Are Elites Meritocratic and Efficiency-Seeking? Evidence from MBA Students*

Marcel Preuss Germán Reyes Jason Somerville Joy Wu

March 2025

Abstract

Elites disproportionately influence policymaking, yet little is known about their fairness and efficiency preferences—key determinants of support for redistributive policies. We investigate these preferences using an incentivized lab experiment with a group of future elites—Ivy League MBA students. We find that elites implement more unequal earnings distributions than the average American, are highly sensitive to both merit-based inequality and efficiency costs of redistribution, and are less likely to hold strict meritocratic views. These findings provide novel insights into how elites' redistributive preferences may shape high levels of inequality and limited redistributive policy in the United States.

*Preuss: Cornell University, email, mp2222@cornell.edu; Reyes (corresponding author): Middlebury College and IZA, email, greyes@middlebury.edu; Somerville: Federal Reserve Bank of New York, email, jason.somerville@ny.frb.org; Wu: University of British Columbia, email, joy.wu@sauder.ubc.ca. For helpful comments and suggestions, we thank Peter Andre, Alexander Cappelen, Peter Matthews, Ricardo Pérez-Truglia, Erik Sørensen, Bertil Tungoden, participants in FAIR NHH and the Cornell Behavioral Economics Research Group. The views expressed in this paper are those of the authors alone and do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System. The experiment reported in this paper was registered in the American Economic Association's registry for randomized controlled trials under ID AEARCTR-0015448. The experiment was reviewed and granted an exemption by the Institutional Review Board at Cornell University (Protocol #0147786).

1 Introduction

Support for redistributive policies depends on how individuals weigh fairness considerations against efficiency costs (e.g., Alesina and Angeletos, 2005; Bénabou and Tirole, 2006). A large body of research shows that, in representative US samples, individuals prefer redistributing income when inequality stems from luck rather than effort and show little sensitivity to efficiency costs (Almås et al., 2020). However, policy outcomes are shaped by more than the preferences of the median voter. Theories of "elite control" in political science argue that elites—individuals with substantial economic, political, or social capital—largely determine which policies get implemented.[1] Consistent with these theories, empirical evidence finds that elites exert a disproportionate influence on policymaking, while the median voter has little or no influence.[2] For example, in a seminal paper, Gilens and Page (2014) show that the likelihood of a policy being implemented in the US is strongly related to the support of the policy by business groups and the richest ten percent of the population and uncorrelated with the preferences of the average American.[3]

Given elites' outsized political and economic influence, measuring their fairness attitudes and efficiency concerns is crucial for understanding redistributive policies and income inequality trends. Unfortunately, there has been relatively little work estimating these preferences, partly due to the difficulty of reaching elites. This paper overcomes this challenge by eliciting incentivized redistribution choices from two cohorts of Cornell MBA students—a *future* business and political elite. Students in our sample are projected to be among the top one percent of earners. Moreover, alumni of the program include multiple individuals in positions of power, including CEOs of Fortune 500 companies, US representatives, board members, and founders of companies.

To provide empirical evidence on the redistributive preferences of MBA students, we

[1]See, among others, Mills (1959), Burch (1980), Ferguson (1995), Winters and Page (2009), Winters (2011), Beard (2012), Domhoff (2013), and Domhoff (2017).

[2]For evidence in the US, see Hacker and Pierson (2010), Gilens (2012), Rigby and Wright (2013), Gilens and Page (2014), Bartels (2016), Page and Gilens (2017), Hertel-Fernandez (2019), and Page et al. (2019). Evidence on the influence of elites on policymaking from other countries is mixed. Single-country studies from Germany, Norway, and the Netherlands support the hypothesis of elites exerting a disproportionate influence on policymaking (Elsässer et al., 2021; Schakel, 2021; Mathisen, 2023). However, in cross-country regressions, the preferences of low-income individuals are more predictive of redistribution than those of high-income individuals (Maréchal et al., 2025).

[3]Related research has documented different channels through which elites impact policy implementation. These channels include networking with policymakers (Page et al., 2013), political donations (Kalla and Broockman, 2016; Hertel-Fernandez et al., 2018), lobbying (Drutman, 2015), and direct participation in policy-making bodies (Carnes, 2018; Eggers and Klašnja, 2018).

follow the impartial spectator experimental paradigm (Cappelen et al., 2013). The experimental design involves "workers" and "impartial spectators" across three stages: production, earnings, and redistribution. In the production stage, workers—recruited through an online labor market platform—engage in a real-effort task. In the earnings stage, we randomly paired workers and determined their earnings based on a winner-takes-all payment scheme. We determined the winner of each pair based on either task performance or random chance. Thus, earnings inequality was either due to merit or luck. In the redistribution stage, impartial spectators (MBA students) choose the final earnings allocations for worker pairs. Since spectators redistribute earnings between others rather than themselves, their choices reflect pure fairness motives uncontaminated by self-interest. Each worker pair differs on the source of inequality (merit vs. luck) and the cost of redistributing earnings (no cost vs. costly redistribution). Using these redistributive decisions, we classify spectators according to established fairness ideals in the literature and compare the distribution of fairness views among MBA students to that of the general population.

We report four main findings. First, MBA students implement earnings distributions that are more unequal than those of the average American. When worker earnings are determined by luck, MBA students implement a Gini coefficient of 0.43. This level of inequality is substantially higher than that estimated with the same methodology in representative US samples, which is on the order of 0.36 (Almås et al., 2020). The difference between the inequality implemented by MBA students and the average American represents approximately 35 percent of the difference in inequality implemented by individuals in the US and Scandinavia.

Second, MBA students' redistributive decisions react strongly to the source of inequality. When worker earnings are assigned based on task performance, MBA students implement earnings distributions with a Gini coefficient that is, on average, about 0.18 Gini points higher than the Gini implemented when worker earnings are assigned at random. This "source-of-inequality" effect is of a similar magnitude to that estimated in US samples, which is on the order of 0.20 (Almås et al., 2020).

Third, MBA students' redistributive choices are highly responsive to the efficiency cost of redistribution. When worker earnings are randomly assigned, introducing an efficiency cost of redistribution increases the implemented Gini coefficient by 0.20 Gini points. This elasticity of redistribution is an order of magnitude larger than that estimated on US samples, which typically finds an elasticity close to, and statistically indistinguishable from, zero (Almås et al., 2020).

Fourth, MBA students are less likely to be strict meritocrats and libertarians relative to the general public. In our sample, 9.9 percent of MBA students are classified as egalitarians, 23.2 percent as libertarians, 22.7 percent as meritocrats, and 44.3 percent do not fit any of these three fairness ideals. The fraction of egalitarians is similar to that estimated in US samples, while the fractions of meritocrats and libertarians are lower, and the fraction that cannot be classified into any of the main ideals is much larger (e.g., Almås et al., 2020; Cohn et al., 2023; Preuss et al., 2025). Using a repeated-measure design, we find that many of these unclassified spectators display weak meritocratic tendencies—they redistribute more when inequality stems from luck than from performance, but still allow luck to command an earnings premium. Analysis of open-ended responses regarding perceived drivers of US inequality further reveals that these unclassified spectators blend a belief in the value of hard work with recognition of unequal opportunities.

We conduct a replication study with a different sample of future elites: undergraduate business students from the same Ivy League University. The results validate our main findings across all four dimensions: higher baseline inequality, strong sensitivity to merit-based inequalities, marked responsiveness to efficiency costs, and distinct distribution of fairness ideals. The consistency of our findings across both undergraduate and graduate business populations strengthens the validity of our empirical approach and results.

This paper contributes to the literature that studies the relationship between fairness views and income redistribution. Substantial empirical evidence indicates the source of inequality—effort versus luck—affects individuals' attitudes toward redistribution.[4] More narrowly, recent work has focused on estimating the distribution of fairness ideals in representative samples of the population (Almås et al., 2020; Müller and Renes, 2021; Cohn et al., 2023; Andre, 2024). Our main contribution is to estimate fairness ideals in a sample of *future* elites who will likely influence policymaking. We compare our findings to those in the existing literature in the main text.

Two papers closely related to ours are Fisman et al. (2015) and Cohn et al. (2023). In Fisman et al. (2015), Yale Law School (YLS) students allocate resources between themselves and others while varying the cost of redistributing resources. The authors find that YLS students are more efficiency-focused and selfish than American adults. Like them,

[4]Empirical work using observational data includes Corneo and Gruner (2000), Fong (2001), Alesina and La Ferrara (2005), and Reyes and Gasparini (2022). Empirical work using lab experiments includes Cappelen et al. (2007), Cappelen et al. (2010), Cappelen et al. (2013), Cappelen et al. (2022), Almås et al. (2010), Almås et al. (2011), Durante et al. (2014), Mollerstrom et al. (2015), Dong et al. (2022), Bhattacharya and Mollerstrom (2022), Andre (2024), and Preuss et al. (2025).

we also find that future elites are more efficiency-seeking than the average American. We extend their findings by studying choices without selfish motives to isolate fairness preferences. Cohn et al. (2023) use survey data to study the fairness ideals of the richest five percent of Americans and find that they are more tolerant of inequality than the bottom 95 percent. Our paper complements their work in three main ways. First, we measure how efficiency concerns affect redistribution. Second, our in-class recruitment procedure addresses individuals' self-selection—possibly based on social preferences—into surveys. Third, while Cohn et al. (2023) focus on high-income individuals, we study future elites, many of whom do not come from wealthy families.[5]

Finally, we provide novel evidence on the factors driving earnings inequality in the labor market. Empirical evidence indicates that firm wage-setting policies contribute significantly to the variance in log-earnings (e.g., Card et al., 2018). However, why firms pay different wages to observationally equivalent workers is not well understood.[6] An often overlooked fact is that firm compensation schemes and wage-setting policies are typically designed by managers (Acemoglu et al., 2022; He and le Maire, 2022), whose fairness views may inform their decisions. Our sample of MBA students is ideally suited to study managerial attitudes toward fair compensation, as many of them will become business managers.[7] We find substantial variation in implemented earnings inequality across MBA students, highlighting a novel explanation for firm-level earnings inequality.

2 Experimental Design

We follow the standard impartial-spectator paradigm (Cappelen et al., 2013; Almås et al., 2020). The experiment has two types of participants—workers and impartial spectators—and is divided into three stages: a production stage, an earnings stage, and a redistribution stage (Appendix Figure A2 shows the flow of the experiment).

[5] These two are linked, yet income is only one of many markers of "eliteness." Other dimensions, like education, are as important or even more (Mathisen, 2023).

[6] Recent work studying firm wage-setting includes Hall and Krueger (2012), Caldwell and Harmon (2019), Dube et al. (2020), Hjort et al. (2020), Derenoncourt et al. (2021), Lachowska et al. (2022), Cullen et al. (2022), Hazell et al. (2022), and Reyes (2025).

[7] In our sample, over 90 percent of students report aspiring to become a manager responsible for overseeing employees in the future.

2.1 Stages of the Experiment

In the production stage, workers have five minutes to complete a real-effort encryption task (Appendix Figure A1 shows an example). Workers are informed that completing more encryptions increases their chances of earning a bonus, but do not know how final earnings are determined. In the earnings stage, workers are randomly paired and the winner of each pair is determined based on either the number of encryptions completed in the production stage ("performance") or a coin flip ("luck"). Winners are initially allocated earnings of $6, and losers are allocated $0. Workers never learn these pre-redistribution earnings.

In the redistribution stage, impartial spectators choose the final earnings allocation for three worker pairs. Each pair differs in how the winner was determined and whether there is a cost to redistribute earnings, as described below. Spectators can redistribute amounts ranging from $0 to $6 in $0.50 increments. We present each decision as an adjustment schedule. We incentivize spectators by randomly selecting one of their decisions for implementation.[8]

After the redistribution decisions, spectators complete an exit survey. This survey contains questions about demographics, socioeconomic background, career aspirations, social views, and an attention check. One MBA cohort also answered an open-ended question about what they believe are the main drivers of income inequality in the US.

2.2 Treatment Conditions

We study three environments, presented to spectators in a randomized order (see Appendix Figure A3 for screenshots of each treatment). In the *luck* treatment, the winner of the worker pair was determined by a coin flip. In the *performance* treatment, the winner of the worker pair is the worker who completed more encryptions. In the *efficiency cost* treatment, the winner was determined by a coin flip and redistribution incurs an "adjustment cost" that reduces the total earnings available to participants. For every $1.00 reduction in the winner's earnings, the loser's earnings increase by only $0.50, resulting in a net loss of total income.

[8]To mitigate the impact of anchoring effects on redistribution decisions, we communicated to the spectators that the workers were not informed about whether they won or lost their match or the exact amount they would earn in each scenario, but would only be told their final earnings.

3 Data and Empirical Design

3.1 Participants and Recruitment

Workers. We recruited 800 US-based individuals on Prolific to work on the encryption task. Workers were paid a fixed participation fee of \$2 upon task completion and received an additional payment of up to \$6 based on the decision of a randomly chosen spectator (Appendix B.1 shows more information on the worker sample).

Spectators. Our sample consists of 271 MBA students from two consecutive cohorts (2023 and 2024). The redistributive decisions were made in-person during mandatory first-year classes as part of a classroom experiment. Table 1 presents summary statistics of the sample. Most MBA students are aged 24-31 (83 percent), male (55 percent), and US-born (56 percent). MBA students strongly prefer private sector careers (84 percent) and managerial roles (91 percent), with most planning to work in the US after graduation (94 percent). The majority voted in recent elections (69 percent) and believe hard work leads to a better life (81 percent).

To benchmark our results, we compare the distributive choices of MBA students with data from three studies of the US general population that use the same methodology when estimating the distribution of fairness ideals: Almås et al. (2020), Cohn et al. (2023), and the Survey of Consumer Expectations (SCE), initially collected by Preuss et al. (2025). For each study, we compare our results using the same outcome measures they report—Gini coefficients for Almås et al. (2020) and share of earnings redistributed for Cohn et al. (2023) and Preuss et al. (2025).[9]

3.2 Regression Model

We estimate linear models of the form:

$$\text{Gini}_{ip} = \beta_0 + \beta_1 \text{Performance}_p + \beta_2 \text{EfficiencyCost}_p + \varepsilon_{ip}, \tag{1}$$

where Gini_{ip} is the Gini coefficient of the final earnings allocation in worker pair p implemented by spectator i, Performance_p and EfficiencyCost_p are indicators that equal one if

[9] These latter two papers do not include an efficiency cost condition, which affects the total amount of income that can be redistributed. When comparing our findings to them, we compute the share of earnings redistributed net of efficiency costs.

pair p competed in the performance or efficiency cost treatments and zero otherwise, and ε_{ip} is the error term. The omitted category is the luck treatment. Our baseline specification uses all redistributive decisions. We also present estimates using the first decision of each spectator, including spectator fixed effects, and using fraction of earnings redistributed as the outcome. We cluster standard errors at the spectator level.

The three parameters of interest are β_0, β_1, and β_2. β_0 measures the average Gini when worker earnings are randomly assigned and there is no redistribution cost. β_1 measures the causal impact of assigning worker earnings based on performance (relative to assigning their earnings at random) on implemented inequality. β_2 measures the elasticity of the Gini coefficient with respect to the efficiency cost of redistribution. Appendix C.3 interprets these coefficients through the lens of a potential-outcomes framework.

4 Origin of Income Differences and Implemented Inequality

4.1 Regression Estimates

Table 2 presents estimates of equation (1). Columns 1 and 2 pool all redistributive decisions from spectators. Column 1 includes no further controls; thus, identification is based on both between- and within-subject variation. Column 2 includes spectator fixed effects; thus, identification relies entirely on within-subject variation. Columns 3 and 4 use only the first decision of spectators; thus, identification is based on between-subject variation.

Our estimates reveal that both merit-based earnings inequality and efficiency costs substantially increase implemented inequality. When worker earnings are randomly assigned, spectators implement a Gini coefficient equal to $\hat{\beta}_0 = 0.420$ (columns 1 and 2). Assigning worker earnings based on their performance increases the implemented Gini coefficient by about $\hat{\beta}_1 = 0.240$ Gini points ($p < 0.01$), or 57 percent of the luck condition Gini. Similarly, introducing a cost to redistributing earnings increases the Gini coefficient by $\hat{\beta}_2 = 0.188$ Gini points ($p < 0.01$), or 44 percent of the luck condition Gini.

The patterns are similar using only the first decision of each spectator, albeit the impact of the performance condition is slightly smaller and the standard errors larger (columns 3 and 4). For example, in column 3 we estimate that assigning worker earnings based on performance relative to luck increases the Gini coefficient by $\hat{\beta}_1 = 0.191$ Gini points ($p < 0.01$), or 44 percent of the luck condition Gini. Still, given the magnitude of the standard errors, we cannot reject equality of coefficients between columns 2 and 3 at the conventional significance levels.

The results are robust to several sample restrictions and alternative dependent variables. Appendix B.3 shows robustness to (i) excluding spectators who failed the attention check (Appendix Table B2); (ii) excluding spectators who rushed through the experiment (Appendix Table B3); (iii) excluding spectators who allocated strictly more earnings to the loser than to the winner (Appendix Table B4); (iv) estimating the regression separately for each cohort (Appendix Table B5) and (v) using the net-of-efficiency-cost share of earnings redistributed as the outcome (Appendix Table B6).

4.2 Are Elite Redistributive Choices Different from the Average American's?

Our estimates of implemented inequality when earnings are randomly assigned are larger than those estimated in previous work. In their US-representative sample, Almås et al. (2020) find that the average Gini coefficient implemented by spectators is 0.363 (see their Table 3, column 1). The corresponding estimate among MBA students is 0.432 (see Table 2, column 3). Thus, MBA students implement earnings distributions that, on average, are about 0.07 Gini points more unequal than those implemented by the average American. To put this figure in perspective, it is equal to 35 percent of the US-Norway implemented inequality gap in Almås et al. (2020).

Our estimates of how the source of inequality impacts redistributive choices are similar in magnitude to those in the literature. Almås et al. (2020) estimate that the performance condition increases the Gini coefficient in their US sample by 0.195 Gini points (on a baseline of 0.363). Our comparable specification yields an increase of 0.183 Gini points (on a baseline of 0.432, see Table 2, column 3). These source-of-inequality effects are similar in magnitude and statistically indistinguishable at conventional significance levels. Using a different outcome, Cohn et al. (2023) find that the performance condition decreases the share of earnings redistributed by 14.4 percentage points (on a baseline of 41.8 percent, see their Table 2, column 1), while Preuss et al. (2025) estimate a decrease of 20.5 percentage points (on a baseline of 33.6 percent, see their Table 2, column 1). Our corresponding estimate is 11.3 percentage points (on a baseline of 32.3 percent, see Appendix Table B6, column 3). Thus, our effects when measuring the share of earnings redistributed are comparable to those of Cohn et al. (2023), though somewhat smaller than those estimated by Preuss et al. (2025).

Conversely, our estimate of the elasticity of the Gini with respect to the efficiency cost of redistribution is substantially larger than estimates based on the general population. Almås et al. (2020) estimate that the efficiency condition increases the Gini coefficient by

0.01 Gini points in their US sample (see their Table 3, column 1), a coefficient that is statistically indistinguishable from zero. In contrast, our estimate of the corresponding elasticity in the same specification is 0.195 Gini points (Table 2, column 3).

Taken together, our findings reveal stark differences between the redistributive choices of future elites and the general population. Future elites are more tolerant of inequality than the average American, as reflected in their implementation of more unequal earnings distributions. While both elites and the general population show similar sensitivity to whether inequality stems from luck or effort, responding with comparable magnitude to the source of inequality, they differ markedly in how they weigh efficiency considerations. Unlike the average citizen, elites strongly respond to efficiency costs, with the effect of introducing redistribution costs being commensurate in magnitude to the source-of-inequality effect.

4.3 Heterogeneity

We find heterogeneity in redistributive behavior across several dimensions of MBA student characteristics (see Appendix B.4 for details). Males and high socioeconomic status (SES) students show stronger responses to efficiency costs compared to females and low SES students, respectively. Individuals who view success in life as primarily luck-dependent display less meritocratic behavior, showing smaller differences in their redistribution decisions between luck and performance treatments, while those planning to remain in the US demonstrate greater sensitivity to efficiency costs. We find no significant heterogeneity in redistributive choices based on managerial aspirations or political engagement.

5 The Distribution of Fairness Ideals among Future Elites

5.1 Measuring Fairness Ideals

To formalize how spectators make redistribution decisions, we develop a statistical framework that models fairness ideals as mappings from initial earnings distributions to final allocations (see Appendix C). Following the literature, we focus on three main fairness ideals: egalitarian, libertarian, and meritocratic. Egalitarian spectators equalize the workers' earnings regardless of the role luck played in the income-generating process. Libertarian spectators leave the initial earnings unchanged regardless of the circumstances that produced earnings differences. Meritocratic spectators adjust their redistributive decisions based on whether inequality stems from merit or luck: they equalize earnings when inequality is entirely luck-based (i.e., there is no merit to the earnings allocation), but redistribute less when inequality reflects performance differences.

Measuring these fairness ideals empirically presents a challenge, as reconstructing the complete mapping from circumstances to choices would require observing an infinite number of counterfactual decisions. To address this challenge, we need to extrapolate spectator behavior from a limited set of observed choices. We do this using two complementary designs. The first approach relies on between-subject comparisons, using only the first redistributive decision of each spectator and excluding those who saw the efficiency cost environment first. This is the standard design used in the literature (e.g., Almås et al., 2020; Cohn et al., 2023) and allows us to benchmark our results against previous work. The second approach leverages within-subject variation through multiple measures across the luck and performance treatments. This novel approach allows us to identify the specific fairness ideal held by each individual spectator, rather than just aggregate shares. We extend the standard identification assumptions to accommodate these multiple observations per spectator (see Appendix C).

Each approach offers distinct advantages and limitations. The first-choice design provides clean comparisons across individuals and avoids biases arising from sequential decisions, but is more vulnerable to measurement error and choice noise. The repeated-measure design reduces measurement error by incorporating more information about each spectator's behavior, but requires assuming that initial choices do not influence subsequent decisions. We present results using both approaches to establish robustness and facilitate comparison with existing research.

5.2 Estimates of Fairness Ideals

Table 3 presents estimates of the fraction of egalitarians, libertarians, meritocrats, and unclassified individuals using spectators' first choices. Panel A shows the estimates in our MBA sample and in representative samples of the US population, taken from Almås et al. (2020), Cohn et al. (2023), and estimated using the SCE data collected by Preuss et al. (2025). Figure 1 plots these estimates.

Based on the spectators' first choices, we estimate that 9.9 percent of MBA students are egalitarians, 23.2 percent are libertarians, 22.7 percent are meritocrats, and 44.3 percent adhere to other fairness ideals (Table 3, Panel A). These estimates are similar to those obtained using the repeated-measure design, which classifies 6.5 percent as egalitarians, 15.3 percent as libertarians, 28.7 percent as meritocrats, and 49.4 percent as adhering to other fairness ideals (Appendix Figure A4). The differences in the proportions of each fairness ideal between the two designs are not statistically significant at conventional levels.

The distribution of fairness ideals among MBA students differs markedly from that of the average citizen (Table 3, Panel B). The share of libertarians and meritocrats is smaller in the MBA population than in US representative samples. For example, Almås et al. (2020) estimate that 29.4 percent and 37.5 percent of Americans are libertarians and meritocrats, respectively. These shares are substantially larger than those we estimate in our sample (23.1 and 22.7 percent, respectively). Perhaps most strikingly, while only 9-17 percent of the general population cannot be classified into one of these three standard fairness ideals (depending on the study), this "other" category encompasses about 44.3 percent of future elites.

In Table 3 Panel C, we compare the distribution of fairness ideals among MBA students to that of high-income Americans. Prior work generally finds that high-income Americans are less frequently classified as egalitarian and more frequently as meritocratic than the average American, although findings vary considerably across studies. In contrast, we find that MBA students are less frequently classified as meritocrats than high-income Americans. Instead, a larger proportion of these future elites fall outside the three conventional fairness ideal classifications typically studied in the literature. The subsequent section examines the behavior of these unclassified spectators.

5.3 Understanding the Fairness Views of Future Elites

What are the characteristics of individuals who do not conform to the standard fairness ideals? To answer this, we first assess whether unclassified fairness views reflect deliberate choices. Then, we identify systematic patterns in redistribution decisions using the repeated-measure design and examine the characteristics associated with these patterns.

Are Non-Standard Fairness Views Deliberate or Random? A natural concern is that spectators classified as "other" might be randomly clicking through the survey rather than making deliberate choices. Four pieces of evidence argue against this possibility. First, unclassified spectators spend just as much time making their redistribution decisions as those who fit standard fairness ideal categories (Appendix Table A3). Second, they pass the embedded attention check at the same rate as other spectators.[10] Third, the joint distribution of their redistribution choices across the luck and performance conditions shows systematic patterns rather than the uniform distribution we would expect from random clicking (discussed below). Fourth, our replication study with a different future elite—undergraduate business students—finds similar rates of unclassified spectators (Section 6), suggesting this group represents meaningful preferences rather than careless responses.

Redistributive Patterns Leading to Unclassified Spectators. To identify systematic patterns in choices that lead to unclassified fairness ideals, Table 4 shows the joint distribution of redistribution choices in the performance and luck conditions. Colored cells highlight the redistributive choices that lead to the fairness ideals shown in Table 3. Non-highlighted cells represent combinations that lead to unclassified spectators.

The most common unclassified choice pattern involves spectators redistributing more in the luck condition than in the performance condition, but not fully equalizing earnings when inequality stems from luck. Specifically, 11.1 percent of spectators redistribute \$2 or \$1 in luck and \$0 in performance, while 8.4 percent redistribute \$2 in luck and \$1 in performance. These spectators behave as "weak meritocrats"—in the sense that they reward effort differences while also allowing luck to command some premium by not fully equalizing earnings in the luck condition. Together, these choices account for 19.5 percent of all spectators (or 39.5 percent of unclassified spectators). For conciseness, we refer to spectators who implemented any of these choices as "moderates."

Moderates implement more unequal earnings distributions than meritocrats. On average, moderates redistribute 18.8 percent of earnings and implement a Gini coefficient of 0.624, whereas meritocrats redistribute 30.8 percent of earnings and implement a Gini coefficient of 0.383. These behaviors are statistically different at $p < 0.01$. The key distinction between moderates and meritocrats is that moderates preserve some inequality even when it results purely from chance, contradicting the meritocratic principle that only merit-based differences should be rewarded.

Correlates of Fairness Ideals. To identify characteristics associated with being a moderate in relation to other fairness ideals, Appendix Table A4 presents bivariate regressions

[10] In our data, 6.9 percent of all spectators fail the attention check. A bivariate regression of an indicator for failing the attention check on the "other ideal" dummy yields a statistically insignificant $\hat{\beta} = -0.004$ (p-value $= 0.88$).

estimates using indicator variables for each fairness ideal as outcomes and individual characteristics as regressors.

Several individual characteristics are related with fairness ideals. Individuals who believe success in life is mainly due to luck and connections rather than hard work are more likely to be egalitarians ($p < 0.10$) and less likely to be moderates ($p < 0.05$). In contrast, individuals who believe working long hours is necessary are more likely to be moderates ($p < 0.01$). Men are more likely to be libertarians ($p < 0.01$) and less likely to be meritocrats ($p < 0.10$). Finally, politically active students, as measured by voting in recent elections, are more likely to be meritocrats ($p < 0.01$).

Inequality Narratives. To further understand moderates in relation to other fairness ideals, we next analyze MBA students' explanations for inequality in the US. We allowed individuals to explain their views on the main reasons behind inequality in an unstructured manner and then classified responses into topics based on keywords.[11] We identified seven topics: (1) educational barriers, (2) unequal opportunities, (3) bias and discrimination, (4) economic factors, (5) government and politics, historical and culture, and (7) other. Using these classifications, we compute the fraction of individuals mentioning each topic separately by fairness ideal. Appendix Table A5 and Appendix Figure A5 presents the probability distribution of topics calculated separately for each fairness ideal.[12]

We find systematic differences in how different groups explain inequality. Educational barriers is the most frequently cited factors in explaining inequality. However, the narratives differ markedly across fairness ideals: Meritocrats emphasize educational barriers more frequently (36.1 percent) compared to libertarians (13.3 percent) and moderates (22.2 percent). Moderates are more likely to discuss unequal opportunities and discrimination (14.8 and 18.5 percent, respectively) compared to other groups. Egalitarians in our sample did not mention economic factors or government and politics as sources of inequality, but frequently cite educational barriers and historical-cultural factors (both 25.0 percent). Despite these differences, certain factors like historical and cultural influences are mentioned with similar frequency across all groups (ranging from 13.3 percent to 25.0 percent).

[11] For instance, responses containing terms like "school" or "studying" were categorized under educational barriers, while mentions of discrimination, race, or gender were classified under bias and discrimination.

[12] Appendix Figures A6 and A7 present word clouds of the responses separately for each fairness ideal and topic.

6 Replication with Elite Undergraduate Business Students

To probe the validity of our results, in Appendix D we conduct a replication analysis using a sample of *undergraduate* Cornell business students from the Dyson School of Applied Economics and Management (henceforth "Dyson students"). This is another sample of *future* elites, but a more homogeneous group in terms of age and country of origin (Appendix Table D1).

This sample reveals four key findings that are broadly aligned with our main results. First, Dyson students implement similarly unequal earnings distributions as MBA students. When worker earnings are determined by luck, they implement a Gini coefficient of 0.41—a level of inequality very similar to MBA students and substantially higher than representative US samples.

Second, Dyson students show an even stronger response to the source of inequality than MBA students. When earnings are assigned based on performance rather than luck, they implement distributions that are 0.31 Gini points more unequal, compared to 0.23 for MBA students.

Third, Dyson students' sensitivity to efficiency costs mirrors that of MBA students. When redistribution incurs efficiency costs, they increase the Gini coefficient by 0.19 points—nearly identical to the 0.18 point increase observed in the MBA sample and substantially larger than in representative samples.

Fourth, like MBA students, Dyson students are less likely to conform to standard fairness ideals compared to the general public. However, the distribution of ideals differs somewhat: undergraduate business students show lower rates of egalitarianism (1.9 percent vs. 9.9 percent for MBA students), similar rates of libertarianism (23.9 percent vs. 23.2 percent), and higher rates of meritocracy (37.6 percent vs. 22.7 percent). Like MBA students, a substantial fraction of spectators are moderates (24.5 percent vs. 19.5 percent for MBA students).

7 Conclusion

This paper examines which types of inequalities future elites consider worthy of redistribution and how much importance they assign to efficiency. We find that MBA students are more tolerant of inequality and more responsive to efficiency concerns than the general population.

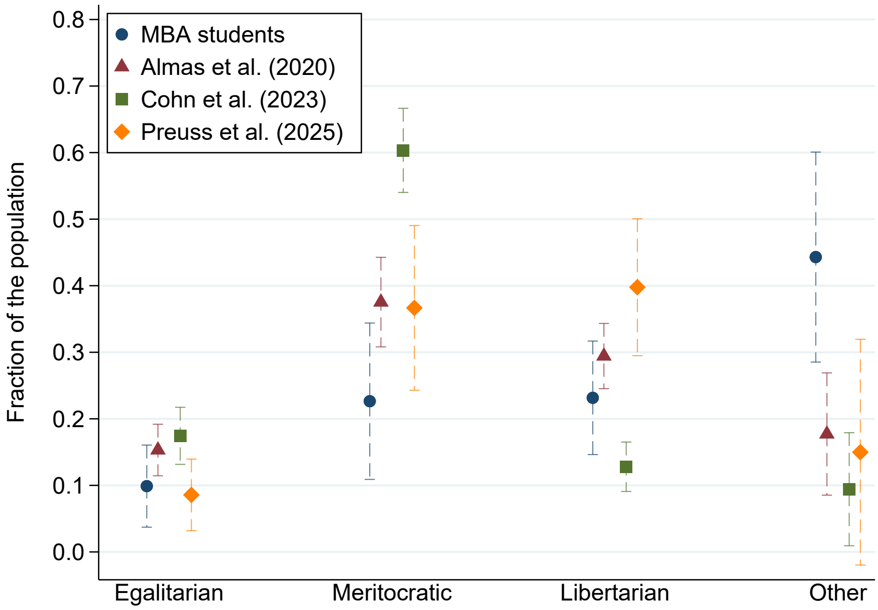
Our results help explain a puzzle in the political economy of inequality: While most Americans express strong preferences for more equal income distributions (Norton and Ariely, 2011, 2013), the United States maintains the highest income inequality among OECD countries (Chancel et al., 2022). Our findings provide a possible explanation for this apparent disconnect: The individuals with disproportionate influence over policy decisions—future elites—implement substantially more unequal earnings distributions than the average American, and thus may oppose the redistributive policies that the majority of citizens would prefer.

Our results also contribute to understanding cross-country differences in the size of the welfare state. It is well known that the US and Europe have stark differences in redistributive policies (Alesina et al., 2001). While many factors are behind these differences (Alesina and Glaeser, 2004), it is often argued that efficiency concerns may be a contributing factor. Yet, previous work has documented that the average American has little regard for efficiency concerns, and much less so than individuals in Scandinavia (Almås et al., 2020). This discrepancy can be reconciled by our evidence: While the average citizen has little regard for efficiency concerns, future economic and political leaders care substantially about efficiency and thus may oppose higher levels of redistribution if they believe redistributive policies entail high costs.

Our findings open several avenues for future research. While MBA students exhibit strong efficiency-seeking preferences, the direction of causality remains unclear—individuals with such preferences may self-select into business programs, or these programs may shape their preferences. Moreover, elites are not a homogeneous group; ideological differences exist across Silicon Valley, Wall Street, and Capitol Hill elites (Broockman et al., 2019). Measuring the fairness and efficiency preferences of different elite groups and understanding how these views translate into policy influence is a promising area for future research.

Figures and Tables

Figure 1: The distribution of fairness ideals among MBA students and the US



Notes: This figure shows estimates of the fraction of egalitarians, libertarians, and meritocrats in various studies. All estimates are based on a between-subject design that uses one redistributive choice per spectator. The fraction of egalitarians is given by the fraction of spectators who equalize earnings among workers when the winner is determined by performance. The fraction of libertarians is given by the fraction of spectators who do not redistribute earnings between workers when the earnings are randomly assigned to workers. The fraction of meritocrats is given by the difference between (i) the fraction of spectators who redistribute more to the winner when worker earnings are assigned based on performed minus (ii) the fraction of spectators who redistribute more to the winner when worker earnings are randomly assigned. The remaining spectators are classified as having "other" ideals. Vertical dashed lines represent 95% confidence intervals calculated using robust standard errors clustered at the spectator level.

We estimate the distribution of fairness ideals in the Preuss et al. (2025) data using only data from the first decision of spectators in the "lucky outcomes" condition, in which the winner of a worker pair is determined by a coin flip with some probability and by performance with the remaining probability. We only keep the subset of decisions where the coin flip determined the outcome with probability one (which is equivalent to our "luck" condition) or when performance determined the outcome with probability one (which is equivalent to our "performance" condition.)

Table 1: Summary statistics of the MBA student sample

	Mean (1)	SD (2)	N (3)
Panel A. Demographic characteristics			
Age $\leq$23	0.031	0.174	258
Age 24–27	0.380	0.486	258
Age 28–31	0.453	0.499	258
Age $\geq$32	0.136	0.343	258
Male	0.554	0.498	260
Cohort 2023	0.509	0.501	271
Cohort 2024	0.491	0.501	271
Born in the USA	0.562	0.497	256
Panel B. Financial situation while growing up			
Always had enough money for necessities and luxuries	0.198	0.399	258
Always had enough for necessities and occasional luxuries	0.422	0.495	258
Usually had enough for necessities, rarely for luxuries	0.279	0.449	258
Sometimes did not have enough money for necessities	0.081	0.274	258
Frequently did not have enough money for necessities	0.019	0.138	258
Panel C. Employment preferences			
Planning on getting a job in the USA	0.941	0.237	253
Working long-hours is sometimes necessary	0.811	0.392	254
Wants career in a non-profit	0.173	0.379	254
Wants to become an entrepreneur	0.484	0.501	254
Wants career in private sector	0.839	0.369	254
Work-life balance is more important than a high salary	0.524	0.500	254
Aspire to be a manager	0.913	0.282	254
Panel D. Voting behavior and social views			
Voted in the last elections	0.693	0.462	251
Success is luck and connections	0.362	0.482	254
Hard work brings a better life	0.815	0.389	254
Completed all three redistributive decisions	0.959	0.198	271
Passed attention check	0.933	0.250	254
Minutes spent in survey	4.553	1.398	271

Notes: This table shows summary statistics of MBA students in our sample. All variables are based on data self-reported by MBA students in the exist survey of the study. Employment preferences and social views are based on MBA students' agreement with several statements in a five-point Likert scale grid. For each statement, we define an indicator variable that equals one if the student selects "strongly agree" or "agree," and zero otherwise.

Table 2: Implemented Gini coefficient across environments

	Dependent variable: Gini coefficient			
	All redistributive decisions		First decision only	
	(1)	(2)	(3)	(4)
Performance condition	0.240***	0.242***	0.191***	0.184***
	(0.029)	(0.035)	(0.052)	(0.054)
Efficiency condition	0.188***	0.187***	0.206***	0.211***
	(0.024)	(0.029)	(0.057)	(0.060)
Constant	0.420***	0.420***	0.432***	0.425***
	(0.024)	(0.018)	(0.040)	(0.071)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	793	793	271	271
N (individuals)	271	271	271	271

Notes: This table displays estimates of β_0, β_1, and β_2 from equation (1). The omitted treatment is the luck condition. The outcome is the Gini coefficient of the final earnings allocation in worker pair p implemented by spectator i, Gini_{ip}. The Gini coefficient takes a value between zero and one, where zero denotes perfect equality (both workers have the same post-redistribution earnings) and one denotes perfect inequality (one worker holds all earnings). We calculate the Gini coefficient as:

$$\text{Gini}_{ip} = \frac{|\text{Income Worker 1} - \text{Income Worker 2}|}{\text{Income Worker 1} + \text{Income Worker 2}}.$$

The specifications in columns 2 and 4 include additional controls. In column 2, we include spectator fixed effects. In column 4, we control for gender, age bins, parental financial situation while growing up, and a dummy for being born in the US. Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 3: Distribution of fairness ideals: Elites vs. Average citizens

	Percentage of...			
	Egalitarians (1)	Libertarians (2)	Meritocrats (3)	Other ideals (4)
Panel A. MBA students				
MBA students (spectators' first choices)	9.89	23.16	22.65	44.30
	(3.15)	(4.35)	(5.99)	(8.05)
MBA students (repeated-measure design)	6.51	15.33	28.74	49.43
	(1.08)	(1.58)	(1.98)	(2.76)
Panel B. Average American				
SCE – Average American	8.57	39.77	36.67	14.99
	(2.75)	(5.25)	(6.31)	(8.66)
Almås et al. (2020) – Average American	15.32	29.43	37.54	17.72
	(1.98)	(2.50)	(3.43)	(4.69)
Cohn et al. (2023) – Average American	17.45	12.80	60.33	9.42
	(2.19)	(1.89)	(3.22)	(4.33)
Panel B. High-income samples				
SCE – USA income over 100k	3.23	44.44	40.32	12.01
	(3.23)	(12.05)	(13.27)	(18.22)
Almås et al. (2020) – USA income over 100k	14.08	22.67	41.92	21.33
	(4.16)	(4.87)	(7.11)	(9.57)
Cohn et al. (2023) – USA top 5 percent	8.97	25.15	59.14	6.75
	(2.38)	(3.33)	(4.37)	(5.99)
Panel C. Low-income samples				
SCE – USA income below 100k	10.81	38.57	35.14	15.48
	(3.63)	(5.86)	(7.32)	(10.06)
Almås et al. (2020) – USA income below 100k	15.65	31.40	36.33	16.63
	(2.25)	(2.89)	(3.92)	(5.37)
Cohn et al. (2023) – USA bottom 95 percent	17.83	12.06	60.54	9.57
	(3.06)	(2.75)	(4.62)	(6.19)

Notes: This table shows estimates of the fraction of egalitarians, libertarians, and meritocrats in various studies. Estimates in Panels B–D are based on a between-subject design that uses one redistributive choice per spectator. See Appendix C for the definition and estimation of each fairness ideal.

We estimate the distribution of fairness ideals in the Survey of Consumer Expectations (SCE), collected by Preuss et al. (2025), using only data from the first decision of spectators in the "lucky outcomes" condition, in which the winner of a worker pair is determined by a coin flip with some probability and by performance with the remaining probability. We only keep the subset of decisions where the coin flip determined the outcome with probability one (which is equivalent to our "luck" condition) or when performance determined the outcome with probability one (which is equivalent to the "performance" condition.)

In Panels C and D, we estimate heterogeneity in fairness ideals based on the income of the spectator. Panel C shows estimates for high-income samples. In Almås et al. (2020) and the SCE data, these are individuals with a yearly income of over $100,000 per year. In Cohn et al. (2023), these are individuals in the top 5 percent of the income distribution. Panel D shows estimates for the rest of the individuals.

Table 4: Joint distribution of redistribution in luck and performance conditions

Luck Condition	Earnings Redistributed in Performance Condition						
	$0	$1	$2	$3	$4	$5	$6
$0	0.153	0.031	0.027	0.011	0.000	0.000	0.008
$1	0.034	0.057	0.023	0.008	0.004	0.000	0.000
$2	0.077	0.084	0.080	0.008	0.000	0.000	0.000
$3	0.138	0.069	0.080	0.065	0.000	0.000	0.004
$4	0.000	0.004	0.015	0.004	0.000	0.000	0.000
$5	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$6	0.000	0.000	0.000	0.004	0.004	0.004	0.004

Libertarians
Egalitarians
Meritocrats

Notes: This table shows the joint distribution of redistribution choices across luck and performance conditions, excluding the efficiency cost treatment. Each cell represents the proportion of spectators who chose to redistribute $\$x$ dollars in the luck condition (rows) and $\$y$ dollars in the performance condition (columns). For example, 15.3 percent of spectators chose to redistribute $0 in both conditions, while 6.5 percent of spectators chose to redistribute $3 (i.e., equalize earnings) in both conditions.

The orange shaded cell indicate spectators classified as egalitarians based on the repeated-measure design (equal redistribution in both conditions), the green shaded cell indicates spectators classified as libertarians (no redistribution in either condition), and the blue shaded cells indicate spectators classified as meritocratic (earnings equalization in the luck condition and more redistribution in luck than performance). Individuals who made redistribution choices that fall outside the shaded areas are classified as having “other” fairness ideals.

Appendix

A Appendix Figures and Tables

Figure A1: Example of the worker encryption task

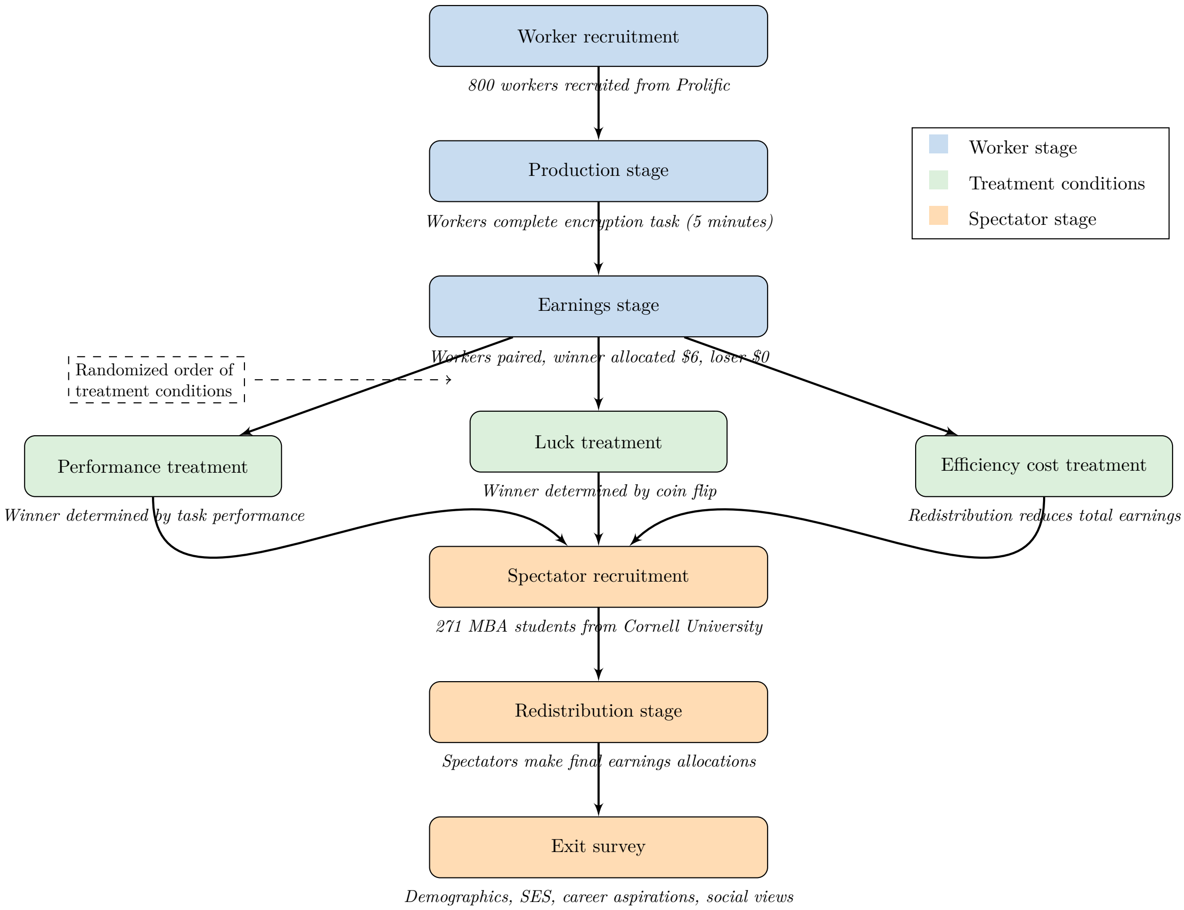
Q	X	D	A	C	V	U	R	P	W	L	Y	G
754	579	860	708	344	725	950	314	532	595	654	838	327
Z	**F**	**M**	**N**	**T**	**B**	**K**	**O**	**H**	**S**	**E**	**I**	**J**
190	776	627	980	830	803	603	673	536	490	545	445	925

Please translate the following word into code:

RPZ:

Notes: This figure shows an example of an encryption completed by workers. For each three-letter "word," workers receive a codebook that maps letters to three-digit numbers. After encrypting one word, a new word appears along with a new codebook. The words, codes, and the sequence of letters in the codebook are randomized for each new word. Feedback on the correctness of encryptions is not provided. Workers have a total of five minutes to complete as many encryptions as possible within this time frame.

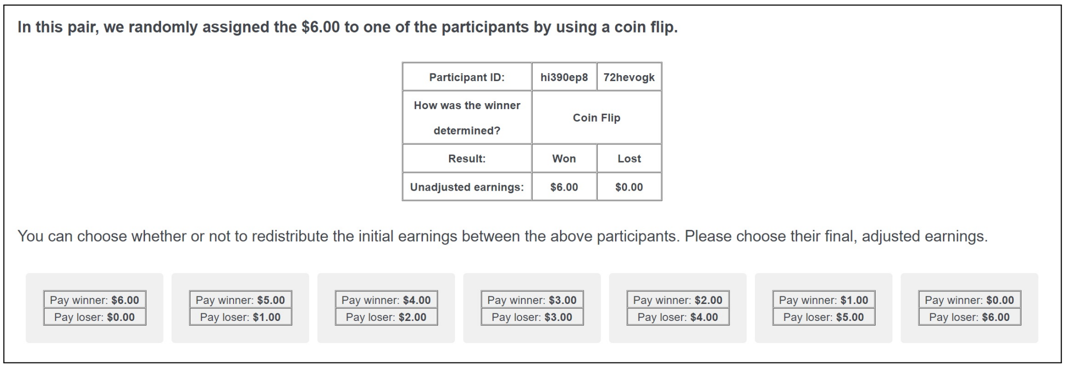
Figure A2: Flow of the experiment



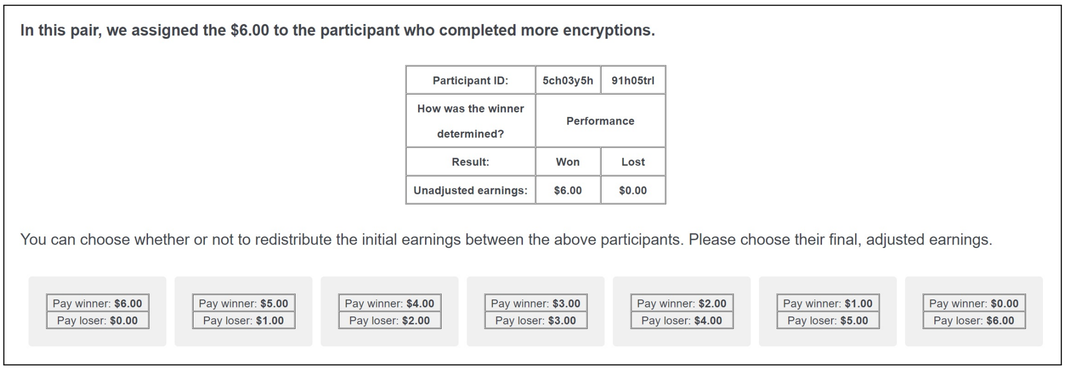
Note: This figure illustrates the three-stage experimental design. In the production stage, workers complete an encryption task. In the earnings stage, workers are paired and initial earnings are assigned based on either performance or luck. In the redistribution stage, MBA student spectators determine final earnings allocations across three treatment conditions presented in randomized order.

Figure A3: Screen with redistributive decisions

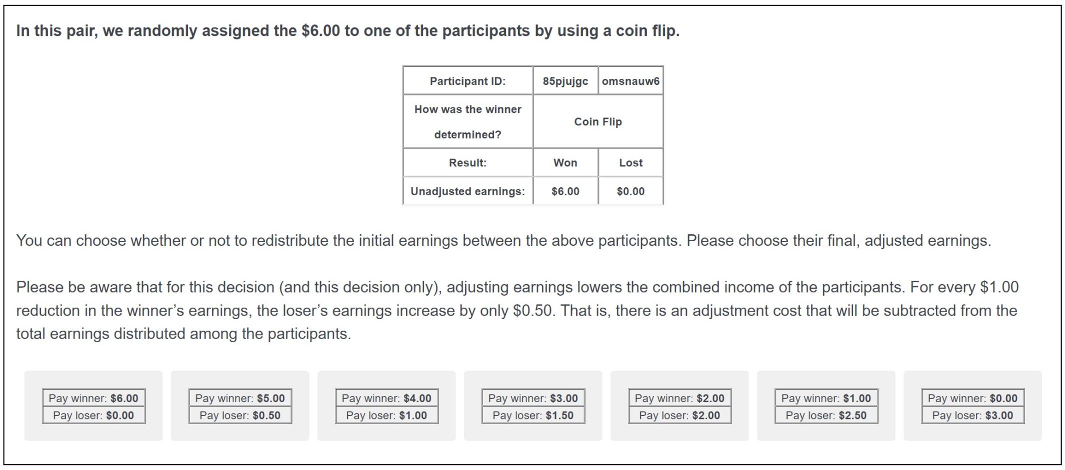
Panel A. Luck condition



Panel B. Performance condition

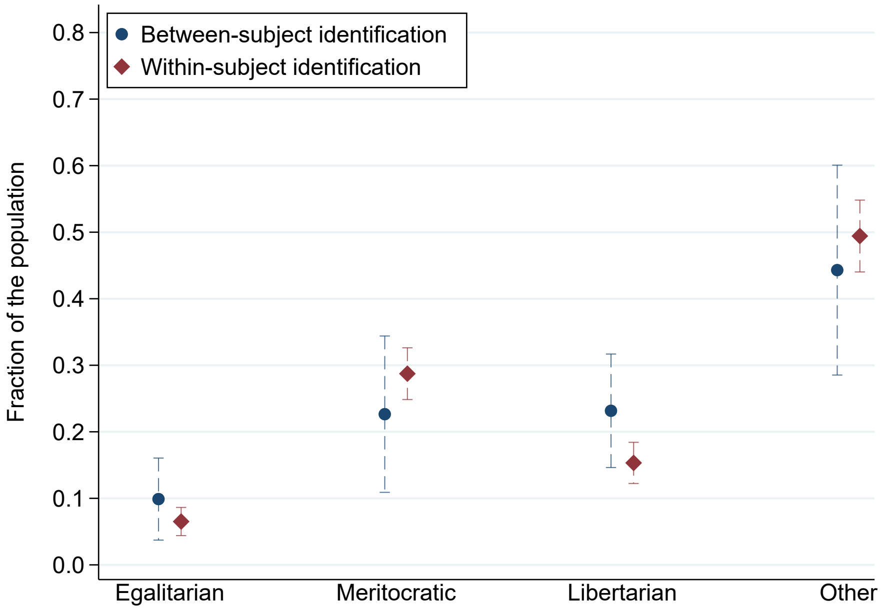


Panel C. Efficiency-cost condition



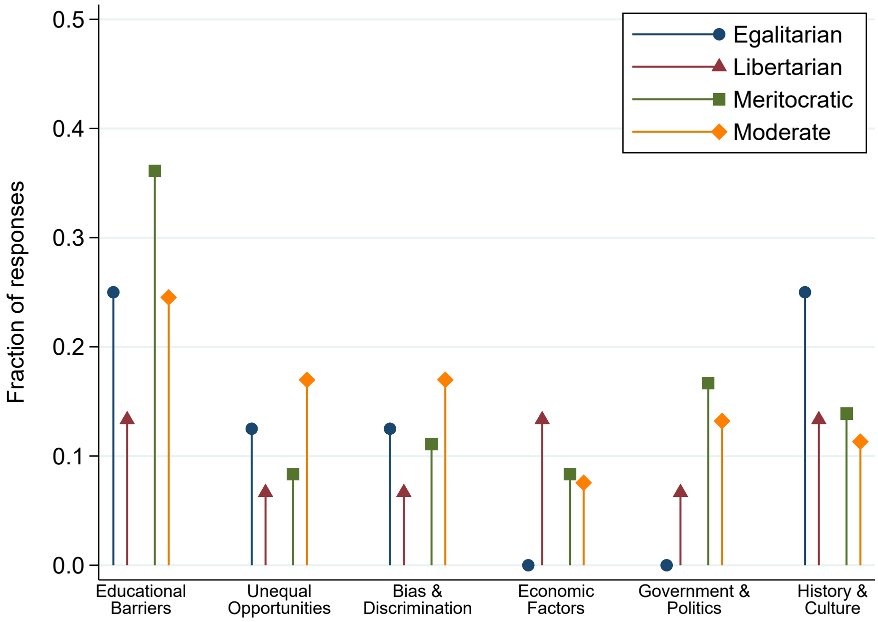
Notes: This figure shows screenshots of the redistribution screen shown to spectators for each worker pair condition.

Figure A4: Fairness ideals: between- and within-subject identification



Notes: This figure shows estimates of the fraction of egalitarians, libertarians, and meritocrats using two different research designs. See Section C for the definition and estimation of each fairness ideal. Estimates shown in circles are based on a between-subject design that uses one redistributive choice per spectator. Estimates shown in diamonds are based on a within-subject design that uses two redistributive choice per spectator. Vertical dashed lines represent 95% confidence intervals calculated using robust standard errors clustered at the spectator level.

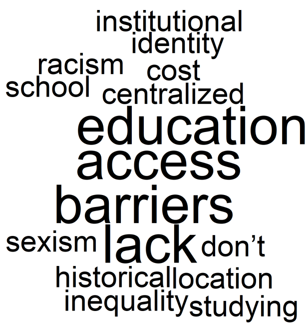
Figure A5: Narratives about inequality and fairness ideals



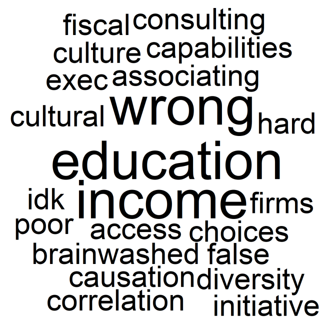
Notes: This figure shows the distribution of explanations for inequality in the US across different fairness ideals. Each marker represents the fraction of spectators within a fairness ideal category who mention a given factor as a source of inequality. Topics were classified based on keyword analysis of open-ended responses. Educational barriers includes mentions of schooling, education quality, and knowledge. Unequal opportunities refers to access to jobs and economic mobility. Bias and discrimination includes references to racism, sexism, and bias. Economic factors encompass wealth, income, and financial barriers. Government and politics covers government policies and regulations. History and culture refer to broad institutional and structural barriers.

Figure A6: Word clouds of inequality explanations by fairness ideal

Panel A. Egalitarians

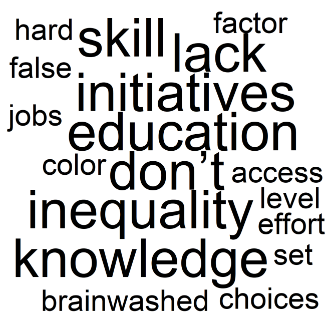


Panel B. Libertarians



Panel C. Meritocrats

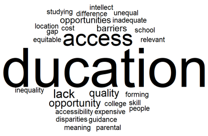
Panel D. Moderates



Notes: This figure plots word clouds showing the distribution of words used to explain why there is inequality in the US. The size of each word is proportional to its frequency within each fairness ideal.

Figure A7: Word clouds of inequality explanations by category

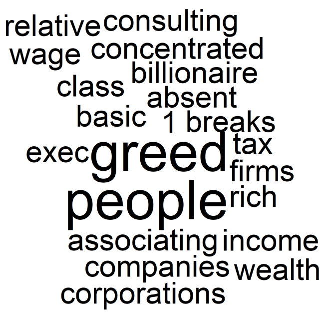
Panel A. Educational Barriers



Panel B. Unequal Opportunities

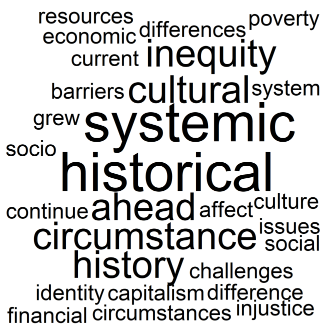
Panel C. Bias & Discrimination

Panel D. Economic Factors



Panel E. Government & Politics

Panel F. History & Culture



Notes: This figure plots word clouds showing the distribution of words used within each category of reasons for inequality in the US. The size of each word is proportional to its frequency within each category.

Table A1: Summary statistics of the sample by first treatment shown

		First condition shown		
	All (1)	Luck (2)	Performance (3)	Efficiency (4)
Panel A. Demographic characteristics				
Age $\leq$23	0.031	0.043	0.034	0.013
Age 24–27	0.380	0.419	0.315	0.408
Age 28–31	0.453	0.387	0.483	0.500
Age $\geq$32	0.136	0.151	0.169	0.079
Male	0.554	0.521	0.589	0.553
Born in the USA	0.562	0.606	0.545	0.527
Panel B. Financial situation while growing up				
Always had enough money for necessities and luxuries	0.198	0.191	0.169	0.240
Always had enough for necessities and occasional luxuries	0.422	0.447	0.438	0.373
Usually had enough for necessities, rarely for luxuries	0.279	0.277	0.281	0.280
Sometimes did not have enough money for necessities	0.081	0.074	0.090	0.080
Frequently did not have enough money for necessities	0.019	0.011	0.022	0.027
Panel C. Employment preferences				
Planning on getting a job in the USA	0.941	0.978	0.899	0.946
Working long-hours is sometimes necessary	0.811	0.806	0.851	0.770
Work-life balance is more important than a high salary	0.524	0.505	0.448	0.635
Wants career in private sector	0.839	0.806	0.851	0.865
Wants career in a non-profit	0.173	0.204	0.138	0.176
Wants to become an entrepreneur	0.484	0.430	0.483	0.554
Aspire to be a manager	0.913	0.903	0.920	0.919
Panel D. Voting behavior and social views				
Voted in the last elections	0.693	0.714	0.701	0.658
Success is luck and connections	0.362	0.355	0.414	0.311
Hard work brings a better life	0.815	0.828	0.816	0.797
Passed attention check	0.933	0.968	0.908	0.919
Minutes spent in survey	4.553	4.560	4.640	4.454
Completed all three redistributive decisions	0.959	0.989	0.989	0.894
Number of individuals	271	95	91	85
Number of redistributive decisions	793	284	271	238
F-statistic	–	1.042	1.049	1.034
p-value F-statistic	–	0.410	0.404	0.417

Notes: This table shows summary statistics of MBA students in our sample. All variables are based on data self-reported by MBA students in the exist survey of our study. Employment preferences and social views are based on MBA students' agreement with several statements in a five-point Likert scale grid. For each statement, we define an indicator variable that equals one if the student selects "strongly agree" or "agree," and zero otherwise.

Column 1 shows the summary statistics for all MBA students in our sample. Columns 2–4 divide the sample according to the first condition shown to the students. In column 2, the first redistributive decision was between two worker pairs where earnings were randomly assigned. In column 3, the first redistributive decision was between two worker pairs where earnings were determined by performance on the encryption task. In column 3, the first redistributive decision was between two worker pairs where earnings were randomly assigned and there was an efficiency cost.

Table A2: The impact of the order in which spectators saw each condition

	Dependent variable: Gini coefficient			
	Separately by condition			
	Luck	Performance	Efficiency	Pooled
	(1)	(2)	(3)	(4)
Luck × Screen 2	−0.014			−0.014
	(0.059)			(0.059)
Luck × Screen 3	−0.022			−0.022
	(0.059)			(0.060)
Performance × Screen 2		0.028		0.028
		(0.050)		(0.050)
Performance × Screen 3		0.087*		0.087*
		(0.052)		(0.052)
Efficiency × Screen 2			0.017	0.017
			(0.057)	(0.057)
Efficiency × Screen 3			−0.105*	−0.105*
			(0.058)	(0.058)
Constant	0.432***	0.623***	0.638***	0.565***
	(0.040)	(0.034)	(0.041)	(0.022)
N (decisions)	261	263	269	793
N (individuals)	261	263	269	271

Notes: This table displays estimates of order effects on the Gini coefficient. In columns 1–3, we regress the Gini coefficient on dummies for seeing a given condition on the second and third screen. The constant represents the average Gini coefficient for spectators who saw a given condition on the first screen. In column 4, we interact all conditions with the order dummies. Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A3: Time spent on redistribution screens by spectators with unclassified fairness ideals

	Dependent variable: Time spent (seconds)			
		By redistribution condition		
	All screens	Performance	Luck	Efficiency Cost
	(1)	(2)	(3)	(4)
Other ideal	0.382	−1.280	2.311	−2.770
	(4.467)	(1.983)	(1.674)	(2.974)
Constant	73.822***	21.266***	19.336***	35.338***
	(3.489)	(1.467)	(1.225)	(2.104)
N (individuals)	260	263	261	269

Notes: This table presents regression estimates of the relationship between having an unclassified fairness ideal and time spent on redistribution decision screens. A spectator is considered an "other" ideal if their redistribution choices do not align with the standard fairness categories of egalitarianism, libertarianism, or meritocracy. The dependent variable in column 1 is the total time spent across all redistribution screens. In columns 2 through 4, the dependent variables represent time spent in the performance-based earnings, luck-based earnings, and efficiency-cost conditions, respectively. Standard errors clustered at the spectator level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table A4: Correlates of fairness ideals

	Dependent Variable:			
	Egalitarian (1)	Meritocrat (2)	Libertarian (3)	Moderate (4)
Male	−0.038	−0.102*	0.146***	−0.082
	(0.032)	(0.057)	(0.042)	(0.050)
Aged 28 or over	0.009	−0.008	−0.009	0.006
	(0.016)	(0.026)	(0.021)	(0.025)
Born USA	0.007	−0.026	0.064	−0.027
	(0.031)	(0.058)	(0.044)	(0.051)
Stay USA	0.001	−0.260*	0.080	0.002
	(0.067)	(0.133)	(0.069)	(0.107)
Always enough money	−0.009	−0.015	0.030	0.055
	(0.032)	(0.058)	(0.045)	(0.050)
Voted last elections	0.041	0.159***	0.007	−0.044
	(0.030)	(0.056)	(0.048)	(0.057)
Success luck network	0.065*	−0.048	0.015	−0.109**
	(0.036)	(0.059)	(0.048)	(0.047)
Hard work better life	0.030	−0.034	0.032	0.075
	(0.035)	(0.075)	(0.055)	(0.056)
Long hours necessary	0.031	−0.103	−0.042	0.130***
	(0.034)	(0.077)	(0.062)	(0.049)
Work−life balance	0.033	−0.043	−0.038	0.093*
	(0.031)	(0.057)	(0.046)	(0.049)
Career in priv. sector	−0.037	0.086	0.067	−0.095
	(0.049)	(0.072)	(0.053)	(0.074)
Career in a non−profit	0.056	−0.023	−0.021	0.019
	(0.051)	(0.074)	(0.058)	(0.067)
Wants entrepreneur	0.044	−0.029	0.049	−0.020
	(0.032)	(0.057)	(0.046)	(0.049)
Wants manager	−0.026	−0.079	0.019	0.008
	(0.064)	(0.107)	(0.077)	(0.087)
Mean Dep. Var.	0.063	0.277	0.181	0.188
N (Spectators)	271	271	271	271

Notes: This table shows estimates of the correlates of having a given fairness ideal. The regression equation is:

$$Y_i = \alpha + \gamma X_i + \nu_{ip},$$

where Y_i is a fairness ideal and X_i is an individual-level characteristic.

Each column shows the result for a different dependent variable. In column 1, the outcome equals one if the student divides earnings equally in the luck and performance environments. In column 2, the outcome equals one if the student does not redistribute earnings in either the luck or the performance environments. In column 3, the outcome equals one if the student equalizes earnings in the luck environment but gives strictly more to the winner in the performance environment. In column 4, the outcome equals one if the student is classified as a moderate (as defined in Section 5.3).

Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A5: Relationship between inequality narratives and fairness ideals

	Fraction of each group mentioning each type of explanation					
	Educational Barriers (1)	Unequal Opportunities (2)	Bias & Discrim. (3)	Economic Factors (4)	Gov't & Politics (5)	History & Culture (6)
Egalitarian	0.250	0.125	0.125	0.000	0.000	0.250
	(0.157)	(0.120)	(0.120)			(0.157)
Libertarian	0.133	0.067	0.067	0.133	0.067	0.133
	(0.090)	(0.066)	(0.066)	(0.090)	(0.066)	(0.090)
Meritocrat	0.361	0.083	0.111	0.083	0.167	0.139
	(0.082)	(0.047)	(0.054)	(0.047)	(0.064)	(0.059)
Moderate	0.222	0.148	0.185	0.037	0.148	0.148
	(0.082)	(0.070)	(0.077)	(0.037)	(0.070)	(0.070)
N (individuals)	86	86	86	86	86	86

Notes: This table shows the relationship between fairness ideals and inequality explanations using data from the 2024 cohort. Each column represents a different source of inequality identified through keyword analysis of open-ended responses. We exclude individuals who didn't provide a reason for why there is inequality in the US (12.7 percent) or who do not fit any of the fairness ideals. Standard errors in parentheses.

B Empirical Appendix

B.1 Worker Sample

This appendix provides details on the characteristics and task performance of the worker sample.

Appendix Table B1 provides summary statistics on workers. The sample is diverse in terms of age, gender, and racial background. The average worker is approximately 40 years old, with a standard deviation of 13.8 years. About 49 percent of workers are male, and 95 percent were born in the United States. The majority identify as White (70 percent), followed by Black (12 percent), Asian (9 percent), and individuals of mixed or other racial backgrounds. Nearly all workers reside in the United States and report English as their primary language. Workers in our sample exhibit a range of employment situations. About 50 percent report working full-time, while 16 percent work part-time, and 11 percent are unemployed.

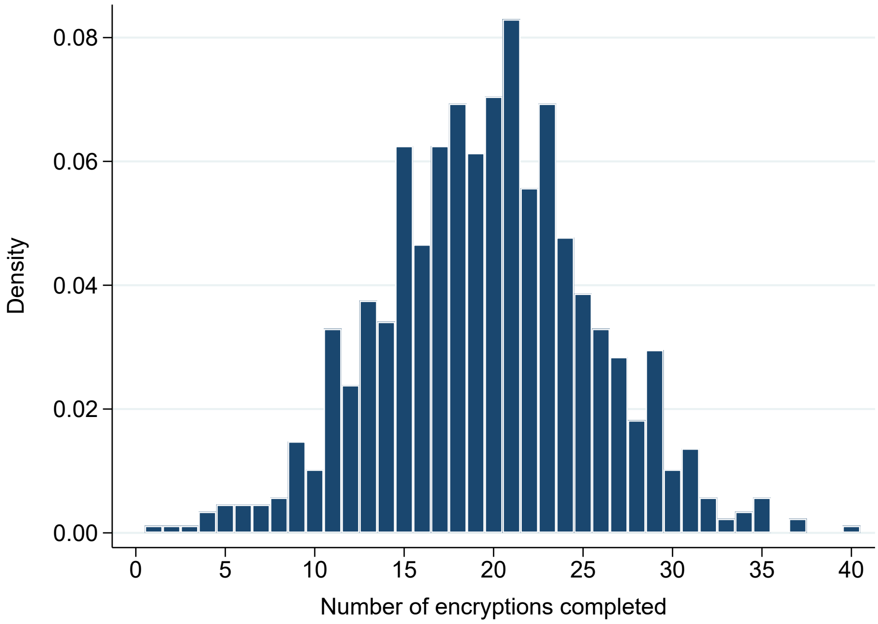
Appendix Figure B1 shows the distribution of encryption task performance. Workers completed an average of 19.67 encryptions, with a standard deviation of 5.91. The average number of encryption attempts was 20.92. The distribution is approximately normal, with most workers completing between 10 and 30 encryptions.

Table B1: Summary statistics of the worker sample

	Mean (1)	SD (2)	N (3)
Panel A. Demographic characteristics			
Age	40.403	13.829	863
Male	0.487	0.500	871
White	0.697	0.460	855
Black	0.116	0.320	855
Asian	0.090	0.286	855
Mixed race	0.065	0.248	855
Other race	0.032	0.175	855
Born in the USA	0.945	0.229	869
Lives in the USA	1.000	0.000	880
Language is English	0.947	0.223	875
Panel B. Employment status			
Is a student	0.136	0.343	589
Works full-time	0.503	0.501	475
Works part-time	0.162	0.369	475
Unemployed	0.112	0.315	475
Panel C. Performance on the encryption task			
Tasks completed	19.670	5.910	880
Tasks attempted	20.919	5.821	880

Notes: This table shows summary statistics of our worker sample. Variables in Panels A and B are based on data provided by Prolific. Variables in Panels C are based on worker performance on the encryption task.

Figure B1: Distribution of tasks completed in the worker task



Notes: This figure shows the distribution of the total number of correct three-word encryptions completed by workers. The mean number of encryptions completed is 19.6 and the standard deviation is 5.8.

B.2 Descriptive Evidence

This appendix presents descriptive evidence on the inequality implemented by spectators and their redistribution choices across experimental conditions.

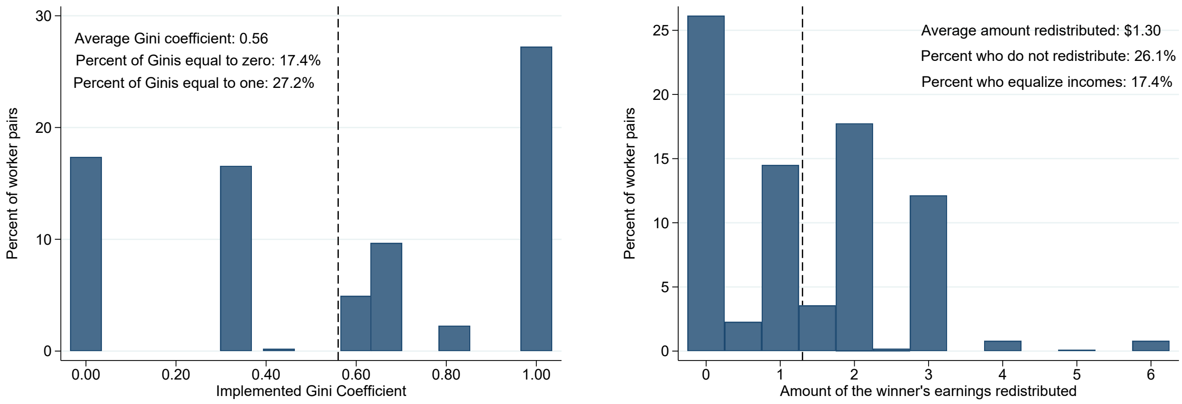
Appendix Figure B2 shows a histogram of the implemented Gini coefficients (Panel A) and amount of earnings redistributed (Panel B). There is substantial dispersion in the level of implemented inequality by spectators. On average across worker pairs, spectators implemented a Gini coefficient of 0.56 and redistributed $1.30 of the winner's earnings to the loser. The two modal Gini coefficients are one (perfect inequality, 34.8 percent of worker pairs) and zero (perfect equality, 22.2 percent).

Appendix Figure B3 presents the average Gini coefficient (Panel A) and the share of earnings redistributed (Panel B) across different experimental conditions. Panel A shows that the level of inequality implemented by spectators varies significantly by condition. In the luck treatment, where earnings are randomly assigned, the average Gini coefficient is 0.43. In contrast, inequality is substantially higher in the performance and in the efficiency cost conditions. The efficiency cost condition generates the highest inequality, with an average Gini coefficient of 0.63. Panel B illustrates the fraction of earnings redistributed across conditions. Spectators redistribute the highest share of earnings in the luck condition, while redistribution decreases sharply in the performance and efficiency cost treatments.

Figure B2: Histogram of the Gini coefficient and earnings redistributed

Panel A. Gini coefficient

Panel B. Earnings redistributed

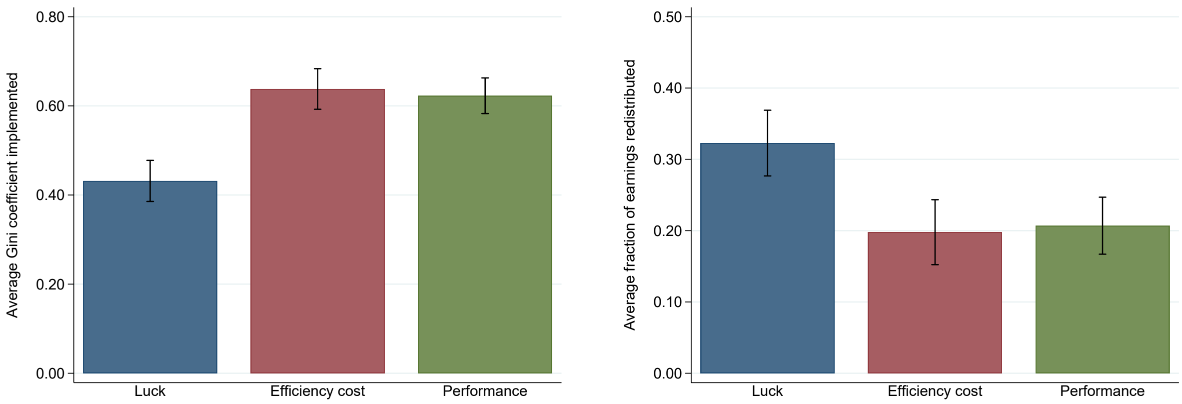


Notes: This figure shows a histogram of the implemented Gini coefficients (Panel A) and amount of earnings redistributed (Panel B). To produce this figure, we use data on all spectator redistributive decisions.

Figure B3: Average Gini and earnings redistributed by condition

Panel A. Gini coefficient

Panel B. Earnings redistributed



Notes: This figure shows the average implemented Gini coefficients (Panel A) and amount of earnings redistributed (Panel B) across each condition. To produce this figure, we only use the first redistributive decision of each spectator.

B.3 Robustness Checks

This appendix presents several robustness checks of our main results. We examine the sensitivity of our findings to different sample restrictions and alternative outcome measures. All robustness checks follow the specification in equation (1) and present results using both within-subject and between-subject variation.

First, we verify that our results are not driven by inattentive participants. Appendix Table B2 reproduces our main analysis excluding spectators who failed an embedded attention check in our survey. The attention check asked participants to select a specific response option within a matrix of survey questions. The estimates remain virtually unchanged after excluding inattentive respondents, suggesting that our findings are not driven by participants who may have responded carelessly.

Second, we examine whether our results are affected by participants who may have rushed through the experiment without careful consideration of their choices. Appendix Table B3 presents estimates excluding spectators who completed the survey in less than 2.18 minutes, corresponding to the bottom five percent of the completion time distribution. The magnitude and statistical significance of our main effects remain stable in this restricted sample.

Third, we assess the robustness of our findings to potentially inconsistent response patterns. Appendix Table B4 shows results after excluding spectators who allocated strictly more earnings to the loser than to the winner in at least one worker pair—a pattern that could indicate confusion about the task. Our main conclusions about the source-of-inequality effect and efficiency concerns remain unchanged in this restricted sample.

Fourth, we examine whether our results differ systematically across the two MBA cohorts in our sample. Appendix Table B5 presents estimates from equation (1) estimated separately for MBA students from the 2023 and 2024 cohorts. The effect of the performance condition is remarkably stable across cohorts, ranging from 0.235 to 0.245 in the within-subject specifications without controls. Similarly, the efficiency condition effects are consistent across cohorts, with estimates of 0.182 and 0.195 for the 2023 and 2024 cohorts respectively. The baseline levels of inequality, captured by the constants, are also similar across cohorts (0.419 and 0.421).

Finally, we verify that our results are not sensitive to our choice of dependent variable. Appendix Table B6 presents estimates using the net-of-efficiency-cost share of earnings redistributed as the outcome variable instead of the Gini coefficient. This alternative specification directly measures redistribution behavior while accounting for efficiency costs.

The results remain qualitatively similar, confirming that our findings about how MBA students respond to performance differences and efficiency costs are robust to different ways of measuring redistributive choices.

Across all these robustness checks, the key patterns in our data—MBA students' greater tolerance for inequality, similar sensitivity to the source of inequality as the general population, and stronger response to efficiency costs—remain stable and statistically significant.

Table B2: Robustness check of main effects to excluding inattentive spectators

	Dependent variable: Gini coefficient			
	All redistributive decisions		First decision only	
	(1)	(2)	(3)	(4)
Performance condition	0.242***	0.242***	0.186***	0.186***
	(0.030)	(0.036)	(0.054)	(0.057)
Efficiency condition	0.186***	0.186***	0.194***	0.202***
	(0.025)	(0.030)	(0.062)	(0.063)
Constant	0.415***	0.415***	0.430***	0.437***
	(0.026)	(0.019)	(0.040)	(0.073)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	711	711	237	237
N (individuals)	237	237	237	237

Notes: This table displays is analogous to Table 2, but excludes students who failed the attention check. See notes to Table 2 for details. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table B3: Robustness check of main effects to excluding spectators who rushed through the experiment

	Dependent variable: Gini coefficient			
	All redistributive decisions		First decision only	
	(1)	(2)	(3)	(4)
Performance condition	0.249***	0.248***	0.206***	0.202***
	(0.029)	(0.036)	(0.053)	(0.055)
Efficiency condition	0.181***	0.180***	0.186***	0.194***
	(0.024)	(0.030)	(0.059)	(0.061)
Constant	0.421***	0.421***	0.430***	0.430***
	(0.025)	(0.019)	(0.040)	(0.073)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	762	762	257	257
N (individuals)	257	257	257	257

Notes: This table displays is analogous to Table 2, but excludes students who completed the suvey in less than 2.18 minutes (corresponding to the bottom five percent of the total completion time distribution). See notes to Table 2 for details. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table B4: Robustness check of main effects to excluding spectators who allocated strictly more earnings to the loser

	Dependent variable: Gini coefficient			
	All redistributive decisions		First decision only	
	(1)	(2)	(3)	(4)
Performance condition	0.249***	0.248***	0.206***	0.202***
	(0.029)	(0.036)	(0.053)	(0.055)
Efficiency condition	0.181***	0.180***	0.186***	0.194***
	(0.024)	(0.030)	(0.059)	(0.061)
Constant	0.421***	0.421***	0.430***	0.430***
	(0.025)	(0.019)	(0.040)	(0.073)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	762	762	257	257
N (individuals)	257	257	257	257

Notes: This table displays is analogous to Table 2, but excludes students who allocated strictly more earnings to the loser than to the winner in at least one worker pair. See notes to Table 2 for details. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table B5: Robustness check of main effects to estimating the regression separately for each cohort

	Dependent variable: Gini coefficient			
	All redistributive decisions		First decision only	
	(1)	(2)	(3)	(4)
Panel A. 2023 Cohort				
Performance condition	0.235***	0.234***	0.180**	0.140*
	(0.042)	(0.052)	(0.075)	(0.079)
Efficiency condition	0.182***	0.184***	0.195**	0.187**
	(0.034)	(0.042)	(0.078)	(0.086)
Constant	0.419***	0.419***	0.438***	0.439***
	(0.035)	(0.027)	(0.053)	(0.114)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	403	403	138	138
N (individuals)	138	138	138	138
Panel B. 2024 Cohort				
Performance condition	0.245***	0.251***	0.202***	0.218***
	(0.039)	(0.048)	(0.075)	(0.078)
Efficiency condition	0.195***	0.191***	0.220***	0.246***
	(0.034)	(0.041)	(0.084)	(0.088)
Constant	0.421***	0.421***	0.424***	0.422***
	(0.035)	(0.025)	(0.060)	(0.095)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	390	390	133	133
N (individuals)	133	133	133	133

Notes: This table displays is analogous to Table 2, but estimated separately for MBA students of the 2023 cohort (Panel A) and 2024 cohort (Panel B). See notes to Table 2 for details. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table B6: Robustness check of main effects to using the share of earnings redistributed as the outcome

	Dependent variable: Share of earnings redistributed			
	All redistributive decisions		First decision only	
	(1)	(2)	(3)	(4)
Performance condition	-0.123^{***}	-0.124^{***}	-0.116^{***}	-0.121^{***}
	(0.016)	(0.019)	(0.031)	(0.031)
Efficiency condition	-0.103^{***}	-0.106^{***}	-0.125^{***}	-0.145^{***}
	(0.014)	(0.017)	(0.033)	(0.033)
Constant	0.313^{***}	0.314^{***}	0.323^{***}	0.305^{***}
	(0.014)	(0.010)	(0.024)	(0.037)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	793	793	271	271
N (individuals)	271	271	271	271

Notes: This table displays is analogous to Table 2, but the dependent variables is the net-of-efficiency-cost share of earnings redistributed. See notes to Table 2 for details. ***, ** and * denote significance at the 1%, 5% and 10% levels.

B.4 Heterogeneity

This appendix examines heterogeneity in the source-of-inequality effect and the elasticity of redistribution with respect to an efficiency cost based on the characteristics of MBA students. Informed by existing literature, we focus on six dimensions of heterogeneity.

Gender. Existing research documents gender differences in redistributive preferences (Almås et al., 2020; Cohn et al., 2023; Preuss et al., 2025). We define an indicator that equals one if the individual is a male.

Household socioeconomic status while growing up. Previous work has shown that experiencing inequality while growing up can affect redistribution (Roth and Wohlfart, 2018). We define an indicator that equals one if the individual describes the financial situation of their family while growing up as "very comfortable" (always had enough money for necessities and luxuries) or "comfortable" (always had enough money for necessities and occasional luxuries).

Beliefs about the role of luck in determining success. Previous work indicates many individuals accept income disparities when they are a consequence of effort differences but choose to reduce income differences that are due to circumstances beyond individuals' control, such as luck (Alesina et al., 2012; Cappelen et al., 2007, 2013). We define an indicator that equals one if an individual agrees with the statement, "Hard work doesn't generally bring success—it's more a matter of luck and connections."

Managerial aspirations. Firm wage-setting policies are an important determinant of overall earnings inequality (Card et al., 2018). Alumni from the MBA program that we study often become managers and directly affect the earnings of their employees by setting their wages. We define an indicator that equals one if an individual agrees with the statement "I aspire to be a manager responsible for overseeing other employees in the future."

Political engagement. We may expect elites to exert influence in US policy outcomes insofar they are politically engaged. We measure political engagement using an indicator for planning to stay in the US after graduating and an indicator for voting in the last elections.

To measure the heterogeneous effect based on a covariate X_i, we estimate a specification of equation (1) where we control for the covariate X_i and the interaction between the covariate X_i and the treatment dummies. Specifically, our regression specification is

$$\text{Gini}_{ip} = \beta_0 + \beta_1 \text{Performance}_p + \beta_2 \text{Efficiency}_p + (\tilde{\beta}_0 + \tilde{\beta}_1 \text{Performance}_p + \tilde{\beta}_2 \text{Efficiency}_p) X_i + \mu_{ip},$$

where all variables are defined as in equation (1) and X_i is the dimension of heterogeneity of interest. We estimate the parameters using the between-subject design (as in Table 2, column 3). Appendix Table B7 presents the results. Each column shows estimates based on a different heterogeneity variable.

We find substantial variation in how student characteristics shape responses to the source of inequality and efficiency costs. Males and females show similar reactions to performance-based inequality, though males exhibit a stronger response to efficiency conditions. While high and low SES students respond similarly to the source of inequality, high SES students show stronger reactions to efficiency costs. Students who believe success depends primarily on luck show a weaker response to the performance condition and somewhat muted reactions to efficiency costs. Those planning to stay in the US respond particularly strongly to efficiency costs. We find no significant variation in redistributive preferences based on managerial aspirations or political engagement.

Table B7: The heterogeneous impact of each treatment on the Gini coefficient

	Heterogeneity variable:					
	Male (1)	High SES (2)	Success is luck (3)	Aspires manager (4)	Stay in US (5)	Voted in elections (6)
Heterogeneity var.	0.035	−0.117	0.137	0.144	0.087**	−0.046
	(0.079)	(0.085)	(0.088)	(0.107)	(0.041)	(0.084)
Performance condition	0.223***	0.148*	0.276***	0.180	0.296***	0.128
	(0.075)	(0.088)	(0.062)	(0.151)	(0.083)	(0.092)
Efficiency condition	0.092	0.026	0.268***	0.370*	−0.167**	0.238**
	(0.089)	(0.103)	(0.071)	(0.218)	(0.084)	(0.097)
Performance condition	−0.036	0.093	−0.217*	0.013	−0.092	0.107
× heterog. var.	(0.105)	(0.109)	(0.114)	(0.162)	(0.100)	(0.113)
Efficiency condition	0.211*	0.285**	−0.196	−0.187	0.407***	−0.054
× heterog. var.	(0.117)	(0.125)	(0.130)	(0.227)	(0.104)	(0.122)
Mean heterog. var.	0.554	0.620	0.362	0.913	0.941	0.693
N (individuals)	260	258	254	254	253	251
N (decisions)	260	258	254	254	253	251

Notes: This table reports estimates of the heterogeneous impact of each condition on the Gini coefficient using only the first redistributive choice of each MBA student. We estimate an augmented version of equation (1) that adds the interaction between a given covariate X_i with all treatment dummies. Specifically, the regression equation is:

$$\text{Gini}_{ip} = \beta_0 + \beta_1 \text{Performance}_p + \beta_2 \text{Efficiency}_p + (\tilde{\beta}_0 + \tilde{\beta}_1 \text{Performance}_p + \tilde{\beta}_2 \text{Efficiency}_p) X_i + \mu_{ip}.$$

Each column shows the result for a different covariate X_i. In column 1, X_i equals one if the student is a male and zero otherwise. In column 2, X_i equals one if the student reports that the financial situation of their family while growing up was "very comfortable" (always had enough money for necessities and luxuries) or "comfortable" (always had enough money for necessities and occasional luxuries), and takes the value zero otherwise. In column 3, X_i equals one if the student agrees with the statement, "Hard work doesn't generally bring success—it's more a matter of luck and connections," and takes the value zero otherwise. In column 4, X_i equals one if the student agrees with the statement "I aspire to be a manager responsible for overseeing other employees in the future" and takes the value zero otherwise. In column 5, X_i equals one if the student plans to get a job in the US after graduating from the MBA program and zero otherwise. In column 6, X_i equals one if the student voted in the last elections where they were eligible to vote and zero otherwise.

Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

C Empirical Framework

This appendix presents a statistical framework of income redistribution that closely follows our experimental setup. We use the framework to define the different types of fairness ideals and the identification assumptions.

C.1 Defining Fairness Ideals

We begin by formalizing how spectators make redistribution decisions based on their fairness ideals. Consider a spectator who observes the initial earnings distribution $(w_H, w_L) \in \mathbb{R}_+ \times \mathbb{R}_+$ of two workers who competed for a fixed prize, where $w_H > w_L$ represents the earnings of the worker who won the competition (the "high-earnings" worker) and w_L the earnings of the worker who lost (the "low-earnings" worker).

We study an environment in which worker earnings are allocated based on some combination of performance and luck. Let $z_p \in [0, 1]$ denote the probability that the outcomes of a worker pair p were determined by chance. z_p can be interpreted as the role that luck plays in determining income inequality. When $z_p = 0$, the initial earnings are determined by workers' performance. The worker with a better performance earns w_H, and the other worker earns w_L; thus, inequality is due to differences in performance. When $z_p = 1$, earnings are randomly assigned to workers, and therefore inequality is entirely due to luck. Spectators observe w_H, w_L, and z_p but do not observe worker performance.

Let Y_{ip} be the earnings redistributed from the high- to the low-earnings worker in worker pair p by spectator i. Since the amount of earnings redistributed determines the level of inequality in the final earnings, Y_{ip} can also be interpreted as the level of inequality implemented by spectator i. We assume that a spectator's choice of how much earnings to redistribute, Y_{ip}, is guided by their *fairness ideal*, that is, their preferences for what constitutes a fair earnings allocation given the role played by luck in determining worker earnings, z_p. We model fairness ideals as a mapping from initial distributions to final earnings distribution. Following the literature, we focus on three main types of fairness ideals:

Definition 1 (Fairness ideals)**.**

- *Spectator i is an* egalitarian *if* $Y_{ip}(z_p) = \frac{w_H + w_L}{2}$ *for all* z_p.
- *Spectator i is a* libertarian *if* $Y_{ip}(z_p) = 0$ *for all* z_p.

- *Spectator i is a* meritocrat *if $Y_{ip}(z_p)$ is strictly increasing in z_p and $Y_{ip}(1) = \frac{w_H + w_L}{2}$.*

Egalitarian spectators equalize the workers' earnings regardless of the role luck played in the income-generating process. Libertarian spectators leave the initial earnings unchanged regardless of the circumstances that produced earnings differences. Meritocratic spectators condition their redistributive decisions based on the source of inequality. Specifically, as the role of chance in determining earnings z_p increases, they redistribute more earnings and, when inequality is entirely luck-based (i.e., there is no merit to the earnings allocation), they equalize earnings.

It is straightforward to link the aggregate level of redistribution in a population of spectators, $\mathbb{E}[Y_{ip}]$, to the distribution of fairness ideals. Let α_E, α_L, and α_M, be the proportion of egalitarians, libertarians, and meritocrats in a population. By the law of iterated expectations

$$\mathbb{E}[Y_{ip}] = \alpha_E \frac{w_H + w_L}{2} + \alpha_M Y_{ip}^M + (1 - \alpha_E - \alpha_L - \alpha_M) Y_{ip}^O, \tag{C1}$$

where $Y_{ip}^M \equiv \mathbb{E}[Y_{ip}|\text{Meritocrat}]$ and $Y_{ip}^O \equiv \mathbb{E}[Y_{ip}|\text{Other ideal}]$ are the average earnings redistributed conditional on being a meritocrat and having other fairness ideals, respectively.

Equation (C1) highlights two reasons why elites may have different redistributive choices than non-elites. First, the distribution of fairness ideals among elites (the α's) may differ from those among non-elites. Second, Y_{ip}^M and Y_{ip}^O may differ for elites and non-elites. In other words, elites who follow a meritocratic fairness ideal or do not conform with any of the fairness ideals defined above may redistribute different amounts than the corresponding non-elites.

C.2 Identification of Fairness Ideals

Research design. Our first research design relies on comparisons *across* subjects, using only the first redistributive decision of each spectator and excluding those who saw the efficiency cost environment first. We identify the fraction of egalitarians by the fraction of individuals who divide earnings equally when the winner is determined by performance. We identify the fraction of libertarians by the fraction of individuals who redistribute no earnings when the winner is determined by chance. Finally, we identify the fraction of meritocrats by the difference between (i) the fraction of individuals who allocate more earnings to the winner when worker outcomes are determined by performance and (ii) the fraction of individuals who allocate more earnings to the winner when they are determined by luck. We refer to the remainder of the population as having "other" fairness ideals.

Our second research design relies on *within*-subject comparisons across worker pairs, using all redistributive decisions except those from the efficiency cost environment. We classify a spectator as an egalitarian if they divide earnings equally in both the luck and performance environments, as a libertarian if they do not redistribute earnings in either environment, and as a meritocrat if they equalize earnings in the luck environment but give strictly more to the winner in the performance environment. We refer to individuals who do not fit any of these classifications as having "other" fairness ideals.

Identification assumptions. For the between-subject design, we follow the standard assumptions in the literature (e.g., Almås et al., 2020; Cohn et al., 2023), which we formalize through the lens of our statistical framework. For the within-subject design, we extend these assumptions to account for multiple observations per spectator.

To identify egalitarians in the between-subject design, our identification assumption is that individuals who divide earnings equally when worker earnings are assigned based on performance would have also divided earnings equally under any other environment. Formally, if $Y_{ip}(z_p) = \frac{w_H+w_L}{2}$ for $z_p = 0$, then $Y_{ip}(z_p) = \frac{w_H+w_L}{2}$ for all z_p. In the within-subject design, our identification assumption is that individuals who divide equally in the luck *and* performance environments would have divided equally under any other environment. Formally, if $Y_{ip}(z_p) = \frac{w_H+w_L}{2}$ for $z_p = 0$ *and* $Y_{ip'}(z_{p'}) = \frac{w_H+w_L}{2}$ for $z_{p'} = 1$, then $Y_{ip}(z_p) = \frac{w_H+w_L}{2}$ for all z_p.

To identify libertarians in the between-subject design, our identification assumption is that individuals who do not redistribute earnings in the performance environment would not redistribute earnings under any other environment. Formally, if $Y_{ip}(z_p) = 0$ for $z_p = 1$, then $Y_{ip}(z_p) = 0$ for all z_p. In the within-subject design, our identification assumption is that individuals who do no redistribute earnings in the luck nor performance environments would not redistribute earnings under any other environment. Formally, if $Y_{ip}(z_p) = 0$ for $z_p = 0$ *and* $Y_{ip'}(z_{p'}) = 0$ for $z_{p'} = 1$, then $Y_{ip}(z_p) = 0$ for all z_p.

To identify meritocrats in the between-subject design, the identification assumption is that if a spectator gives a greater share to the more productive worker in the performance condition, they would not have given less to the productive worker in the luck condition. In the within-subject design, our identification assumption is that those who equalize earnings in the luck environment but give strictly more to winners in the performance environment would strictly redistribute more earnings as the role of luck increases. Formally, if $Y_{ip}(1) >$

$Y_{ip}(0)$, then, $Y_{ip}(z_p) > Y_{ip}(z'_p)$ whenever $z_p > z'_p$.

There are advantages and disadvantages to both the between- and within-subject designs for identification. To understand these, it is important to remember that a fairness ideal is a mapping from circumstances to choices. Reconstructing this mapping requires observing an infinite number of counterfactual choices. The research designs "extrapolate" spectator behavior based on a limited set of observed choices: one in the between-subject design and two (sequential) choices in the within-subject design. The between-subject design, using a single choice, avoids the need to assume absence of sequential-decision bias, but is more susceptible to measurement error and choice noise. In contrast, the within-subject design, using two choices, mitigates the measurement error concerns by incorporating more information about spectators' behavior, at the cost of assuming that the first choice does not influence the second.

C.3 A Statistical Model of Redistribution and Inequality Source

Recall Y_{ip} represents the earnings redistributed from the high- to the low-earnings worker in worker pair p by spectator i. We model Y_{ip} as a function of the role played by luck in determining worker earnings, z_p.[13] Considser the two environments studied by most experimental work: worker earnings are determined by performance ($z_p = 0$) or by chance ($z_p = 1$). Let $Y_{ip}(0)$ be the amount redistributed if earnings are determined by performance and $Y_{ip}(1)$ the amount redistributed if outcomes were determined by chance. These two redistribution levels denote potential outcomes for different levels of luck, but only one of the two outcomes is observed for a given worker pair. The observed redistribution, $Y_{ip}(z_p)$, can be written in terms of these potential outcomes as

$$Y_{ip}(z_p) = Y_{ip}(0) + \underbrace{\Big(Y_{ip}(1) - Y_{ip}(0)\Big)}_{\text{“Source-of-inequality effect”}(\beta_i)} z_p, \tag{C2}$$

where $Y_{ip}(1) - Y_{ip}(0) \equiv \beta_i$ measures the effect of changing the income-generating process from chance to performance, or "source-of-inequality effect," for short.

Suppose that we observed spectator choices for two worker pairs, p and p', where earnings in pair p are determined by performance ($z_p = 0$) and earnings in pair p' are randomly assigned ($z_{p'} = 1$). Then, one could compare average redistribution in the pair

[13] We abstract from modeling Y_{ip} as a function of w_H and w_L for simplicity. In our experiment, w_H and w_L are constant across worker pairs, and the only variable that changes across worker pairs is z_p.

where worker earnings were randomly assigned, $\mathbb{E}[Y_{ip}|z_p = 1]$, with average redistribution where worker earnings were determined by performance, $\mathbb{E}[Y_{ip'}|z_{p'} = 0]$. This comparison can be written as

$$\begin{aligned}\mathbb{E}[Y_{ip}|z_p = 1] - \mathbb{E}[Y_{ip'}|z_{p'} = 0] = &\underbrace{\mathbb{E}[Y_{ip}(1)|z_p = 1] - \mathbb{E}[Y_{ip}(0)|z_p = 1]}_{\text{Term 1: Source-of-inequality effect}} \\ &+ \underbrace{\mathbb{E}[Y_{ip}(0)|z_p = 1] - \mathbb{E}[Y_{ip'}(0)|z_{p'} = 0]}_{\text{Term 2: Sequential-decision bias}}. \end{aligned} \tag{C3}$$

Equation (C3) shows that comparing the redistributive behavior of spectators for different worker pairs yields the sum of two terms. The first one is the effect of the source of inequality on earnings redistributed. The second term is a potential bias that arises when comparing sequential decisions. This term captures mechanisms such as anchoring effects, contrast effects, and learning effects. To address this potential bias, most literature uses a between-subject design where spectators make only one decision. We provide both between-subject estimates (using only the first decision) and within-subject estimates (using the decisions in the luck and treatment conditions) for comparison.

In addition to measuring the source-of-inequality effect, we also examine how introducing an efficiency cost affects redistribution (Y_{ip}). We analyze this using the same framework, holding constant the source of inequality and re-interpreting z_p as an indicator for redistribution having a cost. In this case, β_i in equation (C2) and Term 1 in equation (C3) measure the elasticity of redistribution to the efficiency cost of redistribution.

D Replication: Dyson Business Students

This appendix presents results from our replication analysis using undergraduate business students from Cornell University's Dyson School of Applied Economics and Management.

D.1 Sample Characteristics

Appendix Table D1 presents summary statistics of the Dyson sample. The sample consists primarily of young students (mean age 19.5 years), with a roughly equal gender split (54.3 percent male). The majority were born in the US (74.5 percent) and report relatively high socioeconomic status during childhood—71.7 percent had enough money for necessities and at least occasional luxuries while growing up. 80.9 percent aspire to managerial positions, 72.8 percent want careers in the private sector, and 51.5 percent plan to pursue an MBA. Only 20.3 percent report voting in recent elections, likely reflecting their young age.

D.2 Implemented Inequality

Appendix Table D2 presents estimates of equation (1) for the Dyson sample. When worker earnings are randomly assigned, Dyson students implement a Gini coefficient of 0.417 (column 1), remarkably similar to the MBA sample. The performance condition increases the implemented Gini coefficient by 0.310 Gini points ($p < 0.01$), or 74.3 percent of the baseline Gini. The efficiency cost condition increases the Gini coefficient by 0.195 points ($p < 0.01$), or 46.8 percent of the baseline. These effects are robust to including spectator fixed effects (column 2) and using only spectators' first choices (columns 3-4).

D.3 Distribution of Fairness Ideals

Appendix Table D3 presents the distribution of fairness ideals in the Dyson sample. Using the between-subject design, we find that 1.9 percent are egalitarians, 23.9 percent are libertarians, 37.6 percent are meritocrats, and 36.6 percent have other fairness ideals. The within-subject design yields similar estimates. Compared to MBA students, undergraduates show lower rates of egalitarianism (1.9 vs. 9.9 percent), higher rates of meritocracy (37.6 vs. 22.7 percent), and similar rates of libertarianism (23.9 vs. 23.2 percent). Like MBA students, they are less likely to conform to standard fairness ideals than the general population. A substantial fraction of Dyson students (24.5 percent) behave as "moderates" (Appendix Table D4).

Table D1: Summary statistics of the Dyson sample

	Mean (1)	SD (2)	N (3)
Panel A. Demographic characteristics			
Average age	19.534	0.689	161
Male	0.543	0.500	162
Born in the USA	0.747	0.436	162
Panel B. Financial situation while growing up			
Always had enough money for necessities and luxuries	0.244	0.431	156
Always had enough for necessities and occasional luxuries	0.474	0.501	156
Usually had enough for necessities, rarely for luxuries	0.231	0.423	156
Sometimes did not have enough money for necessities	0.038	0.193	156
Frequently did not have enough money for necessities	0.013	0.113	156
Panel C. Employment preferences			
Working long-hours is sometimes necessary	0.776	0.418	161
Wants career in a non-profit	0.199	0.400	161
Wants to become an entrepreneur	0.516	0.501	161
Wants career in private sector	0.727	0.447	161
Work-life balance is more important than a high salary	0.596	0.492	161
Aspire to be a manager	0.807	0.396	161
Wants to do an MBA	0.516	0.501	161
Panel D. Attitudes toward pay determination			
How much responsibility should decide pay	0.994	0.079	161
How well someone works should decide pay	1.000	0.000	161
How hard someone works should decide pay	0.957	0.205	161
Panel E. Voting behavior and social views			
Voted in the last elections	0.204	0.404	152
Success is luck and connections	0.280	0.450	161
Hard work brings a better life	0.863	0.345	161
Completed all three redistributive decisions	0.970	0.171	167
Passed attention check	0.938	0.242	161
Minutes spent in survey	5.674	2.849	167

Notes: This table shows summary statistics of Dyson students in our sample. All variables are based on data self-reported by Dyson students in the exist survey of our study. Employment preferences and social views are based on Dyson students' agreement with several statements in a five-point Likert scale grid. For each statement, we define an indicator variable that equals one if the student selects "strongly agree" or "agree," and zero if the student selects "neither agree nor disagree," "disagree," or "strongly disagree." For the attitudes toward pay determination, we define an indicator variable that equals one if the student selects "essential," "very important," or "fairly important" and zero if the student selects "not very important" or "not important at all."

Table D2: Implemented Gini coefficient across environments (Dyson sample)

	Dependent variable: Gini coefficient			
	All redistributive decisions		First decision only	
	(1)	(2)	(3)	(4)
Performance condition	0.311***	0.304***	0.334***	0.330***
	(0.036)	(0.044)	(0.071)	(0.072)
Efficiency condition	0.198***	0.194***	0.157**	0.152*
	(0.028)	(0.035)	(0.078)	(0.080)
Constant	0.416***	0.420***	0.413***	0.441***
	(0.031)	(0.023)	(0.060)	(0.087)
Additional controls?	No	Yes	No	Yes
N (redistributive decisions)	494	494	167	167
N (individuals)	167	167	167	167

Notes: This table displays estimates of β_0, β_1, and β_2 from equation (1) estimated on the Dyson sample. The omitted treatment category is the luck condition. The specifications in columns 2 and 4 include additional controls. In column 2, we include spectator fixed effects. In column 4, we control for gender, parental financial situation while growing up, and a dummy for being born in the US. Heteroskedasticity-robust standard errors clustered at the spectator level in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table D3: Distribution of fairness ideals: elites vs. average citizens

	Percentage of...			
	Egalitarians (1)	Libertarians (2)	Meritocrats (3)	Other ideals (4)
Panel A. MBA and undergraduate business students				
MBA students (spectators' first choices)	9.89	23.16	22.65	44.30
	(3.15)	(4.35)	(5.99)	(8.05)
MBA students (repeated-measure design)	6.51	15.33	28.74	49.43
	(1.08)	(1.58)	(1.98)	(2.76)
Dyson students (spectators' first choices)	1.85	23.91	37.60	36.63
	(1.85)	(6.36)	(7.78)	(10.22)
Dyson students (repeated-measure design)	6.13	15.95	30.67	47.24
	(1.33)	(2.03)	(2.56)	(3.53)
Panel B. Average American				
SCE – Average American	8.57	39.77	36.67	14.99
	(2.75)	(5.25)	(6.31)	(8.66)
Almås et al. (2020) – Average American	15.32	29.43	37.54	17.72
	(1.98)	(2.50)	(3.43)	(4.69)
Cohn et al. (2023) – Average American	17.45	12.80	60.33	9.42
	(2.19)	(1.89)	(3.22)	(4.33)
Panel C. High-income samples				
SCE – USA income over 100k	3.23	44.44	40.32	12.01
	(3.23)	(12.05)	(13.27)	(18.22)
Almås et al. (2020) – USA income over 100k	14.08	22.67	41.92	21.33
	(4.16)	(4.87)	(7.11)	(9.57)
Cohn et al. (2023) – USA top 5 percent	8.97	25.15	59.14	6.75
	(2.38)	(3.33)	(4.37)	(5.99)
Panel D. Low-income samples				
SCE – USA income below 100k	10.81	38.57	35.14	15.48
	(3.63)	(5.86)	(7.32)	(10.06)
Almås et al. (2020) – USA income below 100k	15.65	31.40	36.33	16.63
	(2.25)	(2.89)	(3.92)	(5.37)
Cohn et al. (2023) – USA bottom 95 percent	17.83	12.06	60.54	9.57
	(3.06)	(2.75)	(4.62)	(6.19)

Notes: This table shows estimates of the fraction of egalitarians, libertarians, and meritocrats in various studies and samples. See notes to Table 3 for details.

Table D4: Joint distribution of redistribution in luck and performance treatments (Dyson sample)

		Earnings Redistributed in Performance Condition						
		\$0	\$1	\$2	\$3	\$4	\$5	\$6
Luck Condition	\$0	0.160	0.061	0.018	0.000	0.000	0.000	0.000
	\$1	0.061	0.037	0.025	0.006	0.006	0.000	0.000
	\$2	0.117	0.067	0.049	0.006	0.000	0.000	0.000
	\$3	0.166	0.067	0.074	0.061	0.000	0.000	0.000
	\$4	0.000	0.000	0.000	0.000	0.000	0.000	0.006
	\$5	0.000	0.006	0.000	0.000	0.000	0.000	0.000
	\$6	0.000	0.000	0.000	0.006	0.000	0.000	0.000

Libertarians
Egalitarians
Meritocrats

Notes: This table shows the joint distribution of redistribution choices across luck and performance conditions in the Dyson sample, excluding the efficiency cost treatmento. See notes to Table 4 for details

References

Acemoglu, D., A. He, and D. le Maire (2022, March). Eclipse of Rent-Sharing: The Effects of Managers' Business Education on Wages and the Labor Share in the US and Denmark.

Alesina, A. and G.-M. Angeletos (2005, August). Fairness and Redistribution. *American Economic Review 95*(4), 960–980.

Alesina, A., G. Cozzi, and N. Mantovan (2012, December). The Evolution of Ideology, Fairness and Redistribution. *The Economic Journal 122*(565), 1244–1261.

Alesina, A. and E. Glaeser (2004, March). *Fighting Poverty in the US and Europe: A World of Difference*. Oxford University Press.

Alesina, A., E. L. E. L. Glaeser, and B. Sacerdote (2001). Why Doesn't the United States Have a European-Style Welfare State? *Brookings Papers on Economic Activity 2001*(2), 187–277.

Alesina, A. and E. La Ferrara (2005, June). Preferences for redistribution in the land of opportunities. *Journal of Public Economics 89*(5-6), 897–931.

Almås, I., A. W. Cappelen, J. T. Lind, E. Ø. Sørensen, and B. Tungodden (2011, August). Measuring unfair (in)equality. *Journal of Public Economics 95*(7-8), 488–499.

Almås, I., A. W. Cappelen, E. O. Sorensen, and B. Tungodden (2010, May). Fairness and the Development of Inequality Acceptance. *Science 328*(5982), 1176–1178.

Almås, I., A. W. Cappelen, and B. Tungodden (2020, May). Cutthroat Capitalism versus Cuddly Socialism: Are Americans More Meritocratic and Efficiency-Seeking than Scandinavians? *Journal of Political Economy 128*(5), 1753–1788.

Andre, P. (2024, April). Shallow Meritocracy. *The Review of Economic Studies*, rdae040.

Bartels, L. M. (2016). *Unequal Democracy: The Political Economy of the New Gilded Age* (2 ed.). New York: Russell Sage.

Beard, C. A. (2012). *An Economic Interpretation of the Constitution of the United States*. New York: Simon and Schuster. [1913].

Bénabou, R. and J. Tirole (2006). Belief in a just world and redistributive politics. *Quarterly Journal of Economics*, 48.

Bhattacharya, P. and J. Mollerstrom (2022). Lucky to Work. *Available at SSRN 4244266*.

Broockman, D. E., G. Ferenstein, and N. Malhotra (2019). Predispositions and the Political Behavior of American Economic Elites: Evidence from Technology Entrepreneurs. *American Journal of Political Science 63*(1), 212–233.

Burch, P. H. (1980). *Elites in American History.* New York: Holmes and Meier. 3 vol.

Caldwell, S. and N. Harmon (2019). Outside options, bargaining, and wages: Evidence from coworker networks. *Unpublished manuscript, Univ. Copenhagen*, 203–207.

Cappelen, A. W., A. D. Hole, E. Ø. Sørensen, and B. Tungodden (2007, May). The Pluralism of Fairness Ideals: An Experimental Approach. *American Economic Review 97*(3), 818–827.

Cappelen, A. W., J. Konow, E. Ø. Sørensen, and B. Tungodden (2013, June). Just Luck: An Experimental Study of Risk-Taking and Fairness. *American Economic Review 103*(4), 1398–1413.

Cappelen, A. W., J. Mollerstrom, B.-A. Reme, and B. Tungodden (2022, August). A Meritocratic Origin of Egalitarian Behaviour. *The Economic Journal 132*(646), 2101–2117.

Cappelen, A. W., E. Ø. Sørensen, and B. Tungodden (2010, April). Responsibility for what? Fairness and individual responsibility. *European Economic Review 54*(3), 429–441.

Card, D., A. R. Cardoso, J. Heining, and P. Kline (2018, January). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics 36*(S1), S13–S70.

Carnes, N. (2018). *The Cash Ceiling: Why Only the Rich Run for Office—and What We Can Do about It.* Princeton, NJ: Princeton University Press.

Chancel, L., T. Piketty, E. Saez, and G. Zucman (2022). *World inequality report 2022.* Harvard University Press.

Cohn, A., L. J. Jessen, M. Klašnja, and P. Smeets (2023, September). Wealthy Americans and redistribution: The role of fairness preferences. *Journal of Public Economics 225*, 104977.

Corneo, G. and H. P. Gruner (2000, December). Social Limits to Redistribution. *American Economic Review 90*(5), 1491–1507.

Cullen, Z. B., S. Li, and R. Perez-Truglia (2022). What's my employee worth? the effects of salary benchmarking. Technical report, National Bureau of Economic Research.

Derenoncourt, E., C. Noelke, D. Weil, and B. Taska (2021). Spillover effects from voluntary employer minimum wages. Technical report, National Bureau of Economic Research.

Domhoff, G. W. (2013). *Who Rules America: The Triumph of the Corporate Rich* (7 ed.). New York: McGraw-Hill.

Domhoff, G. W. (2017). *The power elite and the state.* Routledge.

Dong, L., L. Huang, and J. W. Lien (2022). "they never had a chance": Unequal opportunities and fair redistributions. *Working Paper*.

Drutman, L. (2015). *The Business of America is Lobbying: How Corporations Became Politicized and Politics Became More Corporate.* Oxford University Press.

Dube, A., A. Manning, and S. Naidu (2020). Monopsony and Employer Mis-optimization Explain Why Wages Bunch at Round Numbers. NBER Working Paper #24991.

Durante, R., L. Putterman, and J. van der Weele (2014, August). Preferences for redistribution and perception of fairness: An experimental study: Preferences for redistribution: An experiment. *Journal of the European Economic Association 12*(4), 1059–1086.

Eggers, A. C. and M. Klašnja (2018). Wealth, fundraising, and voting in the us congress. In *8th Annual Conference of the European Political Science Association, Vienna*, pp. 21–23.

Elsässer, L., S. Hense, and A. Schäfer (2021). Not just money: unequal responsiveness in egalitarian democracies. *Journal of European Public Policy 28*(12), 1890–1908.

Ferguson, T. (1995). *Golden rule: The investment theory of party competition and the logic of money-driven political systems.* University of Chicago Press.

Fisman, R., P. Jakiela, S. Kariv, and D. Markovits (2015, September). The distributional preferences of an elite. *Science 349*(6254).

Fong, C. (2001, November). Social preferences, self-interest, and the demand for redistribution. *Journal of Public Economics 82*(2), 225–246.

Gilens, M. (2012). *Affluence and Influence: Economic Inequality and Political Power in America.* Princeton University Press.

Gilens, M. and B. I. Page (2014, September). Testing Theories of American Politics: Elites, Interest Groups, and Average Citizens. *Perspectives on Politics 12*(3), 564–581.

Hacker, J. S. and P. Pierson (2010). *Winner-Take-All Politics: How Washington Made the Rich Richer–and Turned Its Back on the Middle Class.* New York, NY: Simon & Schuster.

Hall, R. E. and A. B. Krueger (2012). Evidence on the incidence of wage posting, wage bargaining, and on-the-job search. *American Economic Journal: Macroeconomics 4*(4), 56–67.

Hazell, J., C. Patterson, H. Sarsons, and B. Taska (2022). National wage setting. Technical report, National Bureau of Economic Research.

He, A. X. and D. le Maire (2022, December). Managing Inequality: Manager-Specific Wage Premiums and Selection in the Managerial Labor Market.

Hertel-Fernandez, A. (2019). *State Capture: How Conservative Activists, Big Businesses, and Wealthy Donors Reshaped the American States—and the Nation.* New York: Oxford University Press.

Hertel-Fernandez, A., T. Skocpol, and J. Sclar (2018). When political mega-donors join forces: how the koch network and the democracy alliance influence organized us politics on the right and left. *Studies in American Political Development 32*(2), 127–165.

Hjort, J., X. Li, and H. Sarsons (2020). Across-country wage compression in multinationals. Technical report, National Bureau of Economic Research.

Kalla, J. L. and D. E. Broockman (2016). Campaign Contributions Facilitate Access to Congressional Officials: A Randomized Field Experiment. *American Journal of Political Science 60*(3), 545–558.

Lachowska, M., A. Mas, R. Saggio, and S. Woodbury (2022). Wage posting or wage bargaining? a test using dual jobholders. *Journal of Labor Economics (forthcoming)* (w28409).

Maréchal, M. A., A. Cohn, J. Yusof, and R. Fisman (2025). Whose preferences matter for redistribution? cross-country evidence. *Journal of Political Economy Microeconomics 3*(1), 000–000.

Mathisen, R. B. (2023, May). Affluence and Influence in a Social Democracy. *American Political Science Review 117*(2), 751–758.

Mills, C. W. (1959). *The Power Elite.* New York: Oxford University Press. Galaxy edition, [1956].

Mollerstrom, J., B.-A. Reme, and E. Ø. Sørensen (2015, November). Luck, choice and responsibility — An experimental study of fairness views. *Journal of Public Economics 131*, 33–40.

Müller, D. and S. Renes (2021, May). Fairness views and political preferences: Evidence from a large and heterogeneous sample. *Social Choice and Welfare 56*(4), 679–711.

Norton, M. I. and D. Ariely (2011, January). Building a Better America—One Wealth Quintile at a Time. *Perspectives on Psychological Science 6*(1), 9–12.

Norton, M. I. and D. Ariely (2013). American's desire for less wealth inequality does not depend on how you ask them. *Judgment and Decision Making 8*(3), 2.

Page, B. I., L. M. Bartels, and J. Seawright (2013, March). Democracy and the Policy Preferences of Wealthy Americans. *Perspectives on Politics 11*(1), 51–73.

Page, B. I. and M. Gilens (2017). *Democracy in America?: What Has Gone Wrong and What We Can Do About It.* Chicago, IL: University of Chicago Press.

Page, B. I., J. Seawright, and M. J. Lacombe (2019). *Billionaires and Stealth Politics.* Chicago: University of Chicago Press.

Preuss, M., G. Reyes, J. Somerville, and J. Wu (2025). Inequality of opportunity and income redistribution. *Journal of Political Economy Microeconomics (accepted).*

Reyes, G. (2025). Coarse Wage-Setting and Behavioral Firms. *Review of Economics and Statistics (accepted).*

Reyes, G. and L. Gasparini (2022, December). Are fairness perceptions shaped by income inequality? evidence from Latin America. *The Journal of Economic Inequality 20*(4), 893–913.

Rigby, E. and G. C. Wright (2013). Political parties and representation of the poor in the american states. *American Journal of Political Science 57*(3), 552–565.

Roth, C. and J. Wohlfart (2018, November). Experienced inequality and preferences for redistribution. *Journal of Public Economics 167*, 251–262.

Schakel, W. (2021). Unequal policy responsiveness in the netherlands. *Socio-Economic Review 19*(1), 37–57.

Winters, J. A. (2011). *Oligarchy.* New York: Cambridge University Press.

Winters, J. A. and B. I. Page (2009). Oligarchy in the united states? *Perspectives on politics 7*(4), 731–751.