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Overcorrection for Social-Categorization Information Moderates Impact Bias in Affective Forecasting

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Abstract

Plural societies require individuals to forecast how others—both in-group and out-group members—will respond to gains and setbacks. Typically, correcting affective forecasts to include more relevant information improves their accuracy by reducing their extremity. In contrast, we found that providing affective forecasters with social-category information about their targets made their forecasts more extreme and therefore less accurate. In both political and sports contexts, forecasters across five experiments exhibited greater impact bias for both in-group and out-group members (e.g., a Democrat or Republican) than for unspecified targets when predicting experiencers' responses to positive and negative events. Inducing time pressure reduced the extremity of forecasts for group-labeled but not unspecified targets, which suggests that the increased impact bias was due to overcorrection for social-category information, not different intuitive predictions for identified targets. Finally, overcorrection was better accounted for by stereotypes than by spontaneous retrieval of extreme group exemplars.

Keywords

judgment, social cognition, emotions, open data, open materials, preregistered

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Plural societies require members to anticipate the pleasures and pains of others—both within and outside their social groups. These affective forecasts guide the consequential and quotidian political, legal, and medical decisions people make on behalf of others (e.g., Blumenthal, 2004; Ditto, Hawkins, & Pizarro, 2005; Halpern & Arnold, 2008; Mellers & McGraw, 2001). For instance, whether people classify interrogation techniques as acceptable or as torture is influenced considerably by their capacity to imagine the pain the techniques induce (Nordgren, McDonnell, & Loewenstein, 2011).

When predicting how a future event will make them feel, affective forecasters often insufficiently correct their initial simulation of the forecasted event for unintuitive features of the event and the context in which it will be experienced (Gilbert & Wilson, 2007). Midwesterners overestimate how happy they would be if they lived in California, for example, because they focus on its better weather and fail to account for the droughts and traffic that Californians experience (Schkade & Kahneman, 1998; Ubel, Loewenstein, & Jepson, 2005). People exhibit impact bias—overestimating the hedonic impact of future events—for themselves, as well as in "empathic forecasts" for close and distant others (Igou, 2008; Pollmann & Finkenauer, 2009). However, prompting affective forecasters to correct for the event's features and context usually makes their forecasts more accurate (e.g., Dunn, Brackett, Ashton-James, Schneiderman, & Salovey, 2007; Hsee & Zhang, 2004; Morewedge, Gilbert, & Wilson, 2005; Wilson, Wheatley, Meyers, Gilbert, & Axsom, 2000).

We suggest that when predicting how a future event will make other people feel, affective forecasters may overcorrect their initial simulations to account for information about the social categories to which other people belong. Social predictions combine information about

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normative responses to an event (distributional information) and the particular person experiencing it (case-based information; e.g., Kahneman & Tversky, 1973; Morewedge & Todorov, 2012). When social-categorization information is salient, people tend to overweigh stereotypes when making mental-state inferences, particularly for dissimilar out-group members (Ames, 2004a, 2004b; Robbins & Krueger, 2005). For example, forecasters expect Black relative to White, and male relative to female, targets to be angrier in response to negative events (Moons, Chen, & Mackie, 2015). We suggest that social-category information leads forecasters to overweigh stereotypes and focus less on normative responses to an event, which then causes them to make more extreme and less accurate affective forecasts for other people. We predicted that this would be the case even for in-group members, but particularly for out-group members. This prediction may seem to contradict infrahumanization research, which indicates that people tend to attribute reduced emotional capacity and duration to out-group relative to in-group members (e.g., Gaunt, Sindic, & Leyens, 2005; Haslam, 2006; Leyens et al., 2003). However, these dehumanization studies have focused on discrete secondary emotions, whereas we focus on the magnitude of positive-negative affective responses.

We conducted four experiments with Republicans and Democrats and one experiment with college football fans. In Experiment 1a, we compared the accuracy of affective forecasts for unspecified targets and for in-group and out-group members of both political parties for 2014 U.S. midterm election outcomes. In Experiment 1b, we conceptually replicated these results in a field experiment at the 2014 Harvard-Yale football game. We again conceptually replicated these findings in Experiment 2 and tested our predicted direction of correction for in-group and out-group targets by comparison with forecasts made about one's own feelings and those of an unspecified target. In Experiment 3, we induced time pressure to examine whether forecasts for group-labeled targets improved when forecasters' ability to correct for stereotypes was impaired. Finally, in Experiment 4, we tested whether overcorrection is driven by stereotypes, as we predicted, or by participants' recruitment of more extreme exemplars in group-labeled conditions. (Experimental materials, data, and analysis code for all five experiments reported in this article can be downloaded from the Open Science Framework at https://osf.io/9e5au/.)

Experiment 1a: 2014 U.S. Midterm Elections

The 2014 U.S. Senate midterm elections were fraught with anticipation. The Democratic party held the majority in the prior cycle; however, 36 seats were up for election. Polls indicated that the Republicans had a 62% chance of holding on to all of their seats and taking several more from the Democrats, which would give Republicans the majority in the next cycle (the Republican party ultimately won the Senate majority). We predicted that both Democratic and Republican voters would make more extreme and less accurate affective forecasts for targets identified by party affiliation than for targets whose affiliation was unspecified. In addition, we predicted that forecasters would be most likely to exhibit the impact bias for targets labeled as out-group members.

Method

Participants. We aimed for a minimum of 100 participants per condition after exclusions in order to have 80% power to detect a small effect size. We recruited 1,153 forecasters through Amazon Mechanical Turk (MTurk). These participants all reported living in the United States and were recruited on November 3, 2014, and before the polls closed on November 4, 2014. Of these, 269 did not identify with either the Democratic or Republican party and were excluded from analyses, which left 884 forecasters (369 women, 515 men; mean age = 32.5 years, *SD* = 11.1). On November 5 and 6, 2014, we recruited a different group of 217 experiencers. Thirty-one experiencers did not identify with either the Democratic or Republican parties and were excluded from further analyses.

We further excluded 26 participants who made predictions or self-reports greater than 3 standard deviations from the mean of their condition (e.g., forecasting maximal happiness for a target whose party loses the Senate majority or reporting maximal unhappiness for a target whose party wins the Senate majority). Thus, our final pool consisted of 859 forecasters (359 women, 500 men; mean age = 32.46 years, *SD* = 11.15) and 185 experiencers (95 women, 90 men; mean age = 35.15 years, *SD* = 12.18).

Procedure. All participants first reported their political affiliation and identification with both the Democratic and Republican parties by rating their agreement with three statements regarding whether they value, like, and feel connected with each party. These items were rated on analog 100-point scales ranging from 0, *strongly disagree*, to 100, *strongly agree*. Afterward, participants read about the importance of controlling the Senate majority.

Forecasters saw the close poll results, answered a comprehension check, and were then randomly assigned to make one of six affective forecast for how a target (a "person," "Democrat," or "Republican") would feel on the day after the election if his or her party either won or lost the Senate majority. These ratings were made on a 200-point scale ranging from −100, *extremely unhappy*, to 100, *extremely happy*.

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Experiencers saw the results of the Midterm election, answered a comprehension check, and reported how they currently felt after the election using the same 200-point scale ("How do you feel right now, on the day after the midterm election, that your party [won/lost] the majority of the seats in the Senate?").[1] Self-report data did not differ between experiencers surveyed on November 5 and November 6 (ps > .250).

All participants then completed three measures of their involvement in the election: how much they were planning to or had monitored news about the election, how involved they had been with election campaigns, and whether they planned on voting or had voted during the elections. We collected these data for exploratory purposes; we do not discuss results related to these measures further. Finally, participants reported their age and gender.

Results

Manipulation check. Given their high internal consistency, measures of group liking, valuing, and connection were recoded from −100 to 100 (such that 0 reflected a neutral response) and averaged to create a general-evaluation index (Cronbach's αs = .94 and .92 for in-group and out-group members, respectively). On average, participants evaluated the in-group more positively (M = 34.12, SD = 40.99) than the out-group (M = −59.45, SD = 37.83; mean difference = 93.57, 95% confidence interval, or CI = [89.99, 97.14]), $t(1043) = 51.29$, $p < .001$.

Forecasted and experienced affect. Democrats and Republicans did not differ in the extremity of their forecasts for members of their in-group (ps > .221) and out-group (ps > .250). Thus, we collapsed across parties so forecasts for in-group and out-group targets could be compared.

Forecasts for targets whose party won. There was a significant main effect of condition on forecasted affect for how in-group, out-group, and unspecified targets would feel if their party won, $F(3, 502) = 17.22$, $p < .001$, $\eta^2 = .09$ (see Fig. 1a). A trend analysis showed that the data were well described by a linear trend (b = 190.37, 95% CI = [133.74, 247.00]), $t(503) = 6.61$, $p < .001$. Forecasts for how targets would feel if their party won the election were most extreme for out-group members, less extreme for in-group members, and least extreme for unspecified targets. Forecasts for unspecified targets were most similar to experiencer reports.

These more extreme forecasts for group-labeled targets made them less accurate. Pairwise comparisons with experiencer reports revealed that forecasts for in-group targets (M = 77.13, SD = 28.54) and out-group targets (M = 82.53, SD = 23.99) significantly overestimated how happy experiencers were when their party won (M = 62.83, SD = 30.79); mean difference between in-group forecasts and experiencer reports = 14.30, 95% CI = [3.57, 25.02], $t(210) = 3.43$, $p = .003$, and mean difference between out-group forecasts and experiencer reports = 19.70, 95% CI = [8.97, 30.42], $t(210) = 4.72$, $p < .001$. In contrast, forecasts made for unspecified targets (M = 61.41, SD = 31.59) did not differ significantly from experiencer reports (mean difference = −1.42, 95% CI = [−12.01, 9.16]), $t(222) = -0.35$, $p > .250$.[2] Forecasts made for out-group targets did not differ significantly from forecasts made for in-group targets (mean difference = 5.40, 95% CI = [−3.38, 14.18]), $t(280) = 1.58$, $p > .250$.

Forecasts for targets whose party lost. For clarity of presentation, forecasted affect for targets whose party lost the election was reverse-coded so that 100 represented maximal unhappiness and −100 represented maximal happiness. There was a significant main effect of condition on forecasted affect for how unspecified, in-group, and out-group targets would feel if their party lost, $F(3, 534) = 8.65$, $p < .001$, $\eta^2 = .05$ (see Fig. 1b). A trend analysis showed that the data were well described by a linear trend (b = 146.37, 95% CI = [84.64, 208.10]), $t(535) = 4.66$, $p < .001$. As with winning, forecasts for how targets would feel if their party lost the election were most extreme for out-group members, less extreme for in-group members, and least extreme for unspecified targets, for whom forecasts were most similar to experiencer reports.

Again, the more extreme forecasts for group-labeled targets made them less accurate. Pairwise comparisons with experiencer reports revealed that forecasts for in-group targets (M = 64.97, SD = 29.06) and out-group targets (M = 67.94, SD = 35.19) significantly overestimated the unhappiness of experiencers when their party lost (M = 53.19, SD = 35.94); mean difference between in-group forecasts and experiencer reports = 11.78,[3] 95% CI = [1.71, 21.84], $t(260) = 3.02$, $p = .014$, and mean difference between out-group forecasts and experiencer reports = 14.75, 95% CI = [4.48, 25.02], $t(247) = 3.70$, $p = .001$. By contrast, forecasts made for unspecified targets (M = 52.45, SD = 25.17) did not differ significantly from experiencer reports (mean difference = −0.74, 95% CI = [−10.91, 9.43]), $t(253) = -0.19$, $p > .250$. Finally, forecasts made for out-group targets did not differ significantly from forecasts made for in-group targets (mean difference = 2.97, 95% CI = [−6.63, 12.59]), $t(281) = 0.80$, $p > .250$.

Discussion

Forecasters made more extreme and less accurate predictions when they knew the group to which their target belonged, for both in-group and out-group targets. We

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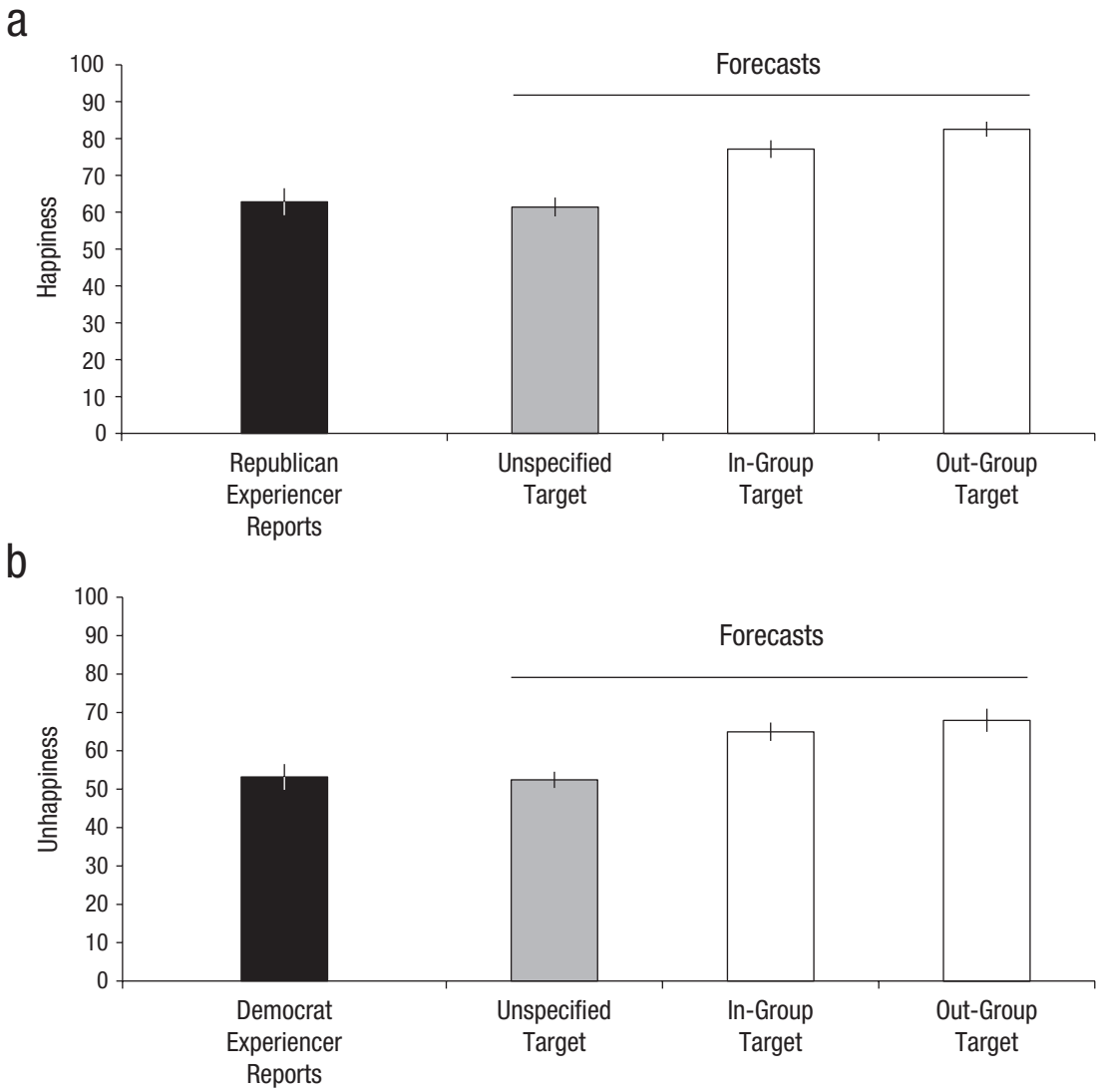

Fig. 1. Results from Experiment 1a: mean forecaster rating of (a) how happy each of the three targets would feel if their party won and (b) how unhappy each of the three targets would feel if their party lost, along with the mean rating of (a) Republican experiencers whose party actually won and (b) Democrat experiencers whose party actually lost. On the *y*-axis, 0 indicates neutral affect. Error bars represent ±1 *SEM*.

explored whether these differences could be replicated with losses in a different competitive intergroup context in the experiments that followed.

Experiment 1b: Harvard Versus Yale Football

We conceptually replicated the results of Experiment 1a with a field experiment in a different context: the 2014 Harvard-Yale football game. The two teams had similar records going into the game—Harvard: 9 wins, 0 losses; Yale: 8 wins, 1 loss—so the outcome was highly uncertain. In this experiment, we examined forecasts only for losses, the frame that exhibited the directionally weaker effect in Experiment 1a. We predicted that football fans would make more extreme and less accurate affective forecasts for targets identified by team affiliation than for unspecified targets. In addition, we predicted that forecasters would be most likely to exhibit the impact bias for identified out-group members.

Method

Participants. We aimed for a minimum of 100 participants per condition after exclusions in order to have 80% power to detect a small effect size. On November 22, 2014, we surveyed forecasters at tailgate parties outside Harvard Stadium prior to the start of the annual Harvard-Yale football game. All of the 309 forecasters self-identified as fans of one of the two schools (232 identified with

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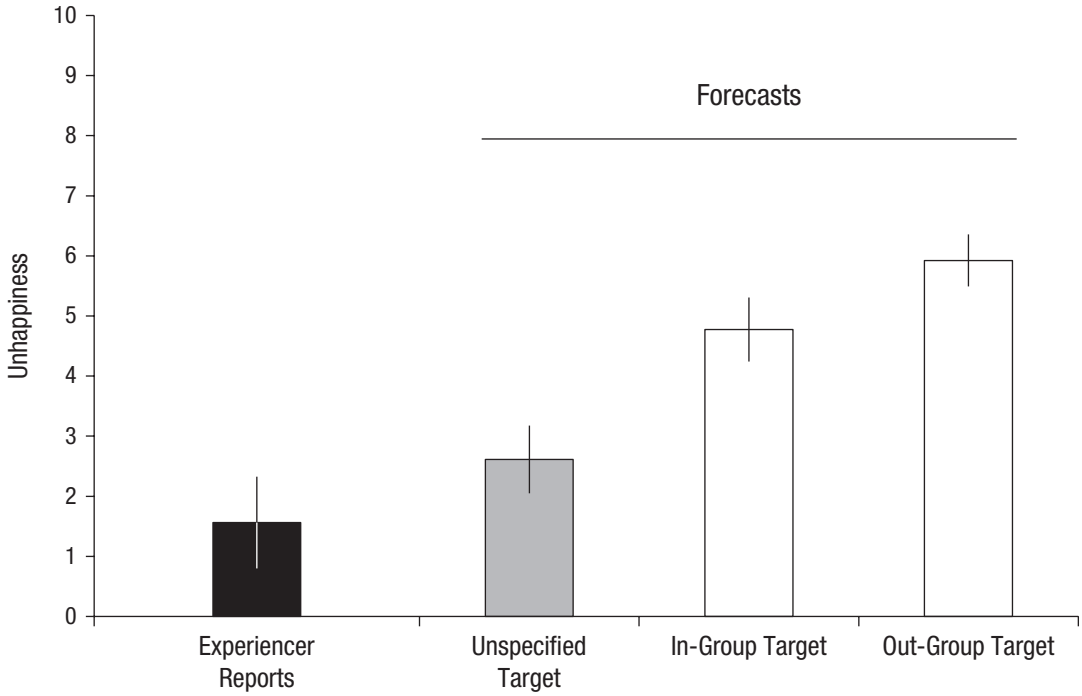

Fig. 2. Results from Experiment 1b: mean forecaster rating of how unhappy each of the three targets would feel if their team lost, along with the mean rating of Yale experiencers whose team actually lost. On the *y*-axis, 0 indicates neutral affect. Error bars represent ±1 *SEM*.

Harvard, 77 with Yale; 122 women, 187 men; mean age = 34.34 years, *SD* = 14.63). After the conclusion of the game, which Yale lost, we polled 51 self-identifying Yale fans (i.e., experiencers) as they left the stadium (23 women, 28 men; mean age = 26.12 years, *SD* = 11.33). In order for Yale fans to believe that this was a general survey and not a prank, we polled Harvard fans in the same locations. Harvard experiencer data were discarded because forecasts were made only about loss outcomes.

We excluded 2 forecasters who made predictions greater than 3 standard deviations from the mean of their conditions (e.g., forecasting maximal happiness for a target whose team loses the game). All experiencers passed this check. Thus, our final pool consisted of 307 forecasters (230 Harvard fans and 77 Yale fans; 122 women, 185 men; mean age = 34.42 years, *SD* = 14.65) and 51 experiencers.

Procedure. Forecasters first reported their team affiliation and then rated how much they like, value, and feel connected with each of the two schools on 7-point Likert scales ranging from −3, *strongly disagree*, to 3, *strongly agree*. They then forecasted how they thought one of three assigned targets ("a person," "a Harvard fan," "a Yale fan") would feel right after the football game if the target's team lost. Forecasts were made by marking an 11.25-cm-long line with end points labeled *extremely unhappy* and *extremely happy*. Forecasters could then report their level of intoxication, age, and gender. Experiencers were asked to rate how they felt ("How do you feel right now?") by marking an identical line with the same end points, and then could report their age and gender.

Results

Manipulation check. On average, forecasters who answered the identification questions expressed higher levels of liking, valuing, and feeling connected with the in-group (M = 2.14, SD = 1.33) compared with the out-group (M = −1.46, SD = 1.81; mean difference = 3.60, 95% CI = [3.33, 3.86]), $t(281) = 26.59$, $p < .001$.[4]

Forecasted and experienced affect. We overlaid transparencies on the questionnaires to code forecaster and experiencer line-mark ratings on a scale ranging from −10, *extremely happy*, to 10, *extremely unhappy*. Harvard and Yale fans did not differ in the extremity of their forecasts for members of their in-group ($p > .250$) and out-group ($p > .250$). Thus, we collapsed across schools so forecasts for in-group and out-group targets could be compared.

There was a significant main effect of condition on forecasted affect for how unspecified, in-group, and out-group targets would feel if their team lost, $F(3, 354) = 11.46$, $p < .001$, $\eta^2 = .09$ (see Fig. 2). A trend analysis showed that the data were well described by a linear trend (b = 30.33, 95% CI = [20.04, 40.63]), $t(355) = 5.80$, $p < .001$. Forecasts for losing the game were most extreme

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for out-group members, less extreme for in-group members, and least extreme for unspecified targets, for whom forecasts were most similar to experiencer reports.

Again, the more extreme forecasts for group-labeled targets made them less accurate. Pairwise comparisons with experiencer reports revealed that forecasts for in-group targets (M = 4.78, SD = 5.34) and out-group targets (M = 5.92, SD = 4.37) significantly overestimated how unhappy experiencers would be (M = 1.56, SD = 5.44); mean difference between in-group targets and experiencers = 3.22, 95% CI = [0.89, 5.53], $t(149) = 3.57$, $p = .002$; mean difference between out-group targets and experiencers = 4.36, 95% CI = [2.05, 6.67], $t(151) = 4.86$, $p < .001$. By contrast, forecasts made for unspecified targets (M = 2.61, SD = 5.78) did not differ significantly from experiencer reports (mean difference = 1.05, 95% CI = [−1.25, 3.35]), $t(154) = 1.18$, $p > .250$. Forecasts made for out-group targets did not differ significantly from forecasts made for in-group targets (mean difference = 1.14, 95% CI = [−0.75, 3.05]), $t(200) = 1.56$, $p > .250$.

Discussion

In a field setting with different social categories, affective forecasters made more extreme and less accurate predictions, relative to experiencers, when they knew the group membership of the target whose feelings they were forecasting.

Experiment 2: Online Tournament

In Experiment 2, we attempted to conceptually replicate Experiments 1a and 1b, and to assess whether forecasts of one's own feelings would reflect the impact bias (e.g., mirror the in-group forecast). We predicted that forecasts for group-labeled targets, but not for unspecified targets, would be more extreme and least accurate, relative to experiencer reports.

Method

Participants. Again, we aimed for a minimum of 100 participants per condition after exclusions. We recruited 692 participants using MTurk. We excluded 116 participants from analyses because they did not identify with either the Democratic or Republican party and an additional 60 participants for failing the comprehension checks, which consisted of successfully identifying the participant's own team and the other team in the tournament and acknowledging that the teams were competing rather than cooperating. Finally, we excluded 4 participants who made forecasts or reports greater than 3 standard deviations from the mean in the incorrect direction (i.e., forecasting or reporting maximal happiness given a loss). This left us with 512 participants (218 women, 294 men; mean age = 32.71 years, SD = 10.87).

Procedure. Participants who self-identified with one of the two major political parties completed the group-evaluation scales used in Experiment 1. They were then informed of an ongoing word-search tournament between two teams, the Democrats and the Republicans. The winning team's political party would receive a $200 donation. Participants always saw that their in-group was losing by a small margin of two points. After the word-search task was explained, participants watched a simulation of the task, ostensibly to understand the game.

Forecasters then predicted how one of four specific targets (i.e., "you," "a person," "a Democrat," "a Republican") would feel right after watching his or her team lose the tournament in the final round. Forecasts were made on a scale from −100, *extremely unhappy*, to 100, *extremely happy*. Experiencers were told instead that they had just watched the very last round of the tournament, and the opposing team had won. Experiencers then reported how they felt on the same scale. All participants then completed the same manipulation checks used in the previous experiments and were debriefed after reporting their age, gender, and ethnicity.

Results

Manipulation check. Again, ratings from the liking, valuing, and feeling-connected sliding scales were recoded from −100 to 100 and averaged to create a general-evaluation index (Cronbach's αs = .95 and .91 for in-group and out-group members, respectively). On average, participants evaluated the in-group more positively (M = 34.31, SD = 41.85) than the out-group (M = −55.47, SD = 39.68; mean difference = 89.78, 95% CI = [84.79, 94.78]), $t(511) = 35.28$, $p < .001$.

Forecasted and experienced unhappiness. As with the losing conditions in Experiment 1a, forecasts were reverse-coded so that 100 represented maximal unhappiness. There was a significant main effect of condition on participants' forecasts predicting how unspecified, in-group, and out-group targets, as well as they themselves, would feel if their team lost, $F(4, 507) = 4.65$, $p = .001$, $\eta^2 = .04$ (see Fig. 3). As in the previous experiments, the data were well fit to a linear trend (b = 132.38, 95% CI = [67.38, 197.38]), $t(509) = 4.00$, $p < .001$.

Planned contrasts revealed that forecasts for group-labeled targets were more extreme than experiencer reports, which replicated the findings of Experiments 1a and 1b. Experiencer reports (M = 42.56, SD = 34.58) were not significantly different from forecasts that participants made for themselves (M = 46.15, SD = 30.49; mean

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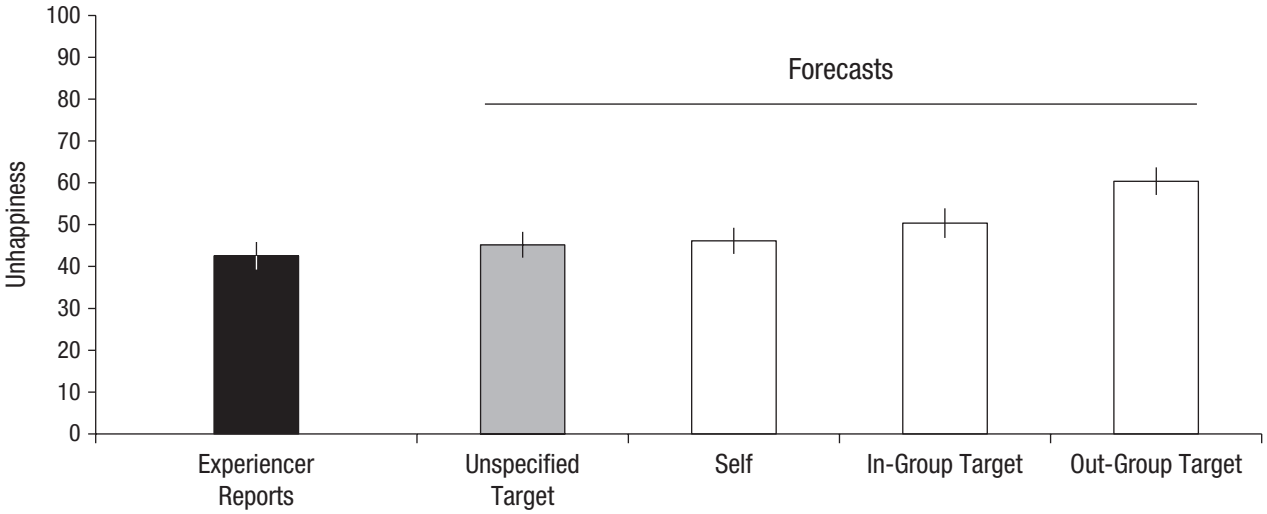

Fig. 3. Results from Experiment 2: mean forecaster rating of how unhappy each of the four targets would feel if their team lost, along with the mean rating of experiencers whose team actually lost. On the *y*-axis, 0 indicates neutral affect. Error bars represent ±1 *SEM*.

difference = −3.59, 95% CI [−12.69, 5.51]), $t(204) = -0.78$, $p > .250$, nor were they significantly different from forecasts made for unspecified targets ($M = 45.19$, $SD = 31.62$; mean difference = −2.63, 95% CI = [−11.49, 6.23]), $t(214) = -0.58$, $p > .250$. Experiencer reports were, however, marginally less extreme than forecasts made for in-group targets ($M = 50.38$, $SD = 35.01$; mean difference = −7.82, 95% CI = [−16.84, 1.21]), $t(207) = -1.70$, $p = .089$, and significantly less extreme for out-group targets ($M = 60.38$, $SD = 33.55$; mean difference = −17.82, 95% CI = [−26.73, −8.92]), $t(212) = -3.93$, $p < .001$. A targeted post hoc comparison of in-group and out-group forecasts indicated that they did not differ significantly (mean difference = 10.00, 95% CI = [−2.79, 22.81]), $t(199) = 2.14$, $p = .205$.

Discussion

Relative to experiencers, forecasters were most extreme and least accurate for group-labeled targets. Forecasts for one's self or an unspecified person were no different from experiencer reports.

Experiment 3: Different Intuitions Versus Overcorrection

In Experiment 3, we used time pressure to discern whether forecasters generate different intuitive predictions for group-labeled and unspecified targets or, as we predicted, whether they anchor on the same intuitive prediction and subsequently correct for social-categorization information in the group-labeled conditions. If the former is the case, then time pressure should exacerbate the difference between forecasts for group-labeled and unspecified targets. In contrast, our correction hypothesis suggests that time pressure should decrease these differences, because forecasters making predictions for group-labeled targets under time pressure should be less able to correct from their initial anchor.

Method

Participants. We aimed for a minimum of 100 participants per condition after exclusions. We were uncertain as to how many people would not be able to respond within the time limit in the time-pressure condition. Thus, we collected data until all of the conditions had a minimum of 100 participants. We used MTurk to recruit 2,724 participants, none of whom had participated in Experiment 2. We excluded participants who did not identify as either Democrat or Republican ($n = 459$), participants who stated that they thought the tournament was fake ($n = 2$), and participants in the time-pressure condition who did not make a response within the time limit ($n = 343$). Four comprehension checks asked participants to correctly identify, respectively, their own team, the other team, that the two teams were competing, and the target of their prediction (i.e., "a Democrat, "a Republican," "not specified," "other"); we excluded 455 participants for failing any one of these checks. Additionally, we excluded 20 participants who made forecasts greater than 3 standard deviations from the mean (i.e., predicted that the target would feel maximal happiness given a loss). This left us with 1,445 participants (875 women, 570 men; mean age = 32.62 years, $SD = 10.32$).

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Procedure. All participants made a forecast for a target who was unspecified, an in-group member, or an out-group member, following the procedure used in Experiment 2. Participants randomly assigned to the control condition answered the same question with the same format as those in Experiment 2 and had unlimited time to respond. Participants randomly assigned to the time-pressure condition saw the question (i.e., the forecast) displayed for 6 s, after which they had to make their forecast on an analog slider bar within 4 s (participants were informed of these time restrictions before seeing the question).[5] All participants then completed the same manipulation checks used in Experiment 2 and reported their age, gender, and ethnicity.

Results

Manipulation check. Again, ratings from the liking, valuing, and feeling-connected sliding scales were recoded from −100 to 100 and averaged to create general-evaluation indices (Cronbach's αs = .92 and .87 for in-group and out-group targets, respectively). On average, participants evaluated the in-group more positively (M = 41.08, SD = 37.30) than the out-group (M = −52.48, SD = 38.11; mean difference = 93.56, 95% CI = [90.64, 96.50]), $t(1444) = 62.62$, $p < .001$.

Forecasted unhappiness. As in the previous experiments, forecasts were reverse-coded so that 100 represented maximal unhappiness. A two-factor analysis of variance (ANOVA) revealed a main effect of time pressure, $F(1, 1439) = 27.67$, $p < .001$, a nonsignificant main effect of target, $F(2, 1439) = 2.14$, $p = .118$, and a marginal interaction between the two, $F(2, 1439) = 2.42$, $p = .089$ (see Fig. 4). As in our previous three experiments, a significant linear trend emerged in the control condition (b = 100.45, 95% CI = [44.22, 156.68]), $t(826) = 3.51$, $p < .001$; however, this effect was not seen for forecasts made under time pressure (b = −12.42, 95% CI = [−89.42, 64.57]), $t(613) = -0.32$, $p > .250$.

Supporting the correction hypothesis, results showed that forecasts made for in-group targets in the control condition (M = 56.68, SD = 29.28) were significantly more extreme than forecasts made for in-group targets in the time-pressure condition (M = 48.05, SD = 38.72; mean difference = 8.63, 95% CI = [2.75, 14.52]), $t(504) = 2.88$, $p = .004$. Similarly, forecasts for out-group targets made in the control condition (M = 60.85, SD = 30.17) were also significantly more extreme than forecasts made for out-group targets in the time-pressure condition (M = 47.04, SD = 42.18; mean difference = 13.81, 95% CI = [8.21, 19.40]), $t(564) = 4.84$, $p < .001$. For unspecified targets, forecasts made in the control condition (M = 52.16, SD = 25.40) did not differ significantly from forecasts made in the time-pressure condition (M = 48.25, SD = 34.64; mean difference = 3.91, 95% CI = [−3.05, 10.88]), $t(371) = 1.10$, $p > .250$. In the control condition, forecasts made for out-group targets did not differ significantly from forecasts made for in-group targets (mean difference = 4.17, 95% CI = [−1.21, 9.54]), $t(602) = 1.52$, $p = .128$.

Discussion

Relative to participants in the control condition, those in the time-pressure condition made less extreme forecasts for identified targets. The results suggest that more extreme forecasts for identified targets are due to overcorrection for social-category information rather than different intuitive predictions.

Experiment 4: Investigating the Source of Overcorrection

In Experiment 4, we examined why group labels exacerbate the impact bias via overcorrection. Group labels might drive participants to retrieve more extreme exemplars when making forecasts (e.g., participants may imagine how an extreme partisan would feel). Alternatively, group labels might activate stereotypes, shifting participants' entire distribution of forecasts (e.g., Democrats and Republicans in general would be more upset by a loss). In this experiment, participants made affective forecasts for an individual target and then estimated how that person would rank with regard to other members of his or her category in the extremity of his or her response, which allowed us to test the exemplar hypothesis. We also included a fourth group, Buddhists, to test whether stereotyping underlies the exacerbated impact bias for group-labeled targets. If so, participants should exhibit a reversal of the impact bias for this stereotypically unreactive group (e.g., Crane, 2006). (Preregistration materials for this study can be found on the Open Science Framework at https://osf.io/x8efz.)

Method

Participants. We aimed for a minimum of 100 participants per condition after exclusions. We recruited 851 participants using MTurk, none of whom had participated in Experiments 2 or 3. Participants who did not identify as either Democrat or Republican (n = 134) were excluded from analyses. Three comprehension checks asked participants to correctly identify the target of their forecast and the correct number of peers the target was then ranked against (i.e., 100), and to acknowledge that the two parties were competing in a tournament. We excluded 165 participants who failed at least one of these checks. Additionally, we excluded 7 participants who

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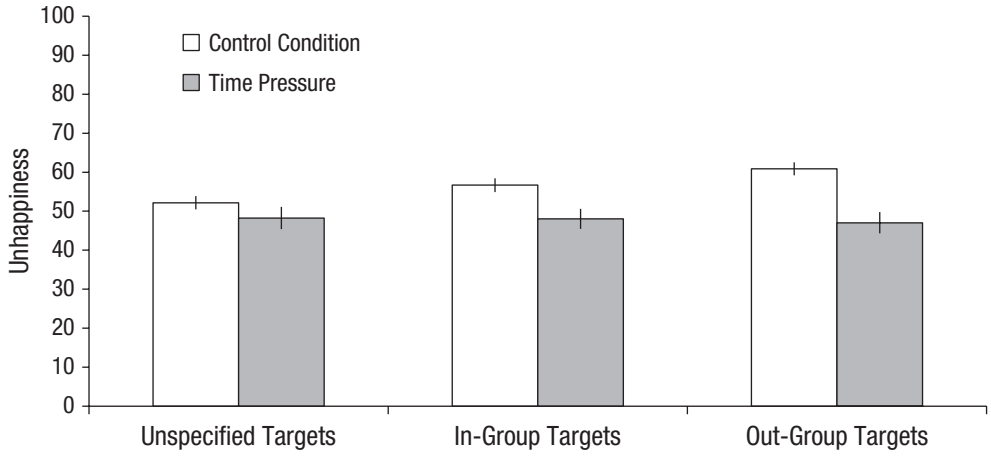

Fig. 4. Results from Experiment 3: mean forecaster rating of how unhappy each of the three targets would feel if their team lost, separately for participants in the control and time-pressure conditions. On the *y*-axis, 0 indicates neutral affect. Error bars represent ±1 *SEM*.

made forecasts greater than 3 standard deviations from the mean (i.e., predicted that the target would feel maximal happiness given a loss). Our final pool consisted of 545 participants (307 women, 238 men; mean age = 32.47 years, *SD* = 10.63).

Procedure. Participants who self-identified with one of the two major political parties completed the same group-evaluation scales used in Experiment 1. They then imagined an ongoing, problem-solving tournament between the two teams, the Democrats and the Republicans (based on the procedure in Experiments 2 and 3).

Participants then predicted how a specific target (i.e., "Buddhist X," "Person X," "Democrat X," "Republican X") would feel right after watching his or her team lose the tournament in the final round. Participants made predictions on a scale from −100, *extremely unhappy*, to 100, *extremely happy*. On the subsequent page, they indicated how that target would rank among 100 of his or her peers who also watched their party lose the tournament—for example, "Relative to these other Buddhists, from the least unhappy Buddhist (1 out of 100) to the most unhappy Buddhist (100 out of 100), how unhappy would Buddhist X be?" All participants then completed the same manipulation checks used in the previous experiments and reported their age and gender.

Results

Manipulation check. Again, ratings from the liking, valuing, and feeling-connected scales were recoded from −100 to 100 and averaged to create general-evaluation indices (Cronbach's αs = .91 and .88 for in-group and out-group targets, respectively). On average, participants evaluated the in-group more positively (M = 31.83, SD = 40.64) than the out-group (M = −50.94, SD = 37.92; mean difference = 82.77, 95% CI = [77.68, 87.84]), $t(544)$ = 32.00, $p < .001$.

Forecasted unhappiness. As in the previous experiments, forecasts were reverse-coded so that 100 represented maximal unhappiness. An ANOVA revealed a main effect of target, $F(3, 541) = 48.44$, $p < .001$, $\eta^2 = .21$ (see Fig. 5). Again, the data were well fit to a linear trend (b = 334.09, 95% CI = [276.77, 391.41]), $t(542) = 11.45$, $p < .001$.

Replicating the results of Experiments 1a, 1b, and 2, and the control condition in Experiment 3, post hoc comparisons revealed that participants made more extreme forecasts for political group-labeled targets than for unspecified targets. By contrast, participants made less extreme forecasts for Buddhist-labeled targets than for unspecified targets. Forecasts made for unspecified targets (M = 60.58, SD = 28.68) were directionally less extreme than, though not significantly different from, forecasts for political in-group targets (M = 61.76, SD = 26.63; mean difference = 1.18, 95% CI = [−8.28, 10.64]), $t(256) = 0.32$, $p > .250$, and significantly less extreme than forecasts made for political out-group targets (M = 77.76, SD = 23.76; mean difference = 17.18, 95% CI = [7.76, 26.59]), $t(260) = 4.70$, $p < .001$. Forecasts for the unspecified targets were, however, significantly more extreme than forecasts for Buddhist targets (M = 36.46, SD = 36.61; mean difference = −24.12, 95% CI = [−33.98, −14.27]), $t(229) = -6.30$, $p < .001$. Finally, forecasts made for out-group targets were significantly more extreme than forecasts made for in-group targets (mean difference = 16.00, 95% CI = [7.59, 24.39]), $t(312) = 4.90$, $p < .001$.

An ANOVA of rankings of the target among the target's peers (peer-rank estimates) showed a significant effect of condition, $F(3, 541) = 8.03$, $p < .001$, $\eta^2 = .04$ (see Fig. 5). The data fit a relatively flat linear trend, though it was still

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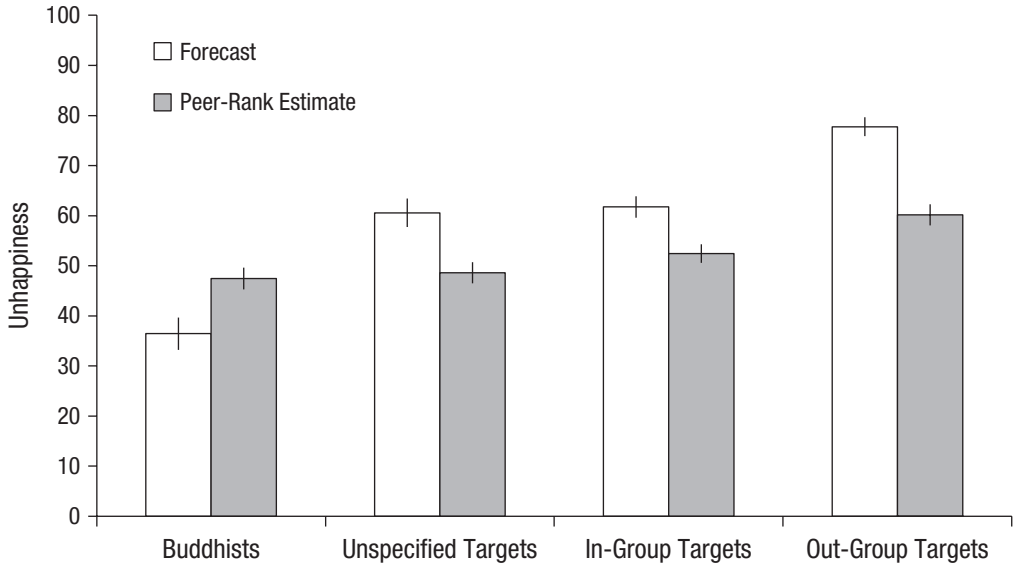

Fig. 5. Results from Experiment 4: mean forecaster rating of how unhappy each of the four targets would feel if their team lost, along with peer-rank estimates for each target. On the *y*-axis, 0 indicates neutral affect. Error bars represent ±1 *SEM*.

significantly different from 0 (b = 112.47, 95% CI = [64.87, 160.06]), $t(542) = 4.64$, $p < .001$. Post hoc comparisons showed that peer-rank estimates for unspecified targets (M = 48.60, SD = 21.56) did not differ significantly from peer-rank estimates for in-group targets (M = 52.46, SD = 22.97; mean difference = 3.86, 95% CI = [−4.08, 11.80]), $t(256) = 1.25$, $p > .250$, or Buddhist targets (M = 47.45, SD = 24.66; mean difference = −1.15, 95% CI = [−9.42, 7.12]), $t(229) = -0.36$, $p > .250$. Peer-rank estimates for out-group targets (M = 60.18, SD = 26.65) were, however, significantly higher than peer-rank estimates for unspecified targets (mean difference = 11.58, 95% CI = [3.68, 19.48]), $t(260) = 3.78$, $p = .001$.

Finally, a linear trend analysis concatenating the two dependent variables (i.e., forecast and peer-rank estimate) and dummy coding the type of dependent variable showed that the linear trends of forecast and peer-rank estimate were different from one another at a level of marginal significance, $t(1084) = -1.93$, $p = .054$. In other words, the linear trend of the forecasts was steeper than the linear trend of the peer-rank estimates.

Discussion

The results of Experiment 4 suggest that the overcorrection observed in Experiment 3 was indeed driven by adjustment for group stereotypes to a greater extent than by retrieval of extreme exemplars in the group-labeled conditions. Participants forecasted that the stereotypically unreactive group—Buddhists—would be least unhappy after suffering a loss, followed by unspecified and political in-group targets, with political out-group targets rated as most unhappy. These results indicate that participants' forecasts were influenced by stereotypes, even for their in-group. By contrast, participants' ratings of the relative extremity of each target were more similar across conditions. Forecasters did not recruit more extreme exemplars when making predictions for group-labeled targets, with the exception of out-group targets.

General Discussion

When forecasting the emotional impact that positive and negative events will have on other people, considering social-category information appeared to paradoxically increase the prevalence of impact bias. In contrast to the general palliative effect of correction on affective forecasts and intuitive judgments (Chaiken & Trope, 1999; Frederick, 2005; Gilbert & Wilson, 2007; Morewedge & Kahneman, 2010), correction (or in this case, overcorrection) appeared to underlie the increased impact bias exhibited for targets identified by their social categories. This effect held for both in-group and out-group targets. Though there was a reliable trend for out-group forecasts to be more extreme than in-group forecasts, they were only significantly different from one another in one experiment. Furthermore, we found that overcorrection was relatively better explained by stereotype activation in group-labeled conditions than by the spontaneous retrieval of extreme exemplars.

Beyond demonstrating the impact of social-category information on affective forecasting, these results enrich the understanding of the interplay of simulation and theory theory in social cognition. Forecasters appear

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to initially anchor on a simulation of how they or an unspecified other would respond to an event and then correct from that anchor if their theories suggest that the target or the target's group members might react differently. Thus, the extremity of an affective forecast may index the extent to which the forecaster's representation of his or her target is biased by stereotype information.

More broadly, these results make a practical contribution to the literature by elucidating how impact bias may escalate the spiral of conflict (Kennedy & Pronin, 2008). For example, negotiators may eschew conflict-reducing solutions because they overestimate their in-group's disappointment if they compromise. Similarly, negotiators may overestimate out-group members' pleasure in response to their concessions, which could lead to an expectancy violation when out-group members seem unenthused. Given the reliance on affective forecasts for decisions made for other people, future research in this area may help to reduce bias in proxy decisions in consequential legal, medical, and political contexts.

Action Editor

Ralph Adolphs served as action editor for this article.

Author Contributions

All authors developed the study concept and designed the experiments. T. Lau collected and analyzed the data under the supervision of C. K. Morewedge and M. Cikara. All authors cowrote the manuscript and approved the final version of the manuscript for submission.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Open Practices

All data and materials have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/9e5au/. The hypotheses, method, and analysis plan for Experiment 4 were preregistered at the Open Science Framework and can be accessed at https://osf.io/x8efz/. The complete Open Practices Disclosure for this article can be found at http://pss.sagepub.com/content/by/supplemental-data. This article has received badges for Open Data and Open Materials. More information about the Open Practices badges can be found at https://osf.io/tvyxz/wiki/1.%20View%20the%20Badges/ and http://pss.sagepub.com/content/25/1/3.full.

Notes

1. Across all experiments, we asked specifically about participants' affective responses to the event's outcome rather than their global affect.
2. There are many factors that determine whether or not people exhibit the impact bias in affective forecasting. Levine, Lench, Kaplan, and Safer (2012), for example, demonstrated two procedural factors that can attenuate impact bias. First, impact bias may be reduced when affective forecasts and experiencer reports are made immediately before and after the event (as opposed to when forecasts and experiences are separated by days, weeks, or months). Second, impact bias may be reduced when participants report feelings about the specific event rather than their global affect (e.g., "How would you feel about your candidate losing the election?" vs. "If your candidate lost the election, how happy would you feel?"). We incorporated these two factors in the methods of all of our experiments, which may explain why participants did not exhibit impact bias for self and unspecified targets.
3. Because of rounding, the mean differences reported in this article vary in some cases by 0.01 from the output readers will receive if they run our analysis code on the publically shared data.
4. Not every participant completed the identification measures. This statistic was computed using data from participants who answered both identification questions.
5. To determine the time limit in the time-pressure condition of Experiment 3, we calculated the average reaction time in Experiment 2 for each condition. The minimum average reaction time occurred in the self condition (M = 13.00 s, SD = 6.01). Thus, for Experiment 3, we decided to set the entire reaction time limit—reading and responding—to 10 s. We then conducted a pilot study testing this procedure (6 s to read the prompt and 4 s to respond) on a separate set of participants (N = 40) who were asked to make a forecast for either an out-group member or an unspecified target. Only 4 participants in this pilot study were unable to answer within the time limit.

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