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Praise-Many, Blame-Fewer: A Common (and Successful) Strategy for Attributing Responsibility in Groups

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It is often unclear how to apportion praise after a group's success and blame after a group's failure. Should all members share responsibility or only a select few? In this article, we examine how people do solve this apportionment problem and how they should solve this problem. Seven empirical studies ($N = 1,052$) reveal that people frequently rely on a strategy of praise-many, blame-fewer, a tendency found across several different domains: high-profile sports championships, hierarchical business decisions, and first- and third-person judgments of impromptu work teams. Agent-based models test the success of different apportionment strategies under different conditions. These models suggest that in many circumstances it is adaptive to praise broadly after success and to blame more narrowly after failure—even with only minimal insight into individual skill—although effects vary depending on the motivation of group members to improve after being blamed.

Keywords: responsibility attribution, agent-based modeling, social evaluation, group dynamics, group performance

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Armies, political parties, sports teams, and corporations frequently battle each other for resources and prestige. Although the performance of these groups hinges on the actions of its members, it is often unclear exactly how the inputs of individuals translate into the outcomes of groups (Kelley & Michela, 1980). This causal uncertainty leads to a key issue for groups, the apportionment problem: How should responsibility for successes and failures be distributed among group members? Should CEOs praise all employees after a successful merger (broad apportionment) or only a few superstars (narrow apportionment)? Should coaches blame their entire team for a loss (broad apportionment) or only the worst performers (narrow apportionment)?

The apportionment problem involves making judgments under uncertainty (Tversky & Kahneman, 1974), which is typically studied by comparing how people do make judgments (descriptive

research) with how people should make judgments (normative research). Past descriptive research on the apportionment problem has shown that group size influences whether people adopt a case-based view (evaluating people's responsibilities independently) or a class-based view (evaluating the group's responsibility as a whole; Teigen & Brun, 2011), and studies also reveal that apportionments of blame within groups are sensitive to how "pivotal" (Zultan, Gerstenberg, & Lagnado, 2012) and how intentional (Lagnado & Channon, 2008) someone's actions seem to be. Past normative research has also examined how ideal decision makers should allocate blame and praise on the basis of causality, knowledge, intentionality, coercion, and moral wrongfulness (Shaver, 1985) and how factors such as mental illness should play into judgments of blameworthiness (Robinson, 1992). These findings and others have been reviewed at length elsewhere (Lagnado, Gerstenberg, & Zultan, 2013; Malle, Guglielmo, & Monroe, 2012; Weiner, 1995) and have been integrated into general theories of praise and blame (Alicke, 2000; Malle, Guglielmo, & Monroe, 2014).

Here we complement this past work by examining a different aspect of the apportionment problem, namely, how assignments of responsibility in groups vary based on whether they involve blame (because of a group failure) or praise (because of a group success). Some studies have examined how attributions of responsibility vary across positive and negative events. For example, Nordbye and Teigen (2014) found that people viewed winners of high-profile chess games as more responsible for the game's outcome than losers, and Guglielmo and Malle (2019) found that people's judgments of blame are more extreme than their judgments of praise for individual actions. But this past work did not investigate how the breadth of apportionment might vary across praise and

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blame in a variety of group settings. In this article, we compare the apportionment of blame and praise across a variety of different domains, both when individuals are onlookers and when they are group members. By means of seven experimental studies and a set of agent-based models (ABMs), we ask the following questions: Do people apportion praise differently than blame to people in groups? And, could an asymmetry in praise and blame apportionment be functional at the group level?

How Do We Assign Blame and Praise Within Groups?

People's allocation of praise and blame often hinges on who they see as responsible for positive or negative outcomes (Lagnado & Channon, 2008; Malle et al., 2014). Football fans might judge the player who missed the final, critical, catch as responsible for the team's loss and will blame them accordingly. Alternatively, people in an organization might see the employee whose insight was pivotal for a project's success as responsible for its outcome and will praise them. Responsibility and praiseworthiness or blameworthiness even correlate in extraordinary situations where causality does not necessarily track blameworthiness. For example, if a child fatally shoots his or her sibling with their parents' gun, the child caused the outcome, but the parents are deemed both responsible and to blame for their child's death (Lagnado & Channon, 2008). Because people's apportionment of praise and blame is closely yoked to their attributions of responsibility (Fincham & Jaspars, 1979; Halpern & Pearl, 2005; Lagnado et al., 2013; Malle et al., 2014; Weiner, 1995), understanding how people attribute responsibility for positive versus negative outcomes is crucial for understanding how people apportion praise versus blame in groups.

We suggest that when people assign responsibility for positive or negative events, they show an asymmetry in judgment, which assumes that many people are responsible for positive events but fewer people are responsible for negative events. This praise-blame asymmetry may stem from the relative costliness of each form of judgment (Guglielmo & Malle, 2019). Praise is relatively cost-free. People typically enjoy being praised, and there is seldom a social penalty for the person doing the praising. Blame, however, has a high social cost (Malle et al., 2014). Blaming another person in a way that is seen as unjustified or excessive can lead to the deterioration of relationships, retaliation, and revenge (Dreber, Rand, Fudenberg, & Nowak, 2008; McCullough, Kurzban, & Tabak, 2013). In the workplace, blame that is perceived as unjustified fuels employee resentment (Aquino, Tripp, & Bies, 2001) and decreases workplace commitment (Podsakoff, Bommer, Podsakoff, & MacKenzie, 2006). Because inaccurate blame is costly (Malle et al., 2014), it requires justification in a way that praise simply does not (Voiklis & Malle, 2017).

Other psychological theories also support the existence of an asymmetry in blame and praise, even when praise and blame are similarly costly. For example, according to the broaden-and-build theory of positive emotions, positive outcomes—and the positive affect they generate—broaden attentional focus (Fredrickson, 2013) and facilitate higher levels of action identification (Valacher & Wegner, 1987). In contrast, negative affect narrows attention (Fredrickson & Branigan, 2005), promoting vigilance and attention to salient threats (Isen & Daubman, 1984). Although broaden-and-build is not inherently a theory of group attributions,

it predicts that following group success, group members' broad attentional focus should lead them to recognize a multitude of individuals' contributions to the outcome, whereas failure should lead group members to narrow their attention and fixate on a smaller number of responsible individuals. Taken together, these findings suggest what we call the *praise-many, blame-fewer apportionment tendency*.

At first blush, predicting that blame is more focused than praise seems to contradict the popular psychological principle that "bad is stronger than good" (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). Decades of research on attention (Fiske, 1980), emotional states (Taylor, 1991), and evaluation of categories (Ito, Larsen, Smith, & Cacioppo, 1998) have revealed the greater power of negativity versus positivity (Rozin & Royzman, 2001). Consistent with this prediction, recent research has found that blame ratings are higher in severity than praise ratings for actions that were matched on relative extremity of negativity and positivity (Guglielmo & Malle, 2019). However, the greater severity of blame need not translate to more people blamed; it could simply translate to caring more about blame. In many cases, the strength of negativity should lead to a more intense search for specific scapegoats to blame. After positive outcomes, even those only casually involved can be praised (Bastian, Laham, Wilson, Haslam, & Koval, 2011; Pizarro, Uhlmann, & Salovey, 2003), whereas after negative outcomes, people often search for a specific individual or individuals to scapegoat (Boeker, 1992; Rothschild, Landau, Sullivan, & Keefer, 2012).

How Should We Assign Blame and Praise Within Groups?

Individuals may show a praise-many, blame-fewer tendency, but is this strategy functional for groups over time? To answer this question, we first need to understand how praise and blame impact both group and individual behaviors. We can then predict how these immediate impacts might influence groups over time.

Praise and blame differentially impact group composition. Praise increases interpersonal commitment (Algoe, Kurtz, & Hilaire, 2016) and social reputation (Henrich & Gil-White, 2001). Inasmuch as praise translates into feeling valued, praise will also increase organizational commitment (Eisenberger, Huntington, Hutchison, & Sowa, 1986). Thus, praise increases the likelihood that groups retain their members over time. In contrast, blame lowers reputation and prestige, and decreases the likelihood that an individual will reproduce or remain in the group (Barkow et al., 1975; Hill, 1984). Furthermore, unjust and unwarranted blame often translates into increased resentment (Aquino et al., 2001) and decreased workplace commitment (Podsakoff et al., 2006). Given that people often perceive their own wrongdoings as relatively less blameworthy than other's misdeeds (Elshout, Nelissen, & van Beest, 2017; Stillwell, Baumeister, & Del Priore, 2008), it is likely that even deserved blame might feel undeserved, increasing resentment and decreasing commitment.

If praise encourages retention and blame encourages defection, one might initially predict that a praise-many, blame-many strategy would be most effective. Consistent with the game theory maxim of "win-stay, lose-shift" (Nowak & Sigmund, 1993), praising maximally following success and blaming maximally

following failure would allow organizations to keep strong groups together and maximally change weak groups.

However, a broad apportionment strategy for both praise and blame would be suboptimal in many contexts. If an organization lacks insight into those who deserve to be praised or blamed, a broad apportionment strategy might retain poorly performing members following success and remove excellently performing members following failure. Additionally, a broad-blame strategy would be suboptimal when a high turnover rate is costly for groups (Park & Shaw, 2013; Ton & Huckman, 2008). In general, turnovers decrease profitability (Park & Shaw, 2013), translate into a loss of social capital (Osterman, 1987), and create coordination costs, as new group members must learn new skills and adapt to group norms (Kacmar, Andrews, Van Rooy, Steilberg, & Cerrone, 2006). Of course, if groups can replace their members from a highly skilled pool without transaction costs, this turnover penalty might be partially mitigated. Given the general costliness of group member replacement, a blame-fewer strategy might be more effective over time than a blame-many strategy.

Factors beyond retention should also affect the functionality of praise and blame. There is an extensive literature in educational psychology on the impact of praise and blame on individual motivation (Ashby & O'Brien, 2007; Meyer & Offenbach, 1962; Weiner, 1985). Praise and positive reinforcement, more generally, increase desirable behaviors (Meyer & Offenbach, 1962), recommending a praise-many strategy. To the extent that blame functions as a form of positive punishment, blame may also increase people's motivation to improve their performance in the future (Clutton-Brock & Parker, 1995; Mowrer, 1960). Thus, a blame-many strategy might become increasingly effective when more team members find blame motivating. However, motivation to change after blame might be uncommon. People see their own wrongdoings as less severe (Elshout et al., 2017), view themselves as less responsible than others for team failures (Forsyth, Berger, & Mitchell, 1981), and resent unjust accusations of wrongdoing (Aquino et al., 2001). When blame leads to resentment, not motivation, a praise-many, blame-fewer strategy should be more effective at improving group performance over time.

Current Research

We use a multimethod approach to investigate the apportionment problem, revealing and contrasting the descriptive and normative solutions to this enduring challenge. In seven studies, we examine how people make apportionment decisions across college basketball (Study 1), American football (Study 2), hierarchical corporations (Study 3), and online work teams (Studies 4 through 7). These domains are intentionally diverse. We examine apportionment in both hierarchical groups (Study 3) and more egalitarian groups (Studies 4 through 7), both when raters highly identify with a team (Study 1) and when they are more passive observers (Study 2), and from first- (Study 4, 6, and 7) and third-person perspectives (Study 5). We look both at the general attribution of responsibility (Studies 1 through 6) and specific judgments of praise and blame (Study 7). We hypothesize that across all these settings, people will hold more people responsible for success than they hold responsible for failure (i.e., the praise-many, blame-fewer tendency).

Via a set of ABMs, we then test how people should make apportionment decisions by simulating populations of competing groups under different conditions. ABMs are useful in social science research because they can illustrate how complex group-level phenomena emerge from interacting agents following basic rules over time (for a helpful overview of ABMs in social science, see Jackson, Rand, Lewis, Norton, & Gray, 2017). ABMs also have the benefit of providing researchers with greater control relative to field studies, lab experiments, or archival studies, as agents' behaviors can be carefully specified and studied over thousands of iterations. Of course, this high level of control often comes at the cost of realism. For example, previous models make assumptions that moving homes incurs no costs (Schelling, 1971) and that once a couple starts dating, they are permanently removed from the dating pool (Kalick & Hamilton, 1986). Therefore, we use agent-based modeling primarily as a theory-building tool to examine whether a tendency to praise many and blame fewer (tested in the empirical Studies 1 through 7) could, under certain conditions, lead to more successful group outcomes over the course of thousands of group competitions.

Our models test the hypothetical effectiveness of varying apportionment strategies (e.g., broad vs. narrow praise/blame), under the assumption that praise makes groups more likely to retain members over time, whereas blame decreases retention. We acknowledge that blame does not always translate to lower retention. Some groups (e.g., family units) will retain all members regardless of blame and praise, and other groups (e.g., impromptu groups) may retain no members regardless of blame and praise. To increase the model's external validity, Study 6 quantifies the degree that praise increases group retention and blame decreases group retention in an experimental setting, and we use these coefficients in our model. We also model how the effects of blame and praise change under three key contextual parameters. First, we vary the extent that blame motivates individuals in groups to increase their skill level. Second, we vary how much insight group members have into who deserves to be praised or blamed. Finally, because the costliness of turnovers depends in part on whether there is a highly skilled pool, we vary whether groups replace individuals from a pool that increases in skill over time or remains the same over time. We make no a priori hypothesis concerning how different apportionment strategies should affect group performance.

Study 1: Basketball Rivalry

The first study examined two games between college basketball rivals (University of North Carolina, Chapel Hill [UNC] and Duke University). UNC lost one game and won the other, creating a natural experiment. We examined whether UNC students would broadly praise winning team members but more narrowly blame losing team members. Studies 1 and 2 were both approved by UNC Institutional Review Board (IRB; 15-0319).

Method

Participants. Fifty (UNC's loss) and 51 (UNC's win) participants (58% female, $M_{\text{age}} = 19.37$) were recruited from public places around the UNC campus on the day after the UNC loss against Duke and UNC's win during the 2015-2016 season. Studies 1 and 2 were conducted for an undergraduate thesis with data

collection occurring from Spring 2015 to Spring 2016, explaining the timeframe for these studies. We did not conduct an a priori power analysis for this first study, but a sensitivity analysis suggests that with a sample of 100 participants, power of .80, and alpha at .05, we would be able to detect an effect size of the outcome difference at $f = .28$, $\eta^2 = .07$.

Procedure and measures. Participants completed a paper-and-pencil survey in which they made two apportionment decisions: one assigning responsibility for the win and one assigning responsibility for the loss. To accomplish this task, they were given a checklist of all active team members and the head coach for both teams (see the online supplemental materials for details) and told to check any team members they believed were responsible for the outcome of the game. Participants then rated how much they cared about UNC's basketball team and then reported their age and gender. Participants on average reported caring highly about the game ($M = 7.71$, $SD = 2.30$, on a 10-point scale). To make comparisons between games easier, we converted the sum of players selected into proportion of players.

Results

We ran a 2 (outcome: win, loss) \times 2 (game: Duke win, UNC win) mixed-model analysis of variance (ANOVA) and found a significant main effect of outcome, with more players praised after a win ($M = .60$, $SD = .30$) than blamed after a loss ($M = .41$, $SD = .29$), $F(1, 99) = 36.93$, $p < .001$, partial $\eta^2 = .27$, (M difference = .19, 95% CI [.13, .25]). These results provide initial evidence that people praise many and blame fewer.

The ANOVA also revealed a significant interaction between outcome and game, $F(1, 99) = 6.60$, $p = .01$, partial $\eta^2 = .06$. Analysis of the simple main effects showed that UNC students held a larger proportion of the UNC players responsible for a win ($M = .73$, $SD = .28$) than Duke players for a Duke win ($M = .47$, $SD = .30$), $F(1, 99) = 20.61$, $p < .001$, partial $\eta^2 = .17$, (M difference = .26, 95% CI [.15, .37]). There was also a trend suggesting that UNC students held a smaller proportion of players responsible for a UNC loss ($M = .36$, $SD = .31$) than Duke players for a Duke loss ($M = .46$, $SD = .27$), $F(1, 99) = 3.08$, $p = .08$, partial $\eta^2 = .03$, (M difference = .10, 95% CI [-.01, .22]). In other words, UNC students were inclined to give more praise to and withhold more blame from the UNC basketball team relative to the Duke basketball team. This imbalance likely reflects the strong rivalry between UNC and Duke—UNC students think not only the best of their team, but also the worst of Duke's team. Although such rivalry makes students invested in the outcome of games, it also limits the generalizability of these findings, as it is possible that attributions are self-serving (Forsyth et al., 1981). We therefore sought to examine apportionment decisions in another arena.

Study 2: NFL Playoffs

To test the generalizability of the results from Study 1, we examined apportionment decisions in another sports domain: NFL playoff games.

Method

Participants. The Monday following each major game, 100 participants were recruited online through Amazon Mechanical

Turk (MTurk). Participants who failed an informational attention check were eliminated prior to data analysis. The importation of the effect size found in Study 1 (partial $\eta^2 = .27$) into a power analysis using G*Power 3.1.9.2 (Faul, Erdfelder, Buchner, & Lang, 2009) suggested that a relatively small sample size was needed to detect a significant main effect of game outcome at power of .80, but we nonetheless aimed for 100 participants per game.

The final data set included 87 participants for Super Bowl 2015, 94 for the 2016 AFC Championship (64% male, $M_{\text{age}} = 35$), 92 for the NFC Championship, (65% male, $M_{\text{age}} = 35$), and 85 for Super Bowl 2016 (72% male, $M_{\text{age}} = 37$), for a total sample size of 358. Because of researcher error, demographic information was not collected for Super Bowl 2015. As with our other MTurk studies, all participants reported being U.S. residents, and all had HIT (i.e., Human Intelligence Task in MTurk) approval rates of over 95%.

Procedure. We selected the four most important games in the data collection timeframe (February 2015 through February 2016): Super Bowl 2015, Super Bowl 2016, and the 2016 Division Championship games. We surmised that these games would receive wide interest but that they would incite less personal investment in our sample than would UNC–Duke basketball. The Monday after each game, all participants answered the following question for both the winning and the losing teams, presented in random order: “Of the players listed below, who should be held responsible for the [team]’s loss/win yesterday? Check all that apply.” Participants were then presented with a list of nine (Super Bowls 2015 and 2016 and 2016 NFC and AFC Championships) or 11 (Super Bowl 2016) key players and the head coach for each team. Players were selected by the lead author based on the box scores provided by ESPN and checked by a research assistant with greater familiarity with football (see the online supplemental materials for full lists). Box scores were used because they show players who were active in the game, and they rank players on passing, rushing, receiving, fumbles, interceptions, returns, and kicking.

Results

Consistent with a praise-many, blame-fewer tendency, a 2 (outcome: win, loss) \times 4 (game) mixed-model ANOVA revealed a main effect of outcome, $F(1, 354) = 83.68$, $p < .001$, partial $\eta^2 = .19$, (M difference = .12, 95% CI [.09, .14]). A greater proportion of players were selected as responsible for the outcome when the team won ($M = .36$, $SD = .30$), than when the team lost ($M = .24$, $SD = .24$). There was no interaction with game, $F(3, 354) = .67$, $p = .57$, partial $\eta^2 = .006$, suggesting that the effect held constant through each of the games (see Figure 1 for results split by game).

One question is whether these judgments reflect a general psychological proclivity or a truth about sports—for a win, everything typically needs to go right, so a whole team has to contribute; for a team to lose, only one thing has to go wrong. This objection is particularly relevant for Super Bowl 2015, as one key mistake in the last seconds of the game led to the Seahawks' loss and the Patriots' win. Changing just one play could have reversed the outcome of the game, making the final call both pivotal and critical (Lagnado et al., 2013). Our data suggest, however, that people praise many and blame fewer, even in situations in which post-game analyses propose that many players are at fault. The Panthers' loss in 2016 was not close, and the counterfactual outcome

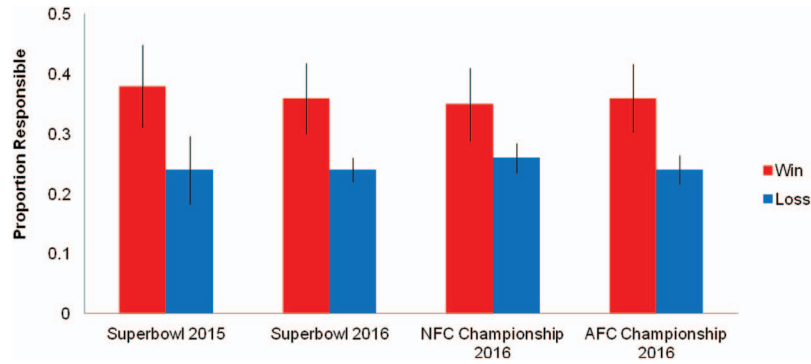


Figure 1. Proportion of football team members held responsible for a win versus a loss, split by game. Error bars indicate 95% confidence intervals (Study 2). See the online article for the color version of this figure.

would have required multiple changes. Furthermore, if only the final act is pivotal, then praise should only be ascribed to the defensive lineman whose pickoff ended the Seahawks' final drive. Examining the means reveals substantial consistency across games (see Figure 1).

Study 3: Workplace Decisions

We next examined whether people used a praise-many, blame-fewer tendency in a very different domain: a hypothetical business decision. The study was run under UNC IRB 12–1585.

Method

Participants. One hundred 83 participants completed the study through MTurk, and 22 were excluded for failing an informational manipulation check (e.g., select only option *x*), leaving 161 participants (52% female, $M_{\text{age}} = 38$). Power analyses based on the effect sizes from the previous two studies suggested that we would need a sample size below 50, but we aimed for a sample between 50 and 100 participants per cell.

Procedure. All participants read the following vignette about the chain of command involved in a risky business investment that either succeeds or fails:

Rob is the CEO of a business and has recently learned about a high-risk investment, that could double his company's worth, but could also lead to bankruptcy. Rob consults Gray, a senior adviser at the firm, who agrees that it's a good investment. Rob orders Tim, a mid-level employee, to oversee the investment. Mark, a low-level employee prepares the paperwork that helps finalize the investment. The investment fails [succeeds]. The company goes into bankruptcy [doubles its worth], and over 100 employees are laid off [hires over 100 new employees]. (Note: The fail condition is underlined, the succeed condition is in brackets.)

After reading the vignette, participants saw a list of all four actors named in the vignette (CEO, senior adviser, middle manager, low-level employee), and they were asked to check off all people that they thought were responsible for the failure/success of the business. They then completed demographics questions.

Results

Consistent with a praise-many, blame-fewer tendency, participants selected more of the four employees as responsible when the

investment succeeded and doubled the company's earnings ($M = 2.81$, $SD = 1.18$) than when the investment failed and led to bankruptcy ($M = 1.77$, $SD = .76$), $t(159) = 6.69$, $p < .001$, 95% CI [.74, 1.36], $d = 1.05$. As the means reveal (see Figure 2), this difference in apportionment was smallest (2%) at the top of the chain of command, $\chi^2(N = 161) = .22$, $p = .64$, 95% CI [-7.53, 11.57], and larger at the bottom (44%), $\chi^2(N = 161) = 40.39$, $p < .001$, 95% CI [30.77, 55.87]. In addition to replicating the finding that praise is more likely to be broadly distributed, whereas blame is more narrowly assigned, this study suggest that blame is focused at the top, a finding consistent with previous work in organizational behavior (Zemba, Young, & Morris, 2006).

Study 4: Actual Group Performance

The previous studies all involve impersonal third-party judgments. Here we use an online team task to examine how people apportion responsibility when their own group succeeds or fails. Studies 4 through 7 were approved by UNC IRB 15–0463.

Method

Participants. Because this study involved ratings of actual behavior, we expected more noise and anticipated a smaller effect size than what we found in Study 3. An a priori power analysis using G*Power 3.1.9.2 (Faul et al., 2009) suggested that a total sample size between 128 and 200 would be sufficient to detect an

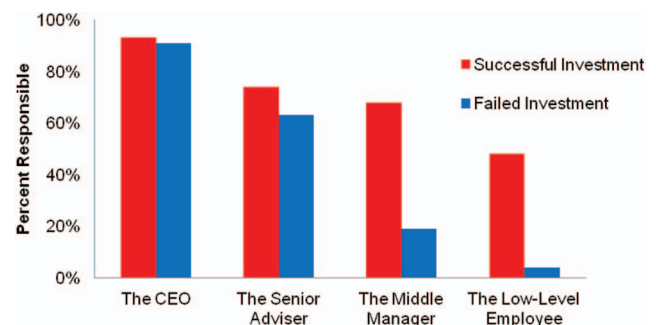


Figure 2. Percentage of participants who held each employee responsible for a successful or failed business investment. (Study 3). See the online article for the color version of this figure.

effect d between .4 and .5 with power = .80. One hundred fifty-nine participants completed the study through MTurk, though 11 participants were excluded for expressing suspicion at our game ($N = 148$, 59% female, $M_{\text{age}} = 36$). We ran all of our analyses for Studies 4 through 7 after excluding participants who expressed suspicion at the design of the game in an open-ended response box, though effects remained significant when we reran the tests with the inclusion of these participants.

Procedure. On starting the study, participants learned that they were going to be solving anagrams as part of a team. They were told that if their team solved enough anagrams (an unspecified amount), they would receive a 40% payment bonus. Participants assigned themselves a nickname, and then saw a waiting gif before seeing four other ostensible teammates' nicknames appear on screen. Participants then completed seven easy anagrams (e.g., SEDK = DESK), before briefly (~1 s) seeing an eighth, unsolvable anagram (e.g., UNAGAT). The screen then auto-advanced to a stop sign. After a slight delay, participants in the loss condition were then told that their team failed to solve enough anagrams, and that they would not earn the bonus. In the win condition, participants read that their team successfully completed enough anagrams and would receive the bonus.

Participants then saw a table with the number of anagrams ostensibly solved by each team member (see Table 1). The participant always completed seven puzzles, and the other players completed 10, nine, five, and four puzzles. Importantly, these numbers were the same in each condition and were evenly distributed around the participant's scores (i.e., +3, +2, -2, -3).

Participants were then asked to select which members were responsible for the outcome of the game (i.e., they made an apportionment decision). The dependent variable was the average number of other teammates held responsible for success and failure. Given that people have a robust self-serving bias (Kunda, 1987), participants' ratings of their own responsibility were not included in this average. Finally, participants were asked demographic questions and debriefed. At the end of the study, all participants earned the bonus.

Results

Consistent with the praise-many, blame-fewer tendency, a between-subjects t test revealed that participants held more players responsible in the win condition ($M = 2.75$ out of 4, $SD = 1.16$)

Table 1
Anagrams Completed by Each Player and Percentage of Participants Who Held Each Player Responsible (Study 4)

Player	Anagrams completed	Percentage responsible	Percentage win	Percentage responsible loss
Player 1 (Kitties123)	9	91%	7%	
Participant	7	70%	32%	
Player 3 (XOXOK)	5	43%	81%	
Player 4 (bimoz)	4	43%	93%	
Player 5 (Wompa_Stompa)	10	97%	6%	

Note. For easy viewing, players scoring worse (better) than the participant appeared in red (blue), however no such colors were used when "anagrams completed" was shown to participants. See the online article for the color version of this figure.

than in the loss condition ($M = 1.86$, $SD = .74$), $t(146) = 5.54$, $p < .001$, 95% CI [.58, 1.21], $d = .91$. Because participants are explicitly told about individual contributions, this study allowed us to examine whether praise and blame are distributed based on merit. Blame for losing appeared to be isolated to the two players who played the worst, with only 7% of participants blaming the above average participants. However, praise for winning was more evenly distributed, with 43% of participants assigning responsibility to the two players who played the worst, a significantly higher percent (36%) than for above average players who were blamed, $\chi^2(N = 148) = 25.06$, $p < .001$, 95% CI [21.83, 48.76]. This pattern suggests that blame may align more to principles of equity (Walster, Walster, & Berscheid, 1978) than to praise, which was still assigned to players who performed at a below-average rate.

Study 5: Third Party Ratings of Group Performance

Here we sought to replicate Study 4 with neutral third-party observers. This study was preregistered at <https://aspredicted.org/yt5ys.pdf>.

Method

Participants. An a priori power analysis using G*Power 3.1.9.2 (Faul et al., 2009) suggested a total sample size of 32 participants would be necessary to detect the large effect size we found in Study 4 ($d = .91$) with power = .80. Nonetheless, in the spirit of larger sample sizes, we preregistered the study to include 200 participants. One hundred ninety-two participants completed the study through MTurk, though 15 participants were excluded for expressing suspicion at our game ($N = 177$, 54% male, $M_{\text{age}} = 36$).

Procedure. Instead of participating in the anagram task itself, as in the previous study, in this study participants read about the task and then learned of its outcome. Participants saw the same table as in Study 4, with the exception that the participant's name was replaced by a generic screen name (e.g., "SeeShells5"). The table was described as depicting the number of puzzles each player completed in a group game, which was described as a group anagram challenge. After seeing the table, participants read that the team either won or lost and participants then selected the number of players they viewed as responsible for the outcome of the study. As in the previous study, the dependent variable was the average number of players selected as responsible for the outcome of the game. However, in this version, all five players were included in this average, and we also added a "none of the above" option to detangle answers left blank from those representing the belief that no one was responsible.

Results

Consistent with the praise-many, blame-fewer tendency, more players were held as responsible in the win condition ($M = 2.86$, $SD = 1.31$) than in the loss condition ($M = 1.91$, $SD = .87$), $t(175) = 5.70$, $p < .001$, 95% CI [.62, 1.29], $d = .85$, see Table 2. Of note, 48% more participants held Player 2, the player that performed at average, responsible for the win relative to the loss, $\chi^2(N = 177) = 43.68$, $p < .001$, 95% CI [33.91, 59.99], and 17% more participants held the worst player responsible for the win

Table 2
Anagrams Completed and Percentage of Participants Who Held Each Player Responsible (Study 5)

Player	Anagrams completed	Percentage responsible win	Percentage responsible loss
Player 1 (Kitties123)	9	83%	9%
Player 2 (SeeShells5)	7	61%	13%
Player 3 (XOXOK)	5	29%	78%
Player 4 (bimoz)	4	26%	82%
Player 5 (Wompa_Stompa)	10	87%	9%
None of the above		3%	8%

Note. For easy viewing, players scoring worse (better) than the participant appeared in red (blue), however no such colors were used when “anagrams completed” was shown to participants. See the online article for the color version of this figure.

(Player 4) than the best player responsible for the loss (Player 5), $\chi^2(N = 177) = 8.86, p = .003, 95\% \text{ CI } [5.16, 28.65]$. Combined with the previous study, these findings suggest that more team members are held responsible for a win than a loss, both when people are members of the team and invested in the outcome, and when people are mere observers.

Study 6: Responsibility and Team Retention in Iterative Game

We next examined apportionment decisions in an iterative game that allowed players to remove other players, allowing us to examine the link between judgments of praise and blame and decisions about retention (which we incorporated in our ABMs).

Method

Participants. Consistent with the previous study, 200 participants completed the study on MTurk, though 10 participants were removed from analysis for expressing suspicion, as in the previous two studies ($N = 190, 41\% \text{ female}, M_{\text{age}} = 36$).

Procedure. This study was a replication of the Study 4, with three key differences. First, we highlighted the fact that participants were competing in a multi-round game, by repeating the phrase “Round 1.” Next, although participants saw their own score in the responsibility matrix, participants’ own names were removed from the responsibility question (because we wanted to maintain consistency with the next question and did not want participants to kick themselves off the team.) Finally, in anticipation of the next round, participants were given the option to keep or remove any player on their team, with any removed player being replaced by a randomly selected online participant.

Results

Replicating the previous two studies, significantly more players were held responsible for the win ($M = 2.55, SD = 1.08$) than the loss ($M = 2.22, SD = .79$), $t(188) = 2.40, p = .02, 95\% \text{ CI } [.06, .60], d = .35$. To test the rate at which praise and blame judgments translated into retention judgments we computed the percent of participants who were removed from the team after being blamed or praised. Only 14% of praised players were removed from the team (i.e., 86% retention rate), whereas 85% of blamed players

were removed from the team (15% retention rate). This study suggests that even in an iterative game, more team members are held responsible for a win than a loss, and these judgments probabilistically translate into retention judgments.

Study 7: Replication With New Items

Throughout this article, we equate assigning praise and blame with assigning responsibility for success versus failure. Although responsibility is closely related to praise and blame, research has identified some differences between these constructs (Malle et al., 2014), and so we wanted to ensure that, at least in our paradigms, praise/blame and responsibility functioned similarly. This study was a replication of Study 4, which examined assignments of responsibility in an impromptu group task. However, instead of responsibility, we directly assessed judgments of blame and praise using a more continuous Likert-type scale, which also addresses any concerns arising from using binary measures in the previous studies. This study was preregistered at <https://aspredicted.org/e3e4j.pdf>.

Method

Participants. Two hundred participants completed the study through MTurk. Twelve participants were removed from the data set for expressing suspicion ($N = 188, 46.3\% \text{ female}, M_{\text{age}} = 36$).

Procedure. This study replicated Study 4, with one change: Instead of the binary responsibility question, participants saw a list of all team members (including their own name) and were asked, “How much praise (blame) does each teammate deserve for the success (failure) of your team?”, which was answered on a scale ranging from 1 (*no praise [blame] at all*) to 5 (*a lot of praise [blame]*).

Results

Table 3 shows the percentage of participants who held each player at least somewhat praiseworthy or blameworthy, as indicated by ratings above 1 (i.e., *not at all*) and the average ratings for praise and blame. Averaging across praise–blame scores assigned to the participant’s teammates, we found that significantly more praise was assigned to the winning team ($M = 3.91, SD = .60$)

Table 3
Percent of Participants Who Held Each Player at Least Somewhat Responsible and Average Ratings for Praise or Blame (Study 7)

Player	Anagrams completed	Praiseworthiness	Blameworthiness
Player 1 (Kitties123)	9	99%; 4.57 (.68)	25%; 1.29 (.54)
Participant	7	99%; 3.86 (.79)	54%; 1.86 (.88)
Player 3 (XOXOK)	5	98%; 3.17 (.99)	77%; 3.01 (1.34)
Player 4 (bimoz)	4	93%; 3.03 (1.13)	78%; 3.35 (1.54)
Player 5 (Wompa_Stompa)	10	100%; 4.86 (.43)	11%; 1.15 (.47)

Note. In the praiseworthiness and blameworthiness columns, the first number indicates the percentage of participants who held the player at least somewhat responsible (scores over 1). The second number is the mean rating for praise or blame. Standard deviations are in parentheses. See the online article for the color version of this figure.

than blame to the losing team ($M = 2.20$, $SD = .77$), $t(185) = 9.85$, $p < .001$, $d = 2.47$. Praise ratings were also significantly higher for the worst performing member of the winning team than blame ratings for the best performing player on the losing team, $t(186) = 16.17$, $p < .001$, $d = 2.36$, once again suggesting that people are more liberal with praise.

The percentage of players assigned at least some praise or blame reveals a stark contrast in how blame and praise are distributed in teams. Around 90% of participants assigned at least some praise to all players on the winning team; however, when the team lost, just under 10% of participant assigned at least some blame to all players. Similarly, the worst performing team member in the success condition was praised 93% of the time, but the best performing team member in the failure condition was blamed only 11% of the time. These patterns are consistent with a tendency to praise many and blame fewer.

The average ratings for praise and blame show that praise is in general higher in magnitude than blame. For example, praise assignments were higher for the player that completed 10 anagrams than were blame assignments for the player who completed four anagrams, $t(186) = 9.21$, $p < .001$, $d = 1.34$.¹ This severity finding seems to contradict previous research which finds that blame is more severe than praise for individual moral violations (Guglielmo & Malle, 2019). It is possible that in this setting, the severity of blame was muted because all players were trying to help the team win, even if some were less successful in the end. Future research should examine whether there are systematic differences between responsibility attributions in groups for well-intended failures versus immoral actions.

Studies 1 Through 7: Interim Discussion

Across seven studies, we found consistent evidence that people praise many and blame fewer. This effect held across ratings of major sports competitions, hypothetical business interactions, and actual team projects. Although these combined studies suggest that people attribute responsibility more broadly after successes versus failures, it is unclear whether this tendency is adaptive. We use ABMs—calibrated on our descriptive findings (Study 6)—to test whether using a praise-many, blame-fewer approach helps groups win more over time.

How People Should Make Apportionment Decisions: ABMs

In this section, we use ABMs to examine which apportionment strategy is the most adaptive across time within a competitive group landscape—defining *adaptiveness* as the ability to cultivate higher skill teams. Using ABM also allowed us to examine whether the functionality of apportionment strategies varied based upon (a) insight into who deserves praise and blame, (b) who replaces individuals who leave groups, and (c) the tendency to learn and improve after blame.

Method

Plain Text Conceptual Summary

Imagine groups in a competitive environment. These groups could be sports teams playing in a competitive league, or large

societies fighting wars for territory or resources. In either case, group success or failure is tied to the overall skill of group members.

After victories or defeats, groups need to apportion praise (in the case of a victory) or blame (in the case of a defeat). As suggested by past research (Henrich & Gil-White, 2001; Hill, 1984) and the present Study 6, this apportionment decision has consequences: Individuals who are praised are more likely to stay with the group over time—either because their contract is renewed (in the case of a sports team) or they garner more resources to aid with reproduction (in the case of a society)—whereas individuals who are blamed are more likely to leave the group—either because they are released from a team (in the case of a sports team) or fail to reproduce (in the case of a society). Therefore, the composition of the group often changes—at least in part—on the basis of how praise and blame are apportioned. Which apportionment strategy is most effective for a group's long-term success?

We tested the functionality of different apportionment strategies by creating a sample of 20 groups that apportioned praise and blame at different rates. We then examined how these different strategies translated to group performance over time. In any given round, two randomly selected groups competed with one another, with the winner of the competition depending both on overall group skill and some luck. The winning group praised some proportion of members based on its praise parameter, whereas the loser blamed some proportion of members based on its blame parameter.

Being praised increased the likelihood that group members would be retained, whereas being blamed lowered that likelihood. Running this simulation over 10,000 rounds revealed which apportionment strategies were most (and least) beneficial to continued group success. We also varied the following three conditions in the simulation: (a) the extent that blame motivated players to improve their skill, (b) the accuracy of praise and blame (e.g., insight into individual skill level), and (c) the tendency for replacement team members to increase their skill over time.

Technical Model Overview

Step 1: Game phase. For each simulation, 20 groups were constructed, each consisting of 150 agents, a size selected to reflect Dunbar's (1993) number—the typical size of pre-Neolithic societies. However, we note that substantive results replicated in smaller groups (see the online supplemental materials). Each group member had a “skill” score a —normally distributed around a mean of 1 with a standard deviation of .15.

In each of 10,000 rounds within a given simulation, two groups x and y were randomly selected from the population of groups to compete against one another. This competition involved summing the a skill scores of all individuals within each group, each adjusted by a degree of random error ϵ (ϵ was sampled from a distribution with $\mu = 0$ and $\sigma = .15$). This represented how high-skill individuals will usually—but not always—contribute more than low-skill individuals. The group with the highest aggregated skill score won the game. This process is mathematically summarized in Equation 1.

¹ This additional analysis was not in our preregistration. It was added to the article in response to a reviewer's question.

$$o_i = \sum_{P_x=1}^{n_x} (a_{p_{x,i}} + \epsilon_{p_{x,i}}) - \sum_{P_y=1}^{n_y} (a_{p_{y,i}} + \epsilon_{p_{y,i}}). \quad (1)$$

Equation 1 illustrates the mathematical formulation of each game phase as follows: At round $i = 1$, skill a was drawn from a normal distribution with $\mu = 1$ and $\sigma = .15$ and was then stored for future rounds. The outcome o of a round i depended on the difference between the sum of abilities of all players on two teams x and y , along with some degree of random error ϵ , which was drawn from a distribution with $\mu = 0$ and $\sigma = .15$. If the difference was positive, team x won. If the difference was negative, team y won.

Step 2: Assignment of praise and blame. After the game phase ended, the defeated group blamed a certain proportion of players d and the victorious team praised a proportion of players v . Both d and v were randomly assigned to each group at the beginning of the simulation and varied independently from each other. These coefficients reflected groups' apportionment strategies and they remained fixed over the course of the simulation, which allowed us to test how different apportionment strategies corresponded to group performance over time. An insight parameter s determined whether praise and blame tracked players' performance. We initially set s at .50, indicating that 50% of praised players were actually the highest performers, whereas 50% of blamed players were actually the lowest performers. However, we varied s in the following sensitivity analyses.

Step 3: Impact of praise and blame. In our model, praise or blame translated into increased or decreased likelihoods for retention. Drawing directly from the results of Study 6, praised agents were 86% likely to be retained, whereas blamed agents were only 15% likely to be retained. To keep group size constant, agents who left the group were replaced by sampling from the original pool of players ($\mu_a = 1$, $\sigma_a = .15$). However, during sensitivity analyses we tested for how effects changed when we allowed the resampling pool to coevolve with the abilities of the groups. This might represent the improvement of a sports team free agent pool as rostered players also improve.

We also considered whether blame could act as a form of positive punishment, thereby motivating individuals to improve (Mowrer, 1960). The exact impact of punishment on motivation and improvement depends on the domain (Steel, Silson, Stagg, & Baker, 2016) and may also depend on individuals' learning mindsets (Dweck, 2008) and how individuals conceptualize blame. To simulate a variety of possibilities, we varied a blame-contingent improvement parameter l in sensitivity analyses.

Results

We ran 10 simulations, with each simulation containing populations of 20 teams competing over 10,000 rounds. Here, we explain our results in plain text and plot out illustrative effects. It is generally considered inappropriate to interpret inferential analyses on simulation results, because simulations can be run an infinite number of times, potentially biasing statistical power (e.g., samples can be larger than their corresponding populations; Jackson et al., 2017). Nevertheless, it is still possible to conduct statistical tests to estimate effect sizes and probabilities, and our supplemental analyses include such analyses. However, we urge readers to interpret these tests with caution.

Across our 10 simulations, we observed an interaction of praise and blame apportionment. Praising broadly and blaming more narrowly appeared to be the most functional strategy for cultivating high-skill groups, especially when broad praise was paired with narrower blame. In other words, the praise-many, blame-fewer tendency observed in Studies 1 through 6 seems to lead most robustly to highly skilled groups over time. Figure 3 plots this interactive effect by showing how each team performed as a function of their praise and blame apportionments. The second most effective apportionment strategy was broadly praising and blaming (an analog of "win-stay, lose-shift"), whereas the least effective apportionment strategy was to blame broadly and praise narrowly.

Although it was functional to praise more broadly than blame, maximal praise and minimal blame was not the best strategy. Instead, the most skilled players were cultivated in groups that praised broadly and blamed moderately. Praise appeared to peak and plateau at approximately 80%, whereas blame reached an asymptote between 30% and 40%, such that <30% levels of blame apportionment were less functional. Figure 4 communicates these effects using boxplots of the praise and blame apportionment quintiles. Figure 5 displays a heatmap, which communicates the average agent skill level of each combination of praise and blame apportionment quintile. Together, these effects show that praise linearly cultivated high-skill groups, whereas blame had a more quadratic effect on skill level.

Why did groups with moderate blame and high praise develop members with the highest abilities? The evolutionary game theory strategy of "win-stay, lose-shift" predicts that maximal praise and blame should produce the most skilled teams over time (Nowak & Sigmund, 1993) because they represent maximum consistency after wins and minimum consistency after losses. But we found

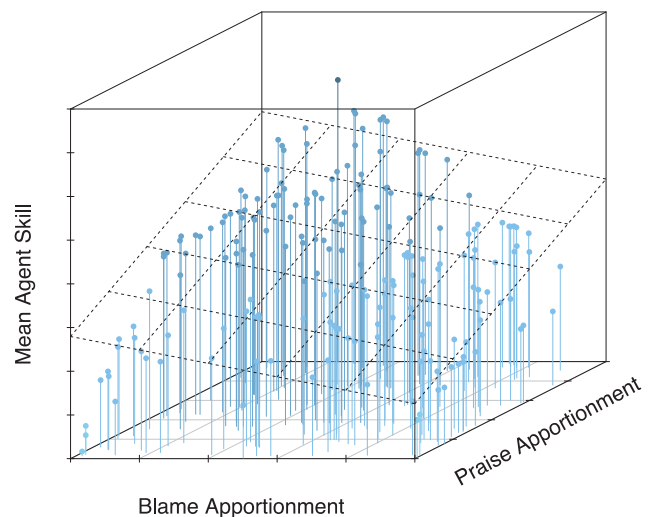


Figure 3. Mean agent skill by blame apportionment and praise apportionment. Each individual point corresponds to a group. Darker and higher points correspond to higher skill groups. The dotted plane represents the interactive effect of blame and praise apportionment on skill: Groups cultivated highest skill when they blamed relatively few agents following defeats and praised many agents following victories. See the online article for the color version of this figure.

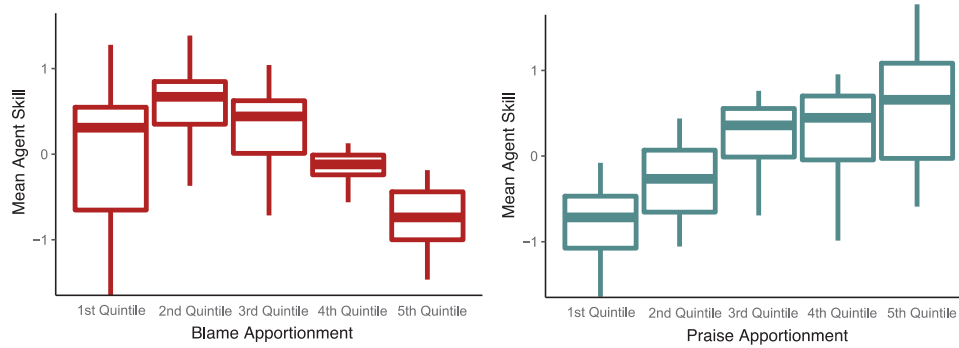


Figure 4. Boxplots displaying the mean agent skill at each quintile of blame apportionment (left panel) and praise apportionment (right panel). See the online article for the color version of this figure.

that, although praising maximally was successful, blaming maximally produced lower quality groups than did narrower blame apportionment strategies. This might have occurred because high rates of blame make otherwise successful groups unstable. If highly skilled groups blamed most of their members for losses, they would lose most of their highly skilled individuals and replace them with mediocre performers. Consistent with this explanation, groups that praised broadly after success but also blamed broadly following failure had a more variable (operationalized via standard deviation) skill level over time, compared with groups that used other apportionment strategies (see the online supplemental materials for details).

Exploring Results Under Other Conditions

Varying motivation. To explore how our model's effects varied based on individual's motivation to improve after blame, we ran an additional 11 simulations of 20 teams and 1,000 rounds. Each simulation varied the extent that players improved after receiving blame (and remaining with the team) in 10% increments.

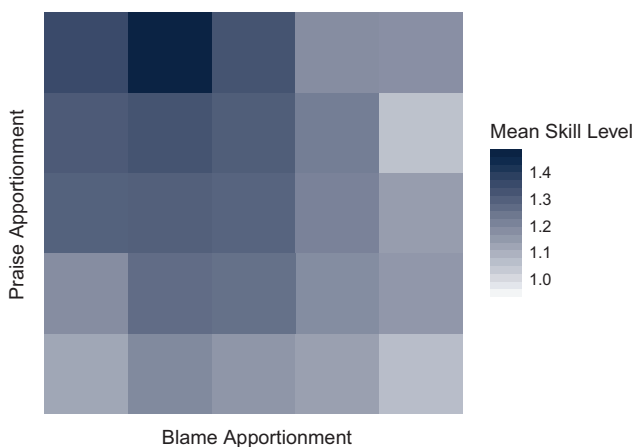


Figure 5. A heatmap displaying the mean skill level at different levels of praise and blame apportionment. The most effective strategy for cultivating high skill appeared to involve moderate levels of blame following failure and maximal praise following success. See the online article for the color version of this figure.

Specifically, the first simulation modeled players as improving at 0% after each instance of blame, the second simulation modeled players as improving at 10%, and so forth until players doubled their skill each time they were blamed (100% improvement). It is unrealistic, of course, to assume that players could double their skill after being blamed a single time, thus our manipulations functioned more as a proof of concept than an approximation of real-world dynamics.

Analyzing these models showed, unsurprisingly, that the more agents learned from blame, the more functional it became to blame agents after failure. Nevertheless, it was never functional to blame at a high rate because that removed too many players from groups to maintain high-skill teams over time. Moreover, because blaming players removed more members of the group, it also became even more important to praise as many individuals as possible in order to keep high-skill groups together. These effects are displayed in Figure 6, which is a heatmap that displays the effects of praise and blame apportionment across simulations in which agents improve less than 50% of their skill after blame (left panel) and more than 50% (right panel). In both sets of simulations, it was optimal to praise virtually all individuals following success and blame fewer individuals (35% to 50%, depending on improvement rate) after failure.

Varying insight. One of the challenges of solving the apportionment problem is that individual contributions to group outcomes are often unclear. To model this uncertainty, a sensitivity analysis examined how the results of our model might change depending upon insight into the individual member skill. In 10 additional simulations, we varied the proportion of players that were praised and blamed correctly (i.e., blamed for having the lowest performance and praised for having the highest performance). We increased the level of insight by 10% in each run, such that the lowest insight run praised or blamed 10% of members deservingly and 90% randomly.

Analyses of these models showed that as groups gained insight it became functional to apportion less praise and blame, though it was always better to assign relatively more praise than blame. These effects interacted such that groups with less blame also benefitted the most from having less praise. These effects suggest that groups with low insight must rely on broader strategies, such as blaming more members following failures to ensure that low-skill individuals are removed and praising more people following

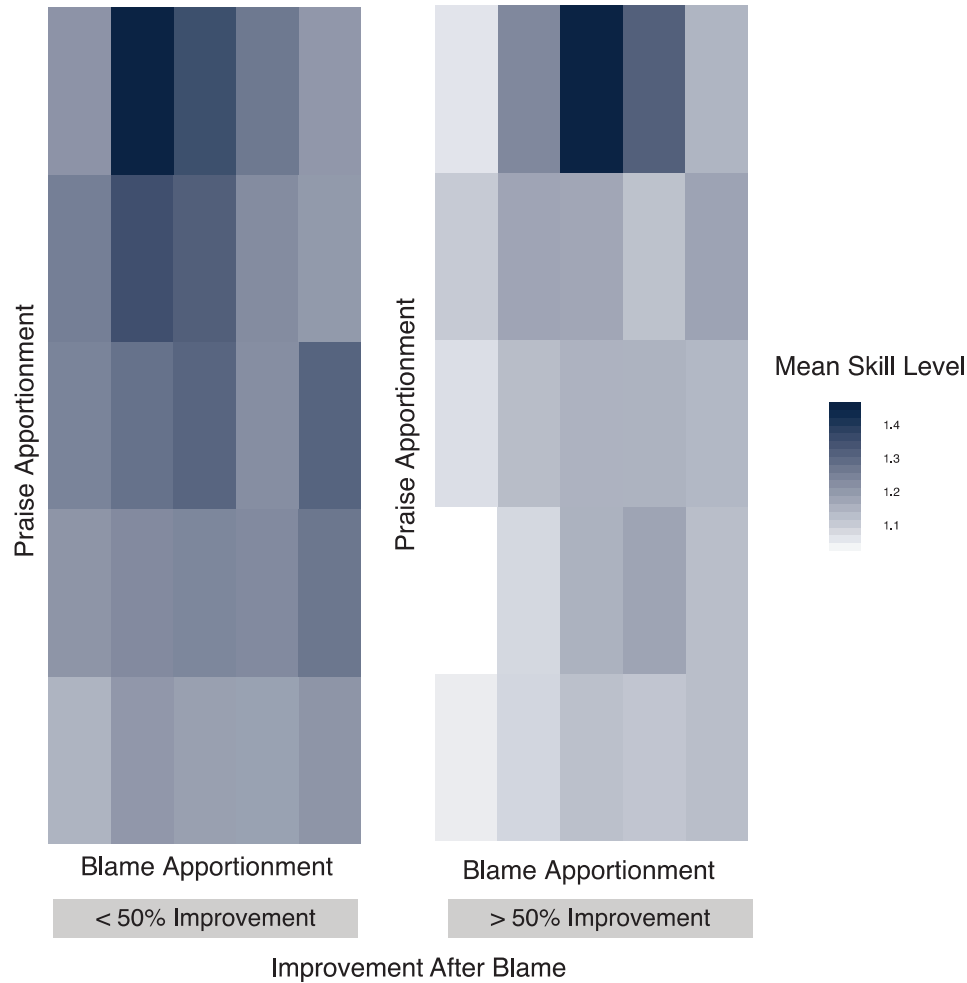


Figure 6. The effects of praise and blame apportionment on skill level in groups based on high versus low improvement rates. As individuals improved more after blame, it became more functional to increase blame apportionment, but it was never functional to increase blame apportionment to high amounts. See the online article for the color version of this figure.

successes to ensure that high-skill individuals remain, and that groups with high insight can afford to be more precise, such as blaming a smaller cohort of low-skill individuals following failure and praising a smaller cohort of high-skill individuals following success. These effects are displayed in Figure 7, which is a heatmap that displays the effects of praise and blame apportionment across simulations in which agents had less than 50% insight (left panel) and more than 50% (right panel). It is important to note, however, that these nuances did not change the broader pattern of results that we observed in our initial models: It was always significantly more functional to blame fewer players and to praise more players.

Varying resampling abilities. One limit to the generalizability of our initial model was that the unassigned player pool did not vary from the initialization stage. Therefore, we ran another 20 models in which we varied how groups resampled after removing members who were blamed and who were not praised. In 10 runs, groups resampled from a distribution of agents with $\mu = 0$ and $\sigma = .15$, as in our earlier models. In the other 10 runs, groups

resampled from a distribution of agents where $\sigma = .15$ but μ changed according to the mean of all agents within groups. This mimicked the dynamic of a sports league, where free agents' abilities will likely coevolve with rostered players' abilities over time. We found that varying this resampling strategy did not change the functionality of blame apportionment or praise apportionment. Low or moderate blame apportionment and high praise apportionment cultivated the highest skill group members regardless of whether resampling coevolves with groups' abilities.

Model Discussion

Under most circumstances, it was functional to praise as many group members as possible after group success and to blame fewer group members—approximately 40%—after group failure. This strategy allowed groups to retain high-skill members over time and build highly performing teams. Although this overall pattern persisted across different sensitivity analyses, more blame was more functional when blame motivated agents to improve and when

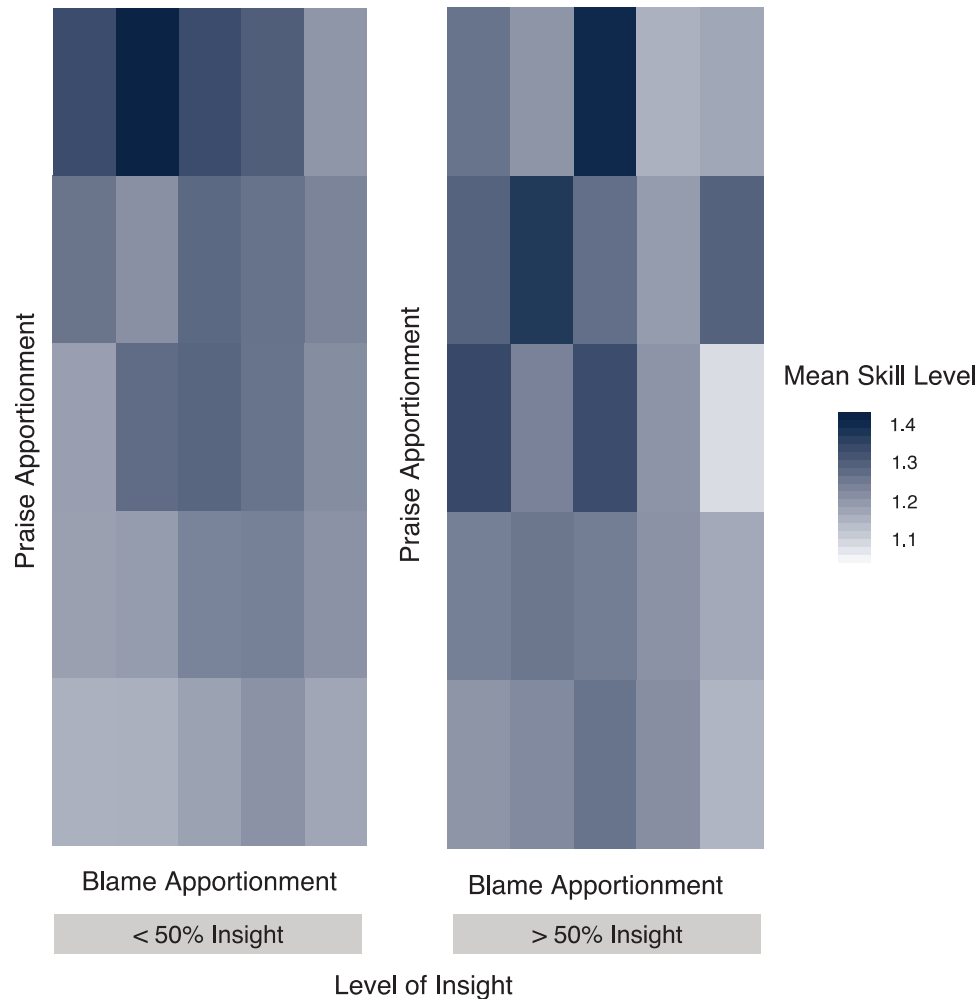


Figure 7. The effects of praise and blame apportionment on skill level in groups based on high versus low insight rates. Praising many and blaming fewer was functional under both high and low insight. However, in groups with little insight, it was more functional to apportion blame to a higher amount, whereas groups with high insight could be more precise in their blame. See the online article for the color version of this figure.

groups had little insight into individual skill. Even in these cases, it was still more functional to broadly praise than it was to broadly blame.

General Discussion

Our studies investigated how people do solve the apportionment problem and how they should solve it to be maximally functional at the group level. People praise many and blame fewer in college basketball (Study 1), NFL playoffs (Study 2), hypothetical business scenarios (Study 3), and novel behavioral games (Studies 4 through 7). Our observed blame–praise discrepancy replicates across all of these studies, speaking to the phenomenon’s robustness.

A set of ABMs suggests that the praise-many, blame-fewer strategy is an effective strategy for optimizing collective skill over time. Sensitivity analyses reveal that, although it always makes sense to give broader praise than blame, the precise maximally functional level of blame and praise hinges on whether individuals

learn from blame and the level of insight into individual skill. In general, broad praise (after successes) and more narrow blame (after failures) allows teams to ratchet up the skill of their players over time, even with only minimal insight into the “true” skill of players.

These results suggest a real-world actionable strategy for team leaders. One common adage in the sports world is to “never change a winning team.” Even though this strategy might limit growth when teams just barely win (Lefgren, Platt, & Price, 2014), our model suggests broad praise is optimal over time and that managers should fight the urge to blame broadly after a loss. Not only does widespread blame create toxic “blame cultures” (Catino, 2009), our models suggest that it also cultivates suboptimal performance over time.

An Evolutionary Strategy?

Human cultural evolution involves frequent competition among social groups, with success hinging on increasing collective skill.

Past research has emphasized that groups' fitness in intergroup competition is contingent on intragroup cooperation, which is facilitated by religious belief (Norenzayan et al., 2016), collective rituals (Whitehouse et al., 2014), and costly signaling (Henrich, 2009) but that even cooperative groups may be defeated if their members lack skill. Our work suggests how such skill may be developed by praising broadly and blaming more narrowly.

Our findings also further reveal convergence between psychological strategies and culturally functional properties, a multilevel convergence already found with ethnocentrism (Hammond & Axelrod, 2006) and cooperation (Rand et al., 2014). Of course, there is no way to infer from our behavioral studies that people's behavior emerges for the same reasons driving our model's findings. We do not claim that the asymmetry in praise and blame emerges because of its functionality. Indeed, it is difficult to marshal causal evidence for many culturally functional individual behaviors; we find only that a praise-many, blame-fewer strategy is frequently used and is functional over generations.

Caveats and Future Directions

There are several caveats to these findings. First, our empirical studies included data collected both in person from U.S. undergraduate students in the southeastern United States and online, but all data were collected with U.S. participants. Previous research suggests that attribution of blame within an organization differs by culture (Zemba et al., 2006). Therefore, it is still an open question if the blame-many, praise-fewer tendency appears universally.

It is also unclear whether the praise-many, blame-fewer strategy would still be adaptive in highly differentiated groups. In the ABM, skill was defined along a single dimension, which is a design that resembles small societies, where skill level and individual contribution is clear (Henrich et al., 2010). In larger, highly differentiated societies, individuals have a range of skills (Henrich & Gil-White, 2001), and because each member contributes in different ways, skill is opaquer. However, given that the strategy was effective with minimal insight, it is plausible that the praise-many, blame-fewer strategy will increase group skill level over time even in these highly differentiated groups.

Another caveat concerns what it means, precisely, to praise many and blame fewer. Across our behavioral studies, for example, praise varied widely (on average between 36% in the football games and 70% in the business vignette), as did blame (between 24% in football and 44% in Study 6). This variation reflects the breadth of contexts we used to examine the apportionment problem: In organizational teams (Study 3), all members could have feasibly been responsible for success or failure, but most members of sports rosters never actually play in games (Studies 1 and 2). Although different contexts lead to different absolute amounts of blame and praise (Forsyth et al., 1981; Forsyth, Zyzniewski, & Giammanco, 2002), every study revealed a robust relative difference such that praise was more broadly assigned than was blame.

Finally, it is important to note that—as a simplifying assumption—we modeled blame and praise as binary when in real-life they undoubtedly vary along a gradient. Future research should look at graded solutions to the apportionment problem and

examine how they intersect with individual motivation to create the most effective teams (Henderlong & Lepper, 2002).

Conclusion

How people attribute responsibility to individuals is a question of great interest to legal theorists (Cane, 2002; Moore, 2009), psychologists (Alicke, 1992; Lagnado et al., 2013), and philosophers (Eshleman, 2014; Smiley, 2017). Understanding how people do and should apportion responsibility to members of groups is also of practical importance to coaches, lieutenants, bosses, and managers. Across a variety of domains, we found consistent evidence that people exhibit a praise-many, blame-fewer tendency. Fortunately for managers invested in their teams' performance, ABMs suggest that the common praise-many, blame-fewer strategy is often successful over time.

This project was inspired by years of watching Tar Heel basketball. During most postgame interviews, Roy Williams, UNC's men's basketball head coach, praised the effort of many of his young players. However, after a devastating defeat to Duke, Coach Williams' struck a very different chord when he stated, "I say it's my fault" (Papke, 2016). Although it is possible that Williams' broad praise, and narrow blame reflects his well-known humility, we were curious if people generally have a psychological tendency to praise many and blame fewer. To examine this question, we combined some of the authors' expertise in moral psychology (Schein & Gray, 2015, 2018), with expertise in evolutionary and dynamical perspectives (Jackson et al., 2017), to examine how people do and should apportion blame and praise to members of groups. Across seven studies and a series of ABMs, we gained additional evidence that William's intelligence extends far beyond expert play calls. Not only do people have a tendency to praise many and blame fewer, an organizational strategy of praising many and blaming fewer is generally beneficial over time.

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