Ideology selectively shapes attention to inequality

Hannah B. Waldfogel[a], Jennifer Sheehy-Skeffington[b], Oliver Hauser[c], Arnold K. Ho[d], Nour S. Kteily[a]

[a] Department of Management and Organizations, Northwestern University, Evanston, IL 60208

[b] Department of Psychological and Behavioural Science, London School of Economics and Political Science, London, U.K.

[c] Department of Economics, University of Exeter Business School, Exeter, U.K.

[d] Department of Psychology, University of Michigan, Ann Arbor, MI 48109

Classification: Social Sciences/Psychological and Cognitive Sciences

Keywords: Ideology; Inequality; Egalitarianism; Politics; Attention

Address correspondence to: hannah.waldfogel@kellogg.northwestern.edu or n-kteily@kellogg.northwestern.edu

Significance Statement

Inequality between groups is all around us—but who tends to notice, and when? Whereas some individuals assert rampant inequality and demand corrective interventions, others exposed to the same contexts retort that their peers see certain inequalities where none exist and selectively overlook inconvenient others. Across 5 studies (total N = 8,779), we consider how individuals' ideological beliefs shape their proclivity to naturalistically attend to—and accurately detect—inequality in the world around them, depending on which groups bear inequality's brunt. Our results suggest that social egalitarians (vs. anti-egalitarians) are more naturally vigilant for and accurate at detecting inequality when it affects societally disadvantaged groups (e.g., the poor, women, racial minorities), but not when it (equivalently) affects societally advantaged groups (e.g., the rich, men, Whites).

Abstract

Contemporary debates about addressing inequality require a common, accurate understanding of the scope of the issue at hand. Yet little is known about who notices inequality in the world around them, and when. Across five studies (N=8,779) employing various paradigms, we consider the role of ideological beliefs about the desirability of social equality in shaping individuals' attention to—and accuracy in detecting—inequality across the class, gender, and racial domains. In Study 1, individuals higher (vs. lower) on social egalitarianism were more likely to naturalistically remark on inequality when shown photographs of urban scenes. In Study 2, social egalitarians were more accurate at differentiating between equal versus unequal distributions of resources between men and women on a basic cognitive task. In Study 3, social egalitarians were faster to notice inequality-relevant changes in images in a change-detection paradigm indexing basic attentional processes. In Studies 4 and 5, we varied whether unequal treatment adversely affected groups at the top or bottom of society. In Study 4, social egalitarians were, on an incentivized task, more accurate at detecting inequality in speaking time in a panel discussion that disadvantaged women, but not when inequality disadvantaged men. In Study 5, social egalitarians were more likely to naturalistically point out bias in a pattern-detection hiring task when the employer was biased against minorities, but not when majority group members faced equivalent bias. Our results reveal the nuances in how our ideological beliefs shape whether we accurately notice inequality, with implications for prospects for addressing it.

Introduction

Inequality between social groups is, by some measures, hard to miss (1-4). Yet despite widespread public discussion of the persistence of inequality along economic, racial, and gender lines, there are divergent views about the extent to which it is a problem, and which groups bear its brunt. These divergences reflect more than motivated reasoning anchored in individuals' desire to advance their own class, race, or gender group interest; they are also indicative of biases in line with one's ideological preferences. Those on the political left—who tend to value group-based equality—claim that the other side is willfully blind to inequality against groups at the bottom of society. Those on the political right—who tend to be more tolerant of group-based disparities—argue that the other side sees inequality where none exists (or where any inequality in fact harms groups at the top of society). Consider, for example, the heated exchanges about whether racial microaggressions are pervasive features of contemporary society, or whether they represent trumped-up fictions by ideologically-blinkered subscribers to 'victimhood culture' (5).

There will likely be little progress in agreeing on how to address inequality as long as there is such disagreement regarding the extent to which it exists and who it affects. How might those on the political left and right come to such different conclusions about the extent of inequality in the world around us? Here, we propose it is because individuals' ideological beliefs about the desirability of group-based equality shape their attention to and accuracy in detecting inequality in the first place. Drawing on and extending research on motivated processes underlying social cognition, we consider how variation in social egalitarianism—the ideological belief in the desirability of equality between groups— might shape our proclivity to *notice* inequality in the world around us. Whereas existing research focuses on how motivations cause us to actively evaluate, interpret, rationalize, and distort information with which we are confronted in order to fit our pre-existing beliefs, our work sheds light on an upstream attentional mechanism by which the different ideologies we are committed to can lead us to experience different realities.

Existing research suggests that we are often motivated processors of information, construing the world in ways that align with and further our personal goals or those of the collectives to which we belong (6-12). Beyond individual or group-based motives, our ideological belief systems play a role in shaping our information processing, too. Both gun control advocates and opponents evaluate evidence that favors their pre-existing positions as more compelling than evidence that challenges them (13, 14). Individuals motivated to justify the societal status quo are less likely to remember information about climate change suggesting the need for action (15). And individuals on the political left and right interpret the same video of protestors' behavior differently depending on whether they believe that the protestors are protesting against entities or causes they ideologically favor—restrictions on abortion or the military, respectively (16).

One ideological belief specifically relevant to inequality is social dominance orientation (SDO; 17). Individuals lower in SDO—social egalitarians—believe that all groups in society should be equal; individuals higher in SDO are more tolerant of the notion of a hierarchy of group standing in society. This difference in tolerance for group-based inequality is one of the main factors that distinguishes political liberals from conservatives (18, 19). And as with conservatism, individuals' level of social egalitarianism (as captured by SDO) can shape their social cognition in ways that align with their respective worldviews. For example, individuals lower in SDO evaluate a newspaper article supporting affirmative action as more valid than a similar article opposing it, whereas individuals higher in SDO show the reverse pattern (20). Social egalitarians apply a more exacting standard when judging the diversity of organizations, requiring an organization to be heterogeneous on more dimensions before labeling it diverse than individuals higher in SDO (21). And highlighting a proclivity to adopt different interpretive frames, individuals high in SDO judge the same gain in power by disadvantaged groups as more dramatic than do individuals low in SDO (22).

Prior research has directly examined how individuals differ in their judgments about the degree of societal inequality (or closely related constructs) as a function of their ideological beliefs, including SDO. Some research suggests that political liberals and individuals who question the legitimacy of the status quo perceive more income and wealth inequality in society than do political conservatives and those who justify the status quo (23-25). Other research suggests that political conservatives estimate greater socio-economic mobility than do political liberals (with some of this work arguing that liberals underestimate actual mobility and other work proposing that conservatives overestimate it; 26-28). Focusing specifically on ideological beliefs about the desirability of equality, one paper found that individuals lower in SDO perceived larger status differences between ethnic groups (e.g., between Whites and ethnic minorities), reflective of more inequality, whereas those higher in SDO tended to perceive smaller discrepancies, minimizing inequality (29).

Still, the research noted above cannot clearly point to motivated perception as an explanation, because it fails to rule out the possibility that ideology shapes abstract judgements about the degree of economic inequality in society by affecting the information people are exposed to in their daily lives rather than their processing of that information. For example, anti-egalitarians could conclude that there is less inequality in society if they happened to be less likely than egalitarians to live in areas that expose them to large discrepancies between those at the top and the bottom (30). One recent paper provided clearer evidence of differences in information processing rooted in egalitarianism (31). Across a number of studies, the authors found that individuals lower (vs. higher) in SDO perceived more social inequality (measured mostly as larger gaps in power between groups at the top and bottom of the social hierarchy). Importantly, these differences emerged even when participants were exposed to and asked to evaluate identical stimuli, suggesting ideological differences in processing the same information about inequality. In one study, participants evaluated the steepness of a series of visually-depicted hierarchical organizations. Social egalitarians judged the same stimuli as having steeper hierarchies than did individuals more tolerant of social hierarchy. In a subsequent surprise memory task, the authors assessed objective accuracy by presenting the previously-encountered organizations beside more and less hierarchical distractors and asking participants to select which hierarchy they previously saw. Individuals higher in SDO were more likely to underestimate inequality previously encountered whereas individuals lower in SDO were (marginally) more likely to overestimate it.

Taken together, research suggests that when we're explicitly asked to judge an aspect of the world relevant to our ideological beliefs, we sometimes apply standards, evaluate information, or adopt interpretive frames in ways that help us rationalize conclusions consistent with our ideological worldviews (as we do on behalf of ourselves and our groups). Individuals' motivated *interpretation* of information is thus one mechanism by which those on the left and right might come to disagree so strongly about whether the poor and the rich, men and women, or racial majorities and minorities are treated equally.

Here, we consider a complementary but distinct possibility. We propose that, as a consequence of our ideological dispositions, we might *naturalistically attend* to different information in the world around us, thereby experiencing different realities even when exposed to the same environments. In particular, we suggest that relative to individuals more tolerant of group-based hierarchy, social egalitarians—ideologically committed to the goal of reducing the gap between socially disadvantaged and advantaged groups—are vigilant for and perceptually 'ready' to notice inequality when it is present (32-34). Indeed, relative to individuals more tolerant of hierarchy, those who strongly believe in the need to make the world more equal might be more likely to chronically encode the world in inequality-relevant terms. Consider two people sitting in a workplace meeting in which the men in the room happen to disproportionately dominate the conversation. An individual committed to group-based equality might, naturalistically, be more likely to vigilantly encode the proportion of airtime dominated by men as compared to women. By contrast, an individual dispositionally more tolerant of inequality might not think to encode the conversation through the lens of gender-based speaking time share. These two individuals might then arrive at meaningfully different conclusions about the existence of inequality in speaking time. Of note, this process does not require any downstream motivated rationalization by those who oppose or tolerate inequality. Rather, it reflects differences arising early in the cognitive stream as a function of the differential *motivational relevance* of evidence about inequality—that is, the degree to which evidence of inequality is seen as worth attending to (35).

Our theorizing builds on research about the effects of motivation on selective attention outside the domain of ideological beliefs (36-37). Hungry individuals, relative to those low in hunger, show a greater attentional bias for food-related stimuli (38), and addicts give preferential attention to the object of addiction relative to control stimuli (39). Preferential attention to motivationally-relevant stimuli occurs in social contexts, too. Individuals for whom the threat of social exclusion was made experimentally salient were faster than control participants to identify smiling faces within a crowd (40). Low-SES individuals, who prioritize interdependence with others, are more likely than high-SES individuals (who prioritize independence) to naturalistically attend to faces of other people in their environment (41). And work on goal-directed cognition has shown that individuals asked to write about instances in which they treated members of disadvantaged groups (e.g., obese people, homosexuals) unfairly (vs. fairly) generated a goal to compensate that led them to pay more attention to goal-relevant (but task-irrelevant) words like 'justice' and 'fairness' on a reaction time-task (42; see also 34).

Here, we investigated across five studies (including ten samples and five distinct paradigms; total $N = 8{,}779$) whether chronic differences in ideological beliefs about the desirability of group-based equality would shape individuals' attention to and accuracy in detecting inequality. Study 1 examined naturalistic attention to cues of inequality in urban scenes. Study 2 examined basic social cognition using a Go-No Go task analyzed using a signal detection framework, to assess whether spontaneous attention to inequality manifested in greater accuracy at detecting inequality in resource distribution. Study 3 used a speeded change-detection task to naturalistically index individuals' visual attention to inequality-relevant aspects of social scenes. Because inequality is more motivationally relevant to them, we predicted in our first three studies that individuals strongly committed to social equality would be more attentive to and more accurate at detecting evidence of inequality than individuals more tolerant of inequality. In Studies 4 and 5, we moved beyond inequality impacting only socially disadvantaged groups, and manipulated the social standing of inequality's victims, allowing us to consider two competing predictions regarding the link between egalitarianism and attention to inequality. On the one hand, to the extent that inequality *per se* is motivationally relevant for social egalitarians, they should attend to evidence of inequality irrespective of whether the group receiving unequal treatment is socially advantaged or disadvantaged. On the other hand, recent research suggests that social egalitarians are primarily motivated by *closing the gap between groups in society*, thereby treating targets differently as a function of these targets' societal group status (e.g., preferentially empathizing with and amplifying successes of disadvantaged over advantaged group members; 43-45). From this perspective, it is specifically inequality that *harms socially disadvantaged groups* that is motivationally relevant for social egalitarians, and thus, any link between social egalitarianism and heightened attention to inequality might apply selectively to instances in which the inequality harms groups at the bottom of society.

Study 1

The primary aim of Study 1 was to examine how an individual's (anti-)egalitarianism (assessed by their social dominance orientation) predicts their spontaneous tendency to notice inequality in everyday urban scenes. We examined this across five samples of participants (total $N = 2{,}204$) who viewed a series of 6-10 photographs of urban scenes, half of which contained cues relevant to economic inequality. For each image, we simply asked participants to report what they noticed, without making any mention of inequality.

We developed a coding scheme to analyze participants' open-ended responses that could isolate 'direct' from 'indirect' mentions of inequality, the former involving an explicit mention of inequality in the scene and the latter involving the citing of cues concerning *both* low and high status targets in an image (e.g., a luxury car, a homeless person; see Figure 1 for examples of inequality-relevant and neutral images). Although we were centrally interested in attention to inequality *per se*, exploratory analyses also considered the extent to which participants reported ('1') or failed to report ('0') high status and low status cues separately (see SI Section 2.5).

We conducted a meta-analysis across all five samples to examine the correlations between SDO and mentions of inequality (see SI Section 2.8 for forest plots). SDO was significantly negatively correlated with *Direct Inequality*, fixed effects model: $z = -2.89$, $p = .004$, $r = -.06$, random effects model: $z = -2.19$, $p = .03$, $r = -.07$. In addition, SDO was significantly negatively correlated with *Indirect Inequality*, fixed effects model: $z = -3.44$, $p < .001$, $r = -.07$, random effects model: $z = -2.93$, $p = .003$, $r = -.08$. That is, whether through reporting it as a salient issue or picking up on inequality-relevant details in a scene, those low (versus high) in anti-egalitarianism were more likely to notice inequality in images of contemporary urban life—images similar to those they might encounter in their own everyday lives. This is the first demonstration of ideological differences in spontaneous attention to inequality, going further than previous work that has focused on the interpretation of information about inequality when inequality is explicitly identified as a dimension of interest.

Study 2

The findings of Study 1 suggest that an ideological commitment to reducing social inequality facilitates spontaneous attention to inequality in everyday urban scenes. Still, it is possible that individuals who are more tolerant of hierarchy are just as likely to notice inequality cues, but simply less likely to *report* noticing them. On the other hand, if, as we argue, ideological beliefs shape the extent to which one is chronically cognitively attuned to inequality-related stimuli, then this should be reflected in greater *accuracy* at detecting inequality in a rapid-response cognitive task. Study 2 ($N = 1{,}406$) assessed this possibility using the signal detection paradigm.

We employed a Go-No Go task that asked participants to judge, across 120 trials, whether two distributions of a socially relevant resource were equal or unequal to one another. On any given trial, participants saw the same picture of a group of men and a group of women (separated by a divider), each with a set of moneybags associated with them. On 'equal' trials, the distribution of moneybags associated with men and women was equal (Fig. 2, left panel). On 'unequal' trials, the group of men had more moneybags than the group of women did (in this experiment, inequality therefore was always at the expense of the socially disadvantaged group) (Fig. 2, right panel).

On 'Go' trials, participants were told to hit the space bar. On 'No Go' trials, participants were asked to refrain from hitting any key on the keyboard. Trials advanced after 6 seconds or (if sooner) when participants hit the space bar. We counterbalanced whether participants were instructed to hit the space bar ('Go' trials) when the two distributions of moneybags were equal or unequal. We used the signal detection framework to calculate our key dependent variables: sensitivity (*d'*) and response bias (*c*). Sensitivity (*d'*) in this case indexes an individual's ability to accurately differentiate between equal and unequal trials. Larger *d'* values indicate more accuracy at distinguishing equal from unequal trials. In practical terms, having a larger *d'* value means an individual was more likely to correctly notice inequality when it was present and the absence of inequality when it was absent. Response bias (*c*) indexes participants' bias towards responding in a particular direction (i.e., a bias towards stating that the distributions are equal or unequal). A *c*-value of 0 indicates no bias in responding. We coded *c*-values such that positive values always indicate a bias towards responding that the two images are equal and negative values always indicate a bias towards responding that the two images are unequal. In practical terms, having a negative *c*-value means an individual is inclined to see inequality even in its absence, and an individual who has a positive *c*-value sees equality even in its absence.

As predicted, we found that SDO was significantly negatively correlated with *d'*, $r = -.08$, $p = .002$, suggesting that individuals lower (vs. higher) in SDO were more accurate at the task. In contrast, the relationship between *c* and SDO was not significant, $r = -.01$, $p = .76$.

Thus, using a speeded task assessing basic social cognition, social egalitarians—individuals chronically motivated to reduce the gap between groups at the top and bottom of society—were more accurate than anti-egalitarians at arbitrating whether inequality was present or absent, consistent with the possibility that they were more attentionally vigilant for it. We did not find any evidence suggesting that social egalitarians have a bias towards claiming inequality. That is, egalitarians' response pattern was marked by more accurately arbitrating whether inequality was present or absent, rather than simply a lower threshold for claiming inequality (even in its absence).

Study 3

The goal of Studies 3a-3b was to combine the strengths of Study 1 in terms of its focus on naturalistic attention to inequality cues, and the strengths of Study 2 in terms of its focus on the processing of inequality-related information early in the cognitive stream. Both Studies 3a and 3b relied on a speeded task indexing attention, and omitted any reference to inequality during the task, which we did to provide a direct index of spontaneous attention to inequality.

Participants completed 10 trials of a flicker task (46) in which they were presented with a set of two images, shown sequentially and repeatedly, and asked to indicate the first point at which they noticed the detail that differed between the two images. In inequality trials, the change involved a detail relevant to signs of economic inequality (e.g., a homeless man's bag disappearing; see Figure 3). In neutral trials, the change was irrelevant to social inequality (e.g., a message disappearing from a bus LED screen) (see SI Section 4.1 for all images). Once participants hit the space bar to indicate they noticed the change, they were asked to describe in detail what changed in the image.

We were primarily interested in how many views of the flickering sequence passed before participants (correctly) noticed changes occurring in inequality-relevant images. This number served as a proxy for their attention to different parts of the image (those paying closer attention at baseline to parts of the scene in which the change occurs should be faster to notice the change). We also controlled for how long it took participants to (correctly) notice changes occurring in the neutral images, which served as a proxy for the ability of participants to detect general changes in images. If participants identified the change correctly (as rated by manual coders), we reported their score as the number of views after which they hit the space bar (e.g., 11, if they hit the space bar after 11 views of the sequence). If participants reported the change incorrectly, we set their time at the maximum of 25 views irrespective of when they hit the spacebar (as preregistered). We averaged participants' number of views for each of the inequality-relevant and neutral sets of images.

Using our preregistered analysis plan for Study 3a (N = 1,027), we found our expected positive correlation between SDO and the average number of views for inequality images (r = .15, p < .001), which held even when controlling for the average number of views for neutral images (b = .08, t (1024) = 3.07, p = .002; here and throughout, we used ordinary least squares regression, unless otherwise specified). This suggests that individuals lower in SDO were more attentive to inequality (i.e., they needed less time to identify the inequality-relevant change) and that this could not be accounted for controlling for more general attentiveness on the task (i.e., performance on neutral trials).

Despite this supportive evidence, we decided to replicate Study 3a in Study 3b (N = 1,474), with a conservative adjustment in preregistered exclusion criteria. Specifically, we excluded participants with low rates of overall accuracy in identifying the changes in images (i.e., those without at least 3 out of 5 trials correct in *each* of the inequality-relevant and neutral categories). We also included the number of views only for trials on which participants were accurate, and improved upon the set of neutral images (see Methods for more details and SI Section 4.2 for rationale).

We averaged participants' number of views (on correct trials) for each of the inequality-relevant and neutral sets of images. We observed that SDO was significantly positively correlated with the average number of views on inequality trials, r = .10, p < .001. When controlling for the average number of views on neutral trials, SDO was a marginally significant predictor of the average number of views on inequality trials, b = .04, t (1471) = 1.89, p = .059. These relationships were robust when meta-analyzing across Studies 3a and 3b (zero-order r = .13, z = 6.35, p < .001; controlling for neutral trials, b = .06, z = 2.82, p = .005), including when analyzing both studies using Study 3b's updated exclusion criteria (zero-order r = .11, z = 5.52, p < .001; controlling for neutral trials, b = .05, z = 2.32, p = .02).

Thus, across two sub-studies without any prompting regarding the theme of inequality, we obtained evidence suggesting that individuals more committed to social egalitarianism are chronically more visually attentive to cues of inequality in everyday urban scenes.

Study 4

One notable aspect of Study 3 was that all of the inequality-relevant changes involved low status targets (e.g., homeless people). This raises the possibility that egalitarians are particularly attuned to inequality *only* when it involves bias against groups that they ideologically favor (i.e., socially disadvantaged groups). This would also be consistent with the findings of Study 2, in which the disadvantaged group in the Go-No Go task, women, is also a disadvantaged group in society.

We thus turned in Study 4 (N = 1,467) to examine, using a financially incentivized task, how the link between an individual's (anti-)egalitarianism and their attention to and accuracy in detecting inequality might depend on the target of that inequality. Specifically, we examined how the relationship between (anti-)egalitarianism and accuracy in detecting inequalities in the distribution of talking time between men and women on a panel differed depending on whether it was men (a socially advantaged group) or women (a socially disadvantaged group) who took up a disproportionate share of the talking time.

All participants watched a 4 minute and 30 second video depicting a discussion panel consisting of two men and two women. Participants were randomly assigned to one of two conditions (edited from the same source material): (1) a condition in which the men spoke 1.5x longer than the women or (2) a condition in which the women spoke 1.5x longer than the men. Prior to watching the video, participants were incentivized to pay close attention to the video as they would be answering a series of memory questions afterwards, with the individuals responding most accurately receiving a $50 prize (participants were not told what aspects of the video we were interested in, and inequality was never mentioned). By providing a financial incentive for all to focus on the task, we reduce the possibility that any link between SDO and accuracy/attention to inequality is affected by higher SDO individuals simply responding more carelessly to experiments in general (and/or experiments that appear to them to investigate inequality).

Our key dependent measures were all generated from a question that asked participants to "Please select the chart that you think best represents the ratio of speaking time for men and women." Participants were randomly presented with seven pie charts to choose from, depicting the following speaking time ratios: (1) 35% men:65% women, (2) 40% men:60% women, (3) 45% men:55% women, (4) 50% men:50% women, (5) 55% men:45% women, (6) 60% men:40% women, (7) 65% men:35% women (see SI Figure 31). In Condition 1, the correct answer was 60% men: 40% women. In Condition 2, the correct answer was 40% men: 60% women.

We dichotomously examined whether or not participants selected the correct answer: Participants received a score of '1' if they selected the correct pie chart for their condition and a score of '0' otherwise. We also dichotomously coded whether participants made a selection indicating (separately) underestimation and overestimation of the inequality actually faced by the disfavored target in their bias condition (a score of '0' indicated the absence of underestimation or overestimation; a score of '1' indicated that participants' selection was an underestimate or overestimate, depending on the measure). We also report in SI Section 5.6 (consistent) results examining *degree* of underestimation (note that we could not assess continuous levels of overestimation because—for reasons we explain in SI Section 5.5— there was only one pie chart choice reflecting overestimation).

Given that our dependent variables in this study were dichotomous, we used binomial logistic regression throughout. We observed a marginally significant interaction effect, $b = .19$, $p = .08$, 90% [.01, .36], between SDO and task condition in predicting accurate pie chart selection (see SI Figure 32). In the condition where men spoke more than women, we observed a negative main effect of SDO on accuracy, $b = -.19$, $p = .01$, odds ratio (OR) = .83, 95% [.70, .96], with egalitarians significantly more likely to select the accurate pie chart than those higher on anti-egalitarianism. In contrast, in the condition where women spoke more than men, there were no significant differences between individuals lower and higher in SDO in terms of accuracy, $b = -.01$, $p = .92$, OR = .99, 95% [.86, 1.14]. At low levels of SDO (-1SD below the mean; $M_{SDO} = 2.58$, $SD = 1.29$), task condition was not a significant predictor of accuracy; individuals lower in SDO were equally likely to select the correct speaking time pie chart in Condition 1 (where men spoke more) versus Condition 2 (where women spoke more), $b = -.05$, $p = .80$, OR = .95, 95% [.66, 1.36]. At high levels of SDO (+1SD above the mean), however, individuals were significantly more likely to select the correct pie chart in Condition 2 (where women spoke more) relative to Condition 1 (where men spoke more), $b = .43$, $p = .03$, OR = 1.54, 95% [1.04, 2.29].

Turning to our measure of underestimation, we observed a significant interaction effect, $b = -.20$, $p = .01$, 95% [-.37, -.04], between SDO and bias condition (see Figure 4). In the condition where men spoke more than women, individuals lower (vs. higher) in SDO were significantly less likely to underestimate the level of inequality, $b = .16$, $p = .01$, OR = 1.17, 95% [1.04, 1.31]. In contrast, when women spoke more than men, SDO did not significantly predict underestimation, $b = -.05$, $p = .40$, OR = .95, 95% [.85, 1.06]. Examining the interaction another way, individuals lower in SDO (-1 SD) were more likely to underestimate inequality when women spoke more than when men spoke more, $b = .76$, $p < .001$, OR = 2.14, 95% [1.60, 2.89]. Individuals higher in SDO (+1 SD), by contrast, were no more likely to underestimate inequality in one condition versus the other, $b = 0.24$, $p = .11$, OR = 1.27, 95% [.95, 1.70].

Finally, we observed no significant interaction effect between SDO and bias condition on overestimation, $b = .11$, $p = .19$, 95% [-.06, .29] (see SI Figure 33). When men spoke more than women, we observed no significant association between SDO and the likelihood of overestimating inequality, $b = -.05$, $p = .44$, OR = .95, 95% [.85, 1.07]. The same was true when women spoke more than men, $b = .07$, $p = .29$, OR = 1.07, 95% [.94, 1.22]. For those both lower and higher in SDO (-/+ 1SD), there was a significant main effect of task condition, such that individuals were less likely to overestimate the level of inequality when women spoke more than men relative to when men spoke more than women (at -1SD: $b = -.84$, $p < .001$, OR = .43, 95% [.31, .59]; at +1SD: $b = -.55$, $p < .001$, OR = .58, 95% [.42, .79]).

Across the three measures, then, when women were disadvantaged, social egalitarians (vs. those more tolerant of social hierarchy) had (a) a significantly more accurate score on our measure of accuracy, (b) were significantly less likely to underestimate inequality, and (c) were no more likely to overestimate inequality. These accuracy advantages for social egalitarians tended to dissipate (but not *reverse*) when men were disadvantaged.

Study 5

In Study 5 ($N = 1,201$), we again examined how an individual's (anti-)egalitarianism differentially predicts their attention to unequal treatment depending on the social standing of the target of that inequality, this time in the domain of racial biases in hiring. Specifically, we examined how (anti-)egalitarianism predicted attention to racial bias in hiring across two experimental conditions: (1) a condition in which there was anti-minority bias in hiring and (2) a condition in which there was (equivalent) anti-White bias in hiring. In addition, we went further than previous studies by considering downstream consequences, examining whether individuals who noticed inequality were more likely than those who did not notice it to want to investigate the hiring process.

Participants read about an organization called Connection Consulting that had just completed their hiring process and were shown the resumes of 56 applicants who varied across 5 dimensions (GPA, major, race, hometown, and hobby; see SI Figure 37). Half of the applicants were White, and half of the applicants were racial minorities (Latino, Asian, Black). After viewing each candidate's resume, participants learned whether that applicant was hired or not. Participants were randomly assigned to one of two conditions, which differed only in terms of the correlation between race and likelihood of being hired: In Condition 1, being a minority (vs. White) was correlated at $r = -.29$ with the likelihood of being hired, whereas in Condition 2, being a minority (vs. White) was correlated at $r = +.29$ with the likelihood of being hired. In both conditions, the task was structured such that GPA was correlated at $r = +.57$ with the likelihood of being hired and the correlation between all other factors (major, hometown, hobby) and being hired was 0.

We assessed the extent to which participants noticed inequality across the two conditions by asking participants, after they completed the resume task, to "Please note anything that stood out to you about the hiring process." We then coded for whether participants naturalistically mentioned inequality in the hiring process. For this metric, which we termed *naturalistic notice bias*, we dichotomously coded whether or not participants—correctly—mentioned unequal treatment against the group actually disadvantaged within their experimental condition. Participants in Condition 1 received a score of '1' if they mentioned inequality against minorities and a score of '0' otherwise. Participants in Condition 2 received a score of '1' if they mentioned inequality against Whites and a '0' otherwise. Note that we also assessed attention to inequality using three other metrics, including by directly asking participants about their perceptions of bias against both Whites and minorities on self-report scales (analyses yielded comparable conclusions; see SI Sections 6.4-6.6).

We also assessed a downstream consequence of noticing inequality, namely, the extent to which participants endorsed investigating Connection Consulting for its hiring practices, termed *desire to investigate* (five-item scale; sample item: "A third party should investigate Connection Consulting's hiring practices"; $\alpha = .94$).

Using binomial logistic regression, we observed a significant interaction effect, $b = 0.44$, $p < .001$, 95% [0.26, 0.62], between SDO and bias-direction condition in predicting whether participants naturalistically (and correctly) noticed bias. In the anti-minority bias condition, we observed our predicted main effect of SDO, $b = -.36$, $p < .001$, OR = .70, 95% [.61, .79]: in line with the conclusions of Studies 1-4, individuals lower (vs. higher) in SDO were significantly more likely to notice bias against racial minorities when it was present. In contrast, in the anti-White bias condition, we observed a positive but non-significant trend between SDO and naturalistically mentioning racial bias ($b = 0.08$, $p = .22$, OR = 1.08, 95% [.95, 1.23], see Figure 5, top panel; of note, this positive association between SDO and perceived bias against Whites was significant using self-reported measures of perceived bias, see SI Section 6.5). At low levels of SDO (-1SD below the mean—$M_{\text{SDO}} = 2.77$, $SD = 1.43$), bias-direction condition was a significant predictor of naturalistically noticing bias; individuals lower in SDO were significantly more likely to naturalistically mention bias in Condition 1 (anti-minority bias condition) versus Condition 2 (anti-White bias condition), $b = -1.25$, $p < .001$, OR = .29, 95% [.20, .41]. At high levels of SDO (+1SD above the mean), there was no significant difference between the likelihood of naturalistically noticing bias across the two conditions, $b = 0.001$, $p = 1.00$, OR = 1.00, 95% [.69, 1.44]. Individuals even higher in SDO (+2SD above the mean) were significantly more likely to naturalistically mention bias in the anti-White bias versus anti-minority bias condition, $b = 0.65$, $p = .03$, 95% [0.06, 1.24]. Of note, it was low SDOs in the condition where there was bias against minorities who exhibited the highest overall likelihood of (correctly) noting bias (about 50.6%).

We also observed a significant interaction between SDO and task condition in predicting the desire to investigate Connection Consulting, $b = 0.50$, $p < .001$, 95% [0.37, 0.63]. In the anti-minority bias condition, individuals higher (vs. lower) in SDO reported significantly less desire to investigate, $b = -0.27$, $p < .001$, 95% [-0.36, -0.18], whereas when there was anti-White bias, we found that individuals higher (vs. lower) in SDO reported a significantly greater desire to investigate, $b = 0.23$, $p < .001$, 95% [0.13, 0.32] (see Figure 5, bottom panel). Individuals lower in SDO (-1SD below mean) reported a significantly greater desire to investigate in the anti-minority versus anti-white bias condition, $b = -1.15$, $p < .001$, 95% [-1.41, -0.89], whereas individuals higher in SDO (+1SD above mean) reported a marginally greater desire to investigate in the anti-White versus anti-minority bias condition, $b = 0.25$, $p = .055$, 95% [-0.01, 0.51].

We next examined evidence for moderated mediation. We entered SDO as the predictor, *naturalistic notice bias* as the mediator, and desire to investigate as the outcome measure, with bias condition as a moderator of each of the *a*, *b*, and *c* paths (see SI Figure 41). In the anti-minority bias condition, there was a significant negative indirect effect of SDO on desire to investigate via naturalistically (and correctly) noticing the bias, $b = -.12$, SE = .02, 95% [-.16, -.08]. In contrast, in the anti-White bias condition, there was no significant indirect effect of SDO on desire to investigate via *naturalistic notice bias*, $b = .02$, SE = .02, 95% [-.02, .06]. For individuals lower in SDO (-1SD below mean), the indirect effect of task condition on desire to investigate via naturalistically noticing bias was significantly negative, $b = -.44$, SE = .07, 95% [-.58, -.30]. For individuals higher in SDO (+1SD above mean), the indirect effect of task condition on desire to investigate via naturalistically noticing bias was not significant, $b = -.002$, SE = .05, 95% [-.09, .09]. Of note, results using self-reported bias in place of *naturalistic notice bias* replicated these moderated mediation results and further revealed a significantly positive indirect effect in the anti-White bias condition and among high SDOs (see SI Section 6.6).

Discussion

Inequality between groups is one of the predominant issues of our time, and yet, individuals often disagree across ideological lines about its extent, its victims, and what, if anything, to do about it. Prior research suggests that, when confronted with evidence of or specifically asked about inequality, individuals engage in motivated reasoning, interpreting information in ways that align with their propensity to favor or oppose egalitarian social intervention. But being explicitly asked to evaluate inequality is the least representative of the ways we might encounter it in the world. As we go about our daily lives engaging in mundane activities, from everyday commutes through urban areas to attending conferences or participating in recruitment efforts in our organizations, we regularly encounter cues of group-based inequality: discrepancies between rich and poor, gender-based differences in recognition and airtime, and race-based discrimination in who gets hired. Who notices these cues, and when? Extending research showing how ideological preferences shape how we rationalize inequality-related information, our work shows how they also affect the likelihood that we attend to such information in the first place. Supplemental analyses further suggest that these differences are specific to our ideological beliefs, and cannot simply be accounted for by our racial, gender, or class group memberships (see SI Section 7). Considering differences in basic attention to inequality can thus shed new light on the growing ideological polarization characteristic of contemporary policy debates.

We reasoned that because inequality is chronically motivationally relevant to those who strongly oppose group-based hierarchy, these social egalitarians would be more likely to scan for and notice inequality than those more tolerant of group-based hierarchy. Consistent with our reasoning, in Study 1, those lower (vs. higher) in anti-egalitarianism (as indexed by social dominance orientation) were more likely to naturalistically mention inequality when we simply showed them a variety of everyday social scenes, some of which contained inequality-relevant cues. In Study 2, using a very basic speeded cognitive task, egalitarians were also better at accurately differentiating distributions of resources which favored men over women from equal distributions. Combining naturalistic scenes with a visual attention paradigm, Study 3 found that social egalitarians (vs. anti-egalitarians) were faster to detect inequality-relevant changes to visual scenes, suggesting a heightened attentional focus to any evidence of inequality.

Inequality in Studies 1-3 always adversely impacted societally disadvantaged groups (e.g., women, the poor, minorities). Thus, these three studies raised a key theoretical question—do social egalitarians chronically attend to all types of inequality, or do they notice some inequalities more than others? To test this, in addition to introducing new forms of inequality, Studies 4-5 varied the social standing of the group impacted by inequality. Leveraging social contexts in which inequality has been hotly debated, we experimentally manipulated whether participants encountered panels in which men versus women dominated speaking time (Study 4) or hiring processes in which White versus minority candidates were disadvantaged (Study 5). We replicated our findings of ideological bias in inequality attention in these novel contexts, again observing that social egalitarians (vs. anti-egalitarians) were significantly more likely to naturalistically (and accurately) notice inequality when it was traditionally disadvantaged groups on the receiving end. Critically, however, egalitarians were not more likely (and were sometimes less likely) than anti-egalitarians to notice when inequality negatively impacted traditionally advantaged groups. These differences were consequential, occurring despite the fact that participants were financially incentivized to engage with the task and honestly report their perceptions (Study 4), and predicting downstream desires to investigate a company's hiring practices (Study 5).

Practically, our findings shed light on why we might so often come to disagree about the state of the world. Social egalitarians and the wider political left might be bewildered and frustrated when others fail to notice or encode (and thereby seem to downplay) the mistreatment that traditionally disadvantaged groups so often experience (and for which egalitarians remain vigilant). As a function of their own perceptual tendencies, on the other hand, individuals more tolerant of inequality between groups (typically on the political right) might come to feel that egalitarians are seeing inequality where none exists or come to feel aggrieved at what they might consider a hypocritical tendency to selectively attend to some types of inequality but not others.

Theoretically, our findings not only contribute new evidence supporting an attentional mechanism by which motivations can influence inequality perception (36), but also extend a range of recent work suggesting that (anti-)egalitarians' perceptions and behavior are deeply impacted by the social standing of those they encounter. For example, whereas work historically suggested that egalitarians are dispositionally more empathic than anti-egalitarians, recent research illustrates that egalitarians express more empathy towards the suffering of socially disadvantaged targets but less for that of advantaged targets (44). Similarly, in contrast to those on the political right, those on the political left preferentially amplify the successes of women and racial minorities (e.g., by tweeting about them) over those of men and Whites (45), a differentiation that is statistically mediated by their desire to help bring about intergroup equality. This work suggests that social egalitarians are primarily invested in closing the gap between groups at the bottom and those at the top, which might require a selective focus on improving the lot of traditionally disadvantaged groups (despite any seeming contradictions implied by preferential treatment in service of group-based equality). Our finding here that social egalitarians are more attentive to evidence of inequality faced by socially disadvantaged versus advantaged groups is highly consistent with this emerging proposition.

At the same time, it is important to note that our results do not support any notion that egalitarians saw inequality that did not exist. In Study 2, we found a significant link between egalitarianism and higher *d'* scores (accuracy at differentiating equality from inequality), but no relationship between egalitarianism and *c* (the tendency to claim inequality independent of accuracy). Moreover, in Study 4, social egalitarians were (a) more accurate and (b) less likely to underestimate speaking-time inequality disadvantaging women, but not more likely to overestimate inequality affecting women. It is also worth noting that the interactions by target status we observed in Studies 4 and 5 tended not to be 'full cross-over' interactions— that is, the egalitarian 'advantage' in noticing inequality impacting low-status groups often appeared larger than anti-egalitarians' comparable advantage in noticing inequality impacting high-status groups. Indeed, the single highest score for accurately noticing bias in Study 5 was among egalitarians encountering inequality disadvantaging low-status groups (see Figure 5), as was the single lowest score for underestimating inequality in Study 4 (see Figure 4). And notably, when men spoke more (Study 4) or Whites were advantaged (Study 5), egalitarians were no less likely to notice than anti-egalitarians. In sum, egalitarians appear to be especially apt to notice inequality affecting those at the bottom where it exists, as opposed to seeing inequality where none exists or being especially likely to overlook inequality affecting those at the top.

Despite the contributions of our work, there are several limitations worth noting. For one, the effect sizes we observed were, despite their robustness, typically small. Although this is unsurprising given that we were typically dealing with difficult speeded cognitive tasks and obscuring from participants our interest in inequality, we cannot readily conclude from our findings that there are overwhelming differences in how individuals lower and higher in (anti-)egalitarianism attend to their social environments. Still, our effect sizes are consistent with other similar research (42, 48), and because we were investigating naturalistic attention to inequality of the type that individuals are likely to encounter on a very regular basis, even small differences can add up. We attempted here to test our theorizing across a broad range of experimental paradigms. Still, in examining our effects further, it would be valuable to further diversify the paradigms we employed, and to move beyond lab-based methods to further consider attention to inequality 'in the wild'. For example, it would be worth considering daily diary methods in which individuals are asked at random intervals of the day to report on interactions or events that stood out to them (49), and code for whether individuals are differentially likely to mention inequality-relevant topics as a function of their ideological leanings. It would also be interesting to use eye-tracking goggles to examine what individuals visually attend to during their daily commutes. It would be especially valuable to explore whether these types of differences in attention to inequality outside the lab shape support for real-world social policies, as our analysis of the desire to investigate 'Connection Consulting' preliminarily suggests. Beyond different methods, it is also important to test our patterns in different social and cultural contexts— although our work has the advantage of considering inequality across a number of distinct domains (class, gender, race), most of our work was conducted with U.S. participants, and it remains to be seen whether we would obtain the same results in non-WEIRD (50) contexts or in contexts where the topic of inequality is less politicized.

Finally, future work could consider ways in which we might be able to nudge individuals to pay more attention to (or become more accurate at detecting) inequality. In the current work, we generally attempted to limit participants' awareness of our interest in inequality because we were specifically interested in spontaneous attention to inequality. But, if we instead directly nudged people to try to encode inequality in the world around them, might we be able to durably reduce the types of bias blind spots that society regularly laments—such as those in hiring, representation, and inclusiveness—and to do so in a way that brings people across the ideological divide onto the same page?

Conclusion

Although inequality is one of the most pressing issues of our time, we often disagree about the scope of the problem, the identity of its victims, and the appropriate actions to take. We highlight the role that ideological motives play in this process by—selectively—shaping our attention to inequality in the world around us.

Methods Section

Studies 2-5 were pre-registered (see SI Section 1 for preregistration links and information regarding a solitary deviation in Study 4). Additional details of sample demographics and sensitivity or power analyses for all studies are available in the SI Appendix.

Study 1. Sample 1a consisted of 227 participants from MTurk of whom 200 provided data on all focal variables. Sample 1b consisted of 527 participants from MTurk of whom 507 provided data on all focal variables. Sample 1c was collected using Prolific Academic and included 522 participants residing in the U.K. of whom 519 provided data on all focal variables. Sample 1d consisted of 738 participants from MTurk of whom 607 provided data on all focal variables.

Across samples 1a-1d, participants were asked to complete a Visual Attention Task. Participants were shown a series of images and for each image, were given the following instructions: "What stands out to you in this image? Please list three things that stand out to you." The task instructions were altered slightly for Studies 1b and 1c. Participants in these studies saw the following instructions: "From the image above, please list the first <u>3 concrete details</u> (e.g., objects, characters, clothing) that you notice."

We used a variety of focal and distractor images across each study, sampling across a broad range of stimuli (see SI Section 2.4). The focal images each depicted inequality-relevant scenes. Specifically, these images juxtaposed, in the same visual scene, certain cues reflecting high status (e.g., wealthy women receiving pedicures, luxury vehicle) and low status (e.g., employees at a nail salon, a homeless person's cart). The distractor images were scenes without any obvious inequality-relevant content.

Across samples 1a-1d, we coded participant responses (i.e., what they wrote stood out to them about each image) to the inequality-relevant images according to a coding scheme which captured both explicit mentions of the principle of inequality as well as a pattern of observations that indirectly indicated attention to inequality. We coded a response as '1' for *Direct Inequality* if the response explicitly mentioned status differences in the image or remarked explicitly on the fact that the scene depicted inequality. To assess *Indirect Inequality*, we coded for whether participants mentioned *both* high and low status cues associated with each of the inequality-relevant images (see SI Section 2.5 for detailed coding scheme information). Across samples, one rater coded the entire dataset for both direct and indirect attention to inequality. To assess coding reliability, a second rater coded a subset of half of the responses for each image (all κs >

.70). In Samples 1a, 1c, and 1d, we assessed (anti-)egalitarianism using the 16-item SDO_7 scale (αs > .85); in Sample 1b, we used the 8-item $SDO_{7(s)}$ (18; α = .92).

For Sample 1e, we conducted our study in 2 waves, one week apart, beginning with a sample of 571 participants using Amazon's Mechanical Turk. 368 participants (64.4%) returned to complete the second wave (see SI Section 2.6 for attrition analyses). In wave 1, participants filled out the 16-item SDO_7 measure (α = .95). In wave 2, participants completed the same Visual Attention Task. Here, though, we experimentally manipulated the task instructions, with half of participants receiving *General Impression* task instructions ("What is your impression of the image? Please write at least 3 sentences") and the other half receiving *Concrete Details* task instructions ("Please list three features of the image that stand out to you"). We reasoned that the relationship between (anti-)egalitarianism and attention to inequality might be more apparent with the *Direct Inequality* outcome measure in the *General Impression* instructions condition, but more pronounced with the *Indirect Inequality* outcome measure in the *Concrete Details* condition (see SI Section 2.7 for relevant analyses). Participant responses were coded using the coding scheme described above.

Study 2. In total, we collected data from 1,591 participants using Amazon's Mechanical Turk of whom 1,544 provided data on all focal variables. As preregistered, and based on a relevant simulation (see SI Section 3.4), we excluded participants who had over 17 consecutive 'Go' responses or 'No Go' responses. We chose this threshold as an indicator of inattentive responding which could, if correlated with SDO, artificially inflate associations between SDO and accuracy (conclusions were equivalent without this exclusion; see SI Section 3.4). Excluding 185 participants who surpassed this threshold left us with a final sample of 1,406 participants for analyses (88.4% of the original sample).

To assess participants' sensitivity to inequality, we developed a Go-No Go task. We presented participants across a series of trials with images composed of two arrays of objects that were either equal or unequal and asked them to judge—at speed (to prevent counting)—whether the arrays were equal or unequal. We created 120 stimuli pairs (60 equal, 60 unequal), each depicting two arrays of moneybags. In each pair, one array of moneybags was presented beneath three icons of men and the other was presented beneath three icons of women. For each stimulus pair, the number of moneybags depicted below the men was either (1) equal to the number of moneybags shown below the women or (2) greater than the number of moneybags shown below the women, consistent with societal differences in gender equality. We varied the number and spatial distribution of money bags across pairs (see SI Section 3.3). We counterbalanced the task instructions participants received. In one version of the task, participants were asked to hit the space bar when the two distributions of moneybags were unequal ('Go' trials) and to refrain from hitting any key on the keyboard when the two distributions of moneybags were equal ('No Go' trials). In the other version, the instructions were reversed. Trials advanced after six seconds, or if sooner, when participants hit the space bar.

We assessed (anti-)egalitarianism using the 16-item SDO_7 scale (18). Responses were provided on a 1 ('Strongly Disagree') to 7 ('Strongly Agree') scale (α = .95).

Study 3a. We collected data from 1,027 participants using Amazon's Mechanical Turk, split about evenly between Republicans and Democrats (to ensure a wide range of SDO scores). Because we preregistered no exclusions, this number represented our final sample.

Participants completed 10 trials of a flicker task (47), including five inequality-relevant and five neutral trials, presented in a random order. Participants viewed an original image for 1 second, followed by a blank screen for 250 milliseconds. This was followed by a changed version of the original image for 350 milliseconds, followed by a second blank screen for 250 milliseconds. This sequence repeated until participants hit the spacebar to indicate they noticed the change, upon which they were asked to describe in detail what changed in the image. In inequality trials, the change involved an inequality-relevant cue (e.g., a homeless man's bag disappearing). In neutral trials, the change was irrelevant to social inequality (e.g., a message disappearing from a bus LED screen). We pretested the stimuli sets, ensuring that the changes differed significantly on perceived inequality-relevance (see SI Section 4.1).

The flickering sequence repeated at maximum 25 times before moving to the next trial, during which time participants were asked to hit the spacebar once they noticed the change. At that point (or after the 25 maximum repetitions were up), participants were asked to describe the change in detail. If participants identified the change correctly (as rated by manual coders), we reported their score for that trial as the number of views at which they hit the spacebar (e.g., 11, if they hit the space bar after 11 views of the sequence). As preregistered, if participants reported the change incorrectly, we automatically set their time for that trial at the maximum of 25 views.

We assessed (anti-)egalitarianism using the 16-item SDO_7 scale ($\alpha = .95$).

Study 3b. We collected data from 1,514 participants using Amazon's Mechanical Turk, split about evenly between Republicans and Democrats. The task procedure for Study 3b was identical to that of Study 3a except we replaced two neutral images that had relatively higher rates of inaccurate responding and updated our preregistered analytic criteria (see SI Section 4.2). We pretested all images in Study 3b to ensure that over 90% of participants correctly noticed the change for each image. As preregistered (and in contrast to Study 3a), if participants reported the change incorrectly, we ignored their time for that image. As preregistered, we excluded participants who received more than 4 'incorrect' responses across all 10 trials or more than 2 'incorrect' responses across either of the neutral or inequality-relevant trials (ensuring that for each participant there were, at minimum, times from 3 'correct' trials entering into both the inequality and neutral composites). With exclusions applied, our sample was 1,474 participants (97.4% of full sample).

We assessed (anti-)egalitarianism using the 16-item SDO_7 scale ($\alpha = .94$).

Study 4. We conducted this study with a sample of 2,130 participants using Amazon's Mechanical Turk, split about evenly between Democrats and Republicans. Of these, 1,467 provided data on all focal variables after the exclusions reported below (approximating our intended sample size of 1,600 after exclusions; see SI Section 5.2).

All participants watched a video lasting 4 minutes and 30 seconds depicting a panel of two men and two women discussing designing technology for users (see SI Section 5.4 for links to the videos). Participants were randomly assigned to one of two conditions: (1) a condition in which the men spoke 1.5x longer than the women or (2) a condition in which the women spoke 1.5x longer than the men. Within each condition, we counterbalanced the version of the video participants watched. Participants watched one of two versions of the same panel, in which we varied which gender spoke first and which gender spoke last (to vary which gender might have been more salient due to primacy or recency effects). Prior to watching the video, participants were informed that, after the video, they would be answering a series of memory questions and that the individuals who respond most accurately to those questions would receive a $50 prize. After watching the video, participants were asked to "describe, to the best of your ability, what the video was about." As preregistered, we began by excluding participants ($n = 175$) we determined as clearly not indicating knowledge of what was in the video (based on ratings from blind coders to an open-ended question asking participants to summarize the video's contents).

In addition, we excluded participants who missed an attention check embedded in our survey (*n* = 19 additional participants) and participants who our software indicated did not complete the survey in the default full screen mode (*n* = 469 additional participants), leaving us with a final sample of 1,467 participants.

We assessed (anti-)egalitarianism using the 16-item SDO_7 scale ($\alpha = .94$).

Study 5. We conducted this study with a sample of 1,603 participants using Amazon's Mechanical Turk, split about evenly between Republicans and Democrats. As preregistered, we included only the 1,394 participants (86.9%) who passed an attention check, of whom, 1,201 provided data on all focal variables.

Participants read about an organization called Connection Consulting that had just completed their hiring process. Participants saw the resumes of 56 applicants who varied across 5 dimensions (GPA, major, race, hometown, and hobby). Half of the applicants were White, and half of the applicants were racial minorities (Latino, Asian, Black). The applicants were presented in proportions consistent with racial group representation in the United States Census. After viewing each candidate's resume, participants learned whether that applicant was hired or not (see SI Figure 37 for sample stimuli). Participants were randomly assigned to one of two conditions. In both conditions, the task was structured such that GPA was correlated at +.57 with the likelihood of being hired. Candidates' GPAs ranged from 3.4 to 4.0 in 0.1 increments. Candidates were assigned to one of seven majors (assigned in equal numbers to Whites and minorities, and in equal numbers across each GPA category). In addition, candidates were assigned to one of 28 hometowns and one of 28 hobbies (each appearing once for White candidates and once for minority candidates). Across both conditions, we structured the task such that the correlation between other factors (major, hometown, hobby) and the likelihood of being hired was 0. The only difference between the two conditions was the correlation between race and likelihood of being hired: In Condition 1 (anti-minority bias), being a minority (vs. White) was correlated at -.29 with the likelihood of being hired, whereas in Condition 2 (anti-White bias), being a minority (vs. White) was correlated at +.29 with the likelihood of being hired.

We assessed (anti-)egalitarianism using the 16-item SDO_7 scale ($\alpha = .95$).

References

1. F. Alvaredo, L. Chancel, T. Piketty, E. Saez, G. Zucman. "Trends in global income inequality" in *World Inequality Report 2018* (Belknap Press, 2018), pp. 38-93.
2. N. Graf, A. Brown, E. Patten. The narrowing, but persistent, gender gap in pay. *Pew Research*. Available at https://www.pewresearch.org/fact-tank/2019/03/22/gender-pay-gap-facts/. Accessed September 16, 2020.
3. A. Hegewisch, V. Lacarte. Gender inequality, work hours, and the future of work. *Institute for Women's Policy Research*. Available at https://iwpr.org/iwpr-issues/employment-and-earnings/gender-inequality-work-hours-and-the-future-of-work/. Accessed September 16, 2020.
4. Z. Obermeyer, B. Powers, C. Vogeli, S. Mullainathan, Dissecting racial bias in an algorithm used to manage the health of populations. *Science*. **366**, 447-453 (2019). https://doi.org/10.1126/science.aax2342

5. R. Voigt et al, Language from police body camera footage shows racial disparities in officer respect. *Proc Natl Acad Sci.* **114**, 6521-6526 (2017). https://doi.org/10.1073/pnas.1702413114
6. F. Barbash. The war on 'microaggressions:' Has it created a 'victimhood culture' on campuses? *Washington Post*. Available at https://www.washingtonpost.com/news/morning-mix/wp/2015/10/28/the-war-over-words-literally-on-some-american-campuses-where-asking-where-are-you-from-is-a-microaggression/. Accessed September 16, 2020.
7. Z. Kunda, The case for motivated reasoning. *Psychol Bull*. **180**, 480-498 (1990). https://doi.org/10.1037/0033-2909.108.3.480
8. R. F. Baumeister. "The self" in *The Handbook of Social Psychology*, D. T. Gilbert, S. T. Fiske, G. Lindzey, Eds (McGraw-Hill, 1998), pp. 680-740.
9. C. Sedikides, E. A. Rudich, A. P. Gregg, M. Kumashiro, & C. Rusbult, Are normal narcissists psychologically healthy?: Self-esteem matters. *J Pers Soc Psychol*. **87**, 400-416 (2004). https://doi.org/10.1037/0022-3514.87.3.400
10. D. Dunning, M. Perie, A. L. Story, Self-serving prototypes of social categories. *J Pers Soc Psychol*. **61**, 957-968 (1991). https://doi.org/10.1037/0022-3514.61.6.957
11. P. H. Ditto, D. F. Lopez, Motivated skepticism: Use of differential decision criteria for preferred and nonpreferred conclusions. *J Pers Soc Psychol*. **63**, 568-584 (1992). https://doi.org/10.1037/0022-3514.63.4.568
12. A. Waytz, L. L Young, J. Ginges, Motive attribution asymmetry for love vs. hate drives intractable conflict. *Proc Natl Acad Sci*. **111**, 15687-15692 (2014). https://doi.org/10.1073/pnas.1414146111
13. R. P. Eibach, J. Ehrlinger, "Keep your eyes on the prize": Reference points and racial differences in assessing progress toward equality. *Pers Soc Psychol Bull*. **32**, 66-77 (2006). https://doi.org/10.1177/0146167205279585
14. C. S. Taber, M. Lodge, Motivated skepticism in the evaluation of political beliefs. *American Journal of Political Science*. **50**, 755-769 (2006). https://doi.org/10.1111/j.1540-5907.2006.00214.x
15. C. G. Lord, L. Ross, M. R. Lepper. Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. *J Pers Soc Psychol*. **37**, 2098-2109 (1979). https://doi.org/10.1037/0022-3514.37.11.2098
16. E. P. Hennes, B. C. Ruisch, I. Feygina, C. A. Monteiro, J. T. Jost, Motivated recall in the service of the economic system: The case of anthropogenic climate change. *J Exp Psychol Gen*. **145**, 755-771 (2016). https://doi.org/10.1037/xge0000148
17. D. M. Kahan, D. A. Hoffman, D. Braman, D. Evans, J. J. Rachlinski, "They saw a protest": Cognitive illiberalism and the speech-conduct distinction. *Stanford Law Review*. **64**, 851-906 (2012).
18. A. K. Ho et al, The nature of social dominance orientation: Theorizing and measuring preferences for intergroup inequality using the new SDO_7 scale. *J Pers Soc Psychol*. **109**, 1003-1028 (2015). https://doi.org/10.1037/pspi0000033
19. J. T. Jost, J. Glaser, A. W. Kruglanski, F. J. Sulloway, Political conservatism as motivated social cognition. *Psychol Bull*. **129**, 339-375 (2003). https://doi.org/10.1037/0033-2909.129.3.339

20. J. Graham, J. Haidt, B. A. Nosek, Liberals and conservatives rely on different sets of moral foundations. *J Pers Soc Psychol*. **95**, 1029-1046 (2009). https://doi.org/10.1037/a0015141
21. J. T. Crawford, L. Jussim, T. R. Cain, F. Cohen, Right-wing authoritarianism and social dominance orientation differentially predict biased evaluations of media reports. *Journal of Applied Social Psychology*. **43,** 163-174 (2013). https://doi.org/10.1111/j.1559-1816.2012.00990.x
22. M. M. Unzueta, E. D. Knowles, G. C. Ho, Diversity is what you want it to be: How social-dominance motives affect construals of diversity. *Psychol Sci*. **23**, 303-309 (2012). https://doi.org/10.1177/0956797611426727
23. R. P. Eibach, T. Keegan. Free at last? Social dominance, loss aversion, and white and black Americans' differing assessments of racial progress. *J Pers Soc Psychol*. **90**, 453-467 (2006). https://doi.org/10.1037/0022-3514.90.3.453
24. M. I. Norton, D. Ariely. Building a better America – one wealth quintile at a time. *Perspect Psychol Sci*. **6**, 9-12 (2011). https://doi.org/10.1177/1745691610393524
25. M. W. Kraus, J. M. Rucker, J. A. Richeson. Americans misperceive racial economic equality. *Proc Natl Acad Sci*. **39**, 10324-10331 (2017). https://doi.org/10.1073/pnas.1707719114
26. J. R. Chambers, L. K. Swan, M. Heesacker. Better off than we know: Distorted perceptions of incomes and income inequality in America. *Psychol Sci*. **25**, 613-618 (2014). https://doi.org/10.1177/0956797613504965
27. J. R. Chambers, L. K. Swan, M. Heesacker. Perceptions of U.S. social mobility are divided (and distorted) along ideological lines. *Psychol Sci*. **26**, 413-423 (2015). https://doi.org/10.1177/0956797614566657
28. S. Davidai, T. Gilovich. Building a more mobile America – one income quintile at a time. *Perspect Psychol Sci*. **10**, 60-71 (2015). https://doi.org/10.1177/1745691614562005
29. S. Davidai, T. Gilovich. How should we think about Americans' beliefs about economic mobility? *Judgment and Decision Making.* **13**, 297-304 (2018).
30. K. Kahn, A. K. Ho, J. Sidanius, F. Pratto. The space between us and them: Perceptions of status differences. *Group Processes and Intergroup Relations*. **12**, 591-604 (2009). https://doi.org/10.1177/1368430209338716
31. R. J. Dawtry, R. M. Sutton, C. G. Sibley. Why wealthier people think people are wealthier, and why it matters: From social sampling to attitudes to redistribution. *Psychol Sci*. **26**, 1389-1400 (2015). https://doi.org/10.1177/0956797615586560
32. N. S. Kteily, J. Sheehy-Skeffington, A. K. Ho. Hierarchy in the eye of the beholder: (Anti-)egalitarianism shapes perceived levels of social inequality. *J Pers Soc Psychol*. **112**, 136-159 (2017). https://doi.org/10.1037/pspp0000097
33. J. A. Bargh, F. Pratto. Individual construct accessibility and perceptual selection. *Journal of Experimental Social Psychology*. **22**, 293-311 (1986). https://doi.org/10.1016/0022-1031(86)90016-8
34. J. S. Bruner. On perceptual readiness. *Psychol Rev*. **64**, 123-152 (1957). https://doi.org/10.1037/h0043805
35. G. B. Moskowitz, P. Li, C. Ignarri, J. Stone. Compensatory cognition associated with egalitarian goals. *Journal of Experimental Social Psychology*. **47**, 365-370 (2011). https://doi.org/10.1016/j.jesp.2010.08.010

36. L. T. Phillips et al. Inequality in people's minds. https://psyarxiv.com/vawh9/ (26 September 2020)
37. T. Ro, C. Russell, N. Lavie. Changing faces: A detection advantage in the flicker paradigm. *Psychol Sci*. **12**, 94-99 (2001). https://doi.org/10.1111/1467-9280.00317
38. C. Summerfield, T. Egner. Expectation (and attention) in visual cognition. *Trends Cogn Sci*. **13**, 403-409 (2009). https://doi.org/10.1016/j.tics.2009.06.003
39. K. Mogg, B. P. Bradley, H. Hyare, S. Lee. Selective attention to food-related stimuli in hunger: are attentional biases specific to emotional and psychopathological states, or are they also found in normal drive states? *Behav Res Ther*. **36**, 227-237 (1998). https://doi.org/10.1016/S0005-7967(97)00062-4
40. L. C. Hogarth, K. Mogg, B. P. Bradley, T. Duka, A. Dickinson. Attentional orienting towards smoking-related stimuli. *Behav Pharmacol*. **14**, 153-160 (2003). http://dx.doi.org/10.1097/00008877-200303000-00007
41. C. N. DeWall, J. K. Maner, D. A. Rouby. Social exclusion and early-stage interpersonal perception: Selective attention to signs of acceptance. *J Pers Soc Psychol*. **96**, 729-741 (2009). https://doi.org/10.1037/a0014634
42. P. Dietze, E. D. Knowles. Social class and the motivational relevance of other human beings: Evidence from visual attention. *Psychol Sci*. **27**, 1517-1527 (2016). https://doi.org/10.1177/0956797616667721
43. G. B. Moskowitz. Preconscious effects of temporary goals on attention. *Journal of Experimental Social Psychology*. **38**, 397-404 (2002). https://doi.org/10.1016/S0022-1031(02)00001-X
44. B. J. Lucas, N. S. Kteily. (Anti-)egalitarianism differentially predicts empathy for members of advantaged versus disadvantaged groups. *J Pers Soc Psychol*. **114**, 665-692. https://doi.org/10.1037/pspa0000112
45. N. S. Kteily, M. D. Rocklage, K. McClanahan, A. K. Ho. Political ideology shapes the amplification of the accomplishments of disadvantaged vs. advantaged group members. *Proc Natl Acad Sci*. **116**, 1559-1568 (2019). https://doi.org/10.1073/pnas.1818545116
46. V. Badaan, J. T. Jost. Conceptual, empirical, and practical problems with the claim that intolerance, prejudice, and discrimination are equivalent on the political left and right. *Current Opinion in Behavioral Sciences*. **34**, 229-238 (2020). https://doi.org/10.1016/j.cobeha.2020.07.007
47. R. A. Rensink, J. K. O'Regan, J. J. Clark. To see or not to see: The need for attention to perceive changes in scenes. *Psychol Sci*. **8**, 368-373 (1997). https://doi.org/10.1111/j.1467-9280.1997.tb00427.x
48. M. W. Kraus, B. Torrez, J. W. Park, F. Ghayebi. Evidence for the reproduction of social class in brief speech. *Proc Natl Acad Sci.* **116**, 22998-23003 (2019). https://doi.org/10.1073/pnas.1900500116
49. S. Goudarzi, R. Pliskin, J. T. Jost, E. D. Knowles. Economic system justification predicts muted emotional responses to inequality. *Nat. Commun.* **11**, 383 (2020). https://doi.org/10.1038/s41467-019-14193-z
50. J. Henrich, S. J. Heine, A. Norenzayan. The weirdest people in the world? *Behav Brain Sci.* **33**, 61-83 (2010). https://doi.org/10.1017/S0140525X0999152X

Figure 1. Examples of images used in Study 1. The top row of images are examples of inequality-relevant images; the image on the left contains a luxury car (high status cue) and a homeless man with a shopping cart (low status cue) and the image on the right contains a business woman in the center (high status cue) and homeless people in the foreground (low status cue). The bottom row of images are examples of neutral images.

Figure 2. Sample stimuli from Study 2. A sample image of an 'equal' trial appears on the left; a sample image of an 'unequal' trial appears on the right. Across stimuli, and for both equal and unequal trials, we varied the total number of moneybags that appeared, and how they were visually arrayed.

Figure 3. An example of an inequality-relevant original image and changed image with the change identified.

Figure 4. Predicted probability of participants underestimating inequality in pie chart selection by condition in Study 4. A score of '0' corresponds to an accurate or overestimating selection and '1' corresponds to underestimating inequality. Note that data points on this graph are "jittered" via R to aid in visualization (values of this variable are only '0' or '1').

Figure 5. The link between social dominance orientation and each of naturalistically noticing bias (top panel) and desire to investigate 'Connection Consulting' (bottom panel) as a function of experimental condition (whether bias was against minorities or against Whites). Note that data points on both panels of the figure are "jittered" via R to aid in visualization.

Supplemental Information Appendix for **Ideology selectively shapes attention to inequality**

1. Preregistration Information

1.1 Preregistration Links

1.1.1 Study 2 preregistration - https://aspredicted.org/blind.php?x=4kj9pa
1.1.2 Study 3a preregistration – https://aspredicted.org/blind.php?x=zu8xv8
1.1.3 Study 3b preregistration - https://aspredicted.org/blind.php?x=ze84z6
1.1.4 Study 4 preregistration – https://aspredicted.org/blind.php?x=dp74ry
1.1.5 Study 5 preregistration - http://aspredicted.org/blind.php?x=m8gc9w

1.2 Deviations from Preregistration

There were no deviations from the preregistration for any of the studies, with the exception of one deviation in Study 4. In the Study 4 preregistration, we said we that we would include both dichotomous and continuous measures of (in)accuracy, but that we would prioritize our measures of 'degree' of inaccuracy over the dichotomous measures. Upon reflection, however, we later realized that, because of the structure of our task, it would be difficult to make clear inferences from one of the continuous measures of accuracy (we include details as to why in SI Appendix Section 5.5 below). We therefore decided to prioritize the dichotomous measures in the main text and included the relevant continuous measures—clarifying what inferences are and are not appropriate from these measures—in SI Appendix Section 5.6. We note that the conclusions drawn from the relevant continuous measures were consistent with the conclusions drawn from the dichotomous measures (namely, egalitarianism vs. anti-egalitarianism was associated with greater accuracy in the condition where women spoke less than men, but not in the condition where men spoke less than women).

2. Study 1

2.1 Study 1a-1e Sample Characteristics

2.1.1 Study 1a Sample

Full sample size: 227
Sample that provided data on all focal variables: 200 (88.1% of full sample)
Age: $M = 34.9$, $SD = 10.7$; Gender: 41.5% Female, 58.5% Male
Ethnicity: 148 Caucasian/White, 18 Asian/Asian American; 19 Black/African American; 9 Latino/Hispanic; 2 Native American; 4 Biracial

2.1.2 Study 1b Sample

Full sample size: 527
Sample that provided data on all focal variables: 507 (96.2% of full sample)
Age: $M = 35.8$, $SD = 10.8$; Gender: 54.4% Female, 45.4% Male
Ethnicity: 384 Caucasian/White, 32 Asian/Asian American; 48 Black/African American; 27 Latino/Hispanic; 2 Middle Eastern; 2 Native American; 9 Biracial; 1 Other; 2 n/a

2.1.3 Study 1c Sample

Full sample size: 522
Sample that provided data on all focal variables: 519 (99.4% of full sample)
Gender: 50.9% Female, 49.1% Male
Ethnicity: 481 Caucasian/White, 16 Asian, 8 Black, 2 Latino/Hispanic, 2 Middle Eastern, 8 Biracial, 2 Other

2.1.4 Study 1d Sample

Full sample size: 738
Sample that provided data on all focal variables: 607 (82.2% of full sample)
Age: $M = 35.7$, $SD = 10.9$; Gender: 49.3% Female, 50.7% Male
Ethnicity: 449 Caucasian/White, 45 Asian/Asian American; 55 Black/African American; 35 Latino/Hispanic; 2 Middle Eastern; 4 Native American; 19 Biracial; 1 Other

2.1.5 Study 1e Sample

Full wave 1 sample: 571
Sample that provided data on all focal variables: 368 (64.4% of full sample)
Age: $M = 38.9$, $SD = 12.9$; Gender: 56.5% Female, 43.5% Male
Ethnicity: 274 Caucasian/White, 25 Asian/Asian American; 15 Black/African American; 16 Latino/Hispanic; 2 Native American; 11 Biracial; 2 Other, 23 n/a

2.2 Study 1a-e Coding and Scale Reliabilities

2.2.1 Study 1a

SDO scale reliability: $\alpha = .95$
Coding reliability: Direct Inequality code ($\kappa = .95$), High Status code ($\kappa = .70$), Low Status code ($\kappa = .84$)

2.2.2 Study 1b

SDO scale reliability: $\alpha = .92$
Coding reliability: Direct Inequality code ($\kappa = .77$), High Status code ($\kappa = .81$), Low Status code ($\kappa = .76$)

2.2.3 Study 1c

SDO scale reliability: $\alpha = .85$
Coding reliability: Direct Inequality code ($\kappa = .89$), High Status code ($\kappa = .92$), Low Status code ($\kappa = .81$)

2.2.4 Study 1d

SDO scale reliability: $\alpha = .95$
Coding reliability: Direct Inequality code ($\kappa = .77$), High Status code ($\kappa = .88$), Low Status code ($\kappa = .80$)

2.2.5 Study 1e

SDO scale reliability: $\alpha = .94$
Coding reliability: Direct Inequality code ($\kappa = .71$), High Status code ($\kappa = .79$), Low Status code ($\kappa = .78$)

2.3 Study 1a-1e Sensitivity Analyses

Sensitivity analyses suggested that with these sample sizes, we had 80% power to detect a correlation of $r = .20$ (Sample 1a), $r = .12$ (Sample 1b), $r = .12$ (Sample 1c), $r = .11$ (Sample 1d), and $r = .15$ (Sample 1e).

2.4 Study 1a-1e Images

2.4.1 Study 1a Images

SI Figure 1. The first three images are the inequality-relevant images, and the second three images are the distractor images.

2.4.2 Study 1b-1c Images

SI Figure 2. The first three images are the inequality-relevant images, and the second three images are the distractor images (here, referencing a separate social issue, environmental damage).

2.4.3 Study 1d Images


News


586415398


STAFF

SI Figure 3. The first five images are the inequality-relevant images, and the second five images are the distractor images.

2.4.4 Study 1e Images

SI Figure 4. The first four images are the inequality-relevant images, and the next four images are the distractor images.

2.5 Study 1 Coding Scheme Information

We developed a coding scheme to analyze participants' open-ended responses. First, we examined direct mentions of inequality, in which participants explicitly remarked on the inequality in the image (*Direct Inequality*). Participant responses were coded as '1' for *Direct Inequality* if the response explicitly mentioned status differences in the image or remarked explicitly on the fact that the scene depicted inequality (if not, the response was coded as '0'). Next, we focused on indirect indices of attention to inequality. Each inequality-relevant image contained certain cues associated with high status (e.g., women receiving pedicures, luxury car) and other cues associated with low status (e.g., nail salon employees, a homeless person). Beyond directly commenting on inequality, individuals might indirectly reveal themselves to have noticed inequality in an image by mentioning both a high *and* low status cue within the same image (*Indirect Inequality*). If participant responses mentioned both high and low status cues for an inequality-relevant image, we gave the response a score of '1' for the *Indirect Inequality* category; if participant responses mentioned only high or low status cues (or neither), we scored the response a '0'. Although we were centrally interested in attention to inequality *per se*, we also examined, in exploratory analyses, the extent to which participants reported ('1') or failed to report ('0') high status and low status cues separately (see SI Figures 9-12).

To illustrate this coding scheme in more detail, we will use an example image from Study 1e, particularly, the image containing the yellow luxury car and the man on the rickshaw (see the third image in SI Figure 4). Examples of the types of responses that received a '1' on *Direct Inequality* were: "I see a divide between two classes. The yellow car represents wealth and entitlement while the man powered bike represent hard work and tough times. It hits home of the inequality of wealth in this location" and "the inequality embodied in an image." Participants received a '1' for high status cues when they remarked explicitly on the luxury car (e.g., "fancy car") and received a '1' for low status cues when they remarked explicitly on the rickshaw (e.g., "the old bike"). Note that the above response "I see a divide between two classes. The yellow car represents wealth and entitlement while the man powered bike represents hard work and tough times. It hits home of the inequality of wealth in this location" would also receive a '1' for high status cues (e.g., "the yellow car represents wealth") and a '1' for low status cues (e.g., "man powered bike"). And thus, this response would also receive a '1' on *Indirect Inequality.*

2.6 Study 1e Attrition Analyses.

We conducted attrition analyses to compare those who completed only wave 1 with those who completed both waves. The two sets of participants did not significantly differ in SDO scores, F (1, 569) = 2.65, p = .10 or gender, χ^2 (2, N = 552) = 2.25, p = .13. The only exception was age, where we observed that participants who completed both waves were slightly older than those who completed only wave 1, F (1, 545) = 4.69, p = .03

(controlling for age did not affect our main findings). Thus, those completing both waves did not differ markedly from those who completed only wave 1.

2.7 Study 1 Supplemental Results

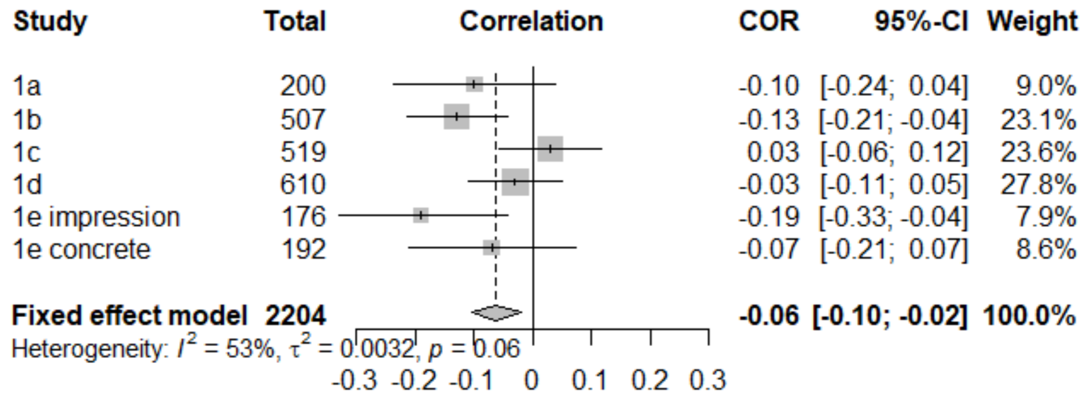
Correlation between SDO and Inequality Cues by Sample

	Direct Inequality	Indirect Inequality	High Status Cues	Low Status Cues
Sample 1a	-.10	-.07	-.05	-.13†
Sample 1b	-.13**	-.10*	-.01	-.11*
Sample 1c	.03	.01	.01	-.02
Sample 1d	-.03	-.09*	-.06	-.11**
Sample 1e – Concrete Details condition	-.07	-.19**	-.14†	-.20**
Sample 1e – General Impression condition	-.19*	-.06	-.07	-.08

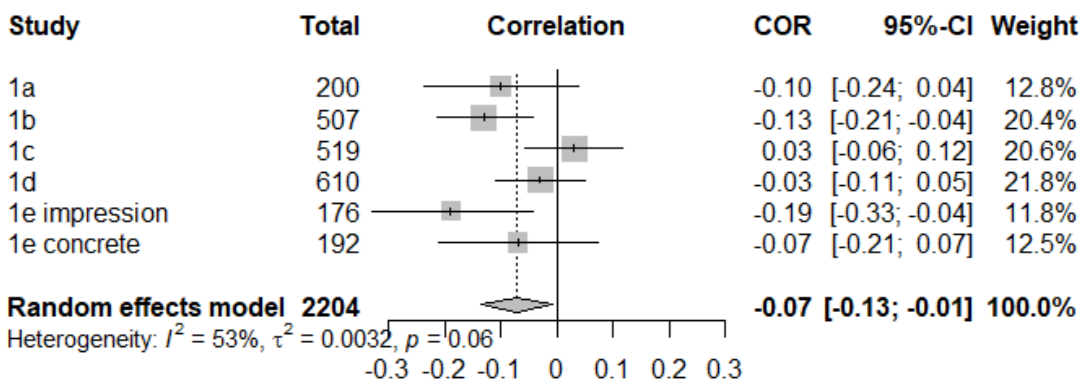
Note: † p < .1. * p <.05. ** p < .01.

We reasoned in Study 1e that the link between SDO and Direct Inequality might be somewhat stronger when the task instructions asked for participants' general impressions of the images (vs. requesting three concrete details that stood out) and that the reverse might be true for the relationship between SDO and Indirect Inequality. The patterns we observed were directionally consistent with this, but the interactions between SDO and task instruction condition (i.e., concrete details vs. general impressions) were not statistically significant (Direct Inequality: b = -.09, p = .24; Indirect Inequality: b = .10, p = .20).

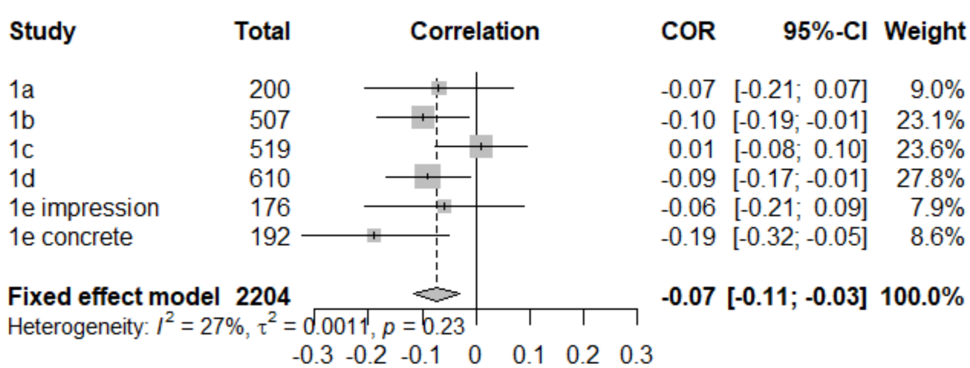
2.8 Study 1 Forest Plots



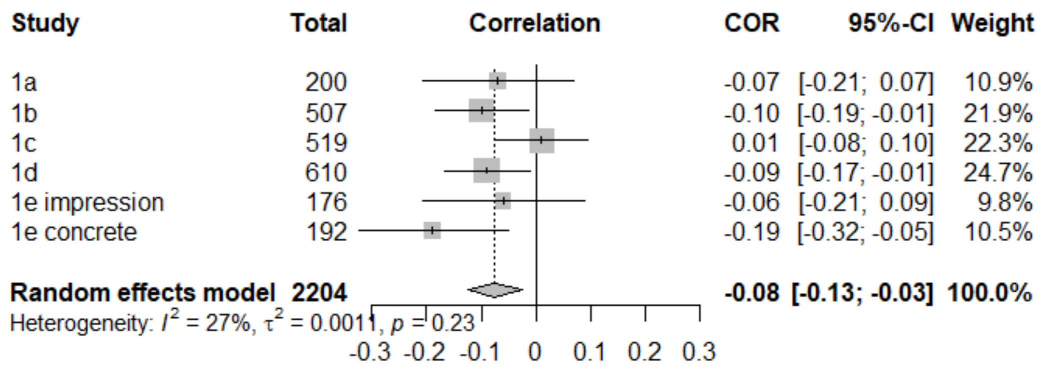
SI Figure 5. Forest plot of *direct inequality* fixed effects meta-analysis



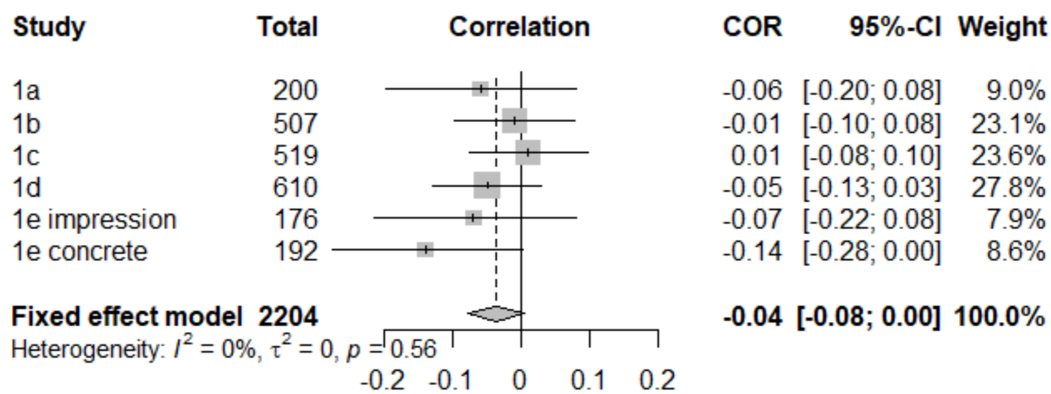
SI Figure 6. Forest plot of *direct inequality* random effects meta-analysis



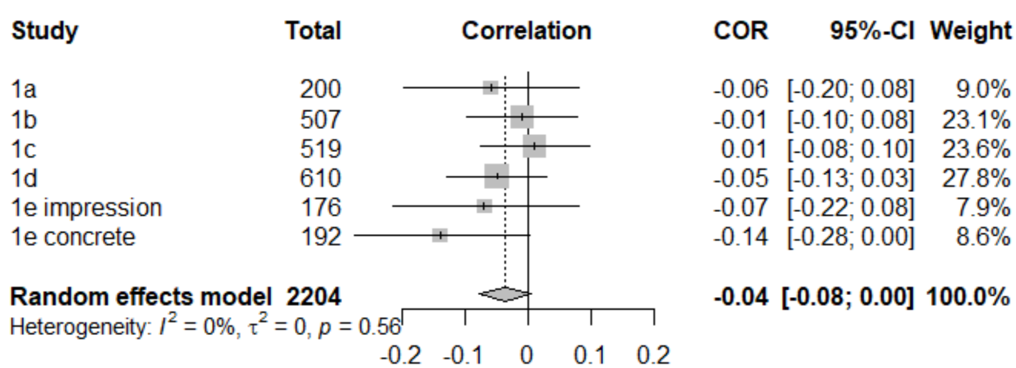
SI Figure 7. Forest plot of *indirect inequality* fixed effects meta-analysis



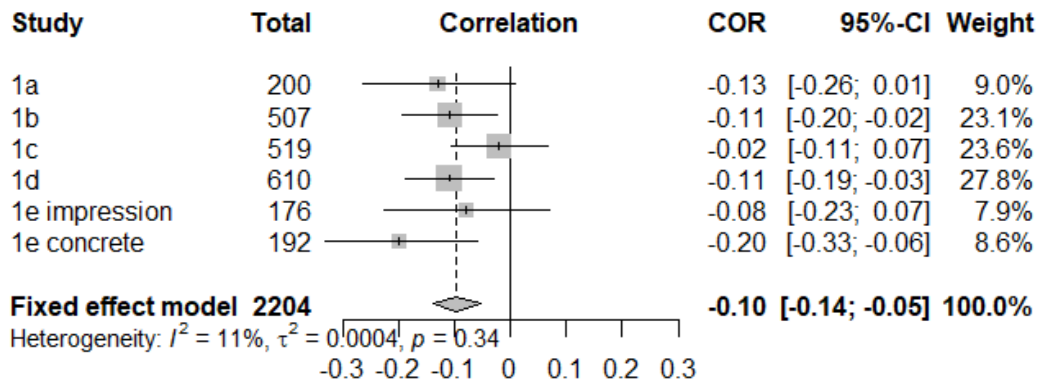
SI Figure 8. Forest plot of *indirect inequality* random effects meta-analysis



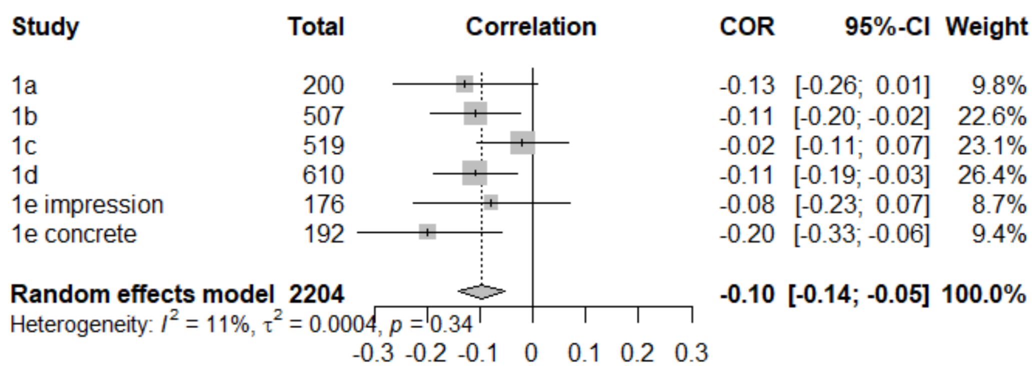
SI Figure 9. Forest plot of *high-status cues* fixed effects meta-analysis



SI Figure 10. Forest plot of *high-status cues* random effects meta-analysis



SI Figure 11. Forest plot of *low-status cues* fixed effects meta-analysis



SI Figure 12. Forest plot of *low-status cues* random effects meta-analysis

3. Study 2

3.1 Study 2 Sample Characteristics

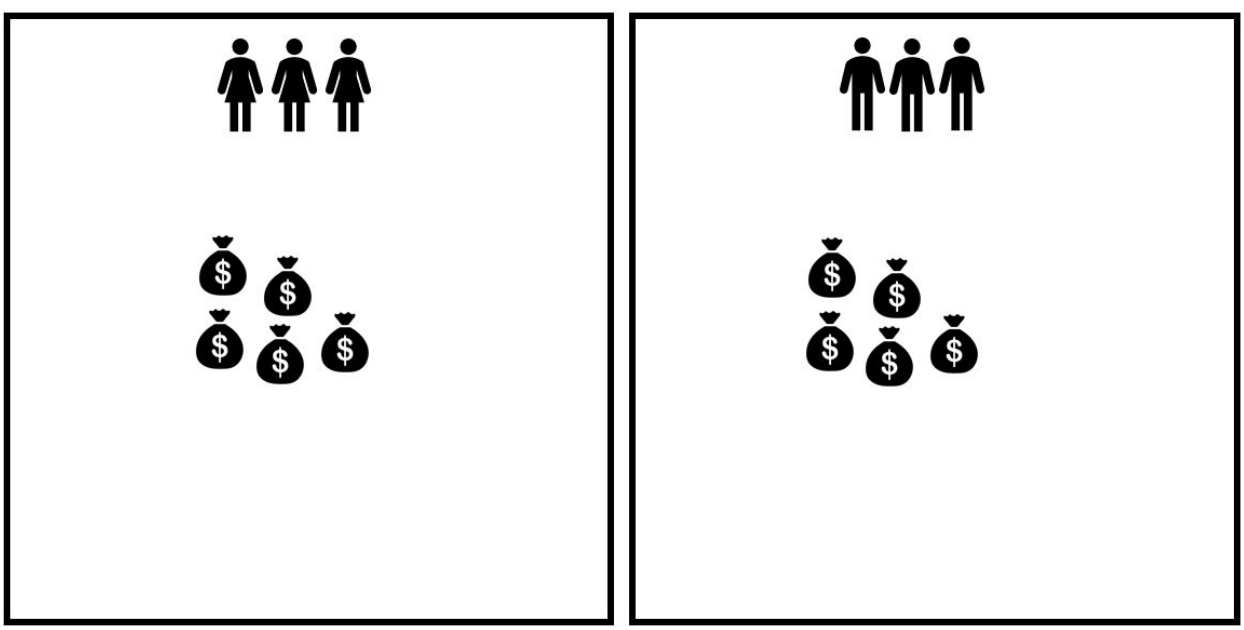
Full sample size: 1,591
Sample size with exclusions: 1,406 (88.4% of original sample)
Age: M = 40.1, SD = 12.7; Gender: 61.9% Female, 37.9% Male, .2% Other
Ethnicity: 1,120 Caucasian/White, 74 Asian/Asian American; 110 Black/African American; 62 Latino/Hispanic; 7 Native American; 28 Biracial, 1 Middle Eastern, 3 Other, 1 n/a
SDO scale reliability: α = .95

3.2 Study 2 Power Analysis

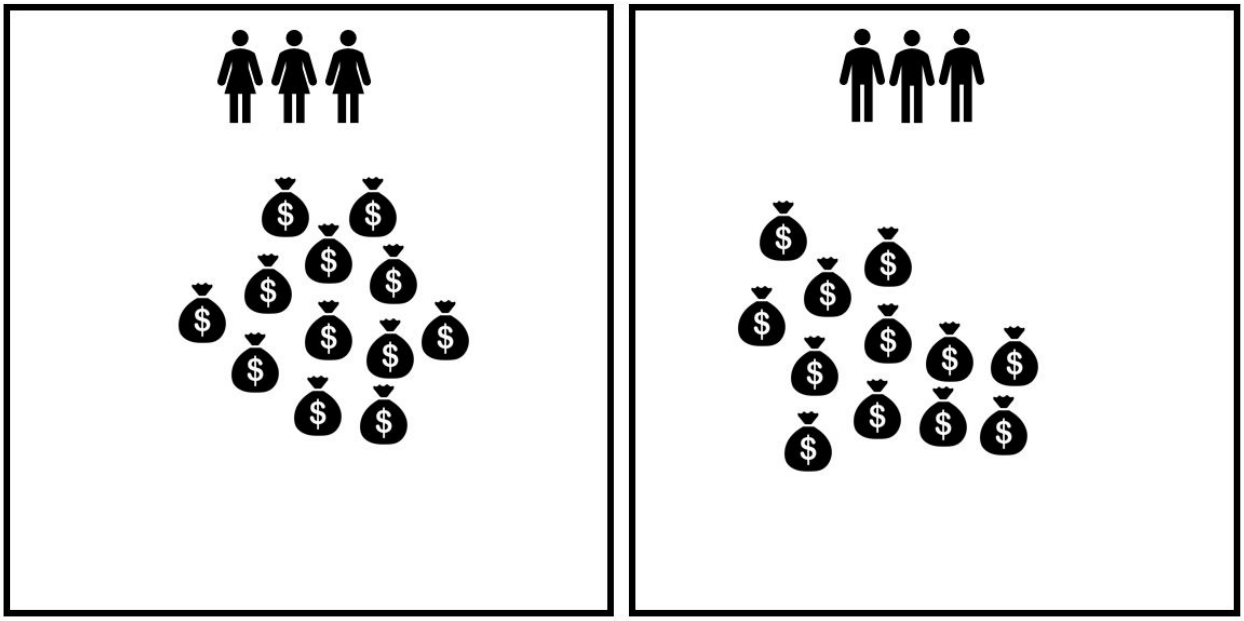
To detect an association of $r = .10$ with 80% power, the required sample size was roughly 780 participants. Because we had two versions of the task, we aimed to collect data from 1,600 participants (approximately 800 participants per task version).

3.3 Stimuli Development

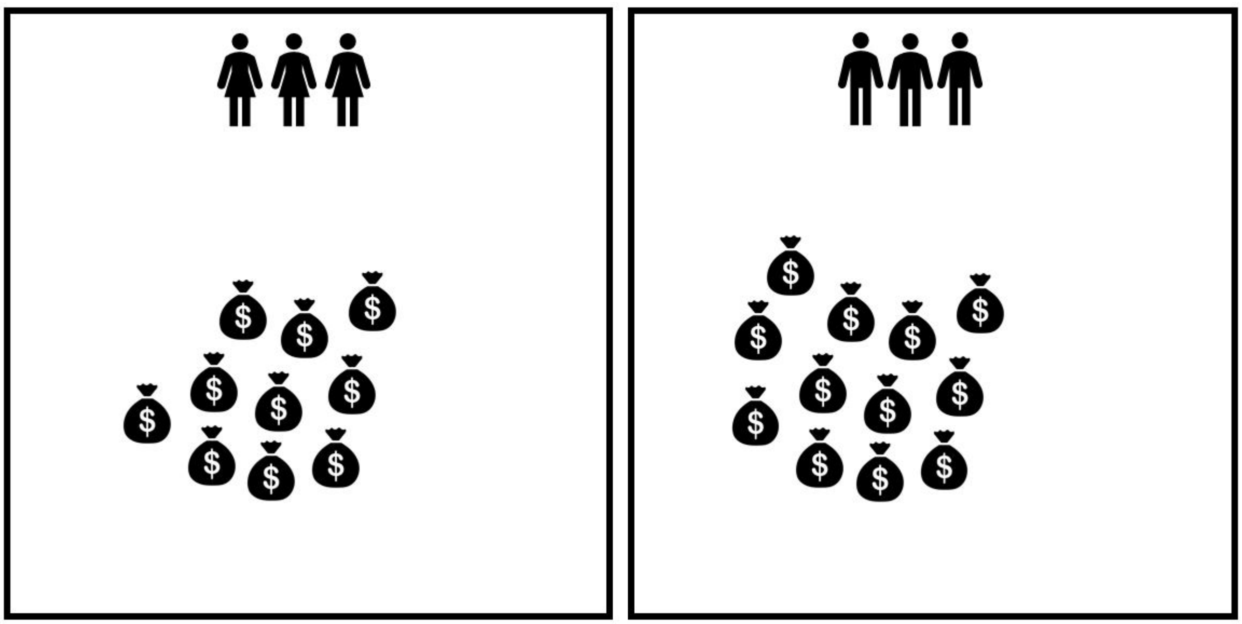
We developed a large set of stimuli (120 trials) that varied on three key dimensions: (1) the overall number of moneybags, (2) the proportion by which the moneybags differed from equality, and (3) whether the two arrays of moneybags shared a structural 'base' (see figures below for examples). The number of moneybags ranged from 5 to 45 items per array. The 'equal' image pairs depicted an equal number of moneybags in each array, but we systematically varied the proportion of difference in the unequal trials. One 'class' of unequal pairs differed by an amount less than 20% and a second type differed by an amount between 20% and 30%. For example, an image pair that had 20 moneybags in one array and 25 in another would differ by 25% (thereby falling into the second 'class' of images). Finally, we varied whether the two images in each pair came from the 'same' or 'different' structural base, reflecting how the moneybags were spatially arranged across the screen. Image pairs with the 'same' base had an identical arrangement across the screen: for equal trials, the two arrays were identical copies of one another; for unequal trials, we created a larger array and then simply deleted some of the moneybags to create the smaller array. Image pairs with a 'different' structural base had different spatial arrangements of moneybags. For example, even when the arrays had an equal number of moneybags, they were organized differently. The same was true for unequal different base trials.



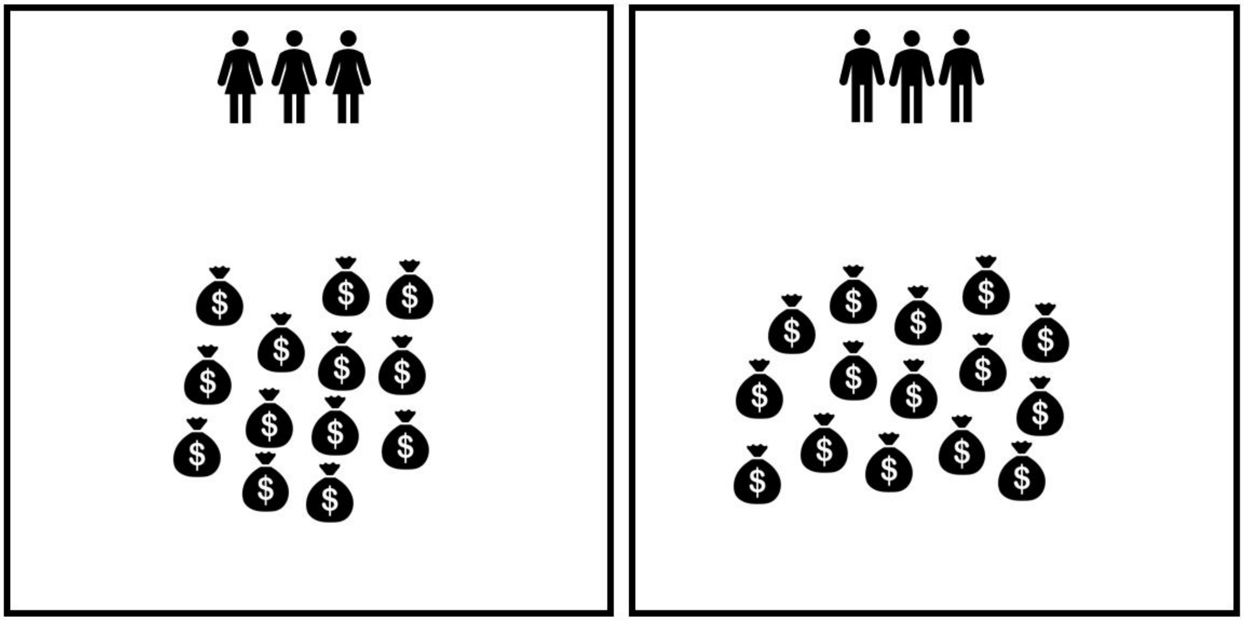
SI Figure 13. Example of an equal trial with 'same' structural base.



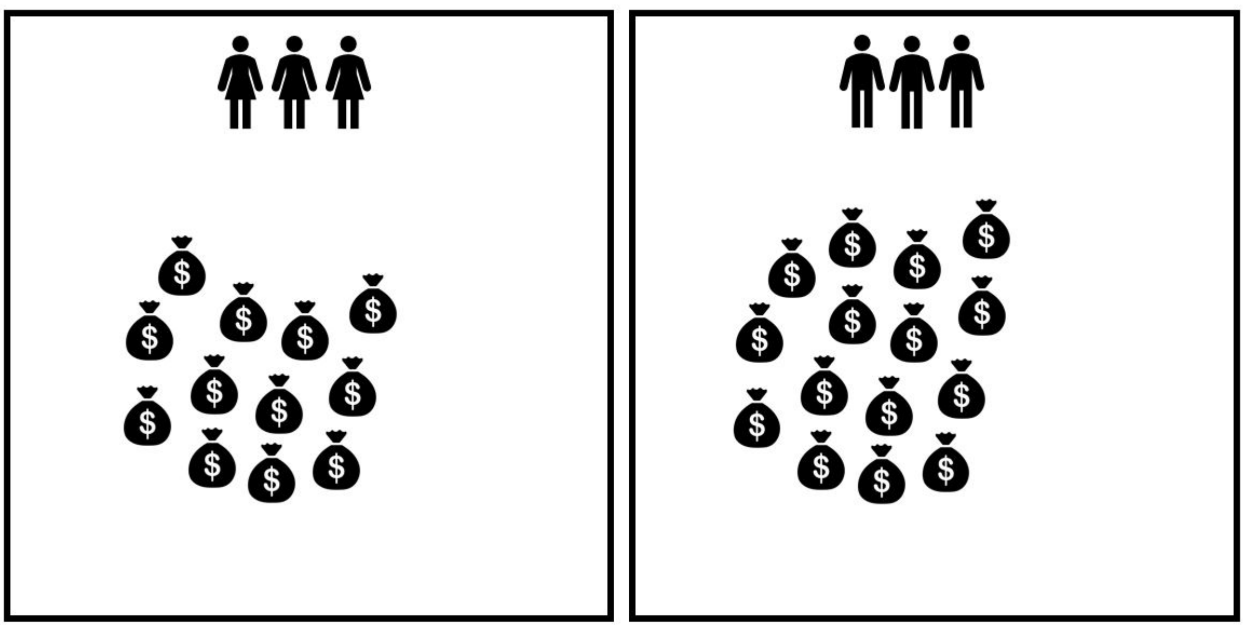
SI Figure 14. Example of an equal trial with ‘different’ structural base



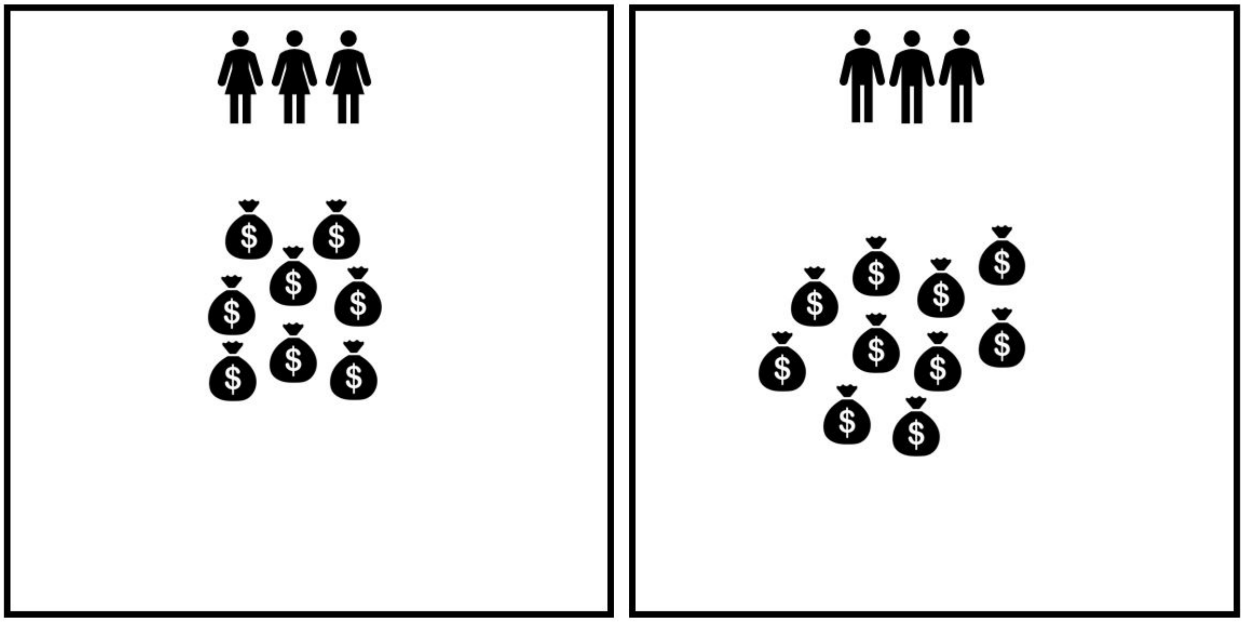
SI Figure 15. Example of an unequal trial with ‘same’ structural base with difference under 20%



SI Figure 16. Example of an unequal trial with ‘different’ structural base with difference under 20%



SI Figure 17. Example of an unequal trial with ‘same’ structural base with difference between 20% and 30%



SI Figure 18. Example of an unequal trial with 'different' structural base with difference between 20% and 30%

3.4 Consecutive Response Exclusion

We preregistered one central exclusion criterion: Based on a 1000-round simulation of the 120-trial task, we determined that the likelihood of having 17 'Go' trials or 'No Go' trials in a row was highly statistically improbable (less than .001%). Thus, we planned to exclude participants who had over 17 consecutive 'Go' responses or 'No Go' responses, reasoning that that likely reflected inattentive responding (which could, if correlated with SDO, artificially inflate negative correlations between SDO and accuracy).

We obtained consistent results among the full sample of participants (i.e., including those with over 17 consecutive 'Go' responses or 'No Go' responses): The correlation between SDO and *d*' was significant, r = -.10, p < .001, and the correlation between SDO and *c* was not significant, r = .01, p = .65.

3.5 Results by Task Condition

In the version of the task where participants were asked to hit the space bar when the two arrays were equal and refrain from hitting any keys otherwise, we found that SDO was negatively correlated with *d'*, however, this relationship was not significant, r = -.06, p = .14. The relationship between SDO and *c* was not significant, r = - .02, p = .54.

In the version of the task where participants were asked to hit the space bar when the two arrays were *not* equal to one another and refrain from hitting any keys otherwise, we found a significant negative relationship between SDO and *d'*, $r = -.11$, $p = .006$. The relationship between SDO and *c* was not significant, $r = .01$, $p = .90$.

4. Study 3

4.1 Study 3a Supplemental Information

4.1.1 Study 3a Sample Characteristics

Sample that provided data on all focal variables: 1,027

Age: $M = 40.8$, $SD = 12.6$; Gender: 55.3% Female, 44.7% Male

Ethnicity: 828 Caucasian/White, 45 Asian/Asian American; 74 Black/African American; 48 Latino/Hispanic; 8 Native American; 18 Biracial/Mixed Race, 3 Middle Eastern, 3 Other

4.1.2 Study 3a Power Analysis. To detect an association of $\beta = .10$ using linear multiple regression with a two-tailed test and 90% power, the suggested sample size was 1,046.

4.1.3 Study 3a Pilot. We conducted a pilot test with 60 participants to ensure that the vast majority of participants were able to correctly identify the changes in each image. We also measured the average number of times participants viewed the flickering sequence before identifying the change (avg number of repeats).

	% Correctly identifying change	Avg number of repeats (sd)
Inequality image 1	90.0%	6.8 (7.2)
Inequality image 2	96.7%	6.1 (5.5)
Inequality image 3	90.0%	7.4 (6.9)
Inequality image 4	91.7%	5.9 (6.2)
Inequality image 5	95.0%	4.8 (6.3)
Neutral image 1	86.7%	9.1 (8.3)
Neutral image 2	96.7%	4.4 (4.4)
Neutral image 3	96.7%	4.7 (4.6)
Neutral image 4	96.7%	5.1 (4.6)
Neutral image 5	88.3%	9.9 (6.9)

Finally, we asked a separate sample of 58 participants to indicate their agreement with the following, "This image is relevant to inequality" on a scale from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*).

	Avg Relevance to Inequality

Inequality image set	4.4
Neutral image set	2.7

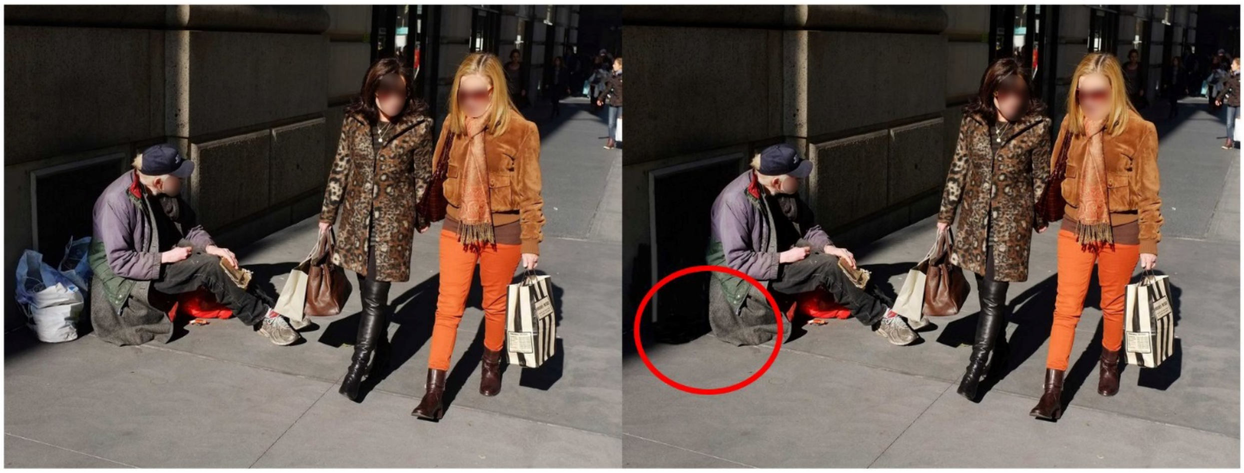
Paired samples t-test, $t\ (57) = 8.16$, $p < .001$

4.1.4 Study 3a Images

SI Figure 19. Inequality image 1

SI Figure 20. Inequality image 2

SI Figure 21. Inequality image 3



SI Figure 22. Inequality image 4

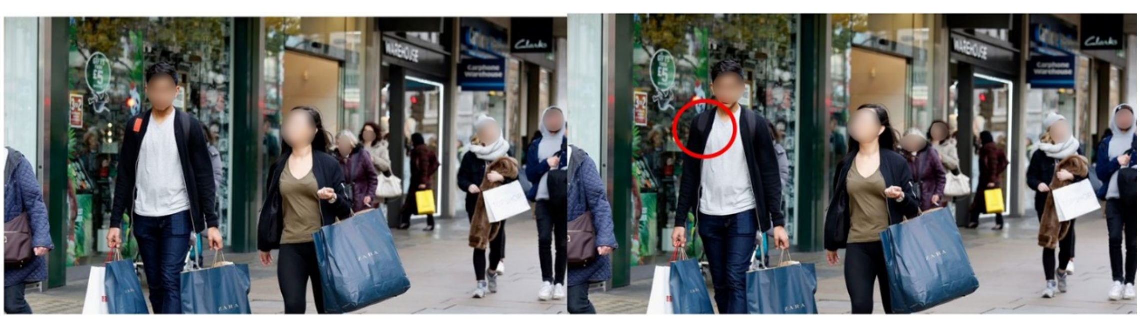
SI Figure 23. Inequality image 5

SI Figure 24. Neutral image 1

SI Figure 25. Neutral image 2

SI Figure 26. Neutral image 3

SI Figure 27. Neutral image 4



SI Figure 28. Neutral image 5

4.1.5 Study 3a Supplemental Results by Image

	% Correctly identifying change	Avg number of repeats (sd)
Inequality image 1	95.0%	6.0 (5.8)
Inequality image 2	97.3%	5.4 (4.6)
Inequality image 3	92.5%	6.8 (6.5)
Inequality image 4	98.0%	5.1 (4.2)
Inequality image 5	95.4%	4.6 (5.6)
Neutral image 1	78.1%	10.6 (8.9)
Neutral image 2	97.8%	4.6 (4.4)
Neutral image 3	98.0%	4.3 (4.4)
Neutral image 4	98.5%	5.1 (3.9)
Neutral image 5	83.3%	11.4 (7.9)

4.2 Study 3b Updated Exclusion Criteria and Rationale

As noted in the main text, using our preregistered analysis plan for Study 3a, we found our expected positive correlation between SDO and the average number of views for inequality images ($r = .15$, $p < .001$), which held even when controlling for the average number of repeats for neutral images ($b = .08$, $t\,(1024) = 3.07$, $p = .002$). This suggests that individuals lower in SDO were more attentive to inequality (i.e., needed less time to identify the inequality-relevant change) and that this could not be accounted for controlling for more general attentiveness on the task (i.e., performance on neutral trials). Despite this supportive evidence, we reasoned that our preregistered analysis plan of setting incorrect trials to the maximum score of 25 risked confounding attention to a particular cue (as indexed by a lower number of views) with accuracy in identifying that cue (a failure of which is treated as equivalent to 25 views). If individuals higher in SDO generally tended to be less correct across all trials, then these individuals would also receive slower times, potentially confounding accuracy and attention (there was some evidence suggesting a correlation between SDO and accuracy when we assessed accuracy as getting all 10 trials correct: $r = -.12$, $p < .001$; but not when assessing accuracy as getting 8 or 9 trials correct: $r = .05$, $p = .15$, and $r = .04$, $p = .16$, respectively). In addition, we found that whereas over 92% of responses were accurate for eight of the images, participants had more difficulty correctly identifying the change in two of our neutral images (i.e., Neutral Images 1 and 5; accuracies of 78% and 83%, respectively).

With these aspects of Study 3a in mind, we replicated our results among a new sample of 1,514 participants in Study 3b. We updated our neutral images and ensured, using pre-testing, that the overwhelming majority of participants would (after some, varying, number of presentations) be able to *correctly* identify the change (indeed, all images in Study 3b had a 91% or higher rate of correct responses). We also revised our preregistered exclusion criteria to make them less susceptible to accuracy concerns. In particular, we included times *only* from trials on which participants correctly identified the change, and restricted our analyses to participants who had a high overall rate of accuracy (at least 3 in 5 accurate responses in each of the neutral and 'inequality-relevant' categories). Of note, this exclusion criterion makes for a highly conservative test, insofar as it excludes trials in which individuals high in SDO failed to get a correct response *because* of inattention to inequality. With our exclusion criteria applied, our sample was 1,474 participants (97.4% of our original sample). See also SI Sections 4.4 and 4.5 for additional robustness checks, analyzing our results in a variety of different ways.

4.3 Study 3b Supplemental Information

4.3.1 Study 3b Sample Characteristics

Full sample: 1,514

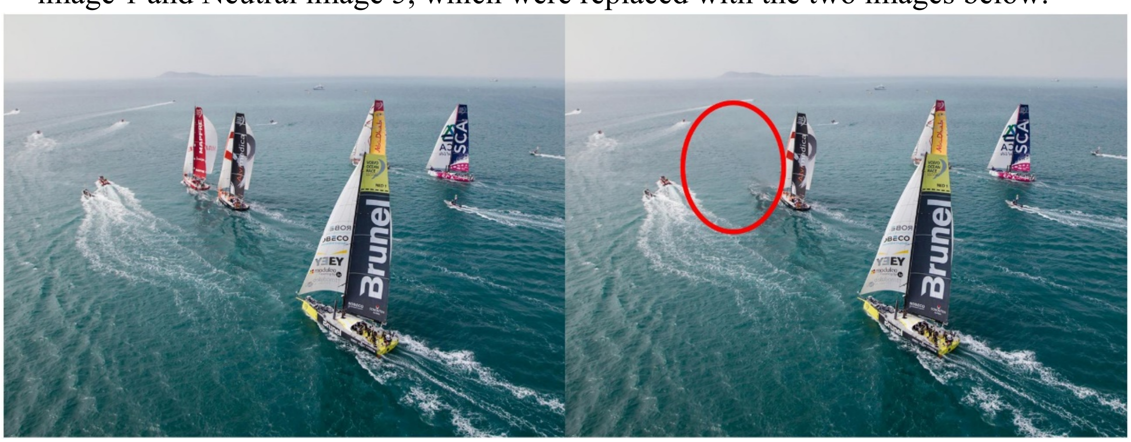
Sample after exclusions: 1,474 (97.4% of full sample)

Age: *M* = 37.6, *SD* = 12.1; Gender: 50% Female, 50% Male

Ethnicity: 1,085 Caucasian/White, 109 Asian/Asian American; 140 Black/African American; 82 Latino/Hispanic; 17 Native American; 37 Biracial/Mixed Race, 3 Middle Eastern, 1 Other

4.3.2 Study 3b Power Analysis. To detect an association of β = .10 using linear multiple regression with a two-tailed test and 95% power, the suggested sample size was 1,293.

4.3.3 Study 3b Updated Images. All stimuli were identical to Study 3a except for Neutral image 1 and Neutral image 5, which were replaced with the two images below.



SI Figure 29. Updated neutral image 1

SI Figure 30. Updated neutral image 5

4.3.4 Study 3b Supplemental Results by Image

Image	% Correctly identifying the change	Avg number of repeats (SD)
Inequality 1	94.6%	5.5 (4.5)
Inequality 2	97.3%	4.7 (3.9)
Inequality 3	91.6%	6.0 (5.7)
Inequality 4	97.2%	4.6 (3.7)
Inequality 5	94.6%	4.3 (4.9)
Neutral image 1	97.7%	4.8 (3.9)
Neutral image 2	97.7%	4.2 (3.7)
Neutral image 3	96.8%	3.9 (3.5)
Neutral image 4	98.2%	4.7 (3.4)
Neutral image 5	96.6%	5.3 (4.9)

4.4 Study 3 Robustness Checks

Analysis of Study 3b data using Study 3a's preregistered analysis plan. When analyzing Study 3b's data using Study 3a's preregistered analysis plan (i.e., retaining all participants; setting the number of repeats on incorrect trials to the max of 25 repeats), we find a positive correlation between SDO and the average number of views for inequality images (r = .17, p < .001), which holds when controlling for the average number of views for neutral images (b = .07, t (1507) = 3.96, p < .001).

Analysis of Study 3a data using Study 3b's preregistered analysis plan. When analyzing Study 3a using Study 3b's preregistered analysis plan (including times *only* from trials on which participants correctly identified the change, and including *only* those participants who had a high overall rate of accuracy with at least 3 in 5 accurate responses in each of the neutral and 'inequality-relevant' categories), we find a positive correlation between SDO and the average number of views for inequality images ($r = .10$, $p = .002$), which holds when controlling for the average number of views for neutral images ($b = .084$, $t\ (1000) = 3.17$, $p = .002$).

Analysis of Study 3a and 3b data using only times on accurate trials, but retaining all participants. When analyzing Study 3b while using only times on accurate trials but retaining all participants, we find a positive correlation between SDO and the average number of views for inequality images ($r = .13$, $p < .001$), which holds when controlling for the average number of views for neutral images ($b = .042$, $t\ (1493) = 2.28$, $p = .023$). Analyzing Study 3a using this same analytic criteria yields a positive correlation between SDO and the average number of views for inequality images ($r = .10$, $p = .001$), which holds when controlling for the average number of views on neutral images ($b = .086$, $t\ (1020) = 3.30$, $p = .001$). These relationships remain robust when meta-analyzing across both studies (zero order: $r = .12$, $z = 5.93$, $p < .001$, controlling for neutral trials: $b = .06$, $z = 3.00$, $p = .003$).

Analyses using log-transformed versions of average inequality views and average neutral views. When we examined the distribution of the average number of inequality views and the average number of neutral views, we observed that these variables were right-skewed (Study 3a: inequality repeats, skewness = 2.44; neutral repeats, skewness = 1.27; Study 3b: inequality repeats, skewness = 3.45; neutral repeats, skewness = 3.70). As a robustness check, we therefore conducted our analyses again after log-transforming these variables (in all cases, the log-transformed variables had a skewness statistic below 1).

All regression analyses reported in this section use OLS regression. Using our preregistered analysis plan for Study 3a to analyze the Study 3a data, we find our expected positive correlation between SDO and the logged average number of views for inequality images ($r = .13$, $p < .001$), which held even when controlling for the logged average number of views for neutral images ($b = .087$, $t\ (1024) = 3.08$, $p = .002$).

Using our preregistered analysis plan for Study 3b to analyze the Study 3b data, we find our expected positive correlation between SDO and the logged average number of views for inequality images ($r = .09$, $p < .001$), which held when controlling for the logged average number of views for neutral images ($b = .042$, $t\ (1471) = 1.98$, $p = .048$).

As we did in the main analyses, we analyzed Study 3a's data again using our preregistered analysis plan for Study 3b. We again find a positive correlation between SDO and the logged average number of views for inequality images ($r = .09$, $p = .006$), which held when controlling for the logged average number of views for neutral images ($b = .081$, $t\ (1000) = 2.90$, $p = .004$).

These relationships were robust both when meta-analyzing the results of Studies 3a and 3b using each study's unique preregistration criteria (zero-order: $r = .11$, $z = 5.34$, $p < .001$, controlling for neutral trials: $b = .06$, $z = 3.03$, $p = .003$) and when analyzing both studies using Study 3b's preregistration criteria (zero-order: $r = .09$, $z = 4.49$, $p < .001$, controlling for neutral trials: $b = .06$, $z = 2.87$, $p = .004$).

4.5 Study 3 Analyses Controlling for Inaccuracy

Analysis of Study 3a and 3b data controlling for the number of inaccurate responses. We additionally considered the relationship between SDO and the average number of inequality views while controlling for the average number of neutral views and for the number of trials participants answered incorrectly (log-transformed given right-skew). When analyzing Study 3a data, we find that there is a significant relationship between SDO and the logged average inequality repeats controlling for the logged average number of views on neutral images and the logged total number of trials participants answered incorrectly ($b = .060$, $t\,(1023) = 2.12$, $p = .034$). Conducting this same analysis with Study 3b's data yields a marginally significant relationship between SDO and the logged average inequality repeats ($b = .039$, $t\,(1510) = 1.86$, $p = .06$). This relationship remains robust when meta-analyzing across the two samples, $b = .05$, $z = 2.39$, $p = .02$.

5. Study 4

5.1 Study 4 Sample Characteristics

Full sample size: 2,130
Sample that passed all three exclusions (described in detail below): 1,467 (68.8% of full sample).
Age: $M = 38.9$, $SD = 12.4$; Gender: 56.6% Female, 42.9% Male, .5% Other
Ethnicity: 1,084 Caucasian/White, 116 Asian/Asian American; 119 Black/African American; 91 Latino/Hispanic; 4 Native American; 39 Biracial/Mixed Race, 5 Middle Eastern, 9 Other

5.2 Study 4 Exclusion Criteria

We preregistered that we would exclude participants we determined (based on ratings from blind coders to our question asking participants to summarize what the video was about) as clearly not indicating knowledge of what was in the video. Of the 2,130 participants who completed the task, 1,955 passed the first exclusion based on their description of what was in the video (91.8% of full sample). In addition, we planned to exclude participants who missed an attention check embedded in our survey. Of the 2,130 participants who completed the task, 2,090 passed the attention check (98.1%). Finally, we preregistered that we would exclude participants who did not complete the survey in the default full screen mode (our survey platform records whether participants close the full screen). Of the original 2,130 participants, 1,569 kept the task in full screen mode (73.7%). In total, 1,467 participants passed all three exclusion criteria (68.8% of the full sample).

5.3 Study 4 Power Analysis

Based on a correlation of $r = .10$ between SDO and perceptions of unequal talking time in any given condition, we needed about 780 participants to achieve 80% power. Following our preregistration plan, we sought to collect data from 800 participants per condition, for a total of 1,600 participants. This sample size was intended to be based on the number of participants after our exclusion criteria was met.

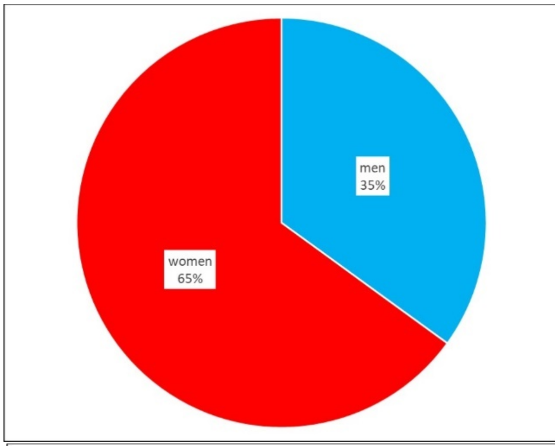
5.4 Study 4 Video Stimuli

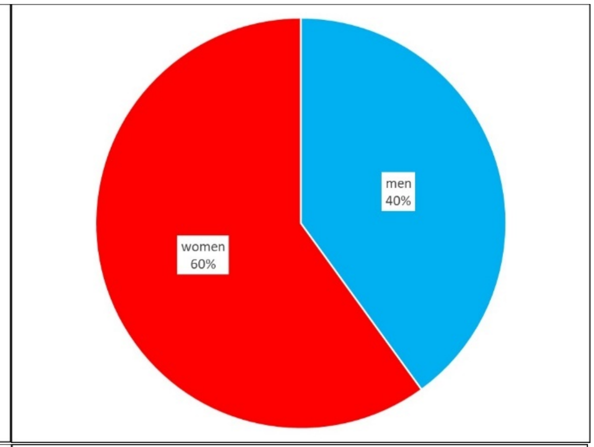
To develop the video stimuli, we began by finding a video of an inequality-irrelevant panel discussion with equal numbers of men and women on the panel. We chose a 34-minute video of a panel discussing designing technology for users that consisted of two men and two women. From the 34-minute video, we created two sets of approximately 4 minute and 30 second videos (four videos total)– one set of videos in which the men on the panel spoke 1.5x as long as the women and a second set of videos in which the women on the panel spoke 1.5x as long as the men. Recognizing the potential for primacy and recency effect, we counterbalanced which gender spoke first and last. In the set of videos where men spoke more than women, in one video, a woman spoke first and a man spoke last and in the other, a man spoke first and a woman spoke last. We similarly varied gender speaking order in the set of videos where women spoke more than men; one video began with a woman speaking and ended with a man speaking and the other began with a man speaking and ended with a woman speaking. Instead of splicing the precise same video clips together in a different order for each video (and having the videos be nonsensical), we used a different 4 minute 30 second portion of the 34-minute video, in order to have more naturalistic stimuli.

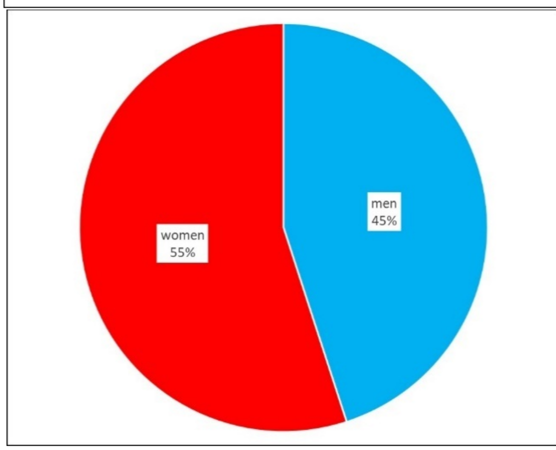
All four of the videos can be found at the following link: https://osf.io/e9j28/?view_only=e8c59a43cf6444b7a57c867ea08a7209.

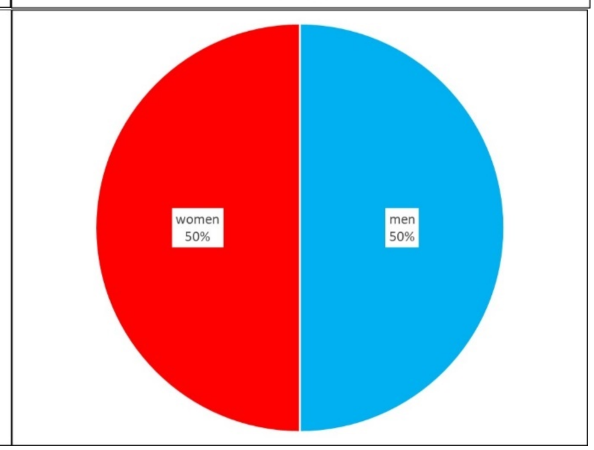
5.5 Study 4 Key DV

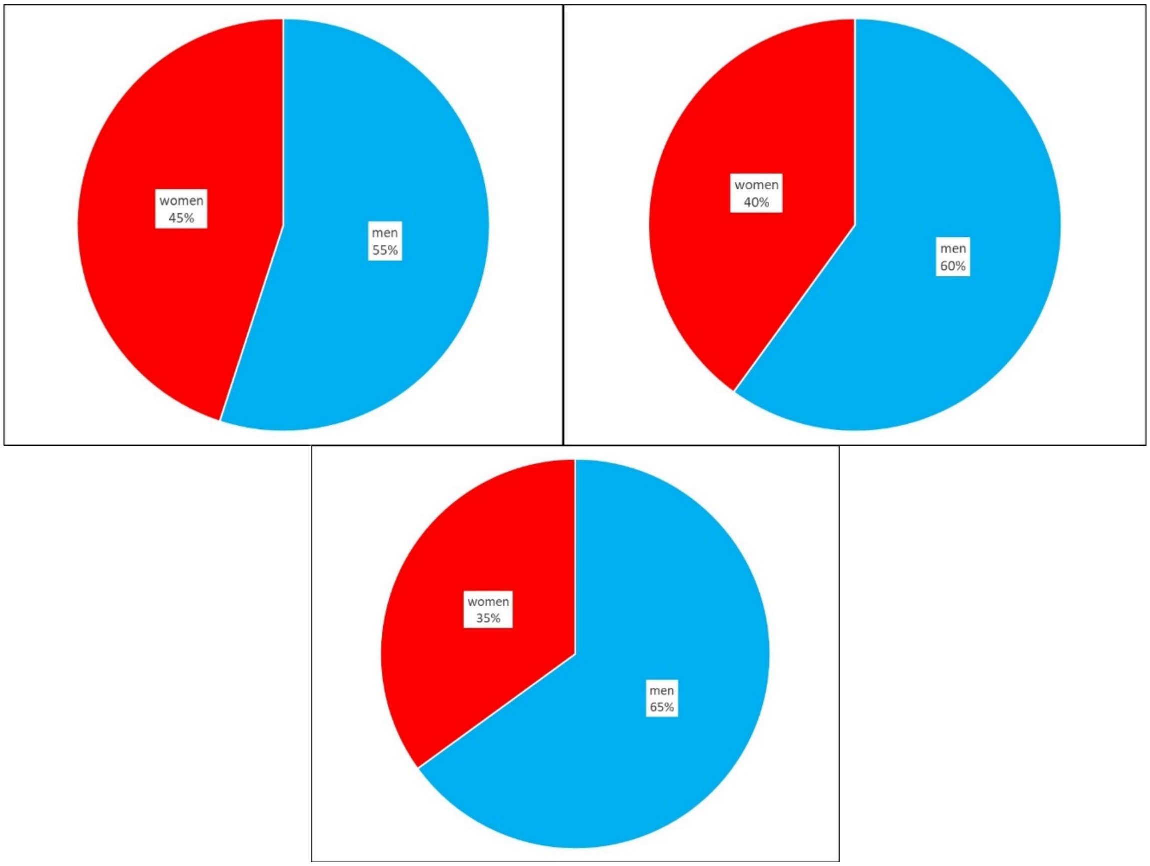
Our key dependent variable asked participants to “Please select the chart that you think best represents the ratio of speaking time for men and women.” Participants were randomly presented with seven pie charts to choose from, depicting the following speaking time ratios: (1) 35% men: 65% women, (2) 40% men: 60% women, (3) 45% men: 55% women, (4) 50% men: 50% women, (5) 55% men: 45% women, (6) 60% men: 40% women, (7) 65% men: 35% women.


men
35%
women
65%


men
40%
women
60%


men
45%
women
55%


women
50%
men
50%



SI Figure 31. The seven pie charts participants selected from for our key dependent measure.

From this measure, we calculated two sets of accuracy measures. Our first approach examined the various components of (in)accuracy dichotomously (as reported in the main text; i.e., our dichotomous measures of each of accurate selection, underestimation, and overestimation).

Second, we examined the various components of (in)accuracy continuously, capturing degree as well as direction. For degree of underestimation, participants received a score of 0 if accurate, but then received an increasingly negative score depending on how far their chosen estimate underestimated. For example, in Condition 1 (in which women spoke less than men), where option 6 is the correct answer, picking option 3—an underestimate of inequality—would yield a score of -3, whereas picking option 1 would yield the maximum score of -5. Thus, degree of underestimation could range from 0 to -5. In both conditions, there was only one choice that reflected an overestimate. Thus, the degree of overestimation in our paradigm reduces to the dichotomous measure already available in the main text (0 if accurate; +1 if selecting the overestimating option).

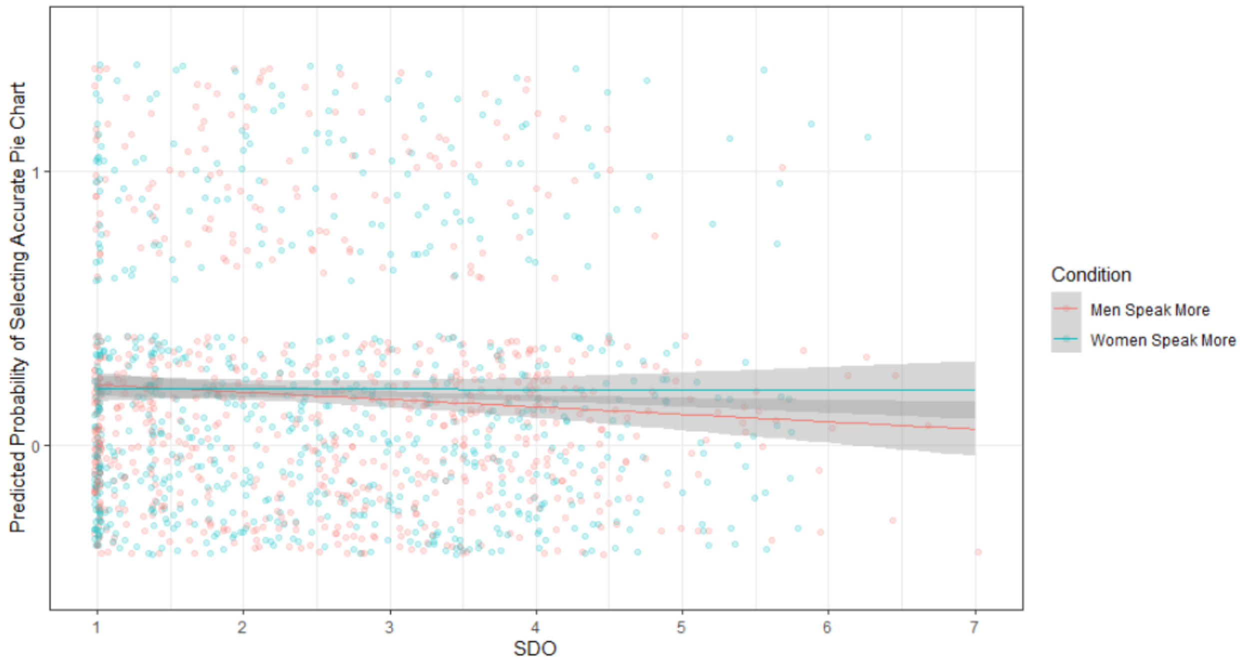
Our design therefore has the possible disadvantage of yielding an imbalance in the ‘potential’ to capture underestimation versus overestimation. We note that this was necessary in order to keep an equivalent number of option choices on either side of a 50:50 midpoint mark. Given the actual lopsided speaking time ratio, having an equal number of overestimating and underestimating choices would have required having the 50:50 mark appear further 'down the list' of options, problematically cuing participants to the presence of speaking-time inequality and the likely identity of its 'victim'. Crucially, the setup of our design (including the fact that we are better able to capture continuous variation in underestimation than overestimation) is identical across both conditions, so this cannot explain any differences in the effects of egalitarianism as a function of condition (i.e., as a function of which gender group spoke less).

Of note, our preregistration also said that we would consider a metric that combines accuracy, overestimation, and underestimation, giving participants a score of -1 if they underestimated, a score of 0 if they were accurate, and a score of +1 if they overestimated. As noted in SI Appendix Section 1.2 above, we realized upon reflection, that while this metric *does* clearly capture a relative tendency towards overestimation versus underestimation (positive scores reflecting a tendency towards overestimation over underestimation; negative scores reflecting the opposite), this metric is confusing as a measure of *accuracy*. In particular, we realized that egalitarians (or anti-egalitarians) could (as a group) receive an average score of 0 (reflecting perfect accuracy) under two diametrically opposed scenarios: (1) if every single egalitarian participant made a perfectly accurate selection, and (2) if *no* single egalitarian participant was accurate, but exactly half of egalitarian participants overestimated (+1) and exactly half underestimated (-1). The inferential difficulty in interpreting a combined measure as reflective of accuracy is further compounded if we combine the 'degree' measures of underestimation and overestimation into one score ranging from -5 to +1 (with 0 corresponding to an accurate selection), given the lopsidedness of the measure (i.e., the fact that it can take larger negative numbers than positive numbers). For these reasons, we do not focus on these combined measures in the main text (although we include the results using them in SI Appendix Section 5.6 for the sake of completeness).

Given the concerns raised about using the combined continuous measure as an indicator of accuracy, we decided to focus in the main text on the three dichotomous outcome measures (i.e., whether or not people made the accurate selection; whether or not they underestimated; whether or not they overestimated). Without the (problematic) combined continuous metric ranging from -5 to +1, we would have had only one continuous measure to include in the main text: degree of underestimation (with only one choice reflecting overestimation, the 'degree' measure of overestimation reduces to the dichotomous measure). We note that there are no inferential issues interpreting degree of underestimation, and we include it in SI Appendix Section 5.6 below—the results using our degree of underestimation measure confirm the conclusions using the dichotomous measure in the main text.

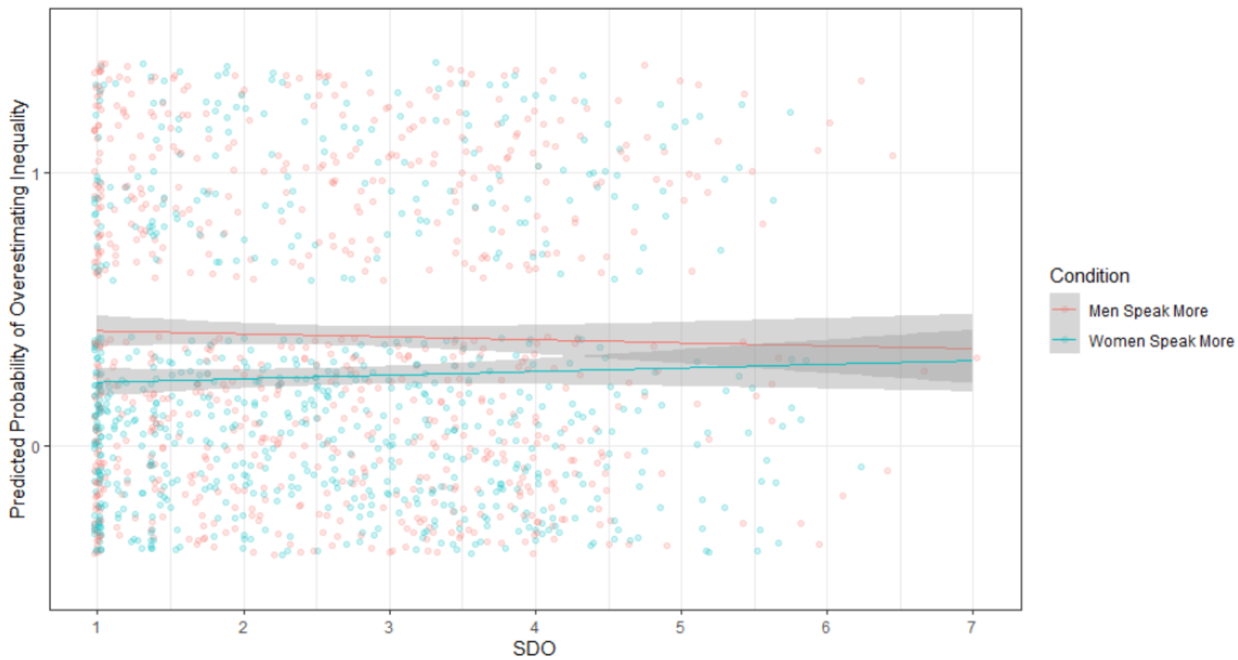
5.6 Study 4 Supplemental Figures and Results

5.6.1 Dichotomous Accuracy Figure



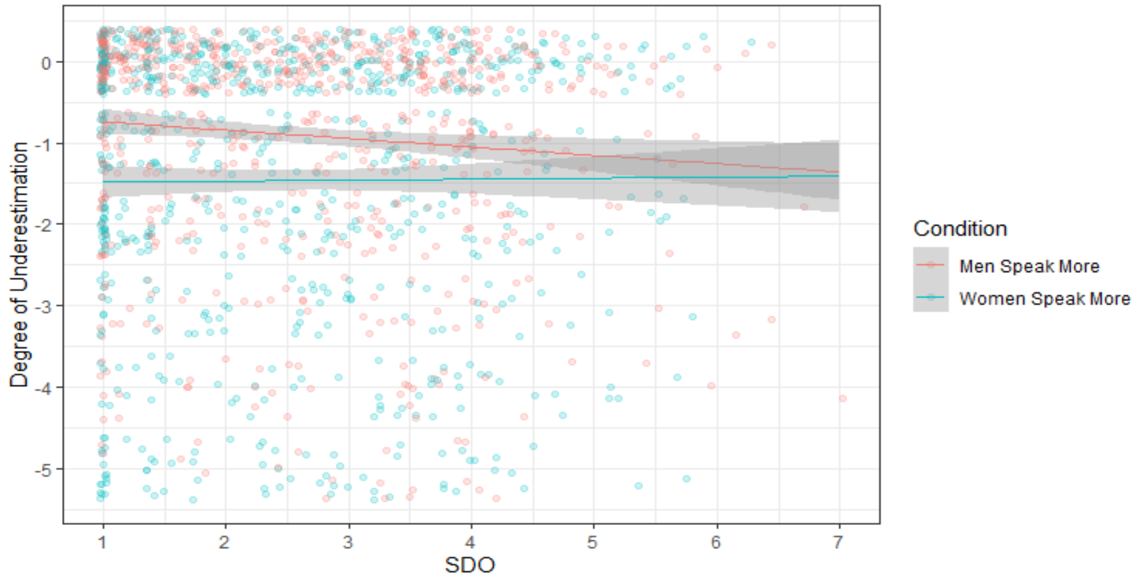
SI Figure 32. Predicted probability of participants selecting accurate pie chart by condition. 1 corresponds to an accurate selection and 0 corresponds to an inaccurate selection. Note that data points on this figure are “jittered” via R to aid in visualization (values of this variable are only ‘0’ or ‘1’).

5.6.2 Dichotomous Overestimation Figure



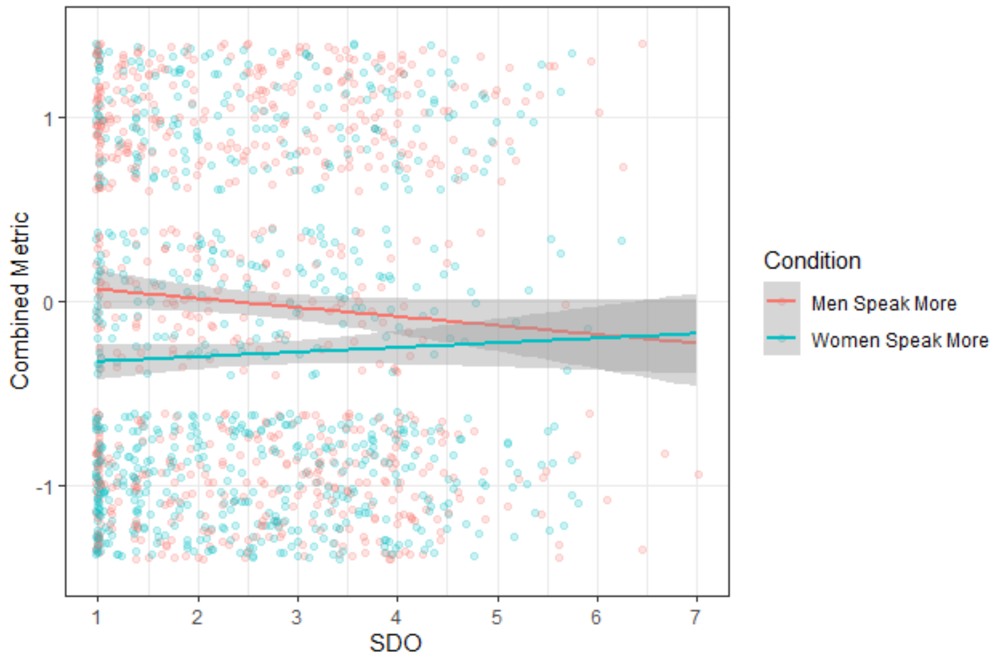
SI Figure 33. Predicted probability of participants overestimating accurate pie chart by condition. 1 corresponds to an overestimating selection, 0 corresponds to an accurate or underestimating selection. Note that data points on this figure are "jittered" via R to aid in visualization (values of this variable are only '0' or '1').

5.6.3 Degree of Underestimation Results and Figure. Next, we examined the degree to which participants underestimated inequality. We observed a marginally significant interaction effect, $b = .11$, $p = .06$, 90% [.01, .22], between SDO and task condition in predicting the degree to which participants underestimated inequality. In Condition 1 (where men spoke more than women), we observed that individuals lower (vs. higher) in SDO were significantly less likely to underestimate the degree of inequality, $b = -.10$, $p = .02$, 95% [-.19, -.02] (see SI Figure 35). In Condition 2 (where women spoke more than men), there were no significant differences between individuals lower vs. higher in SDO in the degree to which they underestimated inequality, $b = .01$, $p = .78$, 95% [-.07, .10]. Individuals both lower (-1SD) and higher (+1SD) in SDO were significantly less likely to underestimate the degree of inequality in Condition 1 (where men spoke more than women) than in Condition 2 (where women spoke more than men) (lower SDO, $b = -.71$, $p < .001$, 95% [-.93, -.49]; higher SDO, $b = -.41$, $p < .001$, 95% [-.63, -.19]).



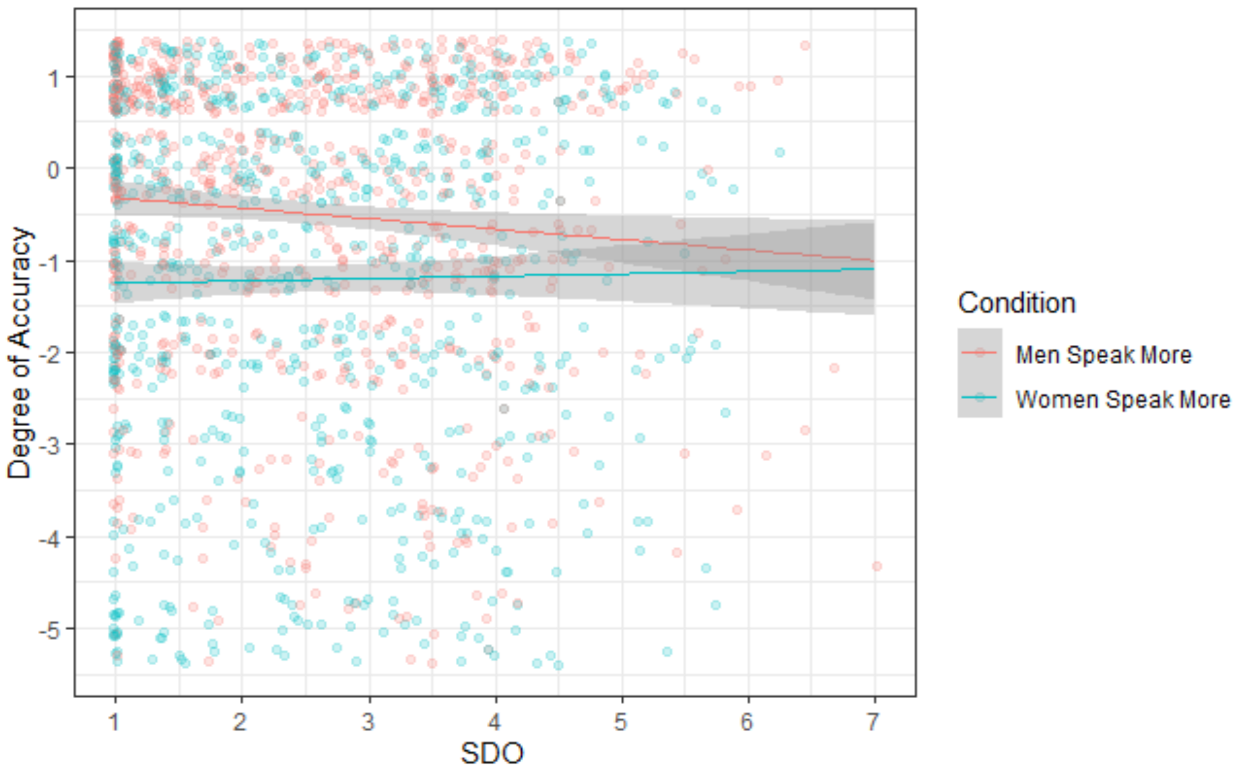
SI Figure 34. Relationship between SDO and degree of underestimation in identifying speaking-time distribution by gender in condition 1 (‘men speak more’) versus condition 2 (‘women speak more’). Accurate and overestimating responses are scored as 0. Note that data points on this figure are “jittered” via R to aid in visualization (values of this variable are only ‘0’, ‘-1’, ‘-2’, ‘-3’, ‘-4’, or ‘-5’).

5.6.4 Combined Measure of Accuracy Results & Figure*. We also conducted analyses using a metric that combined accuracy, overestimation, and underestimation into one score. Participants received a score of -1 if they underestimated inequality, a score of 0 if they were accurate, and a score of +1 if they overestimated inequality. Using this metric, we observed a significant interaction effect, $b = .07$, $p = .04$, 95% [.004, .14], between SDO and task condition in predicting this combined measure. In Condition 1 (where men spoke more than women), we observed a negative main effect of SDO, $b = -.05$, $p = .05$, 95% [-.10, -.00], with higher levels of anti-egalitarianism corresponding to a greater proclivity to underestimate versus overestimate inequality. In contrast, in Condition 2 (where women spoke more than men), there were no significant differences as a function of levels of SDO, $b = .03$, $p = .32$, 95% [-.02, .07]. For both individuals lower and higher in SDO (-/+ 1SD), scores on the combined accuracy metric were significantly higher in Condition 1 relative to Condition 2 (lower SDO: $b = -.37$, $p < .001$, 95% [-.50, -.24]; higher SDO: $b = -.18$, $p = .01$, 95% [-.31, -.05]), reflecting that participants were, in both cases, relatively less likely to overestimate versus underestimate inequality when women spoke more than when men spoke more. **As noted in SI Section 5.5, whereas higher predicted scores as a function of SDO on this combined measure do reflect a relative tendency towards greater overestimation versus underestimation, a predicted score of 0 on this measure cannot be interpreted as reflecting perfect accuracy.*



SI Figure 35. Predicted likelihood of participants selecting accurate pie chart by condition. 0 corresponds to an accurate selection, -1 corresponds to selecting an underestimate of inequality, +1 corresponds to selecting an overestimate of inequality. Note that data points on this figure are "jittered" via R to aid in visualization (values of this variable are only '-1', '0', or '1').

5.6.5 Degree of Accuracy Results and Figure*. We also conducted analyses using an additional metric intended to capture degree of accuracy. Participants received a score of 0 if they were accurate, their score on the degree of underestimation if they underestimated and a +1 if they overestimated. Scores on this metric could therefore range from -5 to +1. Using this metric, we observed a marginally significant interaction effect, $b = .14$, $p = .06$, 90% [.02, .26], between SDO and task condition in predicting this combined measure. In Condition 1 (where men spoke more than women), we observed a negative main effect of SDO, $b = -.11$, $p = .03$, 95% [-.22, -.01]. In contrast, in Condition 2 (where women spoke more than men), there were no significant differences as a function of levels of SDO, $b = .03$, $p = .63$, 95% [-.08, .13]. For both individuals lower and higher in SDO (-/+ 1SD), scores on the degree of accuracy metric were significantly higher in Condition 1 relative to Condition 2 (lower SDO: $b = -.89$, $p < .001$, 95% [-1.15, -.63]; higher SDO: $b = -.53$, $p < .001$, 95% [-.79, -.27]), reflecting that participants were, in both cases, relatively less likely to overestimate versus underestimate inequality when women spoke more than when men spoke more. **As noted in SI Section 5.5, whereas higher predicted scores as a function of SDO on this combined measure do reflect a relative tendency towards greater overestimation versus underestimation, a predicted score of 0 on this measure cannot be interpreted as reflecting perfect accuracy.*



SI Figure 36. Relationship between SDO and degree of accuracy by condition. Accuracy is scored such that an accurate response is 0. Positive scores (ranging from 0 to 1) indicate overestimating inequality and negative scores (ranging from 0 to -5) indicate underestimating inequality. Note that data points on this figure are "jittered" via R to aid in visualization (values of this variable are only '1', '0', '-1', '-2', '-3', '-4', or '-5').

6. Study 5

6.1 Study 5 Sample Characteristics

Full sample size: 1,603
Sample that provided data on all focal variables: 1,201 (74.9% of full sample)
Age: *M* = 40.6, *SD* = 13.1; Gender: 56.0% Female, 43.7% Male, .3% Other
Ethnicity: 944 Caucasian/White, 63 Asian/Asian American; 94 Black/African American; 60 Latino/Hispanic; 8 Native American; 25 Biracial/Mixed Race, 5 Middle Eastern, 2 Other

In order to collect data from an approximately equal number of Republicans and Democrats, all participants were asked "which political party do you most identify with?" and selected either Republican, Democrat, or Independent. Participants who selected Independent (*n* = 380) were then asked to indicate, "as of today, do you lean more Republican or Democrat?" Due to a survey error, the participants who selected Independent did not fill out the Social Dominance Orientation scale and could therefore not be included in our primary analyses. Of note, however, when we conducted our (preregistered) secondary analyses using political conservatism as a predictor in place of SDO, we obtained the same patterns as with SDO whether we did or did not include these 380 respondents. Moreover, our distribution of SDO scores was comparable to our other studies.

6.2 Study 5 Power Analysis

Based on a correlation of r = .10 between SDO and perceiving bias in any given condition, we needed about 780 participants to achieve 80% power.

6.3 Study 5 Task Structure

Participants read about an organization called Connection Consulting that had just completed their hiring process. Participants saw the resumes of 56 applicants who varied across 5 dimensions (GPA, major, race, hometown, and hobby). Half of the applicants were White, and half of the applicants were racial minorities (Latino, Asian, Black). The applicants were presented in proportions consistent with their representation in the United States Census. For example, Black individuals make up roughly 34% of the minority population in the US (US Census). Our task was structured such that out of 28 minority applicants, 10 (~35%) were Black. After viewing each candidate's resume, participants learned whether that applicant was hired or not. Participants were randomly assigned to one of two conditions. In both conditions, the task was structured such that GPA was correlated at +.57 with the likelihood of being hired. Candidates' GPAs ranged from 3.4 to 4.0 in 0.1 increments. Candidates were assigned to one of seven majors balanced across other factors. In addition, candidates were assigned to one of 28 hometowns and one of 28 hobbies balanced across other factors. Across both conditions, we structured the task such that the correlation between other factors (major, hometown, hobby) and the likelihood of being hired was 0. The only difference between the two conditions was the correlation between race and likelihood of being hired: In Condition 1 (anti-minority bias), being a minority (vs. White) was correlated at -.29 with the likelihood of being hired, whereas in Condition 2 (anti-White bias), being a minority (vs. white) was correlated at +.29 with the likelihood of being hired. In both conditions, Asians, Blacks, and Latinos did not have different probabilities of being hired from one another. For each applicant, participants were presented with resume information (e.g., GPA, major, etc.) and clicked forward to see whether the applicant was hired (see SI Figure 36).

6.3.1 Study 5 Stimuli Example

SI Figure 37. Resume task stimuli example.

6.4 Study 5 Additional DVs

6.4.1 *Relative Naturalistic Notice Bias*. After completing the resume task, participants were simply asked, in general, to note anything that stood out to them about the hiring process. Specifically, the instruction read “Please note anything that stood out to you about the hiring process.” We coded whether participants naturalistically mentioned inequality in the hiring process. We accounted for any (incorrect) mentions of bias against the group that was favored in the participants’ condition. On this metric, participants could receive a score of -1, 0, or +1. Participants received a score of 0 if they did not mention bias, a score of +1 if they (correctly) mentioned bias against the category disfavored in their experimental condition and a score of -1 if they (incorrectly) mentioned bias against the category that was in fact *favored* in their condition. We term this variable ‘relative naturalistic notice bias’.

6.4.2 Self-Report Bias Judgments:
Absolute Bias Judgments. We directly asked participants to self-report their perceptions of bias within Connection Consulting’s hiring process. After giving their open-ended response about their general impression of the task, we directly asked participants to indicate their level of agreement with each of the following statements on a 1 (‘Strongly disagree’) to 7 (‘Strongly agree’) scale: (a) ‘Connection Consulting was biased against non-White students’, and (b) ‘Connection Consulting was biased against White students’. For this metric, which we termed ‘absolute bias judgments’, we examined results looking simply at perceptions of bias against the target who in fact encountered bias in the relevant condition. Thus, for those in Condition 1, our measure of self-reported bias was their rating of statement (a), whereas for those in Condition 2, it was their rating of statement (b).

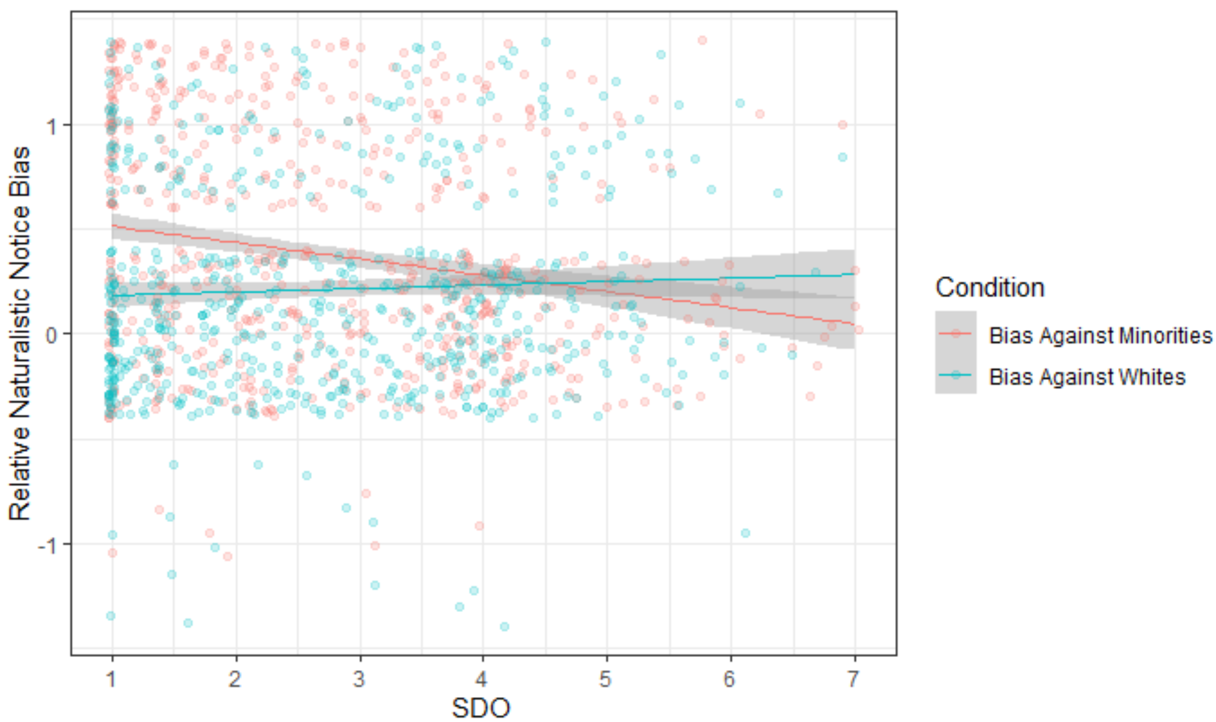
Relative Bias Judgments. We examined results looking at perceptions of unequal treatment against the target who did encounter inequality in the relevant condition while also incorporating assessments of bias against the target who did not face bias in the relevant condition. Thus, for Condition 1, we calculated *relative bias judgments* by subtracting self-reported ratings of bias against Whites from ratings of bias against non-Whites. For Condition 2, we calculated *relative bias judgements* by subtracting ratings of bias against non-Whites from ratings of bias against Whites (see SI Appendix Section 6.5.2 below for the highly consistent results we obtained when we instead looked at ratings of bias against Blacks and Whites separately).

6.4.3 *Desire to Investigate.* As noted in the main text, we assessed a downstream consequence of noticing inequality, namely, the extent to which participants endorsed investigating Connection Consulting for its hiring practices, termed *desire to investigate*. To measure this variable, participants endorsed their level of agreement with each of the following statements on a 1 (‘Strongly disagree’) to 7 (‘Strongly agree’) scale ($\alpha = .94$): (1) ‘A third party should investigate Connection Consulting’s hiring practices’, (2) ‘Connection Consulting should reconsider its hiring practices’, (3) ‘Connection Consulting’s hiring practices should be reviewed’, (4) ‘Connection

Consulting's hiring practices seem fair (reverse coded)', and (5) 'Connection Consulting's hiring practices appear to be legitimate (reverse coded)'.

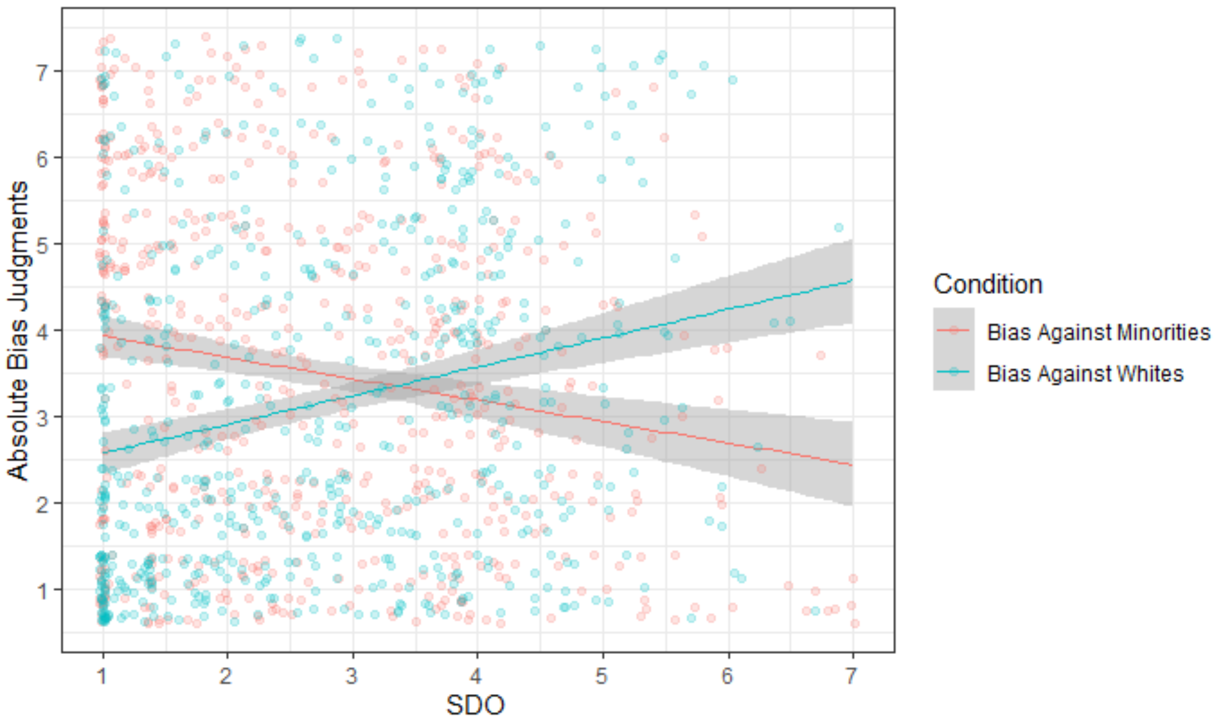
6.5 Study 5 Supplemental Moderation Analyses

6.5.1 Relative Naturalistic Notice Bias Analyses & Figure. We observed a significant interaction effect between SDO and task condition in predicting 'relative naturalistic notice bias', $b = 0.09$, $p <.001$, 95% [0.06, 0.13]. In the anti-minority bias condition, we observed the predicted main effect of SDO on 'relative naturalistic notice bias', $b = -0.08$, $p < .001$, 95% [-0.10, -0.05], such that individuals lower (vs. higher) in SDO were significantly less likely to mention anti-minority bias. In the anti-White bias condition, we found a non-significant positive association between SDO and mentioning anti-White bias, $b = 0.02$, $p = .24$, 95% [-0.01, 0.04]. At low levels of SDO (-1SD below the mean), task condition significantly predicted 'relative naturalistic notice bias'; individuals lower (vs. higher) in SDO were significantly more likely to mention bias in Condition 1 (anti-minority bias condition) versus Condition 2 (anti-white bias condition), $b = -0.30$, $p < .001$, 95% [-0.38, -0.22]. At high levels of SDO (+1SD above the mean), there was no significant difference between likelihood of mentioning 'relative naturalistic notice bias' across the two conditions, $b = -0.03$, $p = .41$, 95% [-0.11, .04] (see SI Figure 37).



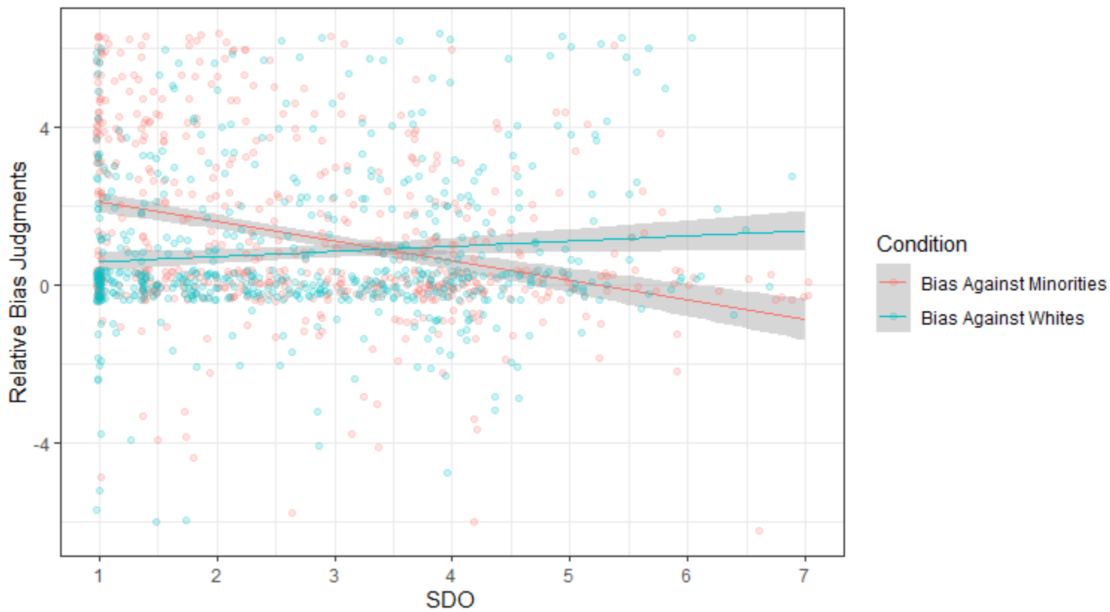
SI Figure 38. Relationship between SDO and 'relative naturalistic notice bias' by condition. Note that data points on this figure are "jittered" via R to aid in visualization (values of this variable are only '-1', '0', or '1').

6.5.2 Absolute Bias Judgments Analyses & Figure. We next considered responses to our self-report questions about the extent of racial bias in Connection Consulting. For our measure of ‘absolute bias judgments’, we observed a significant interaction effect between SDO and task condition, $b = 0.58$, $p < .001$, 95% [0.43, 0.74]. In the anti-minority condition, we observed the predicted main effect of SDO on ‘absolute bias judgments’, $b = -0.25$, $p < .001$, 95% [-0.36, -0.14], such that individuals lower (vs. higher) in SDO reported significantly more (anti-minority) bias. In contrast, in the anti-White bias condition (Condition 2), individuals higher (vs. lower) in SDO were significantly more likely to report (here, anti-White) bias, $b = 0.33$, $p < .001$, 95% [0.22, 0.44] (see SI Figure 38). Examining the interaction another way, individuals lower in SDO (-1SD below mean) reported significantly more bias in Condition 1 (anti-minority bias), $b = -1.16$, $p < .001$, 95% [-1.47, -0.85] relative to Condition 2, whereas individuals higher in SDO (+1SD above mean) reported significantly more bias in Condition 2 (anti-White bias) relative to Condition 1, $b = 0.48$, $p = .002$, 95% [0.17, 0.79].



SI Figure 39. Relationship between SDO and ‘absolute bias judgments’ by condition. Note that data points on this figure are “jittered” via R to aid in visualization.

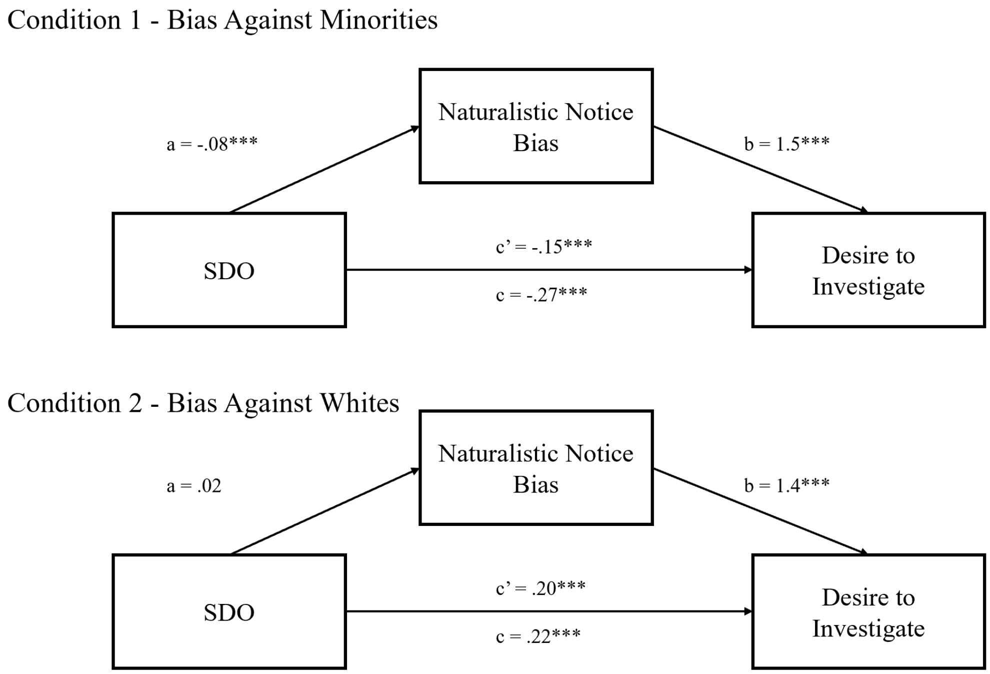
6.5.3 Relative Bias Judgments Analyses & Figure. We observed a significant interaction effect between SDO and task condition in predicting *relative bias judgements*, $b = 0.63$, $p < .001$, 95% [0.47, 0.78]. In the condition with bias against minorities (Condition 1), we found the predicted main effect of SDO on relative bias judgements, $b = -0.49$, $p < .001$, 95% [-0.61, -0.38], such that individuals higher (vs. lower) in SDO report significantly less bias. In the condition with bias against Whites (Condition 2), however, we found that individuals higher (vs. lower) in SDO are significantly *more* likely to report bias, $b = 0.13$, $p = .02$, 95% [0.02, 0.24] (see SI Figure 39). Individuals lower (vs. higher) in SDO (-1SD below mean) reported significantly more bias in Condition 1 (anti-minority bias), *b* = -1.29, *p* < .001, 95% [-1.61, -0.98] relative to Condition 2, whereas individuals higher (vs. lower) in SDO (+1SD above mean) reported significantly more bias in Condition 2 (anti-White bias) relative to Condition 1, *b* = 0.47, *p* = .004, 95% [0.15, 0.79].



SI Figure 40. Relationship between SDO and relative bias judgements across condition. Relative bias judgment is computed as the difference score between judged bias against minorities versus Whites in condition 1 ('bias against minorities') and as the difference score between judged bias against Whites versus minorities in condition 2 ('bias against Whites'). Note that data points on this figure are "jittered" via R to aid in visualization.

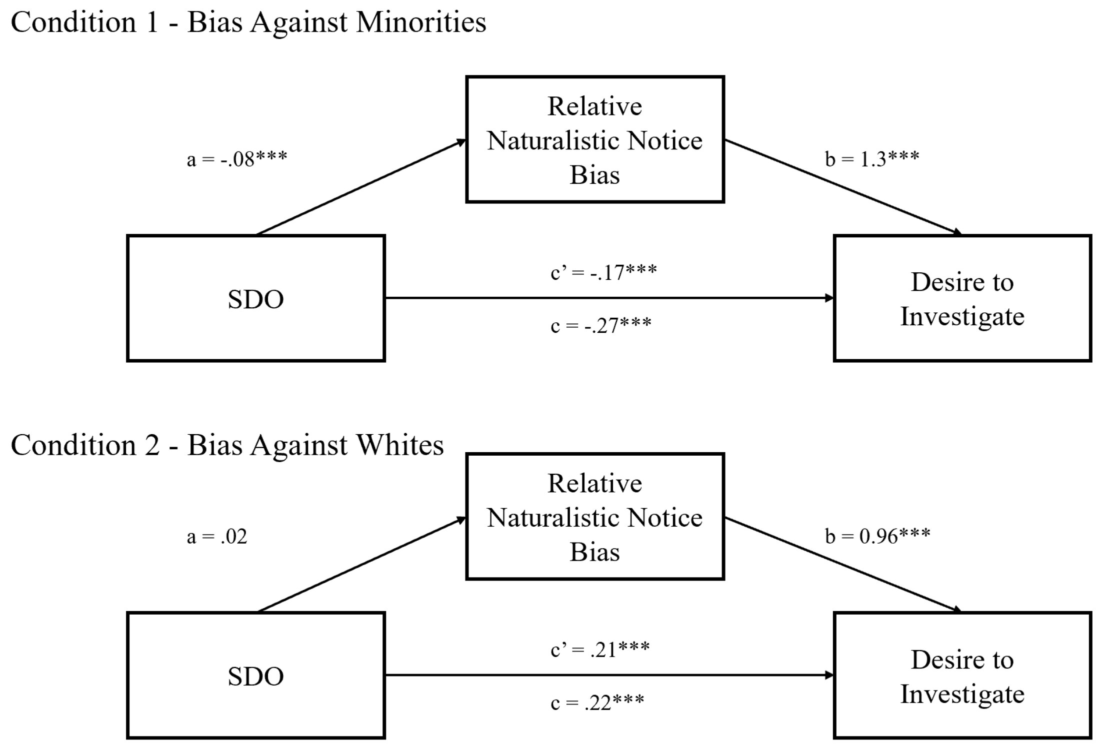
6.6 Study 5 Supplemental Mediation Analyses

6.6.1 Naturalistic Notice Bias Mediation Figure



SI Figure 41. Mediation model linking SDO to the desire to investigate 'Connection Consulting' via the tendency to naturalistically notice bias across task condition. ****p* <.001

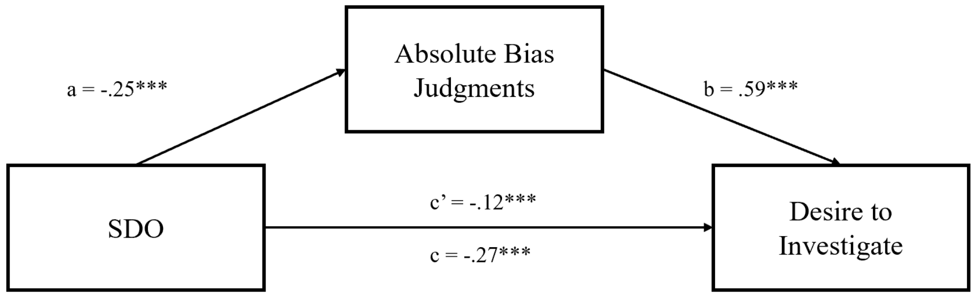
6.6.2 Relative Naturalistic Notice Bias Mediation Analyses & Figure. We entered SDO as the predictor, 'relative naturalistic notice bias' (see SI Section 6.4) as the mediator, and desire to investigate as the outcome measure, with bias condition as a moderator of each of the a, b, and c paths. In the anti-minority bias condition, there was a significant negative indirect effect of SDO on desire to investigate via 'relative naturalistic notice bias', *b* = -.10, *SE* = .02, 95% [-.14, -.06]. In contrast, in the anti-White bias condition, there was no significant indirect effect of SDO on desire to investigate via 'relative naturalistic notice bias', *b* = .02, *SE* = .01, 95% [-.01, .04]. For individuals lower in SDO (-1 SD below mean), the indirect effect of task condition on desire to investigate via 'relative naturalistic notice bias' was significantly negative, *b* = -.37, *SE* = .06, 95% [-.50, -.25]. For individuals higher in SDO (+1 SD above mean), the indirect effect of task condition on desire to investigate via 'relative naturalistic notice bias' was not significant, *b* = -.03, *SE* = .04, 95% [-.11, .05].



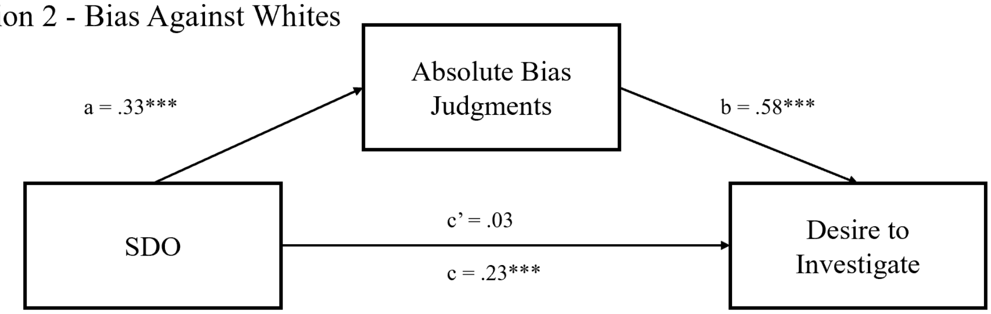
SI Figure 42. Mediation model linking SDO to the desire to investigate 'Connection Consulting' via 'relative naturalistic notice bias' across task condition. ***p <.001

6.6.3 Absolute Bias Judgments Mediation Analyses & Figure. We entered SDO as the predictor, 'absolute bias judgments' (see SI Section 6.4) as the mediator, and desire to investigate as the outcome measure, with bias condition as a moderator of each of the a, b, and c paths. In the anti-minority bias condition, there was a significant negative indirect effect of SDO on desire to investigate via 'absolute bias judgments', b = -.15, SE = .03, 95% [-.21, -.08]. In contrast, in the anti-White bias condition, there was a significant positive indirect effect of SDO on desire to investigate via 'absolute bias judgments', b = .19, SE = .03, 95% [.13, .26]. For individuals lower in SDO (-1 SD below mean), the indirect effect of task condition on desire to investigate via 'absolute bias judgments' was significantly negative, b = -.70, SE = .10, 95% [-.90, -.51]. For individuals higher in SDO (+1 SD above mean), the indirect effect of task condition on desire to investigate via 'absolute bias judgments' was significantly positive, b = .28, SE = .09, 95% [.11, .46].

Condition 1 - Bias Against Minorities

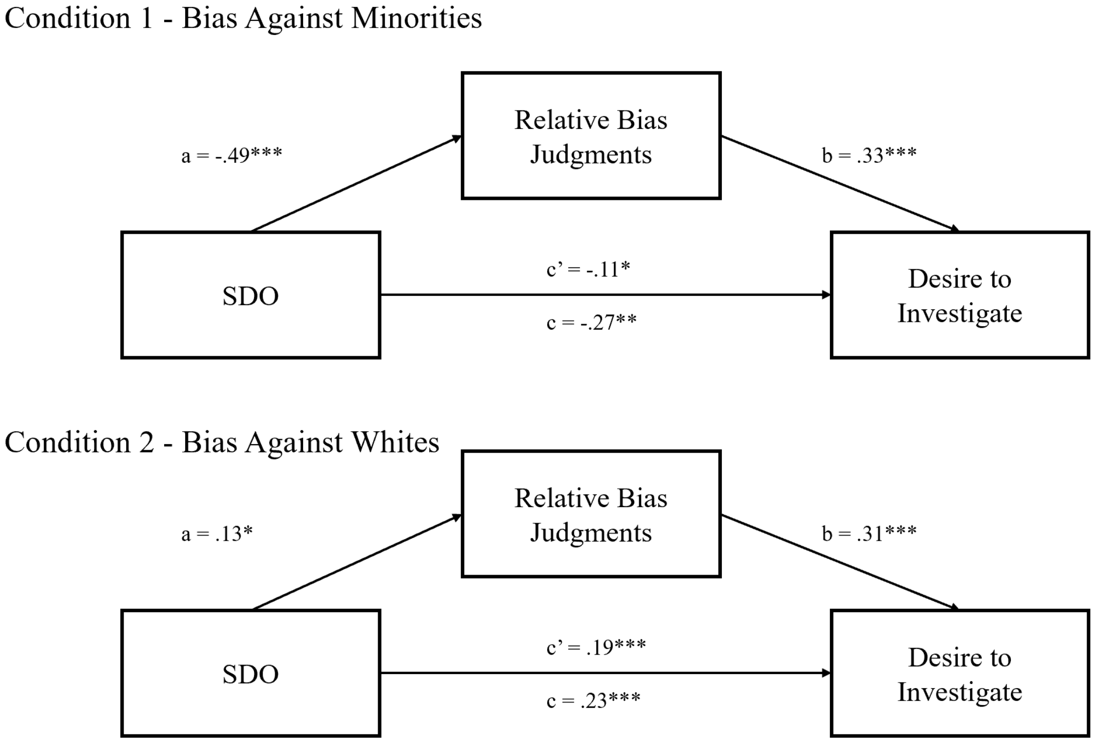


Condition 2 - Bias Against Whites



SI Figure 43. Mediation model linking SDO to the desire to investigate 'Connection Consulting' via ''absolute bias judgments' across task condition. ****p* <.001

6.6.4 Relative Bias Judgments Mediation Analyses & Figure. We entered SDO as the predictor, 'relative bias judgments' (see SI Section 6.4) as the mediator, and desire to investigate as the outcome measure, with bias condition as a moderator of each of the a, b, and c paths. In the anti-minority bias condition, there was a significant negative indirect effect of SDO on desire to investigate via 'relative bias judgments', *b* = -.16, *SE* = .02, 95% [-.21, -.12]. In contrast, in the anti-White bias condition, there was a significant positive indirect effect of SDO on desire to investigate via 'relative bias judgments', *b* = .04, *SE* = .02, 95% [.004, .08]. For individuals lower in SDO (-1 SD below mean), the indirect effect of task condition on desire to investigate via 'relative bias judgments' was significantly negative, *b* = -.46, *SE* = .07, 95% [-.60, -.33]. For individuals higher in SDO (+1 SD above mean), the indirect effect of task condition on desire to investigate via 'relative bias judgments' was significantly positive, *b* = .13, *SE* = .05, 95% [.04, .23].



SI Figure 44. Mediation model linking SDO to the desire to investigate 'Connection Consulting' via 'relative bias judgments' across task condition. ***p <.001

7. Main Analyses for all Studies Controlling for Relevant Group Membership (i.e., Gender, Race, and Social Class)

We conducted all main analyses controlling in each study for participants' relevant demographic group memberships. These included (depending on study) subjective social class (1=lower working class, 2=working class, 3=upper working class, 4=lower middle class, 5=middle class, 6=upper middle class, 7=upper class), gender (1=male, 2=female), and/or race (0=white, 1=racial minority). In Studies 1 and 3, we controlled for social class. In Study 2, we controlled for gender. In Study 4, we controlled for gender, as well as its interaction with experimental condition. In Study 5, we controlled for race, as well as its interaction with experimental condition. Note that all of conclusions pertaining to SDO are equivalent across studies if we include all three variables (and their interactions with experimental condition, in Studies 4 and 5) as controls.

7.1 Study 1 Analyses

We conducted a meta-analysis across all five samples to examine the associations between SDO and mentions of inequality while controlling for participant subjective social class. Controlling for participant social class, SDO remained significantly negatively related to Direct Inequality, fixed effects model: $z = -3.12$, $p = .002$, $r = -.07$, random effects model: $z = -2.39$, $p = .02$, $r = -.07$. In addition, SDO remained significantly negatively correlated with Indirect Inequality, fixed effects model: $z = -3.72$, $p < .001$, $r = -.08$, random effects model: $z = -3.05$, $p = .002$, $r = -.08$.

Controlling for SDO, participant social class was not significantly related to Direct Inequality, fixed effects model: $z = 1.06$, $p = .29$, $r = .02$, random effects model: $z = 1.06$, $p = .29$, $r = .02$, or Indirect Inequality, fixed effects model: $z = 0.32$, $p = .75$, $r = .007$, random effects model: $z = 0.32$, $p = .75$, $r = .007$.

7.2 Study 2 Analyses

Regression output predicting *d'*

Predictor	Estimate	Standard error	t-value
(Intercept)	.03	.03	.86
SDO	-.08**	.03	-2.81
Gender	-.08	.06	-1.41

Note: ** p < .01.

Regression output predicting *c*

Predictor	Estimate	Standard error	t-value
(Intercept)	-.05	.03	-1.36
SDO	-.02	.03	-.57
Gender	.12*	.06	2.20

Note: * p < .05.

7.3 Study 3 Analyses

Study 3 meta-analysis. The relationship between SDO and average number of views on inequality images was robust when meta-analyzing across Studies 3a and 3b when controlling for participant social class ($b = .12$, $z = 6.05$, $p < .001$), including when additionally controlling for neutral trials ($b = .05$, $z = 2.53$, $p = .01$).

When controlling for SDO, the relationship between participant social class and average number of views on inequality images was not significant when meta-analyzing across Studies 3a and 3b ($b = -.004$, $z = -.17$, $p = .86$), as was also the case when additionally controlling for neutral trials ($b = .003$, $z = .14$, $p = .89$).

7.4 Study 4 Analyses

Regression output predicting *Dichotomous Accuracy*

Predictor	Estimate	Standard error	z-value
(Intercept)	-.93†	.50	-1.84
Condition	-.21	.31	-.67
SDO	-.41*	.17	-2.34
Gender (Male)	.55	.43	1.28
Condition*SDO	.20†	.11	1.90
Condition*Gender	-.29	.27	-1.06

Note: † p < .1. * p <.05. ** p < .01.

Regression output predicting *Dichotomous Underestimation*

Predictor	Estimate	Standard error	z-value
(Intercept)	-1.48***	.40	-3.72
Condition	.89***	.25	3.56
SDO	.37**	.13	2.82
Gender	-.67*	.24	-1.97
Condition*SDO	-.21*	.08	-2.54
Condition*Gender	.34	.22	1.58

Note: * p <.05. ** p < .01. *** p <.001

Regression output predicting *Dichotomous Overestimation*

Predictor	Estimate	Standard error	z-value
(Intercept)	.52	.41	1.26
Condition	-.88***	.27	-3.30
SDO	-.15	.14	-1.11
Gender	.33	.35	.94
Condition*SDO	.11	.09	1.22
Condition*Gender	-.16	.23	-.69

Note: *** p <.001

7.5 Study 5 Analyses

Regression output predicting *Naturalistic Notice Bias*

Predictor	Estimate	Standard error	z-value
(Intercept)	2.48***	.45	5.51
Condition	-1.87***	.29	-6.35
SDO	-.81***	.15	-5.54
Race	-.48	.49	-.97
Condition*SDO	.44***	.09	4.76
Condition*Race	.16	.32	.51

Note: *** p <.001

Regression output predicting *Desire to Investigate*

Predictor	Estimate	Standard error	z-value
(Intercept)	6.16***	.34	18.15
Condition	-1.78***	.22	-8.25
SDO	-.76***	.11	-7.21
Race	.55	.37	1.50
Condition*SDO	.49***	.07	7.37
Condition*Race	-.14	.23	-.62

Note: *** p <.001