

(WHEN) DO CONSUMERS PREFER UNCERTAINTY?
CONSUMERS' REACTIONS TO UNCERTAIN ADVICE AND UNCERTAIN
PROMOTIONS

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ABSTRACT

(WHEN) DO CONSUMERS PREFER UNCERTAINTY? CONSUMERS' REACTIONS TO UNCERTAIN ADVICE AND UNCERTAIN PROMOTIONS

Celia Gaertig

Joseph P. Simmons

Research has shown that, although uncertainty is often disliked, consumers sometimes seem to prefer uncertainty to certainty. The goal of this dissertation is to further understand the circumstances under which consumers prefer, rather than dislike, uncertainty across different domains. In Chapter 1, we investigate preferences for uncertainty in the domain of advice giving. There is a widespread belief that advisees prefer, and thus reward, advisors who offer certainty, even for events that are inherently uncertain. In contrast, we find that consumers do not dislike, and sometimes prefer, uncertain advice. Specifically, they do not dislike advisors who express uncertainty by providing ranges of outcomes, giving numerical probabilities, or saying one event is “more likely” than another. In addition, when faced with an explicit choice, people are more likely to choose an advisor who provides uncertain advice over certain advice. In Chapter 2, we extend our investigation to preferences for uncertainty in the domain of price promotions. We test why and when consumers may prefer an uncertain price promotion, such as a 10% chance to get a product for free, to an equivalent sure discount. We find that uncertain price promotions are relatively more effective only when the equivalent sure discounts feel small. Specifically, we find that uncertain promotions are

relatively more effective when the sure discounts are actually smaller, when the sure discounts are made to feel smaller by presenting them alongside a larger discount, and when the sure discounts are made to feel smaller by framing them as a percentage-discount rather than a dollar amount. This suggests that people's preferences for uncertainty are more strongly tethered to their perceptions of the size of the sure outcome than they are to their perceptions of the probability of getting the uncertain reward. Taken together, this dissertation challenges long-held beliefs about how uncertainty affects consumers' judgments and decisions and highlights the circumstances under which consumers prefer, rather than dislike, uncertainty.

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INTRODUCTION

Uncertainty is ubiquitous in consumer decisions. Many of the most common and important consumer decisions, from home purchases to financial investments, involve uncertainty. Understanding how consumers react to uncertainty is therefore of utmost importance for marketers. Previous research demonstrates that uncertainty is often disliked (e.g., Gneezy, List, & Wu, 2006; Mislavsky & Simonsohn, 2017; Simonsohn, 2009). However, recent research has also identified situations in which consumers seem to prefer uncertainty to certainty (e.g., Goldsmith & Amir, 2010; Mazar, Shampanier, & Ariely, 2016; Shen, Fishbach, & Hsee 2014). This work suggests that consumers may not always dislike, and sometimes prefer, uncertainty. In this dissertation, we further investigate the circumstances under which consumers prefer or dislike uncertainty across different domains.

In Chapter 1, titled “Do People Inherently Dislike Uncertain Advice?”, we investigate preferences for uncertainty in the domain of advice giving. Consumers often ask for and rely on advice. Many psychologists and laypeople believe that advisees prefer, and thus reward, advisors who offer certainty. However, this belief comes, at least in part, from studies showing that consumers dislike advisors who express themselves without confidence. But do consumers dislike uncertain *advice* itself? In a series of eleven experimental studies (N = 4,806) across a variety of prediction domains (e.g., sports predictions, stock forecasts), we demonstrate that people do not inherently dislike uncertain advice. Specifically, we find that people do not dislike advisors who express uncertainty by providing ranges of outcomes, giving numerical probabilities, or saying

that one event is “more likely” than another. In addition, we find that, when asked to choose between two advisors, people are actually *more* likely to choose an advisor who incorporates uncertainty into his advice.

The findings from Chapter 1 make important theoretical contributions to the literature by carefully disentangling the constructs of advisor confidence and advice certainty. These findings also have broad practical implications. Consumers often seek out and rely on advice, particularly in situations that involve uncertainty. Advisors should express themselves with confidence, but they do not need to provide false certainty.

In Chapter 2, titled “Why (and When) Are Uncertain Price Promotions More Effective Than Equivalent Sure Discounts?”, we extend our investigation to preferences for uncertainty in the domain of price promotion. In a series of seven experimental studies (N = 11,238), we test why and when consumers may prefer uncertain price promotions, such as a 10% chance to get a product for free, to standard sure discounts. We find that uncertain price promotions are relatively more effective only when the equivalent sure discounts feel small. Specifically, we demonstrate that uncertain price promotions are relatively more effective when the sure discounts are actually smaller, or when the sure discounts are made to feel smaller by presenting them alongside a larger discount. Importantly, we also show that merely framing a sure price discount as a percentage rather than a dollar amount can make it feel smaller, thus making the uncertain promotion relatively more attractive.

The findings from Chapter 2 are inconsistent with two leading explanations of consumers’ preferences for uncertain over certain promotions – diminishing sensitivity

and the overweighting of small probabilities – and suggest that people’s preferences for uncertainty are more strongly tethered to their perceptions of the size of the sure outcome than they are to their perceptions of the probability of getting the uncertain reward. These findings also have important practical implications, as they highlight when uncertain promotions can be effective and when they are not.

Taken together, this dissertation challenges long-held beliefs about how uncertainty affects consumers’ judgments and decisions and highlights the circumstances under which consumers prefer, rather than dislike, uncertainty.

CHAPTER 1

DO PEOPLE INHERENTLY DISLIKE UNCERTAIN ADVICE?

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ABSTRACT

Research suggests that people prefer confident to uncertain advisors. But do people dislike uncertain *advice* itself? In eleven studies ($N = 4,806$), participants forecasted an uncertain event after receiving advice, and then rated the quality of the advice (Studies 1-7, S1-S2) or chose between two advisors (Studies 8-9). Replicating previous research, confident advisors were judged more favorably than advisors who were “not sure.” Importantly, however, participants were *not* more likely to prefer certain advice: They did not dislike advisors who expressed uncertainty by providing ranges of outcomes, numerical probabilities, or by saying that one event is “more likely” than another. Additionally, when faced with an explicit choice, participants were *more* likely to choose an advisor who provided uncertain advice over an advisor who provided certain advice. Our findings suggest that people do not inherently dislike uncertain advice. Advisors benefit from expressing themselves with confidence, but not from communicating false certainty.

INTRODUCTION

Is it better for an advisor to be accurate or overconfident? Although there are seemingly obvious benefits to being accurate (e.g., a good reputation), many psychologists and laypeople believe that advisees prefer, and thus reward, advisors who offer certainty, even for events that are inherently uncertain. For example, in his book *Thinking, Fast and Slow*, Kahneman (2011) writes, “Experts who acknowledge the full extent of their ignorance may expect to be replaced by more confident competitors, who are better able to gain the trust of clients. An unbiased appreciation of uncertainty is a cornerstone of rationality—but it is not what people and organizations want” (p. 263). Similarly, in their book *Superforecasting*, Tetlock and Gardner (2015) write, “A confident yes or no is satisfying in a way that maybe never is” (p. 138). And, anecdotally, when we teach the perils of overconfidence to MBA students, they frequently counter with the claim that consumers have an inherent distaste for uncertainty, and that they must therefore give overconfident advice in order to be persuasive and successful.

Many forecasters seem to have internalized this belief, often giving advice that is too certain. For example, people tend to place excessively narrow confidence intervals around their forecasts (Moore & Healy, 2008; Moore, Tenney, & Haran, in press; Soll & Klayman, 2004). This tendency to be overconfident is present in competitive market settings (Radzevick & Moore, 2011), and there is compelling evidence that social motives, such as the desire to appear credible to others, are drivers of overconfidence (Anderson, Brion, Moore, & Kennedy, 2012; Van Zant, 2017).

Psychologists’ belief that people inherently dislike uncertain advice comes (at least in part) from studies showing that people dislike advisors who express themselves without

confidence. For example, research shows that people may rely on a “confidence heuristic,” according to which they infer that advisors who are more confident possess greater knowledge (Price & Stone, 2004). In addition, there is evidence that individuals who express confidence are judged as more competent by their peers and obtain higher status in their groups (Anderson et al., 2012). Indeed, to justify their claim that people inherently dislike “maybes” over more certain “yeses or nos,” Tetlock and Gardner (2015) cite research showing that “people trust more confident financial advisors over those who are less confident even when their track records are identical. And people equate confidence and competence, which makes the forecaster who says something has a middling probability of happening less worthy of respect” (p. 138).

Thus, because there is compelling evidence that people dislike advisors who lack *confidence*, scholars have concluded that people dislike advice that lacks *certainty*. However, that need not be the case, as the confidence with which advisors communicate may be different from the certainty implied by what they say. For example, although recipients of advice may almost always dislike an advisor who speaks in a way that makes her seem unsure (e.g., “I’m not sure but I think the stock price will increase”), they may not dislike an advisor who confidently communicates uncertainty (e.g., “There is a 60% chance that the stock price will increase”).

Some research supports this notion. For example, research in settings that provide participants with rapid and unambiguous feedback (i.e., settings in which people can easily compare advisors’ forecasts to actual outcomes) shows that people prefer advisors who are calibrated rather than overconfident (Sah, Moore, & MacCoun, 2013; Tenney,

MacCoun, Spellman, & Hastie, 2007; Tenney, Spellman, & MacCoun, 2008). Additionally, research by Du, Budescu, Shelly, and Omer (2011) shows that people prefer financial forecasts that are imprecise in settings in which they believe imprecision to be warranted. Still, we do not know whether people tolerate uncertain advice in the absence of feedback, nor whether the tolerance for imprecise financial advice generalizes to other domains and other expressions of uncertainty.

RESEARCH OVERVIEW

Our research investigates whether advisors have an incentive to provide false certainty or merely an incentive to speak and act confidently.

To investigate whether people inherently dislike uncertain advice, it is important to study events that are inherently uncertain rather than knowable. Indeed, people may dislike uncertain advice about events that are knowable not because of an inherent distaste for uncertainty, but because of an inherent distaste for obviously bad advice. For example, an advisor who says that there is 50% chance that Florida is south of New York will be universally untrusted, not because of an inherent distaste for uncertainty, but because being uncertain about something that is so easily knowable is truly diagnostic of incompetence. More generally, it is important to manipulate the uncertainty of the advice while holding the quality of the advice constant. This ensures that people do not like one advisor more than another simply because her advice is more accurate.

Additionally, uncertain advice can take many forms, from imprecision (e.g., “The stock price will increase by 1-6%”) to statements of probability (e.g., “There is a 55% chance that the stock price will increase”) to non-numerical statements of uncertainty

(e.g., “The stock price is more likely than not to increase”). It is important for investigations of uncertain advice to investigate its various forms. After all, it could be that people do not inherently dislike uncertain advice, but that they object to particular forms of it.

In eleven studies, we asked participants to forecast a future (and hence inherently uncertain) event after receiving advice, and we asked them to rate the quality of the advice (Studies 1-7 and S1 and S2) or to choose between two advisors (Studies 8 and 9). In all studies, we manipulated whether the advice itself was certain or uncertain, and we operationalized uncertain advice in seven different ways. In six of the first seven studies we also manipulated whether the advisor expressed confidence or said that s/he was not sure. In all studies, the quality of the advice was the same across conditions, allowing us to compare people’s evaluations of equally good uncertain versus certain advice. Consistent with previous research, we expected people to dislike advisors who said they were unsure about the advice they were giving. More important, however, was the comparison between people’s evaluations of certain and uncertain advice. Do people inherently dislike uncertain advice, or not?

STUDIES 1-6

In Studies 1-6, we asked participants to predict the outcomes of upcoming sporting events. Before each prediction, participants received and evaluated advice. The six studies followed a similar procedure, and so we describe them all at once. All of our studies were pre-registered, and the links to those pre-registrations can be found in the Appendix. The data and materials are available here: <https://osf.io/ew34q/>.

Method

Participants

We conducted Studies 1-6 using U.S. participants from Amazon.com's Mechanical Turk (MTurk). We advertised Studies 1 and 2 as "a survey for NBA basketball fans" and Studies 3-6 as "a survey for Major League Baseball (MLB) fans." Participants received \$1 for completing the study and they could earn up to an additional \$1-4 for accurate forecasting performance. In Studies 1, 2, and 5, we decided in advance to recruit 300 participants, and in Studies 3, 4, and 6, we decided in advance to recruit 400, 600, and 900 participants, respectively. Our analyses included data from all participants who evaluated the advice for at least one of the games. This left us with final samples of 306, 308, 411, 618, 305, and 916 in Studies 1-6, respectively. These samples averaged 33-35 years of age and were 28-42% female.

Procedure

The six studies followed a similar procedure. In each study, participants were asked to predict the outcomes of a series of sporting events on the day on which the games were played. Participants in Studies 1 and 2 predicted NBA games, and participants in Studies 3-6 predicted MLB games. For each study, we randomly selected eight games that began no earlier than 7 pm on the selected game day. We posted the study in the morning of the game day to ensure that data collection would be completed before the games started. For each game, participants were presented with the game's start time, as well as the names of the home and visiting teams. For the MLB games, participants also saw the names of the teams' probable starting pitchers. In each study, the order of presentation of the games

was randomized between subjects, and the games were presented on the screen one at a time.

For each of the games that participants were asked to forecast, we told them that, “You will receive advice to help you make your predictions. For each question, the advice that you receive comes from a different person.” Importantly, participants always received objectively good advice, based on data from well-calibrated betting markets. For each game, we independently manipulated the certainty of the advice and/or the confidence of the advisor, and the nature of these manipulations is described in detail below. Thus, across games, participants were exposed to different kinds of advice (i.e., certain or uncertain advice delivered by either an unsure or confident advisor).

In Studies 1-4 and 6, we manipulated the confidence of the advisor by either preceding the advice with an expression of low confidence (e.g., “I am not sure, but I think that the Chicago Cubs will win the game”) or not (e.g., “The Chicago Cubs will win the game”). In Study 6, we also added a condition in which the advice was preceded by the statement, “I am very confident that...” In Study 5, the advice was always confidently stated.

Apart from the minor procedural differences that we describe below, the main differences among the six studies were (1) the kind of prediction that participants were asked to make, and (2) the ways in which we manipulated advice uncertainty. Table 1 displays which advice uncertainty manipulations were used in which studies, and shows an example of how the manipulations were phrased.

In Studies 1 and 2, participants were asked to predict how many points would be scored in a series of basketball games. For these predictions, we manipulated advice certainty vs. uncertainty by manipulating the precision of the advisor’s prediction. In the precise/certain conditions, the advisor forecasted an exact point total. In the imprecise/uncertain conditions, the advisor forecasted a range that was either 20 points wide (in the *range 20* conditions of Studies 1 and 2) or 40 points wide (in the *range 40* condition of Study 2).

In Studies 1, 3, 4, 5, and 6, participants were asked to predict which basketball or baseball team would win each game.¹ For these predictions, we manipulated advice certainty vs. advice uncertainty by manipulating whether or not the advisor made a probabilistic prediction. In the certain conditions, the advisor simply said, “The [predicted team] will win this game.” Because there are many different ways for an advisor to make a probabilistic statement, across the studies we tried out five different phrasings, including three numerical (e.g., “There is a 57% chance that the Chicago Cubs will win this game” in the *exact chance* conditions) and two non-numerical (e.g., “The Chicago Cubs are more likely to win this game” in the “*more likely*” conditions) instantiations of uncertainty. See Table 1 for a complete description of these manipulations.

¹ In Study 1, we asked participants to make both types of predictions, points scored and winners, separated into randomly ordered blocks of four games each.

Table 1. The Manipulations of Certain vs. Uncertain Advice in Studies 1-6

<u>Predicting Points Scored: Precise vs. Imprecise Advice</u>			
<u>Advice Type</u>	<u>Condition</u>	<u>Studies</u>	<u>Example of Advice Phrasing</u>
Certain	Precise	1, 2	"The Bucks and the Cavaliers will score 207 points."
Uncertain	Range 20	1, 2	"The Bucks and the Cavaliers will score between 197 and 217 points."
Uncertain	Range 40	2	"The Bucks and the Cavaliers will score between 187 and 227 points."

<u>Predicting Winners: Certain vs. Probabilistic Advice</u>			
<u>Advice Type</u>	<u>Condition</u>	<u>Studies</u>	<u>Example of Advice Phrasing</u>
Certain	Certain	1, 3, 4, 5, 6	"The Chicago Cubs will win this game."
Uncertain	Exact Chance	1, 3, 5	"There is a 57% chance that the Chicago Cubs will win this game."
Uncertain	Approximate Chance	3, 6	"There is about a 57% chance that the Chicago Cubs will win this game."
Uncertain	Percent Confident	5	"I am 57% confident that the Chicago Cubs will win this game."
Uncertain	"Probably"	3, 4	"The Chicago Cubs will probably win this game."
Uncertain	"More Likely"	4, 6	"The Chicago Cubs are more likely to win this game."

Advice evaluation. After receiving the advice, we asked participants to rate its quality. Specifically, they indicated how knowledgeable, competent, and credible they perceived the advisor to be, how much they trusted the advisor, whether they would seek additional information or advice from the advisor in the future, and how persuasive and accurate the advice was (1-7 scales; 1 = “not at all” to 7 = “extremely”/“definitely”). We averaged these seven items to create a single measure of advice evaluation (all α 's $\geq .93$).

Table 2 shows the exact wording of these questions.

Table 2. Advice Evaluation Measures in Studies 1-6

How knowledgeable is this advisor? (1 = not at all; 7 = extremely)
How competent is this advisor? (1 = not at all; 7 = extremely)
How credible is this advisor? (1 = not at all; 7 = extremely)
How much do you trust this advisor? (1 = not at all; 7 = extremely)
Would you seek additional information or advice from this person in the future? (1 = not at all; 7 = definitely)
How persuasive is this advice? (1 = not at all; 7 = extremely)
How accurate is this advice? (1 = not at all; 7 = extremely)

Incentivized predictions. We also asked participants to make their own predictions for each of the games and we incentivized them to be accurate. For questions that asked about total points scored in NBA games (Studies 1 and 2), the five participants who performed the best (i.e., whose predictions were the closest to the actual game outcomes across all games) received a \$3 bonus. For questions that asked about the winner of a given game (Studies 1 and 3-6), those participants who predicted the outcome of a certain number of games correctly (all games for NBA games and 6 out of 8 for MLB games) received a \$1 bonus.

Sports knowledge. At the end of the survey, we presented participants with a set of six knowledge questions about the sport they were predicting. Specifically, we asked them to identify the teams of four different players and to identify which teams had the best and worst records at the time of the study. They were asked to answer these questions without looking up the answers.

Demographics. At the end of the study, we assessed participants' age and gender. For Studies 3-6, we also asked participants to indicate their favorite MLB team. Finally, in Studies 3-6, we included other exploratory measures that are described in full in the Supplement.

Results

Analysis Plan

We preregistered to analyze the data of each of these studies separately. However, presenting the results from each of these individual studies will make for a needlessly repetitive, tedious, and opaque results section. Thus, for ease of presentation, we decided

to merge the data from these six studies into one dataset, and to present the results all at once. The independent and dependent variables of the analyses we present in the text do not differ from our pre-registrations. The results of the pre-registered analyses for the individual studies are in the Online Supplement, and the means and standard deviations for each game are presented in Tables 3 and 4.

Each participant who fully completed the study contributed eight observations to the dataset, one for each game that they predicted.² We present the results in two sections, one containing the findings of the points scored predictions, for which uncertain advice was operationalized as imprecision, and the other containing the findings of the winner predictions, for which uncertain advice was operationalized as probabilistic statements. Within each section, we conducted separate regression analyses for each of the uncertain advice conditions. These analyses tested whether each particular form of uncertain advice was evaluated more positively or negatively than certain advice. Except for the analyses of percent confident advice, which was never presented in an “unsure” manner, we regressed participants’ advice evaluation on (1) the uncertain advice condition (-.5 = certain advice; +.5 = uncertain advice), (2) the advisor confidence condition (-.5 = unsure advisor; +.5 = confident advisor), and (3) the interaction between the two conditions. For example, in the analyses of the exact chance advice condition, we regressed participants’ advice evaluation on (1) the exact chance advice condition (-.5 = certain advice; +.5 = exact chance advice), (2) the advisor confidence condition (-.5 = unsure advisor; +.5 = confident advisor), and (3) the interaction between the two conditions. (For the “percent

² Study 6 contained an error that caused the advice for one game to be displayed incorrectly, rendering its results invalid. We excluded this game from our analyses and from Table 4.

confident” condition, we omitted the advisor confidence condition and the interaction term because they were constants). All of our regressions included fixed effects for game, and clustered standard errors by participant to account for the non-independence of observations. We report the results of the interactions only when they are significant. The Online Supplement shows the full results.

In addition, to test whether participants liked very confident advisors more than confident advisors in Study 6, we regressed participants’ advice evaluation on the very confident condition (-.5 = confident advisor; +.5 = very confident advisor). We again included fixed effects for game and clustered standard errors by participant.

Main Analyses

Points Scored Predictions: Uncertainty Operationalized as Imprecision

Table 3 shows the results for each game. As predicted, and consistent with past research, there was a large and significant main effect of advisor confidence in these analyses, $t_s > 7.19$, $p_s < .001$: Advisors who said “I am not sure but...” were evaluated more negatively than advisors who expressed themselves confidently.

More importantly, participants did *not* evaluate uncertain advice more negatively than certain advice. In fact, they evaluated advice in the form of 20-point ranges more *positively* than certain advice, $b = .139$, $SE = .059$, $t(612) = 2.36$, $p = .019$. In addition, they evaluated advice in the form of 40-point ranges *no differently* from certain advice, $b = -.014$, $SE = .086$, $t(305) = -0.16$, $p = .872$.

Thus, these studies provide no evidence that people inherently dislike uncertain advice in the form of ranges. In fact, participants preferred advice that spanned a 20-point

range to certain advice, and they did not significantly dislike uncertain advice that spanned a very large (40-point) range. While it is obviously the case that making the uncertain ranges even wider would eventually cause participants to disfavor it – for example, nobody would value advice such as, “The teams will score between 0 and 1,000 points” – our results suggest that people do not inherently dislike uncertain range advice when the ranges are of a reasonable width.

Table 3. Studies 1-2: Points Scored Prediction Results by Game

Unsure Advisor									
Study	Game	Certain Advice Forecast	Actual Point Total	Certain Advice		Uncertain Advice			
						Range 20		Range 40	
				<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
1	Bucks vs. Cavaliers	207	217	3.60	1.31	3.73	1.31		
1	Magic vs. Pistons	210	220	3.55	1.20	3.44	1.40		
1	76ers vs. Nuggets	215	207	3.30	1.37	3.35	1.26		
1	Mavericks vs. Trailblazers	215	212	3.38	1.40	3.84	1.26		

2	Raptors vs. Grizzlies	197	194	3.55	1.38	3.79	1.42	3.55	1.39
2	76ers vs. Hornets	197	191	3.40	1.50	3.40	1.34	3.48	1.27
2	Wizards vs. Suns	214	205	3.18	1.56	3.65	1.42	3.56	1.26
2	Nets vs. Knicks	199	196	3.39	1.31	3.76	1.32	3.87	1.41
2	Cavaliers vs. Hawks	199	218	3.85	1.42	4.02	1.49	3.83	1.72
2	Mavericks vs. Pistons	206	187	3.58	1.44	3.69	1.43	3.57	1.34
2	Magic vs. Bucks	197	223	3.49	1.28	3.49	1.40	3.44	1.36
2	Celtics vs. Warriors	222	215	3.81	1.41	3.88	1.64	3.91	1.49
Confident Advisor									
Study	Game	Certain Advice Forecast	Actual Point Total	Certain Advice		Uncertain Advice			
						Range 20		Range 40	
				<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
1	Bucks vs. Cavaliers	207	217	4.28	1.13	4.52	1.22		
1	Magic vs. Pistons	210	220	4.29	1.28	4.01	1.23		
1	76ers vs. Nuggets	215	207	3.96	1.34	4.16	1.51		
1	Mavericks vs. Trailblazers	215	212	4.20	1.39	4.72	1.03		

2	Raptors vs. Grizzlies	197	194	4.05	1.16	4.36	1.18	3.92	1.26
2	76ers vs. Hornets	207	191	3.91	1.33	4.26	1.44	3.99	1.33
2	Wizards vs. Suns	214	205	3.95	1.51	4.03	1.22	4.10	1.28
2	Nets vs. Knicks	199	196	4.31	1.53	4.33	1.15	4.26	1.37
2	Cavaliers vs. Hawks	199	218	4.35	1.57	4.41	1.14	4.13	1.37
2	Mavericks vs. Pistons	206	187	4.56	1.22	4.55	1.14	4.29	1.29
2	Magic vs. Bucks	197	223	4.43	1.33	4.49	1.43	3.91	1.24
2	Celtics vs. Warriors	222	215	4.41	1.37	4.16	1.27	4.17	1.57

Note. Within the uncertain advice columns, bolded means indicate that participants evaluated uncertain advice significantly more positively than certain advice, and italicized means indicate that participants evaluated uncertain advice significantly more negatively than certain advice ($p < .05$).

Table 4. Studies 1, 3-6: Winner Prediction Results by Game

Unsure Advisor															
Study	Predicted Winner	Predicted Loser	Chance Advice Probability	Certain Advice		Exact Chance		Approximate Chance		Uncertain Advice Percent Confident		"Probably"		"More Likely"	
				M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
1	Wizards	Hawks*	58%	3.03	1.20	3.68	1.22								
1	Celtics*	Raptors	55%	3.17	1.31	3.85	1.17								
1	Suns*	Lakers	73%	3.39	1.30	3.96	1.41								
1	Warriors*	Clippers	83%	3.55	1.50	4.41	1.64								
3	Orioles*	Yankees	52%	2.95	1.23	3.39	1.20	3.33	1.20			2.98	1.23		
3	Blue Jays*	Rangers	60%	3.05	1.31	3.88	1.33	3.75	1.19			2.90	1.24		
3	Marlins*	Diamondbacks	57%	2.89	1.05	3.53	1.26	3.83	1.33			3.06	1.43		
3	Reds*	Brewers	51%	2.94	1.27	3.07	1.06	3.50	1.46			2.96	1.12		
3	Cubs*	Nationals	57%	3.08	1.22	4.24	1.28	3.83	1.33			3.17	1.41		
3	Red Sox*	White Sox	51%	2.91	1.15	3.44	1.30	2.93	1.28			2.64	1.05		
3	Astros	Mariners*	52%	2.79	1.22	3.14	1.22	3.46	1.12			2.68	1.17		
3	Mets	Padres*	63%	2.83	1.20	4.34	1.14	4.06	1.23			3.40	1.28		
4	Phillies	Braves*	62%	3.17	1.25							3.33	1.29	3.35	1.27
4	Nationals*	Marlins	57%	3.43	1.40							3.46	1.33	3.34	1.34
4	Mariners*	Reds	56%	3.29	1.44							3.26	1.25	3.47	1.38
4	Indians*	Red Sox	52%	2.91	1.26							2.94	1.21	3.12	1.33
4	Blue Jays*	Twins	55%	3.43	1.27							3.33	1.32	3.61	1.44
4	White Sox	Royals*	61%	3.15	1.28							3.48	1.23	3.40	1.36
4	Astros	Rangers*	61%	3.14	1.29							2.90	1.32	3.18	1.33
4	Cubs*	Giants	64%	3.50	1.48							3.48	1.30	3.21	1.48
6	Pirates*	Mariners	60%	3.15	1.24			4.09	1.31					3.22	1.24
6	Cardinals*	Mets	55%	3.08	1.37			3.76	1.09					3.38	1.39
6	Cubs*	White Sox	66%	3.46	1.37			4.01	1.20					3.30	1.18
6	Brewers	Diamondbacks*	57%	3.21	1.17			3.84	1.18					3.19	1.24
6	Twins	Braves*	59%	3.19	1.28			3.57	1.34					3.20	1.29
6	Astros*	Yankees	55%	3.28	1.33			3.59	1.35					3.03	1.17
6	Royals*	Angels	53%	3.36	1.17			3.76	1.20					3.55	1.39
Confident Advisor															
Study	Predicted Winner	Predicted Loser	Chance Advice Probability	Certain Advice		Exact Chance		Approximate Chance		Uncertain Advice Percent Confident		"Probably"		"More Likely"	
				M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
1	Wizards	Hawks*	58%	3.82	1.29	4.13	1.19								
1	Celtics*	Raptors	55%	4.20	1.48	4.22	1.28								
1	Suns*	Lakers	73%	4.27	1.43	4.78	1.10								
1	Warriors*	Clippers	83%	4.85	1.45	5.33	1.15								
3	Orioles*	Yankees	52%	4.54	1.33	<i>4.00</i>	1.16	3.65	1.14			3.57	1.30		
3	Blue Jays*	Rangers	60%	4.21	1.27	4.53	0.95	4.54	1.28			3.94	1.15		
3	Marlins*	Diamondbacks	57%	4.30	1.25	4.41	1.05	4.44	1.13			3.35	1.11		
3	Reds*	Brewers	51%	4.25	1.25	4.05	1.12	3.78	1.25			3.84	1.16		
3	Cubs*	Nationals	57%	4.30	1.23	4.43	1.16	4.18	1.08			3.82	1.33		
3	Red Sox*	White Sox	51%	4.74	1.34	3.85	1.21	3.94	1.06			3.63	1.15		
3	Astros	Mariners*	52%	4.39	1.54	3.99	1.20	3.63	1.33			3.65	1.34		
3	Mets	Padres*	63%	4.77	1.34	4.77	1.08	4.75	0.90			3.92	1.31		
4	Phillies	Braves*	62%	4.54	1.31							<i>4.11</i>	1.30	4.62	1.19
4	Nationals*	Marlins	57%	4.64	1.31							<i>4.13</i>	1.21	4.36	1.15
4	Mariners*	Reds	56%	4.64	1.27							<i>4.15</i>	1.28	4.43	1.12
4	Indians*	Red Sox	52%	3.90	1.37							3.60	1.08	3.76	1.26
4	Blue Jays*	Twins	55%	4.62	1.41							4.38	1.24	4.49	1.06
4	White Sox	Royals*	61%	4.48	1.35							<i>3.89</i>	1.23	4.35	1.35
4	Astros	Rangers*	61%	3.97	1.37							3.81	1.27	4.07	1.25
4	Cubs*	Giants	64%	4.62	1.36							4.22	1.29	4.39	1.36
5	Orioles*	Yankees	52%	3.75	1.29	4.11	1.21			3.73	1.17				
5	Red Sox	Blue Jays*	62%	4.46	1.48	4.64	1.12			4.65	1.25				
5	Nationals	Reds*	60%	4.27	1.35	4.37	1.34			4.39	1.03				
5	Rangers*	Mariners	57%	4.20	1.30	4.44	1.03			4.24	1.07				
5	Rays*	Twins	53%	4.20	1.35	4.19	1.05			3.94	1.09				
5	Giants*	Cardinals	52%	4.18	1.40	4.09	1.17			3.88	1.13				
5	Dodgers*	Braves	67%	4.41	1.43	4.68	1.10			4.64	1.23				
5	Padres*	Rockies	59%	4.04	1.34	4.36	1.12			4.26	1.02				
6	Pirates*	Mariners	60%	4.21	1.24			4.38	1.03					4.23	1.23
6	Cardinals*	Mets	55%	4.35	1.22			4.30	1.13					4.25	1.19
6	Cubs*	White Sox	66%	4.42	1.32			4.86	1.11					4.44	1.20
6	Brewers	Diamondbacks*	57%	4.12	1.21			4.21	1.10					4.34	1.00
6	Twins	Braves*	59%	4.20	1.25			4.27	0.95					4.34	1.16
6	Astros*	Yankees	55%	3.98	1.45			4.07	1.09					3.87	1.32
6	Royals*	Angels	53%	4.27	1.21			4.12	1.19					4.15	1.16
Very Confident Advisor															
Study	Predicted Winner	Predicted Loser	Chance Advice Probability	Certain Advice		Exact Chance		Approximate Chance		Uncertain Advice Percent Confident		"Probably"		"More Likely"	
				M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
6	Pirates*	Mariners	60%	4.49	1.22			4.43	1.00					4.66	1.18
6	Cardinals*	Mets	55%	4.45	1.13			4.17	1.10					4.50	1.12
6	Cubs*	White Sox	66%	4.56	1.32			4.63	1.19					4.71	1.20
6	Brewers	Diamondbacks*	57%	4.44	1.27			4.48	1.06					4.51	1.17
6	Twins	Braves*	59%	4.06	1.25			4.61	1.24					4.41	1.23
6	Astros*	Yankees	55%	4.05	1.40			3.95	1.25					3.93	1.31
6	Royals*	Angels	53%	4.54	1.18			<i>4.06</i>	1.19					4.50	1.47

Notes. Within the uncertain advice columns, bolded means indicate that participants evaluated uncertain advice significantly more positively than certain advice, and italicized means indicate that participants evaluated uncertain advice significantly more negatively than certain advice ($p < .05$). The actual winner of each game is marked with an asterisk (*).

Winner Predictions: Uncertainty Operationalized as Probabilistic Statements

Table 4 shows the results for each game. As in the previous section, there was a large and significant main effect of advisor confidence in all regressions, $t_s > 16.42$, $p_s < .001$: Advisors who said “I am not sure but...” were evaluated more negatively than advisors who expressed themselves confidently. We also found, in Study 6, that advisors who preceded their advice by saying, “I am very confident that ...” were evaluated more positively than advisors who did not express themselves with such high confidence, $b = .132$, $SE = .039$, $t(914) = 3.37$, $p = .001$. More important are the comparisons between participants’ evaluations of certain advice and uncertain advice, to which we now turn.

Participants evaluated “exact chance” advice (e.g., “There is a 57% chance that the Chicago Cubs will win the game”) more *positively* than certain advice (e.g., “The Chicago Cubs will win the game”), $b = .400$, $SE = .047$, $t(1,014) = 8.46$, $p < .001$. Moreover, a significant interaction with advisor confidence, $b = -.587$, $SE = .092$, $t(1,014) = -6.40$, $p < .001$, revealed that participants evaluated “exact chance” advice significantly more positively than certain advice when the advisor said that s/he was unsure, $b = .694$, $SE = .074$, $t(648) = 9.38$, $p < .001$, and marginally more positively than certain advice when the advisor was confident, $b = .106$, $SE = .056$, $t(960) = 1.89$, $p = .059$.

Participants also evaluated “*approximate* chance” advice (e.g., “There is about a 57% chance that Chicago Cubs will win the game”) more positively than certain advice, $b = .269$, $SE = .043$, $t(1,306) = 6.29$, $p < .001$. There was again a significant interaction with advisor confidence, $b = -.649$, $SE = .078$, $t(1,306) = -8.33$, $p < .001$. People evaluated

“approximate chance” advice more positively than certain advice when the advisor was unsure, $b = .593$, $SE = .055$, $t(1,116) = 10.75$, $p < .001$, but no differently from certain advice when the advisor was confident, $b = -.057$, $SE = .060$, $t(1,133) = -0.95$, $p = .343$.

In Study 5, we introduced a *percent confident* condition, in which participants received confident advice in the form of “I am X% confident that...” We found that participants evaluated this advice the same as certain advice, $b = .027$, $SE = .079$, $t(302) = 0.34$, $p = .736$.³

The results of the “probably” condition were different, as participants did evaluate advice of the form, “The [predicted team] will probably win the game,” more negatively than they evaluated certain advice, $b = -.236$, $SE = .038$, $t(1,023) = -6.14$, $p < .001$. This effect was significantly stronger when the advice came from an advisor who was confident, $b = -.527$, $SE = .076$, $t(1,023) = -6.94$, $p < .001$. Specifically, participants evaluated this form of uncertain advice no differently from certain advice when the advisor was unsure, $b = .028$, $SE = .053$, $t(951) = 0.53$, $p = .596$, but more negatively than certain advice when the advisor was confident, $b = -.499$, $SE = .055$, $t(961) = -9.00$, $p < .001$. Thus, people do seem to dislike uncertain advice from a confident advisor who uses the word “probably”.

This raises an important question: Do people inherently dislike all forms of uncertain advice that are non-numerical, or do they simply dislike it when advisors use the word “probably?”

³ The percent confident advice contained a typo: It read, “I am X% confident that the [predicted team] win this game.”

The results of the “more likely” condition suggest the latter. Participants evaluated advice of the form, “The [predicted team] is more likely to win the game,” no differently from certain advice, $b = -.003$, $SE = .033$, $t(1,516) = -0.08$, $p = .940$. These evaluations were not dependent on whether the advice came from an advisor who was “not sure,” $b = -.110$, $SE = .067$, $t(1,516) = -1.64$, $p = .101$.

In sum, we find that people do not inherently dislike uncertain advice that contains numerical probabilities and they also do not dislike uncertain advice that uses the words “more likely.” More specifically, we found that people evaluated “exact chance” advice and “approximate chance” advice more positively when the advisor said that s/he was unsure. When the advisor expressed confidence, people evaluated “exact chance” advice, “approximate chance” advice, and “percent confident” advice as no different from certain advice.

People’s evaluation of “more likely” advice did not depend on the confidence of the advisor; they evaluated “more likely” advice no differently from certain advice regardless of whether the advisor was confident or “not sure.” For advice that used the word “probably,” the results were different: We found that people evaluated “probably” advice no differently from certain advice when the advisor said that s/he was unsure, but when the advisor expressed confidence, they evaluated “probably” advice more negatively than certain advice.

Because Studies 1-6 were so similar, it is reasonable to consider whether these results hinge on specific aspects of their design. Here we consider two such aspects. First, in these studies, we manipulated the nature of advice within subjects (i.e., participants were

randomly assigned to different advice for each game they predicted). This should make participants more sensitive to the differences between certain and uncertain advice. For example, it could be that participants receiving “probably” advice dislike it only once they have been exposed to other types of advice. To see whether our effects would be different in a between-subjects design, we re-ran our analyses on the first game that participants predicted. These analyses have less power, but the size and direction of the effects are illuminating. As the two right columns of Table 5 show, participants did not significantly or substantially dislike *any* form of uncertain advice when it was the first piece of advice that they received.

Table 5. Studies 1-6: Regression Results Based on All Observations and Just The First Observation

Uncertain Advice Condition	All Observations		First Observation Only	
	Effect of Uncertain Advice (vs. Certain Advice) on Advice Evaluation		Effect of Uncertain Advice (vs. Certain Advice) on Advice Evaluation	
	Unsure Advisor	Confident Advisor	Unsure Advisor	Confident Advisor
Range 20	b = 0.16, SE = .073, p = .031	b = 0.12, SE = .078, p = .132	b = 0.15, SE = .212, p = .477	b = 0.18, SE = .199, p = .374
Range 40	b = 0.12, SE = .109, p = .275	b = -0.15, SE = .11, p = .190	b = -0.30, SE = .257, p = .241	b = -0.15, SE = .242, p = .525
Exact Chance	b = 0.69, SE = .074, p < .001	b = 0.11, SE = .056, p = .059	b = 0.80, SE = .192, p < .001	b = 0.10, SE = .125, p = .417
Approximate Chance	b = 0.59, SE = .055, p < .001	b = -0.06, SE = .060, p = .343	b = 0.51, SE = .149, p = .001	b = 0.10, SE = .132, p = .435
Percent Confident		b = 0.03, SE = .079, p = .736		b = -0.07, SE = .163, p = .688
"Probably"	b = 0.03, SE = .053, p = .596	b = -0.50, SE = .055, p < .001	b = -0.01, SE = .162, p = .962	b = -0.09, SE = .131, p = .503
"More Likely"	b = 0.05, SE = .047, p = .263	b = -0.06, SE = .047, p = .224	b = 0.07, SE = .136, p = .599	b = 0.12, SE = .110, p = .303

Note. These results come from regressing advice evaluation on the uncertain advice condition in analyses that include fixed effects for game and clustered standard errors. Positive (negative) coefficients indicate that the uncertain advice was evaluated more favorably (negatively) than the certain advice, and the coefficients are interpretable as the average mean difference between the uncertain advice condition and the certain advice condition. For example, the first result in the table indicates that, when the advisor was unsure, participants evaluated "range 20" advice 0.16 scale points more favorably than certain advice.

Second, all of these studies were conducted in the domain of sports, and so it is possible that people’s tolerance of uncertain advice is restricted to this domain. To test this, we conducted another study (N = 413; Study S1 in the Online Supplement), in which we asked participants to predict whether the high temperature of eight cities on a future date would be higher or lower than a particular temperature (e.g., “Will the high temperature in Denver, CO on October 21, 2017 be higher than 74 degrees Fahrenheit?”).

As in Studies 1-6, participants received advice for each of the forecasts that they made and we asked them to evaluate the advice. For each forecasting question, we manipulated whether the advisor was confident or unsure, and whether the advice was certain or uncertain (in the form of “more likely” advice). Participants evaluated confident advisors more positively than “unsure” advisors, $b = 1.095$, $SE = .070$, $t(412) = 15.67$, $p < .001$, but they did not evaluate “more likely” advice more negatively than certain advice, $b = -.014$, $SE = .049$, $t(412) = -.29$, $p = .771$. Thus, the results of this weather forecasting study closely resemble those of the sports prediction studies, suggesting that our findings are not limited to the domain of sports.

Additional Analyses

Analyses of Advice Following

In our investigation, we were chiefly interested in how people evaluate advice. Thus, we specified advice evaluation to be our critical dependent variable in all of our pre-registrations. But we can also analyze the degree to which people followed the advice that they received. Were participants more or less likely to follow the advice when the advice was uncertain?

To answer this question, we have to define what it means for a participant to “follow the advice.” For the winner predictions, this is easy: Following the advice means predicting the same winning team as the advisor. But for the points scored predictions, this is not obvious, because the advice in the certain conditions (e.g., “The teams will score 200 points”) is different from the advice in the range conditions (e.g., “The teams will score between 180 and 220 points”). Thus, for this example, a participant who

predicted 190 total points scored would be deviating from the certain advice (200 points), but his/her prediction would still fall within the uncertain range advice (180-200 points). Given this difficulty in defining what it means to "follow advice" for the points scored predictions, we restrict our analyses to the winner predictions, assessing whether or not participants predicted the same winning team as the advisor.

As in the analyses of advice evaluations, we ran separate analyses for the different forms of uncertain advice. In each of these analyses, we regressed whether participants followed the advice (1 = they followed the advice; 0 = they did not follow the advice) on (1) the uncertain advice condition (-.5 = certain advice; +.5 = uncertain advice), (2) the advisor confidence condition (-.5 = unsure advisor; +.5 = confident advisor), and (3) the interaction between the two conditions. We included fixed effects for game and clustered standard errors by participant. (Again, the advisor confidence condition and the interaction term were necessarily omitted from analyses of the "percent confident" condition). We present OLS regressions here because the coefficients are easy to interpret (i.e., as percentage point differences between conditions); logistic regressions yielded nearly identical results.

The results were fairly consistent across each type of uncertain advice. In all analyses, there was a significantly positive effect of advisor confidence, indicating that participants were more likely to follow the advice of confident advisors than advisors who said they were not sure, $bs > .047$, $ts > 2.76$ $ps < .007$. Across all of the analyses, there was only one significant difference in advice following between the certain and uncertain advice conditions: A significant positive effect of "exact chance" advice, $b = .030$, $SE = .015$,

$t(1,014) = 2.01, p = .044$, indicated that participants were *more* likely to follow the advisor's advice when it was uncertain rather than certain. There were no significant interactions between advisor confidence and advice uncertainty.

Thus, consistent with the advice evaluation results, participants were no less likely to follow uncertain advice than to follow certain advice.

Discussion

These results suggest that people do not inherently dislike uncertain advice. They do not disvalue uncertain advice that comes in the form of ranges, numerical probabilities, or "more likely." The only distaste for uncertainty that we observed was very specific: People seem not to like "probably" advice from a confident advisor when it is not the first piece of advice that they see. Otherwise, uncertain advice seems to go unpunished.

In Studies 1, 3, 5, and 6, participants received uncertain advice in form of numerical probabilities. Exploratory analyses of our data suggest that people's evaluation of numerical probabilistic advice may depend on the exact probability provided. For example, a close examination of Table 4 shows that, in the face of a confident advisor, participants judged probabilistic advice more negatively than certain advice for some of the games for which the advisor stated a probability very close to 50% (i.e., 51% or 52%). In contrast, in the face of a confident advisor, participants sometimes judged probabilistic advice more positively than certain advice when the advisor stated a much higher probability (e.g., 73% and 83%). This suggests that people's fondness for probabilistic advice may depend on whether the stated probability is perceived to be

sufficiently informative (e.g., sufficiently different from 50% for a binary decision). We tested this in Study 7.

STUDY 7

In Study 7, we again asked participants to predict the outcomes of upcoming sporting events and to evaluate the advice that they received prior to making each prediction. We focused our investigation on uncertain advice in the form of an “approximate chance” prediction that was rounded to the nearest 5% (e.g., “There is about a 60% chance that ...”), and we manipulated across games what probability was contained in the uncertain advice.

Study 7 also extends our investigation in other ways. First, we conducted this study in the laboratory. Second, we increased the incentives for accurate forecasting performance to ensure that participants would be sufficiently motivated to make accurate predictions and to consider the advice carefully. Third, we asked participants to predict how many hits two teams would accumulate in a given MLB game. Since this is an outcome people are less familiar with, they should be more desirous of good advice. Finally, we assessed participants’ advice evaluation by asking only about the advice itself, rather than also asking participants to judge the quality of the advisor.

Method

Participants

We conducted Study 7 in the laboratory. (We also replicated Study 7’s design and results with an MTurk sample. We report this study in the Online Supplement as Study S2.) Participants completed the study as part of a ½-hour or 1-hour lab session for which

they received \$5 or \$10, respectively. In addition, participants could earn up to an additional \$6 for accurate forecasting performance (\$1 for each correct prediction). We pre-registered to conduct multiple batches of lab sessions until we obtained at least 300 participants. We ended up running three batches of lab sessions in July and August of 2017, resulting in a final sample size of 309 participants (average age: 27 years; 60% female).

Procedure

Participants predicted the outcomes of a series of MLB games prior to the games being played. For each batch of lab sessions, we selected 6 games that began no earlier than 7 pm on the last day of each lab session batch. For each game, participants were presented with the game's start time, the names of the home and visiting teams, and the names of the teams' probable starting pitchers. They were asked to predict whether the two teams would combine to accumulate more than X hits in the game, where X differed for each game. The order of presentation of the games was randomized between subjects, and the games were presented on the screen one at a time.

As in Studies 1-6, participants learned that they would receive advice to help them make their predictions. For each game, we then independently manipulated the certainty of the advice and the confidence of the advisor. We manipulated advice certainty vs. uncertainty by manipulating whether the advisor gave "approximate chance" advice (e.g., "There is about a 60% chance that the two teams will accumulate more than 15.5 hits.") or not (e.g., "The two teams will accumulate more than 15.5 hits."). We manipulated

advisor confidence by manipulating whether the advisor preceded their advice by saying “I am not sure, but I think that ...” or not.

We also manipulated across games whether the uncertain version of the advice offered a moderate probability (55% or 60%), an extreme probability (90 or 95%), or a probability in between (70% or 80%). Importantly, we computed the probabilities and hit thresholds so that participants received good advice for each game. First, we randomly assigned the six probabilities (55%, 60%, 70%, 80%, 90%, and 95%) to the six games. Second, using data from the 2015 MLB season, we could determine, for example, that roughly 60% of the games had more than 15.5 hits. Thus, for the game that was assigned the 60% probability, participants were asked to predict whether the two teams would accumulate more or fewer than 15.5 hits, and the advisor in the *approximate chance advice* condition said, “There is about a 60% chance that the two teams will accumulate more than 15.5 hits in this game.” The Online Supplement shows exactly which predictions participants made and what advice they received.

Advice evaluation. After receiving the advice, we asked participants to rate the advice. We used a different set of items to assess advice evaluation in this study than we used in Studies 1-6. Specifically, participants indicated how persuasive, accurate, good, and reliable the advice was, and how smart it was to follow the advice (1-7 scales; 1 = not at all, 7 = extremely). We averaged these five items to create a single measure of advice evaluation ($\alpha = .94$).

Incentivized predictions. We also asked participants to make their own predictions for each of the games and we incentivized them to be accurate. Participants predicted

whether the two teams would accumulate more or fewer hits than the hit threshold assigned to each game. Participants received a \$1 bonus for each correct prediction, and, since they made six predictions in this study, they could earn up to an additional \$6.

Motivation. We asked participants in this study to indicate how motivated they were to make accurate predictions (1 = not at all motivated, 7 = extremely motivated). Participants were made aware that their answer to this question would not affect their bonus payment.

MLB knowledge. At the end of the survey, we presented participants with the same six knowledge questions about Major League Baseball that we used in Studies 1-6.

Demographics. We also asked participants to indicate how closely they follow Major League Baseball (1 = “not at all closely” to 7 = “extremely closely”) and to indicate their favorite MLB team. Finally, we collected participants' age and gender.

Results

Analysis Plan

Each participant contributed six rows to the dataset, one for each of the games that they predicted. We pre-registered to run two different regression analyses for this study, one investigating only the effects documented in Studies 1-6 and the other that also investigated whether extreme uncertain advice was more preferable to more moderate uncertain advice. Because the latter regression answers all of the questions we are interested in here, it is the one that we report.

In what follows, we report the results from regressing the average advice evaluation on (1) the “not sure” condition (contrast-coded), (2) the approximate-chance condition

(contrast-coded), (3) the interaction between the “not sure” condition and the approximate-chance condition, (4) a mean-centered measure of the extremity of the uncertain advice, and (5) the interaction of this mean-centered measure of extremity and the approximate-chance condition. We clustered standard errors by participant. Because extremity varied across games, this regression did not include fixed effects for game.

Main Analysis

Consistent with the findings from Studies 1-6, there was a large and significant main effect of advisor confidence in this regression, $b = .873$, $SE = .064$, $t(308) = 13.67$, $p < .001$: Advisors who said “I am not sure but...” were evaluated more negatively than advisors who expressed themselves confidently.

More importantly, participants did *not* evaluate “approximate chance” advice more negatively than certain advice. In fact, they evaluated “approximate chance” advice more *positively* than certain advice, $b = .528$, $SE = .063$, $t(308) = 8.33$, $p < .001$. The interaction between the advisor confidence condition and the “approximate chance” advice condition was significant as well, $b = -.395$, $SE = .115$, $t(308) = -3.44$, $p = .001$. The preference for “approximate chance” advice was stronger when the advisor was unsure, $b = .725$, $SE = .085$, $t(305) = 8.51$, $p < .001$, than when the advisor was confident, $b = .330$, $SE = .086$, $t(305) = 3.85$, $p < .001$.

We also found a significant main effect of the extremity of the uncertain advice, $b = .018$, $SE = .002$, $t(308) = 11.19$, $p < .001$, and a significant interaction between this extremity measure and the approximate chance advice condition, $b = .021$, $SE = .004$, $t(308) = 5.69$, $p < .001$. As shown in Figure 1, this interaction indicates that people’s

preference for uncertain vs. certain advice was greater when the uncertain advice was associated with a larger probability.

Additional Analyses

Analyses of Advice Following

To assess whether participants were more likely to follow some types of advice rather than others, we followed the same analytic approach as in the previous section, regressing whether a participant followed the advice (0 = did not follow; 1 = followed) on (1) the “not sure” condition (contrast-coded), (2) the approximate-chance condition (contrast-coded), (3) the interaction between the “not sure” condition and the approximate-chance condition, (4) a mean-centered measure of the extremity of the uncertain advice, and (5) the interaction of this mean-centered measure of extremity and the approximate-chance condition. We clustered standard errors by participant.

This analysis generated three significant main effects. First, participants were more likely to follow advice from a confident advisor than from an unsure advisor, $b = .046$, $SE = .019$, $t(308) = 2.37$, $p = .018$. Second, participants were more likely to follow uncertain advice than certain advice, $b = .056$, $SE = .019$, $t(308) = 3.03$, $p = .003$. Third, participants were more likely to follow advice for games associated with an extreme probability, $b = .006$, $SE = .001$, $t(308) = 9.62$, $p < .001$, probably because advice for these games was more unambiguously wise.

Thus, participants in Study 7 not only judged uncertain advice more favorably than certain advice; they were also more likely to follow it.

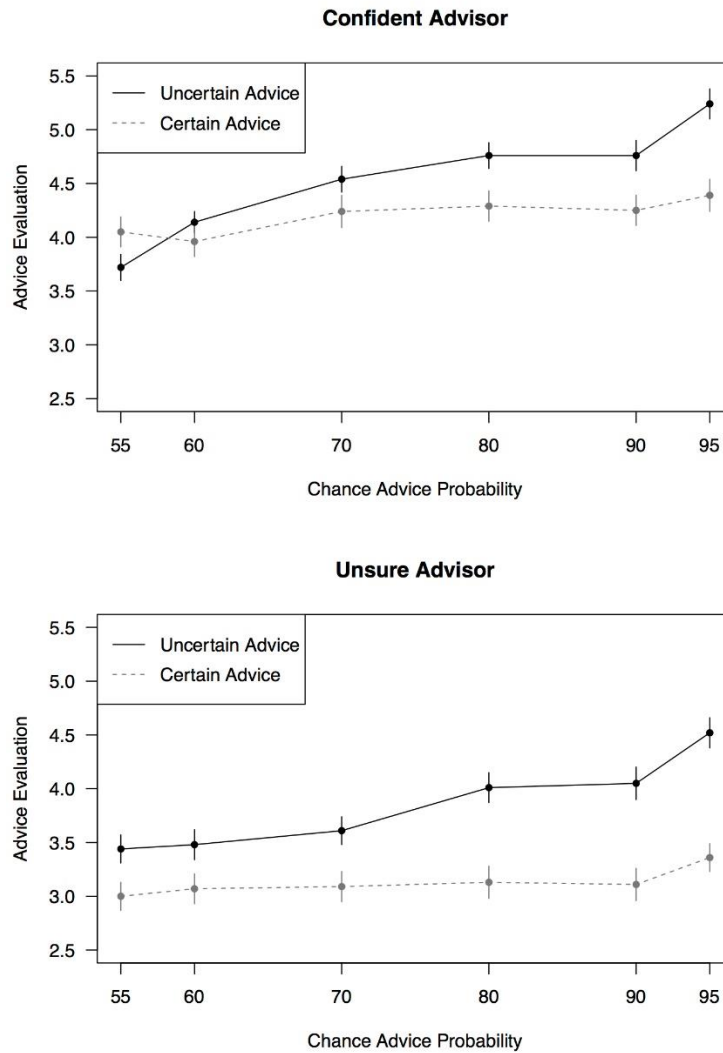


Figure 1. Results of Study 7: Mean advice evaluation as a function of the probability associated with the uncertain advice, separately for confident and unsure advisors. People’s more positive evaluation of uncertain versus certain advice is more pronounced when the uncertain advice (and thus the event itself) is associated with a more extreme probability. This is true both when the advisor is confident (top panel) and when the advisor is unsure (bottom panel). Error bars represent plus or minus one standard error.

Discussion

Study 7’s results confirm those of Studies 1-6: People do not seem to inherently dislike uncertain advice. In fact, we found the opposite, as people judged uncertain advice

more favorably than certain advice, especially when the uncertain advice contained a more extreme probability. This result is interesting, particularly as past work on risky decision-making suggests that people are less sensitive to the differences among middling probabilities and more sensitive to the difference between certainty and some degree of uncertainty (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Although that may be true about the perception of risky prospects, it does not appear to be true about the perception of advice. It seems that people prefer an advisor who correctly says that an event is about 95% likely over an advisor who simply says that the event will happen.

So far, participants in our studies were simply asked to rate the quality of advice. Thus, we do not know whether people will tolerate uncertain advice when people are directly choosing between two advisors, as they sometimes have to do. To investigate this, we conducted Studies 8 and 9.

STUDIES 8 AND 9

In Studies 8 and 9, we asked participants to predict baseball games and stock prices. For each item, they received similar advice from two advisors, one who provided certain advice and one who provided uncertain advice, and indicated which advisor they preferred. The two studies were very similar and so we describe them together.

Method

Participants

We conducted Studies 8 and 9 using U.S. participants from Amazon's Mechanical Turk (MTurk). We advertised Study 8 as a "survey for Major League Baseball (MLB)

fans” and we advertised Study 9 as a “survey about making stock predictions.” Participants received \$0.60 for completing each of the studies. In Study 8, participants could also earn an additional \$1 for accurate prediction performance. We decided in advance to recruit 400 participants for both studies. We analyzed data from all participants who indicated their advisor preference for at least one of the advisor pairs. This left us with a final sample of 408 participants in each study. The samples were 47% and 41% female and averaged 35 and 34 years, respectively.

Procedure

The two studies followed a similar procedure. Participants saw a series of four prediction questions (about baseball in Study 8 or stocks in Study 9), and for each one they received advice from two advisors. The advisors always agreed in their forecasts, but they differed in their certainty: One of the two advisors provided certain advice and the other advisor provided uncertain advice. For each advisor pair, we manipulated whether the certain advice was presented first (by Advisor 1) or second (by Advisor 2). Before making their own prediction, participants were asked to indicate which advisor they preferred. In each study, the four prediction questions were presented on the screen one at a time in randomized order. The two studies differed with respect to (1) the prediction domain and (2) the ways in which we manipulated advice uncertainty.

In Study 8, participants were asked to predict how many points would be scored in a series of baseball games. We randomly selected four games that were played on August 5, 2016, and that began no earlier than 7 pm. As in Studies 1-6, we posted the study on the morning of the game day to ensure that data collection was completed before the

games started and we provided participants with details about each game. Participants also saw advice from two advisors. The advisor who provided certain advice simply stated that, “The [predicted team] will win this game.” The advisor who provided uncertain advice either provided approximate chance advice (e.g., “There is about a 67% chance that the Chicago Cubs will win this game”) or used the words “more likely” (e.g., “The Chicago Cubs are more likely to win this game”). We manipulated between subjects which two games featured an advisor who provided approximate chance advice versus “more likely” advice. As in our previous studies in the domain of sports, participants received objectively good advice in all of the experimental conditions, which was based on data from well-calibrated betting markets.

In Study 9, participants were asked to predict the stock prices of four different companies. We randomly selected four companies from the 20 companies from the NASDAQ Stock Market with the largest market capitalization. Participants saw the name of the company and its stock symbol and were asked to predict whether the stock price of the company would be higher or lower in a year from the day the study was conducted. As in Study 8, participants saw advice from two advisors. The advisor who provided certain advice simply said that, “The stock price of [company] in a year will be higher [lower] than it is today.” The advisor who provided uncertain advice used the words “more likely” (e.g., “The stock price of Starbucks in a year is more likely to be higher than it is today”). Given that there is no objectively good advice for stock price predictions, we manipulated whether the two advisors predicted that the stock price would be higher versus lower in a year.

Dependent Measures

Advisor choice. After receiving the advice, we asked participants to indicate which advisor they preferred. In Study 8, participants indicated their preference by answering, “From which of the two advisors would you prefer to receive advice for upcoming games,” and, in Study 9, participants indicated their preference by answering the question, “From which of the two financial advisors would you prefer to receive advice for future stock predictions?”

Incentivized predictions. We also asked participants to make their own predictions. In Study 8, we incentivized participants to make accurate predictions by providing a \$1 bonus to all participants who predicted the winner of at least three of the four games correctly. Because in both studies the advisor who provided certain advice and the one who provided uncertain advice always agreed in their advice (i.e., they provided directionally consistent advice), analyses of participants’ own predictions could not tell us whether they more closely followed certain versus uncertain advice. Thus, we do not analyze participants’ own predictions.

Knowledge. At the end of each study, we presented participants with questions aimed at assessing their knowledge about the domain for which they made predictions. In Study 8, we assessed participants’ knowledge about baseball by asking them the same six MLB knowledge questions that we used in Studies 3-6. In Study 9, we asked participants to self-report how much they know about stocks in general and about each of the four companies using 7-point scales that ranged from 1 = “nothing” to 7 = “a lot.”

Demographics. At the end of the study, we assessed participants' age and gender. In Study 8, we also assessed participants' favorite MLB team.

Results

We preregistered to analyze the data of the two studies separately. However, for ease of presentation, we decided to merge the two studies into one dataset and to report the results of the merged dataset. Otherwise, the analyses follow our pre-registration plan. We provide the item-by-item results in Tables 6 and 7 and we report the results from the pre-registered analyses for the individual studies in the Online Supplement.

We conducted two separate regressions, one for the approximate chance advice condition (which we used only in Study 8) and one for the “more likely” advice condition (which we used in both Study 8 and Study 9). In each analysis, we regressed whether or not the participant chose Advisor 2 (1 = yes; 0 = no) on whether Advisor 2 provided uncertain or certain advice (1 = uncertain advice; 0 = certain advice). We included fixed effects for game/item and clustered standard errors by participant. We present the results from OLS regressions here because the coefficients are easy to interpret (i.e., as percentage point differences between conditions); logistic regressions yielded nearly identical results.

In both regressions, we found a large and significantly *positive* effect of the uncertain advice condition, indicating that more participants preferred Advisor 2 when Advisor 2 provided uncertain advice than when Advisor 2 provided certain advice. This was true both when the uncertain advice came in the form of approximate chance advice and in the form of “more likely.” When one advisor provided certain advice and the other

approximate chance advice, 82.4% of participants chose Advisor 2 when Advisor 2 provided approximate chance advice, but only 16.2% of participants chose Advisor 2 when Advisor 2 provided certain advice, $b = .661$, $SE = .032$, $t(407) = 20.39$, $p < .001$. When one advisor provided certain advice and the other “more likely” advice, 70.7% of participants chose Advisor 2 when Advisor 2 provided “more likely” advice, but only 28.0% of participants chose Advisor 2 when Advisor 2 provided certain advice, $b = .427$, $SE = .030$, $t(810) = 14.09$, $p < .001$.

Thus, as in Study 7, participants seemed to actually prefer advisors who provided uncertain advice to advisors who provided certain advice. It is possible that we observed this effect because participants who disagree with the advice perceive the uncertain advice to be less wrong than the certain advice. For example, if a participant believes that the Reds are going to beat the Pirates, but an advisor tells them that the Pirates are going to beat the Reds, the participant may prefer the advisor who says that the Reds *might* win rather than an advisor who implies that they definitely will not. To examine the viability of this explanation, we re-ran the analyses, restricting the sample to those instances in which the participant gave the same prediction as the advisor, and thus agreed with the advice. This did not impact the results. Even when analyzing only those who agreed with the advice, we found that participants in Studies 8 and 9 strongly preferred the uncertain advice to the certain advice ($ps < .001$).

Together, these results demonstrate a strong preference for uncertain advice over certain advice when participants are faced with an explicit choice.

Table 6. Study 8: Percentage of Participants Who Chose Advisor 2 by Game

Uncertain Advice	Predicted Winner	Predicted Loser	Winning Probability	Percentage of Participants Who Chose Advisor 2			
				When Advisor 2 Gave Uncertain Advice		When Advisor 2 Gave Certain Advice	
				<i>N</i>	<i>M</i>	<i>N</i>	<i>M</i>
Approximate Chance	Pirates*	Reds	59%	103	80.6%	101	22.8%
	Astros*	Rangers	62%	103	85.4%	101	11.9%
	Mariners*	Angels	63%	101	82.2%	102	15.7%
	Cubs*	Athletics	67%	101	81.2%	103	14.6%
"More Likely"	Pirates*	Reds	59%	103	81.6%	100	21.0%
	Astros*	Rangers	62%	100	69.0%	103	22.3%
	Mariners*	Angels	63%	101	80.2%	103	18.4%
	Cubs*	Athletics	67%	101	73.3%	102	24.5%

Note. The actual winner of each game is marked with an asterisk (*).

Table 7. Study 9: Percentage of Participants Who Chose Advisor 2 by Item

Advice Direction	Company	Percentage of Participants Who Chose Advisor 2			
		When Advisor 2 Gave "More Likely" Advice		When Advisor 2 Gave Certain Advice	
		<i>N</i>	<i>M</i>	<i>N</i>	<i>M</i>
Higher in a year	Comcast	101	65.3%	101	25.7%
	Starbucks	101	60.4%	101	28.7%
	The Priceline Group	91	65.9%	110	30.0%
	Qualcomm	88	72.7%	113	31.0%
Lower in a year	Comcast	101	72.3%	99	32.3%
	Starbucks	100	73.0%	100	31.0%
	The Priceline Group	111	66.7%	90	33.3%
	Qualcomm	114	68.4%	88	39.8%

GENERAL DISCUSSION

In eleven studies, we found that people do not inherently dislike uncertain advice. We observed this in studies of sports, weather, and stocks. We observed this in studies that operationalized uncertain advice as imprecision, as statements of numerical probability, and as statements of non-numerical uncertainty. And we observed this in studies in which people directly evaluated the advice and in studies that asked people to choose between an advisor who provided certain advice versus one who provided uncertain advice. The

only reliable distaste for uncertainty that we observed was that people seem to not like it when confident advisors use the word “probably,” and even this effect was not evident when the word “probably” was used by the first advisor that they saw. Taken together, our results challenge the belief that advisors need to provide false certainty for their advice to be heeded. Advisors do not have a realistic incentive to be overconfident, as people do not judge them more negatively when they provide realistically uncertain advice.

Although we investigated various forms of uncertain advice in our studies, we cannot conclude that people are never less tolerant of uncertain advice. We can speculate that people may prefer certain advice in domains in which they expect to receive certain advice, or in circumstances in which they want advisors to be persuasive rather than informative. For example, a manager who *wants* to hire a particular job candidate may prefer to hear that that candidate is definitely the best one rather than probably the best one. These idiosyncratic possibilities aside, our investigation should lay to rest the belief that people are generally and inherently intolerant of uncertain advice.

CHAPTER 2

WHY (AND WHEN) ARE UNCERTAIN PRICE PROMOTIONS MORE EFFECTIVE THAN EQUIVALENT SURE DISCOUNTS?

Celia Gaertig

Joseph P. Simmons

ABSTRACT

Past research suggests that offering customers an uncertain promotion, such as an X% chance to get a product for free, is always more effective than providing a sure discount of equal expected value. In seven studies (N = 11,238), we find that uncertain price promotions are more effective than equivalent sure discounts only when those sure discounts are or seem small. Specifically, we find that uncertain promotions are relatively more effective when the sure discounts are actually smaller, when the sure discounts are made to feel smaller by presenting them alongside a larger discount, and when the sure discounts are made to feel smaller by framing them as a percentage-discount rather than a dollar amount. These findings are inconsistent with two leading explanations of consumers' preferences for uncertain over certain promotions – diminishing sensitivity and the overweighting of small probabilities – and suggest that people's preferences for uncertainty are more strongly tethered to their perceptions of the size of the sure outcome than they are to their perceptions of the probability of getting the uncertain reward.

INTRODUCTION

It is hard to go a day without being exposed to a price promotion, and that is because price promotions are among the most important tools in the marketer's arsenal. The vast majority of price promotions come in the form of sure discounts, meaning that consumers know for sure what price discount they will receive with their purchase. However, retailers sometimes introduce *uncertain* price promotions, those that offer a probabilistic discount. For example, several companies, including Dell, Banana Republic, Glasson, and hotels.com, have launched mystery coupon campaigns that offer consumers an unknown discount on a purchase. Some of those coupons offer consumers 100% off of the sale price, thus giving them the product for free. Similarly, some companies, such as Media Markt, have offered a 100% discount to every 10th or 100th customer (see also Mazar, Shampanier, & Ariely, 2017).

Given that these two types of price promotions co-exist in the marketplace, it is natural to ask which is better: offering consumers a sure discount on a purchase, or offering them an X% chance to get the product at an even greater discount? Although the ubiquity of sure discounts might lead one to infer that they are more effective, recent research on this question suggests the opposite: Consumers seem to prefer uncertain promotions to equivalent promotions that offer a discount or reward with certainty (Goldsmith & Amir, 2010; Mazar et al., 2017; also see Shen, Fishbach, & Hsee, 2014). In an important paper, Mazar, Shampanier, and Ariely (2017) report the results from several experiments in which they found that people were more likely to purchase a product when it came with a chance to get it for free than when it came with a sure price discount

of equal expected value. This suggests that marketers should make more use of uncertain promotions than they currently do.

Mazar, Shampanier, and Ariely's (2017) explanation for why people tend to prefer uncertain price promotions to equivalent sure discounts hinges on consumers' diminishing sensitivity to increasing prices, the fact that consumers are less sensitive to changes in price as the price increases. For example, consumers tend to value saving \$10 on a \$20 purchase more highly than they value saving \$10 on a \$2,000 purchase. This basic psychophysical fact is captured in Tversky and Kahneman's (1981) classic jacket-and-calculator experiment, in which they found that more people were willing to travel 20 minutes to receive \$5 off of a \$15 calculator than to receive \$5 off of a \$125 jacket.

To understand why diminishing sensitivity to prices would result in a preference for uncertain price promotions over equivalent sure discounts, let's consider a product originally priced at \$10. Imagine that this product is offered either with a sure discount of 20% off or with a 20% chance to get it for free (hereafter called the "chance-for-free promotion"). Importantly, these two promotions offer the same expected value for the price of the product, namely \$8. According to diminishing sensitivity, the value of a price, $v(x)$, is equal to x^α , where $\alpha < 1$. Prior research suggests that $\alpha = .88$ in some contexts (Prelec, 1998), so we will use that value for this example.

In this example, the value of the sure discount is equal to the value of the original price ($\$10^{.88} = \7.59) minus the value of the discounted price ($\$8^{.88} = \6.23), which is \$1.36. The value of the chance-for-free promotion is equal to the value of the original price ($\$10^{.88} = \7.59) minus the value of the original price times the probability of paying

the original price ($\$7.59(.80) = \6.07), which is $\$1.52$. Thus, the chance-for-free promotion ($\$1.52$) is valued more highly than the sure discount ($\$1.36$).

Indeed, it is generally true that when a sure discount and a chance-for-free promotion result in the same expected value for a product, and the chance-for-free promotion offers a p chance to get the product for free, then diminishing sensitivity means that the value of the chance-for-free promotion will always be higher than the value of the sure discount (Mazar et al., 2017). This is because, under diminishing sensitivity, the discounted price will always feel larger than a $(1-p)$ chance of getting the regular price. A diminishing sensitivity explanation of consumers' price promotion preferences therefore predicts that consumers will always prefer a chance-for-free promotion to a sure discount of equal expected value.⁴

In this article, we provide evidence for a different explanation for why people would prefer an uncertain chance-for-free promotion to a sure discount of equal expected value, one that does not predict that people will always prefer chance-for-free promotions to sure price discounts. Specifically, we suggest that a chance-for-free promotion will be more effective than a sure discount of equal expected value only when the sure discount

⁴ Mazar, Shampanier, and Ariely (2017) also considered a version of their diminishing sensitivity account that incorporates the probability weighting function of prospect theory. This account makes two unique predictions: (1) consumers will be more likely to prefer uncertain promotions over sure discounts when the probability of obtaining the uncertain promotion is smaller, and (2) consumers will prefer the uncertain promotion unless the probability of obtaining the uncertain promotion is quite large (e.g., greater than .6). Although their findings do not definitively rule out the operation of probability weighting, they do seem to be more consistent with an account of diminishing sensitivity that does *not* incorporate probability weighting. Indeed, Mazar, Shampanier, and Ariely (2017) conclude that “our findings may be better explained by diminishing sensitivity to prices without weighted probabilities” (p. 257). Thus, we focus here on what happens under diminishing sensitivity in the absence of probability weighting.

feels trivially small. When the sure discount feels large, consumers will be more likely to prefer the sure discount to an equivalent chance-for-free promotion.

The notion that the size of the sure discount is likely to matter for people's choices is in line with previous work on the "peanuts effect" (Markowitz, 1952; Prelec & Loewenstein, 1991; Weber & Chapman, 2005). Although decision-makers are generally risk averse (Kahneman & Tversky, 1979), it has been demonstrated that risk-aversion decreases with decreasing monetary amounts (Prelec & Loewenstein, 1991; Weber & Chapman, 2005). That is, decision-makers are more willing to take risks when playing for smaller monetary amounts, an effect termed the "peanuts effect." Nevertheless, our hypothesis does not follow directly from past work on the peanuts effect. Whereas previous research suggests that the psychology of "peanuts" applies only to objectively minuscule amounts (e.g., cents), we will show that it applies to any amount that seems small within the context in which it is considered. For example, we will suggest that a discount of \$11 can feel like almost nothing at all in the context of a very large amount, and that in such cases, people will forego that discount in order to pursue a chance at a larger discount.

Although our hypothesis is straightforward, its implications are far-reaching, both theoretically and practically. Theoretically, our hypothesis implies that diminishing sensitivity and related theories cannot explain consumers' preferences for uncertain promotions. Practically, it suggests that any manipulation that makes a sure discount *seem* small will increase the relative effectiveness of a chance-for-free promotion. Thus, our account suggests that chance-for-free promotions will not only be more effective

when sure discounts are *objectively* small, but that they will also be more effective when objectively sizable sure discounts are considered within a context that makes them feel small or framed in way that makes them feel small. For example, we will show that how you frame discounts – as percent reductions vs. dollars off – can change how big a sure discount feels, and thus whether consumers prefer a chance-for-free promotion or the sure discount. In so doing, we will demonstrate that chance-for-free promotions are not always more effective than equivalent sure discounts, and we will delineate the conditions under which they are.

RESEARCH OVERVIEW

Our research investigates whether consumers' preferences for a chance-for-free promotion over a sure discount are influenced by how small or large the sure discount feels. We focused on investigating uncertain promotions that offered a chance to get a product for free because such promotions have been a primary focus of prior research (Mazar et al., 2017), and because consumers (and survey takers) are likely to easily understand them. For example, it is probably easier for consumers to compute the expected value of a 10% chance of getting a \$400 product for free than to compute the expected value of a 50% chance of getting a \$400 product at an 80% discount.

Across seven studies, we used different strategies to make a sure discount be/feel large or small, including (1) varying the percentage associated with it (e.g., 10% vs. 1%), (2) varying the price of the product (e.g., \$480 vs. \$48), (3) varying whether or not the discount was presented in the context of a larger discount, and (4) varying whether the sure discount was presented as a dollar amount or a percentage. In line with prior

research, we measured consumers' preferences either by assessing whether they chose a promoted product over competing products or by directly asking them to choose between an uncertain promotion and a sure discount for a given product.

We report all of our measures, manipulations, exclusions, and how we determined our sample sizes. We pre-registered all of our studies, and we provide the link to the pre-registrations in the Appendix. All of our data and materials are available at this link: <https://tinyurl.com/UncertainPromotions>.

STUDIES 1A AND 1B

In Studies 1a and 1b, we asked participants to choose among three hotels, one of which came with a promotion. We manipulated whether the promotion was certain or uncertain by manipulating whether it came in the form of a sure discount or a chance-for-free promotion, and we manipulated whether the sure discount was small or large by manipulating the percentage associated with the promotion. For example, in the “1%” condition of Study 1a, participants either learned that the \$210 hotel was offering a sure discount of 1% off of the original price of the hotel (i.e., \$2.10 off) or that it was offering a 1% chance to get the hotel booking for free. Similarly, in the “10%” condition of Study 1a, participants either learned that the \$210 hotel was offering a sure discount of 10% off of the original price of the hotel (i.e., \$21 off) or that it was offering a 10% chance to get the hotel booking for free. We expected that participants would be more likely to forego the sure discount when it was relatively small (\$2.10) than when it was relatively large

(\$21), and thus that the chance-for-free promotion would be relatively more effective in the “1%” condition than in the “10%” condition.

Method

Participants

We conducted Studies 1a and 1b using U.S. participants from Amazon.com’s Mechanical Turk (MTurk). Participants received \$0.30 for participation. In Studies 1a and 1b, we decided in advance to recruit 1,500 and 2,100 participants, and we wound up with final samples of 1,502 and 2,039 participants, respectively.⁵ The final sample for each study included all participants who indicated which hotel they would choose. As pre-registered, in Study 1b, we kept only the first response from IP addresses that appeared more than once in the dataset (resulting in 32 exclusions), and we excluded any data from participants whose IP addresses were identical to those in Study 1a (31 participants). The final samples of Studies 1a and 1b averaged 37 and 36 years of age and were 56% and 53% female, respectively.

Procedure

In each of Studies 1a and 1b, we asked participants to imagine that they were choosing among three hotels for an upcoming trip to Chicago. We presented participants

⁵ We have heard about recent cases in which reviewers criticized studies for having samples that were ostensibly too large. We have two things to say about this. First, samples simply cannot be too large, as the false-positive rate of a statistical test is unchanged by how large the sample size is (Simmons 2013). That is, in the presence of a truly null effect, a significant result will emerge only 5% of the time, regardless of how small or large the sample is. Large samples increase the precision of effect size estimates; they do not increase false-positive rates, and they do not alter the size of the effect. Second, although the samples we used in these studies will appear large to some readers, they are arguably not large enough. To have 80% power to detect a fairly large difference in choice shares between conditions on the order of 45% vs. 55%, you need to have more than *600 per cell*. To have 80% power to fully attenuate this effect in a 2 x 2 between-subjects design, you need about *1,200 per cell*, or *4,800* participants in total. That is why our samples are so large in these studies.

with screenshots of each of the three hotels from an online booking website (see Figures 2 and 3). Each screenshot showed a picture of the hotel, its name, price, address, how far it was from downtown Chicago, as well as its average rating, including the number of reviews the hotel had received. In Study 1b, the screenshots also showed when each hotel was last booked. The hotels for each study were similar in price and formed a realistic choice set. For Study 1a, participants saw three hotels priced at \$210, \$209, and \$200, and for Study 1b, participants saw three hotels priced at \$90, \$89, and \$84. In each study, the three hotels were presented to participants in descending order of price, and the hotel for which we manipulated the promotion was presented first in the choice set (and thus was the highest-priced hotel before applying the discount).

Participants learned about the promotion via a note that appeared above the hotel screenshots (see Figures 2 and 3). Participants in Study 1a were randomly assigned to either a No Discount baseline condition or to one of four promotion conditions from a 2 (promotion certainty: certain vs. uncertain) x 2 (promotion percentage: 1% vs. 10%) between-subjects designs. In Study 1b, we included an additional percentage of 5%, thus leading to seven conditions in total for that study.

In both studies, we manipulated whether the promotion was certain or uncertain by manipulating whether the promoted hotel came with a sure discount of X% or with an X% chance of the booking being entirely free (hereafter called the “chance-for-free promotion”). For example, in Study 1b, the note for the sure-discount condition said, “All rooms booked in the next hour will get an X% discount and that discount is not reflected in the price below,” and the note for the chance-for-free promotion said, “All rooms

booked in the next hour will have an X% chance of being entirely free.” The percentage X associated with the promotions was 1% or 10% in Study 1a and 1%, 5%, or 10% in Study 1b. Table 8 displays the exact wording of the manipulations in both studies.

Participants were asked to indicate which of the three hotels they would choose, and we measured whether or not participants chose the promoted hotel (1 = they chose the promoted hotel; 0 = they chose one of the other two hotels). At the end of the study, we assessed participants’ age and gender.

Imagine you had to select one of the following three rooms for an upcoming trip to Chicago, which would you choose? (click on the hotel to make your selection)

Note: The Buckingham is offering a promotion where all rooms booked in the next hour have a 10% chance of being entirely free.

The screenshot displays three hotel listings, each with a radio button for selection. The first listing is for The Buckingham Athletic Club, priced at \$210 (total \$242), with a 4.4/5 user rating and 9 reviews. The second listing is for The James Hotel Chicago, priced at \$209 (total \$238), with a 4.5/5 user rating and 50 reviews. The third listing is for Residence Inn Chicago Downtown/River North, priced at \$200 (total \$231), with no reviews. Each listing includes a 'Select' button, a 'Like' button, and a 'Be the first of your friends to like this.' prompt. The listings also show the number of sites available for each hotel and a distance from the user's location.

Hotel Name	Price	Total Price	User Rating	Reviews	Distance
The Buckingham Athletic Club	\$210	\$242	4.4/5	9	0.6 mi
The James Hotel Chicago	\$209	\$238	4.5/5	50	0.6 mi
Residence Inn Chicago Downtown/River North	\$200	\$231	No reviews	0	0.4 mi

Figure 2. Stimulus presented in Study 1a (uncertain-promotion condition).

Imagine you had to select one of the following three hotel rooms for an upcoming trip to Chicago.

Which hotel room would you choose?

(Please click on the hotel to make your selection.)

Note: The Ramada Plaza is offering a promotion. All rooms booked in the next hour will have a 10% chance of being entirely free.

The screenshot displays three hotel listings, each with a radio button for selection. The first listing is for Ramada Plaza Chicago North Shore, a 3-star hotel in Wheeling, IL, priced at \$90. It has a 'Good 7.8' review score from 206 guests and offers free cancellation. The second listing is for Edward Hotel Chicago, a 3-star hotel in Rosemont, IL, priced at \$89. It has a 'Very Good 8.0' review score from 948 guests and offers free cancellation. The third listing is for Best Western Plus Chicago Hillside, a 3-star hotel in Hillside, IL, priced at \$84. It has a 'Good 7.4' review score from 349 guests and offers free cancellation. All listings include a 'Choose Room' button and a 'Collect nights' icon.

Figure 3. Stimulus presented in Study 1b (uncertain-promotion condition).

Table 8. Wording of the manipulations used in Studies 1a and 1b.

Study	Name of the Promoted Hotel	Price of the Promoted Hotel	Example Wording of the Manipulations	
			Sure Discount	Chance to Get For Free
1a	"Buckingham"	\$210	Note: The Buckingham is offering a 10% discount to reservations made in the next hour and that discount is not reflected in the price below.	Note: The Buckingham is offering a promotion where all rooms booked in the next hour have a 10% chance of being entirely free.
1b	"Ramada Plaza"	\$90	Note: The Ramada Plaza is offering a promotion. All rooms booked in the next hour will get a 10% discount and that discount is not reflected in the price below.	Note: The Ramada Plaza is offering a promotion. All rooms booked in the next hour will have a 10% chance of being entirely free.

Notes. In Study 1a, we manipulated the percentage associated with the promotion to be 1% or 10%, and, in Study 1b, we manipulated it to be 1%, 5%, or 10%.

Results and Discussion

Comparing the promotion conditions to the No Discount condition

Following our pre-registration, we first tested whether participants' likelihood of choosing the promoted hotel in each of the promotion conditions differed significantly from the No Discount baseline condition. We ran separate regression analyses for Studies 1a and 1b. In each analysis, we regressed whether participants chose the promoted hotel (1 = they chose the promoted hotel; 0 = they chose one of the other two hotels) on each of the promotion conditions.⁶

Table 9 shows what percentage of participants chose the promoted hotel in each condition. In Study 1a, each of the four promotion conditions significantly differed from the No Discount condition (all $ps < .001$). In Study 1b, five of the six promotion conditions significantly differed from the No Discount condition ($ps \leq .001$), though the 1% Sure Discount condition did not ($p = .705$). Thus, offering a promotion was generally effective in our studies.

Main analyses

As pre-registered, for our main analyses, we dropped the No Discount baseline condition and focused on the promotion conditions to test whether the certainty of the promotion and the percentage associated with it influenced participants' likelihood of choosing the promoted hotel. We ran separate regression analyses for each of Studies 1a and 1b. In Study 1a, we regressed whether participants chose the promoted hotel (1 =

⁶ In all of our studies that used choice as a dependent variable, we pre-registered to analyze the data using OLS regressions rather than logistic regressions, because the two analyses produce nearly identical results and because OLS coefficients are easier to interpret (i.e., as the percentage-point difference between conditions). In only one case in this paper (specified in Study 1b) did the use of logistic regression change the significance of a result.

they chose the promoted hotel; 0 = they chose one of the other two hotels) on (1) the promotion certainty condition (contrast-coded), (2) the percentage condition (contrast-coded), and (3) their interaction. In Study 1b, we regressed whether participants chose the promoted hotel (1 = they chose the promoted hotel; 0 = they chose one of the other two hotels) on (1) the promotion certainty condition (contrast-coded), (2) the “5%” condition (contrast-coded), (3) the “10%” condition (contrast-coded), (4) the interaction between the promotion certainty condition and the “5%” condition, and (5) the interaction between the promotion certainty condition and the “10%” condition.

In Study 1a, in which the promoted hotel was priced at \$210, participants were more likely to choose the promoted hotel when it came with a chance-for-free promotion than when it came with a sure discount, $b = .061$, $SE = .027$, $t(1,200) = 2.25$, $p = .025$. Participants were also more likely to choose the promoted hotel when the percentage associated with the promotion was 10% than when it was 1%, $b = .199$, $SE = .027$, $t(1,200) = 7.29$, $p < .001$. However, a significant interaction, $b = -.176$, $SE = .054$, $t(1,200) = -3.22$, $p = .001$, revealed that the chance-for-free promotion only made people more likely to choose the promoted hotel in the “1%” condition, $b = .149$, $SE = .036$, $t(598) = 4.12$, $p < .001$. In the “10%” condition there was a slight and nonsignificant tendency for the sure discount to be more effective than the chance-for-free promotion, $b = -.027$, $SE = .041$, $t(601) = -.65$, $p = .515$. That is, for a hotel priced at \$210, people seem to be indifferent between receiving a sure discount of 10% (\$21) on their booking or a 10% chance to get the booking for free. However, when the percentage is 1% and

thus the sure discount is small (\$2.10), the chance-for-free promotion is more effective than the sure discount.

In Study 1b, in which the promoted hotel was priced at \$90, we also found that participants were more likely to choose the promoted hotel when it came with a chance-for-free promotion than when it came with a sure discount, $b = .069$, $SE = .017$, $t(1,745) = 4.16$, $p < .001$. Furthermore, participants were more likely to choose the promoted hotel when the percentage associated with the promotion was 10% than when it was 1%, $b = .167$, $SE = .027$, $t(1,745) = 6.16$, $p < .001$, and when it was 5% than when it was 1%, $b = .092$, $SE = .027$, $t(1,745) = 3.39$, $p = .001$. Neither the interaction between the discount certainty condition and the “10%” condition ($p = .429$), nor the interaction between the discount certainty condition and the “5%” condition ($p = .689$) was significant.⁷ However, looking at Study 1b’s results more closely, we see a trend toward the chance-for-free promotion being more effective as the size of the sure discount decreased (see Table 9). Indeed, although the 1% chance-for-free promotion was significantly more effective than the sure discount of \$0.90, the 10% chance-for-free promotion was not significantly more effective than the sure discount of \$9.

Taken together, the results of Studies 1a and 1b suggest that chance-for-free promotions will be more effective when the size of the sure discount is smaller. Of course, manipulating the size of the sure discount by manipulating the percentage associated with the promotion raises the question of whether the effect we observed is

⁷ Using logistic regression, the interaction between the discount certainty condition and the “10%” condition is significant, $b = .281$, $SE = .154$, $t(1,745) = -2.31$, $p = .021$, and the interaction between the discount certainty condition and the “5%” condition is marginally significant, $b = .380$, $SE = .217$, $t(1,745) = -1.70$, $p = .090$.

driven by the perceived size of the sure discount, or by people’s greater preference for gambles that offer smaller probabilities (i.e., via overweighting of small probabilities; Kahneman & Tversky, 1979).⁸ If the effect is driven by people’s perceptions of the size of the sure discount, then a 10% chance-for-free promotion should be relatively more effective than an equivalent sure discount of 10% when the original price of the product is small than when the original price of the product is large, because the absolute sure discount will be smaller when the original price is smaller. We tested this in Study 2.

Table 9. Results for Studies 1a and 1b.

Study	Price of the Promoted Hotel	Percentage Associated with the Promotion	Size of the Sure Discount	Percentage of Participants Who Chose the Promoted Hotel		Pairwise Comparison
				Sure Discount	Chance to Get For Free	
1a	\$210	1%	\$2.10	20.2%	35.1%	$b = .149, SE = .036, p < .001$
		10%	\$21	48.8%	46.2%	$b = -.027, SE = .041, p = .515$
1b	\$90	1%	\$0.90	3.8%	12.3%	$b = .085, SE = .022, p < .001$
		5%	\$4.50	11.5%	18.4%	$b = .069, SE = .029, p = .019$
		10%	\$9	17.9%	23.2%	$b = .053, SE = .034, p = .115$

Notes. In Studies 1a and 1b, 7.6% and 2.7% of participants, respectively, chose the promoted hotel in the No Discount condition.

STUDY 2

Study 2 was very similar to Studies 1a and 1b. However, in this study, instead of manipulating the percentage associated with the promotions, we manipulated the size of the sure discount by manipulating the price of the hotel for which the discount was offered.

⁸ We will rule out this alternative in the subsequent studies (including Study 2), but it is worth mentioning that there really is not good evidence that people generally overweight small probabilities. First of all, Kahneman and Tversky (1979) themselves suggested that although sometimes people will overweight small probabilities, they will sometimes edit them down to zero (and thus underweight them). Second, as mentioned in Footnote 1, Mazar, Shampanier, and Ariely (2017) results were at least somewhat inconsistent with people overweighting small probabilities. Third, Green, Lee, and Rothschild (2018) have recently shown that what was considered one of the best real-world examples of people’s tendency to overweight small probabilities – the favorite-longshot bias in horse betting – is actually caused by bettors’ reliance on biased information that the race tracks give them.

Method

Participants

We conducted Study 2 using U.S. participants from Amazon.com's Mechanical Turk (MTurk). Participants received \$0.50 for participation. We decided in advance to recruit 2,400 participants for this study, and we wound up with a final sample of 2,302 participants (average age = 37 years; 55% female). The final sample included all participants who indicated their choice, but, as pre-registered, we kept only the first response from IP addresses that appeared more than once in the dataset (resulting in 46 exclusions), and we excluded any participants whose IP addresses were identical to those of participants in Studies 1a and 1b (69 participants).

Procedure

The general procedure of this study was very similar to the procedure of Studies 1a and 1b. We presented participants with screenshots of three hotels and asked them to indicate which hotel they would choose. In this study, participants imagined that they were choosing among three hotels for a trip to the Jersey Shore (see Figure 4). As in Studies 1a and 1b, the hotel that appeared first in the choice set was the promoted hotel.

We manipulated both the promotion type and the price of the promoted hotel. Participants were randomly assigned to one of four conditions from a 2 (promotion certainty: certain vs. uncertain) x 2 (price of promoted hotel: low vs. high) between-subjects design. We manipulated the certainty of the promotion by manipulating whether the promoted hotel came with a sure discount or with a chance of being entirely free, and we held the percentage associated with these promotions constant at 10%. As in Studies

1a and 1b, participants learned about the promotion via a note that appeared above the hotel screenshots. The wording of this note was the same as in Study 1b, except that the name of the hotel was "Econo Lodge." We manipulated the price of the promoted hotel to be low or high by manipulating whether we displayed the hotel's one-night price (\$48) or the 10-night total (\$480). In so doing, we also manipulated the size of the sure discount, as it was \$4.80 for a one-night price of \$48, and \$48 for the 10-night price of \$480.⁹ The prices of the other two hotels were manipulated accordingly, with one-night prices of \$44 and \$42 in the low-price conditions, and 10-night prices of \$440 and \$420 in the high-price conditions.

As in Studies 1a and 1b, we asked participants to indicate which of the three hotels they would choose, and we measured whether or not participants chose the promoted hotel (1 = they chose the promoted hotel; 0 = they chose one of the other two hotels). At the end of the study, we assessed participants' age and gender.

⁹ Because participants in both conditions were considering a discount of 10%, this manipulation should have no effect if consumers' evaluation of discount size is based entirely on percentages rather than on absolute amounts. We think that consumers' evaluation of discount size is likely to be based partly on their evaluation of the size of the percent discount, and partly on the absolute size of the discount (see also Darke & Freeman, 1993). For example, we suspect that at least some people would consider a 10% discount off the cost of a house to be larger than a 10% discount off the cost of a candy bar. As long as this is true, then our manipulation should cause participants to feel that the 10% discount is larger when the original price is \$480 than when it is \$48.

Low-Price Condition


The hotels' prices are displayed as one-night prices:

Imagine you had to select one of the following three hotel rooms for an upcoming trip to the Jersey Shore. Which hotel room would you choose?

(Please click on the hotel to make your selection.)

Note: The Econo Lodge is offering a promotion. All rooms booked in the next hour will have a 10% chance of being entirely free.

Econo Lodge Somers Point (Last booked 10 hours ago)
21 Macarthur Blvd. Somers Point, NJ. 08244 United States. 866-925-8676




Somers Point
• 2.7 miles to Ocean City
• 9.7 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

Good 6.2
120 Hotels.com guest reviews
164 reviews

\$48
Choose Room

Quality Inn Pleasantville (Booked 1 hour ago)
1012 Black Horse Pike, Pleasantville, NJ. 08232 United States. 866-539-9234

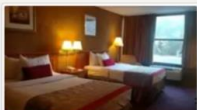


Pleasantville
• 8.3 miles to Ocean City
• 4.2 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

Good 6.8
218 Hotels.com guest reviews
89 reviews

\$44
Choose Room

Ramada West Atlantic City (Last booked 7 hours ago)
8037 Black Horse Pike, Pleasantville, NJ. 08232 United States. 866-538-1314



Pleasantville
• 8.3 miles to Ocean City
• 6.7 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

5.6
659 Hotels.com guest reviews
644 reviews

\$42
Choose Room

High-Price Condition


The hotels' prices are displayed as 10-night prices:

Imagine you had to select one of the following three hotel rooms for an upcoming trip to the Jersey Shore. Which hotel room would you choose?

(Please click on the hotel to make your selection.)

Note: The Econo Lodge is offering a promotion. All rooms booked in the next hour will have a 10% chance of being entirely free.

Econo Lodge Somers Point (Last booked 10 hours ago)
21 Macarthur Blvd. Somers Point, NJ. 08244 United States. 866-925-8676




Somers Point
• 2.7 miles to Ocean City
• 9.7 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

Good 6.2
120 Hotels.com guest reviews
164 reviews

\$480
Your 10 night total
Choose Room

Quality Inn Pleasantville (Booked 1 hour ago)
1012 Black Horse Pike, Pleasantville, NJ. 08232 United States. 866-539-9234




Pleasantville
• 8.3 miles to Ocean City
• 4.2 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

Good 6.8
218 Hotels.com guest reviews
89 reviews

\$440
Your 10 night total
Choose Room

Ramada West Atlantic City (Last booked 7 hours ago)
8037 Black Horse Pike, Pleasantville, NJ. 08232 United States. 866-538-1314



Pleasantville
• 8.3 miles to Ocean City
• 6.7 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

5.6
659 Hotels.com guest reviews
644 reviews

\$420
Your 10 night total
Choose Room

Figure 4. Stimuli presented in Study 2 (uncertain-promotion condition).

Results and Discussion

Figure 5 displays the results. Participants were more likely to choose the promoted hotel when it came with a chance-for-free promotion than when it came with a sure discount, $b = .057$, $SE = .021$, $t(2,301) = 2.76$, $p = .006$, and when the price was low (\$48) than when it was high (\$480), $b = .041$, $SE = .021$, $t(2,301) = 2.01$, $p = .045$. However, a significant interaction between the discount certainty condition and the price condition, $b = .084$, $SE = .041$, $t(2,301) = 2.04$, $p = .041$, revealed that the difference between the two promotion types was only significant for the low-price condition, $b = .099$, $SE = .029$, $t(1,155) = 3.39$, $p = .001$, but not for the high-price condition, $b = .015$, $SE = .029$, $t(1,145) = .51$, $p = .609$. Thus, the smaller the sure discount, the more likely the chance-for-free promotion was to outperform the sure discount. Because the percentage associated with the promotion was held constant at 10% in this study, this effect cannot be explained by consumers' overweighting of small probabilities.

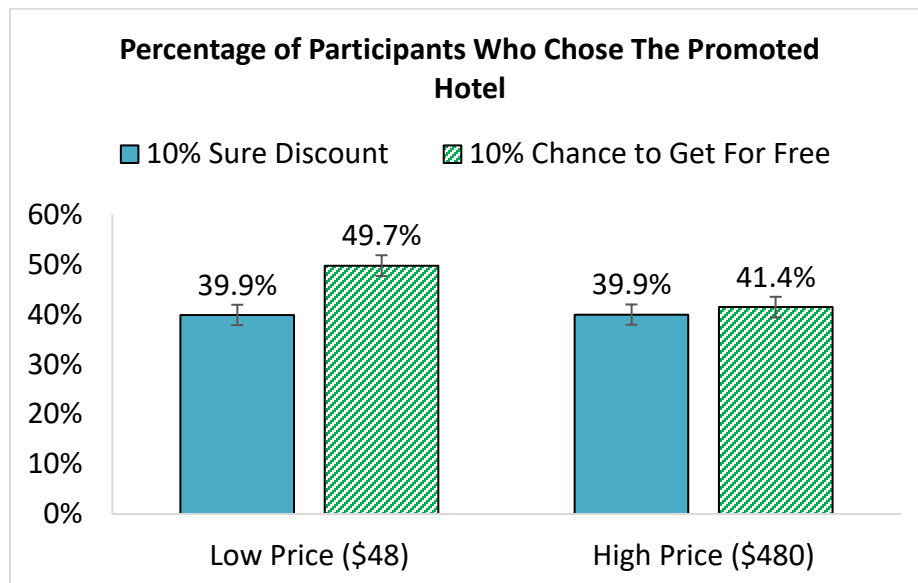


Figure 5. Results of Study 2.

STUDY 3

In Study 3, we manipulated the size of the sure discount by manipulating both the percentage associated with the promotions and the price of the product. But in this study we presented participants with both types of price promotions (i.e., uncertain vs. certain), and asked them to choose which one they would prefer. This design allowed us to test whether our results would extend to situations in which consumers are asked to directly choose between promotion types, the very situations that have been the primary focus of past research (Mazar et al., 2017).

Method

Participants

We conducted Study 3 using U.S. participants from Amazon.com's Mechanical Turk (MTurk). Participants received \$0.50 for participation. We decided in advance to recruit 900 participants for this study, and we wound up with a final sample of 852 participants (average age = 35 years; 52% female). The final sample included all participants who indicated their choice, but, as pre-registered, we kept only the first response from IP addresses that appeared more than once in the dataset (resulting in 11 exclusions), and we excluded any participants whose IP addresses were identical to those of participants in Studies 1a, 1b, and 2 (36 participants).

Procedure

In this study, we presented participants with only one hotel, namely the promoted hotel from Study 2 (i.e., the "Econo Lodge" hotel). We asked participants to imagine that they had selected this hotel for an upcoming trip to the Jersey Shore. Participants also

learned that the hotel came with one of two types of price promotions and that they could choose which type of price promotion they would like to receive. Participants could choose between a certain promotion that came in the form of a sure discount (described as “receiving X% off of the price of the hotel room”) and an uncertain promotion that came in the form of a chance-for-free promotion (described as “an X% chance to get the hotel room for free”). Figure 6 shows the stimuli that we used in Study 3.

We manipulated both the percentage associated with the promotions and the price of the promoted hotel. We randomly assigned participants to one of four conditions of a 2 (promotion percentage: 1% vs. 10%) x 2 (price of promoted hotel: low vs. high) between-subjects design. We manipulated the percentage associated with the promotions to be either 1% or 10%, as we did in Study 1a. And we manipulated the price of the promoted hotel to be either the one-night price (\$48) or the 10-night price (\$480), as we did in Study 2. As a consequence, the size of the sure discount varied across conditions, from 48 cents in the “1%/low price” condition to \$48 in the “10%/high price” condition.

We measured whether or not participants selected the chance-for-free promotion (1 = they selected the chance-for-free promotion, 0 = they selected the sure discount). And at the end of the study, we assessed participants’ age and gender.

Low-price Condition

The hotel's price is the one-night price:

Imagine you selected the hotel below for an upcoming trip to the Jersey Shore.

You learn that your booking comes with one of two types of price promotions, and that you can choose which type of price promotion you would like to receive.

You can choose between receiving 10% off of the price of the hotel room or a 10% chance to get the hotel room for free. The price promotion that you choose will be applied to the price of the hotel room that is stated below.

Econo Lodge Somers Point (Last booked 10 hours ago)
21 Macarthur Blvd, Somers Point, NJ, 08244 United States, 866-925-8676

Somers Point
• 2.7 miles to Ocean City
• 9.7 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

Good 6.2
120 Hotels.com guest reviews
164 reviews

\$48
Choose Room

Which price promotion would you like to receive?

- 10% off of the price of the hotel room
- a 10% chance to get the hotel room for free

High-price Condition

The hotel's price is the 10-night price:

Imagine you selected the hotel below for an upcoming trip to the Jersey Shore.

You learn that your booking comes with one of two types of price promotions, and that you can choose which type of price promotion you would like to receive.

You can choose between receiving 10% off of the price of the hotel room or a 10% chance to get the hotel room for free. The price promotion that you choose will be applied to the price of the hotel room that is stated below.

Econo Lodge Somers Point (Last booked 10 hours ago)
21 Macarthur Blvd, Somers Point, NJ, 08244 United States, 866-925-8676

Somers Point
• 2.7 miles to Ocean City
• 9.7 miles to Atlantic City, NJ (ACY-Atlantic City Intl.)
Collect nights

Good 6.2
120 Hotels.com guest reviews
164 reviews

\$480
Your 10 night total
Choose Room

Which price promotion would you like to receive?

- 10% off of the price of the hotel room
- a 10% chance to get the hotel room for free

Figure 6. Stimuli presented in Study 3 (10% condition).

Results and Discussion

Figure 7 displays the results of Study 3. Participants were more likely to choose the chance-for-free promotion over the sure discount when the percentage was 1% than when it was 10%, $b = .351$, $SE = .032$, $t(851) = 11.02$, $p < .001$, and when the price was low (\$48) than when it was high (\$480), $b = .072$, $SE = .032$, $t(851) = 2.27$, $p = .024$. The interaction was not significant ($p = .462$). The results in Figure 7 further show that the percentage of participants choosing the chance-for-free promotion was largest when the size of the sure discount was smallest (\$0.48), and smallest when the size of the sure discount was largest (\$48). In addition, participants were more likely to prefer a 1% chance-for-free promotion to 1% off when the price was \$480 than they were to prefer a 10% chance-for-free promotion to 10% off when the price was \$48. This suggests that people's evaluation of the size of discounts might partly be based on the absolute size of the discount (which was identical in these conditions: \$4.80) and partly based on the proportional size of the discount (which is greater when getting 10% off than when getting 1% off of the original price).

Thus, this study again suggests that people are more likely to choose an uncertain promotion over a sure discount when the sure discount is smaller, either because the percentage associated with the promotions is small or because the price is small.

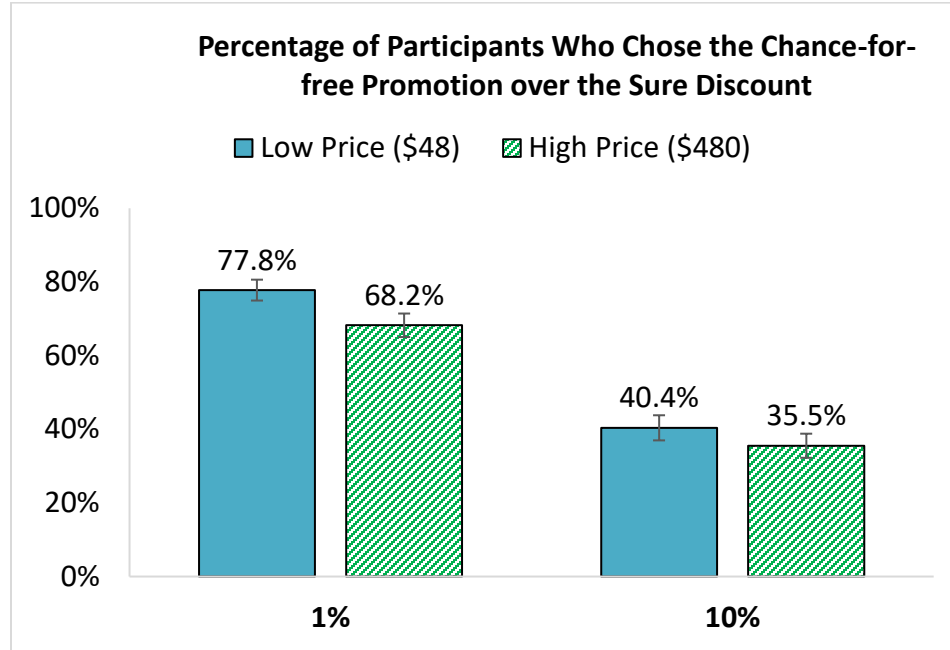


Figure 7. Results of Study 3.

STUDY 4A

In Studies 1-3, we manipulated the objective size of the sure discounts by directly manipulating features of the promotion itself (its percentage) or of the product for which the promotion was offered (the product's price). In Study 4a, we sought to test whether we would observe the same effects by holding the objective size of the sure discounts constant, while changing only how large or small those discounts feel. Specifically, we tried to make the same sure discount feel smaller by presenting it in the context of a large discount.

Method

Participants

We conducted Study 4a using U.S. participants from Amazon.com's Mechanical Turk (MTurk). Participants received \$0.50 for participation. We decided in advance to recruit 1,000 participants, and we wound up with a final sample of 984. The final sample included all participants who indicated their choice, but, as pre-registered, we kept only the first response from IP addresses that appeared more than once in the dataset (resulting in 12 exclusions).¹⁰ The final sample averaged 36 years of age and was 55% female.

Procedure. Participants were asked to imagine that they were about to buy a product, and that the original price of this product was \$11. They also learned that the product came with one of two types of promotions, and that they could choose which type of promotion they would like to receive. One of the promotions was a 10% sure discount described as a dollar amount (i.e., "\$1.10 off of the price of the product"), and the other was a 10% chance to get the product for free. We presented the two promotions to participants in a table and labeled them "Promotion A" and "Promotion B." We randomized the order in which these promotions were presented (i.e., whether the sure discount or the chance-for-free promotion was Promotion A). Figure 8 shows the full scenario.

Importantly, however, *before* participants saw this scenario and indicated their choice for a promotion, we presented them with another scenario (i.e., the context scenario). This context scenario was identical to the scenario described above, except that

¹⁰ In Studies 4a, 4b, and 5, participants with IP addresses that matched IP addresses in the data sets from previous studies were screened out a priori, and thus there was no need to exclude them ex post.

we manipulated the price for the product in that scenario (and thus the sure discount that came with it). Participants were randomly assigned to one of two conditions. For participants in the “high-context-price” condition, the product in the context scenario was priced at \$315 (with a sure discount of \$31.50), and for participants in the “low-context-price” condition, the product in the context scenario was priced at \$15 (with a sure discount of \$1.50). As in the focal scenario, participants learned that the product came with one of the two types of promotions, and that they could choose which promotion they would like to receive. That is, participants made two choices, one for the first (context) scenario, and one for the second (focal) scenario. As pre-registered, we used participants’ choices in the second, focal scenario as our dependent measure. We expected the high-context-price scenario to make the sure discount in the focal scenario seem smaller, and thus to increase participants’ tendency to choose the chance-for-free promotion in the focal scenario.

In both the focal scenario and the context scenario, we asked participants to indicate which promotion they would like to receive on a 6-point scale that ranged from 1, “definitely Promotion A,” to 6, “definitely Promotion B.” Since we randomized the order in which the sure discount and the chance-for-free promotion were presented, we scored all participants’ answers so that 1 = “definitely sure discount” and 6 = “definitely chance-for-free promotion.” At the end of the study, we assessed participants’ age and gender.

Results and Discussion

We regressed participants' ratings of the promotions on the context-price condition. As predicted, participants were more likely to prefer a 10% chance to get the \$11 product for free to the sure discount of \$1.10 when they previously made a choice involving a \$315 product that came with a discount of \$31.50 ($M = 3.60$, $SE = .091$) than when they previously made a choice involving a \$15 product that came with a discount of \$1.50 ($M = 2.68$, $SE = .082$), $b = .918$, $SE = .123$, $t(983) = 7.49$, $p < .001$.¹¹ This result held when we controlled for participants' choices in the first scenario, $b = 1.103$, $SE = .109$, $t(983) = 10.15$, $p < .001$. Thus, in line with our hypothesis, our results indicate that people's preferences for chance-for-free promotions increase when the context makes the equivalent sure discount seem smaller.

STUDY 4B

In Study 4b, we again attempted to manipulate how large or small a sure discount felt by manipulating the context. This time, though, we manipulated the context in a way that did not require participants to make a previous choice.

Method

Participants

¹¹ As pre-registered, we were chiefly interested in participants' choices in the focal scenario. However, we can also analyze participants' choices in the context scenario. In line with our results from Studies 2 and 3, in the context scenario, participants were more likely to prefer the chance-for-free promotion to the sure discount when the original price of the product was low (\$15; $M = 2.68$, $SE = .079$) than when it was high (\$315; $M = 2.34$, $SE = .072$), $b = .343$, $SE = .107$, $t(983) = 3.20$, $p = .001$.

We conducted Study 4b using U.S. participants from Amazon.com’s Mechanical Turk (MTurk). Participants received \$0.50 for participation.¹² We decided in advance to recruit 1,200 participants, and we wound up with a final sample of 1,188. The final sample included all participants who indicated their choice, but, as pre-registered, we kept only the first response from IP addresses that appeared more than once in the dataset (resulting in 15 exclusions). The final sample averaged 36 years of age and was 54% female.

Procedure. We asked participants to imagine that they had just decided to buy a 1-year membership to a gym, for which we manipulated the price and the corresponding discount, as well as a week’s worth of personal training sessions, for which the price was held constant at \$50. Participants were asked to indicate whether they would prefer a sure discount on the personal training sessions, or an equivalent chance-for-free promotion.

As in Study 4a, participants were randomly assigned to one of two conditions. Participants in the “high-context-price” condition learned that the original price of the gym membership was \$480/year and that they would get \$48 off of this price. And participants in the “low-context-price” condition learned that the original price of the gym membership was \$40/month and that they would get \$4 off of this price. The price for the personal training sessions was held constant at \$50. Participants were furthermore informed that the personal training sessions came with one of two types of price promotions, and that they could choose which price promotion they would like to receive.

¹² We initially launched Study 4b with a compensation of \$0.30. However, we decided to increase the compensation to \$0.50 to speed up participant recruitment after about six hours of data collection.

Since both the gym membership and the personal training sessions came with a promotion, we presented participants with an overview of the price promotion packages that they could choose between. This overview always included the sure discount on the gym membership, and varied with respect to whether, for the personal training sessions, participants received a sure discount (“\$5 off of the personal training sessions”) or a chance-for-free promotion (“a 10% chance to get the personal training sessions for free”). Figure 9 shows the exact wording of the scenario across conditions and the choice options that participants faced. We randomized whether the sure discount or the chance-for-free promotion was presented first.

We asked participants to indicate which promotion they would like to receive on a 6-point scale that ranged from 1, “definitely Promotion A,” to 6, “definitely Promotion B.” Since we randomized the order in which the sure discount and the chance-for-free promotion were presented, we scored participants’ answers so that 1 = “definitely sure discount” and 6 = “definitely chance-for-free promotion.” At the end of the study, we assessed participants’ age and gender.

High-context-price Condition

**The price of the gym membership is stated as \$480/year
(with a sure discount of \$48):**

Imagine that you have just decided to buy a 1-year membership to a gym close to your home, as well as a week's worth of personal training sessions. The membership usually costs \$480/year, and a week's worth of personal training sessions costs \$50.

At the time of your purchase, you learn that the membership is being offered at a discount of \$48 off of the yearly membership price. You also learn that the personal training sessions come with one of two types of price promotions, and that you can choose which type of price promotion you would like to receive.

Specifically, when purchasing the gym membership and the personal training sessions, you can choose between receiving one of the following two price promotions:

Promotion A:	Promotion B:
\$48 off of the yearly gym membership & \$5 off of the personal training sessions	\$48 off of the yearly gym membership & a 10% chance to get the personal training sessions for free

Which promotion would you like to receive?

Definitely
Promotion A

Definitely
Promotion B

Low-context-price Condition

**The price of the gym membership is stated as \$40/month
(with a sure discount of \$4):**

Imagine that you have just decided to buy a 1-year membership to a gym close to your home, as well as a week's worth of personal training sessions. The membership usually costs \$40/month, and a week's worth of personal training sessions costs \$50.

At the time of your purchase, you learn that the membership is being offered at a discount of \$4 off of the monthly membership price. You also learn that the personal training sessions come with one of two types of price promotions, and that you can choose which type of price promotion you would like to receive.

Specifically, when purchasing the gym membership and the personal training sessions, you can choose between receiving one of the following two price promotions:

Promotion A:	Promotion B:
\$4 off of the monthly gym membership & \$5 off of the personal training sessions	\$4 off of the monthly gym membership & a 10% chance to get the personal training sessions for free

Which promotion would you like to receive?

Definitely
Promotion A

Definitely
Promotion B

Figure 9. Stimulus presented in Study 4b.

Results and Discussion

We regressed participants' ratings of the promotions on the context-price condition. As predicted, participants were more likely to prefer a 10% chance of getting the \$50 personal training sessions for free over a sure discount of \$5 when they considered the promotions in the context of a \$48 discount on the yearly membership price ($M = 2.81$, $SE = .078$) than when they considered them in the context of a \$4 discount on the monthly membership price ($M = 2.58$, $SE = .075$), $b = .229$, $SE = .108$, $t(1,187) = 2.12$, $p = .034$.

Taken together, Studies 4a and 4b demonstrate that asking consumers to consider the same discount in the context of a larger discount can increase people's relative preference for an uncertain promotion. In the next study, we tested an additional way to manipulate how large a sure discount feels, namely by manipulating how the sure discount is framed.

STUDY 5

In Study 5, we set out to examine whether framing the sure discount as a percentage (e.g., 10% off of \$50) or a dollar amount (e.g., \$5 off of \$50) alters people's likelihood of choosing an uncertain chance-for-free promotion over an equivalent sure discount. In Studies 1a-4b, we established that the perceived size of a sure discount drives people's preferences for uncertain promotions. Thus, if the perceived size of a sure discount is affected by whether the sure discount is presented as a percentage or a dollar amount, then this should also affect people's preferences for uncertain promotions.

Prior work suggests that how a discount is framed may change how large it is perceived to be (e.g., Chen, Monroe, & Lou, 1998; Della Bitta, Monroe, & McGinnis,

1981; DelVecchio, Krishnan, & Smith, 2007; González, Eduardo, Roggeveen, & Grewal, 2016). However, this research provides inconsistent results with respect to the direction of the effect. For example, research by Della Bitta, Monroe, and McGinnis (1981) suggests that framing a sure discount as a dollar amount leads to higher savings perceptions than framing it as a percentage. More recently, Chen, Monroe, and Lou (1998) found that dollar framing increased saving perceptions for high-priced products, but percentage framing increased savings perceptions for low-priced products. However, they did not find any effect on a measure of purchase intentions. Similarly, González et al. (2016) found that dollar framing resulted in both higher saving perceptions and higher purchase intentions for high-priced products, whereas percentage framing directionally, but not significantly, increased saving perceptions and purchase intentions for low-priced products. Given that these findings are inconsistent and somewhat complicated, we conducted a pretest to examine whether a percentage (vs. dollar) framing would make a sure discount feel larger or smaller. The results from this pretest informed our predictions for the main study.

Pretest

We conducted a pretest to examine whether participants perceive the size of a sure discount to be different depending on whether the discount is framed as a percentage or as a dollar amount, and depending on the price of the product.

Participants

We conducted the pretest on Amazon.com's Mechanical Turk (MTurk). Participants received \$0.30 for participation. We decided in advance to recruit 900 participants for

this pretest, and we wound up with a final sample of 867 participants (average age = 36 years; 48% female). The final sample included all participants who provided their rating, but, as pre-registered, we kept only the first response from IP addresses that appeared more than once in the dataset (resulting in 20 exclusions), and we excluded any participants whose IP addresses were identical to those of participants in Studies 1a-3 (18 participants).

Procedure

Participants were asked to imagine that they were about to buy a product and that the product came with a sure discount equal to 10% off. We randomly assigned participants to one of four conditions of a 2 (price of promoted product: low vs. high) x 2 (framing of sure discount: percentage vs. dollar amount) between-subjects design. The original price of the product was \$11 in the low-price condition and \$311 in the high price condition. Furthermore, the discount was either framed as a percentage off of the original price (e.g., “You will get 10% off of the price of the product.”) or as a dollar amount (e.g., “You will get \$1.10 off of the price of the product.”). We asked participants to indicate how small or large the discount felt to them (1 = very small; 7 = very large).

Results

Figure 11, Panel A displays the results of this pretest. Not surprisingly, participants rated the sure discount as smaller in the low-price condition than in the high-price condition, $b = -.276$, $SE = .091$, $t(866) = -3.03$, $p = .003$. More importantly, they rated the discount as smaller when it was framed as a percentage off of the original price than

when it was framed as a dollar amount, $b = -.621$, $SE = .091$, $t(866) = -6.80$, $p < .001$. The interaction was not significant ($p = .801$).

Thus, the framing of the sure discount influenced its perceived size, even though the sure discount always corresponded to getting 10% off of the original price of the product. This pretest suggests that, because a sure discount feels smaller when it is framed as a percentage than when it is framed as a dollar amount, people should be more likely to choose a chance-for-free promotion over a sure discount when the latter is framed as a percentage than when it is framed as a dollar amount. We tested this prediction in Study 5.

Method

Participants

We conducted Study 5 using U.S. participants from Amazon.com's Mechanical Turk (MTurk). Participants received \$0.30 for participation. We decided in advance to recruit 2,500 participants for this study, and we wound up with a final sample of 2,371 participants (average age = 36 years; 52% female). The final sample included all participants who chose a discount, but, as pre-registered, we kept only the first response from IP addresses that appeared more than once in the dataset (resulting in 28 exclusions).

Procedure

In this study, we asked participants to imagine that they were about to buy a product that came with one of two types of promotions, and that they could choose which promotion they would like to receive. We randomly assigned participants to one of four

conditions from a 2 (price of promoted product: low vs. high) x 2 (framing of sure discount: percentage vs. dollar amount) between-subjects design. In line with our pretest, in the low-price condition the original price of the product was \$11, and in the high price condition, it was \$311.

Participants then received information about the two types of price promotions. One of the price promotions was a chance-for-free promotion (“a 10% chance to get the product for free”), and the other was a sure discount that corresponded to getting 10% off of the price of the product. However, we manipulated whether this sure discount was presented as a percentage (i.e., 10% off) or as the equivalent dollar amount (i.e., \$1.10 off in the low-price condition and \$31.10 off in the high-price condition). Figure 10 shows the exact wording of the scenario and the choice option that participants faced. We randomized whether the sure discount or the chance-for-free promotion was displayed first (i.e., which promotion was Promotion A).

We asked participants to indicate which price promotion they would like to receive on a 6-point scale that ranged from 1 = “definitely Promotion A” to 6 = “definitely Promotion B.” Since we randomized the order in which the sure discount and the chance-for-free promotion were presented, we scored participants’ answers so that 1 = “definitely sure discount” to 6 = “definitely chance-for-free promotion.” At the end of the study, we assessed participants’ age and gender.

Percentage-Framing Condition

The sure discount is presented as a percentage (10% off):

Imagine you are about to buy a product.

The original price of the product is \$11.

You learn that the product comes with one of two types of price promotions, and that you can choose which type of price promotion you would like to receive.

You can choose between two promotions:

Promotion A:	Promotion B:
10% off of the price of the product	A 10% chance to get the product for free

The promotion that you choose will be applied to the original price of the product (\$11).

Which price promotion would you like to receive?

Definitely
Promotion A

Definitely
Promotion B

Dollar-Framing Condition

The sure discount is presented as a dollar amount (\$1.10 off):

Imagine you are about to buy a product.

The original price of the product is \$11.

You learn that the product comes with one of two types of price promotions, and that you can choose which type of price promotion you would like to receive.

You can choose between two promotions:

Promotion A:	Promotion B:
\$1.10 off of the price of the product	A 10% chance to get the product for free

The promotion that you choose will be applied to the original price of the product (\$11).

Which price promotion would you like to receive?

Definitely
Promotion A

Definitely
Promotion B

Figure 10. Stimulus presented in Study 5.

Results and Discussion

Figure 11, Panel B displays the results of Study 5. Consistent with our previous studies, participants were more likely to choose the chance-for-free promotion over the sure discount when the price was low (and the sure discount was smaller) than when it was high (and the sure discount was larger), $b = .241$, $SE = .075$, $t(2,370) = 3.20$, $p = .001$. More importantly and in line with the predictions derived from our pretest, participants were also more likely to choose the chance-for-free promotion over the sure discount when the sure discount was framed as a percentage than when it was framed as a dollar amount, $b = .523$, $SE = .075$, $t(2,370) = 6.94$, $p < .001$. The interaction was significant as well, $b = .352$, $SE = .151$, $t(2,370) = 2.34$, $p = .019$, such that the framing of the sure discount had a larger effect in the low-price condition, $b = .699$, $SE = .111$, $t(1,183) = 6.29$, $p < .001$, than in the high-price condition, $b = .347$, $SE = .102$, $t(1,186) = 3.41$, $p = .001$. Further supporting our hypothesis, a comparison of Panels A and B in Figure 11 shows that people were *most* likely to prefer the chance-for-free promotion in the condition in which the sure discount was rated the smallest (i.e., when the price was \$11 and the sure discount was framed as a percentage), and *least* likely to prefer the chance-for-free promotion in the condition in which the sure discount was rated the largest (i.e., when the price was \$311 and the sure discount was framed as a dollar amount). Thus, the results from this study suggest that we can alter people's preferences for uncertain promotions simply by changing whether the sure discount is framed as a percentage or as a dollar amount.

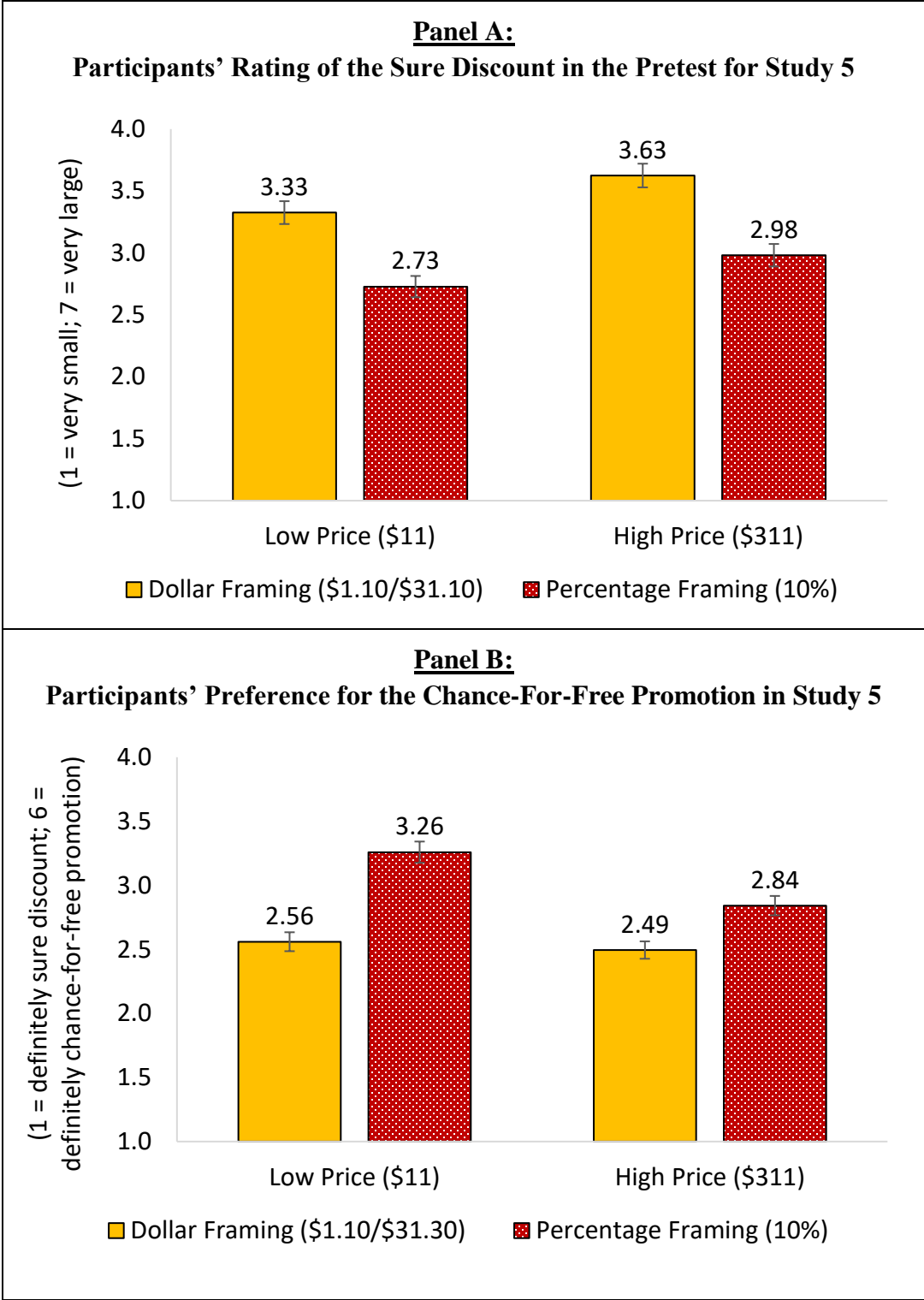


Figure 11. Results of Study 5: Panel A shows the results of the pretest for Study 5 and Panel B shows the results of Study 5.

GENERAL DISCUSSION

Is it more effective to offer customers an uncertain price promotion, such as an X% chance to get the product for free, or to provide them with a sure discount of equal expected value? In this article, we provide evidence that the answer to this question depends on the actual or perceived size of the sure discount. Across seven studies, we found that uncertain price promotions are more effective than sure discounts of equal expected value when those sure discounts are or seem small. Specifically, we showed that uncertain promotions are relatively more effective when the percentage associated with the promotions is smaller (Studies 1a, 1b, and 3), when the original price of the product is smaller (Studies 2, 3, and 5), when the sure discounts are made to feel smaller by presenting them alongside a larger discount (Studies 4a and 4b), and when the sure discounts are made to feel smaller by framing them as a percentage-discount rather than a dollar amount (Study 5).

These findings are inconsistent with two leading explanations for consumers' preferences for uncertain over certain promotions. First, diminishing sensitivity cannot explain these findings, because, as reviewed in the Introduction, diminishing sensitivity implies that consumers will always prefer uncertain chance-for-free promotions to sure discounts of equal expected value (Mazar et al., 2017). Second, it is worth noting that these findings cannot be explained by consumers' overweighting of small probabilities, as we showed that consumers' preferences for uncertain promotions are increased by manipulations that hold the probability of the uncertain promotion constant while making the sure discount seem smaller (e.g., by displaying it as a percentage rather than a dollar

amount). Indeed, our findings suggest that people's preferences for uncertainty are more strongly tethered to their perceptions of the size of the sure outcome than they are to their perceptions of the probability of getting the uncertain reward. If true, this suggests that phenomena that have been long explained in terms of probability weighting, such as people's willingness to purchase lottery tickets and/or insurance (Kahneman & Tversky, 1979), may be better explained in terms of people's perceptions of the size of the sure amount that they are asked to pay. For example, a \$1 payment for a lottery ticket may seem trivially small to a consumer who is considering the many millions she could stand to win. Similarly, a \$750 life insurance premium may seem small to a consumer who is considering how much the million-dollar policy will pay out.

Although Mazar, Shampanier, and Ariely (2017) favored a diminishing sensitivity explanation for the fact that participants in their studies showed a preference for uncertain promotions over sure discounts of equal expected value, almost all of their studies used low-priced products, and thus small sure discounts. For example, their Experiment 1 investigated a discount on a \$0.75 candy bar, and their Experiment 2 investigated a discount on a \$4.50 DVD rental. Although consumers' tendency to prefer the uncertain promotion in their investigation of the \$4.50 DVD rental led Mazar, Shampanier, and Ariely (2017) to "conclude that our findings are less likely an artifact of the 'peanuts' effect" (p. 256), any discount on a good priced so low is likely to seem small to consumers. The only studies in Mazar, Shampanier, and Ariely's (2017) investigation that used a high-priced product were Studies 5a and 5b, in which the promoted product was a hotel priced at \$200/night with a sure discount of 10% (i.e., \$20). Although they

did find that the 10% chance-for-free promotion was more effective than a the 10% sure discount in these studies, they also found, in Study 5a, that the sure discount was no more effective than no discount at all. Because we were surprised by this result, we decided to try to replicate it. The details are in the Supplement. We found that the sure discount was more effective than no discount at getting participants to purchase the promoted \$200 hotel, but, most importantly, we also found that the chance-for-free promotion was *not* more effective than the sure discount. Thus, as we would expect from our theorizing, a fairly sizable sure discount of \$20 on a \$200 product was not less effective than a 10% chance to get the product for free.

Since our theorizing hinges on people's perceptions of the size of sure discounts, it is important to consider what it is that guides these perceptions. Although we are very far from having an exhaustive answer to this question, we can say that these perceptions are likely to be driven by both absolute sizes and relative sizes (see also Darke & Freedman, 1993). Thus, people will judge the same percentage discount to be larger when the product is more highly priced, so that 10% off of a car feels larger than 10% off of a candy bar. At the same time, people will judge the same absolute discount to be smaller when the product is more highly priced, so that a \$1 discount on a car feels smaller than a \$1 discount on a candy bar. For any given evaluation both effects may be in place, and which of these effects is larger or smaller is likely to depend on the context and on the individual.

In sum, our research suggests that people's preferences for uncertain promotions over sure discounts heavily depend on the perceived size of the sure discount. This simple fact

has widespread implications, both theoretically and practically. One practical implication is this: Uncertain price promotions are probably a good idea if you are selling candy bars, but a bad idea if you are selling cars.

APPENDIX

Appendix A: Links to Pre-registrations for Chapter 1

Study 1: <https://aspredicted.org/2rp5k.pdf>
Study 2: <https://aspredicted.org/u6442.pdf>
Study 3: <https://aspredicted.org/4b8j8.pdf>
Study 4: <https://aspredicted.org/ga8xg.pdf>
Study 5: <https://aspredicted.org/ni7zv.pdf>
Study 6: <https://aspredicted.org/758ba.pdf>
Study 7: <https://aspredicted.org/qi57c.pdf>
Study 8: <https://aspredicted.org/zf6qi.pdf>
Study 9: <https://aspredicted.org/4tc3d.pdf>
Study S1: <https://aspredicted.org/kg4zt.pdf>
Study S2: <https://aspredicted.org/ir7eu.pdf>

Appendix B: Links to Pre-registrations for Chapter 2

Study 1a: <http://aspredicted.org/blind.php?x=g66g5c>
Study 1b: <https://aspredicted.org/blind.php?x=zp2sn6>
Study 2: <http://aspredicted.org/blind.php?x=27v2qa>
Study 3: <https://aspredicted.org/blind.php?x=yr2uh9>
Study 4a: <https://aspredicted.org/blind.php?x=tq7v9x>
Study 4b: <http://aspredicted.org/blind.php?x=ze3sg6>
Study 5 Pretest: <https://aspredicted.org/blind.php?x=iz5qj2>
Study 5: <https://aspredicted.org/blind.php?x=ry3n54>
Study S1: <http://aspredicted.org/blind.php?x=se2eg6>

Appendix C: Content of the Web Appendix for Chapter 2

The Web Appendix contains the procedure and results for Study S1 and is available at this link: https://osf.io/3azsn/?view_only=a7c2c3cedd4e4b65b20a3e8116e2cb9e

REFERENCES

- Anderson, C., Brion, S., Moore, D. A., & Kennedy, J. A. (2012). A status-enhancement account of overconfidence. *Journal of Personality and Social Psychology, 103*(4), 718-735.
- Chen, S. S., Kent, B. M., & Lou, Y. (1998). The effects of framing price promotion messages on consumers' perceptions and purchase intentions. *Journal of Retailing, 74*(3), 353-372.
- Darke, P. R., & Freedman, J. L. (1993). Deciding whether to seek a bargain: Effects of both amount and percentage off. *Journal of Applied Psychology, 78*(6), 960-965.
- Della Bitta, A. J., Kent, B. M., & McGinnis, J. M. (1981). Consumer perceptions of comparative price advertisements. *Journal of Marketing Research, 18*(4), 416-427.
- DelVecchio, D. H., Shanker, K., & Smith, D. C. (2007). Cents or percent? The effects of promotion framing on price expectations and choice. *Journal of Marketing, 71*(3), 158-170.
- Du, N., Budescu, D. V., Shelly, M. K., & Omer, T. C. (2011). The appeal of vague financial forecasts. *Organizational Behavior and Human Decision Processes, 114*(2), 179-189.
- Gneezy, U., List, J. A., & Wu, G. (2006). The uncertainty effect: When a risky prospect is valued less than its worst possible outcome. *The Quarterly Journal of Economics, 121*(4), 1283-1309.

- Goldsmith, K., & Amir, O. (2010). Can uncertainty improve promotions? *Journal of Marketing Research*, 47(6), 1070-1077.
- González, E. M., Eduardo, E., Roggeveen, A. L., & Grewal, D. (2016). Amount off versus percentage off—when does it matter? *Journal of Business Research*, 69(3), 1022–1027.
- Green, E. A., Lee, H., & Rothschild, D. (2018). The favorite-longshot midas. *Working Paper*.
- Kahneman, D. (2011). *Thinking, Fast and Slow*. New York: Farrar, Strauss, Giroux.
- Kahneman, D., & Tversky, A. (1979). Prospect Theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263-291.
- Markowitz, H. (1952). The utility of wealth. *Journal of Political Economy*, 60(2), 151–158.
- Mazar, N., Shampanier, K., & Ariely, D. (2017). When retailing and Las Vegas meet: Probabilistic free price promotions. *Management Science*, 63(1), 250–266.
- Mislavsky, R., & Simonsohn, U. (2017). When risk is weird: Unexplained transaction features lower valuations. *Management Science*, 64(11), 5395-5404.
- Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, 115(2), 502-517.
- Moore, D. A., Tenney, E. R., & Haran, U. (in press). Overprecision in judgment. In G. Wu and G. Keren (Eds.), *Handbook of Judgment and Decision Making*. New York: Wiley.
- Prelec, D. (1998). The probability weighting function. *Econometrica*, 66(3), 497–527.

- Prelec, D., & Loewenstein, G. (1991). Decision making over time and under uncertainty: A common approach. *Management Science*, *37*(7), 770–786.
- Price, P. C., & Stone, E. R. (2004). Intuitive evaluation of likelihood judgment producers: Evidence for a confidence heuristic. *Journal of Behavioral Decision Making*, *17*(1), 39- 57.
- Radzevick, J. R., & Moore, D. A. (2011). Competing to be certain (but wrong): Market dynamics and excessive confidence in judgment. *Management Science*, *57*(1), 93-106.
- Sah, S., Moore, D. A., & MacCoun, R. J. (2013). Cheap talk and credibility: The consequences of confidence and accuracy on advisor credibility and persuasiveness. *Organizational Behavior and Human Decision Processes*, *121*(2), 246-255.
- Shen, L., Fishbach, A., & Hsee, C. K. (2014). The motivating-uncertainty effect: Uncertainty increases resource investment in the process of reward pursuit. *Journal of Consumer Research*, *41*(5), 1301–1315.
- Simmons, J. P. (2013, November 4). Samples can't be too large. Retrieved from <http://datacolada.org/6>.
- Simonsohn, U. (2009). Direct risk aversion: Evidence from risky prospects valued below their worst outcome. *Psychological Science*, *20*(6), 686-692.
- Soll, J. B., & Klayman, J. (2004). Overconfidence in interval estimates. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*(2), 299-314.

- Tenney, E. R., MacCoun, R. J., Spellman, B. A., & Hastie, R. (2007). Calibration trumps confidence as a basis for witness credibility. *Psychological Science, 18*(1), 46-50.
- Tenney, E. R., Spellman, B. A., & MacCoun, R. J. (2008). The benefits of knowing what you know (and what you don't): How calibration affects credibility. *Journal of Experimental Social Psychology, 44*(5), 1368-1375.
- Tetlock, P. E., & Gardner, D. (2015). *Superforecasting: The Art and Science of Prediction*. New York: Crown.
- Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211*, 453-458.
- Van Zant, A. B. (2017). Certainty posturing: Evidence of inauthentic certainty displays as strategic impression management. *Working Paper*.
- Weber, B. J., & Chapman, G. B. (2005). Playing for peanuts: Why is risk seeking more common for low-stakes gambles? *Organizational Behavior and Human Decision Processes, 97*(1), 31-46.