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# Not by desire alone: The role of cognitive consistency in the desirability bias

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**Abstract**

We demonstrate that the desirability bias, the elevation of the estimated likelihood of a preferred event, can be due in part to the desire for consistency between the preference for the favored event and its predicted likelihood. An experiment uses a participant's favorite team in Major League Baseball games and a recently devised method for priming the consistency goal. When preference is the first response, priming cognitive consistency moves prediction toward greater agreement with that preference, thereby increasing the desirability bias. In contrast, when prediction is the first response, priming cognitive consistency facilitates greater agreement with the factual information for each game. This increases the accuracy of the prediction and reduces the desirability bias.

Keywords: cognitive consistency, desirability bias, goals, priming, wishful thinking

# 1 Introduction

The desirability bias (DB) is the upward distortion of the estimated likelihood of a desired event and, less frequently, the downward distortion of an undesired event. Its costs can be substantial: for instance, failure to protect against possible negative events like unemployment and unsupportable debt (Williams, 2009; see also Shepperd, Waters, Weinstein & Klein, 2015) and decisions to change career direction when college grades fall short of biased estimates (Serra & DeMarree 2016). Doubts about the validity of the many reports of its occurrence (Krizan & Windschitl, 2007) have been eased by demonstrations of its presence when the desire for one outcome is randomly assigned (Windschitl, Scherer, Smith & Rose, 2013) and when a reward as large as $50 is offered for unbiased accuracy (Massey, Simmons & Amor, 2011; Simmons & Massey, 2012; see also Muren, 2012).

Given the existence of the DB, a natural next question is what causes it. Krizan and Windschitl's (2007) thorough analysis revealed nine mechanisms that could produce a DB. The objective of the present work is to test the goal of cognitive consistency as a tenth cause. In addition, cognitive consistency is a component of three of Krizan and Windschitl's nine mechanisms.

## 1.1 Cognitive consistency

Cognitive consistency (CC) is the consistency among related beliefs. Its history in psychology extends back at least to the work on cognitive dissonance in the 1960s. In the years since, CC has continued to be studied, sometimes under different names (e.g., balance and coherence) and variously conceptualized as a goal, a procedural mindset, and a fundamental property of belief systems (Chaxel & Russo, 2015; Gawronski & Strack, 2012). In the present work, CC is viewed as the goal of enhancing the agreement among related beliefs. (We use the term "belief" broadly, to include preferences.)

The DB is defined in terms of two closely related beliefs, the desire or preference for an event (the Preference) and the estimated or predicted likelihood of that same event (the Prediction). Our claim is that the DB can be driven, in part, by the goal of making the beliefs of Preference and Prediction more consistent and, more specifically, by altering Prediction to become more consistent with Preference. If CC can do this, then a tenth, conceptually distinct mechanism can join Krizan and Windschitl's (2007) list. CC also forms a part of three members of this list, viz., valence priming and negativity bias in the information-search category and differential scrutiny in the information-evaluation category. For instance, valenced priming "is based on the enhanced activation of positively valenced knowledge (knowledge consistent with desired outcome)" (p. 108).

One challenge for a CC-based explanation of the DB is the absence of directionality. Because the DB is only the unidirectional movement of Prediction to better accord with Preference, a consistency-satisfying nondirectional agreement between Preference and Prediction cannot, by itself, account for the DB. Any explanation that relies on CC must



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also include a source of direction and specifically the movement of Prediction to better accord with Preference. For instance, each of the three Krizan and Windschitl (2007) mechanisms mentioned above provides that necessary direction. In valence priming, it is the differential activation only of "knowledge consistent with desired outcome". Note that the opposite directional change, where Preference is altered toward greater agreement with Prediction, is entirely possible. Indeed, it is sufficiently common in political elections to merit its own label, the bandwagon effect (e.g., Mehrabian, 1998; Morwitz & Pluzinski, 1996), and to make familiar the saying that everyone likes a winner (e.g., Ashworth, Geys & Heyndels, 2006). Elster (1983) has also called it a "sour grapes" effect when it works to reduce preferences for outcomes deemed unlikely.

## 1.2 Dominance of preference over prediction

The source of direction that must accompany the nondirectional CC in order to explain the DB is provided by the dominance of the Preference belief. This dominance occurs for two reasons. First, Preference is usually the stronger, more stable belief. In a sports contest, which is the experimental setting of the present work, the Preference for a favorite team is usually rooted in past experience, often originating in youth, and reinforced over time (e.g., Cialdini et al., 1976). Such a Preference inherently resists alteration. Second, of the two beliefs, Preference is more independent of contextual factors. In contrast, Prediction, the estimated likelihood of a favorite team's victory in a particular contest, depends on such factors as the strength of the opponent, the actual players (e.g., which players are currently injured), where the game is being played (home or away), etc. Thus, the greater context-dependence of Prediction leaves it more exposed to influence, while Preference remains largely independent of the same considerations. The import of the relative strength of Preference over Prediction is that any movement toward greater agreement between the two means that Prediction is much more likely to do the moving, at least in a sports context.

## 1.3 Response order: Preference first or prediction first

Should we expect the order of the Preference and Prediction responses to matter, especially under the pressure of an activated goal of CC? Suppose that an experimental paradigm asks, "Which team would you like to win?" followed by something like, "Completely ignoring your personal preference, which team do you believe will win?" We suggest that the combination of collecting the Preference response first and activating the consistency goal might enhance the role of this already dominant belief, leading to increased DB. That is, when the first response is Preference, this belief is activated and, combined with a previously activated consistency goal, drives the subsequent Prediction toward greater agreement with it, hence a greater DB.

However, what should be expected if the response order is reversed (and the consistency goal is activated), so that participants are first required to provide the Prediction? We proffer three possible processes: (a) the continued dominance of Preference, (b) consistency with the facts, and (c) a bandwagon effect, in which the Preference changes to fit the Prediction. The different empirical impacts on Prediction, the DB, and strength of preference expected from these alternative processes enable us to distinguish them.

**Preference still dominates**. The first mechanism is the unchanged dominance of Preference. The strength and stability of Preference, combined with the context-dependence of Prediction, suggest that the consistency goal will produce the same increase in the DB whether Prediction or Preference is the initial response. Order may matter even less when participants know that they will have to provide both responses, one right after the other, as they do in most studies of the DB, including ours. This mechanism would leave Preference dominant and, when CC is primed, yield the same increase in the DB as when Preference is the first response.

**Consistency with facts**. The second mechanism relies on consistency with the facts of the particular baseball game. Consider the stimulus that participants face before their first response, that is, immediately before having to make their Prediction. Because they start by reading the names of the two teams and various facts pertinent to the contest between them, participants can achieve the consistency goal by making their estimates of Prediction accord with these game-specific facts (before confronting the Preference question). If CC drives facts-Prediction agreement rather than Prediction-Preference agreement, the result should be a more fact-based, accurate estimate of Prediction and, therefore, a reduction in the DB.

**A bandwagon effect**. The third process is a sports version of the bandwagon effect in politics in which the candidate most likely to win draws elevated preference ratings. If a bandwagon effect occurs, not only does activating the CC goal not move Prediction toward Preference, but Preference changes to better accord with the Prediction that has just been made. This process predicts that change in the Prediction of a team's success (e.g., as the result of increased consistency with facts) is associated with a corresponding change in Preference for that team. We used a Strength-of-Preference measure to asses such changes.

We do not a priori favor any of these three processes for achieving CC when Prediction is the first response and CC is activated. Instead, we let the data reveal whether the DB increases (indicating the continued dominance of Preference) or decreases (indicating greater consistency with facts) and, in addition, whether Strength of Preference changes in parallel with any change in Prediction (indicating a bandwagon effect).

Note that the above predictions for the order of the Preference and Prediction responses hold under that assumption of an activated goal of CC. The main focus of this work is whether CC can play a role in the DB and, if so, what that role is. If such a role is found, then whether CC affects the DB in ordinary circumstances should depend on the ambient activation level of this goal. However, future work to identify the naturally occurring activation levels of the consistency goal only makes sense once the experimental activation of this goal has first been demonstrated to have an effect. Thus, the following study focuses only on differences between the activated and control conditions for the two response orders.

### 1.4 A sports context

To test the claim that priming CC will increase the DB when Preference is the first response and to reveal the process when Prediction is the first response, we chose the context of sports games, specifically Major League Baseball. This setting has been used in other empirical investigations of the DB (e.g., Babad, 1987; Simmons, Nelson, Galak & Frederick, 2011). This context carries at least two material advantages. First, it should provide an identifiable Preference in the form a participant's favorite team (Massey, Simmons & Armor, 2011). Indeed, we required participants to be baseball fans and to have a favorite team. The existence of such a favorite provides a solid indicator of group identification, which has been shown to predict the DB in past studies (Babad, 1987; Dolan & Holbrook, 2001; Hirt, Zillmann, Erickson & Kennedy, 1992; Markman & Hirt, 2002; Price, 2000).

A second benefit of the sports context is its potential to complete the only other test of the power of the consistency goal to increase the DB. Chaxel, Russo and Wiggins (2016) demonstrated how activating the goal of CC could increase the DB in the context of the Academy Awards. They showed that the number of matches between the preferred and predicted winners of the six major awards rose from a baseline of 2.34 in the control condition to 3.05 for consistency-primed participants. However, because Chaxel et al. had no way to measure the number of matches with zero DB, they could not claim the presence of any DB in the control/unprimed condition. (Maybe 2.34 matches could have been achieved merely by choosing the predictions of credible film critics, thereby ignoring all personal preferences for award winners.) Instead, Chaxel et al. could show only that priming the consistency goal increased the DB relative to the control group. The measure necessary to compute the baseline DB is essentially an authoritative prediction of the likelihood for each award, something problematic for unique events like Academy Awards. However, these predictions are available for Major League Baseball games in the form of the unbiased probability of each team's victory. Therefore, in the present study we should be able both to assess the baseline magnitude of the DB relative to an unbiased standard (which Chaxel et al. could not) and also to compare that baseline to the corresponding effect when CC is primed.

To the above two advantages of the baseball context can be added a third. A numerical magnitude of the DB for every individual prediction enables a stricter test of the influence of CC. Not only should the consistency goal drive Prediction toward greater agreement with Preference (at least when Preference is the first response), but the strength of preference for the favorite team should yield a continuously elevated Prediction. Because this increase in Prediction is equivalent to more DB, greater desire as assessed by a greater strength of preference should monotonically produce a larger DB.

## 2 Method

### 2.1 Participants

Based on pilot data, we initially desired 800 participants. We were able to recruit 741 Mechanical Turk workers: age (M = 33.57, SD = 15.7); gender (69.6% male); English as the first language (98.9%); American citizens (100%). All were required to have a favorite Major League Baseball team and to demonstrate sufficient baseball knowledge.

To ensure that participants were genuinely knowledgeable about Major League Baseball, we constructed a knowledge test comprised of ten 4-alternative multiple choice questions.[1] Over all participants, the mean number correct was 5.62. However, because some individuals might have falsely stated their status as baseball fans or overestimated their baseball knowledge, we eliminated the 23 lowest-scoring participants, those who answered no more than one question correctly.

Participants were initially asked to identify their favorite baseball team. However, when presented with the game involving that team, 9 participants preferred the opponent. We judged these 9 not to have had a favorite team and disqualified them. This left a final sample of 708.

[1]Questions 1, 5, and 10, with the correct answer bolded, were: (1) This team has won 27 World Series Championships, the most in MLB history: Los Angeles Dodgers, Atlanta Braves, **New York Yankees**, or Boston Red Sox; (2) The last realignment of MLB divisions was before the 2013 season, seeing this team switch leagues: **Houston Astros**, Seattle Mariners, Colorado Rockies, or Philadelphia Phillies; (3) The metric ERA+ adjusts a pitcher's ERA (earned run average) according to the pitcher's ballpark and the league's run scoring environment. ERA+ is normalized so that a score of __ reflects the league average: 0, 4, 50, or **100**. (See Supplemental Materials for the full quiz).

## 2.2 Materials and procedure

**Games**. The data were collected in three waves of games during August and September 2014. Each participant responded to 8 Major League Baseball games, one of which always involved the favorite team. Because this game was the only one that assured a clear preference, only it qualified for testing our predictions. The other 7 games served as distractors so that participants would be less likely to detect our focus on the one game involving their favorite team. Note that we chose only days when all 30 MLB teams played (15 teams in each league), so there were always 7 American League games, 7 National League games, and one interleague game that involved a team from each league. This enabled all 8 games to be played by teams from the same league as the favorite, with the exception of the single interleague game that had to appear in both sets of 8 games.

Information for each game matched that commonly given in sports news: the two teams and their win-loss records, the starting pitchers with their respective win-loss records and earned run averages, venue (i.e., the host team), and start time (i.e., a day game or a night game). The two-part Preference response asked, "Which team would you like to see win? How much would you say that you care about who wins this game (strength of preference scale, 0 to 100)?" To make clear in the data analysis that preference was assessed on a continuous scale and was not just the identification of one competing team as the preferred team, we use the label Strength of Preference for this variable. The two-part Prediction response was, "Please predict the winner to the best of your ability and knowledge. This is the team that you believe will win, regardless of whether you want them to win or whether you believe that they should win. Express your confidence in the predicted winner (probability scale, 50 to 100)." As with Strength of Preference, to clearly signal that prediction was measured continuously, we label it Predicted Likelihood.

For all games, authoritative estimates of the probability of each team's winning were created by averaging the predictions of the four models provided by http://TeamRankings.com. The proportion of game winners correctly predicted by these models was .56 over all games during the 2014 Major League baseball season. This value might reasonably be interpreted as an indication of how difficult it is to predict the winner of a typical Major League Baseball game. For completeness, we note that the proportion of correct game winners for the 45 games actually used in our study was .58.

**Consistency prime**. Halfway through the complete set of 8 games, all participants were told "There will be 4 more games for you to give us your opinions about. However, we want them to be independent of any carry-over from your baseball thoughts during the first 4 games. So we have inserted two mind-clearing tasks." The first of these two tasks activated the goal of CC. It was described as "critical reasoning", with instructions that began, "On the next page you will get a double challenge: to explain a conflicting set of facts, and to do so in only 3 minutes. Please work for the full 3 minutes. Provide explanations that go beyond the 'obvious' answer." (See Supplemental Materials for complete instructions and stimuli.) There were two versions of the "critical reasoning" task, one designed to prime the goal of CC, the other a matching control. For those participants receiving the priming manipulation, the goal of cognitive consistency was activated by asking participants to resolve a difficult conundrum, "Why do most people today strongly reject prejudiced social beliefs from a hundred years ago on intrinsic grounds, even though there is basically no intrinsic difference between people today and people from the beginning of the last century?"[2] Those participants assigned to the

Table 1: The complete design, with the leftmost two columns showing the consistency-priming conditions and the two rightmost two columns showing the matched non-priming (control) conditions included to test for an effect of serial position on the DB. The numbers of participants assigned to each of the four conditions/columns are given below each one. The counts in the eight cells indicate the numbers of participants who encountered the game involving their favorite team before or after the consistency-priming or matched non-priming task. Note that all participants in the two leftmost columns saw their first four games (possibly including the game that involved their favorite team) before the priming manipulation. Those games are labeled unprimed/control and were considered control games in our analyses. As a result, about three times as many participants considered the game involving their favorite team while in the unprimed or control condition as in the consistency-primed condition.

| Serial position | Preference first | Prediction first | Preference first | Prediction first |
|---|---|---|---|---|
| 1–4 | Unprimed control (n=82) | Unprimed control (n=96) | Control (n=91) | Control (n=80) |
| | Priming consistency | | Matched non-priming | |
| 5–8 | Primed (n=87) | Primed (n=78) | Control (n=98) | Control (n=96) |
| Total n | 169 | 174 | 189 | 176 |

[2]The use of a conundrum to activate the goal of CC is still new. Its rationale, validation, and application are fully presented in Chaxel et al. (2016). Briefly, the kind of conundrum used to prime consistency contains two facts that cannot easily be reconciled. In the present study those facts were "most people today strongly reject prejudiced social beliefs from a hundred years ago on intrinsic grounds" and "there is basically no intrinsic difference between people today and people from the beginning of the last

control version of the "critical reasoning" task responded to a much easier version of the above question, "Why do most people today strongly reject prejudiced social beliefs from a hundred years ago?" The change from the conundrum to its modified version has been shown to create substantial differences in the activation of the consistency goal (Chaxel et al. 2016).

The second "mind-clearing task" inserted a delay that further activated the consistency goal by not permitting progress toward achieving it (Chaxel & Russo, 2015). This is a standard tactic that increases a primed goal's activation level by frustrating its achievement for a brief period (Fishbach & Ferguson, 2007; Forster, Lieberman & Friedman, 2007). To accomplish this in our experimental procedure, participants had to spend another 3 minutes reading a 300-word article on the evolution of the horse (http://en.wikipedia.org/wiki/Evolution_of_the_horse). They were warned that later they would be tested for knowledge drawn from this article. Note that all participants completed both "mind-clearing" tasks, spending the same total time (3 minutes) on each one. The only difference was having to work on the conundrum (the primed group) or its easier version (the control group).

**Design**. The main design consisted of two factors that were crossed: the priming of the consistency goal (primed versus unprimed/control) and response order (Preference-first or Prediction-first). The rest of the design involved the serial position of the 8 games: an initial set of 4 and a final set of 4 that were always separated by the activation of the consistency goal (or its corresponding control task). The structure of this design is portrayed in Table 1, with consistency priming in the two leftmost columns and matched non-priming in the two rightmost columns. All participants were randomly assigned to one of these four columns.[3]

On each of the three days of data collection, the 8 games in each league were randomly partitioned into the two sets of 4. These, in turn, were randomly assigned to be either the initial or final set of 4 games. For each set of 4, an order of presentation was chosen randomly and reversed for half of the participants. Note that in the two primed conditions (the two leftmost columns in Table 1), the initial 4 games before priming could serve as controls for the final 4 games post-priming, but only if their value as controls was not invalidated by an effect of serial position due to learning, fatigue, or boredom over the 8 games. However, analyses revealed that the DB did not differ reliably across serial position, the two sets of games or the two orders of presentation of these sets. Thus, neither serial position nor these counterbalancing factors is discussed further.

The only substantive result of the test for serial position was to provide three times as many control games as primed games. In our primary analyses below, we focus on games that involved participants' favorite teams. For about half of the participants assigned to the consistency-priming condition (the two leftmost columns in Table 1), the game involving the favorite team occurred in the first set of games, before priming occurred. Those participants are considered to be in the control condition. Thus, for the analyses of favorite games, only 87 + 78 = 165 participants were in the priming condition and the remaining 543 participants were in the control condition.

The responses to the 8 games were followed by the baseball knowledge quiz, the test based on the delay task (the evolution of the horse), and several demographic questions. Finally, participants responded to a two-question suspicion check: Was there anything in the task or in the study that made you suspicious? Was there anything in this study that did not make sense or did not seem to belong? Although some participants provided answers (of which the most frequent stated that the story on the evolution of the horse seemed not to belong), no participant ascertained the purpose of the study.

# 3 Results

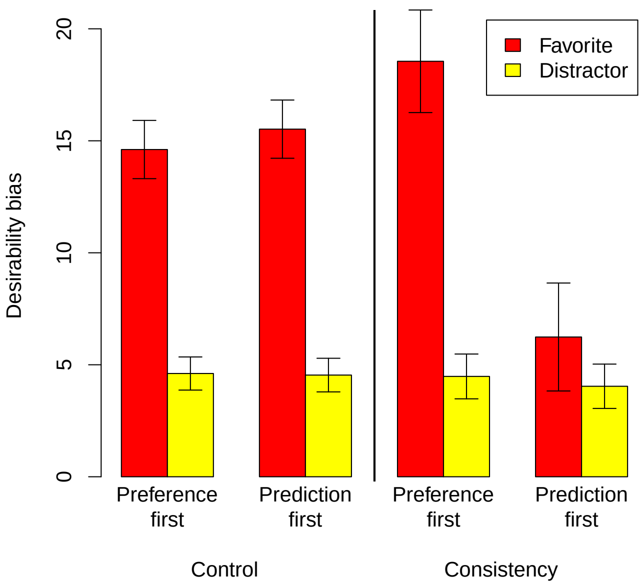
## 3.1 Baseline desirability bias

The DB was calculated as the difference between a participant's Predicted Likelihood of the preferred team's victory and the corresponding likelihood estimated by TeamRankings.com. For games involving participants' favorite teams, the mean DB over control games was 15.06 ($SD = 20.72$), a value well above zero ($t(542) = 16.94$, $p < .001$, $d = 1.46$). This value amounted to a preference-driven upward bias of .15 in participants' predicted probability that their favorite

century." Participants' effort to resolve the inconsistency between these two statements activates the goal of CC. Because they cannot be (easily) reconciled, this goal remains activated and influences the performance of the next task. Further, the level of activation is increased by the insertion of an intervening task that frustrates the achievement of the consistency goal (Chaxel & Russo, 2015). Thus, the goal activation method consisted of two tasks, resolving a conundrum and a goal-frustrating filler task.

[3] Note that random assignment of participants to the four conditions represented by the four columns in Table 1 was not equivalent to the ideal test of the DB described by Krizan and Windschitl (2007). In that test, participants are assigned randomly to Preferences, not conditions. In our sports context, random assignment of each participant to a favorite team would mean something like instructing a participant that their favorite team was to be, say, "the Boston Red Sox for the purposes of this study". Whether such instructed randomization would have succeeded is an open question. However, it would have required not only the pretended commitment to the (randomly) assigned team, but also participants' suspension of their allegiance to their true favorite. We chose the natural association between participants and their respective favorite teams. This made the experiment both more realistic and more validly conclusive if null results were found (instead of blaming a weak realization of the randomly assigned team preference). However, one downside of the random assignment of subjects to conditions rather than to teams is that the frequency distribution of favorite teams over conditions could be uneven. The possible effect of this imbalance on the results is addressed by an alternate measure of the DB that adjusts for it, as described in the presentation of the results.

Figure 1: Mean desirability bias for both favorite and distractor games, separately for priming condition (consistency primed versus control) and for response order (Preference first versus Prediction first). Error bars are *SE*s. Differences among error bars reflect the different frequencies of observations: three times as many observations for control as primed games and seven times as many observations for distractor as favorite games.




team would win. Its magnitude might be judged relative to the .06 probability increment over random performance achieved by TeamRanking.com's predictions across the entire 2014 baseball season (or the .08 increment for the games in this study).

Before proceeding to the main results of the effect of priming CC on the DB, we tested for a difference in the DB between the two control conditions that differed only by whether Preference or Prediction was the first response. Recall that because there was no effect of serial position, each control was comprised of the first 4 (unprimed) games in the primed conditions (Columns 1–2 in Table 1) and all 8 games in the controls that tested for an effect of serial position (Columns 3–4). For all control games involving a favorite team, the mean DB when Preference was the first response was 14.61 ($SD$ = 20.79) and for Prediction-First was 15.52 ($SD$ = 20.68). These two means are shown as the two leftmost red (dark) bars in Figure 1. They were not reliably different, $t(541) = .51$, $p = .61$, $d = .04$. We note that this absence of a difference in response order for unprimed participants is also a substantive result: The order of Preference and Prediction did not matter in our sports context when the consistency goal was not activated.

## 3.2 Priming cognitive consistency

The two principal research questions were (1) did priming CC increase the DB when the Preference response preceded the Prediction response and (2) how did reversing the order of these two responses affect this bias? Because response order made no difference for control games, we combined Preference-first (14.61) and Prediction-first (15.52) controls, yielding a combined control mean of 15.06. Our two research questions could then be answered by a one-way ANOVA predicting DB with condition as a 3-level factor (Control, Primed Preference-first, and Primed Prediction-first) and, more directly, the two planned comparisons of the corresponding two primed groups against the unified control.

Before proceeding with this computation, we needed to consider the possible role of team success as a confounding factor. That is, might team success have influenced the DB separately from either priming the consistency goal or response order? On the one hand, if a favorite team was relatively successful (unsuccessful), participants may have felt more (less) confident in their team's next victory and exhibited a larger (smaller) DB. In either case, the DB might have been positively correlated with team success. On the other hand, because the baseline prediction of successful teams started relatively high, there was less room both for the DB to elevate the Predicted Likelihood and also for priming CC to increase it even further. In such a case, the correlation between team success and the DB might have been negative. Any systematic effect of team success, whether positive or negative, should be removed from the statistical tests. To assess team success, we used the 2014 full-season proportion of games won, which ranged from a high of .605 for the Los Angeles Angels to a low of .395 for the Arizona Diamondbacks. For favorite games, the correlation between this measure of team success and the DB was $r(708) = .35$, $p < .001$. Thus, in spite of a plausible concern about how much higher the DB could rise when it was already likely to be higher for more successful teams, the data showed that it still rose more for the successful teams.

After including favorite-team success measured by win proportion as a covariate, we computed the one-way ANCOVA described above. Results yielded a significant effect of Condition $F(2, 704) = 6.68$, $p = .001$, partial $\eta^2 = .019$, as well as a significant effect of team success $F(1, 704) = 98.68$, $p < .001$, partial $\eta^2 = .123$. However, the answers to our two research questions lay in the two planned comparisons between the primed conditions and the control. First, the mean DB when Preference was the first required response was 18.55 ($SD$ = 21.98), as shown in Figure 1. A planned comparison confirmed that this value was significantly higher than the control mean (15.06), $t(704) = 2.00$, one-sided $p = .023$, $d = .16$. Thus, as expected, priming CC increased the DB when Preference was the initial response.

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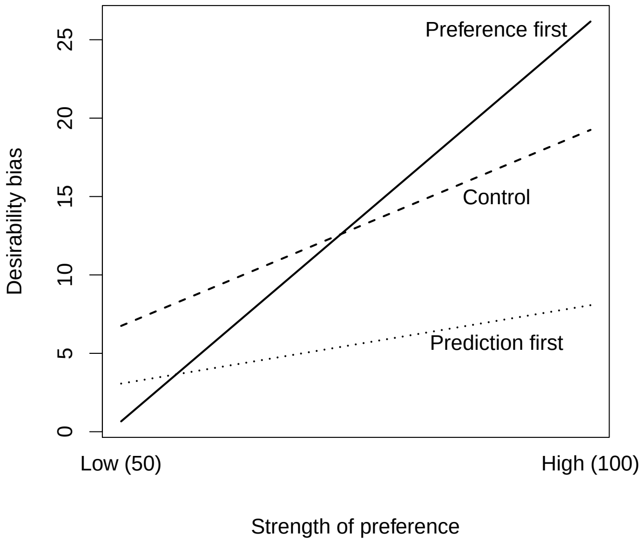
Figure 2: Regression lines for desirability bias on strength of preference by condition.




The answer to the open question of the impact of CC on the DB when Prediction was the first response was a reduction from the 15.06 of the control to 6.24 ($SD = 24.37$). This decrease of 59% in the magnitude of the DB was significant, $t(704) = 2.77$, two-sided $p < .01$, $d = .22$. Despite the decrease, the DB for this condition remained significantly above zero, $t(77) = 2.26$, one-sided $p = .018$, $d = .23$.[4]

For completeness, we replicated the above analysis including the distractor (i.e., non-favorite) games by adding Favorite (favorite versus distractor) as a third factor. The means of the four main conditions for the distractor games are also shown in Figure 1. The analysis, available in the Supplemental Materials, revealed no effects either of priming or response order on DB for the distractor games. There was a non-zero DB for these games (4.41 over the two control conditions). However, the preferences for winners that drove this mean DB might have been driven by negative desires for a team to lose (e.g., a rival of the favorite team) as much as by a second favorite. The mixed sources of preference combined with the absence of reliable differences over conditions discouraged further exploration of the distractor data.

## 3.3 DB and strength of preference

Because the DB is driven by the strength of the desire, which in our experiment was the Strength of Preference for the favorite game, there should have been a positive relation between the magnitudes of Strength of Preference and the associated DB. A regression with Strength of Preference (mean centered), Condition (dummy codes for Preference-first primed and Prediction-first primed, with Control as the excluded category), and their interactions predicting DB was performed to determine whether the consistency and order manipulations influenced the relationship between Strength of Preference and DB (see Table 2). Figure 2 displays the mean DB for different levels of the Strength of Preference and the resulting regression lines. As shown in Figure 2, there was a positive relationship between Strength of Preference and DB for control participants ($r(543) = .21$, two-sided $p < .001$). The relationship was significantly different from zero ($r(87) = .44$, two-sided $p < .001$) and reliably stronger for those in the Preference-first primed condition, $z = 2.21$, two-tailed $p = .027$. When the response order was reversed, the relation between DB and Strength of Preference ($r(78) = .08$, two-sided $p = .46$) is shown by the lowest line in Figure 2. This relationship was not significantly different from zero, but was also was not significantly different from the control group, $z = 1.08$, two-sided $p = .28$.

We also replicated the above analysis for all games (favorites and distractors). We did not include Favorite as a separate factor due the problem of collinearity between favorites and Strength of Preference. The analysis (see Table S6 in Supplemental Materials) revealed a marginal main effect of Prediction-First with less DB in this condition. There was also a Preference-first primed X Strength of Preference interaction, such that those in the Preference-first primed condition with a stronger Strength of Preference showed greater DB, and a marginal Prediction-first primed X Strength of Preference interaction with a reduction of the relationship between Strength of Preference and DB. Overall, these results for all games were rather similar to those in Table 2 for favorite games.

## 3.4 Uneven DB over teams

Because our method did not randomly assign participants to a favorite team, differences in the magnitude of the DB across teams might have created an uneven baseline DB across conditions if random assignment failed to equate the distribution of favorite teams over conditions. This would amount to starting points from which the effects of priming were estimated that may have been different for each condition. In fact, there were such differences across teams and conditions. For instance, for the Yankees-Rangers game, in the control condition the mean DB of the 33 Yankees fans was 23.76 while that of the 7 Rangers fans was –7.54. In the Preference-First primed condition, there were 8 Yankee fans (Mean DB = 35.83) and 1 Ranger fan (DB = –15.83), while in the Prediction-First primed condition there were 2 Yankee fans (mean DB = 25.83) and 5 Rangers fans (mean DB

[4]For completeness, the one-way ANOVA used to answer the two central research questions was partitioned into a 2x2 ANOVA by keeping separate the two control conditions. This analysis (provided in the Supplemental Materials) yielded results similar to those reported above. Specifically, both tests of differences between the two primed conditions and their respective controls yielded statistically significant effects.

Table 2: Condition and strength of preference predicting desirability bias in games involving favorite teams.

| Predictor | B | [95% CI] | SE | Wald $\chi^2$ | $p$ |
|---|---|---|---|---|---|
| Intercept | 15.03 | [13.30, 16.77] | 0.89 | 288.14 | <.001 |
| Pref-first | 3.44 | [–1.23, 8.11] | 2.38 | 2.08 | .150 |
| Pred-first | −8.68 | [–13.58, –3.78] | 2.50 | 12.04 | .001 |
| Preference strength | .25 | [.15, .34] | 0.05 | 24.32 | <.001 |
| Pref-first X Preference strength | .27 | [.01, .52] | 0.13 | 4.28 | .039 |
| Pred-first X Preference strength | −.15 | [–.39, .09] | 0.12 | 1.45 | .229 |

Note. Pref = Preference; Pred = Prediction. Both Preference and Prediction refer to primed games. The Strength of Preference variable was mean-centered ($M$ = 84.74) for this analysis.

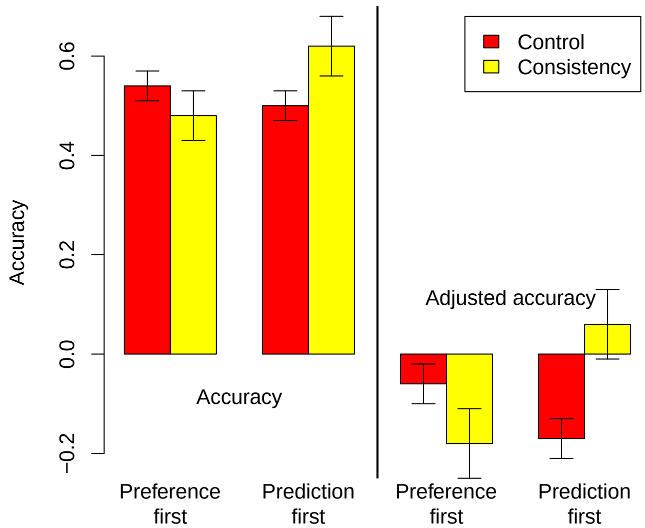
= –24.83). In order to determine whether this uneven distribution of baseline DB over the 30 teams accounted for our (between-condition) effects, we constructed an alternative measure of DB (suggested by a reviewer) that normalized the DB for the two teams in each game. To get this adjusted DB, we regressed participants' Predicted Likelihood that the home team will win for each individual game (including both favorites and distractors) on their Strength of Preference for a home team win (transformed such that –100 was the maximum preference for the visiting team and 100 was the maximum preference for the home team). The intercept from each regression represented the likelihood estimate of a participant who held a neutral preference for either team. The difference between this intercept and each participant's actual Predicted Likelihood for that game estimated the (adjusted) level of the DB. Next, this value was signed positively when participants preferred the home team and negatively when they preferred the visiting team. Finally, these scores were z-transformed separately for each game so that all games could be compared on the same basis. Because this adjusted DB was standardized within-game, an unequal preference for one team within a condition should have been removed. For instance, the standardized DB the for Yankee fans in the control condition was 0.22 while that of Rangers fans was 0.23 (compared to the corresponding raw values of 23.76 and –7.54 reported above).

An ANOVA was performed on this adjusted DB score with Condition as the independent variable, again controlling for team win proportion. The significant effect of Condition remained, $F(2, 704) = 5.64$, $p = .004$, partial $\eta^2 = .016$. More importantly, the mean adjusted DB for the control games was 0.43 ($SD$ = 1.10), a value significantly lower than that for Preference-first primed games $M$ = 0.66 ($SD$ = 1.10), $t(704) = 1.81$, one-sided $p = .035$, $d = .14$. Also, the control value was significantly higher than that for Prediction-first primed games $M$ = 0.04, ($SD$ = 1.30), $t(704) = 2.56$, two-sided $p = .011$, $d = .21$. Given the similarity between results for both the raw and adjusted DB measures, an unbalanced distribution of fans across conditions did not account for the effects of priming and response order. Therefore, subsequent analyses use the original, unadjusted DB measure.

## 3.5 What caused the reduction of the desirability bias when prediction was first?

The results when Prediction was the first response enabled us to distinguish among the three potential processes, viz., the continued dominance of Preference, consistency with game-specific facts, and the bandwagon effect. The observed 59% reduction of the DB when CC was primed and Prediction was the first response (see Figure 1) supported the consistency-with-fact process, which led to a more accurate Prediction and, therefore, a lower DB. The observed reduction in DB simultaneously disqualified the continued dominance of Preference, which required an increase in the DB. The remaining possibility, the bandwagon effect (under consistency priming) required a corresponding decrease in the reported Strength of Preference (compared to the control condition). Always restricting the analysis to when Prediction came first, the mean Strength of Preference in the control and primed conditions, respectively, was 84.88 ($SD$ = 17.82) and 83.62 ($SD$ = 20.98). Their difference, though directionally compatible with some power of Prediction to lower the Strength of Preference, was not statistically reliable ($t(619) = 0.57$, $p = .72$, $d = .05$). The absence of reliable evidence that estimating Prediction first caused a compatible change in the Strength of Preference eliminated the bandwagon effect from consideration. Thus, the pattern of results supported only the consistency-with-facts process as the explanation for the observed effect of priming on the DB when Prediction was the first response.

Figure 3: Accuracy is the proportion of (favorite) games correctly predicted by participants. Adjusted accuracy is accuracy minus the baserate of correct predictions from TeamRankings for the same games.




### 3.6 Prediction accuracy

Finally, we examined whether the increase in DB in the Preference-first primed condition led to a corresponding decrease in accuracy in predicting game outcomes and whether a decrease in DB in the Prediction-first primed condition actually led to increased accuracy. The proportions of participants' correct predictions, our measure of accuracy (0 = incorrect, 1 = correct), are shown in the left panel of Figure 3 for the four conditions formed by the 2x2 design of consistency priming and response order. However, because the distribution of favorite teams differed across conditions, the baserates of accuracy (from TeamRankings) were likely also to differ across conditions. Thus, to evaluate the effect of priming and response order on participants' accuracy, we needed to subtract the TeamRankings' prediction (also 0 = incorrect, 1 = correct) from the participants' accuracy for each of the four conditions. These differences in proportions correct created the four adjusted accuracy scores in the right panel of Figure 3. Note that because the participants' accuracies were distorted by the DB, they were expected to be lower than TeamRankings' predictions. As a result, the adjusted accuracy scores were expected to be negative.

A Prime X Order ANOVA over these adjusted accuracy scores yielded a significant 2-way interaction, $F(1, 704) = 10.82$, $p = .001$, partial $\eta^2 = .015$. Adjusted accuracy was greater in the Prediction-first primed condition (.06 above the proportion of correct predictions made by TeamRankings) compared both to its corresponding control condition ($F(1, 704) = 8.54$, $p = .004$, partial $\eta^2 = .012$) and also to the Preference-first primed condition ($F(1, 704) = 6.76$, $p = .010$, partial $\eta^2 = .010$). Remarkably, this adjusted accuracy for Prediction-first primed was positive. However, this result may well be no more than a statistical anomaly (the .06 did not differ reliably from zero, $t(77) = 0.93$, $p = .356$ $d = .21$). The Preference-first primed prediction's adjusted accuracy (–.18) was the lowest of all, which is not surprising because this condition exhibited the highest DB. Its value was marginally less accurate than the corresponding Preference-first control ($F(1, 704) = 2.91$, $p = .089$, partial $\eta^2 = .004$). Finally, we compared the two control conditions. Unlike prior results, which indicated no difference between Orders in the control condition, Preference-first control predictions were significantly more accurate than Prediction-first controls, –.06 versus –.17, $F(1, 704) = 4.40$, $p = .036$, partial $\eta^2 = .006$). This finding represented a reversal of the effect in the primed condition. Additional analyses that used either logistic regression or Brier scores yielded similar results (see the Supplemental Materials).

Given the ability of priming in the Prediction-first condition to lower the DB (relative to the control condition), it was not surprising that priming when Prediction came first yielded the best accuracy. That this accuracy was (nonsignificantly) superior to the TeamRankings' baserate should be conservatively interpreted as an effect of variability in observed accuracy with small samples. Nonetheless, these results provide additional evidence for increased consistency with the facts as the process by which DB was decreased in this condition.

## 4 Discussion

Our results enlarge the theoretical understanding of the DB in two ways. First, they increase our knowledge of the possible causes of this well-known bias, both by adding the goal of CC as a new cause and by supporting previous claims of CC's role in three other causal mechanisms (Krizan & Windschitl, 2007). The nondirectionality of CC might seem to preclude its driving a directional phenomenon like the DB. However, our experimental paradigm illustrates how a direction can be devised both by one belief's being dominant (Preference in the case of the DB) and also by inserting a direction-inducing stimulus (game-specific facts in the baseball context). The nondirectionality of the consistency goal stems, in part, from its nature as a process goal in contrast to an outcome goal (van Osselaer et al., 2005). The latter type of goal supports targeted outcomes, such as consuming fewer calories, finding the cheapest airfare, or emphasizing an automobile's safety in bad weather. In contrast, process goals like saving effort and enjoying the experience (of the process) do not target any particular outcome. CC is a process goal and exhibits this category's typical property of nondirectionality.

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The second contribution to understanding the DB is less theoretical and more pragmatic. The combination of priming CC and asking the prediction question first reduces this bias by more than half. This tactic of prediction first might be contrasted with previous methods that tap cognitive resources for reducing bias (Bélanger, Kruglanski, Chen & Orehek, 2014; Lench & Bench, 2015). We also note that the present data suggest that response order will not affect the DB unless CC is activated above its chronic baseline. How often this occurs under natural circumstances is an open question.

The observed role of CC may apply not only to judgmental biases but also to any other psychological phenomenon that involves beliefs. For instance, Chaxel et al. (2016) demonstrated that CC can reduce an implicit attitude, the bias against overweight people. They did this by requiring a statement of the explicit attitude (which is less biased), then priming CC, and finally assessing the implicit attitude (using the IAT). Priming CC moved the (more biased) nonconscious implicit attitude to greater agreement with the previously activated (less biased) explicit attitude. It must be repeated that the demonstration of the impact of the CC goal both on the DB and in Chaxel et al. relied on the experimental activation of this goal. Our results showed that without this manipulated activation, there was no difference caused by the order of the Preference and Prediction responses. It seems that under chronic, background levels of activation, the consistency goal may have little or no effect on the DB or, possibly, other JDM phenomena.

The use of the conundrum-based method for priming CC is relatively new. While this method manipulates the consistency goal, there is a second and equally novel method for measuring the activation of this goal during task performance. Carlson, Tanner, Meloy and Russo (2014) interrupted a task and asked for a report of goal activation on a continuum. They showed that a successful report of goal activation requires both assessment during a task (as opposed to a post-task report based on immediate memory) and a continuous response scale (as opposed to a yes-no report of a goal as active or not active). The combination of goal manipulation, as in the above study, and goal measurement, using Carlson et al.'s method, promises testing of goal-based theories of behavior that is more rigorous than heretofore.

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