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Consumers routinely rely on forecasters to make predictions about uncertain events (e.g., sporting contests, stock fluctuations). The authors demonstrate that when forecasts are higher versus lower (e.g., a 70% vs. 30% chance of team A winning a game), consumers infer that the forecaster is more confident in his or her prediction, has conducted more in-depth analyses, and is more trustworthy. Consumers also judge the prediction as more accurate. This occurs because people tend to evaluate forecasts on the basis of how well they predict a target event occurring (e.g., team A winning). Higher forecasts indicate greater likelihood of the target event occurring and signal a confident analyst, while lower forecasts indicate lower likelihood and lower confidence in the target event occurring. Yet because with lower forecasts, consumers still focus on the target event (rather than its complement), lower confidence in the target event occurring is erroneously interpreted as the forecaster being less confident in his or her overall prediction (instead of more confident in the complementary event occurring, i.e., team A losing). The authors identify boundary conditions, generalize to other prediction formats, and demonstrate consequences of their findings.

Keywords: event prediction, subjective probability, accuracy, outcomes, forecasting

Online Supplement: http://dx.doi.org/10.1509/jmr.12.0526

Is a 70% Forecast More Accurate Than a 30% Forecast? How Level of a Forecast Affects Inferences About Forecasts and Forecasters

Consumers routinely listen to forecasters' predictions about a variety of events, such as those relating to sporting contests (e.g., forecast of the likelihood of a team winning in an NCAA basketball game), economic recovery, new product success, health risks (e.g., likelihood of spread of a disease), election outcomes, and so on (for a list of possible predictions, see http://www.predictwise.com). Sometimes the forecasts are higher; sometimes they are lower. Would consumers use the level of a forecast to evaluate the forecast and the forecaster? For example, imagine that an analyst makes a prediction that a certain basketball team, team A, has a 70% or a 30% chance of winning the next game against team B. Would consumers use the level of the forecast—high (70%) or low (30%)—to infer the accuracy of the forecast? Would the level also influence inferences about the forecaster—his or her confidence, depth of analysis, or trustworthiness? Why? These are some questions we investigate in this research.

We demonstrate that when forecasts are higher versus lower, consumers infer that the forecaster is more confident in his or her prediction, has conducted more in-depth analyses,

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ISSN: 0022-2437 (print)
1547-7193 (electronic)

Journal of Marketing Research
Vol. LIII (February 2016), 31–45
DOI: 10.1509/jmr.12.0526

and is more trustworthy. Consumers also judge the prediction as being more accurate. We believe this occurs because of the way in which consumers evaluate probabilistic predictions. We argue that forecasts are judged on the basis of how well they predict the occurrence of a target event (e.g., team A winning)—we refer to this as "target event predictability." Higher forecasts indicate greater likelihood of the target event occurring—high target event predictability—and they (correctly) signal a confident forecaster. In contrast, with lower forecasts, target event predictability is low, and the forecaster is less confident in the occurrence of the target event. Consumers erroneously interpret this lower confidence in the occurrence of the target event as the forecaster being less confident in the overall prediction. This occurs because consumers continue to focus on the target event and fail to recognize the forecaster's confidence in the complementary event occurring (i.e., team A losing).

We report findings from eight studies (three of which are described in the Web Appendix) to provide support for our thesis. In addition, we identify boundary conditions, generalize to other prediction formats beyond numerical probability predictions (e.g., verbal probabilities), and demonstrate effects of our findings on forecaster evaluations. We discuss the conceptual underpinnings of our theory next.

CONCEPTUAL FRAMEWORK

To understand why we expect probability predictions to influence accuracy judgments, it is important to grasp how consumers interpret the level (higher vs. lower) of probabilistic forecasts. Probability concepts are difficult to understand and are often misinterpreted. Windschitl, Martin, and Flugstad (2002) argue that probabilities can be divided into two components—an objective component (normative judgment) and a subjective component (how it is intuitively understood). The intuitive understanding may differ from the information probabilities objectively convey. For example, people sometimes think that random sequences follow patterns (Kahneman and Tversky 1982) or that intensity can be inferred from probability (e.g., a higher-probability earthquake will be stronger and will occur sooner; Keren and Teigen 2001a). Even those with greater ability to understand numerical concepts can be susceptible to making erroneous interpretations. For example, Albert (2003, p. 37) finds that college students in an introductory statistics course were "confused about the classical, frequency, and subjective notions of probabilities." Even scientists have been shown to misunderstand probabilistic concepts (Bruine de Bruin 1998). In the next section, we examine the specific case of how information contained in the level of a forecast may be misinterpreted.

Interpreting Forecasts: The Effects of Focusing Attention on the Target Event or Its Complement

Consider again an analyst making a prediction about a basketball game. Depending on his or her assessment, the forecaster might indicate that team A had a 70% or a 30% chance of winning the game against team B. In this case, team A winning is the target event (T), and team A losing is the complement (~T). Alternatively, the analyst could have provided the same information in a different way: by indicating the chance of team B winning the game, with the corresponding 30% or 70% prediction. In that case, team B winning would be the target event (T), and team B losing would be the complement (~T).

Now, consider the probabilistic forecast itself. When the forecast is higher (70% chance of team A winning the game), the target event is more likely to occur—that is, target event predictability is high—relative to when the forecast is lower. This also implies that the forecaster is more confident in the occurrence of the target event with a higher forecast. Thus, higher forecasts (e.g., 70%) are indeed associated with confidence in the target event occurring.

Now, what happens when the prediction is lower—say, 30%? Such a forecast may be interpreted in two ways: normatively, it indicates that the forecaster is confident that the target event (T) will not occur and that its complement (~T) will occur (objective judgment). Alternatively, it may also be interpreted as indicating that the forecaster is not confident in the prediction at all. That is, the forecaster is uncertain whether the target event (T) or its complement (~T) will occur (i.e., low target event predictability). We argue that consumers frequently interpret forecasts in the latter manner.

We believe this occurs because of the type of information people focus on when interpreting predictions. When a sports analyst indicates a 30% chance of team A winning a game, the focus is on the target event (team A winning), which is explicitly defined, but not on the complementary event (team A losing/team B winning), which is less explicit. This is consistent with Teigen and Brun's (1995, 1999) argument that probabilistic predictions are directional in nature—that is, they selectively focus attention on the occurrence of either a target event or its complement, but not both.

To understand Teigen and Brun's (1995, 1999) thesis, it may be instructive to consider how prediction information is conveyed. One popular approach is to use numbers, such as percentages (e.g., 70%). Another approach is to use verbal phrases, such as "likely," "unlikely," "certain," and "uncertain." To convey probabilistic information, however, two components—a quantifier reflecting the level of the prediction (e.g., 70% or 30%; "very" or "less") and a core term (e.g., "chance" or "likely")—are combined (e.g., "70% chance," "30% chance"; "very likely," "less likely"). Consider verbal probabilities: Teigen and Brun argue that these core terms are "directional" in nature—that is, they affirm or negate an event. By saying team A is "likely" to win the game, the analyst "asks the listener to consider the outcome as described," that is, to focus on the occurrence of the target event (T), indicating that the event may indeed occur (Teigen and Brun 1999, p. 158). However, when the speaker says that team A is "unlikely" to win, the listener is asked to focus on the target event's complement (~T), and thus the embedded signal is that the event may not occur. The associated quantifiers merely accentuate or attenuate beliefs about the properties of the focal event (e.g., how likely it is to occur, how strong its effects might be) but do not change the focus of attention to its complement. In other words, even when an analyst says that team A is less likely to win, people still focus on the possible occurrence of the focal event (team A winning the game) and its consequences. Indeed, in one study, Teigen and Brun (1995, p. 239) find that predicting even a "slight" possibility of an event leads participants to focus on the possible occurrence of the event, whereas stating that an event is "somewhat" uncertain draws attention to the event's possible nonoccurrence.

Teigen and Brun (1995, 1999) show that this basic principle is robust regardless of whether forecasts are expressed using a numerical probability (e.g., "40% probability") or a positive phrase (e.g., "small hope"). They argue that this occurs because probabilistic information invokes directionality—even numerical probabilities (e.g., "40% chance" or "40% probability") rely on a positive core term ("chance" or "probability" of the target event occurring). Therefore, numerical and positive verbal forecasts have positive core terms and invoke a positive direction (focus is on the occurrence of the target, T), but negative verbal forecasts have a negative direction (focus is on the complement, ~T). Nevertheless, these researchers do not test the effects of quantifiers (70% vs. 30%) on perceived accuracy of forecasts or consequences thereof (e.g., evaluation of the forecaster). Their thesis is restricted only to whether focus is on the target event or its complement.

Hypotheses About the Effects of High Versus Low Forecasts

Taken together, previous research has suggested that numerical and positive verbal forecasts draw attention to the target event, but not to its complement, whereas negative verbal forecasts draw attention to the complement. Furthermore, quantifiers (e.g., 70% vs. 30%; "more" vs. "less") merely accentuate or attenuate beliefs about the occurrence of the focal event (e.g., the target event for numerical probabilities). Our primary focus is numerical forecasts, so we restrict our attention to numerical probabilities for now (we do use verbal probabilities in Study 4 to demonstrate robustness and to rule out alternative explanations).

We expect people to evaluate a numerical forecast on the basis of target event predictability, that is, how well the forecast predicts the occurrence of the target event (T). Overall, we expect higher forecasts to lead to more positive inferences about the forecast (accuracy) and the forecaster (confidence, depth of analysis, trustworthiness) relative to lower forecasts. We develop these hypotheses next.

Higher forecasts, by definition, indicate greater likelihood of the target event occurring. This suggests that the forecaster is confident in the occurrence of the target event. Corresponding effects should emerge for judgments of the forecaster's effort expended and accuracy. That is, if making higher predictions causes the forecaster to be evaluated as confident, it should also lead to the inference that the forecaster has done a more thorough job searching for and analyzing information (e.g., studying market conditions, reviewing historic patterns). This assumption, in turn, should lead to the inference that the prediction is accurate. Furthermore, if higher predictions increase positive perceptions of a forecaster's confidence and depth of analysis, and these predictions are perceived as more accurate, then the perception benefits should extend to the forecaster. That is, a forecaster who makes higher predictions should also be judged as being more reliable and trustworthy.

However, what happens when the prediction is lower? As discussed in the previous section, even with lower forecasts (30% chance of team A winning), people continue to focus on the occurrence of the target event (team A winning) but not its complement (team A losing; Teigen and Brun 1995, 1999). Yet the lower forecast does not provide a strong prediction for the occurrence of the target event. As a consequence, people (correctly) evaluate the forecaster as being less confident in the target event occurring. However, because they fail to recognize that the forecaster is confident in the complementary event occurring (team A losing the game), people erroneously believe he or she is less confident in the overall prediction. Corresponding effects should emerge for judgments of effort expended and accuracy. That is, given that making lower predictions leads to the forecaster being evaluated as less confident, it should also lead to the inference that the forecaster has done a poorer job searching for and analyzing information (e.g., studying market conditions, reviewing historic patterns), and correspondingly, the prediction should also be judged as being less accurate. This should also lower trustworthiness judgments. More formally,

H_1: A forecaster making a higher prediction is judged as being more confident in the prediction relative to when he or she makes a lower prediction.

H_2: A forecaster making a higher prediction is judged as having conducted a more in-depth analysis relative to when he or she makes a lower prediction.

H_3: A higher (vs. lower) prediction is judged as being more accurate.

H_4: A forecaster making a higher (vs. lower) prediction is judged as being more reliable and trustworthy.

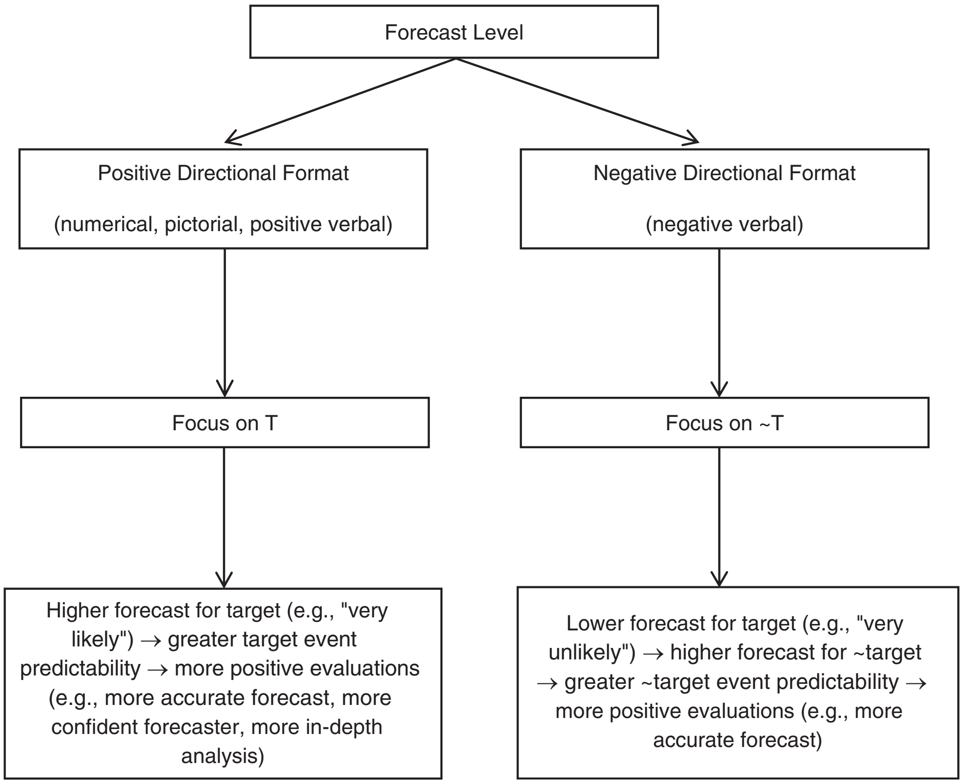
Taken together, we predict that higher (vs. lower) forecasts (e.g., 70% vs. 30%) will lead to more positive overall inferences; that is, they will have a positive impact on inferences about the forecasts themselves (accuracy) as well as about the forecaster (confidence, depth of analysis, and trustworthiness). However, as we find in our empirical investigation (e.g., Study 3b), these effects are restricted to inferences that are directly related to the forecast; they do not appear to transfer to other unrelated aspects. We present a schematic depicting our hypotheses in Figure 1.

It is important to note that associations made regarding the predictions described here are normatively unjustifiable for several reasons. First, objectively, a lower prediction implies that the forecaster is confident that the target event will not occur, rather than that the forecaster is uncertain whether the target event will occur (as we propose that consumers infer). Second, events vary in terms of their likelihood of occurrence—for some events, the likelihood of occurrence may indeed be low. In such cases, the lower prediction may actually be the more accurate one. Third, a higher prediction can also be expressed using lower numbers. Consider again the basketball game between two teams A and B. A 70% (i.e., higher) forecast for team A winning a game (perceived as a more accurate prediction made by a more confident forecaster) can also be expressed as a 30% (i.e., lower) forecast for team A losing the game.

The Moderating Role of Positive Versus Negative Directionality

We argued that judges make a host of inferences from higher predictions: that the forecaster is more confident, analyzed more information, is more accurate, and is more trustworthy. We argued that these inferences occur because of the directionality embedded in probabilistic concepts.

Figure 1
INFERENCES ABOUT FORECASTS AND FORECASTERS FROM LEVEL OF A FORECAST



That is, people usually focus on the occurrence of a target event (T) and not its complement. In particular, with traditional unipolar numerical and positive verbal probability scales, higher quantifiers (e.g., 70% or "very") with core terms (e.g., "chance" or "likely") indicate more of the attribute being measured relative to when lower quantifiers (e.g., 30% or "less") are used. Even pictorial formats (e.g., a pie chart with no numbers but grayed-out sections indicating predictions) allow for such relative directional comparisons because the focus remains on the occurrence of the target event. Thus, if directionality is the underlying reason for our observed effects, we would expect to see our effects replicated for similarly valenced core terms—that is, those that are directionally consistent (i.e., allowing inferences along the same direction, such as those described previously).

However, these effects may be reversed when focus is shifted to the complementary event. Verbal probabilities provide one way to shift focus. Teigen and Brun (1995, 1999) argue that whereas affirmations of probability (e.g., "likely") focus attention on the target event (e.g., team A winning), negations of probability (e.g., "unlikely") shift focus to the complementary event (e.g., team A not winning). If directionality is indeed the underlying reason for higher (vs. lower) predictions being judged as more accurate, our predicted effects should be reversed when lower predictions for target events are made using negations—that is, whereas "very likely" should be judged as being a more accurate prediction than "less likely," "very unlikely" should be judged as being more accurate than "less unlikely." In addition, these effects should be mitigated when we compare across positive and negative core terms—in other words, "very likely" should be judged as being equally accurate as "very unlikely." Although from a semantic perspective, "very unlikely" is comparable to "less likely," we believe the perceived accuracy of such negations will be judged differently because the term "unlikely" leads one to focus on the complementary event and therefore to view the prediction as a high one, rather than a low one that signals low predictability (as "less likely" does). Instead, we believe "very unlikely" will be judged as signaling that the complementary event is very likely to occur and will therefore be judged as being just as accurate as "very likely" (see Figure 1).

Overview of Studies

We test our hypotheses in eight studies, of which we report five in the main article. The remaining studies appear in the Web Appendix. We describe the main studies first.

In Study 1, using a basketball prediction context, we demonstrate the basic accuracy effect: higher forecasts are viewed as more accurate. We also show that our results replicate irrespective of framing of the target event (winning or losing). Furthermore, we find that although a 70% chance of winning and a 30% chance of losing are normatively equivalent predictions, higher predictions (e.g., 70% chance of winning) elicit higher accuracy evaluations relative to lower predictions (30% chance of losing). In Study 2, we show effects of forecast level on evaluations of forecasters themselves.

In Study 3a, using a stock market prediction context, we show effects of forecast level on a wider set of variables: perceived confidence, depth of analysis, and accuracy of the forecaster. In addition to using a direct measure of accuracy, we also demonstrate our effects with an indirect measure of accuracy. That is, we manipulate the contextual background (positive/negative market conditions) against which a prediction is made (chance of a stock being successful) and demonstrate that when a prediction is lower, judges rely more on contextual information to make inferences about the prediction (how successful the stock will be). This is consistent with our predictions; because lower predictions are judged as being less accurate, judges reanalyze information themselves, providing us with an indirect measure of accuracy. In Study 3b, we again use a stock market prediction context (chance of a stock price going up) and replicate our effects with a direct measure of accuracy. As in Study 1, we show that the basic accuracy effect replicates irrespective of the nature of the predicted change (price going up or down).

In Study 4, we document the robustness of our core accuracy effect by demonstrating that these effects emerge for a wide variety of forecast formats (i.e., numerical, pictorial, positive verbal, and negative verbal formats). Consistent with our predictions, our effects emerge only when comparisons of high versus low forecasts are made within directionally consistent formats (e.g., high positive vs. low positive verbal phrases: "very likely" vs. "less likely"), rather than with directionally inconsistent comparisons (e.g., high positive vs. high negative verbal phrases: "very likely" vs. "very unlikely"), even though semantically, a high negative phrase is equivalent to a low positive phrase (both indicate lower likelihood of the target event occurring). Detailed scenarios, motivation for scenarios, and additional analyses and tables are in the Web Appendix.

The Web Appendix contains three additional studies demonstrating the robustness of these effects. In Studies 5a and 5b, we generalize our findings to other formats (frequencies and point spreads). In Study 6, we examine the role of benchmarks. We find that when a strong benchmark exists (e.g., when people have high expectations that the likelihood of an event should be 25%), a slightly higher prediction (30%) is considered more accurate than a slightly lower prediction (20%); however, a much higher prediction (70%) lowers evaluations of accuracy. Together, our set of eight studies rules out certain alternative explanations, generalizes our findings to other formats, and demonstrates the robustness of our observations.

STUDY 1: EFFECT OF WIN–LOSS FRAMING ON INFERENCES ABOUT BASKETBALL PREDICTIONS

In Study 1, we demonstrate the basic effect that higher predictions are judged as more accurate. We also examine the effect of prediction framing by varying whether the target event is a team winning or losing. We expect that, although normatively equivalent, a higher forecast of a team winning (losing) a game will lead to greater accuracy judgments than a lower forecast of a team losing (winning). This also enables us to rule out several alternative explanations for our observed results. In addition, we investigate impacts on behavioral outcomes (i.e., betting intentions).

Participants, Method, and Design

One hundred sixty-one participants (mean age = 21 years; 52% female) successfully completed this study for course credit. They were randomly assigned using a 2 (forecast level: high vs. low) × 2 (prediction framing: team winning vs. team losing) between-subjects design. We presented a prediction from a basketball expert about an upcoming game between teams A and B. All participants learned that the expert had carefully examined the two teams' history, players, and other information. In the winning (losing) framing condition, the expert predicted the chance of team A winning (losing). We also manipulated the level of the forecast. In the high (low) forecast condition, the predicted chance of the target event occurring was 70% (30%).

Participants indicated how much they would bet on team A winning (losing; scale ranged from "not much at all" to "a lot"). Participants also indicated how accurate they thought the prediction was ("not accurate at all" to "very accurate") and how confident they were in the prediction ("not confident at all" to "very confident"). We averaged the latter two items to create a scale measuring accuracy judgments ($\alpha = .91$). All items were measured using seven-point scales.

Results and Discussion

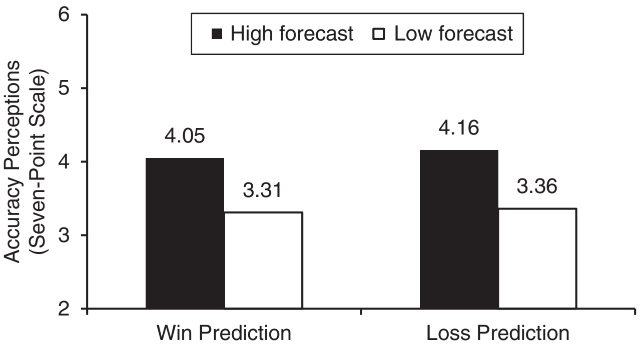
Betting intentions. An analysis of variance (ANOVA) with betting intentions elicited a main effect of forecast. Participants were willing to bet more when the forecast was high ($M_{\text{high forecast}} = 4.16$, $SD = 1.44$ vs. $M_{\text{low forecast}} = 2.21$, $SD = 1.22$; $F(1, 157) = 83.31$, $p < .001$).

The forecast × framing interaction was not significant ($F(1, 157) = 2.44$, $p > .11$), suggesting that irrespective of framing (winning or losing), participants were willing to bet more when the level of forecast was higher (vs. lower). Furthermore, participants were willing to bet more on team A winning with a 70% win prediction than on team A losing with a 30% loss prediction ($M_{\text{high forecast winning}} = 4.30$, $SD = 1.21$ vs. $M_{\text{low forecast losing}} = 2.39$, $SD = 1.32$; $F(1, 157) = 41.07$, $p < .001$); similarly, participants were willing to bet more on team A losing with a 70% loss prediction than on team A winning with a 30% win prediction ($M_{\text{high forecast losing}} = 4.00$, $SD = 1.65$ vs. $M_{\text{low forecast winning}} = 2.03$, $SD = 1.11$; $F(1, 157) = 42.24$, $p < .001$).

Accuracy. An ANOVA with accuracy elicited a main effect only of forecast. Consistent with H_3, judgment of accuracy was higher in the high forecast condition ($M_{\text{high forecast}} = 4.11$, $SD = 1.02$ vs. $M_{\text{low forecast}} = 3.34$, $SD = 1.17$; $F(1, 157) = 19.73$, $p < .001$).

The forecast × framing interaction was not significant ($F(1, 157) = .04$, $p > .84$), suggesting that irrespective of framing (winning or losing), accuracy was judged as higher when forecast was higher. Furthermore, although normatively equivalent, a forecasted 70% chance of winning was considered more accurate than a forecasted 30% chance of losing ($M_{\text{high forecast winning}} = 4.05$, $SD = .97$ vs. $M_{\text{low forecast losing}} = 3.36$, $SD = 1.26$; $F(1, 157) = 8.15$, $p < .005$), and similarly, a 70% chance of losing was considered more accurate than a 30% chance of winning ($M_{\text{high forecast losing}} = 4.16$, $SD = 1.07$ vs. $M_{\text{low forecast winning}} = 3.31$, $SD = 1.08$; $F(1, 157) = 11.71$, $p < .001$; see Figure 2). Table 1 also reports these means.

Figure 2.
EFFECT OF FORECAST AND WIN–LOSS FRAMING IN BASKETBALL GAMES: STUDY 1



Discussion. Because a higher (lower) forecast of winning can be reframed and presented as a lower (higher) forecast of losing, this study enables us to test the influence of higher and lower predictions on perceptions while keeping the actual predictions normatively equivalent. Although these two predictions are normatively equivalent, with higher forecast predictions (e.g., a 70% chance of winning), consumers judge the prediction as being more accurate relative to lower predictions (e.g., a 30% chance of losing), irrespective of win–loss framing.

This study also enables us to rule out two alternative explanations for the observed results. That is, these effects do not occur simply because the higher prediction leads to a positive halo effect or reflects greater optimism, which is then transferred to all the following responses. A higher chance of losing is more negative and less optimistic relative to a lower chance of losing, yet it was considered a more accurate prediction. Next, we investigate some downstream consequences of these judgments; specifically, we show that higher predictions lead to not only higher accuracy judgments but also higher assessments of expert trustworthiness.

STUDY 2: EFFECT OF FORECAST LEVEL ON FORECASTER EVALUATIONS

Participants, Method, and Design

One hundred sixty-two undergraduate students (mean age = 21 years; 72% female) successfully completed this study for course credit. They were randomly assigned to either a high or a low forecast condition. We presented a prediction from a basketball expert about an upcoming game between teams A and B. All participants learned that the expert had carefully examined the two teams' history, players, coaches, and other information. In the high (low) forecast condition, the chance of team A winning was predicted to be 70% (30%).

Participants then indicated their perceptions of prediction accuracy (response scale ranging from "not accurate at all" to "very accurate") and their confidence in the prediction ("not confident at all" to "very confident"). We combined these two items to create our accuracy measure (α = .89).

Table 1
SUMMARY OF MEANS, STUDY 1: WIN–LOSS FRAMING STUDY

	Low Forecast			*High Forecast*		
	Mean	*Median*	*SD*	*Mean*	*Median*	*SD*
Winning						
Betting intentions	2.03	2.00	1.11	4.30[a]	5.00	1.21
Accuracy	3.31	3.25	1.08	4.05[a]	4.00	.97
Losing						
Betting intentions	2.39	2.00	1.32	4.00[a]	4.00	1.65
Accuracy	3.36	3.50	1.26	4.16[a]	4.00	1.07

[a]Cell mean differs from low forecast mean at $p < .005$.
Notes: Values indicate participants' ratings of each item on a seven-point scale.

Participants also indicated how reliable, trustworthy, and knowledgeable about basketball they believed the expert to be ("not reliable at all" to "very reliable"; "not knowledgeable at all" to "very knowledgeable"; "not trustworthy at all" to "very trustworthy," respectively). We aggregated these responses to form the expert evaluation measure (α = .86).

As manipulation checks, we asked participants to indicate what the forecast prediction had been in the scenario (text entry) and whether they thought 70% (30%) was a low or a high chance in the context of winning (losing) a basketball game ("very low chance" to "very high chance"). All items were measured using seven-point scales, unless otherwise noted.

Results and Discussion

Manipulation checks. Participants in the high (vs. low) forecast condition indicated higher forecasts ($M_{\text{high forecast}}$ = 70% vs. $M_{\text{low forecast}}$ = 32%; $F(1, 160) = 953.81$, $p < .001$) and rated the given forecast as larger ($M_{\text{high forecast}}$ = 5.08, SD = .76 vs. $M_{\text{low forecast}}$ = 2.64, SD = .97; $F(1, 160) = 313.55$, $p < .001$).

Accuracy. Consistent with H_3, an ANOVA with accuracy judgments elicited a main effect of forecast; the higher prediction was judged to be more accurate ($M_{\text{high forecast}}$ = 4.24, SD = 1.07 vs. $M_{\text{low forecast}}$ = 3.54, SD = 1.22; $F(1, 160) = 15.27$, $p < .001$).

Expert evaluations. An ANOVA with ratings of the expert indicated a main effect of forecast ($F(1, 160) = 12.29$, $p < .001$), in support of H_4. The expert evaluations improved with higher (vs. lower) predictions ($M_{\text{high forecast}}$ = 5.13, SD = .99 vs. $M_{\text{low forecast}}$ = 4.59, SD = .99). Thus, participants viewed a higher forecast as indicating a more credible estimate and a more credible expert (the effect replicated for each variable; see Table 2).

Discussion. Consistent with H_3, a higher prediction led to greater accuracy perceptions. Consistent with H_4, participants judged the expert to be more trustworthy, reliable, and knowledgeable when the forecast was higher.

In the next two studies, we use a stock market prediction context. Study 3a has two main goals. First, consistent with H_1–H_3, we show that with higher (vs. lower) predictions, the forecaster is perceived as being more confident and as having conducted a deeper analysis, and the forecast is judged as being more accurate. Second, and more importantly, we provide further evidence for our process by demonstrating effects of high and low predictions on

Table 2
SUMMARY OF MEANS, STUDY 2: FORECASTER EVALUATIONS STUDY

	Low Forecast			*High Forecast*		
	Mean	*Median*	*SD*	*Mean*	*Median*	*SD*
Accuracy	3.54	4.00	1.22	4.24[b]	4.00	1.07
Reliable expert	4.13	4.00	1.00	4.77[b]	5.00	1.05
Trustworthy expert	4.35	4.00	1.09	4.84[a]	5.00	1.16
Knowledgeable expert	5.28	5.00	1.30	5.78[a]	6.00	1.14

[a]Cell mean differs from low forecast mean at $p < .01$.
[b]Cell mean differs from low forecast mean at $p < .001$.
Notes: Values indicate participants' ratings of each item on a seven-point scale.

outcomes (stock success expectations). In this study, we use both direct and indirect approaches to measure accuracy perceptions.

We first manipulate contextual background (positive/negative market conditions) against which a forecaster makes a prediction about the chance of a stock being successful. Forecasters use a variety of information to arrive at their predictions. In the context of stock predictions, this could include information about market conditions, past history of a stock, future potential, and so on. Typically, forecasters discuss all the contextual information—that is, all the pros and the cons—that they considered in order to arrive at their prediction. This contextual information is already included in the forecaster's prediction (i.e., the prediction is essentially derived from this information), so reanalyzing this information will not provide additional insights because it is not new information. However, we argue that when assessing stock success expectations, perceivers reanalyze this contextual information when predictions are lower (vs. higher). This is because if lower (vs. higher) predictions signal that the forecaster is less confident, has not conducted an in-depth analysis, and is not accurate, then perceivers will take it upon themselves to review existing contextual information more carefully. Thus, we expect contextual information to have a greater impact on stock success expectations for lower (vs. higher) predictions.

STUDY 3A: EFFECT OF MARKET CONTEXT IN STOCK MARKET PREDICTIONS

Participants, Method, and Design

Ninety-four undergraduate students (mean age = 21 years; 68% female) successfully completed this study for course credit. They were randomly assigned using a 2 (forecast level: high vs. low) × 2 (market context: positive vs. negative) between-subjects design. Participants were asked to imagine that they were considering purchasing stock in a semiconductor company that was planning an initial public offering and that they had come across a report on the company, recently prepared by an analyst from an investment firm.

We used the executive summary of the report to manipulate the market context (positive, negative) as well as forecast (high, low). In the positive (negative) context, participants learned that, going forward, the semiconductor industry was expected to grow (slow down) and that revenues would increase (decrease). All participants were told that companies that survived the next few years were likely to be major players in the future and that the focal semiconductor company had a decent record with reasonably strong fundamentals. Participants then received the analyst's overall prediction, after being explicitly told that the analyst had considered all the pros and the cons of the situation. In the high (low) forecast condition, participants learned that there was a 70% (30%) chance that the company would be successful.

Participants responded to several questions about outcome expectations, such as how successful the company was going to be (response scale ranging from "not successful at all" to "very successful"), how quickly the company was going to be successful ("not quickly at all" to "very quickly"), how profitable the company was going to be in the coming years ("not profitable at all" to "very profitable"), and how likely they would be to invest in this company ("not likely at all" to "very likely"). We aggregated these items to create an outcome perception scale measuring success expectations ($\alpha = .81$). This provides us with an indirect measure of how accurate participants perceived the forecast to be.

Subsequently, participants reported their perceptions of forecast accuracy ("not accurate at all" to "very accurate") and their confidence in the prediction ("not confident at all" to "very confident"). We averaged these responses to form our accuracy score ($\alpha = .90$). Participants also rated how confident they thought the analyst was in this prediction ("not confident at all" to "very confident"), how much information they thought the analyst had reviewed ("not much information at all" to "a lot of information"), and how much time they thought the analyst had spent evaluating pros and cons ("not much time" to "a lot of time"). The average of the last two items formed a combined score for depth of information analysis ($\alpha = .86$). Participants also indicated how reliable they thought a report from this firm would be ("not reliable at all" to "very reliable").

As manipulation checks, participants were asked to indicate how big the company's chance of success was ("not big at all" to "very big") and how likely the semiconductor industry was to grow in the coming years ("not likely at all" to "very likely"). All items were measured using seven-point scales.

Results

Manipulation checks. Forecast was perceived as indicating a bigger chance of success when it was higher ($M_{high\ forecast} = 4.55$, $SD = .90$ vs. $M_{low\ forecast} = 3.28$, $SD = 1.18$; $F(1, 90) = 34.21$, $p < .001$), and the semiconductor industry was expected to grow more when the market context was positive ($M_{positive} = 5.21$, $SD = 1.33$ vs. $M_{negative} = 3.15$, $SD = 1.47$; $F(1, 90) = 48.84$, $p < .001$). No other effects emerged, suggesting that our manipulations were successful.

Success expectations (an indirect measure of perceived accuracy). An ANOVA with success expectations as the dependent measure elicited main effects of forecast ($F(1, 90) = 55.25$, $p < .001$) and market context ($F(1, 90) = 11.92$, $p < .001$). Participants expected greater success when forecast was higher ($M_{high\ forecast} = 4.45$, $SD = .77$ vs.

$M_{low\ forecast}$ = 3.31, SD = .81) and when context was positive ($M_{positive}$ = 4.19, SD = .94 vs. $M_{negative}$ = 3.67, SD = .95).

A significant forecast × context interaction also emerged (F(1, 90) = 5.53, $p < .03$). While context did not influence success expectations in the high forecast condition ($M_{positive}$ = 4.53, SD = .90 vs. $M_{negative}$ = 4.37, SD = .62; F(1, 90) = .66, $p > .41$), when forecast was lower, positive context led to higher success expectations ($M_{positive}$ = 3.76, SD = .82 vs. $M_{negative}$ = 2.87, SD = .53; F(1, 90) = 15.52, $p < .001$). This suggests that even when we did not directly cue forecast accuracy or confidence, participants used predictions to assess whether other information should be reviewed. Correspondingly, contextual information had a stronger influence on outcome expectations when prediction was lower (vs. higher).

Accuracy, expert's confidence, and depth of analysis. An ANOVA with accuracy elicited only a main effect of forecast (F(1, 90) = 8.76, $p < .005$). As posited in H_3, the higher prediction was considered more accurate ($M_{high\ forecast}$ = 4.67, SD = 1.02 vs. $M_{low\ forecast}$ = 3.97, SD = 1.27). Consistent with H_1, an ANOVA with analyst's confidence in the prediction also elicited only a main effect of forecast; higher forecast led to more positive responses ($M_{high\ forecast}$ = 5.33, SD = 1.18 vs. $M_{low\ forecast}$ = 4.77, SD = 1.11; F(1, 90) = 5.60, $p < .02$). Consistent with H_2, an ANOVA with analyst's depth of analysis also elicited only a main effect of forecast (F(1, 90) = 4.46, $p < .05$). Participants perceived the analyst to have conducted a more in-depth analysis when the forecast was higher ($M_{high\ forecast}$ = 5.15, SD = 1.11 vs. $M_{low\ forecast}$ = 4.65, SD = 1.17).

The report from the investment firm was also perceived as being more reliable when the forecast was higher ($M_{high\ forecast}$ = 4.90, SD = .78 vs. $M_{low\ forecast}$ = 4.44, SD = 1.16; F(1, 90) = 5.210, $p < .03$; see Table 3). No other effects emerged, thus providing general support for H_4.

Discussion

Study 3a provides further support for H_1–H_4, suggesting that higher predictions (e.g., 70% chance) are considered more accurate, that they signal that the forecaster is more confident and has conducted a more thorough analysis, and that they indicate a more reliable analysis. Importantly, we also show that these effects occur when prediction accuracy is not explicitly cued. Indeed, contextual background has more of an effect on success expectations when the level of the forecast is lower than when it is higher. When perceivers believe that the analyst is not confident and has not done a thorough analysis, they reanalyze contextual details. This reevaluation is normatively unjustifiable because the contextual details do not provide new insights (and were already included in the prediction, as was made explicitly clear to participants in our study).

While Study 3a demonstrates our effects using a prediction of success (70% or 30% chance that the company would be successful), we did not test our effects using a prediction of failure (e.g., chance the company would fail), for several reasons. First, from an external validity standpoint, although levels of predictions vary significantly for firms issuing initial public offerings, the predictions are usually about success rather than failure. Second, one of our primary objectives was also to measure perceptions of accuracy using indirect measures (e.g., success expectations based on how successful the company was going to be, how quickly the company was going to be successful, how profitable it was going to be), and equivalent but also meaningful measures that use a failure prediction (e.g., how much the company would fail, how quickly the company would fail) are difficult to devise. However, to show that our accuracy predictions are robust to both success and failure predictions in stock market contexts, we conducted Study 3b. In this study, we use a context that is often encountered by consumers—forecasts about the chance of a particular stock price (currently at $50) either going up or going down (by $15)—and measure perceptions of forecast accuracy directly. We also vary the market context to be positive or negative, as in Study 3a. We expect the higher (vs. lower) prediction to be perceived as being more accurate, regardless of the market context (positive or negative) or the valence of the stock price change (up or down).

Table 3
SUMMARY OF MEANS, STUDY 3A: STOCK MARKET STUDY

	Low Forecast			High Forecast		
	Mean	*Median*	*SD*	*Mean*	*Median*	*SD*
Negative Market Context						
Success	2.87	2.88	.53	4.37[d]	4.50	.62
Accuracy	3.98	3.50	1.32	4.84[c]	5.00	.98
Depth of analysis	4.66	4.75	1.07	5.36[c]	5.50	1.07
Expert's confidence	4.73	5.00	1.20	5.44[c]	5.00	1.19
Report's reliability	4.45	4.00	1.14	4.84	5.00	.90
Positive Market Context						
Success	3.76[d]	3.75	.82	4.53[d]	4.88	.90
Accuracy	3.95	4.00	1.25	4.50[a]	5.00	1.06
Depth of analysis	4.64	4.50	1.30	4.94	5.00	1.14
Expert's confidence	4.81	5.00	1.03	5.23	5.00	1.18
Report's reliability	4.43	4.00	1.21	4.96[b]	5.00	.66

[a]Cell mean differs from low forecast mean at $p = .1$.
[b]Cell mean differs from low forecast mean at $p = .06$.
[c]Cell mean differs from low forecast mean at $p < .05$.
[d]Cell mean differs from low forecast mean at $p < .01$.
Notes: Values indicate participants' ratings of each item on a seven-point scale.

STUDY 3B: EFFECT OF MARKET CONTEXT AND PRICE CHANGE IN STOCK MARKET PREDICTIONS

Participants, Method, and Design

Two hundred forty-one panelists (mean age = 31 years; 32.8% female) successfully completed this study in return for a nominal fee. They were randomly assigned using a 2 (forecast level: high vs. low) × 2 (market context: positive vs. negative) × 2 (stock price change: up vs. down) between-subjects design. Participants were asked to imagine that they wanted to invest in the stock market and were considering stocks in the metal industry.

Participants read that they had come across a report on a particular company, recently prepared by an analyst from an investment firm. The market context and forecast manipulations were similar to those of Study 3a. In the positive (negative) context, participants learned that, going forward, the metal industry was expected to grow (slow down) and that revenues would increase (decrease).

Participants were informed that the current price of the focal company's stock was \$50 and were then given the analyst's overall prediction about the company's chance of success (after being explicitly told that the analyst had considered all the pros and the cons of the situation). In the high (low) forecast condition, participants learned that the chance that the stock would go up (down) by \$15 was 70% (30%).

Participants reported perceptions of accuracy (response scale ranging from "not accurate at all" to "very accurate") and their confidence in this prediction ("not confident at all" to "very confident"). We averaged these to form our accuracy score ($\alpha = .85$). As a manipulation check, we asked participants to indicate whether the prediction was about the stock price going up or down (binomial choice). All items were measured using seven-point scales, unless otherwise noted.

Results

Manipulation check. Overall, 93.8% of participants correctly reported the stock price change. That is, they indicated that the stock price was predicted to go up in the up condition and down in the down condition.

Accuracy measure. An ANOVA with accuracy elicited a main effect of forecast ($F(1, 233) = 9.33$, $p < .005$). As predicted in H_3, the higher forecast was considered more accurate ($M_{high\ forecast} = 4.38$, SD = 1.04 vs. $M_{low\ forecast} = 3.95$, SD = 1.20). None of the other main effects were significant.

Importantly, neither of the two-way interactions involving forecasts was significant (forecast by market context: $F(1, 233) = .01$, $p > .93$; forecast by stock price change: $F(1, 233) = .03$, $p > .85$). Furthermore, as expected, regardless of whether market context was positive ($M_{high\ forecast} = 4.46$, SD = .98 vs. $M_{low\ forecast} = 4.02$, SD = 1.17; $F(1, 233) = 5.07$, $p < .03$.) or negative ($M_{high\ forecast} = 4.29$, SD = 1.09 vs. $M_{low\ forecast} = 3.88$, SD = 1.23; $F(1, 233) = 4.29$, $p < .04$), higher forecasts were considered more accurate. Similarly, planned contrasts revealed that regardless of whether the stock was predicted to go up ($M_{high\ forecast} = 4.29$, SD = 1.04 vs. $M_{low\ forecast} = 3.88$, SD = 1.32; $F(1, 233) = 4.18$, $p < .05$) or down ($M_{high\ forecast} = 4.49$, SD = 1.03 vs. $M_{low\ forecast} = 4.03$, SD = 1.06; $F(1, 233) = 5.17$, $p < .03$), higher forecasts were considered more accurate. Thus, accuracy perception of the high and low forecasts was not influenced by either the market context or the direction of price change.

However, the market context × stock price change interaction was significant ($F(1, 233) = 10.15$, $p < .005$). In the positive market context, the forecast was perceived as directionally more accurate when the prediction was about the stock price going up (vs. down; $M_{up} = 4.38$, SD = .99 vs. $M_{down} = 4.10$, SD = 1.18; $F(1, 233) = 1.98$, $p = .16$), and similarly, in the negative market context, the prediction was perceived as more accurate when it was about the stock price going down (vs. up; $M_{up} = 3.79$, SD = 1.31 vs. $M_{down} = 4.42$, SD = .91; $F(1, 233) = 9.43$, $p < .005$). This is normative and expected. Furthermore, the forecast × market context × stock price change interaction was not significant ($F(1, 233) = .54$, $p > .45$; see Table 4), suggesting that the effect of forecast on accuracy inferences was not influenced by the other manipulated factors.

Table 4

SUMMARY OF MEANS, STUDY 3B: STOCK MARKET STUDY

	Low Forecast			High Forecast		
	Mean	*Median*	*SD*	*Mean*	*Median*	*SD*
Negative Market Context						
Stock price going up	3.64	3.50	1.48	3.93	4.00	1.11
Stock price going down	4.14	4.00	.81	4.69[a]	4.75	.94
Positive Market Context						
Stock price going up	4.12	4.00	1.07	4.65[a]	5.00	.85
Stock price going down	3.92	3.50	1.26	4.29	4.50	1.08

[a]Cell mean differs from low forecast mean at $p < .05$.

Notes: Values indicate participants' ratings of prediction accuracy on a seven-point scale.

Discussion

The primary goal of this study was to replicate our accuracy perception results using a stock market context with the type of success and failure predictions that consumers encounter frequently. As we expected, higher forecasts were indeed judged as being more accurate. Importantly, none of the interactions with the level of forecast was significant, suggesting that differences in market context (positive or negative) or direction of stock price change (up or down) did not affect inferences.

A secondary goal of this study was to rule out halo-based and optimism-based explanations—that is, to show that the observed effects do not occur simply because the higher (lower) prediction leads to a positive halo effect or reflects greater optimism, which is then transferred to all the following responses. We address these concerns using two approaches. First, as our results demonstrate, regardless of the valence of the change predicted (price going up or down), higher (vs. lower) forecasts were judged as being more accurate. A higher forecast for price going down is more negative and less optimistic relative to a lower forecast, yet it was considered more accurate. This is similar to the approach we used in Study 1. We also used another approach: we asked participants to indicate whether they agreed with a series of items unrelated to the prediction; one set related to the analyst's character (whether the analyst was "caring," "friendly," "kind," and "warm"; $\alpha = .94$) and the other to how much participants liked the analyst ("I like this person," "I feel close to this person," and "I would like to spend leisure time with this person"; $\alpha = .80$). Running ANOVAs with these two sets of measures as dependent variables did not elicit any significant effects ($ps > .21$). Thus, given that none of the effects with these measures was significant, it appears that level of forecast (high vs. low) affects only variables that are directly related to the prediction context (e.g., accuracy perceptions) and does not seem to transfer to other unrelated measures. Thus, our effects seem to replicate for inferences that represent the same whole, but not for inferences that are not directly related.

In Study 4, we examine the role of the directionality of comparisons by using four probability formats: numerical (70%, 30%), pictorial (a pie chart with no numbers but with a larger [70%] or smaller share [30%] grayed out), a positive verbal scale ("very likely," "less likely"), and a negative verbal scale ("very unlikely," "less unlikely"). We chose the high and low verbal probabilities because they are used often and are generally comparable with the corresponding high and low numerical estimates (Harris and Corner 2011; Reagan, Mosteller, and Youtz 1989). If directionality is the underlying reason for the relative differences in perception of the high and low forecasts for a particular event, then we would expect to replicate our effects within directionally consistent formats (numerical, pictorial, positive verbal, and negative verbal). That is, for formats that focus on the same event and allow directionally consistent comparisons (e.g., positive verbal), higher predictions (e.g., "very likely") would be judged as being more accurate relative to lower predictions ("less likely") because both evoke focus on the target event (T). However, with directionally inconsistent comparisons (e.g., high positive [focus on T] vs. high negative [focus on ~T] verbal phrases, such as "very likely" vs. "very unlikely"), we would not expect differences in accuracy perception, although, semantically, high negative ("very unlikely") is equivalent to low positive ("less likely"), which both indicate lower chance of the target event occurring.

We also investigate whether our observed effects can be explained by anchoring and/or numerosity. Anchoring literature has suggested that numerical anchors influence subsequent judgments (e.g., Epley and Gilovich 2010). An anchoring-based explanation would suggest that higher numerical forecasts (e.g., 70%) would create higher internal numerical anchors, which would then influence subsequent judgments—leading to higher accuracy judgments. If the effects emerge in nonnumerical contexts, then that evidence would rule out an anchoring-based explanation. This study also investigates a numerosity-based explanation (e.g., Bagchi and Davis 2012; Bagchi and Li 2011; Monga and Bagchi 2012; Pelham, Sumarta, and Myaskovsky 1994) for our observed effects—that is, that our effects emanate not because of directionality, as we propose, but because of the largeness of numbers.

STUDY 4: EFFECT OF NUMERICAL, PICTORIAL, AND VERBAL PROBABILITY FORMATS IN BOOK PUBLISHING PREDICTIONS

Participants, Method, and Design

Two hundred forty-seven panelists (mean age = 31.7 years; 32.4% female) successfully completed the survey in return for a nominal fee. We used a book publishing context for this study. Participants were randomly assigned using a 2 (forecast level: high vs. low) × 4 (format: numerical vs. pictorial vs. positive verbal vs. negative verbal) between-subjects design. We excluded responses from two panelists because they had intimate knowledge about the publishing industry; one was an author, and the other was related to a publisher. Retaining these panelists does not change the general pattern of our results.

Participants learned that a book reviewer had just finished reading a book proposal and had made a prediction about the chance of the book being published. In the high (low) forecast numerical condition, the book was predicted to have a 70% (30%) chance of being published. In the pictorial condition, participants saw a pie chart highlighting the chance of the book being published (no numbers appeared, but the displayed pie share was either high [70%] or low [30%]; for the images used, see the study description in the Web Appendix). In the positive verbal condition, the reviewer predicted that this book was "very likely" or "less likely" to be published, whereas in the negative verbal condition, the reviewer predicted that the book was "very unlikely" or "less unlikely" to be published. It is important to note that, for ease of understanding, we treat "very unlikely" ("less unlikely") as the higher (lower) forecast in our analyses because "very" is a higher quantifier relative to "less." However, the higher (vs. lower) forecast with negative verbal condition indicates a lower likelihood of the target event occurring.

We chose these verbal probabilities because they are used often and are generally comparable to the numerical probabilities we used. For example, research has suggested the following equivalences: "very likely" = 90%, and "very unlikely" = 10% (Harris and Corner 2011; Reagan, Mosteller, and Youtz 1989). Reagan, Mosteller, and Youtz (1989) also provide estimates for several of the other verbal probabilities (e.g., "low chance" = 20%, and "high chance" = 80%) as well as a summary of estimates derived by other researchers. Overall, their findings suggest that numerical and verbal probabilities can be compared (see Table 1 in Reagan, Mosteller, and Youtz [1989], p. 434).

We computed an accuracy scale based on responses to two questions (α = .88): how accurate participants thought the prediction was (response scale ranging from "not accurate at all" to "very accurate") and how confident participants were in the prediction ("not confident at all" to "very confident"). As manipulation checks, participants were provided with a dichotomous choice and asked to indicate whether the scenario had said the book had a high or a low chance of getting published. All items were measured using seven-point scales, unless otherwise noted.

Results

Pretest. We conducted a pretest (N = 242) to investigate whether numerical, pictorial, and positive verbal forecasts indeed evoke positive directionality (focus is on the occurrence of the target, T), and negative verbal forecasts evoke negative directionality (focus is on the complement, ~T). We used the same participant pool as in the main study but a different group of participants (mean age = 33 years, 36.1% female). We used the same context and a similar approach as in the main study, but instead of asking participants about accuracy, we asked them about directionality. Specifically, after presenting our scenario, we asked participants to indicate which of the following they thought about more: chance of the book getting published somewhere or chance of the book not getting published at all. As we expected, respondents reported that they thought more about the likelihood of the book getting published (vs. not getting published) with the numerical, pictorial, and positive verbal forecasts (M = 73.2%). In contrast, they thought more about the likelihood of the book not getting published (vs. getting published) with the negative verbal forecast (M = 57.1%). The analysis yielded a main effect of forecast ($\chi^2(1)$ = 18.91, $p < .001$; Table 5 presents all the means). We report findings from the main study next.

Table 5
SUMMARY OF MEANS, STUDY 4 PRETEST: BOOK REVIEW STUDY

Format	Participants with Focus on T (%)	Participants with Focus on ~T (%)
Numerical, low forecast	74.2	25.8
Numerical, high forecast	83.3	16.7
Pictorial, low forecast	53.3	46.7
Pictorial, high forecast	86.2	13.8
Positive verbal, low forecast	51.6	48.4
Positive verbal, high forecast	92.9	7.1
Negative verbal, low forecast	41.9	58.1
Negative verbal, high forecast	43.7	56.3

Notes: Values are means. All pairs of proportions sum to 100.00%.

Manipulation checks. We coded participants' responses to the question about the chance of the book getting published (high vs. low) as correct ("high chance" response in high forecast condition and "low chance" response in low forecast condition) or incorrect ("high chance" response in low forecast condition and "low chance" response in high forecast condition). We submitted this variable to a logistic regression with forecast, format, and the two-way interaction as predictors. The analysis yielded a main effect of forecast ($\chi^2(1) = 7.93$, $p < .01$). Participants in the high forecast condition correctly indicated that the book had a high chance of getting published ($M_{\text{book getting published}} = 98.3\%$) while those in the low forecast condition also correctly indicated that the book had a low chance ($M_{\text{book not getting published}} = 90.6\%$). The format × forecast interaction was not significant; thus, the pattern of results did not vary as a function of the prediction format. Indeed, participants across all formats correctly reported the prediction in the high (low) forecast condition to be larger (ps < .05).

Accuracy. An ANOVA with accuracy elicited a main effect of forecast ($F(1, 237) = 18.01$, $p < .001$). The prediction was considered more accurate when the forecast was higher ($M_{\text{high forecast}} = 4.79$, SD = 1.07 vs. $M_{\text{low forecast}} = 4.18$, SD = 1.17). The main effect of format was not significant ($F(3, 237) = 1.56$, $p = .20$).

The forecast × format interaction was not significant ($F(3, 237) = .22$, $p = .88$). As we expected, when comparing within the four formats, the higher (vs. lower) forecast was generally considered more accurate (numerical: $M_{\text{high forecast [70\%]}} = 4.74$, SD = 1.14 vs. $M_{\text{low forecast [30\%]}} = 3.94$, SD = 1.23; $F(1, 237) = 8.54$, $p < .005$; pictorial: $M_{\text{high forecast}} = 4.66$, SD = 1.09 vs. $M_{\text{low forecast}} = 4.12$, SD = 1.20; $F(1, 237) = 3.19$, $p = .075$; positive verbal: $M_{\text{high forecast ["very likely"]}} = 5.00$, SD = 1.15 vs. $M_{\text{low forecast ["less likely"]}} = 4.48$, SD = .84; $F(1, 237) = 3.15$, $p = .077$; negative verbal: $M_{\text{high forecast ["very unlikely"]}} = 4.77$, SD = .89 vs. $M_{\text{low forecast ["less unlikely"]}} = 4.19$, SD = 1.33; $F(1, 237) = 4.28$, $p < .04$). As discussed previously, we treat "very unlikely" (vs. "less unlikely") as a higher (vs. lower) forecast in our analyses, although it reflects a lower (vs. higher) likelihood of the target event occurring. Nonetheless, because the focus shifts to the complementary event with negative verbal predictions (see the pretest for this study; Teigen and Brun 1995, 1999), we expected the forecast that predicted the occurrence of the complement more strongly ("very unlikely") to be adjudged more accurate.

Furthermore, as we expected, although a high forecast with a positive phrase indicates that the book has a better chance of being published, whereas the high forecast with a negative phrase indicates a poorer chance, the two forecasts were not perceived as different in terms of accuracy ($M_{\text{high forecast ["very likely"]}} = 5.00$, SD = 1.15 vs. $M_{\text{high forecast ["very unlikely"]}} = 4.77$, SD = .89; $F(1, 237) = .67$, $p > .41$). This is because the positive phrase leads to a focus on the book getting published, while the negative phrase evokes a focus on the book not getting published. Similarly, the low forecast made with the positive phrase was not judged differently than the low forecast with the negative phrase ($M_{\text{low forecast ["less likely"]}} = 4.19$, SD = 1.33, vs. $M_{\text{low forecast ["less unlikely"]}} = 4.48$, SD = .84; $F(1, 237) = 1.08$, $p > .29$) because they also evoke focus on different events.

Moreover, the high forecast with a positive phrase was considered more accurate than the low forecast with a negative phrase ($M_{\text{high forecast ["very likely"]}} = 5.00$, SD = 1.15 vs. $M_{\text{low forecast ["less unlikely"]}} = 4.19$, SD = 1.33; $F(1, 237) = 8.03$, $p < .01$). These forecasts are equivalent because, in essence, they both predict that the book has a high chance of being published. Again, although the forecasts are equivalent semantically, the high negative forecast was considered directionally more accurate than the low positive forecast, although the mean difference was not significant ($M_{\text{high forecast ["very unlikely"]}} = 4.77$, SD = .89 vs. $M_{\text{low forecast ["less likely"]}} = 4.48$, SD = .84; $F(1, 237) = .99$, $p = .32$). Other analyses corresponding to these means appear in Table 6.

Discussion

Study 4 provides support for H_3: higher predictions are considered more accurate. Indeed, these effects generally replicate within formats of prediction (numerical, pictorial, positive verbal, and negative verbal conditions) because they elicit focus on the same event, allowing relative comparisons to be made. However, when focus changes, such as when we compare a high forecast with a positive phrase ("very likely"; focus on T) with a high forecast with a negative phrase ("very unlikely"; focus on ~T), we find that the predictions are not judged as being different in terms of accuracy, although semantically the high positive forecast indicates a higher chance for the book to be published, while a higher negative forecast suggests a poorer chance. This result suggests that directionality may be an important factor in the emergence of these effects.

In addition, using pictorial and verbal formats in this study also demonstrates that numbers are not necessary for these effects to emerge, thus ruling out anchoring- and numerosity-based explanations for our observed results. Although we acknowledge that numerosity effects may exacerbate effects in our contexts, we believe that because the core effects occur in contexts devoid of numbers (e.g., with pictorial representations, with verbal probabilities), we can rule out numerosity as being the primary driver behind our findings.

This study also rules out halo-based and optimism-based explanations. That is, these effects do not occur simply because the higher (lower) prediction leads to a positive halo effect or reflects greater optimism, which is then transferred to all the following responses. A higher forecast

Table 6
SUMMARY OF MEANS, STUDY 4: BOOK REVIEW STUDY

	Low Forecast			High Forecast		
Format	*Mean*	*Median*	*SD*	*Mean*	*Median*	*SD*
Numerical	3.94	4.00	1.23	4.74[c]	5.00	1.14
Pictorial	4.12	4.50	1.20	4.66[a]	4.50	1.09
Positive verbal	4.48	4.50	.84	5.00[a]	5.00	1.15
Negative verbal	4.19	4.00	1.33	4.77[b]	5.00	.89

[a]Cell mean differs from low forecast mean at $p < .1$.
[b]Cell mean differs marginally from low forecast mean at $p < .05$.
[c]Cell mean differs marginally from low forecast mean at $p < .01$.
Notes: Values indicate participants' ratings of prediction accuracy on a seven-point scale.

with a negative phrase ("very unlikely") should evoke a more negative overall impression relative to a lower forecast with a negative phrase ("less unlikely"), but in our study it was still judged as being more accurate.

GENERAL DISCUSSION

Summary of Findings

Across several studies, we demonstrate how probability predictions affect accuracy inferences for yet-to-occur events. We use a variety of contexts: sporting contexts (Studies 1 and 2), economy (Studies 3a and 3b), and new product introduction (Study 4). We also provide an additional set of three studies in the Web Appendix.

We make several contributions to the literature. First, we show that prediction estimates are used to make a host of evaluations. Prior literature has suggested that numerical probabilities are directional in nature; that is, judges use probabilities to evaluate whether the target event will occur (T), but rarely do they consider this as signaling the likelihood of the complement occurring (~T). As a consequence, we argue that when making higher forecasts, an analyst will be judged as being more confident in his or her assessment that the target event will occur (which is normative). A lower forecast will lead to an erroneous interpretation that the forecaster is less confident in his or her overall prediction. We argue that this occurs because consumers continue to focus on the target event and fail to recognize that the forecaster is confident in the occurrence of the complementary event. Thus, when making higher predictions, the forecaster is perceived to be more confident, to have conducted a more in-depth and thorough analysis, and to be more accurate (H_1–H_3). Prediction level also affects perceptions of the analyst's trustworthiness (H_4). We also generalize our findings to forecasts made in other formats (pictorial and verbal).

The studies reported in the Web Appendix provide additional support for our findings. In Studies 5a and 5b, we generalize our findings to other formats (frequencies and point spreads). In Study 6, we show that even when strong benchmarks exist, a slightly higher prediction is considered more accurate than a slightly lower prediction. However, a much higher prediction lowers accuracy evaluations.

Our research introduces a novel effect, demonstrates robustness across contexts and formats, and documents downstream consequences. It also provides process support by showing that directionality of forecasts plays an important role in influencing our results. We also rule out a few alternative explanations (anchoring, numerosity, halo effect, and optimism). However, as with any novel effect, it is not possible for us to rule out the existence of all other potential drivers of this effect. In particular, two aspects merit attention.

First, the robustness of our effects: Will these effects occur in all contexts? Although our research suggests that they might, we are not able to rule out all possibilities. For example, consider the valence (i.e., positive vs. negative context) of the forecast. Will higher (vs. lower) forecasts always be judged as being more accurate (and have similar effects on other prediction-related variables), irrespective of the valence of the context in which the forecast was made? In several of our studies, we include forecasts related to both positive and negative changes (e.g., win/loss framing in Study 1, positive/negative price change in Study 3b, positive/negative verbal probabilities in Study 4), and our effects replicated. In some of the Web Appendix studies, we exclusively use negative contexts (e.g., risk of contracting malaria in Study 5a, spread of antibiotic-resistant bacteria in Study 6), and our effects replicated. Although we expect our effects to replicate in most contexts, there might be instances when preference for the more optimistic forecast—high forecast in positive context, but low forecast in negative contexts—may dominate. We leave this for future studies to investigate.

Second, deeper insights into the underlying process: Why do judges interpret lower confidence in the occurrence of the target event as reflecting lower confidence in the overall prediction? Given that there are at least four entities involved in how forecasts are interpreted—a judge, a medium of communication (i.e., language), the forecast itself, and the forecaster—we speculate on the role each of these may play.

Role of the judge. Given that our focus is on subjective interpretations of probabilistic information, the judge's ability and willingness to process information is likely to play an important role. In terms of ability, it is well known that probabilistic concepts are confusing and poorly understood (Albert 2003; Bruine de Bruin 1998; Keren and Teigen 2001a, b). Thus, it is possible that receivers are by and large unaware that a low prediction for the target event reflects a high prediction for the complement and that lower confidence in the target event does not necessarily indicate lower confidence in the overall prediction. It may be important to note that in the studies we report in the Web Appendix (Studies 5a and 5b), we captured both objective and subjective measures of numeracy, and our effects were not influenced by proficiency. This suggests one of two possibilities: (1) regardless of ability, all people fall prey to this effect, or (2) the level of expertise required to understand the relationship between level of forecast and confidence is substantial, and common elicitation techniques (e.g., standard numeracy scales) are not able to help us discriminate the subtleties of this effect. We believe in the latter explanation and urge future researchers to investigate this issue further. While we believe that ability (and poor understanding of probabilities) is likely to be one driver of our observed effects, willingness to carefully consider the information presented could be another driver.

That is, at least some judges, especially the more proficient ones, may actually be able to recognize that lower prediction for the target event implies higher likelihood of occurrence for the complement, if they are motivated enough to process this information. However, it is well known that humans are cognitive misers, and rarely do they change the frame to assess alternative possibilities (Tversky and Kahneman 1981).

Role of medium of communication. It is also possible that lower predictions are poorly understood (relative to higher predictions) because of conversational norms surrounding the use of predictions. In a seminal article, Grice (1975) proposes four maxims of conversational norms: when communicating, people should be informative, truthful, relevant, and clear. Two of the maxims (informative and clear) are relevant in our contexts. Consider an example of a friend indicating her chance of making it to a dinner invitation. If the chance of her making it to the dinner is higher (likely outcome: attend the dinner), it is more informative for her to signal that she will probably be able to attend and say there is a 70% chance she will be able to make it (vs. a 30% chance she will not). In contrast, when the chance of her making it to the dinner is slim (likely outcome: not attending), instead of saying there is a 30% chance of making it, it is more informative for her to signal her likely inability to come by saying that there is a 70% chance she will not be able to make it. Gricean norms also dictate use of clear and unambiguous language. From this perspective, too, a 30% chance of attending (not attending) makes the information more ambiguous, as it really indicates that she probably will not be able to make it (will be able to make it) to the dinner. This is similar to the use of double negatives in language (e.g., saying "this is not untrue" instead of "this is true"), which is considered illogical (Finegan and Besnier 1989, p. 11).

Thus, given the conversational norms surrounding the use of probabilities, in common usage, people offering forecasts may prefer to signal the more likely outcome and therefore use higher (vs. lower) probabilities to make predictions. Therefore, receivers (i.e., judges) may have a better understanding of higher probabilities than they do of lower probabilities, which could be responsible for our pattern of results. That is, owing to lower familiarity, judges do not recognize that lower prediction for the target event reflects higher likelihood of the complement occurring. This asymmetric understanding suggests that judges may be more susceptible to other biases (such as selective hypothesis testing, motivated reasoning, or confirmatory bias) when predictions are lower, and this may be worthy of future investigation. For example, prior beliefs about an event may have a stronger impact when predictions are lower. Indeed, in Study 3a, we find that contextual information has a stronger influence with lower predictions.

Although it appears that judges' ability, willingness, and familiarity with lower forecasts (owing to norms of communication) may explain why lower confidence in the target is viewed as reflecting lower confidence in the overall prediction, we next speculate on some more complicated aspects of probabilistic concepts (e.g., type of uncertainty: aleatory or epistemic) that might also play a role.

Inferences about the event and the forecaster. Consider again a forecast about the chance of a team winning a basketball game. The prediction can reflect either the likelihood of the team winning the game—that is, aleatory uncertainty—or the expert's state of knowledge—that is, epistemic uncertainty. Aleatory uncertainty, which relates to the event, is measured by relative frequency, is represented in relation to a class of possible outcomes, and is attributed to stochastic behavior. In contrast, epistemic uncertainty, which relates to the forecaster, involves missing knowledge concerning a fact that is either true or false. It is measured by confidence in knowledge (Hoffman and Hammonds 1994; Stewart 2000). As Fox and Ülkümen (2011) suggest, although these dimensions are not mutually exclusive, making a judgment under uncertainty entails an attribution to aleatory and/or epistemic sources. Unless an event is purely aleatory or epistemic, it can be interpreted as a mix of both. Thus, it is possible that unless an event is purely aleatory (e.g., a coin flip), people might put more weight on the epistemic (vs. aleatory) dimension of uncertainty, possibly because only epistemic, but not aleatory, uncertainty can be lowered by searching for additional information. Reducing uncertainty through information search might be especially appealing because people want to believe in a predictable world (LeBoeuf and Norton 2012; Paese and Sniezek 1991).

Fox and Ülkümen (2011) further explain that epistemic uncertainty is measured by confidence (or subjective knowledge) and that one's feeling of confidence may be used as a proxy for evaluating likelihood. Given how closely related confidence and likelihoods are, the converse relationship may also hold; that is, the level of a forecast (low vs. high) may be used to infer the forecaster's overall confidence. Therefore, a forecaster making a lower (vs. higher) prediction may be judged as being less confident. This could then lead to the inference that the forecaster has done a poorer job of analyzing information and that the resulting prediction is less accurate. It is important to note that even in this instance, the role of directionality cannot be ruled out completely. That is, if the judge recognizes that lower confidence in the target reflects higher confidence in the complement, then our predicted inferences of confidence, depth of analysis, and accuracy will not emerge. Yet if the judge fails to recognize this, the effects will emerge. Furthermore, Fox and Ülkümen propose that frequency formats are more likely to prime more aleatory thinking. However, our observed results emerge even with frequency formats (see Study 5a in the Web Appendix for a frequency manipulation). Thus, an account based solely on the nature of uncertainty does not appear sufficient to explain our results. Nonetheless, we believe that predicting a purely aleatory event (e.g., coin flip) might attenuate our effects and provide a boundary condition.

In summary, we hope that future studies will shed more light on the robustness of these effects (i.e., whether they are likely to emerge in all contexts) and identify more drivers. Our results suggest that the effects are quite robust and are likely to apply to a wide variety of contexts and formats. Furthermore, although we believe that directionality of forecasts plays an important role in influencing our results, we hope future studies can provide deeper insights into the process and identify aspects relating to the judge (ability and willingness), norms surrounding conversations, and aspects of the forecast (e.g., type of uncertainty) that contribute to these effects. In addition, while we provide evidence to rule out the influence of several factors (i.e., halo effect, optimism, anchoring, numerosity), we hope future studies will consider additional contexts to either completely rule these factors out or understand when they might play a role.

Theoretical Implications

Our research contributes to a large body of literature on descriptive probabilities. Extensive literature streams in judgment and decision making and economics have studied how hypothetical probabilities are interpreted. In fact, the literature on judgment and decision making evolved because Kahneman and Tversky (1972, 1973) recognized that people are not adept at understanding hypothetical probabilistic predictions. This issue is also important in economics. For example, hypothetical probability-based lottery games and gambles are commonly used to learn about decision making and to develop economic thoeries, and they form a core tenet of decision theory (e.g., used to judge rationality, expected utility; Von Winterfeldt and Edwards 1986). Although our research is not restricted to hypothetical probabilities (as used in economics with lottery games), our findings are nonetheless likely to be relevant because we demonstrate a very simple but important effect that has an impact on the interpretation of any probabilistic prediction.

Our research also contributes to research in psychology. For example, Keren and Teigen (2001b) find that judges prefer more extreme (close to 0% or 100%) and higher probabilities because they facilitate decision making; that is, they help reduce uncertainty by discriminating between occurrence and nonoccurrence of outcomes (e.g., whether it will rain or not). Our focus is not on identifying probabilities that judges prefer but rather on understanding how judges interpret prediction accuracy. Yet our findings may also provide an alternative explanation: higher (vs. lower) predictions are preferred because they are perceived as being more accurate.

Our research also helps explain the behavior of forecasters. In his book, Sarvary (2012) notes that older forecasters tend to deviate more often from the consensus (see also Tetlock 2005). Ottaviani and Sorensen (2006) provide an explanation. Using a game-theoretical model, these researchers show that forecasters tend to exaggerate their true predictions so that their visibility increases if the target event occurs (Marinovic, Ottaviani, and Sorensen 2013; Ottaviani and Sorensen 2006). Although they do not suggest that higher predictions are considered more accurate (they argue that they are unique), our findings can provide an explanation: although forecasters might exaggerate predictions to differentiate themselves from competitors, what makes their inflated predictions more appealing is the increased accuracy they signal. However, two words of caution are in order: (1) Our findings (Study 6 in the Web Appendix) suggest that this beneficial effect only occurs if the prediction is slightly higher than that of the consensus. (2) Whereas our effects apply to a wide variety of prediction formats (e.g., numerical, point spreads, verbal), it may be instructive for further research to investigate whether these effects occur for all formats. For example, consider point forecasts. These are precise predictions (e.g., a stock's price is expected to be $15 in a year's time) that are usually devoid of associated probabilistic information (e.g., the chance of the price being $15 is 85%). It is not clear whether our theory would also extend to these formats, and this may be worthy of further investigation.

Practical Implications

With improvements in technology and access to data, dependence on forecasts has increased. Forecasts are made in a wide variety of contexts: from risk of dying at childbirth to living to be 100; from catching a viral infection to dying in a car crash; from finishing college to finding employment. Predictions are made about sporting events, in the political arena, and about the future of economies. Forecasts of resource shortages (water/oil shortage), hazards, and survival of the human race are also made. These forecasts have important consequences and affect decision making.

We find that higher predictions are considered more accurate and forecasters who make higher predictions are judged as being more confident, thorough, and trustworthy. Therefore, consumers may prefer information outlets (e.g., television channels, newspapers, websites) in which forecasters make higher predictions. Thus, analysts, managers, and forecasters (e.g., political pundits, meteorologists, stock analysts) may want to highlight their predictions when they offer a higher forecast for an event, as a way to help build their reputations. Besides, given that these effects occur regardless of framing (e.g., winning or losing), forecasters may want to highlight the outcome for which they can make a higher prediction: predict that team A has a 70% chance of winning when it is more likely to win, but predict that team A has a 70% chance of losing if forecast of winning is only 30%. Furthermore, when event predictions are not high (as in perhaps most contexts), providing contextual details (e.g., market conditions) can influence outcome assessments. Thus, forecasters can strategically highlight key details (pros or cons) that they used to make predictions. These details can sway judgments of forecasts and affect choice.

From the perspective of future studies, it may be useful to identify other moderators of the observed effects. One moderator may be the predictability of the target event. It is possible that a forecaster may be judged as being more confident and accurate when predicting an event that is by its nature difficult to predict. These effects may be attenuated if the event is easier to predict. Alternatively, a different pattern of effects may emerge. In addition, perceptions of prediction accuracy may be influenced by how likely an event is to occur. These effects may be attenuated for events that have a higher likelihood of occurrence. Furthermore, it may also be useful to consider how language influences aspects of prediction judgments. It is possible that qualifying the core term (e.g., "chance," "likely") might lead to a different interpretation of the prediction. For example, "only a 70% chance of winning the game" might appear to be a less accurate forecast than simply "a 70% chance of winning the game." We believe that although a 70% prediction is an objective prediction where the forecaster is not influencing how it is evaluated, "only" a 70% prediction also includes an inference that the forecaster is imputing for the receiver. Such an additional qualifier could have other effects. For example, it could lead to the inference that this is not a high prediction (as it is only 70%). Our thesis is about objective predictions and how they might be evaluated, but we admit that additional qualifiers may also affect how these predictions are judged, and if a prediction is judged as being large, we expect our effects to replicate. We leave this question for future researchers to investigate.

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WEB APPENDIX

Is a 70% Forecast More Accurate than a 30% Forecast? How Level of a Forecast affects Inferences about Forecasts and Forecasters

Rajesh Bagchi and Elise Chandon Ince

STUDY 1– EFFECT OF WIN-LOSS FRAMING ON INFERENCES OF BASKETBALL PREDICTIONS

Scenario Used
You are listening to a basketball expert talking on the radio about the upcoming game between two basketball teams: Team A and Team B. After carefully examining the two teams' history, players, coaches, etc. the expert predicted that Team A has a 70% [30%] chance of winning [losing] the game.

Scenario Motivation
Kunnath, Avinash (2013), "Cal Basketball: What Are Our PAC-12 Tournament Odds?" (accessed August 28, 2013), [available at http://www.californiagoldenblogs.com]
"I would give the Bears 80% chance to win the opening game, 70% chance to win the second game, and then 45% to win the championship game."

Nam, Huynh (2013), "Former Viking Says There Is a 70% Chance Greg Jennings Plays for Minnesota Next Season," (accessed August 28, 2013), [available at http://sportingsota.com]

STUDY 2 – EFFECT OF FORECAST LEVEL ON FORECASTER EVALUATIONS

Expert's evaluations. Independent ANOVAs with ratings of the expert indicated a main effect of forecast. Specifically, with higher (vs. lower) predictions, participants perceived the expert as more reliable ($M_{\text{high forecast}} = 4.77$, SD = 1.05, vs. $M_{\text{low forecast}} = 4.13$, SD = 1.00, $F(1, 160) = 15.82$, $p < .001$), more trustworthy ($M_{\text{high forecast}} = 4.84$, SD = 1.16 vs. $M_{\text{low forecast}} = 4.35$, SD = 1.09, $F(1, 160) = 7.58$, $p < .01$), and more knowledgeable about basketball ($M_{\text{high forecast}} =$ 5.78, SD = 1.14 vs. $M_{\text{low forecast}} = 5.28$, SD = 1.30, $F(1, 160) = 6.96$, $p < .01$, see table 2 in the paper).

Scenario Used
Scenario is the same as the one in study 1.

STUDY 3A – EFFECT OF MARKET CONTEXT IN STOCK MARKET PREDICTIONS

Scenario Used
We are interested in understanding how consumers interpret stock analysis reports.

Imagine that you have some money that you want to invest in the stock market. You are considering whether or not you want to purchase HTC stocks (real name withheld). HTC is in the business of making semiconductor chips for mobile phones and is planning an initial public offering (issuing common stocks to the public for the first time). You could make money if HTC turns out to be a success. But if it fails, you will lose money.

You come across a report on HTC. It turns out that recently, an analyst from an investment firm IRM conducted a thorough analysis of HTC's portfolio. His executive summary (summarizing the overall report) is presented below:

[Negative Information]:

Going forward, I anticipate the semiconductor industry to slow down. The revenues should also decrease. However, companies that can survive for the next few years are likely to be major players in the future. HTC has a decent track record with reasonably strong fundamentals. After considering all the pros and cons I believe that HTC has a 70% [30%] chance of being successful.

[Positive Information]:

Going forward, I anticipate the semiconductor industry to grow. The revenues should also increase. Moreover, companies that can survive for the next few years are likely to be major players in the future. HTC has a decent track record with reasonably strong fundamentals. After considering all the pros and cons I believe that HTC has a 70% [30%] chance of being successful.

Scenario Motivation
Hestla, Amber (2013), "Low Risk Income Strategy Shown To Have a 94% Chance of Success," (accessed August 2, 2013), [available at www.topstockanalysts.com]

STUDY 3B– EFFECT OF MARKET CONTEXT AND PRICE CHANGE IN STOCK MARKET PREDICTIONS

Scenario Used
The scenario was very similar to the one used in 3A with a few exceptions. These exceptions are highlighted below:
Context was similar; it was about purchasing stocks (ATC; although it was not an initial public offering). The market context manipulation (positive, negative) was similar to the one used in 3A. The prediction was worded differently, and is presented below:

You come across a report on ATC. It turns out that recently, an analyst from an investment firm IRM conducted a thorough analysis of ATC's portfolio. The analyst made predictions about ATC's stock price, currently at $50, going up [down] by $15. The analyst's prediction is presented below:

After considering all the pros and cons, I believe the chance that ATC's stock price will go up [down] by $15 is 70% [30%].

STUDY 4 – EFFECT OF NUMERICAL, PICTORIAL, AND VERBAL PROBABILITY FORMATS IN BOOK PUBLISHING PREDICTIONS

Scenario Used

A professional book reviewer, who has been reviewing books professionally for several years now, just finished reading a book proposal. The book reviewer likes the book proposal and offers his opinion, as an expert, about the future potential of this book. The reviewer predicts that this book [is very likely, less likely, very unlikely, less unlikely to be published] [has 70%, 30% chance of getting published] [has the following chance to be published:]

STUDY 5A – EFFECT OF FREQUENCY FORMAT IN DISEASE EVALUATION PREDICTIONS

In the main manuscript with numerical predictions we limited our investigations to percentage predictions. Our theory is more general: it suggests that higher predictions are considered more accurate relative to lower predictions (as we also show with other formats in study 4). We, therefore, investigate if these effects can be generalized to other numerical formats, such as frequencies (used in contexts where number of occurrences of a repeated event can be described: study 5A) and point-spreads (used in sporting contexts: study 5B). Furthermore, we also investigate if objective (based on performance on numeracy tasks) and/or subjective (beliefs about how well one understands predictions) knowledge of numbers affects evaluations. On the one hand, being proficient with numbers should help in understanding statistical information. In that case, higher predictions would not be considered more accurate. However, we believe that understanding probability information requires a degree of mathematical expertise that even highly numerate individuals lack, and hence we expect our effects to replicate. Indeed previous research has shown that even highly educated people have difficulties understanding probabilities and other chance-related concepts (Reyna, et al. 2009). In 5A we use an 11 item numeracy scale developed by Lipkus, Samsa, and Rimer (2001). This scale is one of the most popular scales used to evaluate objective numerical ability (Shapira, Walker, and Sedivy 2009). The scenario used is presented at end of this study.

Participants, Method, and Design

Sixty nine participants (M_{age} = 21, 52.2% Female) successfully completed this study for course credit. They were randomly assigned using a 2 forecast (high, low) x 2 prediction format (percentage, frequency) between-subjects design. Participants were told that they were evaluating the likelihood of contracting Malaria while planning a trip abroad. After a brief description of the disease, participants were presented with statistics provided by a health expert for contracting Malaria after being bitten by an infected mosquito. In the percentage condition, participants read that there was an 80% (20%) chance of contracting Malaria in the high (low) chance condition. In the frequency condition, participants read that 8 (2) out of 10 people contract malaria after being bitten by an infected mosquito.

Participants then indicated how worried they were about contracting malaria (not at all worried/very worried), how likely they were to contract malaria (not at all likely/very likely), and how likely they were to get vaccinated knowing costs and side-effects (not at all likely/very likely). We aggregated these items to form a score of malaria expectations ($\alpha = .72$). Participants then reported perceptions of accuracy (not at all accurate/very accurate) and confidence in the prediction (not at all confident/very confident). We averaged these to form our accuracy score ($\alpha = .91$). Finally, participants were presented with the 11 items of the objective numeracy scale developed by Lipkus et al. (2001) (see scenario detail below for the items).

Results and Discussion

Malaria expectations. An ANOVA with expectations only elicited a main effect of forecast ($F(1, 65) = 102.72$, $p < .001$); expectations were higher when forecast was higher ($M_{high\ forecast} = 6.19$, SD = .62 vs. $M_{low\ forecast} = 4.10$, SD = 1.01). These results replicated for each format (percentage: $F(1, 65) = 52.38$, $p < .001$; frequency: $F(1, 65) = 50.34$, $p < .001$), suggesting that participants interpreted information presented in the different formats equivalently. Expectedly, the forecast by prediction format interaction was not significant ($F(1, 65) = .03$, $p > .86$).

Accuracy. An ANOVA with accuracy as the dependent measure elicited only a main effect of forecast ($F(1, 65) = 11.21$, $p < .001$). The higher prediction was more accurate ($M_{high\ forecast} = 5.69$, SD = .82 vs. $M_{low\ forecast} = 4.96$, SD = .97; see table 1 in web appendix). These effects replicated for both percentage and frequency formats (respectively $F(1, 65) = 6.42$, $p < .05$, and $F(1, 65) = 4.83$, $p < .05$). Expectedly, the forecast by prediction format interaction was not significant ($F(1, 65) = .07$, $p = .80$), suggesting that format did not differentially influence perceptions.

Numeracy Scale. We employed a regression on accuracy, with chance, the continuous mean centered measure of numeracy, and their two way interaction term (Fitzsimons 2008). The numeracy by forecast interaction was not significant (β = -.01, t = -.09, p = .92); thus numeracy did not impact the positive effect of forecast on perceived accuracy.

Discussion. This study provides further support for hypothesis 3 that higher predictions are considered more accurate. It also shows that the effect replicates when the prediction is presented in a different format (notably a frequency format). Additionally, this study demonstrates that numeracy does not influence evaluations. We believe that understanding predictions requires a level of numerical ability that this numeracy scale is not able to capture. Indeed, in several of our studies we used undergraduate students (juniors and seniors) who have more advanced understanding of numbers than the general population (Galesic and Garcia-Romero 2010), yet our results replicated.

It is important to note that this study only considers a negative outcome (i.e. chance of contracting Malaria). Future research could investigate the complement positive event (i.e. chance of not contracting Malaria).

Scenario Used

You are planning a trip abroad. As you start preparing for this trip, you evaluate the chance of contracting Malaria during your trip.

Malaria is a mosquito-borne infectious disease. It begins with a bite from an infected mosquito. A health expert provides travel advisories for those traveling from the US to the place you are traveling to.

The Health Expert provides the following statistics for contracting Malaria in that region:
80% (20%) chance of contracting Malaria after being bitten by an infected mosquito
[8 (2) times out of 10 people contract Malaria after being bitten by an infected mosquito].

Scenario Motivation

Williams, Sarah (2011), "HPV Transmission: 20% Chance an Uninfected Partner Will Pick Up Virus," (accessed August 28, 2013), [available at http://www.livescience.com]

STUDY 5B – EFFECT OF POINT SPREAD FORMAT AND NUMERACY SCALE IN BASKETBALL PREDICTIONS

In this study we consider another format commonly used to present probability information in basketball games—point spreads. We also consider the role of subjective (perceived) knowledge of predictions in influencing evaluations. The scenario used is presented at the end of this study.

Participants, Method, and Design

One hundred and three panelists (M_{age} = 32.8, 41.7% Female) successfully completed this study in return for a nominal fee. Participants were randomly assigned using a 2 forecast (high, low) x 2 format (percentage, point-spread) between subjects design. The scenario indicated that participants were listening to a basketball expert on the radio about an upcoming game between two teams: A and B. After carefully examining the two teams' history, players, coaches, etc. the expert made a prediction. We manipulated the format of prediction. In the percentage conditions, participants in the high (low) value conditions learned that the expert predicted team A to have an 80% (55%) chance of winning. Similarly, in the point-spread conditions, participants were provided equivalent information—either a point spread of +8.5 (high value; this is approximately equivalent to an 80% chance of winning; calculated using the point spread converter available at http://www.sbrforum.com/betting-tools/spread-ml-converter/) or +2 (low value; approximately equivalent to a 55% chance of winning).

Participants also indicated how likely they are to bet on Team A winning (not likely at all/very likely). Participants then indicated perceptions of accuracy (not accurate at all /very accurate) and confidence in the prediction (not confident at all /very confident). We averaged these to form our accuracy score ($\alpha = .91$). Participants were also asked how much they understood basketball predictions (not much at all/a lot), how knowledgeable they were about basketball games (not knowledgeable at all/very knowledgeable) and how often they followed basketball games (not often at all/very often), as subjective measures of numeracy.

Results and Discussion

Betting Likelihood. An ANOVA with betting likelihood as the dependent measure only elicited a main effect of forecast ($F(1, 99) = 14.41$, $p < .001$); participants were more likely to bet when forecast was higher ($M_{\text{high forecast}} = 4.61$, SD = 1.44 vs. $M_{\text{low forecast}} = 3.45$, SD = 1.65). These results replicated for each format (percentage: $F(1, 99) = 13.57$, $p < .001$; point spread: $F(1, 99) = 2.94$, $p < .09$). Neither the format nor the forecast by format interaction were significant ($F(1, 99) = .98$, $p = .33$ and $F(1, 99) = 1.79$, $p = .18$ respectively), suggesting that participants interpreted information presented in the different formats equivalently.

Accuracy. An ANOVA with accuracy as the dependent measure elicited only a main effect of forecast ($F(1, 99) = 11.61$, $p < .001$). Accuracy was higher when the prediction was higher ($M_{\text{high}} = 4.85$, SD = .97; $M_{\text{low}} = 4.06$, SD = 1.33). These results replicated for each format (percentage: $F(1, 99) = 3.81$, $p < .06$; point spread: $F(1, 99) = 8.14$, $p < .01$). Neither the format nor the forecast by format interaction were significant ($F(1, 99) = .95$, $p = .33$ and $F(1, 99) = .47$, $p = .50$ respectively; see table 2 in web appendix). Thus, irrespective of format, percentage or point spread, participants perceived the higher value to be more accurate relative to the lower value.

Subjective numeracy. We employed a regression on accuracy, with forecast, the continuous mean centered measure of understanding basketball predictions, and their two way interaction term. A proficiency by forecast interaction did not emerge ($\beta = .07$, $t = .62$, $p = .53$). We ran similar regressions with how knowledgeable participants were about basketball and how much they follow basketball games, in each case the interaction with forecast was not significant (ps > .62). This attests to the robustness of our findings; indeed those who consider themselves proficient (subjective numeracy) also use predictions to judge accuracy.

Discussion. Our findings replicate even when a point-spread format is used. Further, even those who are proficient with understanding basketball predictions use higher predictions to infer accuracy.

Scenario Used

You are listening to a basketball expert talking on the radio about an upcoming game between two basketball teams: Team A and Team B. After carefully examining the two teams' history, players, coaches, etc. the expert predicted that Team A has a +8.5 [+2] point spread (80% [20%] chance of winning the game).

Scenario Motivation

Same as the one for study 1

NUMERACY SCALE (from Lipkus et al. 2001)
Note: Scale has 11 items (question 8 has two parts)

1. Imagine that we role a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up even (2, 4, or 6)?
2. In the BIG BUCKS LOTTERY, the chances of winning a $10.00 prize is 1%. What is your best guess about how many people would win a $10.00 prize if 1,000 people each by a single ticket to BIG BUCKS?
3. In the ACME PUBLISHING SWEEPSTAKES, the chance of winning a car is 1 in 1,000. What percent of tickets to ACME PUBLISHING SWEEPSTAKES win a car?
4. Which of the following numbers represents the biggest risk of getting a disease?
   ___ 1 in 100, ___ 1 in 1000, ___ 1 in 10
5. Which of the following numbers represents the biggest risk of getting a disease?
   ___ 1%, _ __ 10%, ___ 5%
6. If Person A's risk of getting a disease is 1% in ten years, and person B's risk is double that of A's, what is B's risk?
7. If Person A's chance of getting a disease is 1 in 100 in ten years, and person B's risk is double that of A's, what is B's risk?
8. If the chance of getting a disease is 10%, how many people would be expected to get the disease:
   A: Out of 100?
   B: Out of 1000?
9. If the chance of getting a disease is 20 out of 100, this would be the same as having a ____% chance of getting the disease.
10. The chance of getting a viral infection is .0005. Out of 10,000 people, about how many of them are expected to get infected?

STUDY 6 – EFFECT OF BENCHMARK IN SUPERBUGS PREDICTIONS

We delve into the phenomenon of norms in this study. We demonstrate that when a strong benchmark exists, while a slightly higher prediction is considered more accurate than a slightly lower prediction, a much higher prediction lowers evaluations. This is because a prediction that goes strongly against priors (even higher ones) will not be considered as accurate. We investigate this in the context of the spread of antibiotic resistant bacteria. The scenario used is presented at the end of this study.

Participants, Method, and Design

Sixty two participants (M_{age} = 21.35, 50.0% Female) successfully completed this study for course credit. We provided participants with a benchmark and then varied the forecast to be slightly higher or lower than the benchmark, or much higher than the benchmark.

We adapted a recent report on the presence of antibiotic-resistant bacteria or superbugs in ground meat to create our manipulations. We informed participants that resistance of bacteria to antibiotics is a major health threat. Medical treatment of these drug-resistant infections can be complicated, leading to longer hospital stays, and to untreatable infections. Furthermore, these superbugs can be found in supermarket meats (see scenario below). We then created a benchmark for comparison by informing participants that researchers have shown that the "chance you can ingest superbugs from ground meat is 25%".

Participants then learned of a prediction made by a scientist, Dr. Stevens, who disagrees. Dr. Stevens predicts the forecast to be 30% (slightly higher than the benchmark), 20% (slightly lower), or 70% (much higher than the benchmark).

Participants then indicated how accurate Dr. Stevens' prediction was (not accurate at all /very accurate) and their confidence in the prediction (not confident at all /very confident). We averaged these to form our accuracy measure ($\alpha = .91$).

Results and Discussion

Accuracy. An ANOVA with accuracy elicited a marginal main effect of forecast ($F(2, 59) = 2.89$, $p = .06$). The slightly higher (than benchmark) prediction (30%) was considered more accurate ($M_{\text{slightly higher forecast}} = 4.19$, $SD = .99$) relative to both the slightly lower (20%; $M_{\text{slightly lower forecast}} = 3.55$, $SD = .91$, $F(1, 59) = 3.21$, $p < .08$) as well as the much higher prediction (70%; $M_{\text{much higher forecast}} = 3.41$, $SD = 1.38$, $F(1, 59) = 5.19$, $p < .05$). However, judgments were not different when the prediction was slightly lower (20%) relative to when it was much higher (70%; $F(1, 59) = .17$, $p > .68$; see table 3 in web appendix).

Discussion. This study demonstrates that even when benchmarks exist, slightly higher predictions are more accurate than slightly lower predictions. This benefit disappears when the prediction is much higher. We believe this occurs because a large deviation from strong priors is unlikely to generate positive attributions, and is less believable. Indeed, while older forecasters have been shown to deviate more often from the consensus (Sarvary 2012), our findings suggest that a slight positive deviation but not a large positive deviation will be more beneficial relative to a slight negative deviation.

It is important to note that this study only considers a negative outcome (i.e. chance of finding superbugs in meat). Future research could investigate the complement positive event (i.e. chance of not finding superbugs in meat).

Scenario Used

The Food and Drug Administration (FDA) considers the resistance of bacteria to antibiotics a major public health threat. When bacteria become resistant to an antibiotic, that medicine becomes less effective. Medical treatment of people infected with these drug-resistant organisms can become more complicated, leading to longer hospital stays, increased health care costs, and to untreatable infections.

Researchers have shown that these antibiotic-resistant bacteria or "superbugs" can be found in supermarket meats. Chance that you can ingest superbugs from ground meat is 25%.
However, you read that one scientist, Dr. Stevens, disagrees. Dr. Stevens predicts the chance that ground meat has superbugs is 30 [20, 70]%.

Scenario Motivation

Polis, Carey (2011), "There is a 25% Chance Your Ground Meat Has a Potentially Fatal Bacteria," (accessed August 28, 2013), [available at http://www.huffingtonpost.com]. Citing the New York Time article by Bittman, Mark (2011), "Bacteria 1, FDA 0".

WEB APPENDIX REFERENCES

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WEB APPENDIX TABLES

TABLE 1

SUMMARY OF MEANS: STUDY 5A –FREQUENCY FORMAT STUDY

	Low Forecast			High Forecast		
	Mean	Median	SD	Mean	Median	SD
Percentage Format						
Malaria Expectations	4.08	4.00	1.20	6.20[b]	6.33	0.62
Accuracy	4.85	5.00	1.20	5.65[a]	6.00	0.93
Frequency Format						
Malaria Expectations	4.13	4.17	0.83	6.18[b]	6.33	0.64
Accuracy	5.06	5.00	0.73	5.74[a]	6.00	0.73

[a]Cell mean differs from low forecast mean at $p < .05$ significance.

[b]Cell mean differs from low forecast mean at $p < .01$ significance.

TABLE 2

SUMMARY OF MEANS: STUDY 5B –POINT SPREAD FORMAT STUDY

	Low Forecast			High Forecast		
	Mean	Median	SD	Mean	Median	SD
Percentage Format						
Betting Likelihood	3.39	4.00	1.73	4.96[c]	5.00	1.31
Accuracy	4.25	4.50	1.52	4.88[a]	5.00	0.99
Point Spread Format						
Betting Likelihood	3.50	4.00	1.58	4.25[a]	4.50	1.51
Accuracy	3.87	3.75	1.07	4.81[b]	4.75	0.97

[a]Cell mean differs from low forecast mean at $p < .1$ significance.

[b]Cell mean differs from low forecast mean at $p < .05$ significance.

[c]Cell mean differs from low forecast mean at $p < .01$ significance.

TABLE 3

SUMMARY OF MEANS: STUDY 6 – BENCHMARK STUDY

	Slightly Lower Forecast (20%)			Slightly Higher Forecast (30%)			High Forecast (70%)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Accuracy	3.55	3.50	0.91	4.19[a]	4.00	0.99	3.41	3.25	1.38

[a]Cell mean differs from slightly lower forecast mean at $p < .1$ significance.