ability. The share of counterfactual meritocrats is higher among the high cognitive ability group, but only significant for the group defined by the higher cutoff.

3.4.2 Revealed preferences

Stated fairness preferences change as children grow up and are more cognitive mature. I analyze whether these stated preferences are relevant for behavior.

Figure 3.4a plots the shares assigned to the unlucky individual for four scenarios with distinct effort differences between workers. In all scenarios the unlucky worker's effort is lower or equal than the one exerted by the lucky worker. Importantly, the prexisting earning distribution is always strongly disadvantaging the unlucky worker (7.0% for the unlucky worker in the mean). Figure 3.4b displays the mean share assignment by preferred distribution criteria. Spectators that declare as egalitarians assign the unlucky worker the largest share (44.5% in the mean). In 64.4% of the cases, they assign income equally across workers. In contrast, libertarians assign the lowest share to the unlucky worker (21.5% in the mean). Their assignments are closest to the preexisting earning distribution, which they maintain in 45.5% of the cases. Factual meritocrats assign on average 36.4% to the unlucky worker (44.3% in line with observed effort shares). Counterfactual meritocrats assign more to the unlucky worker (41.4% in the mean). They are the ones that implement the prescribed behavior the least (25.0% of the cases).

Figure 3.4: Assignments to the unlucky worker



Notes: These figures plot the shares assigned to the unlucky workers. Panel (a) is a histogram of the share assigned to the unlucky worker. Panel (b) plots the mean share assigned to the unlucky worker by stated fairness preference. Only the four hypothetical scenarios are included. The mean initial share of 7.0% is plotted as a dashed line in gray in both figures.

Table 3.4 reports estimates for these assignments by fairness view adherence. Compared to factual meritocrats, libertarians assign less to the unlucky worker, while counterfactual meritocrats and egaliatarians assign more. Differences are statistically significant. I also explore which worker is favored in the assignment. Again comparing with factual meritoctats: (i) libertarians favor more the lucky worker, (ii) egalitarians equalize more, and (iii) counterfactual meritocrats favor more the unlucky worker. These differences are in line with the prescribed behavior of each fairness view for the presented scenarios.[47]

Table 3.4: Distribution decisions

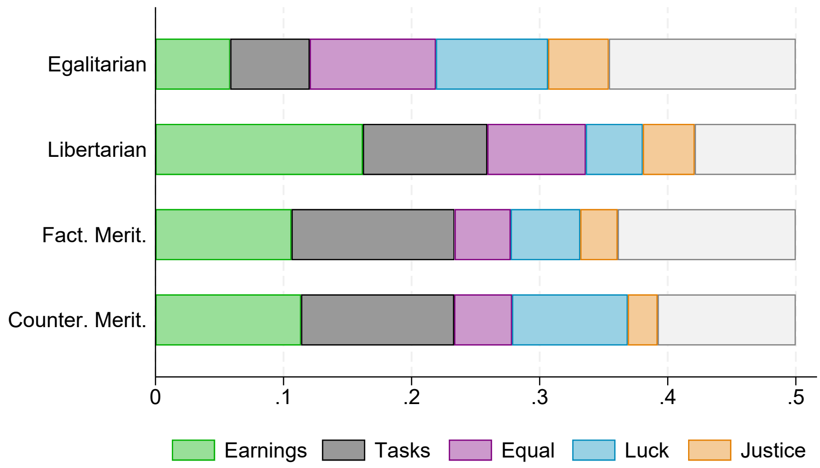
		Favored worker		
	Assign. to unlucky	Lucky	None	Unlucky
	(1)	(2)	(3)	(4)
Egalitarians	.081***	-.384***	.307***	.077*
	(.021)	(.075)	(.072)	(.044)
Libertarians	-.149***	.125***	-.082***	-.043
	(.029)	(.036)	(.024)	(.029)
Counter. Meritocrats	.050**	-.123***	.016	.107***
	(.020)	(.043)	(.028)	(.039)
Mean dep. var.	.370	.740	.152	.109
Observations	792	792	792	792
R^2	.147	.106	.093	.029

Notes: This table reports the coefficients of dummies on preferred distribution criteria on implemented decisions. The independent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. The omitted category is Factual Meritocrats. Lucky worker refers to the worker paid the high piece-rate. Unlucky worker refers to the worker paid the low piece-rate. The dependent variable for column (1) is the assignment to the unlucky worker as a share of total assignments. The dependent variable for columns (2) to (4) are dummies for decisions assigning more to the lucky worker, to none and to the unlucky worker, respectively. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I also explore how spectators justify their decisions, leveraging the open-ended question in the survey. I extract each word used, classify it within concepts and quantify how much each concept repeats within each stated fairness preference (see Figure 3.5). Some key differences appear. Egalitarians talk more about luck, equality, and justice, and little about the work done and the earnings obtained. Libertarians strongly emphasize earnings. Both type of meritocrats center on tasks and earnings. Their explanations are much similar, but counterfactual meritocrats are more likely to mention luck and conditional choices when they explain decisions.

[47]Table J.7 shows estimates for each scenario. I focus on the cases in which the unlucky worker is favored. As all analyzed scenarios have the lucky worker exerting at least as much effort as the unlucky worker, favoring the latter is little expected. Counterfactual meritocrats are the ones that favor the most the unlucky worker. This result is driven by scenarios in which the observed effort of the unlucky worker is lower, but the difference is close enough to think it would revert if both worker have had equal opportunities.

Figure 3.5: Concepts used to justify distribution decisions



Notes: This figure plots the concepts used by spectators to justify their decisions, by preferred distribution criteria. Each color reports the share of words from each concept used over total words. Grey bars report the share of words that do not fit into any of the concepts and continue up to 100%. Earnings include 'points', and verbs 'contribute', 'achieve', 'win'. Tasks include 'tasks', and verbs 'complete', 'fulfill', 'decide', 'effort', 'choose', 'do', 'make'. Equality includes 'equal', 'same', 'team', 'half'. Luck includes 'luck', 'random', and verbs 'receive', 'get', 'chance', 'would', 'could', 'commit'.' Justice includes 'fair', 'unfair', and verbs 'owe', 'deserve'.

3.5 Mechanisms exploration

Older and more cognitive mature children are more likely to adhere to counterfactual meritocracy. I explore plausible explanations for this result, focusing on the procedural aspects of the decision. Counterfactual meritocracy requires spectators to asses what effort would have been exerted by workers in an equal opportunity situation, (i) making it more complex to implement, and (ii) dealing with additional information.

Procedural complexity. Counterfactual meritocracy is more complex and, thus, more costly to implement than the other fairness views analyzed. Its implementation requires case-by-case analysis, translation of efforts into earnings, and belief formation on non-observed equal opportunity situations.[48] Individuals anticipating the complexity cost would be less likely to adhere to counterfactual meritocracy (Banovetz and Oprea, 2023). However, varying implementation capacity across individuals can affect cost assessments (Oprea, 2020), and with it the prevalence of counterfactual meritocracy across groups. I proxy implementation capacity by analyzing consistency with the prescribed behavior among spectators adhering to each stated fairness

[48] I show this increasing complexity indirectly. Decision consistency with the prescribed behavior differs across spectators adhering to each stated fairness view, in line with what expected due to their varying complexity (see Table J.9 for more details). Egalitarians are the most precise, libertarians and factual meritocrats follow. Implementation consistency is significantly lower for counterfactual meritocrats.

view. I show that implementation capacity varies alongside individual characteristics. Table 3.5 shows that older and more cognitive able children are more consistent, even after controlling for the differing difficulty of implementing each fairness view. Results are partly independent, complementing each other. Being better at implementing prescribed behaviors, older and more cognitive able children can be less likely to be deterred of complex fairness views, such as counterfactual meritocracy.

Table 3.5: Implementation consistency

	(1)	(2)	(3)
8th/9th	.190***		.175***
	(.054)		(.055)
High CA		.128**	.092*
		(.054)	(.054)
Dep. var. mean	.423	.423	.423
Effect magn.	45%	32%	-
Observations	792	784	784
R^2	.091	.069	.096

Notes: This table reports the coefficients of dummies on age and cognitive ability groups on implementation consistency. The independent variables are computed as dummy variables. Age groups are formed based on current school grade: valued 1 for students from 8th to 9th grade, and 0 otherwise. Cognitive ability groups are formed based on cognitive ability measurement: valued 1 for students scoring above the median (8 out of 12), and 0 otherwise. The dependent variable is valued 1 for assignments aligned with the prescribed behavior of the stated preference (with a two-sided 5 percentage point margin), and 0 otherwise. Each column reports estimates from a linear model. All estimates control for fairness view adherence. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional information. Counterfactual meritocracy involves an extra step: getting information about the effort that would have been exerted by workers in an equal opportunity situation. Spectators can infer it or, in this experiment, can acquire it by completing a task. The values of the information used, their confidence in it, and the costs incurred in accessing it could explain differences in adherence to counterfactual meritocracy.

Differences are small across age and cognitive ability (see Table 3.6). I find differences in inferences by cognitive ability, but not by age. More able children infer a higher response to beneficial conditions. This translates into a lower effort difference in equal opportunity scenarios and could explain favoring counterfactual rather than factual choices. There are no differences in confidence.[49]

Table 3.6: Additional information

	Inferred differences		Confidence		Acquire info.	
	(1)	(2)	(3)	(4)	(5)	(6)
8th/9th	.041		.046		.120**	
	(.048)		(.055)		(.059)	
High CA		.090*		.029		.056
		(.048)		(.055)		(.061)
Dep. var. mean	.227	.227	.295	.295	.763	.763
Effect magn.	18%	40%	16%	10%	16%	7%
Observations	792	784	792	784	792	784
R^2	.001	.007	.002	.001	.019	.004

Notes: This table reports the coefficients of dummies on age and cognitive ability groups on inferred effort difference for higher piece-rate payment, confidence in inferences, and information acquisition. The independent variables are computed as dummy variables. Age groups are formed based on current school grade: valued 1 for students from 8th to 9th grade, and 0 otherwise. Cognitive ability groups are formed based on Raven's SPM test score: valued 1 for students scoring above the median (8 out of 12), and 0 otherwise. The first dependent variable computes the inferred difference in effort choice for a same player between low and high piece-rate payment. The second dependent variable is valued 1 for spectators declaring and confidence in their inferences, and 0 otherwise. The third dependent variable is valued 1 for spectators acquiting information, and 0 otherwise. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses for columns (1), (2), (3), and (4). Robust standard errors are reported in parentheses for columns (5), and (6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I offered spectators the opportunity to complete a task to acquire information. This situation resembles real life, where such information is not available but inputs for estimating it can be obtained at a cost. I find that older children are more likely to acquire the information. These results can reflect both a higher valuation of the information or a lower cost of obtaining the information. To test whether cheaper access to information impacts decisions, I compare spectators under different treatment conditions in a pre-registered randomized controlled trial (see Appendix K for more details). I find information provision to increase assignments to the unlucky worker (see Table 3.7). The effect is entirely driven by factual meritocrats. With complete information, the gap between assignments to the unlucky worker by factual and counterfactual meritocrats is almost closed. I also test whether preceding decision with counterfactual thinking achieves a similar result, as it forces spectators to make the inferences and have that estimates available to decide. I find no significant difference in assignments to the unlucky worker on

[49]Spectators adhering to distinct fairness views differ in their confidence in their inferences regarding the effort that would have been exerted by workers in an equal opportunity situation (see Table J.14). Meritocrats are more confident than egalitarians and libertarians. Though counterfactual meritocrats are slightly less confident than factual meritocrats (in line with Cappelen et al., 2022), differences are not statistically significant.

aggregate level, nor by fairness view adherence. These results suggest it is not only information availability, but the uncertainty that prevents meritocrats to decide based on counterfactuals (in line with Cappelen et al., 2022).

Table 3.7: Assignments to the unlucky worker

	(1)	(2)	(3)	(4)	(5)	(6)
Counterfactual thinking	.010					
	(.023)					
Information disclosure		.037*	.006	-.044	.060**	-.003
		(.021)	(.040)	(.071)	(.025)	(.033)
Dep. var. mean	.370	.370	.445	.215	.364	.414
Sample	All	All	Egal.	Libe.	Fact.	Counter.
Observations	536	544	68	64	268	144
R^2	.001	.013	.001	.015	.040	.000

Notes: This table reports the treatment coefficients on assigned share to the unlucky worker. The dependent variable is computed as assignment to the unlucky worker as a share of total assignment. The independent variables are treatment condition dummies, comparing the Limited Information (LI) treatment with the Incentivized Counterfactual Thinking (ICT) treatment for column (1) and comparing the Limited Information (LI) treatment with the Complete Information (CI) treatment for the remaining columns. Sample is restricted to the hypothetical scenarios and to each treatment comparisson. Columns (1) and (2) cover all spectators. Columns (3) to (6) cover spectators stating adherence to each fairness view. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Conclusion

Many people face a dilemma when facing unequal opportunities: they want to reward effort, but this is rarely detached from circumstances. I show children increasingly account for circumstance-dependent choices as they grow up and provide evidence that the changes are related to cognitive maturity. I connect the prevalence of that fairness view with its procedural complexity. Older and more able children are better at dealing with the complex procedures it implies, which can explain why they adhere to it more.

Evidence on the impact of procedural complexity can help understanding disagreements about inequality. Difference assessment capacity could influence individual moral decisions, potentially leading to sub-optimal collective choices. Unlike pure preferences, disagreements arising from complexity aversion can be addressed through policy interventions. My findings suggest that informational campaigns can help individual decide without avoiding the use of additional information and improve social welfare.

Concluding remark

This dissertation explores the links between cognition, prosociality, and distributive preferences. It provides empirical evidence on the role of social preferences to explain how high-cognition individuals support policies that are detrimental for their self-interest, and experimentally connects cognition variations with distinctive views about what individuals consider to be fair.

In Chapter 1, I find that most able individuals are more supportive for income redistribution. This result relates to a wide literature exploring the determinants of preference for redistribution, particularly with recent studies accounting for increased support among groups that *a priori* don't benefit directly from it. This trend mimicks the prior acknowledgment of *a priori* benefiting groups that opposed redistribution, which fuelled an earlier development in the literature. The ongoing accumulation of these results underscore the role of non-pecunary interests as drivers for policy support. This is particularly salient in the presence of high-cognition individuals in the modern and lesser class-based political alliances, to which this work provides a behavioral underpinning.

In Chapter 2, I show the previous findings replicate in other topics, such as health. The context in which the estimates are made was characterized by strong concern on health and ample calls for solidarity. These allows to approximate an upper bound for the impact of cognition on distributional preferences. The results also highlight fairness views as a significant type of social preferences that determine redistributive policy support for this pivotal group. This adds to the literature by stressing that perceptions of equality of opportunity play a key role, even when the role of effort in determining outcomes is similar across groups.

In Chapter 3, I find that redistribution when facing inequality of opportunities is larger as cognition increases. This result contributes to the vast literature of fairness and adds to a recent extension that focuses on cases characterized by unequal opportunities. My results are the first to show how children develop their inequality acceptance in such cases, and also provide an additional behavioral underpinning for the acceptance of resulting inequalities: procedural complexity. My findings show that people choose not to account for unequal opportunities due to the cognitive costs implied, and those most cognitively able are less deterred by it. Importantly, I provide evidence for an informational intervention that can help to close those gaps between individuals and yield more equality in cases of unequal opportunities.

Appendix to Chapter 1

A Data characteristics and descriptive statistics

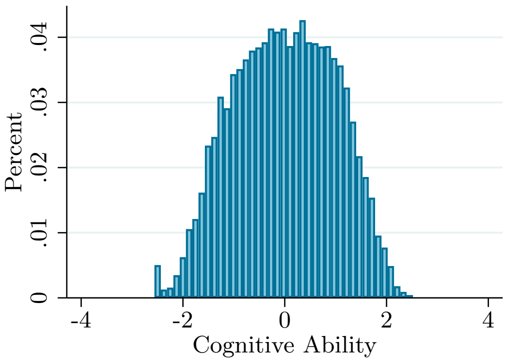
Table A.1: Observations per wave

Year	NCDS58			BCS70		
	Age	Responses	Share	Age	Responses	Share
	(1)	(2)	(3)	(4)	(5)	(6)
1958	Birth	17,634	99%	-	-	-
1965	7	15,051	91%	-	-	-
1969/70	11	14,757	91%	Birth	16,571	96%
1974/75	16	13,917	87%	5	13,135	78%
1980/81	23	12,044	76%	10	14,870	86%
1986	-	-	-	16	11,615	66%
1991	33	10,986	71%	-	-	-
1996	-	-	-	26	9,003	52%
1999/00	42	10,979	71%	30	11,261	66%
2004/05	46	9,534	81%	34	9,665	74%
2008/09	50	9,790	80%	38	8,874	75%
2012/13	55	8,958	78%	42	9,841	75%

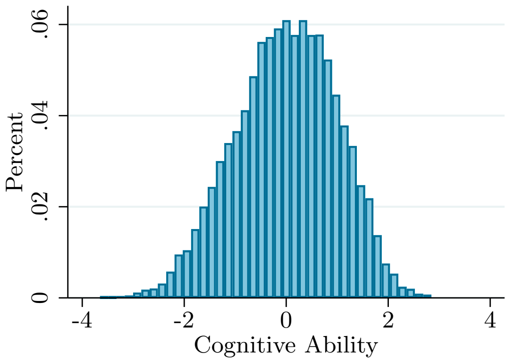
Notes: This table reports statistics for responses to the surveys, by recollection wave. Columns 1 to 3 show statistics for NCDS58 cohort members. Columns 4 to 6 show statistics for BCS70 cohort members. Columns 1 and 4 show cohort members median age at the time of data recollection. Columns 2 and 5 show total responses in the wave. Columns 3 and 6 show response shares in comparisson to first wave responses.

Figure A.1: Distribution of Cognitive Ability

(a) NCDS58 - Age 11



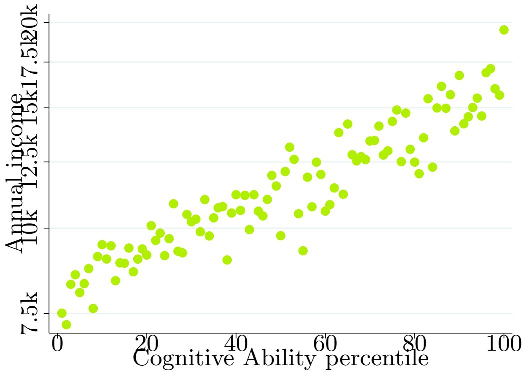
(b) BCS70 - Age 10



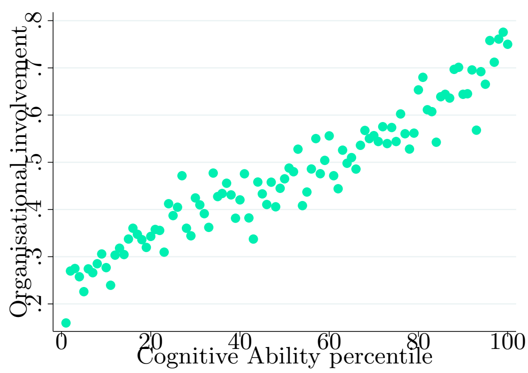
Notes: These figures plot population shares for normalized cognitive ability test scores, by cohort. Cognitive ability was measured at age 10 (11) for BCS70 (NCDS58) cohort members and is normalized within each cohort. Sample size is 14,124 for the NCDS58 cohort and 11,125 for the BCS70 cohort.

Figure A.2: Correlates to Cognitive Ability

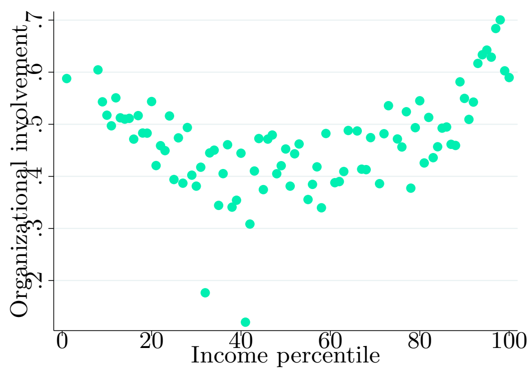
(a) Income



(b) Organisational involvement



(c) Organisational involvement and income



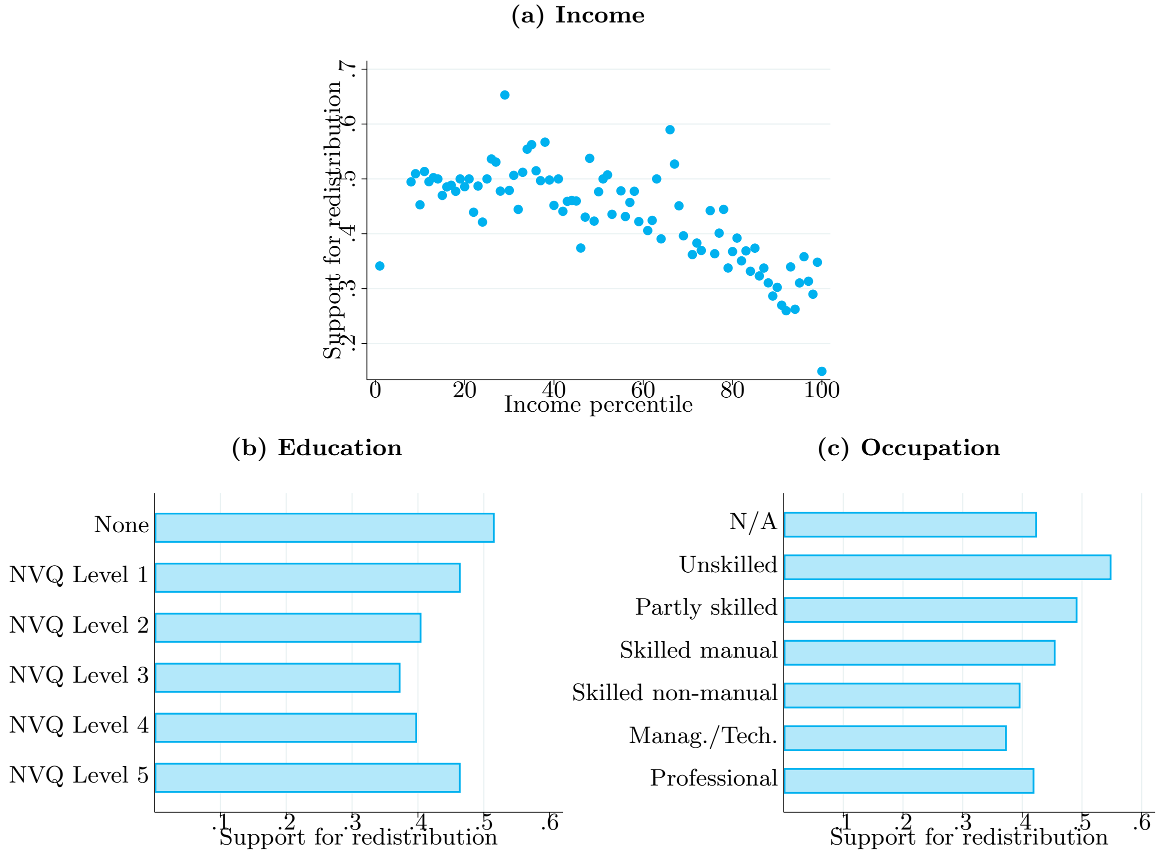
Notes: These figures plot statistics by cognitive ability percentiles for the total sample. Subfigure (a) plots mean income by cognitive ability percentile. Subfigure (b) plots mean organizational involvement by cognitive ability percentile. We additionally include a plot showing the relationship between organisational involvement and income. Subfigure (c) plots mean organizational involvement by income percentile. Cognitive ability was measured at age 10 (11) for BCS70 (NCDS58) cohort members. Income and organizational involvement were at ages 30s (30 for BCS70 and 33 for NCDS58) and 42. The sample used for all plots is the one used in the main analysis, but differs in size due to missing observations in each variable. Sample size is 20,162 for subfigure (a), 24,652 for subfigure (b), and 19,404 for subfigure (c).

Table A.2: Distribution of Preferences for Redistribution

	NCDS58		BCS70		Total
	Age 33	Age 42	Age 30	Age 42	
	(1)	(2)	(3)	(4)	(5)
Strongly disagree	3.4	3.8	4.4	6.8	4.4
Disagree	26.0	23.5	23.2	29.4	25.2
Uncertain	21.1	29.8	31.4	31.1	28.0
Agree	36.7	31.2	31.1	24.5	31.5
Strongly agree	12.7	11.7	9.8	8.1	10.9

Notes: This table reports response shares for preference for redistribution for each wave and its total aggregation. Preferences for redistribution were measured through a 5-point Likert scale for the following statement: *'Government should redistribute income from the better off to those who are less well off'.* Sample size is 7,143 for NCDS58 cohort members at age 33, 7,479 for NCDS58 cohort members at age 42, 6,131 for BCS70 cohort members at age 30, 4,847 for BCS70 cohort members at age 42, and 25,600 in the total aggregation.

Figure A.3: Correlates to Support for Redistribution



Notes: These figures plot mean support for redistribution by income percentiles, educational attainment and occupation for the total sample. All variables were measured at ages 30s (30 for BCS70 and 33 for NCDS58) and 42. Support for redistribution corresponds to agree (4) and strongly agree (5) in the preferences for redistribution questions (coded as a 5-point Likert scale from strongly disagree to strongly agree). The sample used for all plots is the one used in the main analysis, but differs in size due to missing observations in each variable. Sample size is 20,162 for subfigure (a), 25,598 for subfigure (b), and 23,515 for subfigure (c).

B Cognitive Ability Test

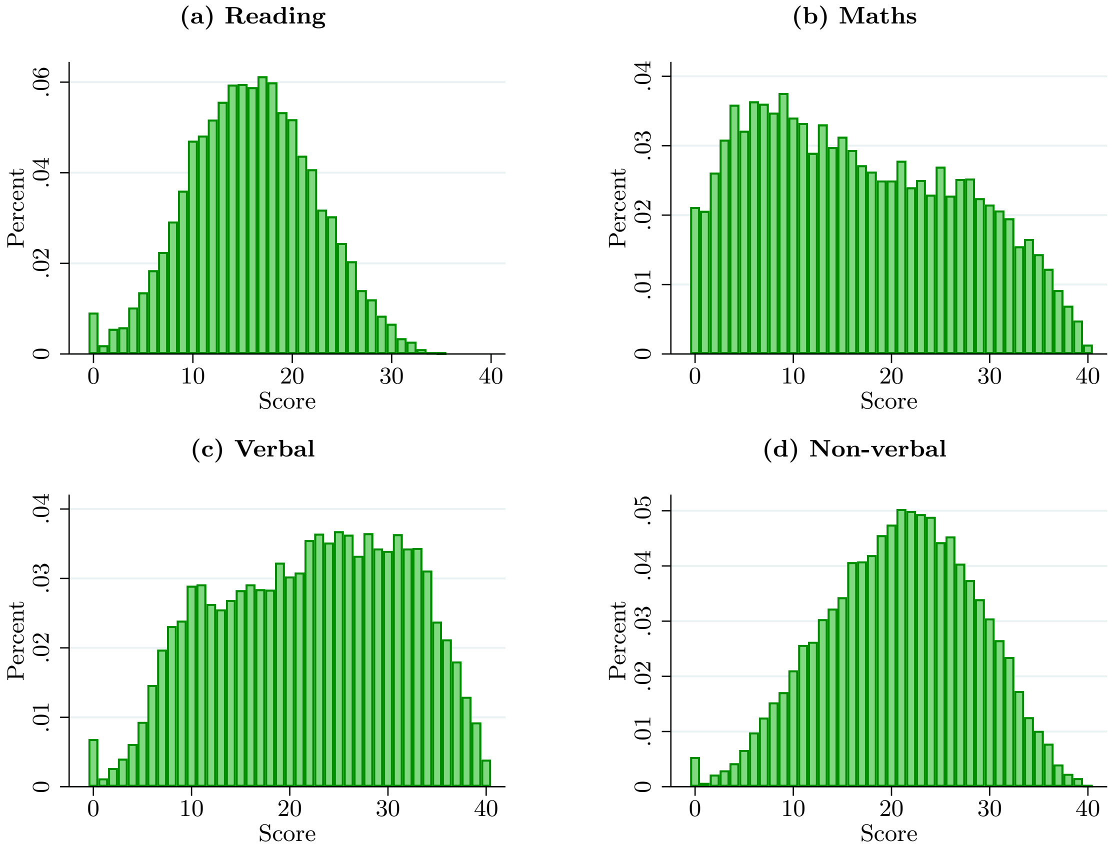
NCDS58. Tests at age 11.

Cognitive ability was measured based on four tests included in the age 11 survey:

1. **Reading comprehension Test:** Assesed using a 35-item test with 5 words to choose the one appropriately completing sentences.
2. **Mathematics Test:** Comprised 40 items involving numerical and geometric work. Most of the questions were answer-directly questions with only a few being involving multiple-choice answers.
3. **General Ability Test:** Two sub-scales from a General Ability test were included.
   (a) **Verbal Task:** Assessed using a 40-item test where children were presented with an example set of four words that were linked either logically, semantically, or phonologically. The children were then given another set of three words. Participants were required to select the missing item from a list of five alternatives.
   (b) **Non-verbal Task:** Assessed using a 40-item test where children were presented with an example set of four shapes or symbols. The children were then given another set of shapes or symbols with a blank. Participants were required to select the missing item from a list of five alternatives.

In total, 14,133 (76.2%) of all children participating in the age 11 survey completed at least one assessment and 14,124 (76.1%) children completed all four assessments.

Figure B.1: Individual test scores, age 11



BCS70. Tests at age 10.

Cognitive ability was measured based on eight tests included in the age 10 survey:

1. **Shortened Edinburgh Reading Test:** A particularly developed version of the Edinburgh Reading Tests appropriate to be used at age 10. Assesed by a test consisting of 67 questions.

2. **Friendly Math Test:** A particularly developed math test to be used at age 10. Assessed by a multiple choice test with 72 increasingly-hard items which included arithmetic, number skills, fractions, algebra, geometry and statistics. The score is designed to provide a full range of mathematical competence, from early age to around age 13. The test was stopped when a child fails six consecutive items.

3. **Spelling dictation Task:** Assessed using a 75-item test where each item was a word followed by a multiple-choice list from which the respondent must pick the one with the same meaning as the first word.

4. **Arithmetic Test:** Assessed using the Applied Psychology Unit (UPU) Arithmetic test which comprised of 60 multiple choice items covering arithmetic, probabilities and area.

5. **British Ability Scales (BAS):** Four sub-scales from the British Ability Scales (BAS) were included.

   (a) **Word Definitions:** Assessed by a list of 37 words, with increasing difficulty. When the child was unable to give a correct or partly correct definition for four successive words, the assessment was stopped.

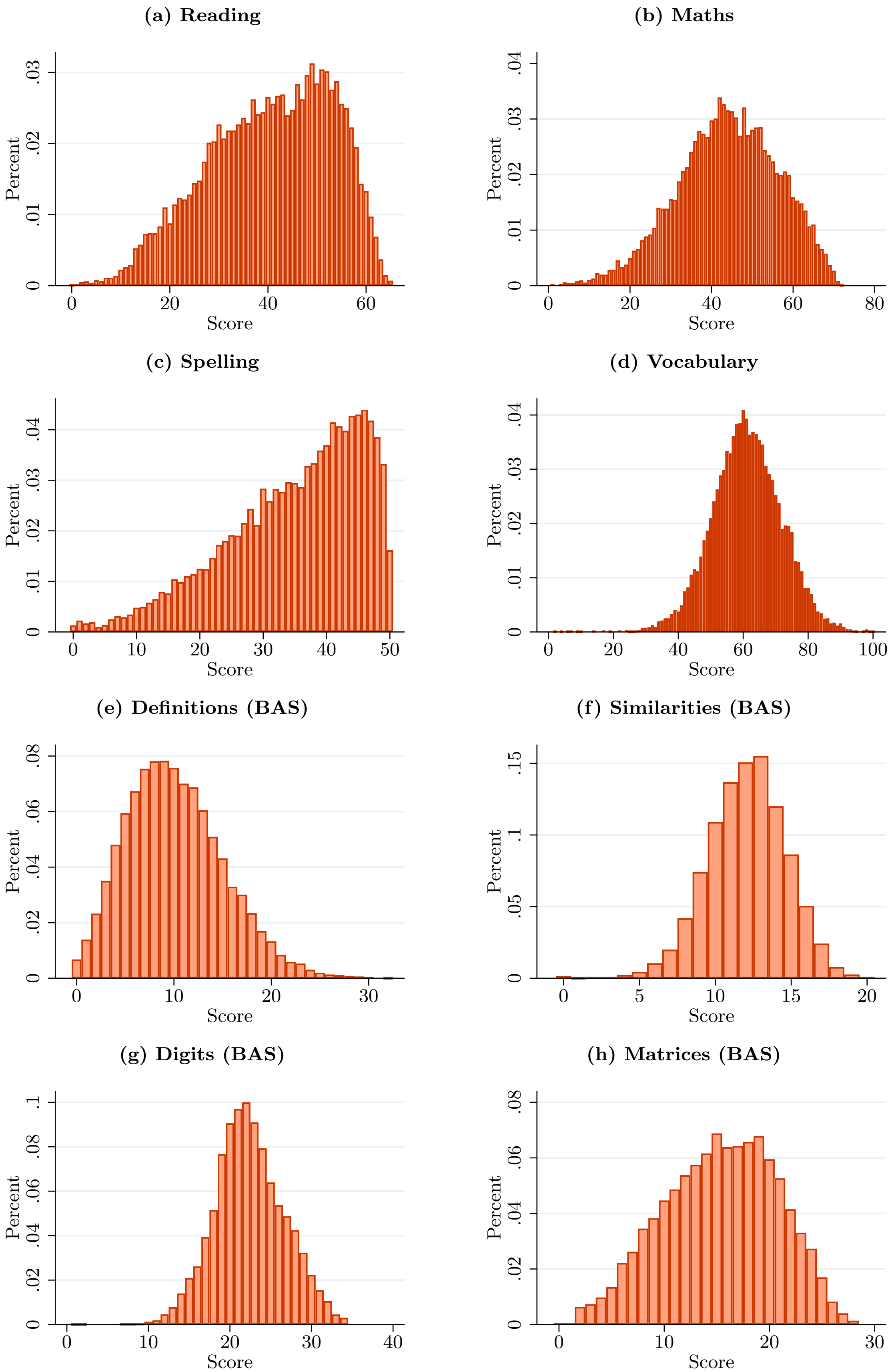
   (b) **Word Similarities:** Assessed by a list of 21 items, with increasing difficulty. For each item a set of three words is enunciated, the child is asked to add another word to the set and to mention what the group has in common. In order to be assessed as correct, both tasks must be completed correctly.

   (c) **Recall of Digits:** Assessed by a list of 34 items, with increasing difficulty. The assessment was stopped when the child answered four consecutive items incorrectly.

   (d) **Matrices:** Assessed by a list of 28 patterns. The assessment was stopped when the child had drawn four successive items incorrectly, or when it was apparent from several periods of lengthy indecision that the level of difficulty was too great.

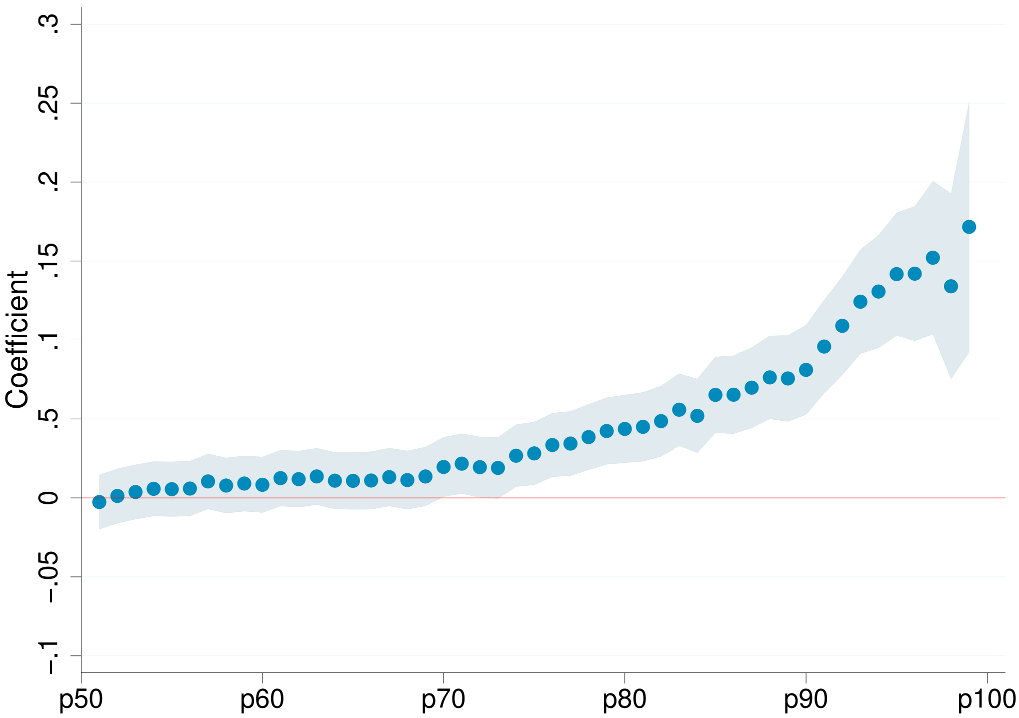
In total, 12,876 (86.5%) of all children participating in the age 10 survey completed at least one assessment and 11,123 (74.8%) children completed all eight assessments.

Figure B.2: Individual test scores, age 10



C Additional results

Figure C.1: $High\_CA$ **coefficients for different thresholds**



Notes: This figure plots estimates for the difference in support for redistribution between high cognitive ability individuals and the rest controlling for all controls included in Table 1.1, using as threshold each percentile starting from the 50^{th}. Confidence intervals at 95% constructed with robust standard errors are plotted as shaded area. Sample size is 19,182 for all estimates.

Table C.1: Support for Redistribution
Heterogeneity across data samples

	Baseline	Year	Cohort
	(1)	(2)	(3)
$High\_CA$	.107***	.099***	.099***
	(0.015)	(.022)	(.019)
$High\_CA$		.011	
* 1999 Dummy		(.022)	
$High\_CA$		.010	
* 2012 Dummy		(.033)	
$High\_CA$			.019
* BCS70 Dummy			(.028)
N	19,182	19,182	19,182
R^2	.061	.061	.061

Notes: This table reports the coefficients for support for redistribution on a dummy for cognitive ability test score in the top 10% and its interaction with population subgroups. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. Mean dependent variable is 0.417 in the estimation sample. All columns report estimates from a linear probability model. Column 1 reports estimates from our main specification. Columns 2 to 3 report estimates adding interactions to the main independent variable to the main specification. Column 2 tests differences by wave year. Column 3 tests differences by cohort. All controls used in Table 1.1 are included. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Support for Redistribution
Separate data samples

	Baseline	NCDS58 1991	NCDS58 2000	BCS70 2000	BCS70 2012
	(1)	(2)	(3)	(4)	(5)
High_CA	.107***	.100***	.092***	.160***	.102***
	(.015)	(.024)	(.023)	(.027)	(.029)
Mean dep. var.	.417	.494	.413	.396	.324
N	19,182	5,706	5,824	4,036	3,616
R^2	.061	.069	.053	.062	.047

Notes: This table reports the coefficients for support for redistribution on a dummy for cognitive ability test score in the top 10%. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. All columns report estimates from a linear probability model. All controls used in Table 1.1 are included. Column 1 reports estimates from our main specification. Column 2 to 5 report estimates for support for redistribution collected in each wave, merged with individual childhood information collected at age 10 (11) for BCS70 (NCDS58) cohort members. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Support for Redistribution
Separate cohorts

	Baseline	NCDS58	BCS70
	(1)	(2)	(3)
High_CA	.107***	.095***	.132***
	(.015)	(.019)	(.023)
Mean dep. var.	.417	.453	.362
N	19,182	11,530	7,652
R^2	.061	.062	.049

Notes: This table reports the coefficients for support for redistribution on a dummy for cognitive ability test score in the top 10%. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. All columns report estimates from a linear probability model. All controls used in Table 1.1 are included. Column 1 reports estimates from our main specification. Column 2 to 3 report estimates for each cohort. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Support for Redistribution
Separate years

	Baseline	1991	2000	2012
	(1)	(2)	(3)	(4)
High_CA	.107***	.100***	.118***	.102***
	(.015)	(.024)	(.017)	(.029)
Mean dep. var.	.417	.494	.406	.324
N	19,182	5,706	9,860	3,616
R^2	.061	.069	.046	.047

Notes: This table reports the coefficients for support for redistribution on a dummy for cognitive ability test score in the top 10%. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. All columns report estimates from a linear probability model. All controls used in Table 1.1 are included. Column 1 reports estimates from our main specification. Column 2 to 4 report estimates for support for redistribution collected in each year, merged with individual childhood information collected at age 10 (11) for BCS70 (NCDS58) cohort members. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Support for Redistribution, Probit model

	Support for Redistribution			
High Cognitive Ability	0.259***	0.334***	0.396***	0.420***
Top 10%	(0.054)	(0.056)	(0.056)	(0.057)
Upbringing conditions		X	X	X
Individual and household			X	X
Education, occupation and income				X
Mundlak term			X	X
N	19,182	19,182	19,182	19,182

Upbringing conditions include sex, ethnicity, and parental education, occupation type and income range. Individual and household characteristics include locus of control, political cynicism, household size, region, share of immigrants, marital status and presence of children. Education and occupation control includes none and categorical values. Income covers net annual income, its quadratic term, and dummies for expectancy of better and of worse welfare on 10 years time.

Clustered standard errors errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: Support for Redistribution, margins at means for Probit model

	Support for Redistribution			
High Cognitive Ability	0.066***	0.086***	0.103***	0.111***
Top 10%	(0.014)	(0.014)	(0.015)	(0.015)
Upbringing conditions		X	X	X
Individual and household			X	X
Education, occupation and income				X
Mundlak term			X	X
N	19,182	19,182	19,182	19,182

Upbringing conditions include sex, ethnicity, and parental education, occupation type and income range. Individual and household characteristics include locus of control, political cynicism, household size, region, share of immigrants, marital status and presence of children. Education and occupation control includes none and categorical values. Income covers net annual income, its quadratic term, and dummies for expectancy of better and of worse welfare on 10 years time.

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: Preferences for Redistribution

Z-score regression

	(1)	(2)	(3)	(4)
High_CA	.070***	.126***	.166***	.187***
	(.029)	(.030)	(.030)	(.031)
Upbringing		X	X	X
Individual and hh.			X	X
Education and labor				X
Mundlak term			X	X
N	19,182	19,182	19,182	19,182
R^2	.011	.020	.051	.077

Notes: This table reports the coefficients for stndarized preferences for redistribution on a dummy for cognitive ability test score in the top 10%. The dependent variable is a standarization of a 5-point Likert scale on preferences for redistribution. Mean dependent variable is -0.001 in the estimation sample. All columns report estimates from a linear model. Upbringing controls include sex, ethnicity, and parental education, occupation type and income range. Individual and household controls include locus of control, political cynicism, household size, region, share of immigrants, marital status and presence of children. Education and labor controls include include categorical values for educational attainment and occupation, net annual income, its quadratic term, and dummies for expectancy of better and of worse welfare on 10 years time. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.8: Preferences for Redistribution

Ordered Probit

	(1)	(2)	(3)	(4)
$High\_CA$	.104**	.189***	.252***	.284***
	(.045)	(.047)	(.047)	(.047)
Upbringing		X	X	X
Individual and hh.			X	X
Education and labor				X
Mundlak term			X	X
N	19,182	19,182	19,182	19,182

Notes: This table reports the coefficients from an ordered probit for preferences for redistribution on a dummy for cognitive ability test score in the top 10%. The dependent variable is a 5-point Likert scale on preferences for redistribution. Upbringing controls include sex, ethnicity, and parental education, occupation type and income range. Individual and household controls include locus of control, political cynicism, household size, region, share of immigrants, marital status and presence of children. Education and labor controls include include categorical values for educational attainment and occupation, net annual income, its quadratic term, and dummies for expectancy of better and of worse welfare on 10 years time. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Margins for $High\_CA$ dummy

	(1)	(2)	(3)	(4)
Strongly disagree	-.006**	-.012***	-.015***	-.016***
	(.003)	(.003)	(.003)	(.003)
Disagree	-.019**	-.034***	-.047***	-.054***
	(.008)	(.008)	(.009)	(.009)
Uncertain	-.003**	-.006***	-.008***	-.009***
	(.001)	(.001)	(.002)	(.002)
Agree	.016**	.029***	.040***	.047***
	(.007)	(.007)	(.007)	(.008)
Strongly agree	.013**	.023***	.030***	.033***
	(.005)	(.006)	(.005)	(.006)

Notes: This table reports estimates of margins of response for a dummy for dummy for cognitive ability test score in the top 10% on an ordered probit for preferences for redistribution. The sample is the same which is used for the ordered probit. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Preferences for Redistribution

Robustness across redistributive policies

	Redistributive policies		
	Income	Health	Education
	(1)	(2)	(3)
$High\_CA$	.107***	.066***	.034***
	(.015)	(.012)	(.010)
Mean dep. var.	.417	.696	.106
N	19,182	19,152	19,154
R^2	.061	.064	.028

Notes: This table reports coefficients for support for different redistributive policies on a dummy for cognitive ability test score in the top 10%. The dependent variables were measured throught 5-point Likert scale, and converted to be valued 1 for responses of agree and strongly agree, and 0 otherwise. All columns report estimates from a linear probability model. All controls used in Table 1.1 are included. Column 1 reports estimates from our main specification, corresponding to policies addressing income redistribution. Column 2 reports estimates for support of health redistribution. Column 3 reports estimates for support of education redistribution. Support for health and educations redistribution were measured at the time of measuring preferences for income redistribution. Support for health redistribution was measured through the following statement: '*The time has come for everyone to arrange their own private health care and stop relying on the National Health Service (NHS)*', being NHS the British publicly funded healthcare system. Support for education redistribution was measured through the following statement: '*Private schools should be abolished*'. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

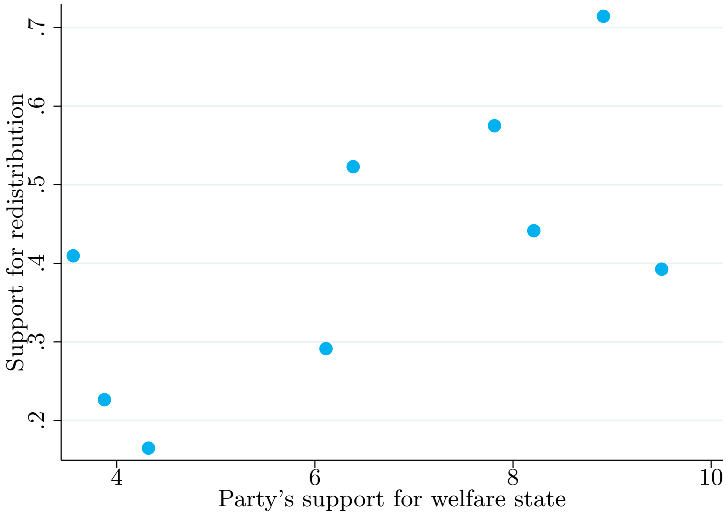
Table C.10: Preferences for Redistribution

Robustness regarding voting behavior

		Voting			
	Voted	Support welfare	Conservative	Labour	Liberal Democrat
	(1)	(2)	(3)	(4)	(5)
$High\_CA$	.025**	.116**	-.071***	.015	.056***
	(.011)	(.058)	(.017)	(.017)	(.014)
Voted		X	X	X	X
Mean dep. var.	.768	6.338	.382	.425	.167
R^2	.075	.185	.102	.113	.044
N	18,831	11,887	12,197	12,197	12,197

Notes: This table reports coefficients for voting behavior on a dummy for cognitive ability test score in the top 10%. The dependent variables were measured throught 5-point Likert scale, and converted to be valued 1 for responses of agree and strongly agree, and 0 otherwise. Columns 1, 3, 4, and 5 report estimates from a linear probability model. Column 2 reports estimates from a linear model. All controls used in Table **??** are included. Column 1 reports estimates for voting in the last election. Column 2 reports estimates for support of welfare state of voted party in last election. Columns 3 to 5 report estimates for voting in last election for each of the biggest three British parties: Conservative, Labour and Liberal Democrats. Voting participation and party voted were measured at the time of measuring preferences for redistribution. Support for welfare state is proxied by the net share of favorable quasi-sentences mentioning the introduction/maintainance/expansion of public services or social security schemes as a fraction of overall number in the party's program, for the election previous to the survey. Parties with information for support for welfare state for 1987, 1997 and 2010 elections include: Conservative, Labour and Liberal Democrats. Voting behavior for Scotland & Wales is excluded due to lack of data for regionalist parties. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.2: Voters' and political parties' stances



Notes: This figures plots mean support for redistribution by support of welfare state of party voted in last election. Political parties' stances are from Project Manifesto Database. Political parties included are Conservative, Labour and Liberal Democrats due to data limitations. Jointly they account for 88-96% vote share in each election. Support for welfare state is proxied by the net share of favorable quasi-sentences mentioning the introduction/maintainance/expansion of public services or social security schemes as a fraction of overall number in the party's program, for the election previous to the survey.

Table C.11: Support for Redistribution

Continuous independent variable

	LPM				Probit	Margins
	(1)	(2)	(3)	(4)	(5)	(6)
CA	-.087***	-.073***	-.041***	-.012		
	(.009)	(.009)	(.010)	(.011)		
Upbringing		X	X	X	X	X
Individual and hh.			X	X	X	X
Education and labor				X	X	X
Mundlak term			X	X	X	X
N	19,182	19,182	19,182	19,182	19,182	19,182
R^2/pseudo-R^2	.017	.023	.050	.074		-

Notes: This table reports the coefficients for support for redistribution on cognitive ability test score. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. Mean dependent variable is 0.417 in the estimation sample. Columns 1 to 4 report estimates from a linear probability model. Column 5 reports estimates from a probit model. Column 6 reports the marginal effect at the mean. Upbringing controls include sex, ethnicity, and parental education, occupation type and income range. Individual and household controls include locus of control, political cynicism, household size, region, share of immigrants, marital status and presence of children. Education and labor controls include include categorical values for educational attainment and occupation, net annual income, its quadratic term, and dummies for expectancy of better and of worse welfare on 10 years time. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.12: Support for Redistribution

Spline independent variables

	(1)	(2)	(3)	(4)
CA	-.155***	-.132***	-.135***	-.137***
Below p50	(0.017)	(.018)	(.018)	(.018)
CA	.149***	.009	.057	.073
Over p50	(.021)	(.044)	(.048)	(.049)
CA		.276***	.104	-.009
Over p75		(.042)	(.089)	(.101)
CA			.442***	.953***
Over p90			(.087)	(.225)
CA				.117
Over p95				(.151)
N	19,182	19,182	19,182	19,182
R^2	.073	.074	.074	.075

Notes: This table reports the coefficients for support for redistribution on splines for cognitive ability test score. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. Mean dependent variable is 0.417 in the estimation sample. Each spline variable contains variation from the cognitive ability test score in a limited subset. Spline knots correspond to specific distribution percentiles. All columns report estimates from a linear probability model. All controls used in Table 1.1 are included. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.13: Support for Redistribution

Robustness across CA measures, for BCS70 cohort

	Age 10	BAS	Age 5
	(1)	(2)	(3)
Panel A. Top 10% threshold			
High_CA	.129***	.088***	.014
	(.023)	(.022)	(.023)
R^2	.057	.053	.048
Panel B. Top 5% threshold			
High_CA	.153***	.116***	.064**
	(.030)	(.030)	(.032)
R^2	.055	.053	.049
Mean dep. var.	.362	.363	.355
N	7,652	7,766	6,514

Notes: This table reports the coefficients for support for redistribution for BCS70 cohort members on dummies for cognitive ability test score in the top 10% and 5%. The dependent variable is valued 1 for responses of agree and strongly agree on preferences for redistribution, and 0 otherwise. All columns report estimates from a linear probability model. All controls used in Table 1.1 are included. Column 1 reports estimates from our main specification, using results from all tests taken at age 10. Column 2 reports estimates using results from BAS taken at age 10 to measure cognitive ability. Column 3 reports estimates using results from all tests taken at age 5. Panel A shows results considering as high cognitive ability those in the top 10% of the test scores. Panel B shows results considering as high cognitive ability those in the top 5% of the test scores. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.14: Change in Preferences for Redistribution

	Change	Pos. change	Neg. change	Intensity
	(1)	(2)	(3)	(4)
High_CA	.006	-.009	.003	.014
	(.016)	(.011)	(.014)	(.035)
Mean dep. var.	.305	.115	.189	-.007
N	9,440	9,440	9,440	9,440
R^2	.013	.008	.013	.014

Notes: This table reports the coefficients for changes in support for redistribution on a dummy for cognitive ability test score in the top 10%. Columns 1 to 3 report estimates from a linear probability model. Column 4 reports estimates from a linear model. All controls used in Table 1.1 are included. Column 1 reports estimates for changes in support for redistribution between 30s and 40s years old. Column 2 and 3 reports estimates for positive (negative) changes in support for redistribution between 30s and 40s years old. Column 4 reports estimates for changes in intensity of support for redistribution between 30s and 40s years old, as measured through standarized measures of preferences for redistribution. Clustered standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix to Chapter 2

D Data characteristics

Table D.1: Observations per wave

Wave	Period	Response share	#
Wave 1	Apr-May 2020	100.0	8,063
Wave 2	Jun 2020	59.4	4,788
Wave 3	Aug 2020	69.0	5,565
Wave 4	Nov-Dec 2020	69.4	5,594
Wave 5	Mar 2021	61.4	4,950
Wave 6	Jun 2021	53.0	4,271
Wave 7	Oct-Nov 2021	50.6	4,082
Wave 8	Feb-Mar 2022	45.2	3,644

Notes: This table reports responses statistics by survey wave. Column (1) shows responses as a percentage of the first-wave response figure. Column (2) shows the total number of responses in each wave.

Table D.2: Response share per waves by country

Wave	Period	Total	FR	DE	IT	ES	SE
Wave 1	Apr-May 2020	100.0	100.0	100.0	100.0	100.0	100.0
Wave 2	Jun 2020	59.4	60.3	59.1	59.1	59.8	58.1
Wave 3	Aug 2020	69.0	69.6	70.6	72.3	71.4	58.0
Wave 4	Nov-Dec 2020	69.4	71.6	66.5	73.3	71.7	61.7
Wave 5	Mar 2021	61.4	64.9	55.2	65.3	65.3	54.1
Wave 6	Jun 2021	53.0	56.3	41.0	56.8	60.9	48.5
Wave 7	Oct-Nov 2021	50.6	54.3	40.2	54.6	57.8	44.5
Wave 8	Feb-Mar 2022	45.2	50.1	34.9	47.7	52.5	39.1

Notes: This table lists responses as a percentage of the first-wave response figure by country. Column (1) shows the total number of responses. Columns (2), (3), (4), (5), and (6) show the response shares for France, Germany, Italy, Spain, and Sweden respectively.

Table D.3: Number of waves responded per person, share by country

Waves responded	#	Total	FR	DE	IT	ES	SE
1 response	1,159	14.4	14.2	16.0	12.6	12.9	16.9
2 responses	748	9.3	8.1	9.4	9.3	8.5	11.8
3 responses	665	8.2	7.1	10.3	7.2	7.2	9.9
4 responses	717	8.9	7.7	13.2	7.5	7.2	8.6
5 responses	686	8.5	7.9	11.3	7.7	6.9	8.9
6 responses	705	8.7	9.1	6.3	10.5	8.1	10.1
7 responses	1,285	15.9	16.4	13.3	16.8	17.2	16.1
8 responses	2,098	26.0	29.5	20.2	28.4	32.0	17.7

Notes: This table shows the number of response waves per individual by country. Column (1) shows the number of indivduals by number of responses. Column (2) shows the shares per number of responses in the total sample, and columns (3), (4), (5), (6) and (7) those for France, Germany, Italy, Spain and Sweden respectively.

Table D.4: Sample characteristics in Wave 1.

(a) Age

	Share (1)
18-24 y.o.	11.5
25-29 y.o.	7.3
30-39 y.o.	17.4
40-49 y.o.	17.9
50-59 y.o.	16.0
60-69 y.o.	19.3
70-79 y.o.	9.7
80+ y.o.	0.8

(b) Educational attainment

	Share (1)
Primary	7.8
Secondary	37.5
Vocational	13.7
University	20.4
Postgraduate	19.8
Other	0.8

(c) Sex

	Share (1)
Male	48.3
Female	51.7
Other/NA	0.1

Notes: These figures refer to the estimation sample. The sample size is 8,063 in all tables.

Table D.5: Sample characteristics. Time-varying characteristics.

(a) Employment status

	Share (1)
Employed full-time	45.9
Employed part-time	10.7
Marginal/Irregular	1.7
Non-employed	12.6
Retired	23.5
Student	5.6

(b) Country of residence

	Share (1)
France	21.2
Germany	20.5
Italy	21.3
Spain	21.7
Sweden	15.4

(c) Household's income

	Share (1)
Less than 1250 Euros	13.4
1250-2000 Euros	23.1
2000-4000 Euros	37.9
More than 4000 Euros	17.8
Non-declared	7.8

Notes: These tables refer to the estimation sample. The sample size is 24,089 for employment status, and 33,231 for country of residence and household income.

Table D.6: Country rankings

		EU			
	World GDP	Budget contribution	Population	Vulnerable population	Lockdown stringency
	(1)	(2)	(3)	(4)	(5)
Germany	4	1	1	1	8
France	7	2	2	3	7
Italy	8	3	3	2	1
Spain	13	4	4	4	3
Sweden	24	12	12	8	13

Notes: This table reports country rankings within the World (column 1) and European Union (columns 2 to 5). Column 1 refers to total Gross Domestic Product in current USD in 2019. Column 2 refers to total national contribution in the EU's 2014-2020 Multiannual Financial Framework. Column 3 refers to estimates of total population by 2019, and column 4 to the population over 65 years old for the same year. Column 5 displays the average 'stringency' index from February 1st 2020 to January 31th 2021. The index is a simple average of all closure and containment indicators (schools, workplaces, public events, gatherings, public transport, 'stay at home' mandates, internal and external movement, and public health campaigns). The sample size for the rankings is 217 for the world, and 27 for the EU. *Sources:* Data for GDP and population is from World Bank. Data for EU budget contribution is from the European Commission. Data for lockdown stringency is from OxCGRT.

E Cognitive Reflection Test

Figure E.1: Cognitive Reflection Test questions

1. **Bat & Ball:** A bat and a ball cost USD 1.10 in total. The bat costs USD 1.00 more than the ball. How much does the ball cost? _____ cents.
2. **Machines:** If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _____ minutes.
3. **Lily pads:** In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days.

Notes: The correct (intuitive) answers are 5 (10) cents, 5 (100) minutes, and 47 (24) days, respectively. The questionnaire required the submission of an open-ended response in order to continue. This may have produced nonsense responses instead of missing values for some individuals. We deal with this by considering as valid responses (non-missing observations) those in the top 10 for each question. Additionally, the open-ended format can generate coding ambivalence. We account for this by collapsing the intended responses into the proper unit of measure considering that they overcome the intuitive response. We thus consider all three responses around 5 cents as correct (i.e. 5, 0.5 and 0.05).

Table E.1: CRT responses

(a) Bat & Ball

Response	Share
10.00	46.8
0.10	20.0
5.00	9.5
0.50	5.7
1.00	5.2
0.05	2.0
2.10	1.2
50.00	1.0
0.00	0.9
100.00	0.6

(b) Machines

Response	Share
100	44.1
5	31.1
500	5.6
20	4.8
1	4.5
50	1.5
10	1.4
0	0.8
10 024	0.5
1000	0.5

(c) Lily pads

Response	Share
24	51.8
47	27.4
12	2.3
48	1.8
96	1.7
1	1.5
2	1.0
10	1.0
0	1.0
5	0.9

Notes: The above three tables report response shares for 10 responses with the highest frequency for each CRT question. In each table, column (1) shows the numeric response and column (2) shows the share of individuals who chose the corresponding numeric response. Among the ~5,500 responses for the test, there where 101, 109 and 112 unique responses for questions 1, 2, and 3 respectively. The responses were very concentrated. The Top 10 responses for each question attracted 93%, 94.6%, and 90.5% of the total, respectively. A common ambivalence in CRT tests is the response 0.05 cents in question 1, as participants mistake the unit of answer (Cents) for Dollars (Sirota and Juanchich, 2018). In our data, a non-negligible share of answers for question 1 make this unit-of-answer mistake. Note that the top 6 responses are variations of 10 and 5 cents, using different decimal position.

Table E.2: CRT results. Comparison with other studies

	Share				
	COME-HERE	Brañas Garza et al. (2019)	Brañas Garza et al. (2012)	Frederick (2005)	
				Total	ES
	(1)	(2)	(3)	(4)	(5)
Panel A. Individual questions					
Bat & Ball	18.5	31.8			
Machines	32.8	40.2			
Lily pads	30.3	47.8			
Panel B. Total scores					
Score = 0	56.0	37.5	67.0	33	64
Score = 1	21.0	23.2	23.0	28	21
Score = 2	13.9	21.1	8.9	23	10
Score = 3	9.0	18.2	1.1	17	5

Notes: This table describes results on the Cognitive Reflection Test for different samples. Panel A shows shares of correct responses for each individual question. Panel B shows total scores from aggregating correct answers (valued 1) in all three questions. The sample size is 5,541 for COME-HERE, 44,558 for Brañas Garza et al. (2019) meta-study, 191 for Brañas Garza et al. (2012), 3,428 for Frederick (2005) total sample, and 138 for Frederick (2005) Spanish sample.

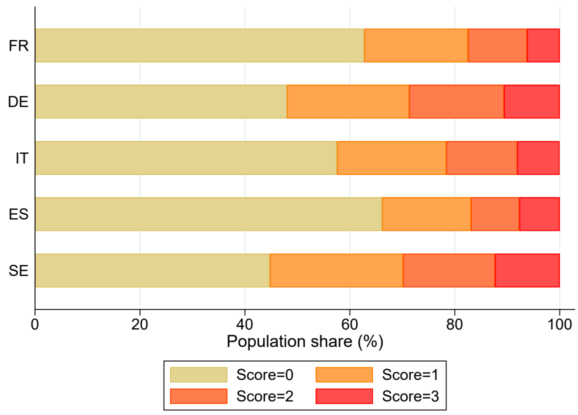
Table E.3: CRT results by country

	Share					
	Total	FR	DE	IT	ES	SE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Individual questions						
Bat & Ball	18.5	10.8	16.3	14.6	15.6	46.7
Machines	32.8	28.3	41.7	34.9	23.6	36.2
Lily pads	30.3	27.1	37.7	30.1	23.8	34.7
Panel B. Total scores						
Score = 0	56.0	63.2	48.1	56.6	65.5	42.8
Score = 1	21.0	18.6	24.2	21.2	17.4	24.9
Score = 2	13.9	11.7	17.6	13.4	9.5	19.1
Score = 3	9.0	6.6	10.1	8.8	7.7	13.2

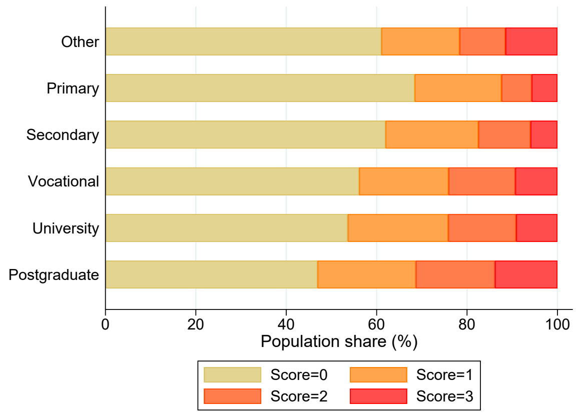
Notes: This table describes results on the Cognitive Reflection Test for different samples. Panel A shows shares of correct responses for each individual question. Panel B shows total scores from aggregating correct answers (valued 1) in all three questions. The sample size is 5,541 for the total, 1,183 for France, 1,210 for Germany, 1,231 for Italy, 1,217 for Spain, and 700 for Sweden.

Figure E.2: CRT scores by categories

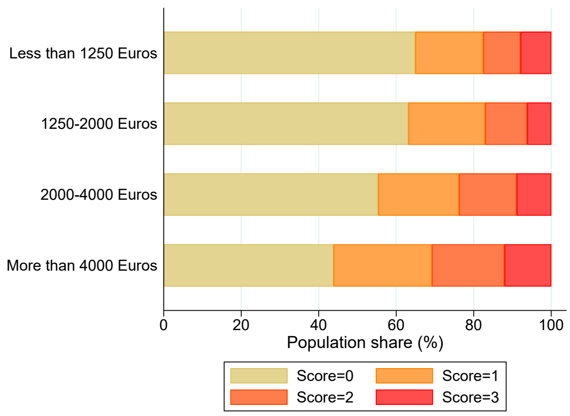
(a) Country



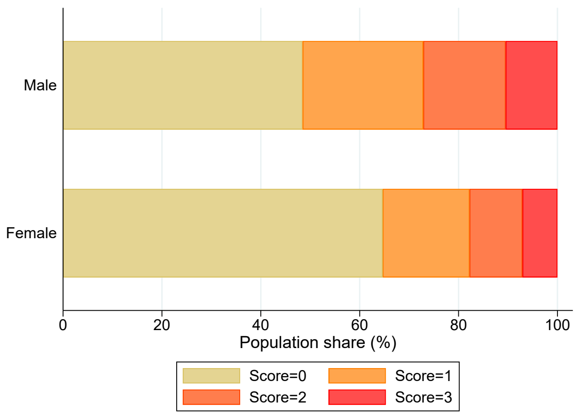
(b) Educational attainment



(c) Household income

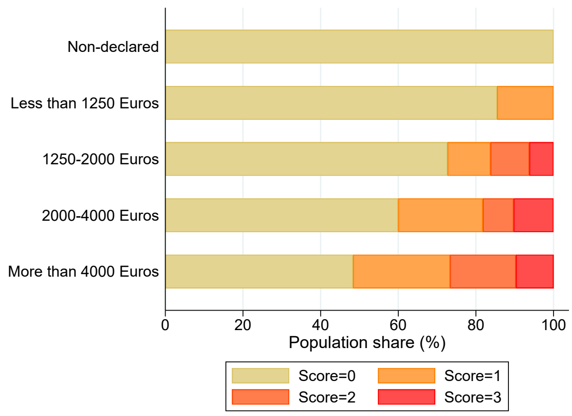


(d) Sex



Notes: These figures plot CRT score shares for each category in the expanded sample.

Figure E.3: CRT scores by household income

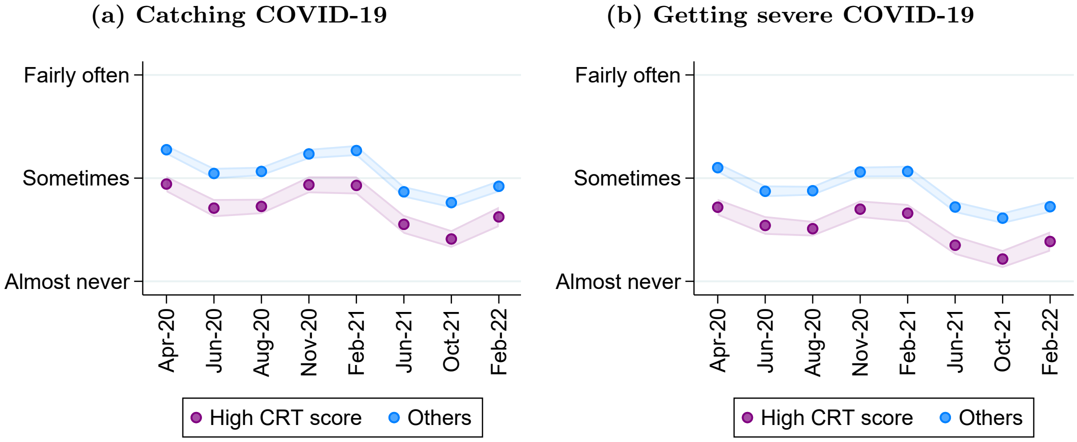


Notes: These figures plot CRT score shares for income categories. Only fully-employed individuals aged between 25 and 60 are considered.

Table E.4: Group comparison

	Total sample	High CRT score	High vs. Low
	(1)	(2)	(3)
Panel A. Baseline characteristics			
Female	.512	.410	-.131***
			(.029)
50+ years	.306	.295	-.014
			(.027)
Employed	.971	.985	.018
			(.020)
Household income 2000+ Euros	.617	.705	.114***
			(.028)
University	.506	.562	.072***
			(.029)
Northern Europe	.341	.465	-.161***
			(.029)
Panel B. Attitudes			
Risk (willigness towards)	.449	.419	-.055***
			(.015)
Patience	.605	.693	.087***
			(.022)
Trust:			
in other people	.443	.456	.007
			(.015)
in other's fairness	.489	.506	.012
			(.014)
in other's helpfulness	.579	.572	-.010
			(.013)
Luck matters (normative)	.441	.412	-.019
			(.018)
Panel C. Perceptions			
Equality of Opportunities	.414	.345	-.097***
			(.015)
Luck matters (positive)	.406	.422	.023**
			(.011)

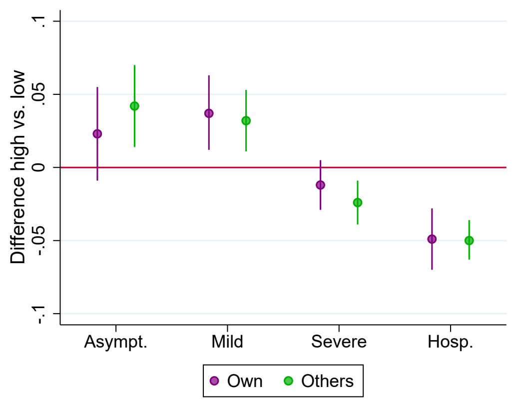
Figure E.4: Concerns about COVID-19



Notes: These figures plot the mean responses to concerns about COVID-19 throughout the pandemic. Responses were valued as follows: Never (1), Almost never (2), Sometimes (3), Fairly often (4), Very often (5), All the time (6). Individuals with high CRT scores are those who score 2 and 3 in the test. CRT scores were measured in August 2020. Confidence intervals at 95% are shaded. The sample size varies in each wave (see Table D.5), and across groups.

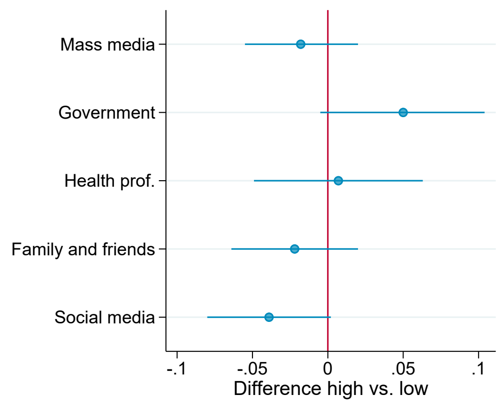
Figure E.5: Perceptions and information consumption

(a) Assigned probabilities to COVID-19 outcomes



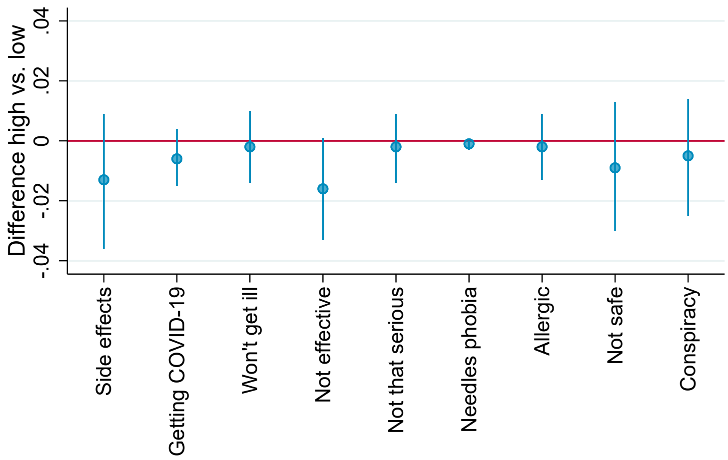
Notes: This figure plots estimates for the differences in the assigned probabilities for COVID-19 outcomes between individuals with CRT scores of 2 and 3 (high score) and those who score 0 and 1 (low score) controlling for socio-demographic characteristics (see the details in Table E.4). Probabilities were reported in August 2020. 'Own' refers to the probabilities for the respondent catching COVID-19. 'Others' refer to probabilities assigned to the general population. The bars are 95% confidence intervals constructed with robust standard errors.

(b) Information sources for COVID-19 pandemic



Notes: This figure plots estimates for the differences in the sources of COVID-19 related information between individuals with CRT scores of 2 and 3 (high score) and those who score 0 and 1 (low score) controlling for socio-demographic characteristics (see the details in Table E.4). Information sources were reported in Feb-Mar 2022. The bars are 95% confidence intervals constructed with robust standard errors.

Figure E.6: Concerns about COVID-19 vaccines



Notes: These figures plot estimates for the differences in concerns about COVID-19 vaccines between individuals with CRT scores of 2 and 3 (high score) and those who score 0 and 1 (low score) controlling for socio-demographic characteristics (see the details in Table E.4). Concerns were surveyed in Feb-Mar 2022. The bars are 95% confidence intervals constructed with robust standard errors.

F Vaccine distribution

Figure F.1: Question used to assess Preferences for Vaccine Distribution in the World

The richest countries of the world are buying about 70% of all vaccines, leaving the poorer and more populated part of the world with the rest. How do you think vaccines should have been purchased?.

- All vaccines should be purchased by an international organization and be distributed according to each country's needs. Countries should contribute to vaccine purchase in proportion to their national wealth.
- All vaccines should be purchased by an international organization and be distributed according each country's contribution to the overall cost of vaccine purchase.
- Countries should be able to buy the vaccines in the market and to distribute them as they wish.

Figure F.2: Question used to assess Preferences for Vaccine Distribution in the EU

A country's infection rate depends on the policies it follows, for example lockdowns, and its share of clinically-vulnerable individuals. How should the European Union distribute vaccines across its Member States, if there are not enough for everyone?.

- Proportional to the Member State's population, irrespective of the country's lockdown measures.
- Proportional to the Member State's clinically vulnerable population, irrespective of the country's lockdown measures.
- Proportional to the Member State's economic contribution to the European Union budget, irrespective of the country's lockdown measures.
- Proportional to the Member State's stringency of lockdown measures enforced.

Figure F.3: Question used to assess Preferences for Vaccine Distribution within the country

Some people are more careful in avoiding infection by the SARS-CoV2 virus, for example by wearing a mask, washing their hands, and respecting confinement limitations. We also know that people with previous health conditions are more at risk of developing Covid-19. At the same time front-line workers are more at risk of getting infected. If there were not enough vaccines for everyone in your country, who should take priority?.

- Those who took more care in avoiding infection, with those who took no care last in the queue.
- Everyone has the same right to the vaccine, so I would run a lottery.
- The most clinically vulnerable and the front-line workers, then the second-most clinically vulnerable, and so on, with those who took no care last in the queue, irrespective of their vulnerability.
- The most clinically vulnerable and front-line workers, with the least clinically vulnerable last in the queue.

Table F.1: Vaccine-distribution questions: labels and classification

Territory	Label	Text	Circumstances	Efforts
World	Market	Countries should be able to buy the vaccines in the market and to distribute them as they wish.	-	Absolute budget
World	Budget contribution	All vaccines should be purchased by an international organization and be distributed according each country's contribution to the overall cost of vaccine purchase.	-	Absolute budget
World	Needs	All vaccines should be purchased by an international organization and be distributed according to each country's needs. Countries should contribute to vaccine purchase in proportion to their national wealth.	Relative budget	-
EU	Budget contribution	Proportional to the Member State's economic contribution to the European Union budget, irrespective of the country's lockdown measures.	-	Budget
EU	Measures enforced	Proportional to the Member State's stringency of lockdown measures enforced.	-	Measures
EU	Population	Proportional to the Member State's population, irrespective of the country's lockdown measures.	Population	-
EU	Vulnerability	Proportional to the Member State's clinically vulnerable population, irrespective of the country's lockdown measures.	Clinically vulnerable population	-
Country	Carefulness	Those who took more care in avoiding infection, with those who took no care last in the queue.	-	Care
Country	Equal	Everyone has the same right to the vaccine, so I would run a lottery.	-	-
Country	Vulnerability+Carefulness	The most clinically vulnerable and the front-line workers, then the second-most clinically vulnerable, and so on, with those who took no care last in the queue, irrespective of their vulnerability.	Clinical vulnerability	Care
Country	Vulnerability	The most clinically vulnerable and front-line workers, with the least clinically vulnerable last in the queue.	Clinical vulnerability	-

Table F.2: Vaccine-distribution responses

(a) World

	Share
	(1)
Market	29.2
Budget contribution	19.1
Needs	51.7

(b) EU

	Share
	(1)
Budget contribution	13.1
Measures enforced	19.2
Population	34.8
Vulnerability	32.9

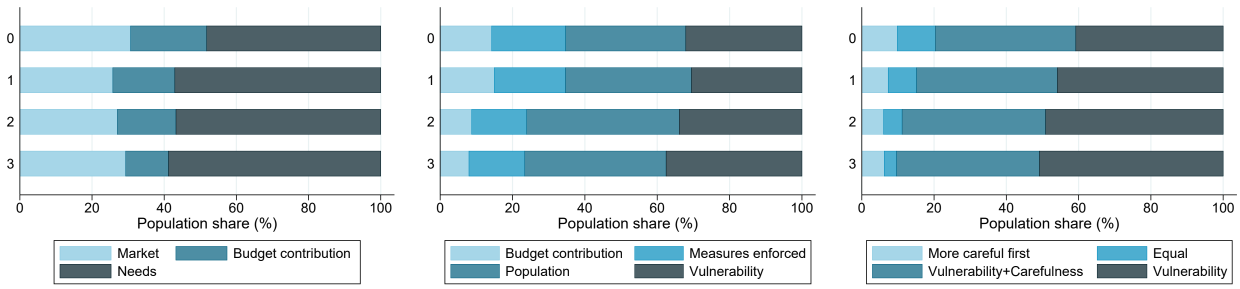
(c) Country

	Share
	(1)
Carefulness	8.8
Equal	8.6
Vulnerability+Carefulness	38.6
Vulnerability	44.0

Notes: These tables list the population shares of preferred vaccine-distribution schemes. The labels used, as in the rest of the paper, are explained alongside the question descriptions in Table F.1. The sample size is 4,950 for all tables.

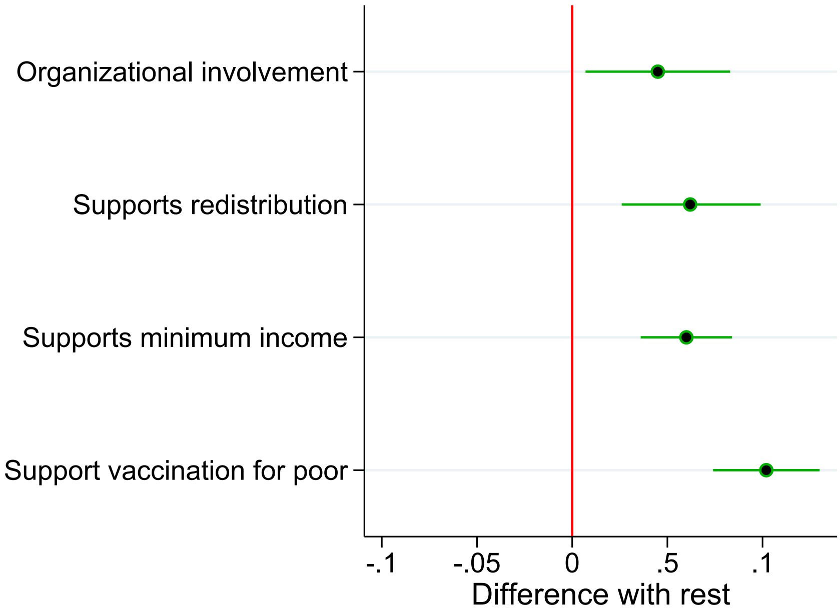
Figure F.4: CRT scores and Preferences for Vaccine Distribution

(a) World **(b) EU** **(c) Country**



Notes: These figures plot the response shares for preferences for vaccine distribution by CRT test scores. CRT scores were measured in August 2020. Preferences for vaccine distribution were measured in March 2021. The sample size is 4,317.

Figure F.5: Correlates for vaccine distribution prioritizing circumstances



Notes: This figure plots the differences for social preferences and behaviors between people who declare priority in vaccine distribution according to circumstances for all questions and the rest of population. Support for income redistribution was measured in March 2021. Support for minimum income was measured in June 2021. Organizational participation and support for helping poor countries vaccination were measured in February-March 2022. The bars are 95% confidence intervals constructed with robust standard errors.

G Additional results

Table G.1: Support for distributional schemes prioritizing circumstances

	(1)	(2)	(3)
$High\_CA$	.286***	.359***	.329***
	(.059)	(.059)	(.060)
Margins for $High\_CA$ dummy at means			
0/3	-.035***	-.042***	-.039***
	(.008)	(.007)	(.007)
1/3	-.062***	-.074***	-.067***
	(.013)	(.012)	(.012)
2/3	-.004	-.005*	-.005*
	(.003)	(.003)	(.003)
3/3	.101***	.122***	.111***
	(.020)	(.019)	(.020)
Socio-demographic		X	X
COVID-19 related			X
N	2,511	2,511	2,511
pseudo-R^2	.005	.456	.459

Notes: This table lists the coefficients and margins from an ordered probit for support for vaccine-distribution schemes prioritizing circumstances on a dummy for CRT scores of 2 and 3. The mean of the dependent variable is 1.97. The margins are estimated at the means of all of the other covariates. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.2: Preferences for Vaccine Distribution in the World

Multinomial Logit

	(1)	(2)	(3)
Market			
$High\_CA$	.022	-.119	-.148
	(.132)	(.128)	(.131)
Budget contribution			
$High\_CA$	-.382**	-.461***	-.402***
	(.153)	(.151)	(.151)
Socio-demographic		X	X
COVID-19 related			X
N	2,511	2,511	2,511
pseudo-R^2	.002	.458	.463

Notes: This table lists the coefficients from a multinomial logit for preferences for vaccine distribution in the World on a dummy for CRT scores of 2 and 3. Needs is the base outcome. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Margins for $High\_CA$ dummy

Market	.027	.004	-.005
	(.025)	(.025)	(.024)
Budget contribution	-.063***	-.066***	-.054**
	(.023)	(.023)	(.023)
Needs	.037	.063**	.060**
	(.029)	(.026)	(.026)

Notes: This table lists the estimates of the response margins for a dummy for CRT scores of 2 and 3 in a multinomial logit for preferences for vaccine distribution in the World. The sample is that used for the multinomial logit. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.3: Preferences for Vaccine Distribution in the EU

Multinomial Logit

	(1)	(2)	(3)
Budget contribution			
High_CA	-.694***	-.697***	-.640***
	(.218)	(.199)	(.197)
Measures enforced			
High_CA	-.331**	-.402**	-.346**
	(.157)	(.163)	(.166)
Population			
High_CA	.005	.050	.064
	(.129)	(.130)	(.132)
Socio-demographic		X	X
COVID-19 related			X
N	2,511	2,511	2,511
pseudo-R^2	.004	.461	.464

Notes: This table reports the coefficients from a multinomial logit for preferences for vaccine distribution in the EU on a dummy for CRT scores of 2 and 3. Vulnerability is the base outcome. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Margins for *High_CA* dummy

Budget contribution	-.081***	-.076***	-.071***
	(.031)	(.024)	(.023)
Measures enforced	-.030	-.042*	-.036
	(.022)	(.022)	(.022)
Population	.058**	.069***	.066***
	(.026)	(.025)	(.025)
Vulnerability	.054**	.049**	.041*
	(.025)	(.024)	(.025)

Notes: This table reports the estimated response margins for a dummy for CRT scores of 2 and 3 in a multinomial logit for preferences for vaccine distribution in the EU. The sample is that used for the multinomial logit. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.4: Preferences for Vaccine Distribution within the country

Multinomial Logit

	(1)	(2)	(3)
Carefulness			
High_CA	-.572***	-.688***	-.567***
	(.207)	(.209)	(.211)
Equal			
High_CA	-.915***	-1.012***	-.968***
	(.237)	(.234)	(.236)
Vulnearability+Carefulness			
High_CA	-.134	-.200	-.182
	(.128)	(.122)	(.123)
Socio-demographic		X	X
COVID-19 related			X
N	2,511	2,511	2,511
pseudo-R^2	.005	.461	.465

Notes: This table reports the coefficients from a multinomial logit for preferences for vaccine distribution within the country on a dummy for CRT scores of 2 and 3. Vulnerability is the base outcome. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Margins for *High_CA* dummy

Carefulness	-.038**	-.043**	-.033*
	(.018)	(.018)	(.018)
Equal	-.065***	-.067***	-.065***
	(.020)	(.019)	(.019)
Vulnerability+Carefulness	.023	.016	.014
	(.028)	(.026)	(.027)
Vulnerability	.080***	.094***	.084***
	(.028)	(.026)	(.026)

Notes: This table reports the estimated response margins for a dummy for CRT scores of 2 and 3 in a multinomial logit for preferences for vaccine distribution within the country. The sample is that used for the multinomial logit. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.5: Total support for distributional schemes prioritizing circumstances

	(1)	(2)	(3)	(4)	(5)	(6)
$High\_CA$	.150***	.117***	.224**	.177***	.118***	.125***
	(.039)	(.026)	(.099)	(.046)	(.038)	(.033)
$High\_CA$ *	-.059					
Male dummy	(.050)					
$High\_CA$ *		.003				
* 60+ years dummy		(.090)				
$High\_CA$ *			-.120			
* Employed dummy			(.102)			
$High\_CA$ *				-.088		
* 2000+ EUR dummy				(.054)		
$High\_CA$ *					-.001	
* University dummy					(.049)	
$High\_CA$ *						-.019
* North Europe dummy						(.049)
N	2,511	2,511	2,511	2,511	2,511	2,511
R^2	.078	.077	.078	.078	.077	.077

Notes: lists the coefficients from linear-probability models on total support for vaccine distribution schemes that focus on circumstances on a dummy for CRT scores of 2 and 3, and its interaction with a set of dummies. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. The male dummy is 1 for men, the 60+ years dummy 1 for those aged 60 years or more, the Employed dummy 1 for those employed in full-time jobs, the 2000+ EUR dummy 1 for those residing in households with total income greater than or equal to 2000 Euros, the University dummy 1 for University and postgraduate education, and the North Europe dummy 1 for individuals living in Germany and Sweden. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.6: Total support for distributional schemes prioritizing circumstances Alternative high-cognition group

	LPM			Probit	Margins
	(1)	(2)	(3)	(4)	(5)
$High\_CA$	.118***	.113***	.098***	.269***	.090***
	(.038)	(.035)	(.035)	(.096)	(.032)
Socio-demographic		X	X	X	X
COVID-19 related			X	X	X
N	2,511	2,511	2,511	2,511	2,511
R^2/pseudo-R^2	.005	.061	.070	.058	-

Notes: This table lists the coefficients for total support for vaccine-distribution schemes that focus on circumstances on a dummy for CRT scores of 3. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317. Columns 1 to 3 report estimates from a linear-probability model, and column 4 those from a probit model. Column 5 lists the marginal effects at the mean. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.7: Support for distributional schemes prioritizing circumstances Alternative high-cognition group

	(1)	(2)	(3)
$High\_CA$	.336***	.333***	.290***
	(.084)	(.083)	(.084)
Margins for $High\_CA$ dummy at means			
0/3	-0.041***	-0.040***	-0.034***
	(0.011)	(0.010)	(0.010)
1/3	-0.073***	-0.069***	-0.060***
	(0.018)	(0.017)	(0.017)
2/3	-0.005	-0.005	-0.004
	(0.003)	(0.003)	(0.003)
3/3	.119***	0.114***	0.098***
	(0.030)	(0.028)	(0.028)
Socio-demographic		X	X
COVID-19 related			X
N	2,511	2,511	2,511
pseudo-R^2	.003	.453	.457

Notes: This table lists the coefficients and margins from an ordered probit for support for vaccine-distribution schemes prioritizing circumstances on a dummy for CRT scores of 3. The mean of the dependent variable is 1.97. The margins are estimated at the means of all of the other covariates. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.8: Total support for distributional schemes prioritizing circumstances Categorical CRT scores

	LPM			Probit	Margins
	(1)	(2)	(3)	(4)	(5)
CRT score=1	.034	.078***	.076***	.222***	.073***
	(.034)	(.027)	(.027)	(.080)	(.027)
CRT score=2	.094***	.149***	.140***	.410***	.139***
	(.032)	(.031)	(.031)	(.089)	(.031)
CRT score=3	.140***	.161***	.145***	.410***	.139***
	(.040)	(.037)	(.037)	(.103)	(0.036)
Socio-demographic		X	X	X	X
COVID-19 related			X	X	X
N	2,511	2,511	2,511	2,511	2,511
R^2/pseudo-R^2	.010	.072	.081	.067	-

Notes: This table lists the coefficients for total support for vaccine-distribution schemes that focus on circumstances on a categorical variable for CRT scores. The omitted category is a CRT score of 0. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317. Columns 1 to 3 report estimates from a linear-probability model, and column 4 those from a probit model. Column 5 lists the marginal effect at the mean. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.9: Total support for distributional schemes prioritizing circumstances Alternative outcome classification

	LPM			Probit	Margins
	(1)	(2)	(3)	(4)	(5)
$High\_CA$	.032**	.039***	.034**	.215**	.032**
	(.013	(.014)	(.014)	(.091)	(.013)
Socio-demographic		X	X	X	X
COVID-19 related			X	X	X
N	2,511	2,511	2,511	2,511	2,511
R^2/pseudo-R^2	.002	.025	.028	.048	-

Notes: This table lists the coefficients for total support for a restrained classification of vaccine-distribution schemes that focus on circumstances on a dummy for CRT scores of 2 and 3. The dependent variable is 1 when all three vaccine distribution schemes favor circumstances. Vaccine-distribution schemes that are considered to favor circumstances are 'Needs' in the case of distribution in the world, and 'Vulnerability' in the EU and within the country. The mean of the dependent variable is 0.084. Columns 1 to 3 report estimates from a linear-probability model, and column 4 those from a probit model. Column 5 reports the marginal effect at the mean. The socio-demographic controls are sex, age group, educational attainment, occupational status, household income, and country of residence. The COVID-19 related controls account for the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table G.10: Total support for distributional schemes prioritizing circumstances Adding/removing controls (scheme convenience)

	(1)	(2)	(3)	(4)	(5)
$High\_CA$	.117***	.114***	.117***	.112***	.110***
	(.023)	(.022)	(.023)	(.022)	(.022)
(+) Medical conditions		X			X
(+) Front-line worker			X		X
(+) Following recommendations				X	X
Wald test	-	.784	.019	3.458	3.046
p-value	-	.376	.890	.063	.081
N	2,511	2,511	2,511	2,511	2,511
R^2	.077	.084	.077	.085	.091

Notes: This table lists the coefficients for total support for vaccine-distribution schemes that focus on circumstances on a dummy for CRT scores of 2 and 3. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317. All columns report estimates from a linear-probability model. Columns 1 to 3 report estimates adding/removing controls to the main specification. The main specification controls are sex, age group, educational attainment, occupational status, household income, country of residence, history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Declared medical conditions (individual dummies for cancer, lung disease, heart disease and diabetes) were collected in April 2020. Front-line are workers in the health system, as measured in April 2020. The declared degree of adherence to recommendations to prevent the spread of COVID-19 were measured via a 7-point Likert scale in March 2021. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Wald test statistics for the equality of the $High\_CA$ coefficient to that in the main specification are reported, with the associated p-values.

Table G.11: Total support for distributional schemes prioritizing circumstances Adding/removing controls (cost perception)

	(1)	(2)	(3)	(4)	(5)
$High\_CA$	.117***	.122***	.117***	.112***	.112***
	(.025)	(.022)	(.023)	(.023)	(.023)
(−) Concerns COVID-19		X			
(+) Concerns COVID-19			X		X
(+) Perceptions COVID-19 prob.				X	X
Wald test	-	2.082	.100	2.805	2.987
p-value	-	.149	.751	.094	.084
N	2,511	2,511	2,511	2,511	2,511
R^2	.077	.076	.078	.079	.081

Notes: This table lists the coefficients for total support for vaccine-distribution schemes that focus on circumstances on a dummy for CRT scores of 2 and 3. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317. All columns report estimates from a linear-probability model. Column 1 reports the estimates in our main specification and columns 2 to 5 those adding/removing controls to the main specification. The main specification controls are sex, age group, educational attainment, occupational status, household income, country of residence, history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Concern about catching COVID-19 was measured in March 2021. The assigned probabilities for the COVID-19 outcomes were measured in August 2020. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Wald test statistics for the equality of the $High\_CA$ coefficient to that in the main specification are reported, with the associated p-values.

Table G.12: Total support for distributional schemes prioritizing circumstances Adding/removing controls (prosociality)

	(1)	(2)	(3)	(4)	(5)
High_CA	.117***	.113***	.085***	.113***	.118***
	(.025)	(.023)	(.022)	(.023)	(.023)
(+) Luck matters		X			
(+) No equality of opportunities			X		
(+) Hypothetical donation				X	
(+) Trust					X
Wald test	-	2.962	25.842	1.208	.345
p-value	-	.085	.000	.272	.557
N	2,511	2,511	2,511	2,511	2,511
R^2	.077	.080	.105	.078	.080

Notes: This table lists the coefficients for total support for vaccine-distribution schemes that focus on circumstances on a dummy for CRT scores of 2 and 3. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317. All columns report estimates from a linear-probability model. Column 1 reports the estimates in our main specification, and columns 2 to 5 those adding/removing controls to the main specification. The main specification controls are sex, age group, educational attainment, occupational status, household income, country of residence, history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Perceptions about role of luck (as opposed to effort), perceptions about equality of opportunity, hypothetical donation to 'a good cause', and trust in people, other's fairness and other's helpfulness were measured in March 2021. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Wald test statistics for the equality of the *High_CA* coefficient to that in the main specification are reported, with the associated p-values.

Table G.13: Total support for distributional schemes prioritizing circumstances Adding/removing controls (prosociality)

	(1)	(2)	(3)
$High\_CA$	.117***	.080***	.092***
	(.025)	(.023)	(.022)
(+) Luck matters		X	
(+) No equality of opportunities		X	
(+) Hypothetical donation		X	
(+) Trust		X	
(+) Prosociality factors			X
Wald test	-	25.622	18.190
p-value	-	.000	.000
N	2,511	2,511	2,511
R^2	.077	.115	.103

Notes: This table lists the coefficients for total support for vaccine-distribution schemes that focus on circumstances on a dummy for CRT scores of 2 and 3. The dependent variable is 1 when all three vaccine-distribution schemes favor circumstances. The mean of the dependent variable is 0.317. All columns report estimates from a linear-probability model. Column 1 reports the estimates in our main specification, and columns 2 to 5 those adding/removing controls to the main specification. The main specification controls are sex, age group, educational attainment, occupational status, household income, country of residence, the history of COVID-19 infection, concern about getting it, and confidence in the national health system to cope with the pandemic. Perceptions about role of luck (as opposed to effort), perceptions about equality of opportunity, hypothetical donation to 'a good cause', and trust in people, other's fairness and other's helpfulness were measured in March 2021. The prosociality factors comes from a PCA on all additional controls included in this table. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Wald test statistics for the equality of the $High\_CA$ coefficient to that in the main specification are reported, with the associated p-values.

Appendix to Chapter 3

H Spectator phase

Procedures

The spectator phase consists of two stages: distribution decisions with incentivized belief elicitations, and surveys. Participants are randomly assigned to different treatment conditions in a 2x2 between-subject setting. Treatments differ on the first stage and are equal in the second stage. Figure 3.1 in the main text details the spectator phase flow.

First stage. I start by laying out the workers phase setting. I explain that real people were hired to work in a number of effort tasks, that commitments were made for a low and high piece-rate value, that the piece-rate value was randomly assigned, and that workers had to follow-up their commitment. Throughout the spectator phase I use visual aid, created with a focus on making the information easy to understand. The piece-rate assignment is explained through flipping a red and blue coin. Those workers who get the red side of the coin are assigned the low piece-rate, while those who get the blue side are assigned the high piece-rate. The low piece-rate worker is labeled as 'Worker A' and is colored in red. The high piece-rate worker is labeled as 'Worker B' and is colored in blue. I explain that workers earn points, which can be later traded for money. The point-to-money conversion rate is 0.05 GBP = 1 points, implying that the low piece-rate is 1 point and the high piece-rate is 10 points. Participants are not aware of the conversion rate.

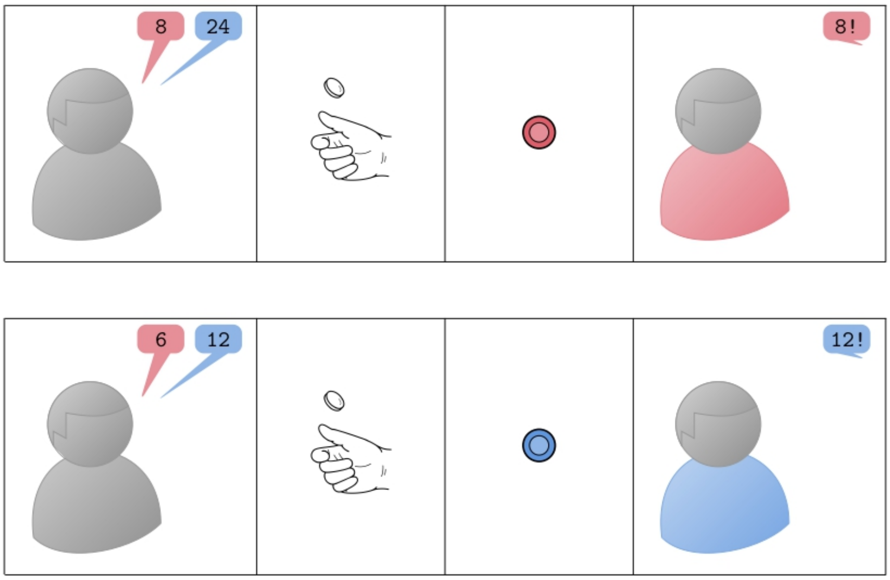
Then, I explain the pair formation, noting that each pair comprises one red worker (receiving the low piece-rate) and one blue worker (receiving the high piece-rate).[50] I inform participants that they will decide how to distribute points within pairs, emphasizing that there is no correct or incorrect answer. I explain participants that they will be presented five pairs, one of which is real and that their decisions could be implemented in real life. I announce that 1 in 10 spectators will make a decision with real consequences. Spectators are aware that workers expect a third-party may influence their payment, but cannot know their identity.

Before starting with the distributions and belief elicitations I run a comprehension test. There

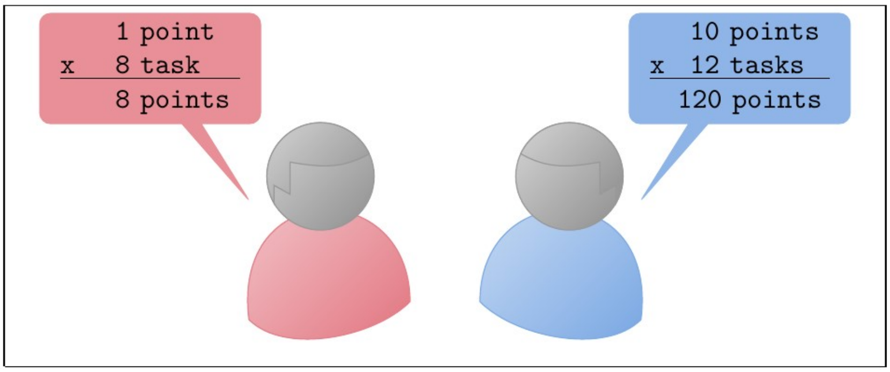
[50] I match workers according to their relative performance within piece-rate, focusing on the differences stemming from unequal opportunities (Roemer, 1993; Ramos and Van de gaer, 2016). This matching assumes that those at the same percentile of the income distribution conditional on their circumstance have exerted the same degree of effort. In my setting, the fundamental assumptions to derive it are met as circumstances are randomly assigned and the worker's payment structure is strictly increasing in exerted effort. For more details, see Fleurbaey (1998).

Figure H.1: Figures used to explain the worker phase

(a) Piece-rate assignment



(b) Pair formation



Notes: These figures were shown to explain the worker phase. Figures (a) show the task commitment and random piece-rate assignment. I use colors to differentiate commitments and assignments to different piece-rates. Red is used for the low piece-rate and blue for the high piece-rate. I use a coin flip to explain the random assignment. Figure (b) shows team formation.

is no limited time or opportunities to answer. Participants are allowed to ask questions to the assisting teachers in the room. Teachers were explained the setting in the weekly coordination meeting, but are unaware of the experiment's research questions. Participants can only start with the distributions and belief elicitations after all questions in the comprehension test are correctly answered. Depending on the treatment, participants are first presented with the distribution decisions or with belief elicitations.

For treatment conditions `LI` and `CI`, participants are first presented with the distribution decisions. Participants decide on the point distribution within pairs in 5 scenarios. After the 5 scenarios, participants respond a post-decision survey. Following, spectators are offered the possibility of gaining additional information to remake decisions. Finally, participants are presented with the belief elicitations.

For treatment condition `ICT`, participants are presented first with the belief elicitations. Participants guess one worker's task commitment for the non-assigned piece-rate in one scenario. Then, participants are presented with the distribution decision for the same scenario. The distribution decision is made as in treatment conditions `LI` and `CI`. For each scenario participants complete the belief elicitation and the distribution decision. After the 5 scenarios, participants respond a post-decision survey. Finally, spectators are offered the possibility of gaining additional information to remake decisions.

Distribution decisions. See Figure H.2 for a screenshot of the distribution decision. Participants decide on the point distribution within pairs for five scenarios. Decisions are made with a slider and aided by a dynamic graph plotting the share assigned to each worker. There is no time limit, but a pop-up window appears 1 minute after the scenario is presented.

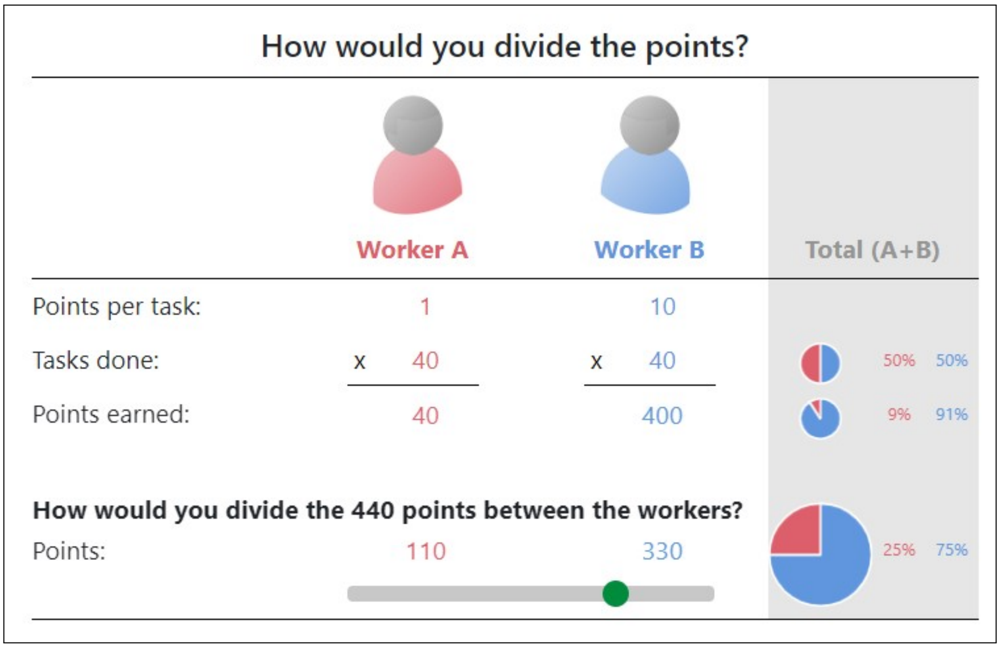
Post-decision survey. After deciding for the five scenarios, participants are randomly presented one decision and asked to justify it. There is a minimum character limit of 100 characters. In the next screen, participants answer a non-incentivized survey. I ask which is their preferred distribution criteria for distributing within pairs. I present a close list, with each statement adhering to (i) egalitarianism, (ii) libertarianism, (iii) factual meritocracy, and (iv) counterfactual meritocracy. Responses are presented in random order. I also ask about the worker they would prefer to be, the identity of the real team, and the degree of understanding of the task.

Gaining additional information. After the post-decision survey, spectators are offered the possibility of gaining additional information to remake decisions. Offered information is on worker's effort commitment under equal opportunities. To access such information, spectators need to complete a counting-zeros task (Abeler et al., 2011). Spectators are able to take or not the opportunity.

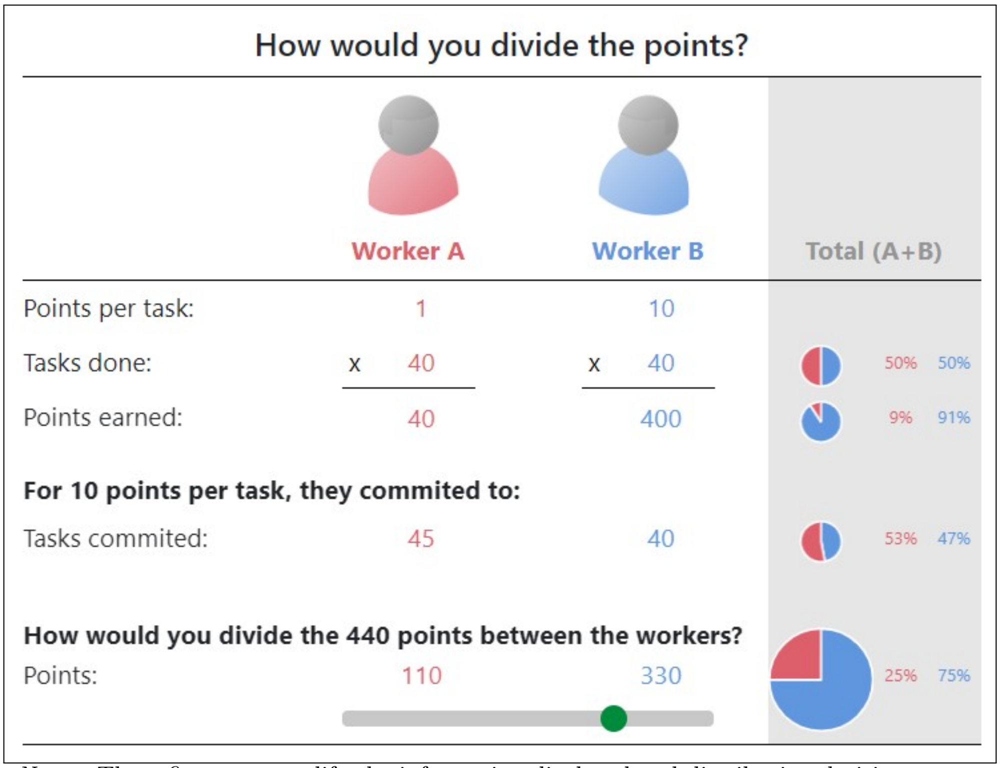
The task consists on counting zeros in a matrix. I present a square matrix composed of 1s and 0s (see Figure H.3). The task is to enter the total number of 0s in the matrix. There is no limited time or opportunities to answer. I ask participants to complete one matrix to acquire information. Participants are able to withdraw from the task at any time, loosing access to the additional information.

Figure H.2: Distribution decision screen, by treatment conditions

(a) LI/ICT treatments

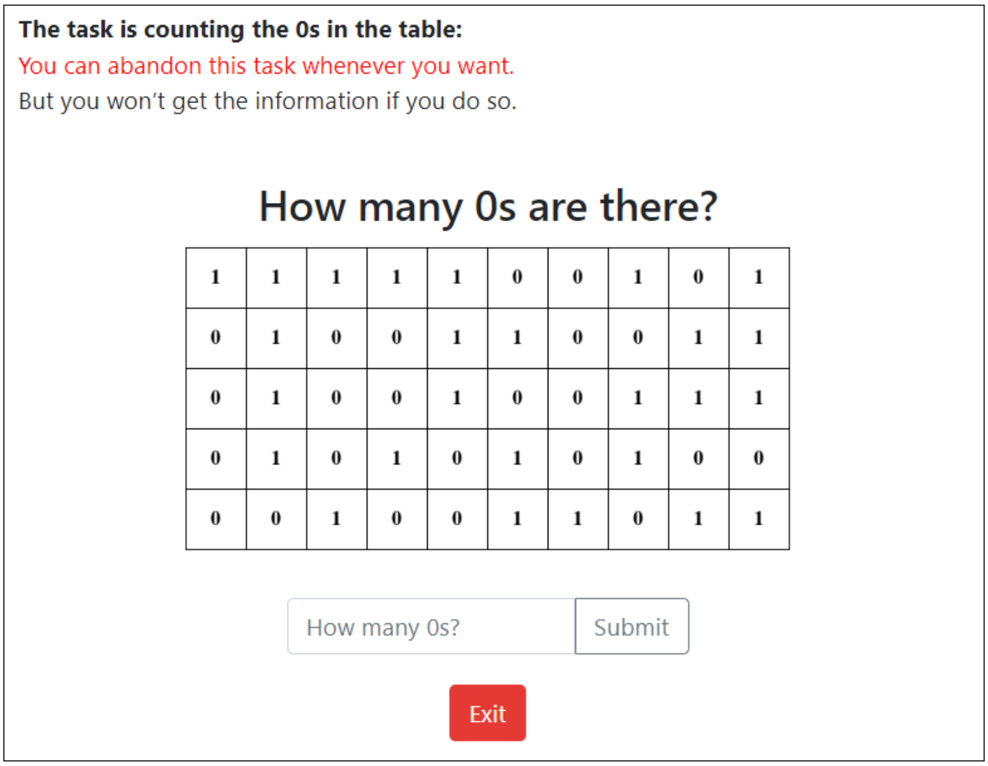


(b) CI treatment



Notes: These figures exemplify the information displayed and distribution decision screen. Each figure shows a pair of workers. In the LI/ICT treatments I provide information about piece-rate payment, tasks completed, and initial earnings for each worker. In the CI treatment I additionally disclose the task commitment for a same piece-rate payment (randomly selected for each pair). I also display shares for tasks and earnings (automatically computed). Participants can modify the allocation by moving the slider. A dynamic graph updates with the spectator's decision.

Figure H.3: Counting-zeros task example



Notes: This screenshot exemplifies the counting-zeros task. The table displayed shows a random sequence of 1s and 0s. The participant is shown the table and asked how many 0s are there in the table. The correct answer for this table is 24.

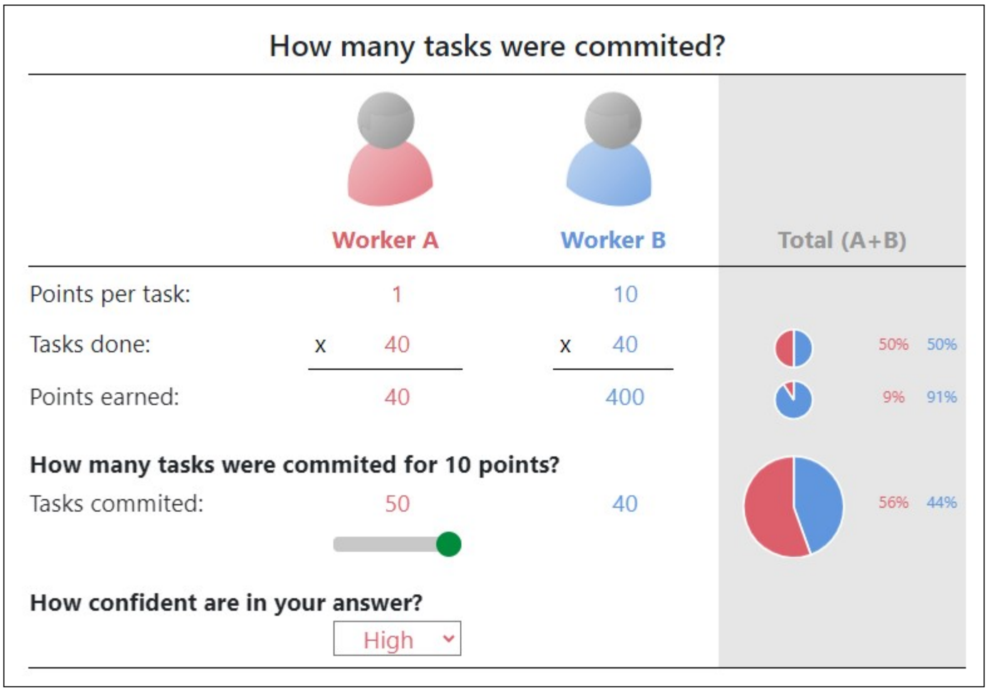
Participants who successfully complete the task are presented with the information and asked to remake their decision for the scenario they guessed as the real one. The remake decision is made at the end of the first stage. Except for the provided information, the decision is made equally to previous decisions.

Belief elicitation. See Figure H.4 for a screenshot of the belief elicitation. Participants guess one worker's task commitment for the non-assigned piece-rate. The worker is randomly selected in each scenario. Guesses are made with a slider and aided by a dynamic graph. There is no time limit, but a pop-up window appears 1 minute after the scenario is presented.

Second stage. I run two surveys: one is incentivized and the other one is non-incentivized.

Incentivized survey. I include the twelve items from Raven's Standard Progressive Matrices (SPM) test (Raven, 1936, 2000). Figure H.5 exemplifies it. Each item is a 3x3 matrix with a missing cell in the bottom right corner. Participants are asked to select the missing cell out of eight choices provided. Participants receive the test instructions before it begins. I require participants to answer a small set of comprehension questions. These refer to time allocation,

Figure H.4: Belief elicitation screen example



Notes: This screenshot exemplifies the information displayed and belief elicitation screen. The figure shows a pair of workers. In all treatment conditions I provide information about piece-rate payment, tasks completed, and initial earnings for each worker. I also display shares for tasks and earnings (automatically computed). Participants are randomly shown task commitments for one piece-rate value and asked to guess for the worker assigned the other piece-rate. Participants can modify the guess by moving the slider. A dynamic graph updates with the spectator's decision.

number of correct options per item and an illustrative item (previously used in the instructions). The test only begins after all comprehension questions are correctly answered.

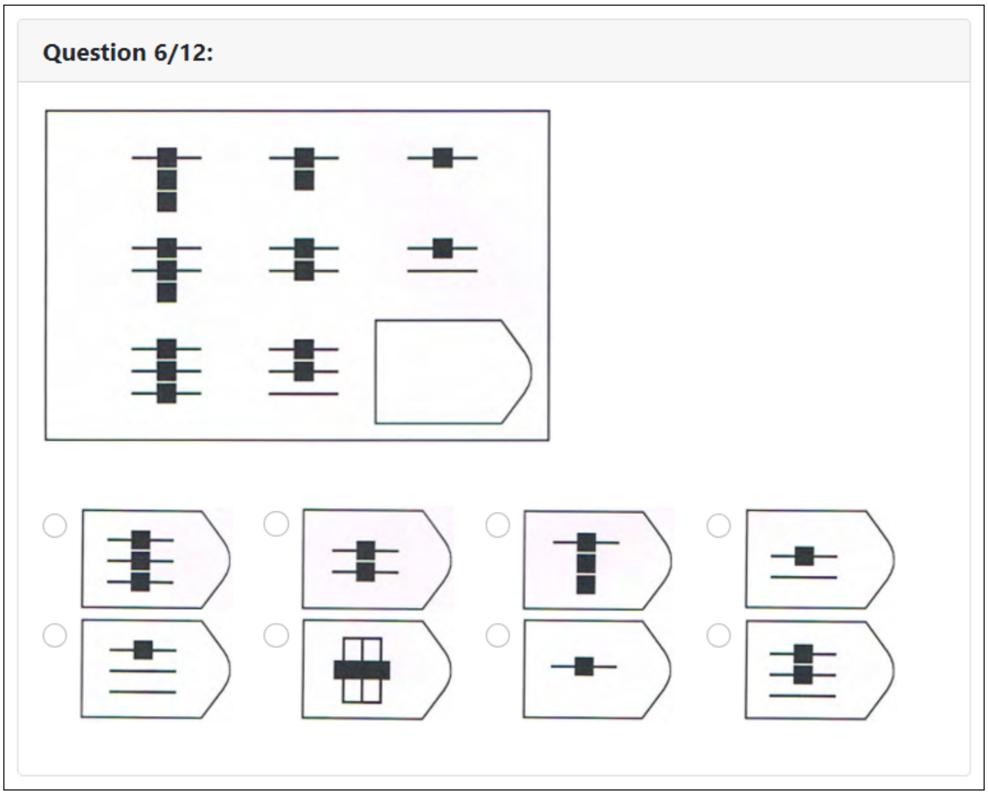
The test is presented in increasing difficulty order. Participants are able to navigate back and forth throughout the test to review and modify their answers. The test lasts up to 6 minutes. All unanswered items are considered incorrect. I incentivize performance by rewarding if correct four randomly picked items.

Non-incentivized survey. I ask participant a small set of questions. These questions concern age, gender, educational background, neighborhood of residence, household size and assets, and canteen consumption. There is no time limit to respond this survey.

After the surveys are completed, participants are thanked and dismissed.

Reward details. At the beginning of the experiment I inform participants that they will all receive rewards. I present three prize baskets, which are on display to see. Each prize basket has escalating prizes and are detailed. I explain that the basket each will obtain depends on

Figure H.5: Raven's Standard Progressive Matrices test example



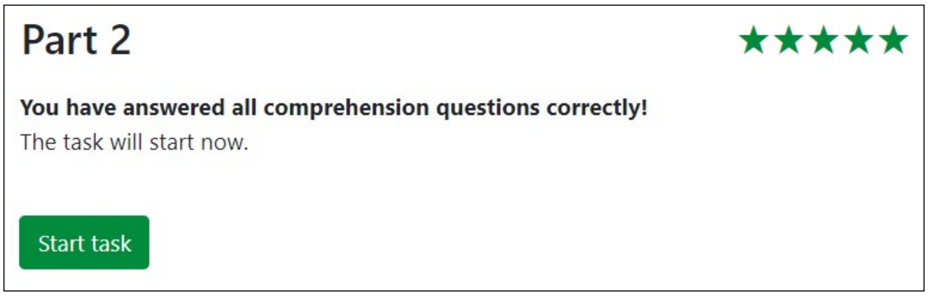
Notes: This screenshot exemplifies Raven's Standard Progressive Matrices (SPM) test. The upper image shows a 3x3 matrix with a missing cell. The task is to guess the image that corresponds to the missing cell. Only one out of the eight possible choices depicted below the matrix is correct. This is item number 6 of the SPM test. The correct answer is choice 5.

how much '*stars*' each accumulates throughout the session.

Participants accumulate '*stars*' in several screens of the experiment. The distribution decisions and non-incentivized survey yield a fix number of '*stars*' for completion. The belief elicitation and the incentivized survey yield '*stars*' depending on response accuracy. The instructions preceding each part of the experiment clearly state how '*stars*' are awarded. The total number of '*stars*' is displayed on the top right corner in each screen of the experiment.

At the end of the experiment, participants are informed how many '*stars*' they earned and which prize basket they obtain. Rewards are delivered in sealed bags anonymously, based on computer's number.

Figure H.6: Screenshots displaying accumulated stars



Notes: This screenshot exemplifies how stars are shown in each screen. Stars are colored in green and always displayed in the top right corner. After a star is earned, a screen pops-up displaying the number of stars earned during 5 seconds.

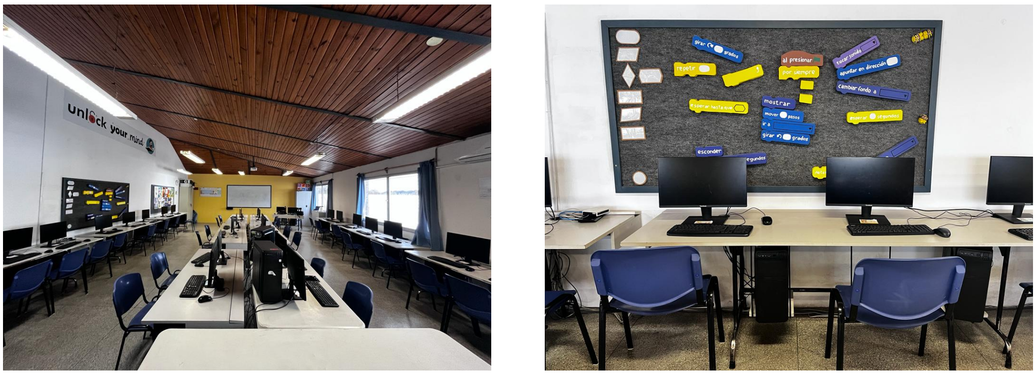
Implementation

I recruited 198 students from a private school in Montevideo on September 2023. Participation was available for all students from 5th grade to 9th grade.

The data recollection was run across four weekdays, in the school's computer lab during regular computing hours. The logistics were arranged in coordination with the school's principal board and the computing team coordination. I use the infrastructure of the school's computer lab, comprising 30 computers. With every class having under 28 students enrolled, I had no problem fitting all participants in the lab.

Figure H.7: Computer lab used

(a) Room **(b) Computer setup**



Notes: These figures show the school's computer lab, where all sessions took place. Figure (a) shows the room from the entrance. Figure (b) shows the computer setups.

I requested approval by the parents of involved students. The school delivered a consent form containing information on the project, with an explicit endorsement. No specific details on the tasks or aim of the research was communicated. Children were also instructed that their participation was voluntary.

I offered participants prize baskets containing canteen products. All participants received a reward worth 75 UYP ($\sim$ 2.00 USD) for participation and could earn products worth up to 265 UYP ($\sim$ 7.00 USD). I set the expected time to complete the study to 30 minutes, below the average computing class duration. The study was fully conducted in Spanish.

Results

The study was completed in 10 sessions throughout four days. Each session consisted of an entire group. Each grade consists of two groups. Sessions were run during computing class and lasted its whole duration.

All parents and students agreed to participate in the study. Attendance to the school was almost complete (see Table H.1). All attending students during computing class participated in the activity. Average value of the prize basket reward was 113 Uruguayan Pesos ($\sim$ 3.00 USD).

Table H.1: School attendance

Grade	Group	Absent (1)	Attendance (2)
5th	East	4	.826
5th	West	2	.920
6th	North	3	.875
6th	South	2	.920
7th	North	2	.905
7th	South	4	.826
8th	North	0	1.000
8th	South	2	.920
9th	North	0	1.000
9th	South	1	.929
5th-9th	**All**	**20**	**.908**

Notes: This table reports school attendance the day each group participated in the study. There are two groups per grade, labeled by the cardinal direction of the classroom. Column (1) reports number of absentees in each group. Column (2) reports the attendance rate for each group.

Table H.2 compares characteristics of our sample with Montevidean population based on data from the 2022 Uruguayan Household Survey. In short, spectators come from households with higher income per capita than the population. The sample is part of a reduced group of households with low material limitations.

Table H.2: Sample characteristics

	Spectators (1)	Population (2)	Difference (3)
Panel A. Individuals			
Male	.563	.515	.048
			(.037)
All education in school	.753	-	-
New to school	.056	-	-
Daily canteen expenditure	.87	-	-
Panel B. Households			
Cars: 2+	.929	.092	.837***
			(.019)
Rooms: 5+	.697	.233	.464***
			(.034)
Income per capita: 1000+	.970	.270	.700***
			(.016)
Under the poverty line	.000	.195	-.194***
			(.009)

Notes: This table reports statistics for the spectator sample and the population. The population sample covers all inidividuals in the same age bracket living in the same city. Panel A refers to individual characteristics. Panel B refers to household characteristics. Rows 5 to 7 show household shares. Row 5 refers to total number of cars in the individual's home. Row 6 refers to total number of rooms (excluding bathrooms and kitchen) in the individual's home. Row 7 and 8 include non-parametrics estimates for the spectator sample based in data from the 2022 Uruguayan Household Survey. All income are expressed in 2023 United States Dollars (USD). Columns (1) and (2) show mean shares. Column (3) shows differences between spectators and general population. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I Worker phase

Procedures

The worker phase consists of the commitment and completion of letter-to-number encryption tasks. Figure I.1 exemplifies one task. Participants are explained how the encryption works and are asked to complete 3 encryptions, as trial. Afterwards, participants are asked to commit to a number of encryptions for each of two piece-rate payments: low (0.05 British Pounds, $\sim$ 0.06 USD), or high (0.50 British Pounds, $\sim$ 0.60 USD). Each participant is randomly assigned to one of the two piece-rate payments and has to follow-up on their commitment for that piece-rate.

Task presentation. I present a '*word*', formed by letters. Every letter has a 3-digit number assigned, displayed in a separate encryption table. Worker's task is to submit the '*code*' assigned to the '*word*'. Workers can only proceed to the next '*word*' if the encryption is done correctly. There is no limited time or opportunities to answer. Once the correct '*code*' is supplied, the workers can proceed to a new '*word*' and encryption table.

Figure I.1: Letter-to-number encryption task example

T	C	R	G	O	K	I	A	P	N	B	V	Z
879	978	054	397	129	170	402	361	328	195	807	785	354

X	W	U	F	S	H	M	E	L	Q	D	J	Y
385	438	218	435	812	157	873	389	573	392	720	214	158

'word': XR

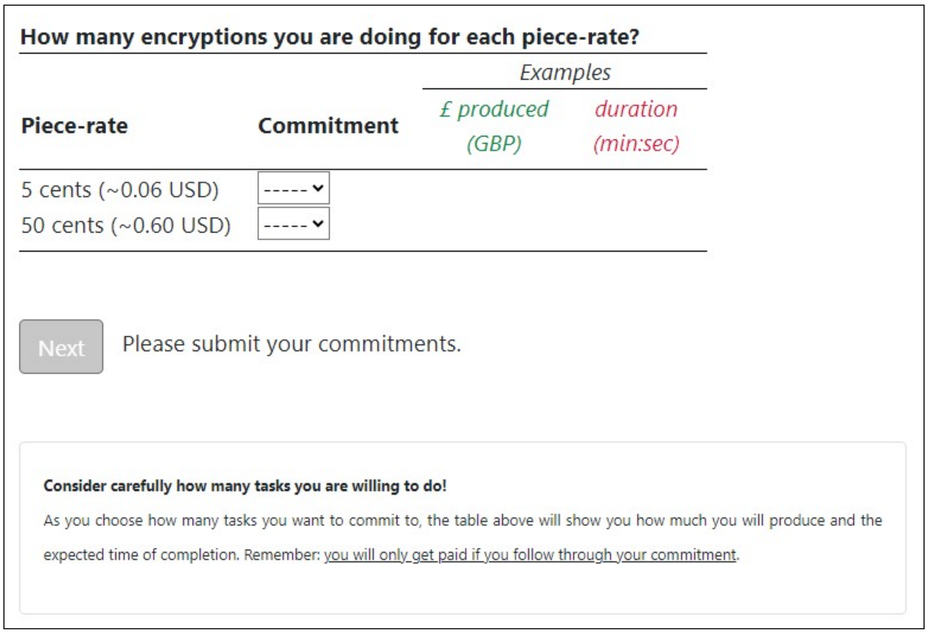
Enter the 'code' Submit

Notes: This screenshot exemplifies the letter-to-number encryption task. The encryption tables are depicted above. The table displays all letters of the English alphabet in random order. Each letter is allocated a 3-digit number. The assigned '*word*' and a filling blank for the '*code*' are depicted below. The 'code' is formed by all digits, with no space between them. Each round the '*word*' and encryption table are randomly chosen. The encryption table changes both the letter order and the numbers assigned to each letter. In this example, the '*word*' is XR and the '*code*' is 385054.

The encryptions take longer as participants advance. The first five encryption '*words*' have one letter. Every five encryptions one letter is added to the '*word*'. I inform participants about the increasing length of the '*word*' and exemplify it.

Task commitment. I inform participants about two possible piece-rate for each encryption succesfully completed: low piece-rate (0.05 British Pounds, ∼ 0.06 USD), or high piece-rate (0.50 British Pounds, ∼ 0.60 USD). I ask participants to commit to how many tasks they will complete under each piece-rate. The minimum number of tasks is 5, the maximum is 50. I ask participants to carefully consider their commitments, and inform them that they need to follow-up on their commitment to receive the payment.

Figure I.2: Task commitment



Notes: This screenshot shows the explanation and form to commit tasks for each piece-rate payment. The last columns automatically generate estimates of money produced and total duration for the corresponding commitment.

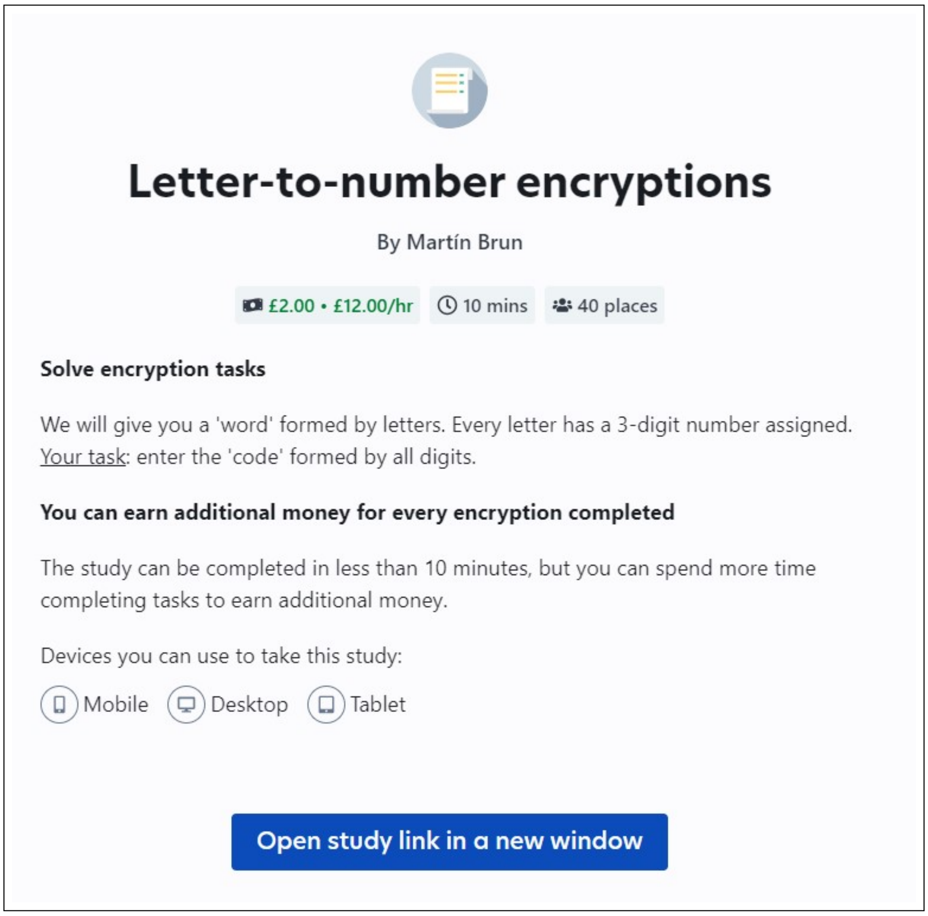
Task completion. The resulting piece-rate is randomly assigned. Participants are required to follow-up on their commitment to obtain the base payment.

Reward details. I inform participants their final payoff can be influenced by a third-party. I restrict information about when, how, why, and who is involved in the income allocation. Workers earn a 2 British Pound (∼2.50 USD) base payment and can earn bonus payment based on their performance.

Implementation

I recruited 40 participants in *Prolific* on August 2023. Figure I.3 depicts the study description in *Prolific*. I offered a 2 British Pound (∼2.50 USD) base payment for completing the study and the possibility of earning additional money.[51] I set the expected time to complete the study to 10 minutes. Participation was available only to workers residing in the United States.

Figure I.3: Prolific study description



Notes: This screenshot shows the information displayed to participants when entering the study in Prolific. The button at the bottom links to the experiment.

[51] *Prolific* works with British Pounds. Participants with sufficient experience in the platform are used to it. Still, I display an approximation for United States Dollars (USD) for the sake of clarity.

Results

The study was completed in less than 2 hours.[52] Median time to complete the study was 8 minutes and 32 seconds. Average payment to participants (including bonus payment) was 7.13 British Pounds (~ 8.55 USD). Total cost was around 285 British Pounds (~ 340 USD).

Table I.1: Sample characteristics

	Mean	Min	Max
	(1)	(2)	(3)
Panel A. Demographic			
Male	.47	.00	1.00
White	.53	.00	1.00
Age	36.89	20	76
Born in U.S.	.75	.00	1.00
Citizen from U.S.	.80	.00	1.00
Panel B. Performance			
Total approvals in Prolific	937	5	3,105
Time to complete task (seconds)	786	220	2,808
Total earnings from task	7.13	2.25	27.00

Notes: This table describes sample characteristics. Column (1) shows means. Column (2) shows minimum values. Column (3) shows maximum values.

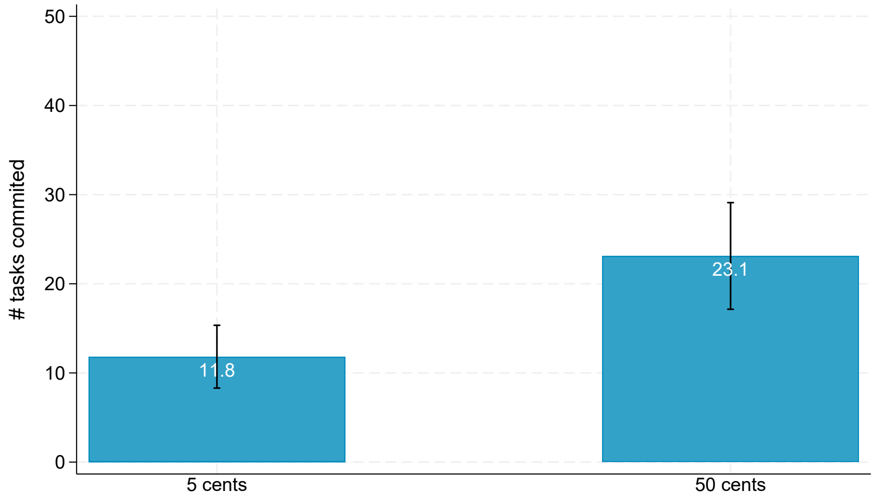
Participants completed an average of 15.9 tasks (SD = 14.5).

Basic assumptions. Figure I.4 shows the mean task commitment for each piece-rate payment. Commitments for all piece-rate payments are statistically different from 5 and from 50 (see columns 2 and 3 in Table I.2 for details). Results are in line with the basic assumptions about worker's behavior.

Implications. To explore commitment differences by piece-rate payments, I rank commitments within each piece-rate payment and compare the number of task commited in each ranking position. Figure I.5 depicts the results. There are workers committing the minimum and maximum number of tasks for all piece-rate payments. In those regions, commitments by piece-rate payments converge to the same number of tasks. For intermediate number of tasks, commitments are larger for the high piece-rate payment.

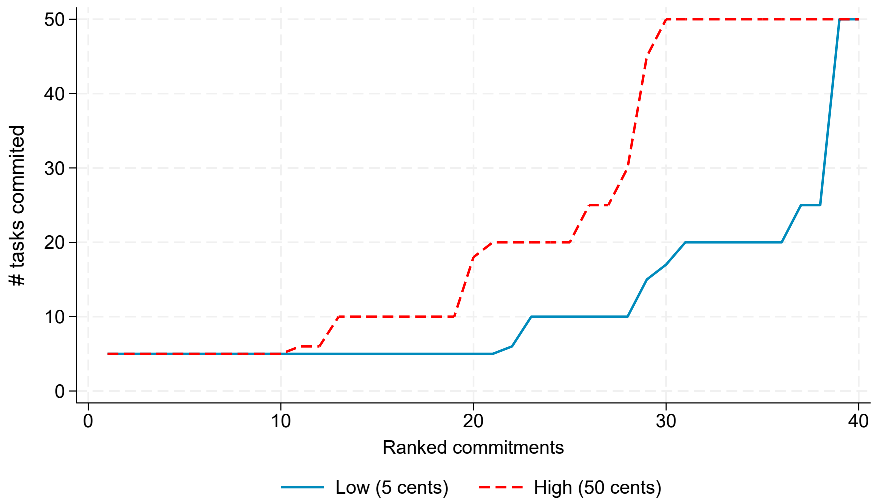
[52] I launched the experiment at 12:00 EDT (09:00 PDT). The last participant completed the study at 13:07 EDT (10:07 PDT). EDT is Eastern Daylight Time (e.g., used in New York City), and PDT is Pacific Daylight Time (e.g., used in Los Angeles).

Figure I.4: Commitment by piece-rate payment



Notes: This figure plots mean task commitments for each piece-rate payment. 95% confidence interval is plotted as bars.

Figure I.5: Commitment ranking by piece-rate payment



Notes: This figure plots ordered task commitments for each piece-rate payment. Commitments are ranked within piece-rate payment (similar to a percentile). For example, rank 20 is the median task commitment for each piece-rate payment.

Column 4 in Table I.2 shows the differences for task compared to the high piece-rate payment. Commitments increase with the piece-rate payment. Raw differences are statistically significant.

We test the differences between task commitment by piece-rate payments using a regression. Results are shown in Table I.3. We run regressions comparing task commitment between low and high piece-rate payments. Commitments increase with the piece-rate payment. Differences are statistically significant for all specifications.

Table I.2: T-tests on commitments by piece-rate payment

	Mean	vs. 0	vs. 50	vs. High
	(1)	(2)	(3)	(4)
Low	11.8	-	-	-11.3***
		[.000]	[.000]	[.002]
High	23.1	-	-	
		[.000]	[.000]	

Notes: These tables describe participant's commitments for different piece-rate payments. Column (1) show mean commitment per piece-rate payment. Columns (2) and (3) show p-values on the differences with the minimum commitment (0 encryptions) and the maximum commitment (50 encryptions), respectively. Column (4) show differences with the High piece-rate payment (50 cents). p-values are reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

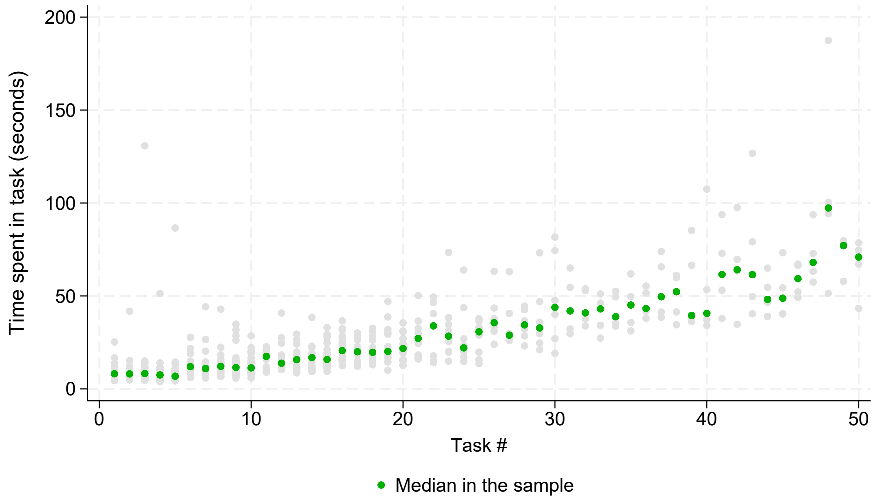
Table I.3: Piece-rate payments drawn

	(1)	(2)
High	11.3***	11.3***
	(2.4)	(3.3)
Individual FE	No	Yes
Observations	80	80
R^2	.122	.787

Notes: This table reports the coefficients for high piece-rate payment on task commitment. The dependent variable is the number of tasks committed. The independet variable is a dummy variable for 'high' piece-rate payment. Low piece-rate payment is 5 cents. High piece-rate payment is 50 cents. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

J Additional results

Figure I.6: Time spent per task



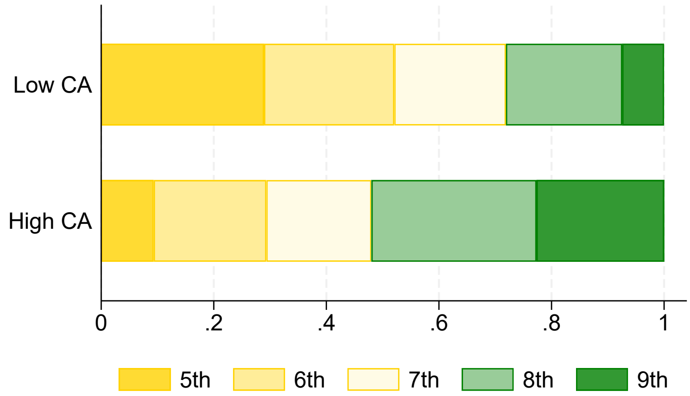
Notes: This figure plots time spent (in seconds) per task by all participants. Median time spent is plotted in green. One outlier is excluded from the plot: more than 600 seconds for task #19.

Table J.1: Stated fairness preferences

		Age			Cognitive Ability		
	Total	5th/7th	8th/9th	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Egalitarians	.131	.177	.054	-.123***	.165	.067	-.099**
				(.043)			(.045)
Libertarians	.111	.113	.108	-.005	.124	.093	-.031
				(.046)			(.045)
Fact. Merit.	.510	.524	.486	-.038	.512	.520	.008
				(.074)			(.074)
Counter. Merit.	.247	.185	.351	.166**	.198	.320	.122*
				(.066)			(.065)

Notes: This table reports stated preferences shares. Columns (1) show refers to the whole sample. Columns (2) to (4) distinguishes by age group. Groups are formed based on current school grade. The first group comprises students from 5th to 7th grade. Ages in those grades range from 10 to 13 years old. The second group comprises students from 8th to 9th grade. Ages in those grades range from 13 to 15 years old. Columns (2) and (3) report the share of each fairness view in each group. Columns (4) reports the difference between the two groups. Columns (5) to (7) distinguishes by cognitive ability. Groups are formed based on the median of the cognitive ability measurement. The first group (low) has scores below the median. The second group (high) has scores above the median. Columns (5) and (6) report the share of each fairness view in each group. Columns (7) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure J.1: Grade distribution within cognitive ability groups



Notes: This figure plots the distribution of participants in each cognitive ability group. Cognitive ability groups are split by the median score in the Raven's SPM test (8 out of 12). Students grade is distinguished. Grades colores in yellow comprise the younger age group. Grades colored in green comprise the older age group. For more details, see Table J.2.

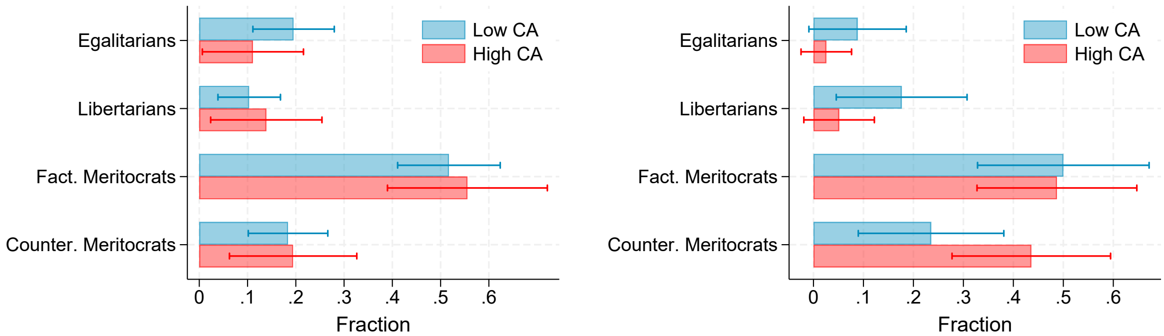
Table J.2: Cognitive Ability and Age

	Cognitive Ability	
	Mean score	Share High
	(1)	(2)
Panel A. Age		
Ages 10-12	.583	.293
Ages 13-15	.700	.534
Panel B. Grade		
Year 5	.532	.167
Year 6	.605	.349
Year 7	.616	.368
Year 8	.688	.468
Year 9	.721	.654

Notes: This table reports cognitive ability measurements by school grade. Column (1) shows mean scores out of 100%. Column (2) shows the share of students above school median score.

Figure J.2: Stated fairness preferences

(a) 5th/7th grade **(b) 8th/9th grade**



Notes: These figures plot preferred criteria for distributing between workers, as declared by spectators. Figure (a) restricts to younger children, from 5th to 7th grade. Differences in proportions are not statistically significant at the 10% level using Fisher's exact test (p-value = .725), Pearson's chi-squared test (p-value = .699), and Likelihood-ratio chi-squared test (p-value = .680). Figure (b) restricts to older children, from 8th to 9th grade. Differences in proportions are not statistically significant at the 10% level using Fisher's exact test (p-value = .107), Pearson's chi-squared test (p-value = .110), and Likelihood-ratio chi-squared test (p-value = .101).

Table J.3: Stated fairness preferences

	Egalitarian				Libertarian			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
8th/9th	-.124***				-.004			
	(.044)				(.046)			
High CA		-.109**	-.098	-.067		-.022	.049	-.123
		(.046)	(.072)	(.054)		(.046)	(.068)	(.077)
Sample	All	All	5th/7th	8th/9th	All	All	5th/7th	8th/9th
Dep. var. mean	.131	.131	.177	.054	.111	.111	.113	.108
Effect magn.	-95%	-83%	-56%	-124%	-3%	-20%	43%	-114
Observations	198	196	123	73	198	196	123	73
R^2	.034	.028	.021	.021	.007	.009	.016	.040

	Fact. Merit.				Counter. Merit.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
8th/9th	-.040				.168**			
	(.073)				(.066)			
High CA		-.013	.015	-.032		.144**	.034	.222**
		(.074)	(.100)	(.121)		(.065)	(.078)	(.110)
Sample	All	All	5th/7th	8th/9th	All	All	5th/7th	8th/9th
Dep. var. mean	.510	.510	.524	.486	.247	.247	.185	.351
Effect magn.	-8%	-3%	3%	-7%	68%	58%	19%	63%
Observations	198	196	123	73	198	196	123	73
R^2	.017	.014	.017	.010	.051	.040	.029	.058

Notes: This table reports the coefficients of dummies on age and cognitive ability groups on preferred distribution criteria. The independent variables are computed as dummy variables. Age groups are formed based on current school grade: valued 1 for students from 8th to 9th grade, and 0 otherwise. Cognitive ability groups are formed based on cognitive ability measurement: valued 1 for students scoring above the median (8 out of 12), and 0 otherwise. The dependent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for sex. Robust standard errors are reported in parentheses for the remaining columns. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.4: Stated fairness preferences

(a) Boys

		Age			Cognitive Ability		
	Total	5th/7th	8th/9th	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Egalitarians	.116	.155	.049	-.106*	.132	.083	-.048
				(.055)			(.061)
Libertarians	.134	.141	.122	-.019	.145	.111	-.034
				(.066)			(.067)
Fact. Merit.	.455	.465	.439	-.026	.474	.417	-.057
				(.098)			(.101)
Counter. Merit.	.295	.239	.390	.151	.250	.389	.139
				(.092)			(.096)

(b) Girls

		Age			Cognitive Ability		
	Total	5th/7th	8th/9th	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Egalitarians	.151	.208	.061	-.147**	.222	.073	-.149*
				(.070)			(.075)
Libertarians	.081	.075	.091	.015	.089	.073	-.016
				(.063)			(.059)
Fact. Merit.	.581	.604	.545	-.058	.578	.585	.008
				(.111)			(.108)
Counter. Merit.	.186	.113	.303	.190**	.111	.268	.157*
				(.092)			(.085)

Notes: These tables report stated preferences shares. Panel (a) restricts to boys. Panel (b) restricts to girls. Column (1) show refers to the whole sample. Columns (2) to (4) distinguishes by age group. Groups are formed based on current school grade. The first group comprises students from 5th to 7th grade. Ages in those grades range from 10 to 13 years old. The second group comprises students from 8th to 9th grade. Ages in those grades range from 13 to 15 years old. Columns (2) and (3) report the share of each fairness view in each group. Column (4) reports the difference between the two groups. Columns (5) to (7) distinguishes by cognitive ability. Groups are formed based on the median of the cognitive ability measurement. The first group (low) has scores on the median or below. The second group (high) has scores above the median. Columns (5) and (6) report the share of each fairness view in each group. Column (7) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.5: Stated fairness preferences

		Age			Cognitive Ability		
	Total	5th/7th	8th/9th	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Egalitarians	.099	.127	.050	-.077*	.131	.048	-.083*
				(.044)			(.044)
Libertarians	.111	.118	.100	-.018	.131	.081	-.051
				(.050)			(.049)
Fact. Merit.	.531	.549	.500	-.049	.535	.532	-.003
				(.082)			(.081)
Counter. Merit.	.259	.206	.350	.144*	.202	.339	.137*
				(.074)			(.073)

Notes: This table reports stated preferences shares. **Sample excludes participants who failed to understand part of the instructions.** Column (1) show refers to the whole sample. Columns (2) to (4) distinguishes by age group. Groups are formed based on current school grade. The first group comprises students from 5th to 7th grade. Ages in those grades range from 10 to 13 years old. The second group comprises students from 8th to 9th grade. Ages in those grades range from 13 to 15 years old. Columns (2) and (3) report the share of each fairness view in each group. Column (4) reports the difference between the two groups. Columns (5) to (7) distinguishes by cognitive ability. Groups are formed based on the median of the cognitive ability measurement. The first group (low) has scores on the median or below. The second group (high) has scores above the median. Columns (5) and (6) report the share of each fairness view in each group. Column (7) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.6: Stated fairness preferences

(a) Age

	6th grade			8th grade		
	5th/6th	7th/9th	Diff.	5th/8th	9th	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Egalitarians	.244	.045	-.200***	.140	.077	-.063
			(.051)			(.059)
Libertarians	.116	.107	-.009	.122	.038	-.084*
			(.045)			(.045)
Fact. Merit.	.465	.545	.080	.517	.462	-.056
			(.072)			(.105)
Counter. Merit.	.174	.304	.129**	.221	.423	.202**
			(.060)			(.102)

(b) Cognitive ability

	Score = 7			Score = 9		
	Low	High	Diff.	Low	High	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Egalitarians	.182	.091	-.091*	.147	.071	-.076
			(.050)			(.049)
Libertarians	.136	.091	-.045	.122	.071	-.050
			(.046)			(.048)
Fact. Merit.	.477	.536	.059	.526	.452	-.073
			(.072)			(.087)
Counter. Merit.	.205	.282	.077	.205	.405	.200**
			(.061)			(.083)

Notes: These tables report stated preferences shares, distinguishing by age and cognitive ability groups. Panel (a) distinguishes by age groups. Age groups are formed based on current school grade. Columns (1) to (3) split groups by 6th grade. The first group comprises students from 5th to 6th grade. Ages in those grades range from 10 to 12 years old. The second group comprises students from 7th to 9th grade. Ages in those grades range from 12 to 15 years old. Columns (4) to (6) split groups by 8th grade. The first group comprises students from 5th to 8th grade. Ages in those grades range from 10 to 14 years old. The second group comprises students 9th grade. Ages in those grades range from 14 to 15 years old. Panel (b) distinguishes by cognitive ability. Columns (1) to (3) split groups starting from a test score of 7. The first group (low) has scores of 7 or below. The second group (high) has scores above 7. Columns (4) to (6) split groups starting from a test score of 9. The first group (low) has scores of 9 or below. The second group (high) has scores above 9. For both panels, columns (1) and (2) report the share of each fairness view in each group. Column (3) reports the difference between the two groups. Columns (4) and (5) report the share of each fairness view in each group. Column (6) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.7: Assignment to unlucky worker

		Observed diff.			
	Total	0	5	10	15
	(1)	(2)	(3)	(4)	(5)
Egalitarians	.081***	.073***	.081***	.088***	.082**
	(.021)	(.025)	(.028)	(.029)	(.035)
Libertarians	-.149***	-.141***	-.144***	-.170***	-.143***
	(.029)	(.038)	(.043)	(.030)	(.038)
Counter. Merit.	.050**	.049*	.060**	.058**	.033
	(.020)	(.027)	(.025)	(.026)	(.027)
Higher counter. share	-	Unlucky	Unlucky	Equal	Lucky
Observations	792	198	198	198	198
R^2	.147	.141	.159	.198	.128

Notes: This table reports the coefficients of dummies on preferred distribution criteria on the assigned share to the unlucky worker. The dependent variable is computed as assignment to the unlucky worker as a share of total assignments. The independent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. The omitted category is Factual Meritocrats. Column (1) covers all decisions in hypothetical scenarios. Columns (2) to (5) cover each a scenario, which differs in the observed effort difference. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses for the first column. Robust standard errors are reported in parentheses for the remaining columns. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.8: Favor unlucky worker

		Observed diff.			
	Total	0	5	10	15
	(1)	(2)	(3)	(4)	(5)
Egalitarians	.077*	.044	.113	.037	.114
	(.044)	(.086)	(.083)	(.056)	(.074)
Libertarians	-.043	-.103*	-.034	-.040**	.006
	(.029)	(.057)	(.052)	(.020)	(.049)
Counter. Merit.	.107***	.056	.166**	.124**	.083
	(.039)	(.068)	(.068)	(.057)	(.051)
Higher counter. share	-	Unlucky	Unlucky	Equal	Lucky
Observations	792	198	198	198	198
R^2	.029	.016	.052	.048	0.030

Notes: This table report the coefficients of dummies on preferred distribution criteria on decisions favoring the unlucky worker. The dependent variable is a dummy valued 1 when assignment to the unlucky worker is larger than the one to the lucky worker, and 0 otherwise. The independent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. The omitted category is Factual Meritocrats. Column (1) covers all decisions in hypothetical scenarios. Columns (2) to (5) cover each a scenario, which differs in the observed effort difference. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses for the first column. Robust standard errors are reported in parentheses for the remaining columns. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.9: Implementation consistency

	(1)	(2)	(3)	(4)
Egalitarians	.201***	.201***	.229***	.214***
	(.072)	(.072)	(.077)	(.078)
Libertarians	.011	.008	.009	-.031
	(.104)	(.104)	(.104)	(.100)
Counter. Merit.	-.193***	-.196***	-.235***	-.259***
	(.055)	(.056)	(.055)	(.055)
Sex FE	No	Yes	Yes	Yes
Age FE	No	No	Yes	Yes
CA FE	No	No	No	Yes
Observations	792	792	792	784
R^2	.058	.058	.093	.133

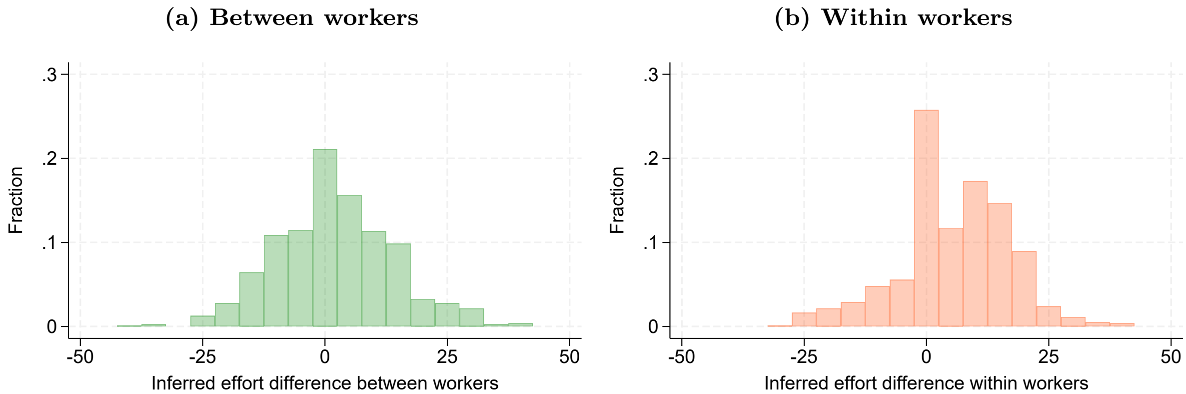
Notes: This table reports the coefficients of dummies on preferred distribution criteria on implementation consistency. The independent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. The omitted category is Factual Meritocrats. The dependent variable is valued 1 for assignments aligned with the prescribed behavior of the stated preference (with a two-sided 5 percentage point margin), and 0 otherwise. Mean dependent variable in the sample is .423. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.10: Inferred effort differences

	(1)	(2)	(3)	(4)
Egalitarians	-.053	-.054	-.021	-.065
	(.073)	(.072)	(.076)	(.070)
Libertarians	-.089	-.075	-.066	-.078
	(.093)	(.091)	(.089)	(.092)
Counter. Merit.	-.029	-.016	-.020	-.023
	(.059)	(.057)	(.059)	(.060)
Sex FE	No	Yes	Yes	Yes
Age FE	No	No	Yes	Yes
CA FE	No	No	No	Yes
Observations	792	792	792	784
R^2	.003	.009	.015	.045

Notes: This table reports the coefficients of dummies on preferred distribution criteria on on inferred effort difference for higher piece-rate payment. The independent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. The omitted category is Factual Meritocrats. The dependent variable computes the inferred difference in effort choice for a same player between low and high piece-rate payment. Mean dependent variable in the sample is .227. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure J.3: Inferred effort difference



Notes: These figures plot mean inferred effort differences. Figure (a) shows inferred differences between workers in a pair when under equal opportunities. Figure (b) shows inferred differences when workers receive high piece-rate in comparisson to low piece-rate.

Table J.11: Inferred effort difference, by observed difference

	Between		Within	
	# Tasks	Relative	# Tasks	Relative
Observed diff.	(1)	(2)	(3)	(4)
0	-2.91		2.91	.095
5	-.74	-.147	5.74	.200
10	3.45	.345	6.55	.290
15	8.33	.555	6.67	.337

Notes: This table describes beliefs by observed effort differences between the lucky worker and the unlucky worker. Columns (1) and (2) show mean inferred effort difference between the lucky and the unlucky worker under equal opportunities. Column (1) reports the difference in number of tasks and column (2) reports the difference as a share of the observed difference under unequal opportunities. Columns (3) and (4) show mean inferred effort difference for high piece-rate versus low piece-rate within the same worker. Column (3) reports the difference in number of tasks and column (4) reports the difference as a share of the observed number of tasks.

Table J.12: Inferred effort difference, by observed difference

(a) Between workers

	Inferred effort diff.	
	(1)	(2)
Observed diff.	.758***	.758***
	(.061)	(.071)
Individual FE	No	Yes
Observations	792	792
R^2	.124	.528

Notes: This table reports the coefficients for observed effort difference on inferred effort difference. The dependent variable is the inferred difference between the number of tasks of the lucky worker and the unlucky worker under equal opportunities. The independent variable is the observed difference under unequal opportunities. Sample is restricted to the hypothetical scenarios, with observed differences in [0,5,10,15]. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Within workers

	Inferred effort diff.	
	(1)	(2)
Observed diff.	.242***	.242***
	(.061)	(.071)
Individual FE	No	Yes
Observations	792	792
R^2	.014	.468

Notes: This table reports the coefficients for observed effort difference on inferred effort difference. The dependent variable is the inferred effort difference for high piece-rate versus low piece-rate within the same worker. The independent variable is the observed difference under unequal opportunities. Sample is restricted to the hypothetical scenarios, with observed differences in [0,5,10,15]. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.13: Inferred effort difference, by worker's luck

Observed diff.	Unlucky worker (1)	Lucky worker (2)	Unlucky vs. Lucky (3)
0	4.75	0.96	-3.79**
			(1.72)
5	6.74	4.76	-1.98
			(1.49)
10	6.75	6.35	-0.40
			(1.54)
15	7.27	5.83	-1.44
			(1.63)
Total	6.40	4.45	-2.72**
			(1.15)

Notes: This table reports inferred effort difference for unlucky and lucky workers. The outcome variable is the inferred effort difference for high piece-rate versus low piece-rate within the same worker. All responses are contemporary to those of vaccine distribution. Columns (1) and (2) show means. Column (3) shows differences between unlucky workers (randomly drawn the Low piece-rate) and the lucky workers (randomly drawn the High piece-rate). Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.14: Inference confidence

	(1)	(2)	(3)	(4)
Egalitarians	-.171**	-.170**	-.166***	-.160**
	(.069)	(.066)	(.062)	(.068)
Libertarians	-.252***	-.290***	-.278***	-.262***
	(.057)	(.059)	(.064)	(.075)
Counter. Merit.	-.033	-.069	-.081	-.093
	(.068)	(.066)	(.066)	(.066)
Sex FE	No	Yes	Yes	Yes
Age FE	No	No	Yes	Yes
CA FE	No	No	No	Yes
Observations	792	792	792	784
R^2	.037	.090	.107	.136

Notes: This table reports the coefficients of dummies on preferred distribution criteria on certainty on effort inferences. The independent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. The omitted category is Factual Meritocrats. The dependent variable is a 5-point Likert scale on confidence on effort infereces for non-observed equal opportunity situations. Mean dependent variable in the sample is .295. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.15: Information acquisition

	(1)	(2)	(3)	(4)
Egalitarians	-.195*	-.195*	-.128	-.126
	(.106)	(.107)	(.106)	(.113)
Libertarians	.046	.039	.052	.068
	(.093)	(.093)	(.092)	(.090)
Counter. Merit.	.044	.037	.028	.025
	(.070)	(.070)	(.067)	(.071)
Sex FE	No	Yes	Yes	Yes
Age FE	No	No	Yes	Yes
CA FE	No	No	No	Yes
Observations	792	792	792	784
R^2	.031	.033	.109	.139

Notes: This table reports the coefficients of dummies on preferred distribution criteria on seeking additional information. The independent variables are valued 1 for each declared preferred distribution criteria, and 0 otherwise. The omitted category is Factual Meritocrats. The dependent variable is valued 1 for spectator that started the task to acquire additional information for deciding, and 0 otherwise. Mean dependent variable in the sample is .763. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

K Counterfactual thinking and information provision

I test the effect of counterfactual thinking and information provision on inequality acceptance in a pre-registered experiment. First, I show balance tests for preceding sample characteristics and for experiment decisions. Following, I present the tested hypothesis and aggregate results.

Balance tests. Treatment assignment is randomized between participants. I test for balance in preceding sample characteristics and in experiment decisions.

Table K.1 shows balance tests for preceding sample characteristics. I separetely test for differences between the baseline treatment condition (`LI`) and each of the other treatments (`ICT` and `CI`). I find no significant differences in preceding sample characteristics between treatment conditions. A joint test of equality of means cannot reject the null hypothesis of equality of means across treatments.

Table K.2 shows balance tests for experiment decisions, both for singular and repeated decisions. Within singular decisions, I find no significant differences in fairness view adherence between treatments conditions. A joint test of equality of means cannot reject the null hypothesis of equality of means across treatments. Only instructions understanding is significantly different for the `ICT` treatment. Participants in the `ICT` treatment condition are less likely to understand most of the instructions. In the `ICT` treatment, participants make inferences before each decision. Not only it differs in the experiment flow, but also requires participants to alternate between tasks. Within repeated decisions, I find significant differences in implemented consistency, inferred differences, and confidence. A joint test of equality of means rejects the null hypothesis of equality of means across treatments at the 1% level.

Table K.1: Balance tests for preceding sample characteristics

	LI	ICT		CI	
	Mean	Mean	Diff.	Mean	Diff.
	(1)	(2)	(3)	(4)	(5)
Age	12.54	12.55	.01	12.45	-.09
			(0.25)		(0.26)
Males	.514	.565	.051	.625	.111
			(0.087)		(0.085)
Current grade	6.88	6.89	.01	6.81	-.06
			(0.23)		(0.23)
At school since kinder.	.750	.677	-.073	.828	.078
			(0.079)		(0.070)
New at school	.028	.081	.053	.063	.035
			(0.040)		(0.036)
Cars in home	2.21	2.08	-.13	2.22	.01
			(.10)		(.11)
Rooms in home	5.90	5.34	-.56	6.30	.40
			(.36)		(.35)
Weekly allowance	24.07	21.16	-2.91	21.04	-3.03
			(6.10)		(6.29)
Weekly canteen exp.	31.15	33.87	2.72	32.59	1.44
			(2.38)		(2.70)

Notes: This table reports sample characteristics across treatment conditions. Column (1) shows the sample in the baseline treatment condition (limited information: `LI`). Columns (2) and (3) shows the sample in the incentivized counterfactual thinking treatment condition (`ICT`). Columns (4) and (5) shows the sample in the complete information treatment condition (`CI`). Columns (1), (2) and (4) report means. Columns (3) and (5) report means difference with the `LI` treatment condition. The F-statistics for joint test of equality of means across treatment conditions are 0.85 (p-value=.569) and 1.43 (p-value=.184), comparing the `LI` with the `ICT` and with the `CI` respectively. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K.2: Balance tests for experiment decisions

(a) Singular decisions

	LI	ICT		CI	
	Mean	Mean	Diff.	Mean	Diff.
	(1)	(2)	(3)	(4)	(5)
Understood most	0.889	.742	-.147**	.813	-.076
			(.067)		(.062)
CA score	7.296	7.887	.591	7.413	.117
			(.397)		(.419)
Egalitarians	.111	.145	.034	.141	.030
			(.059)		(.058)
Libertarians	.139	.097	-.042	.094	-.045
			(.056)		(.055)
Fact. Meritocrats	.528	.548	.021	.453	-.075
			(.087)		(.086)
Counter. Meritocrats	.222	.210	-.013	.313	.090
			(.072)		(.076)
Prefer getting high piece-rate	.986	.984	-.002	.969	-.017
			(.021)		(.026)
Acquire information	.722	.758	.036	.813	.090
			(.076)		(.072)

(b) Repeated decisions

	LI	ICT		CI	
	Mean	Mean	Diff.	Mean	Diff.
	(1)	(2)	(3)	(4)	(5)
Implemen. cons.	.396	.399	.003	.477	.081*
			(.042)		(.043)
Inferred differences	.293	.182	-.111***	.196	-.097**
			(.043)		(.044)
Confidence	.240	.339	.099**	.316	.077**
			(.039)		(.039)

Notes: These tables report participant decisions across treatment conditions. Column (1) shows the sample in the baseline treatment condition (limited information: `LI`). Columns (2) and (3) shows the sample in the incentivized counterfactual thinking treatment condition (`ICT`). Columns (4) and (5) shows the sample in the complete information treatment condition (`CI`). Columns (1), (2) and (4) report means. Columns (3) and (5) report means difference with the `LI` treatment condition. For singular decisions, the F-statistics for joint test of equality of means across treatment conditions are 1.79 (p-value=.152) and 0.96 (p-value=.413), comparing the `LI` with the `ICT` and with the `CI` respectively. For repeated decisions, the F-statistics for joint test of equality of means across treatment conditions are 4.63 (p-value=.003) and 4.10 (p-value=.007), comparing the `LI` with the `ICT` and with the `CI` respectively. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Hypothesis 1: *Spectators are (a) less willing to accept income inequality when counterfactual thinking is incentivized than with incomplete information, but (b) more willing to accept income inequality when compared with complete information.*

The `ICT` treatment creates incentives for spectators to think counterfactually. This can prompt spectators that have previously decided not to engage in counterfactual thinking to do so. It can also make spectators assign a greater weight to their beliefs, as in commitment-bias. As libertarians, egalitarians, and factual meritocrats do not consider counterfactual choices in their decision, I did not expected their decisions to change across treatments. In contrast, counterfactual meritocrats base their decisions in counterfactual choices. If they over-estimate the high-paid worker counterfactual choice, the information will correct beliefs and narrow the gap between counterfactual choices.

I only expected counterfactual meritocrats to change their decisions across treatments and aggregate inequality acceptance to be lower in the `ICT` than in the `LI` (if there were counterfactual meritocrats in the sample). I find no significant difference in inequality acceptance between the `ICT` and the `LI` treatments.

Table K.3: Assignments to the unlucky worker

	(1)	(2)	(3)	(4)	(5)
ICT	.010	.010	-.028	.013	-.012
	(.023)	(.044)	(.064)	(.030)	(.046)
Dep. var. mean	.370	.445	.215	.364	.414
Sample	All	Egal.	Libe.	Fact.	Counter.
Observations	536	68	64	288	116
R^2	.001	.001	.009	.002	.001

Notes: This table reports the treatment coefficients on assigned share to the unlucky worker. The dependent variable in that case is computed as assignment to the unlucky worker as a share of total assignment. The independent variables are treatment condition dummies, comparing the Limited Information (`LI`) treatment with the Incentivized Counterfactual Thinking (`ICT`) treatment. Sample is restricted to the hypothetical scenarios and to each treatment comparisson. Column (1) covers all spectators. Columns (2) to (5) cover spectators stating adherence to each fairness view. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The `CI` treatment discloses counterfactual choices, making spectators' beliefs fully converge to counterfactuals. Assuming spectators would not be fully accurate in their counterfactual thinking, I expected inequality acceptance to be higher in the `ICT` than in the `CI` if there are counterfactual meritocrats. I find no significant difference in inequality acceptance between the

ICT and the CI treatments.

Table K.4: Assignments to the unlucky worker

	(1)	(2)	(3)	(4)	(5)
CI	.027	-.004	-.016	.047*	.008
	(.023)	(.046)	(.080)	(.025)	(0.050)
Dep. var. mean	.370	.445	.215	.364	.414
Sample	All	Egal.	Libe.	Fact.	Counter.
Observations	504	72	48	252	132
R^2	.007	.000	.002	.030	.001

Notes: This table reports the treatment coefficients on assigned share to the unlucky worker. The dependent variable in that case is computed as assignment to the unlucky worker as a share of total assignment. The independent variables are treatment condition dummies, comparing the Incentivized Counterfactual Thinking (ICT) treatment with the Complete Information (CI) treatment. Sample is restricted to the hypothetical scenarios and to each treatment comparisson. Column (1) covers all spectators. Columns (2) to (5) cover spectators stating adherence to each fairness view. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Result 1: There are no differences in inequality acceptance due to counterfactual thinking.

Hypothesis 2: *Spectators are less willing to accept income inequality with complete information than with incomplete information.*

To test Hypothesis 2, I focus on the LI and CI treatments and compare assigned share to the unlucky worker. Similarly to hypothesis 1, I only expected counterfactual meritocrats to change their decisions across treatments and expected inequality acceptance to be lower in the CI (if there were counterfactual meritocrats in the sample).

I find significantly lower inequality acceptance in the CI than in the LI treatment. Contrary to what I expected, the effect is not driven by counterfactual meritocrats but by factual meritocrats.

Table K.5: Assignments to the unlucky worker

	(1)	(2)	(3)	(4)	(5)
CI	.037*	.006	-.044	.060**	-.003
	(.021)	(.040)	(.071)	(.025)	(.033)
Dep. var. mean	.370	.445	.215	.364	.414
Sample	All	Egal.	Libe.	Fact.	Counter.
Observations	544	68	64	268	144
R^2	.013	.001	.015	.040	.000

Notes: This table reports the treatment coefficients on assigned share to the unlucky worker. The dependent variable in that case is computed as assignment to the unlucky worker as a share of total assignment. The independent variables are treatment condition dummies, comparing the Limited Information (LI) treatment with the Complete Information (CI) treatment. Sample is restricted to the hypothetical scenarios and to each treatment comparisson. Column (1) covers all spectators. Columns (2) to (5) cover spectators stating adherence to each fairness view. Each column reports estimates from a linear model. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Result 2: Spectators are less willing to accept income inequality with complete information than with incomplete information.

Hypothesis 3: *Spectators beliefs (a) are biased about worker's counterfactual choices, and (b) this bias varies with cognitive development.*

To test Hypothesis 3, I focus on the `LI` and `ICT` treatments and compare elicited beliefs for the equal-opportunity scenario with worker's commitment for equal piece-rate payments. The equal-opportunity scenario refers to the piece-rate payment for which the spectator elicits their beliefs. Bayesian spectators that aknowledge the impact of piece-rate payments on worker's effort decisions should understand that observed productions are not fully informative of an scenario of equal opportunities. Non-Bayesian spectators can be affected by cognitive biases. I expected spectators' beliefs to be biased favoring lucky workers (assigned the high piece-rate).

I find that aggregate spectators' beliefs are biased. The dependent variable is defined such that is negative when spectators belief effort exertion would have been higher than the counterfactual effort. On average, spectators believe workers would have exerted more effort that the counterfactual. The bias is entirely driven by beliefs regarding lucky workers. Spectators believe lucky workers would have exerted more effort if assigned the low piece-rate. Inferences about unlucky workers are unbiased.

Table K.6: Belief biases

	Worker		
	All	Unlucky	Lucky
	(1)	(2)	(3)
Belief bias	-1.099*	.454	-2.663***
	(.623)	(.842)	(.964)
Observations	536	269	267

Notes: This table reports one-sample mean comparisson tests on difference between counterfactual effort and inferred effort. The dependent variable is defined such that is positive when spectators belief effort exertion would have been lower than the counterfactual effort, and negative otherwise. Sample is restricted to the hypothetical scenarios. Column (1) shows belief bias for all workers. Column (2) shows belief bias for unlucky workers. Column (3) shows belief bias for lucky workers. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I then distinguish by cognitive ability measurements and participants age. Non-Bayesian belief updating is a cognitive bias, which can be lower as cognition develops. I expected belief biases to be lower among high-cognition and older spectators compared to low-cognition and younger spectators. I find that high-cognition spectators are not biased, while low-cognition spectators are biased. I find no significant differences in belief biases by age.

Table K.7: Belief biases, by cognitive ability and age

	Age		CA	
	5th/7th	8th/9th	Low	High
	(1)	(2)	(3)	(4)
Belief bias	-2.892**	-2.336*	-3.667***	-1.412
	(1.425)	(1.172)	(1.318)	(1.432)
Observations	157	110	150	114

Notes: This table reports one-sample mean comparisson tests on difference between counterfactual effort and inferred effort. The dependent variable is defined such that is positive when spectators belief effort exertion would have been lower than the counterfactual effort, and negative otherwise. Sample is restricted to the hypothetical scenarios. Column (1) covers spectators in 5th to 7th grade. Column (2) covers spectators in 8th and 9th grade. Column (3) covers spectators scoring below the median score in the cognitive ability measurement. Column (4) covers spectators scoring above the median score in the cognitive ability measurement. All columns show belief bias for lucky workers. Standard errors clusterized at individual level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Result 3: Spectators are biased about workers effort on equal piece-rate payments. The bias is driven by beliefs about lucky workers. The bias is lower among high-cognition.

Hypothesis 4: *Biased spectators are equally willing to acquire complete information for deciding.*

To test Hypothesis 4, I focus on the `LI` treatment and compare real effort-task completion considering spectator's belief biases. Spectators experience disutility from deviating from what they perceive fair. Biased beliefs can make part of spectators implement allocations they would have disagree having complete information. Those more biased could benefit the most from accurate information. But this is not the only possibility. Spectators may be unaware of their biases and wouldn't be affected of the deviation. Or belief biases could reflect a lack of interest on forming the beliefs. With expectated results much relying on assumptions about spectators preferences, I had no previous expectations about the results.

I find no significant differences in real effort-task completion between biased and unbiased spectators.

Table K.8: Belief biases, by cognitive ability and age

	All	Unbiased	Biased	Diff.
	(1)	(2)	(3)	(4)
Acquire information	.722	.667	.733	.067
				(.150)

Notes: This table reports share of spectators acquiring information. Column (1) shows the whole sample. Columns (2) and (3) distinguishes by biased beliefs. Biased spectators are split by number of biased beliefs in the four hypothetical scenarios. The first group (unbiased) comprises spectators with biased beliefs in less than 3 scenarios, accumulating almost 15% of the sample. The second group (biased) comprises spectators with biased beliefs in at least 3 scenarios, accumulating 75% of the sample. Columns (2) and (3) report the share in each group. Column (4) reports the difference between the two groups. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Result 4: Biased spectators and unbiased spectators are equally willing to acquire complete information for deciding.

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