

## Overprecision Increases Subsequent Surprise

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### Abstract

Overconfident people should go through their lives being surprised that they are so often wrong. Are they? Four studies examined the relationship between confidence and surprise in order to shed light on the psychology of overprecision. Participants reported ex-ante confidence in their beliefs, and after receiving accuracy feedback, they then reported ex-post surprise. Results show that more ex-ante confidence produces less ex-post surprise for correct answers; this relationship reverses for incorrect answers. However, this sensible pattern only holds for some measures of confidence; it fails for confidence-interval measures. These results can help explain the robust durability of overprecision in judgment.

## Overprecision Increases Subsequent Surprise

Overprecision is overconfidence in the accuracy of one's beliefs (Moore, Tenney, & Haran, 2016). This excessive certainty is on display when people are too sure they know how their friends will behave (Dunning, Griffin, Milojkovic, & Ross, 1990), when doctors are too certain of a favored diagnosis (Arkes, Wortmann, Saville, & Harkness, 1981), or when managers issue excessively precise and inaccurate earnings forecasts (Hribar & Yang, 2015). These overly precise beliefs increase the risk of being wrong. When their expectations are violated, people ought to be surprised. Do they *feel* sufficiently surprised? In this paper, we ask how overconfidence contributes to subsequent surprise.

Frequent feedback should help people calibrate their confidence; being routinely wrong should reduce confidence in the next forecast. However, the robustness and durability of overprecision suggests this corrective may be incomplete (Harvey, 1997; Moore et al., 2016). Overprecision is ubiquitous despite the regularity with which people have their confident expectations violated. Underprecision is vanishingly rare (see Moore, Carter, & Yang, 2015). The present research examines how overprecision affects subsequent surprise.

### **Overprecision**

There are innumerable ways in which overly certain beliefs can impair decisions. It contributes, for instance, to managers issuing too much debt when they underestimate the volatility of their firm's future (Hackbarth, 2008), foregoing accounting corrections to their own forecasts of firm returns (Ahmed & Duellman, 2013), and issuing excessively precise and inaccurate earnings forecasts (Hayward & Fitza, 2017; Hribar & Yang, 2015). Those too sure of their beliefs can succumb to other biases which similarly impair decision

making, such as naïve realism (Pronin, Gilovich, & Ross, 2004) or the “false consensus” effect (Krueger & Clement, 1994). Excessive faith in their beliefs can also lead people to discount others’ views (Minson & Mueller, 2012), or even disparage others as biased (Minson, Liberman, & Ross, 2011). Overprecision leads people to do too little to protect themselves against low-probability risks (Mannes & Moore, 2013). And overprecision blinds people to the need to consider other perspectives (Liberman, Minson, Bryan, & Ross, 2012; Ortoleva & Snowberg, 2015). These mistakes can have painful consequences for both individuals and organizations (Mergenthaler, Rajgopal, & Srinivasan, 2012). Given the costly consequences of overprecision, understanding its persistence is important.

We compare different measures of overprecision. Researchers have most often used the confidence interval paradigm created by Alpert and Raiffa (1982). This method consistently finds overprecision (Bazerman & Moore, 2013), though it is controversial. The two most common critiques consider confidence intervals to be too difficult for participants to understand (Cosmides & Tooby, 1996), and that individuals do not naturally think about confidence in terms of confidence intervals (Mannes & Moore, 2013). We directly compare the confidence interval method with more naturalistic measures of confidence.

## **Surprise**

Surprise is one of the basic emotions (Levenson, 2011). The functional role of surprise is to alert the organism that its predictions were in error and direct attention at the surprising stimulus (Itti & Baldi, 2006). This function is sufficiently universal that surprise has proven useful in studying beliefs and expectations among monkeys and human infants (Steckenfinger & Ghazanfar, 2009; Xu & Spelke, 2000). When something unexpected happens, it receives more attention and longer gaze. The level of surprise one experiences

and the duration of subsequent gaze is related to the degree of difficulty making sense of an event (Maguire, Maguire, & Keane, 2011). Seeing someone levitate should be more surprising than seeing them jump in the air. The more unexpected an event, the more intense the emotional reaction to it (Mellers, Schwartz, Ho, & Ritov, 1997).

The more confident one is of one's beliefs, the more surprising it should be when those beliefs turn out to be wrong. However, the research on overprecision in judgment clearly predicts that this surprising event should occur routinely, given the prevalence of overprecision. We seek to connect the literature on surprise with the literature on overprecision in judgment. Research has not yet, to our knowledge, tested the hypothesis that predictions made with greater confidence will produce greater surprise when they turn out to be wrong. We test this prediction, and examine its consequences for subsequent confidence in judgment.

### **Present Research**

We asked participants to report ex-ante confidence for a variety of judgments, and after receiving performance feedback, they then reported ex-post surprise at the result. This research hones in on a key interaction, wherein the relationship between ex-ante confidence and ex-post surprise is moderated by whether one's answer is correct. We present four studies examining this relationship. Study 1 examines the relationships between confidence, correctness, and surprise for both self and others. Study 2 exogenously manipulates confidence and replicates the key finding from the first study. Study 3 uses a different manipulation of confidence and employs a repeated-measures design to explore the effect of confidence on surprise. It also employs a confidence interval elicitation in order to compare different measures of confidence. Finally, in Study 4, we consider lay predictions regarding

how surprised people believe they or others should be. Across the four studies, we employ a variety of different measures of belief precision and subsequent surprise, seeking to shed light onto their relationships with each other.

We report how we determined our sample size, all data exclusions (if any), all conditions, and all measures. Pre-registrations, materials, and data are available:

<http://osf.io/j5vpe/>.

### Study 1: Accuracy and Surprise

Study 1 examined the basic relationship between surprise and overconfidence. We hypothesized that both confidence and correctness would positively predict surprise. We also computed a measure of absolute distance from the true answer as an additional predictor on surprise. We expected higher ex-ante confidence to produce lower ex-post surprise for correct judgments, and for incorrect judgments higher ex-ante confidence to produce greater ex-post surprise. Study 1 seeks the antecedents of surprise, by examining the effect of confidence, correctness, and distance from the truth on subsequent surprise.

### Method

We exposed 430 MTurk workers to a set of five photographs of strangers. Participants had to guess how much each person weighed and report their confidence (on a scale from 0 – 100%) that their answer was within ten pounds of the true weight. After the five images, participants saw the true weight of each person in turn, followed by truthful feedback on whether or not their estimate fell within ten pounds of the true weight. Following each round of feedback, participants reported their surprise on a scale of 0-100.

## Results

Results reveal participants to be overprecise: The average hit rate for estimates within ten pounds of the true weight was 37%, yet average confidence was 66% ( $SD = 20.48$ ). Given the repeated measures design, we employed a multilevel regression model with random slopes. We measured distance by taking the absolute value of the difference between the participants' estimates and the true weight of the person in the photograph.

We conducted a multilevel regression predicting surprise from absolute distance, correctness, confidence, and the interaction between correctness and confidence, all nested at the individual level. The results reveal that absolute distance did indeed positively predict participants' reported surprise,  $\beta = .33$ ,  $t(451) = 14.84$ ,  $p < .001$ . There were also significant main effects of confidence on surprise, wherein greater confidence predicted greater surprise,  $\beta = .11$ ,  $t(451) = 2.98$ ,  $p = .003$ , and for correctness on surprise,  $\beta = .21$ ,  $t(451) = 2.89$ ,  $p = .003$ , where being correct predicted greater surprise. Additionally, there was a significant confidence-correctness interaction effect on surprise,  $\beta = -.21$ ,  $t(451) = -2.82$ ,  $p < .005$ .

We chose to further explore the interaction between confidence and correctness in these results. With subsets of the data for correct and incorrect answers, our multilevel regression found that when participants were correct, confidence no longer predicted greater surprise,  $\beta = -.13$ ,  $t(380) = -1.35$ ,  $p = .17$ . However, absolute distance did predict surprise,  $\beta = .77$ ,  $t(380) = 7.20$ ,  $p < .001$ . When participants were incorrect, more confidence produced more surprise,  $\beta = .23$ ,  $t(439) = 3.34$ ,  $p < .001$ , and greater absolute distance from the truth also produced greater surprise,  $\beta = .52$ ,  $t(439) = 10.47$ ,  $p < .001$ .

These results clearly show that being confident and wrong is associated with greater surprise. However, this study is correlational in nature, leaving open the possibility that both confidence and surprise are caused by some third variable. The next study employs an exogenous manipulation of confidence and provides a proper experimental test of the effects of confidence on surprise.

### Study 2: Exogenously Manipulated Confidence

#### Method

This study sought to clarify the relationship between overconfidence and surprise, testing the hypothesis that people feel confident in their predictions to the extent that their estimates deviate from the ignorance prior (i.e., the flat subjective probability distribution). Their surprise should be driven by the extent to which an outcome's assigned probability was greater than or less than it would have in a flat probability distribution (Ely, Frankel, & Kamenica, 2015).

We showed 432 MTurk participants four photographs of people for a weight guessing task, similar to Study 1. For each photograph, participants saw two plausible options and either zero, one, or three "dummy" or implausible options.

Participants indicated the probability of each option being the true weight of the person in the photograph. Next, they chose the option they felt was most likely to be the true weight and indicated how confident they were (on a scale from 0-100) in their choices. Finally, participants saw the correct answer and indicated how surprised they were (on a scale from 0-100) about the results.

We predicted that the presence of additional alternatives would affect participants' reported maximum probabilities. We also expected to replicate our key interaction between confidence and correctness on surprise.

### Results

We analyzed the repeated measures design using a multilevel regression with individual-level nesting to test our hypotheses. The presence of dummy options significantly decreased participants' maximum probabilities:  $\beta = -.21$ ,  $t(431) = -10.85$ ,  $p < .001$ , suggesting dummy options made participants less sure. We replicate our previous results showing that surprise is positively predicted by both confidence,  $\beta = .46$ ,  $t(434) = 16.45$ ,  $p < .001$ , and correctness,  $\beta = .27$ ,  $t(434) = 3.98$ ,  $p < .001$ , as well as a significant confidence-correctness interaction effect on surprise,  $\beta = -.77$ ,  $t(434) = -11.61$ ,  $p < .001$ .

To explore the confidence-correctness interaction we split the data into two subsets: correct and incorrect answers. For correct answers, confidence did not significantly predict surprise (though the correlation was again negative),  $\beta = -.11$ ,  $t(352) = -1.62$ ,  $p = .11$ . For incorrect answers, greater confidence led to greater surprise,  $\beta = .52$ ,  $t(425) = 15.24$ ,  $p < .001$ , replicating Study 1. This result suggests that being wrong produces a stronger relationship between confidence and surprise than does being correct.

These results made us wonder about the temporal dynamics of surprise and confidence. Would being confident and wrong decrease subsequent confidence? Could this reduce overprecision over time? And how is this moderated by the degree to which people feel personally accountable for being wrong? The feeling that one should have known better makes most sense where uncertainty is epistemic and the answer is knowable (Tannenbaum,



Fox, & Ülkümen, 2017). By contrast, when uncertainty is aleatory, such as the outcome of a coin flip, few people will feel that they should have been able to anticipate the outcome.

### Study 3: Surprise Over Time

The first two studies were poorly designed to test the corrective effect of surprise on subsequent confidence, since they collected all confidence measures before providing feedback about accuracy. Study 3 sought to replicate our key results in our original domain of weight guessing while expanding our scope to two new facets of investigation. Specifically, we examined how aleatory or epistemic questions could affect the relationship between confidence and surprise. Because people are more confident when uncertainty is epistemic than when it is aleatory (Tannenbaum et al., 2016), this manipulation served as an experimental manipulation of confidence, different from that employed in Study 2.

Ten questions were aleatory in nature, where the answer could not be known beforehand: Of ten coins flipped together, how many would land heads up? The other ten weight-guessing questions were epistemic in nature, with answers that participants could conceivably know, given sufficient skill at weight-guessing.

In addition, Study 3 sought to examine the temporal dynamics of confidence and surprise. Does experience help people adjust their expectations and better calibrate their confidence? Does it reduce surprise? We provided our participants with immediate feedback and measured the consequences of that feedback (reported surprise) on their subsequent reports of confidence.

## Method

Our pre-registered research plan called for 115 participants recruited via Amazon Mechanical Turk. We based this number on the effect size from a previous study (available in our [supplemental online materials](#)),  $f^2 = .036$ , and power of 90%.

Study 3 employed a 20-question design; half aleatory and half epistemic. Our operationalization of aleatory questions came in the form of drawing bingo balls labeled 1-100, and guessing weights from images (as in Studies 1 and 2). For each question, we asked participants to provide a best estimate of the answer, as well a high and low estimate to establish a confidence interval. Specifically, we asked for percentiles with only a 25% chance the true answer is above (or below) this high/low estimate. These interquartile percentile ranges also defined which answers were considered ‘correct’ (i.e. whether the true answer was inside or outside of their self-created ‘confidence’ interval). Participants provided three responses per round: a best estimate plus high and low bounds, at the 25<sup>th</sup> and 75<sup>th</sup> percentiles, to form their “confidence” interval. We used a standardized measure of the size of participants’ confidence intervals (their high estimate minus their low estimate divided by their ‘best guess’ estimate) as our alternative confidence measure.

In addition, participants reported confidence on a 1 to 7 scale (from “*Not at all confident*” to “*Extremely confident*”) and reported surprise on a 1-7 scale (from “*Not at all surprised*” to “*Extremely surprised*”) after they learned the right answer.

## Results

Hit rates between the 25<sup>th</sup> and 75<sup>th</sup> percentiles were similar for aleatory (65.83%) and epistemic questions (68.78%),  $t(114) = -1.51$ ,  $p = .13$ . These hit rates suggest that participants were actually underprecise for both bingo ball questions and weight guessing

questions, as both hit rates are greater than 50%. However, the bingo rounds produced lower feelings of confidence ( $M = 4.82$ ) than did the weight rounds ( $M = 5.42$ ),  $t(114) = -8.83$ ,  $p < .001$ . Using a standardized measure of confidence drawn from participants' confidence intervals, dividing the range of their upper and lower estimates by their 'best guess' estimate, there appears a similar relationship: Participants provided larger confidence intervals on average for the bingo rounds ( $M = 64.85$ ) compared to weight rounds ( $M = 45.04$ ),  $t(114) = 23.07$ ,  $p < .001$ . There was also a difference in reported surprise by question type,  $t(114) = -8.10$ ,  $p < .001$ . Participants reported greater surprise for epistemic weight-guessing judgments ( $M = 3.40$ ) than for aleatory bingo-ball judgments ( $M = 2.71$ ),  $t(114) = 8.10$ ,  $p < .001$ .

The effect of confidence and correctness on surprise replicates the results of Study 2: when incorrect, high confidence predicted greater ex-post surprise,  $\beta = .33$ ,  $t(114) = 9.37$ ,  $p < .001$ ; though when correct, higher confidence predicted lower ex-post surprise,  $\beta = -.33$ ,  $t(114) = -12.89$ ,  $p < .001$ .

A multilevel regression predicting surprise with question type, correctness, distance, confidence, and a correctness-confidence interaction reveals a significant main effect of question type: the epistemic weight-guessing questions caused greater surprise than the aleatory bingo ball questions,  $\beta = .15$ ,  $t(119) = 9.63$ ,  $p < .001$ . This analysis also replicated the confidence-correctness interaction from previous studies: confidence increased surprise when they were incorrect,  $\beta = -1.33$ ,  $t(119) = -23.52$ ,  $p < .001$ . Subsetting on correctness identifies the negative relationship between confidence and surprise when correct,  $\beta = -.33$ ,  $t(117) = -12.89$ ,  $p < .001$ , and the positive relationship between confidence and surprise

when incorrect,  $\beta = .33$ ,  $t(115) = 9.37$ ,  $p < .001$ . The aggregated standardized confidence-correctness interaction effect on surprise for these first three studies appear in Figure 1.

However, our other measure of confidence (confidence interval size) produces very different results. The same multilevel model predicting surprise with question type, correctness, distance, and confidence (from interval size), produces a correctness-confidence interaction,  $\beta = .31$ ,  $t(119) = 5.16$ ,  $p < .001$ . Again to seek clearer insights, we ran this new model on data subset by correctness. The negative relationship between confidence and surprise for correct answers is weakened to nonsignificance,  $\beta = -.04$ ,  $t(119) = -1.55$ ,  $p = .12$ . The positive relationship we found previously between confidence and surprise when incorrect is nearly nonexistent,  $\beta = .02$ ,  $t(119) = 0.59$ ,  $p = .56$ .

In order to test the effect of surprise on confidence over time, we employed a lagged regression to see how confidence is predicted by correctness at  $t - 1$  (i.e., how correctness in any given round predicts confidence in the round immediately following). Lagged correctness at  $t - 1$  significantly predicted confidence at time  $t$ ,  $\beta = .07$ ,  $t(115) = 4.12$ ,  $p < .001$ . Did reported surprise impact subsequent confidence similar to how correctness affected subsequent confidence? Adding lagged surprise at  $t - 1$  into the same model showed no significant effect of lagged surprise on confidence,  $\beta = .003$ ,  $t(116) = 0.13$ ,  $p = .89$ . This result suggests a profound failure of the functional role of surprise: it did not reduce subsequent confidence. The inclusion of lagged surprise also left the main effect of lagged correctness on surprise nearly unchanged,  $\beta = .07$ ,  $t(116) = 3.78$ ,  $p < .001$ .

Results of Study 3 introduce significant caveats to our key interaction between confidence and correctness on reported surprise. This study reinforces the importance of the method one uses to elicit confidence, as our key results largely disappear using the

confidence-interval elicitation. These results add to our skepticism of confidence-interval measures and the degree to which they effectively capture subjective feelings of confidence. Our next study sought to replicate our key results and uncover lay beliefs of surprise by asking if people are as surprised as they think they should be.

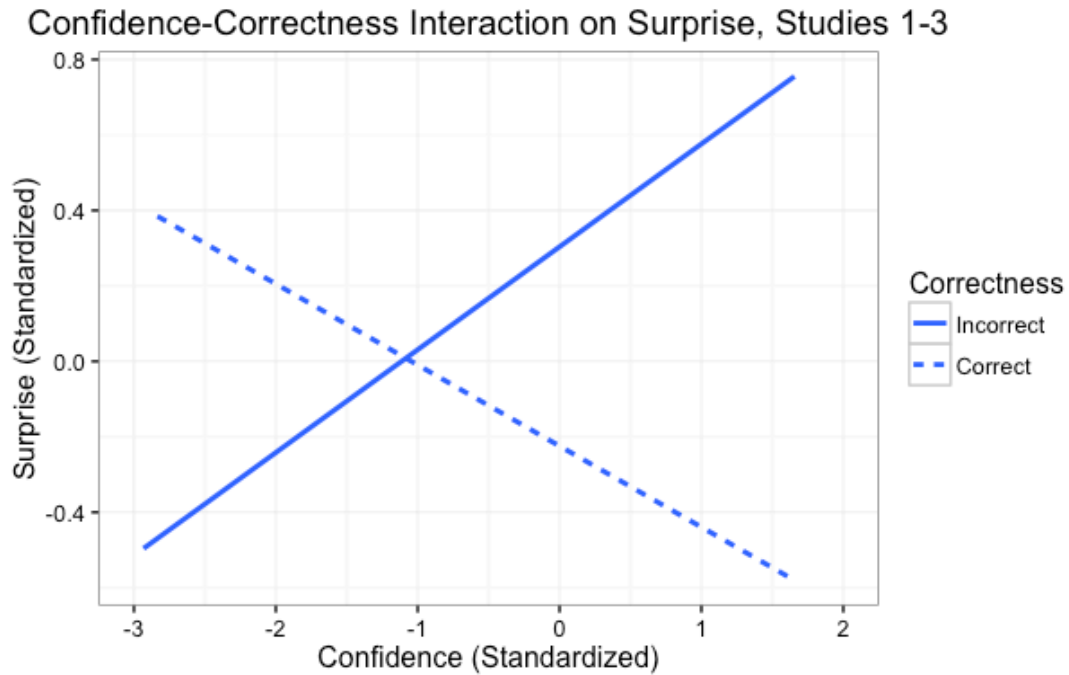


Figure 1. The aggregated standardized interaction effect of confidence and correct answers on reported ex-post surprise, for Studies 1-4. Measures are standardized by z-scoring within each study, then aggregating.

#### Study 4: Predicting Surprise

Study 4 asks whether people are as surprised as they *should* be. The study randomly assigned half the participants to a prediction condition which elicited predictions of surprise for hypothetical correct and incorrect answers. The other half of participants, in the control condition, made no such predictions. Study 4 again employed both aleatory and epistemic judgments.

In choosing which tasks to use, we noted that Study 3 found surprise to be lower for bingo balls than weight-guessing. Since the distribution of bingo balls is uniform, all numbers are equally likely and there is little reason to be surprised by any particular outcome, potentially contributing to diminished “surprisingness.” Therefore, Study 4 replaces bingo with a set of ten coin flips, which has a single-peaked distribution of outcomes and the potential for truly surprising outcomes (such as ten flips all coming up tails).

### Method

A power analysis of the prior studies, where people reported *ex ante* surprise providing average effect sizes of  $f^2=.036$  to  $f^2=.024$  provided a recommended sample size of 105. Wary of losing power from subsetting the data in testing our hypotheses, we aimed for 150 and ended up with 151 participants.

Each survey informed participants that there would be ten rounds of ten coin flips and ten rounds of guessing individuals’ weights from images. For each of the two blocks (which were presented in a random order) participants provided a best guess estimate as well as their confidence in being correct (on a 1-100 scale). Following each round, we informed participants whether they had answered correctly, and then participants reported their surprise at the outcome (on a 1-7 scale). Answers for coin flips counted as correct if they were within one head (out of ten) of the actual outcome. Weight guesses counted as correct if they were within ten pounds of the truth.

We assigned participants to one of two between-subjects conditions: a control condition and a prediction condition, where, in each round, in addition to the procedure described above, participants predicted how surprised they would be if their answer was right and if it was wrong.

## Results

On average, participants were overconfident. They report being 55.5% confident on average, but they are only right 50.3% of the time, one-sample  $t(2804) = 12.1, p < .001$ . This confidence declines with experience. It starts at 60.2% in Round 1 and declines to 52.8% in Round 20. A linear regression predicting confidence with round number, coin/weight, and fixed effects for subject produces a strong effect of round,  $B = -.59, t = -5.08, p < .001$ . There is no significant difference between weight and coin rounds,  $B = -1.55, t = -1.16, p = .25$ . This lack of a difference between weight and coin rounds is remarkable given that participants' guesses are correct 61% of the time for coin rounds but only 39.8% of the time for weight rounds,  $t(3038) = 11.83, p < .001$ .

Were participants as surprised as they predicted? In order to test this, we employed two dependent-measures t-tests to account for the repeated measures design, comparing the predicted surprise for a correct answer to a subsequent correct answer's surprise, and comparing the predicted surprise for an incorrect answer to a subsequent incorrect answer's surprise. Through this we see that participants reported less surprise ( $M = 3.30, SD = 1.91$ ) than they predicted they would ( $M = 3.78, SD = 1.82$ ) when correct,  $t(712) = 7.63, p < .001$ , but they were much more surprised ( $M = 4.77, SD = 1.82$ ) than predicted ( $M = 3.61, SD = 1.74$ ) when incorrect,  $t(761) = -15.56, p < .001$ . These patterns are similar for both coin and weight rounds.

We also explored whether merely the act of prediction had an impact on one's subsequent surprise. We employed a repeated measures one-way ANOVA predicting ex-post surprise by condition, controlling for individual-level error. This analysis shows that condition significantly predicts ex-post surprise,  $F(1, 2888) = 19.41, p < .001$ . A follow up

hierarchical linear regression controlling for individual-level error shows that being in the prediction condition increased ex-post reported surprise,  $\beta = 0.17$ ,  $t(150) = 4.41$ ,  $p < .001$ . Those who predicted their surprise wound up reporting more surprise ( $M = 4.04$ ,  $SD = 2.01$ ) than those who did not ( $M = 3.39$ ,  $SD = 2.04$ ).

In testing a replication of the lagged analysis from Study 3 we ran a similar lagged analysis predicting confidence with correctness at  $t - 1$ . The analysis shows that when it was the only predictor, lagged correctness positively predicted subsequent confidence,  $\beta = .04$ ,  $t(150) = 2.81$ ,  $p < .005$ . However, including lagged surprise wipes out the relationship, leaving only lagged surprise significant,  $\beta = -0.09$ ,  $t(150) = -4.23$ ,  $p < .001$ , where more surprise at  $t-1$  led to less confidence at  $t$ . This contrasts with the result from in Study 3.

To explore whether this failure to replicate was an artifact of eliciting predictions of surprise in the prediction condition, we subset the data on condition and ran the same analyses. In the prediction condition, the relationship stayed significant with less power,  $\beta = -.08$ ,  $t(75) = -2.70$ ,  $p = .007$ . The relationship also holds in the control condition, which presents itself as a direct replication of Study 3 where no predictions are made,  $\beta = -.10$ ,  $t(73) = -3.45$ ,  $p < .001$ . This failure of replication invites the conclusion that the effect of surprise on subsequent confidence is difficult to measure, or just inconsistent.

## GENERAL DISCUSSION

Our results show that ex-ante confidence and ex-post surprise are inextricably linked. Our primary finding is that when people are correct, greater ex-ante confidence produces less ex-post surprise, whereas when they are incorrect, greater ex-ante confidence produces more ex-post surprise. We examine the psychology underlying these relationships and identify moderators that can either suppress or enhance their strength. Studies 1 and 2



establish the link between confidence and surprise, highlighting that correctness is a powerful moderator of the relationship. Studies 2 and 3 employ exogenous manipulations of confidence; their results replicate the correlational results of Study 1. Study 3 finds more powerful confidence-correctness interaction effects on surprise for epistemic questions than for aleatory, consistent with the notion that feeling personally accountable for knowing or not knowing the answer increases the intensity of emotional reactions to being right or wrong. Study 4 finds that people are more surprised about being wrong than they expect to be.

These results suggest several interesting conclusions and questions for future research. One such direction builds from our result finding greater surprise for epistemic questions in Study 3. This result suggests a possible boundary condition in that the amount of overprecision held could be conditional on the domain of knowledge. In other words, it appears that people are more overprecise within specific subjects at which that they could expect to be knowledgeable (such as weight guessing).

What of the utility of surprise? If surprise represents an error in prediction, individuals should seek to maximize accuracy and minimize surprise (Ely et al., 2015). This implies that surprise should lead people to reduce their subsequent confidence. Our results suggest that surprise does not always play this functional role, or that it is difficult to measure consistently. Future research should examine the conditions under which surprise has a corrective effect on subsequent confidence. How quickly does this effect decay and what possible moderators could increase the calibrating power and longevity of feedback on subsequent confidence? Could incorrect answers in epistemic domains more central to one's self-concept 'stick' for a longer period of time, forcing one's re-evaluation

of their believed expertise? Or could the opposite be the case, where the incorrect answer is considered anomalous and the sense of expertise leads persists?

We aspired to measure the effects of overprecision on surprise. In recording participants' ex-ante confidence, their correctness, and their ex-post surprise, we document consistent evidence which suggests that people expect to be correct. If they go into a decision with confidence, they are more surprised with incorrect, and less surprised when correct. We believe these results do more than underscore precision in judgment. Rather, this research approaches the topic with a new paradigm that serves to reveal another layer in the scientific understanding of the psychology of confidence and precision in judgment.

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