The Fun and Function of Uncertainty: Uncertain Incentives Reinforce Repetition Decisions

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This research studies repetition decisions—namely, whether to repeat a behavior (e.g., a purchase) after receiving an incentive (e.g., a discount). Can uncertainty drive repetition? Four experiments, all involving real consequences for each individual participant, document a counterintuitive reinforcing-uncertainty effect: individuals repeat a behavior more if its incentive is uncertain than if it is certain, even when the certain incentive is financially better. This effect is robust; it holds in both lab and field settings and at both small and large magnitudes. Furthermore, the experiments identify two theory-driven boundary conditions for the reinforcing-uncertainty effect: the effect arises (a) only if the uncertainty is resolved immediately and not if the resolution of uncertainty is delayed, and (b) only after, not before, one has engaged in repetitions. These results support a resolution-as-reward account and cast doubt on other explanations such as reference-dependent preferences. This research reveals the hidden value of uncertain incentives and sheds light on the delicate relationship between incentive uncertainty and repetition decisions.

Keywords: risks and uncertainty, motivation, gamification, customer retention, intermittent reinforcement, happiness, gambling, variety seeking, prediction, performance, goal pursuit, behavioral decision theory, incentive design, loyalty program

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Marketers are concerned with not only how to stimulate a one-time action but also how to drive repeated actions, such as repurchase rates and customer retention. Can uncertainty drive repetition? It is commonly assumed that consumers are averse to uncertain gains, and thus one would expect uncertain incentives to lead to fewer repetitions. However, some market observations hint otherwise. Examples include the long-lasting popularity of Kinder Eggs, Gachapon toys, and fortune cookies; the blooming business of subscription boxes in North America (e.g., food: Blue Apron; pet supplies: BarkBox); and the sweeping distribution of cash rewards through various mobile payment methods in East Asia (e.g., WeChat Pay). These marketing practices are all designed such that, after taking each action (e.g., after tap-and-paying with WeChat Pay), the customer receives an uncertain outcome (e.g., an uncertain cash amount) and then decides whether to repeat that action (e.g., whether to use WeChat Pay again). Of course, the effect of outcome uncertainty in real-life observations

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is hard to evaluate due to the lack of benchmarks and control conditions. Nevertheless, we conjecture that, under predictable conditions, an uncertain outcome can lead to more repetitions than a certain outcome, even when the certain outcome is financially better. When repeatedly taking an action and receiving its outcome, the individual has the unique opportunity to resolve the uncertainty, and we posit that uncertainty resolution serves as a mental reward that reinforces repetitions. In this research, we present empirical evidence from both field and laboratory experiments to reveal the hidden value of uncertain incentives in repetition decisions. Our focus is on uncovering a novel phenomenon, while we also offer a theoretical account and provide supportive evidence.

PREDICTIONS FROM PRIOR RESEARCH

Do people repeat an action more when the financial outcome of the action is certain or uncertain? As a stylized example, imagine that a mobile payment company offers its customers a cash reward every time they pay $40 or more with its app. Which of the following two incentive designs would boost customer retention more effectively?

> **Uncertain incentive:** The cash reward is either $2 or $4 with even chances, and the customer will find out whether it is $2 or $4 after each payment.
>
> **Certain incentive of the high value:** The cash reward is always $4.

Most existing research would predict that the customer will use this mobile payment more under the high-value certain incentive than under the uncertain incentive. One obvious reason is that, financially, this certain $4 reward dominates the uncertain $2 or $4 reward. Another reason is that, psychologically, the uncertain incentive is associated with risks, and people are risk-averse about gains (Holt and Laury 2002; Kahneman and Tversky 1979; also see "extreme uncertainty aversion": Gneezy, List, and Wu 2006; Newman and Mochon 2012; Simonsohn 2009).

While most research finds uncertainty aversion, exceptions do exist (Dhar, Gonzalez-Vallejo, and Soman 1995; Goldsmith and Amir 2010; Mažar, Shampanier, and Ariely 2016). One such exception relevant to the present work is the research by Goldsmith and Amir (2010). That research focuses on single-shot decisions and finds that buyers respond as positively to an uncertain promotion as they do to the best possible outcome in this uncertain promotion. An innate optimism account is offered to explain the effect: when the buyer does not know what she will receive, she implicitly expects the best and behaves accordingly. While this account can explain why the buyer may respond to an uncertain promotion as positively as to a certain promotion ex ante, it makes no prediction about whether she is more or less likely to repeat the purchase after receiving the reward. If anything, it would expect the buyer to be less likely to repeat in the uncertain-promotion case than in the certain-promotion case, because she could be disappointed by the actual reward in the uncertain-promotion case. But, as we will elaborate on later, we predict and find the opposite.

Another related finding is a positive uncertainty effect in goal-persistence decisions reported by Shen, Fishbach, and Hsee (2015): consumers work harder to pursue an uncertain reward than to pursue its best possible outcome. This effect requires that the uncertainty of reward remains unresolved before the goal is attained. However, repetition decisions do not meet this requirement; in repetition decisions, since the consumer receives outcome feedback repeatedly, uncertainty is duly resolved at each repetition. Therefore, the finding on goal-persistence decisions cannot be used to predict the effect of uncertainty on repetition decisions with timely outcome feedback. As we will explain, the presence of timely feedback—specifically, the presence of immediate resolution after each repetition—is critical for uncertainty to have a positive effect on repetition decisions.

OUR PREDICTIONS

We propose a *reinforcing-uncertainty effect*: that uncertain incentives can lead to more repetitions than certain incentives. In the mobile payment app example, we predict that an uncertain reward of either $2 or $4 will lead to more mobile transactions than a certain reward of $3. In fact, even when an uncertain incentive is financially worse than a certain incentive—for example, the certain reward is $4 instead of $3—we predict that the uncertain incentive will still lead to more repetitions than the certain incentive. In other words, we predict a positive effect of uncertainty in repetition decisions.

Why can uncertainty be reinforcing? We offer a *resolution-as-reward* account. An uncertain incentive implies that the exact promised financial outcome remains unknown initially, and at the time, it is not immediately clear whether an individual would want to approach or avoid the unknown (Ely, Frankel, and Kamenica 2015; Golman and Loewenstein 2018; Herrnstein and Prelec 1991; Hertwig and Engel 2016; Loewenstein 1994). However, it is a pleasant experience for the individual to resolve uncertainty (Hsee and Ruan 2016; Ruan, Hsee, and Lu 2018; also see neural evidence: Peysakhovich and Karmarkar 2016; and animal research: McDevitt et al. 2016). After the individual has had this resolution experience and has gone through repetitions as such, she will eventually realize that an uncertain incentive not only offers a financial benefit with an unknown magnitude (which she knew from the beginning), but also promises a pleasant experience of discovering the unknown with his action.

Stated more formally, the hidden value in the uncertain incentive is the *uncertainty resolution utility*—namely, how one feels about knowing the unknown. Importantly, uncertainty resolution utility exists in addition to the *outcome acquisition utility*—namely, how one feels about the outcome itself. When an incentive is uncertain, the outcome acquisition utility may be high (if one receives the best outcome in the uncertain incentive) or low (if one receives the worst outcome). However, regardless of the size of the outcome acquisition utility, the uncertainty resolution utility remains positive, because one always moves from an undesirable state of not knowing to a desirable state of knowing (Ruan et al. 2018). That is, even if the mobile payment user does not always receive the best outcome ($4), she may still keep tapping her phone to pay for the pleasure of discovering which cash reward she will receive next time. Over time, even when she has already become numb to receiving a reward (outcome acquisition), she may still have fun finding out the reward (uncertainty resolution).

Compare the motivational mechanisms of certain and uncertain incentives. If a person repeats an action with certain incentives, she experiences only the outcome acquisition utility. By contrast, if a person repeats an action with uncertain incentives, she experiences both the outcome acquisition utility and the uncertainty resolution utility. In other words, under outcome certainty, only one force drives repetition, but under outcome uncertainty, two forces do: outcome acquisition and uncertainty resolution. Thus, we predict that compared with a certain incentive of the *same* expected value, the uncertain incentive will be more reinforcing, and compared with a certain incentive of a *higher* expected value, the uncertain incentive may still be more reinforcing, because the uncertainty resolution utility may offset the disadvantage of the outcome acquisition utility. Putting both together, we predict that:

> **H1:** Uncertain incentives can lead to more repetitions than certain incentives, even when the uncertain incentives are financially worse than the certain incentives (the reinforcing-uncertainty effect).

According to our theory, the critical factor underlying the reinforcing-uncertainty effect is uncertainty resolution, which is rewarding and hence reinforcing. This resolution-as-reward account implies that an uncertain incentive without resolution would not lead to more repetitions. Specifically, the account predicts two boundary conditions for the reinforcing-uncertainty effect.

First, if uncertainty is not immediately resolved after each repetition, uncertain incentives will not be as reinforcing as certain incentives. Uncertainty resolution functions as a positive reinforcer, and as prior research details (Ferster and Skinner 1957; Hsee, Yang, and Ruan 2015; Skinner 1969), a reward reinforces a behavior only if the delivery of the reward is contingent on—that is, immediately follows—the occurrence of the behavior. Therefore, an uncertain incentive with immediate resolution is reinforcing, but an uncertain incentive without immediate resolution (i.e., staying in suspense while deciding whether to repeat the action) loses its uncertainty resolution utility, cannot offset the disadvantage of outcome acquisition utility (if any), and hence is not as reinforcing as a certain incentive. Thus, we hypothesize that:

> **H2:** The reinforcing-uncertainty effect occurs only if the uncertainty is resolved immediately after each repetition and disappears if the uncertainty is not immediately resolved.

Second, if resolution is yet to be experienced—for example, if, before engaging in an activity, one is asked to decide whether to engage in the task—uncertain incentives will not be more motivating than certain incentives of equal or higher expected values. Before engaging in an activity, the individual has no exposure to the resolution experience and is unable to accurately anticipate its positive effect (Andrade and Iyer 2009; Ariely, Loewenstein, and Prelec 2006; Buechel et al. 2014; Hsee et al. 2003, 2015; Woolley and Fishbach 2016; see Hsee and Hastie 2006 for a review). By contrast, after and while engaged in an activity, the individual has enjoyed the resolution experience and will find this experience rewarding. That is, the uncertainty resolution utility kicks in only after repetitions start. Thus, we hypothesize that:

> **H3:** The reinforcing-uncertainty effect occurs through, not before, repetitions; that is, the effect does not occur at entry, when people have yet to engage in repetitions.

Next, we report four studies, of which two are field experiments (studies 1 and 4) and two are lab experiments (studies 2 and 3). We start with a field experiment demonstrating the reinforcing-uncertainty effect, then present converging lab evidence for the resolution-as-reward account to explain the effect, and at last, return to the field and demonstrate the effect at a large magnitude. All studies are incentive-compatible, entail real consequences for each individual participant, and involve no deception. The experimental designs in all studies include two basic conditions: a certain incentive and a dominated uncertain incentive; that is, the uncertain incentive always has a lower expected value than the certain incentive. We report additional studies (in supplementary materials 1 and 2) and additional experimental details and analysis results for all studies (in supplementary materials 3 to 5) in the web appendix.

STUDY 1 (FIELD EXPERIMENT): TESTING THE REINFORCING-UNCERTAINTY EFFECT

Study 1 was designed to test the reinforcing-uncertainty effect (hypothesis 1) and to test the effect in a naturalistic setting: a point-earning exercise program in a running club.

The running club is an independent nonprofit organization operated by college students at the Chinese University of Hong Kong. In the Spring Running event (i.e., our experiment), members could earn points by running, jogging, or speed walking on a standard 400 meter outdoor track during the 15-day event period, from Tuesday, March 17, 2015, to Tuesday, March 31, 2015. We predicted that running club members would complete more laps if they received an uncertain number of points for each lap than if they received a certain, larger number of points for each lap.

Method

Recruitment. The running club distributed a generic recruitment advertisement both on campus (e.g., leaflets in individual mailboxes in school housing facilities) and off campus (e.g., posters at the Mass Transit Railway [MTR] stations in the districts around the university); all materials were in colloquial Cantonese. By the end of the recruitment phase, 111 Hong Kong residents became new members of the club and signed up for the Spring Running event, of which 29 signups were not able to show up for various reasons (e.g., physical injuries and schedule conflicts) and the remaining 82 signups (49 women, average age = 20.03) actually became new members and took part in the Spring Running event. We included all new members as our research participants. (For logistic reasons, we did not have access to old members.)

Prior to the Event. On the weekend before the event, staff at the running club called each new member to explain the Spring Running event and its safety instructions. Then, the staff introduced the point-earning program. Half of the members were randomly assigned to the certain-point condition and were told that after each lap, they would receive five points for sure. The other half were randomly assigned to the uncertain-point condition and were told that after each lap, they would randomly receive either three or five points. At the end of each day, the members would receive a WhatsApp message summarizing the number of points earned on that specific day and the total number of points earned up to that date. After the 15-day event, the members could exchange their points for a gift card from a local café for the equivalent amount in Hong Kong dollars (e.g., 500 points = HK$500, approximately US$65).

During the Event Period. Upon arrival, each member first checked in with club staff and then began exercising on the track. To prevent possible information exchange between the two groups, the staff instructed each member to exercise alone, which usually was the case anyway; if members ran in a couple or a group, which was rare, the staff would advise them not to talk to each other while running. After completing one lap, each member came back to the staff to claim his or her points. The staff always held up two facedown cards with identical backs, one with a red face and one with a black face. The member in the uncertain-point group drew a card, found out the color, and then claimed the points that corresponded to that color (one color represented five points, and the other represented three points). The members in the certain-point group grabbed one of the two cards as a gesture of claiming points and always received five points. To minimize possible information leakage, the staff informed the members in the uncertain-point condition about the meaning of each color at their first drawing only and did not repeat this information later. In both conditions, after claiming the points, the member could decide whether or not to go for another lap.

Results and Discussion

The dependent variable was the number of laps each member completed during the Spring Running event. Consistent with our prediction (hypothesis 1), we observed the reinforcing-uncertainty effect; those in the uncertain-point condition ($M = 13.93$, $SD = 18.51$) exercised for more laps than those in the certain-point condition ($M = 7.45$, $SD = 6.19$; $t(80) = 2.10$, $p = .039 < .05$, 95% CI = [.3511, 12.6060]), even though the uncertain-point condition promised a worse financial outcome. In other words, people literally ran "the extra mile" (precisely, 1.61 more miles) for the uncertain incentive. In additional regression analyses, we found that the reinforcing-uncertainty effect sustained whether or not we controlled for the number of days one came to exercise (controlling: $B = 5.56$, $SE = 2.52$, $p = .030 < .05$, 95% CI = [.5394, 10.5862]; not controlling: $B = 6.48$, $SE = 3.08$, $p = .039 < .05$, 95% CI = [.3511, 12.6060]), and that the incentive manipulation did not affect the number of days ($B = .10$, $SE = .19$, NS), which is not surprising since members were incentivized to exercise for more laps, not to come for more days.

To better appreciate the robustness of these results, one must note the dominated-uncertainty paradigm adopted in this study, as well as in all later studies. In a comparison between an uncertain incentive and a certain incentive of a higher expected value, the null hypothesis is not that the two incentives will produce equal effects; instead, the dominated, uncertain incentive is expected to be less effective. Therefore, our finding that uncertain incentives lead to more repetitions is based on a strong test against uncertain incentives.

In sum, study 1 provides the first demonstration of the reinforcing-uncertainty effect—a strong form of "uncertainty loving" in repetition decisions—and it is a demonstration from the field. The next couple of studies switch to laboratory settings for a better-controlled examination.

STUDY 2: RULING IN THE RESOLUTION-AS-REWARD ACCOUNT

Study 2 was designed to examine the role of uncertainty resolution in the uncertainty-reinforcing effect by manipulating the presence of resolution (hypothesis 2). Based on the resolution-as-reward account, the absence of resolution means the absence of a positive reinforcer, so it should, in turn, lead to the absence of the reinforcing-uncertainty effect.

Method

One hundred three city residents (38 women; average age = 35.39) were recruited by the Downtown Chicago Lab, a private research facility in the Chicago Loop, United States, operated by the Center for Decision Research at the University of Chicago Booth School of Business. All were compensated $3 for their time (20 minutes). We conducted a training program for a calculation test in the lab. Each participant first read about the calculation test: it would start in 20 minutes, and the participant who answered the most questions correctly within 40 seconds would receive a $50 prize.

Each participant was in an individual session with an experimenter who assumed the roles first of the trainer and later of the examiner. During the 20 minute lead time, the participant could complete as many practice rounds (each also lasting 40 seconds) as he or she wanted. To encourage the participant to practice, the trainer gave out stars for each practice round the participant completed. At the end of the study, the stars could be exchanged for candies (one star = one candy).

There were three between-subjects conditions. The number of stars varied across the conditions: either one or two stars in both of the uncertain-prize conditions, and two stars in the certain-prize condition. In all conditions, the experimenter first showed the participant a stack of 200 cards faceup. Then, the experimenter shuffled the cards and held the stack with all cards facedown throughout the study. If the participant decided to do another practice round, he or she drew a card from the stack and placed it on the table. In the certain-prize condition, all cards were printed with two stars, and the participant could examine the card if desired. In both uncertain-prize conditions, half of the cards were printed with two stars and half with one star; in the uncertain-prize/with-resolution condition, the participant could examine the card, whereas in the uncertain-prize/without-resolution condition, the participant could not examine the card at the time it was drawn and instead had to place the card facedown on the table. Those in the latter condition found out how many stars were printed on each card only after the entire preparation period (20 minutes) had passed, but before the test started. Notably, each participant endured the same objective uncertainty whether or not he or she checked out the card after each round, and thus normatively, the two uncertain-prize conditions are equivalent.

Results and Discussion

The dependent variable was practice repetition—that is, the number of practice rounds a participant took. Consistent with hypothesis 1, we found that participants in the uncertain-prize/with-resolution condition ($M = 8.62$, $SD = 3.00$) completed more rounds than those in the certain-prize condition ($M = 4.85$, $SD = 2.88$; $t(66) = 5.28$, $p < .001$, 95% CI = [2.3413, 5.1881]), which replicated the reinforcing-uncertainty effect we observed in the field experiment (study 1). More importantly, in support of the resolution-as-reward account (hypothesis 2), we found that those in the uncertain-prize/with-resolution condition also completed more rounds than those in the uncertain-prize/without-resolution condition ($M = 3.74$, $SD = 1.63$; $t(67) = 8.43$, $p < .001$, 95% CI = [3.7201, 6.0295]), indicating that uncertainty resolution is the driver of the reinforcing-uncertainty effect. In addition, those in the certain-prize condition took marginally more rounds than those in the uncertain-prize/without-resolution condition ($t(67) = 1.98$, $p = .052$, 95% CI = [–.0117, 2.2318]), suggesting that people are averse to risks and smaller benefits. Thus, study 2 demonstrated that uncertainty resolution is critical for the reinforcing-uncertainty effect to occur. Without timely resolution, uncertain incentives do not have an overall advantage over certain incentives. Uncertainty resolution utility is an extra motivational force that only uncertain incentives possess.

STUDY 3: RULING OUT ALTERNATIVE EXPLANATIONS

Study 3 was designed to assess a few possible alternative explanations based on outcome variety. The structure of uncertain incentives has two distinct features: outcome uncertainty and outcome variety. Outcome uncertainty invites resolution, and as study 2 demonstrates, resolution does contribute to the reinforcing-uncertainty effect. Outcome variety introduces a list of alternative explanations: (a) hedonic adaptation (that varied outcomes are more resistant to hedonic adaptation than fixed ones; Frederick and Loewenstein 1999; Kahneman and Thaler 1991); (b) the contrast effect or reference-dependent preferences (that a good outcome appears better when a not-so-good outcome serves as the reference point; Hsee 1996; Morewedge et al. 2009; Tversky and Kahneman 1991; Zhang 2015); and (c) variety seeking (that varied outcomes may be seen as more valuable than fixed outcomes; Fishbach, Ratner, and Zhang 2011; McAlister and Pessemier 1982; Simonson 1990).

Do any of these "variety" explanations contribute to the reinforcing-uncertainty effect? We included a certain-varied condition as a second control to examine whether outcome variety is critical to the reinforcing-uncertainty effect.

Method

Seventy-eight city residents (33 women; average age = 25.73) recruited by the Downtown Chicago Lab participated in voluntary repeated purchases. All participants received $3 as compensation for their time (15 minutes) at the beginning of the study. In the lab, we conducted a sales promotion program that was a low-tech version of the WeChat Pay cash reward promotion. Both the purchases and discounts played out for real for each individual participant.

Each participant was in an individual session with an experimenter, who assumed the role of a salesperson. The participant first read about a sales promotion program for Band-Aid Flexible Fabric bandages: "Buy One Band-Aid, Get One Cash Coupon." The promotion program had the following rules. For every purchase, the buyer would receive a cash amount indicated by the coupon. If the buyer liked receiving the coupons, she should purchase Band-Aids one piece at a time (all participants followed this advice). She was required to make three purchases to get familiar with the promotion program, and after the three mandatory purchases, it was up to her to decide how many more Band-Aids to purchase. All transactions would be realized immediately after each purchase. At the end of the study, the buyer could take home the Band-Aids she bought.

The face value of the coupons, or the discount, varied across conditions: either 10 or 5 cents (in the uncertain-discount condition), 10 cents (in the certain-discount condition), and either 10 or 5 cents (in the yoked, certain-varied-discount condition). In the uncertain-discount and the certain-discount conditions, the salesperson held a stack of 200 facedown coupons throughout the study. After each purchase, the buyer drew a random coupon from the stack, saw the amount, and then indicated whether she wanted to make another purchase. In the uncertain-discount condition, half of the coupons were printed with "10 cents," and the other half with "5 cents." In the certain-discount condition, all coupons were printed with "10 cents." In the yoked condition, the salesperson lined up the coupons on the table in a predetermined sequence that corresponded with the sequence in the uncertain-discount condition, but in this case, all coupons were faceup—the buyer could see the discounts and decide whether to make another purchase based on the upcoming coupon.

Results and Discussion

The dependent variable was purchase repetition—that is, the number of purchases a participant decided to make after the mandatory three purchases. Consistent with hypothesis 1, the participants in the uncertain-discount condition ($M = 13.64$, SD = 5.44) purchased more Band-Aids than those in the certain-discount condition ($M = 9.42$, SD = 5.36; $t(50) = 2.81$, $p < .01$, 95% CI = [1.2067, 7.2457]). Those in the uncertain-discount condition also purchased more Band-Aids than those in the yoked, certain-varied-discount condition ($M = 8.65$, SD = 3.07; $t(50) = 4.10$, $p < .001$, 95% CI = [2.5493, 7.4288]), and as we expected, the participants in the fixed and varied certain-discount conditions made a similar number of purchases ($t < 1$, $p > .5$, NS). These results indicate that it is uncertainty, not variety, that promotes purchase repetition. (In fact, most uncertainty-seeking behaviors are specific to uncertainty and not to variety, though they can be easily confused; also see Webb and Shu 2018).

Studies 2 and 3 revealed that the hidden value within uncertain incentives is uncertainty resolution, not outcome variety. Together, these studies also ruled out another possible explanation for the reinforcing-uncertainty effect in study 1: the earning-target account (Camerer et al. 1997). According to this alternative account, participants possess a specific earning target for the activity they are engaged in, so an uncertain incentive should lead to more repetitions because it has a lower expected value and thus requires more repetitions to reach the earning target. This alternative account is inconsistent with the results of both the control condition of study 2, in which participants did not do more practice rounds for a small incentive (one or two stars with unresolvable uncertainty) than for a large incentive (two stars with certainty), and the control condition in study 3, in which participants did not make more purchases for a small known discount (5 or 10 cents with certainty) than for a large known discount (10 cents with certainty). For further evidence against this earning-target account, see the study in supplementary material 1. In that study, an uncertain incentive was more reinforcing than both a certain incentive of a higher expected value and a certain incentive of the same expected value as the uncertain incentive; the latter result ruled out the earning-target account.

STUDY 4 (FIELD EXPERIMENT): TESTING THE REINFORCING-UNCERTAINTY EFFECT AT A LARGE MAGNITUDE

In study 1, we showed the reinforcing-uncertainty effect in the field with relatively small incentives and with a somewhat playful customer retention program. In study 4, we went back to the field to test the reinforcing-uncertainty effect (hypothesis 1) with more substantial incentives and in a more serious labor market. We designed and tested various incentives on a pay-by-task survey platform (similar to Amazon Mechanical Turk) affiliated with the Chinese University of Hong Kong. The certain pay we offered for each survey, HK$40 for 10 minutes, was more than four times the standard wage of part-time on-campus jobs at any public university in Hong Kong; for example, a business-school graduate student working as a part-time research assistant was paid HK$55 per hour (or HK$9.17 for 10 minutes) at the time of the study. The survey platform had a participant pool of over 3,000 active part-time workers from two major sources: current and past college students recruited from two large public universities (the Chinese University of Hong Kong and the Hong Kong Polytechnic University), and other residents openly recruited from multiple public part-time job websites (e.g., parttime.hk). Both the platform and its surveys were computer-based and mobile-device friendly, so workers could work from wherever they wanted without encountering the lab environment.

Study 4 was also designed to examine whether uncertain incentives have different effects on entry versus repetition (hypothesis 3). Entry refers to whether the participant entered the activity in the first place (namely, completing at least one survey), while repetition refers to the number of repetitions the participant completed after entering the activity. In this study, potential workers were free to decide whether to enter (i.e., whether to work on any surveys), and if so, how many times to repeat (i.e., how many surveys to complete). Thus, the study was intended to showcase the effect of uncertainty on both entry and repetition in a realistic and meaningful within-subject design. For a test of hypothesis 3 in a between-subjects design with random assignment, see the study in supplementary material 1.

Method

We posted a generic recruitment advertisement on the platform. It read (in colloquial Cantonese) that the survey platform would hold a three-week-long "Summer Survey Season" with survey opportunities available on a daily basis, that no other research activities would be conducted on the platform during the same period, and that payment for each survey would be issued upon completion (as is typical for the platform). To avoid undesirable self-selection in the recruitment stage, the advertisement did not specify any incentive scheme. From all respondents (over 3,000), we randomly selected and assigned 480 workers to either the certain-pay condition or the uncertain-pay condition (370 women, average age = 21.60; the sample size was determined in advance of data collection and based on budget constraints).

In the week prior to the survey season, the research assistant sent out a customized email to each worker with his or her individual incentive scheme. The email explained that the Summer Survey Season would last for 21 days, from Monday, August 8, 2016, to Monday, August 28, 2016, and that twice a day, at 8 a.m. and 8 p.m., a new survey would become available for 12 hours and the previous survey would automatically expire; that is, only one survey was available at a time. This procedure was designed to prevent workers from completing all the surveys at once without receiving payment information from the previous task. Therefore, all workers went through the same decision-making process: after completing each survey, all workers first found out the payment for that survey and then decided whether to take the new active survey.

The email also said that each survey was expected to take about 10 minutes to complete and that workers would be paid upon completion of each survey. Workers in the certain-pay condition further read that they would receive HK$40 for each completed survey, whereas workers in the uncertain-pay condition further read that they would receive either HK$20 or HK$40, with even chances, for each completed survey.

Notably, the repetition decision in this study was structured differently from previous lab studies (e.g., study 2). The platform did not require workers to take every survey until they decided to quit; rather, they could take as many surveys as they liked during the 21-day period and could skip as many surveys as they wanted in between. The interval between surveys was substantially longer—from 12 hours to 20 days—than in any of the previous studies, so this structural feature had the potential to dilute the pleasure of uncertainty resolution and challenge the generality of the reinforcing-uncertainty effect.

Results and Discussion

The setting in this field experiment resembled a real labor market, which typically involves self-selection; workers could choose whether to work, and those who chose to work could decide how many times to repeat the work. Accordingly, we analyzed both (a) entry (the percentage who took at least one survey) and (b) repetition (among those who took at least one survey, the average total number of surveys completed and the average probability that a worker completed a survey at each possible survey). Finally, we also explored the combined effect of entry and repetition.

Entry. Among all potential workers who were informed about their pay scheme, we observed that uncertain incentives had a significant negative effect on entry decisions; fewer potential workers chose to take a survey for the uncertain HK$40 or HK$20 pay than for the certain HK$40 pay (67% vs. 88%; $\chi^2 = 28.50$, $p < .001$, 95%

CI = [13.1206, 27.7127]). This negative effect may have occurred either because the expected pay in the uncertain-incentive condition was lower, or because participants were risk-averse, or both.

Repetition. Among the actual workers (those who entered and completed at least one of the 42 possible surveys), we found that uncertain incentives had a significant positive effect on repetition decisions; on average, actual workers incentivized by the uncertain pay completed about six more surveys over the entire survey period ($M = 25.96$, $SD = 13.45$) than actual workers incentivized by the certain pay ($M = 20.31$, $SD = 14.65$; $t(371) = 3.82$, $p < .01$, 95% CI = [2.7397, 8.5667]). Therefore, consistent with hypothesis 1, the reinforcing-uncertainty effect occurred even when incentives were substantial.

We constructed a dynamic decision model to examine, across all possible surveys, the likelihood that an actual worker would take any given survey. We found that an actual worker incentivized by the uncertain pay was, on average, 13% more likely to take any given survey than an actual worker incentivized by the certain pay ($B = .1346$, $SE = .0348$, $p < .01$, 95% CI = [.0661, 0.2031]). This finding sustained even when we controlled for the exact incentive received ($B = .1401$, $SE = .0394$, $p < .01$, 95% CI = [.0627, .2176]; incentive size had no effect: $B = .0164$, $SE = .0363$, NS, suggesting a different mechanism from Yang, Gu, and Galak 2017).

Entry and Repetition Combined. Among all potential workers, we found that by simple counts, a similar total number of surveys was completed under the uncertain pay scheme (4,265 surveys) as under the certain pay scheme (4,180 surveys). Even though the counts are close, the economic value of this difference is remarkable: for a similar output, survey researchers saved HK$42,880 (approximately US$5,500) by adopting the uncertain pay scheme.

With the dynamic decision model, we found that overall, uncertain incentives still had a positive effect. As time went on, a potential worker incentivized by the uncertain pay became significantly more likely to take any given survey than a potential worker incentivized by the certain pay ($B = .0021$, $SE = .0008$, $p < .01$, 95% CI = [.0005, .0036]). This finding is important. It implies that if the maximum number of repetitions had not been restricted—this study allowed only a maximum of 42—the positive uncertainty effect on repetition would have overridden the negative uncertainty effect on entry and yielded a net positive effect. In other words, the more repetitions an activity allows, the larger an advantage the uncertain incentive has over the certain incentive.

GENERAL DISCUSSION

Our research reveals that human reactions to uncertainty are more complex and nuanced than commonly thought. Contrary to what traditional economic theories would prescribe and what other behavioral decision theories would predict, we find a reinforcing-uncertainty effect: people repeat a task more for an uncertain incentive than for a certain incentive, even when the uncertain incentive is financially worse. Empirical evidence from four experiments, in both lab and field, show this positive effect of uncertain incentives on repetition decisions (see supplementary material 4 for a meta-analysis of all studies). We also find empirical evidence in support of the resolution-as-reward account: the resolution of uncertainty operates as a positive reinforcer of repetitions, and this uncertainty resolution utility is the hidden value inside of uncertain incentives (see supplementary material 2 for additional empirical evidence on uncertainty resolution utility). In the remainder of this section, we speculate on how our research is related to other phenomena in the extant literature and suggest directions for future research.

Relationship with Other Positive Uncertainty Effects

It is intuitive and often correct to expect a negative effect of uncertainty (Bragger et al. 1998; Camerer and Weber 1992; Duke, Goldsmith, and Amir 2018; Ellsberg 1961; Fantino, Navarro, and O'Daly 2005; Gneezy et al. 2006; Massey and Wu 2005; von Neumann and Morgenstern 1947; Webb and Shu 2017), so whenever a positive uncertainty effect occurs, we naturally pause and ponder: What is happening? We conjecture that the answer lies in the types of decisions in which uncertainty occurs.

Single-shot decisions (Goldsmith and Amir 2010) present the decision maker with different possible prospects, and the prospect that catches the most attention usually determines the direction of the uncertainty effect (the salience theory, Bordalo, Gennaioli, and Shleifer 2012). This attention account explains why optimistic decision makers behave as if they will receive the best possible outcome (Dhar et al. 1995; Dhar, Gonzalez-Vallejo, and Soman 1999; Gibson and Sanbonmatsu 2004; Goldsmith and Amir 2010; Wagenaar 1989). But importantly, an attention shift does not bring any additional psychological benefits; thus, the uncertain outcome in a single-shot decision cannot produce an effect more positive than its best possible certain outcome.

Single-shot goal-persistence decisions (Shen et al. 2015) have some unique features: there is an uncertain carrot hanging at a distant finish line (goal). When the decision maker is working toward it, the *unresolved* uncertainty can stimulate additional positive energy (e.g., excitement) to motivate the decision maker to work harder, if she indeed focuses on working. This additional positive energy explains why a decision maker would work even harder for an uncertain reward than for its best possible outcome as a certain reward.

Repetition decisions (the focus of this research) have some unique features too: after each repetition, there comes an opportunity to resolve uncertainty. As long as the decision maker keeps repeating the action, she will keep receiving not only the material reward but also the mental reward—uncertainty resolution utility. This additional mental reward explains why the decision maker would repeat the action even more for an uncertain incentive than for a certain, financially better incentive.

In sum, each psychological benefit is unique by itself and is also unique to the decision type that invites it. To identify the types of decisions is to precisely understand the psychological benefits that correspond with each, which in turn is to humbly appreciate the psychology of uncertainty. Future research may further investigate the fine lines between different psychological benefits and may integrate them into one systematic theoretical framework.

Relationship with the Intermittent Reinforcement Effect

Our research builds on and extends the animal learning research on intermittent reinforcement (Deslauriers and Everett 1977; Ferster and Skinner 1957; Hogarth and Villeval 2010; Skinner 1938). Like the typical intermittent reinforcement effect, our effect highlights the positive aspect of uncertainty. However, the typical intermittent reinforcement effect is about behavior extinction after incentives are removed (Hogarth and Villeval 2010; Lehr 1970), while our effect is about behavior acquisition while incentives are present. For example, the typical intermittent reinforcement effect shows that a pigeon is more likely to continue pressing a lever if lever-pressing used to yield uncertain rewards than if it used to yield certain rewards, even though it *currently yields no rewards*. Meanwhile, our effect shows that a human is more likely to repeat an action if the ongoing reward is uncertain than if it is certain. With only a few exceptions (Gonzalez, Eskin, and Bitterman 1963; Goodrich 1959; Ishida, Couvillon, and Bitterman 1992), most studies in the learning literature show negative effects of uncertain rewards at the acquisition stage (Finger 1942a, 1942b; Jenkins and Stanley 1950; Lewis 1956; Lewis and Cotton 1957; Sheffield 1949; Wilson, Weiss, and Amsel 1955). In the few exceptions, the positive effects of uncertain rewards seemed to occur only in special circumstances (e.g., the effect applied only to the initial running speed of a rat, but not to its later running speed), and it is not clear whether these circumstances are relevant to our findings. We expect future research to identify any potential relevancy.

Furthermore, the cause of the typical intermittent reinforcement effect also seems different from the cause of our effect. To our best understanding, the cause of the typical intermittent-reinforcement effect is ignorance: the pigeon that used to receive intermittent incentives, and now receives no incentives, does not know that the incentives have been removed. On the other hand, the cause of our reinforcing-uncertainty effect is uncertainty resolution: the uncertain incentive gives the person the opportunity to enjoy the pleasure of resolving uncertainty. Consistent with this reasoning, our studies show that the reinforcing-uncertainty effect occurs only if the uncertainty is resolved immediately after each repetition (e.g., study 2). This boundary condition would not apply to the typical intermittent reinforcement effect.

Future Directions: Possible Boundary Conditions and Other Moderating Factors

We have identified two boundary conditions for the reinforcing-uncertainty effect: whether one has engaged in the activity, and whether uncertainty is immediately resolved. There are other boundary conditions, however. One obvious boundary condition is the difference in expected value between the certain and uncertain incentives. The reinforcing-uncertainty effect is more likely to occur if the expected value of the uncertain incentive is close to the value of the certain incentive than if the former is far worse than the latter. If the expected value of the uncertain incentive is far worse than the certain incentive, then the uncertain incentive's advantage in the uncertainty resolution utility may not offset its disadvantage in the outcome acquisition utility, and as a result, the reinforcing-uncertainty effect will disappear or reverse. Another boundary condition is the magnitude of the worst possible outcome in the uncertain incentive—in particular, how bad the worst possible outcome is. The reinforcing-uncertainty effect is more likely to occur if the worst possible outcome is still acceptable than if it is not. If the worst possible outcome is below the acceptable threshold, this outcome can be construed as a loss and may trigger the effect of loss aversion, which might reduce or reverse the reinforcing-uncertainty effect.

This research focuses on circumstances in which the probabilities of the uncertain outcomes are known. What happens if the probabilities of the uncertain outcomes are unknown? Previous literature shows ambiguity aversion in single-shot decisions (Fox and Tversky 1995). However, we surmise that ambiguity may promote repetition decisions, because repetition under ambiguity generates not only the pleasure of resolving uncertainty, but also the chance for real learning opportunities and real informational values. For example, if a consumer wanted to identify the different prizes and their respective likelihoods in Qatar's sweepstakes promotion, "Coca-Cola Under the Cap," she would first have to purchase and open a very large number of bottled drinks (assuming the prize information was not previously announced or easy to locate). Therefore, uncertain outcomes with unknown probabilities ("ambiguous" outcomes) may lead to even more repetitions than uncertain outcomes with known probabilities ("risky" outcomes). Of course, this is only our speculation and awaits further research to test.

Other questions that await future research include whether the reinforcing-uncertainty effect is more likely to occur if the probability distribution of the possible outcomes in the uncertain incentive is even (50% vs. 50%) or skewed (e.g., 10% vs. 90%; Parducci 1965; Volpp et al. 2008), if the outcomes are familiar or unfamiliar (Kupor, Liu, and Amir 2018; Morewedge et al. 2009; Shen and Urminsky 2013), and if the decision maker is in a calculation mode or feelings mode (Hsee and Rottenstreich 2004; Rottenstreich and Hsee 2001).

Gambles, Games, and Gamification

Some people love gambling, so one may wonder: Can the reinforcing-uncertainty effect be subsumed by this kind of gambling phenomenon? We doubt so. In gambling, the best possible outcome is typically much better than the outcome of not gambling at all ($0). But in all our experiments, the best possible outcome in the uncertain-incentive condition is not any better than the outcome in the certain-incentive condition. We are not aware of any gambling research that shows that people would choose to gamble if the best possible outcome were not better than not gambling at all. Although our effect cannot be subsumed by the typical gambling phenomenon, our resolution-as-reward account can potentially explain why people enjoy gambling: the resolution of uncertainty each time a gambler plays the slot machine or spins the roulette wheel is reinforcing or even addictive.

One may also wonder: Does the reinforcing-uncertainty effect exist only in mere gamelike situations with trivial consequences? We doubt so, too. Our research shows that this effect can occur in serious contexts with consequential decisions; in study 4, for example, a single worker could potentially have earned up to HK$1,680. Even when the incentive for each repetition is bite-sized—such as whether to recycle a plastic drink bottle for 30 cents or whether to buy a dozen cage-free eggs at a $1.49 discount—the aggregate incentives are sizable across time and populations. Importantly, although the decisions we studied are serious and not games, the implementation of uncertain incentives can transform serious decisions that otherwise are not so fun into decisions that are fun. In other words, adding uncertainty can make an otherwise nongame activity gamelike. Indeed, this is the meaning of "gamification" (Bittner and Schipper 2014; Dicheva et al. 2015; Etkin 2016; Hamari, Koivisto, and Sarsa 2014; Huang, Etkin, and Jin 2017; Huang and Soman 2013; Shen and Hsee 2017). We next offer a few gamification ideas based on our findings.

Marketing and Public Policy Implications

As we noted at the beginning of the article, some companies are already taking advantage of incentive uncertainty in promotions. For example, WeChat Pay, one of the largest mobile payment applications in the world, awards an uncertain cash bonus to a customer once she uses the software to make a purchase. However, marketers and policy makers can do more to take advantage of the benefits of uncertainty when strategizing for retention purposes, especially when they are under budgetary constraints.

In addition to the contexts already tested or discussed, sustainability campaigns are a fascinating and relevant domain. For example, due to social responsibility (or social pressure), marketers incentivize repeated environmentally friendly behavior. Grocery retailers encourage customers to reuse cloth shopping bags with a negligible rebate, such as 10 cents off every purchase at a Whole Foods Market in the United States and Canada. Coffee shops encourage drinkers to bring their own mugs for a small discount, such as HK$3 off every beverage at a Starbucks in Hong Kong. Hotels and resorts encourage guests to "Choose Green" and skip housekeeping with a nominal reward, such as a food or beverage voucher worth £5 for every night at a Starwood hotel in the United Kingdom. Regardless of the baseline effectiveness of these specific incentive programs, we speculate that they would be more effective if the incentives were uncertain. Specifically, we predict that an uncertain rebate will lead to more frequent usage of cloth shopping bags, an uncertain discount will lead to more frequent usage of personal mugs, and an uncertain food or beverage voucher will lead to more skipping of unnecessary housekeeping services.

As another example, several US states currently require consumers who are buying bottled drinks to deposit an amount, included in the price, that is refunded if the bottles are returned to a recycling center or machine. Usually, the size of the refund is printed on the bottle and therefore is certain. However, we recommend changing the certain refund to an uncertain amount, essentially transforming the bottle-recycling machine into a bottle-recycling "slot machine" that we predict will gamify the otherwise tedious recycling activity and encourage people to recycle more. Then, recycling could be rewarding not only for the monetary return but also for the pleasure of uncertainty resolution.

DATA COLLECTION INFORMATION

The first author supervised the data collection for study 1 by staff at a running club in Shatin, Hong Kong, in 2015 and for study 4 by the survey platform research team at CUHK Business School, the Chinese University of Hong Kong, Hong Kong, in 2016. The first author also supervised the data collection for studies 2 and 3 by research

assistants at the Downtown Research Lab, operated by the Center for Decision Research at the University of Chicago Booth School of Business, Chicago IL, United States, in 2014. These data were analyzed by the first and third authors.

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Web Appendix

The Fun and Function of Uncertainty:

Uncertain Incentives Reinforce Repetition Decisions

LUXI SHEN

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The Fun and Function of Uncertainty: Uncertain Incentives Reinforce Behavioral Repetition

Supplementary Material 1

Additional Study 1: Empirical Evidence on "Prediction vs. Performance" as a Boundary Condition

This study carried three goals. One was to replicate the reinforcing-uncertainty effect (H1) in an exhausting physical task: climbing up and down stairs. The second, and most important, goal was to examine the resolution-as-reward account by identifying the boundary condition that the reinforcing-uncertainty effect occurs only during, not before, repetitions (H3). To do so, we contrasted performance (actual repetitions) with prediction (predicted repetitions) in a between-subjects design with random assignment (unlike study 4 in the paper, where this boundary condition was operationalized as self-selection).

The third objective was to assess a possible alternative explanation for the reinforcing-uncertainty effect that is specific to labor supply decisions: earning targets (Camerer et al. 1997). Because the uncertain incentive has a lower expected value than the certain incentive, it requires more repetitions to reach a worker's earning target, if the worker indeed has an earning target. Notably, this speculation was already inconsistent with findings in studies 2 and 3. Nevertheless, to rule out this possibility directly, this study introduced a second control: a certain incentive with the same expected value as the uncertain incentive.

Method

One hundred and thirty-four female college students (average age = 19.82 years old) from the University of Chicago, United States, participated in this study. All participants received a nominal payment ($1) as the flat participation compensation. They could make extra money by climbing up and down six flights of stairs (108 steps in total) for as many round trips as they wanted during a 15-minute period. The study employed a 2 (mode: performance vs. prediction) × 3 (payment: uncertain vs. certain high value vs. certain expected value) between-subjects design. Each participant was in an individual session with an experimenter.

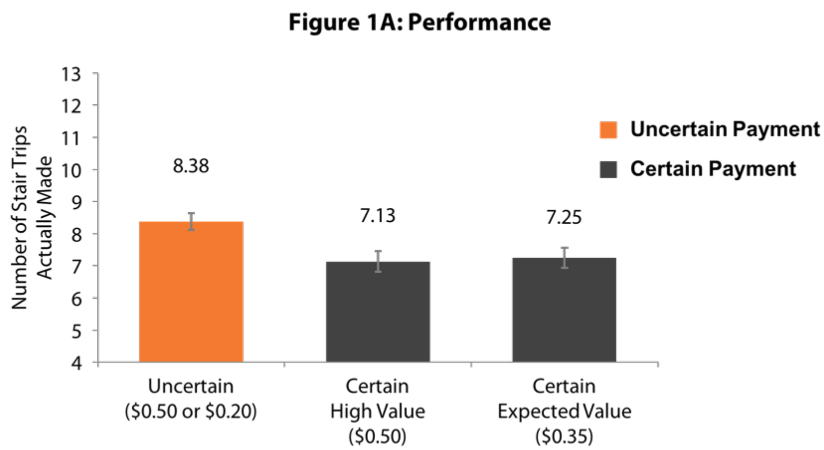
Performance. The dependent variable for the performance conditions, actual repetition, was the number of round trips each participant made. Before any climbing occurred, the experimenter first showed the participant 150 poker chips and an empty, opaque cloth bag, into which the experimenter poured and shuffled all of the chips. Each poker chip represented one per-trip payment, and the face value of the poker chips varied across conditions: In the uncertain-payment condition, half of the poker chips (one color) represented $0.50, while the other half (another color) represented $0.20; the chips were identical aside from color. In both certain-payment conditions, all chips were the same color and thus the same value; in particular, in the certain-payment/high-value condition, each poker chip represented $0.50, while in the certain-payment/expected-value condition, each poker chip represented $0.35. After completing one round trip, the participant drew a poker chip from the bag without looking into it. It was up to her how many round trips to make, and she could take a break whenever she wanted during the 15-minute period.

Prediction. The dependent variable for the prediction conditions, predicted repetition, was the number of round trips each participant predicted she would make. The design and procedures were identical to those in the performance conditions, except that the participants in the prediction conditions did not actually climb the stairs. Instead, they predicted the number of trips they would be willing to make given the per-trip payment in their respective conditions.

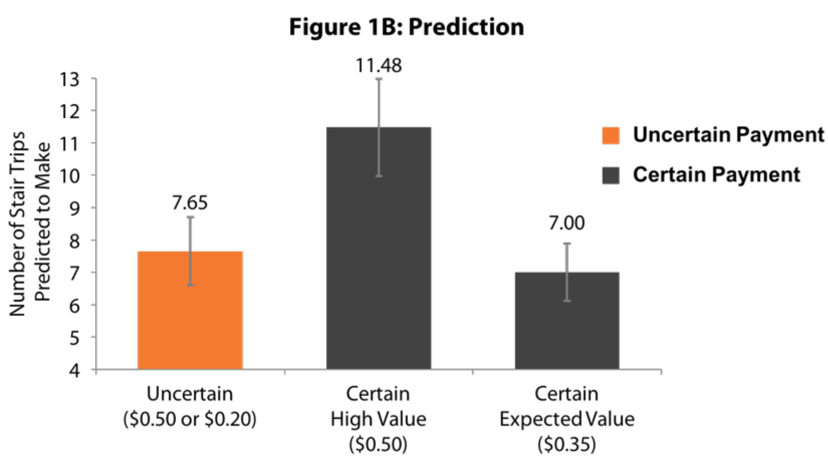
Results and Discussion

Figures 1A and 1B present the results. Consistent with our hypothesis (H3), we found a two-way interaction between mode (performance vs. prediction) and payment (uncertain vs. certain high value vs. certain expected value) on repetition ($F(2, 134) = 6.07$, $p < .01$, $\eta^2 = 0.08$), indicating that uncertain incentives had different effects on repetition in terms of both prediction and performance. We note that because the repetition was elicited differently in the performance and prediction conditions, we should not and did not compare repetition results for each payment across modes. Instead, we analyzed repetition results within each mode and interpreted the result pattern for each mode.

Figures 1A and 1B: Performance and Prediction Results



Notes: The error bars indicate the standard error of each condition.
In the performance mode, uncertain payment led to the greatest number of actual repetitions.



Notes: The error bars indicate the standard error of each condition.
In the prediction mode, certain-high-value payment led to the greatest number of predicted repetitions.

Performance (actual repetitions). Participants in the uncertain-payment condition (M = 8.38, SD = 1.28) repeated the trip more times than both those in the certain-payment/high-value condition (M = 7.13, SD = 1.57; t(46) = 3.03, $p < .01$, 95% C.I. = [0.4183 , 2.0817]) and those in the certain-payment/expected-value condition (M = 7.25, SD = 1.51; t(46) = 2.78, $p < .01$, 95% C.I. = [0.3117, 1.9383]), with no significant difference between the two certain conditions (t < .5, $p > .7$, *n.s.*). The difference between the uncertain- and certain-payment conditions is not negligible; as we have all experienced, the last stair trip is always more exhausting than the one before it. These results support our prediction that payment uncertainty increases repetitions in actual performance.

With the two certain-payment conditions together, the performance results provide a clean demonstration of the reinforcing-uncertainty effect in labor supply decisions. The inclusion of the certain-payment/expected-value condition ruled out the possibility that workers in an uncertain payment scheme have to "work more due to a smaller wage" (substitution effect); in fact, participants worked harder for an uncertain payment than for a certain payment of the same expected value. The inclusion of the certain-payment/high-value condition ruled out the possibility that workers in an uncertain payment scheme optimistically believe they will receive the best possible outcome (Dhar et al. 1995, 1999; Goldsmith and Amir 2010) and "work more for a larger wage" (income effect); in fact, participants worked even harder for an uncertain payment than for the best possible payoff in the uncertain payment.

Predictions (predicted repetitions). Participants who were offered a certain per-trip payment of $0.50 (M = 11.48, SD = 6.88) predicted that they would make more stair trips than both those who were offered a certain per-trip payment of $0.35 (M = 7.00, SD = 4.06; t(40) = 2.57, $p = .014 < .05$, 95% C.I. = [0.9517, 8.0007]) and those who were offered an uncertain per-trip payment with a $0.35 expected value (M = 7.65, SD = 4.72; t(39) = 2.07, $p = .045 < .05$, 95% C.I. = [0.0809, 7.5715]). Participants in the certain-payment/expected-value condition and the uncertain condition predicted similar repetitions ($t < .5$, $p > .6$, *n.s*). These results support our theory (H3) that the reinforcing-uncertainty effect does not arise before people engage in the activity. Notably, however, the predictors in the uncertain-payment condition did not significantly underestimate actual performance. At first glance, this result seems contradictory to our theory that predictors underappreciate the power of uncertainty, but it is not necessarily contradictory. It is possible that predictors did underappreciate the power of uncertainty, and at the same time were overconfident about future performance (as most people generally are). We speculate that the effect of overconfidence (which is not specific to our theory) may have canceled out the effect of underestimation, thus making the final prediction seem rather accurate.

Our theory posits that before engaging in an activity, people are unable to predict the reinforcing-uncertainty effect; namely, they are unable to predict that the performance in the uncertain-payment condition is better than that in the certain-payment/high-value condition. The present study supported this proposition. Our theory is mute about whether people overestimate or underestimate the absolute level of performance in any individual condition. The answer to that question depends on factors unrelated to our theory, such as wishful-thinking, overconfidence, and ignorance of the difficulty of the task.

Supplementary Material 2

Additional Study 2: Empirical Evidence on Uncertainty Resolution Utility

This study was designed to demonstrate the reinforcing-uncertainty effect (H1) and to provide process evidence for the resolution-as-reward account. This study focused on two basic conditions—a certain incentive and an uncertain incentive of a lower expected value—and explored another common marketing scenario: gift card purchase. We predicted that uncertainty in price would reinforce purchase repetitions.

More importantly, this study inspected the decision-making process for repeated purchases under price uncertainty. We measured each participant's feeling about the uncertainty they resolved; the rating of their resolution experience represented the uncertainty resolution utility. We also measured each participant's feeling about the price they received; the rating of price attractiveness represented the outcome acquisition utility. Based on our theory, we expected that resolution experience would mediate the effect of price uncertainty on purchase repetitions, controlling for price attractiveness.

Method

Four hundred thirty-four workers on Amazon's Mechanical Turk (269 women; average age = 37.45 years old) in the United States participated in repeated purchases in this study. All participants received a nominal payment ($0.35) for their participation, and five percent were randomly selected to receive an extra cash prize of $25 and play out their purchase decisions for real. All participants were offered a series of opportunities to purchase Amazon Gift Cards at a discounted price. Each card was worth $5. Half of the participants read that the price would always be $3.50 (the certain-price condition), and the other half read that the price would be either $3.50 or $4.50 with even chances, but they would not find out which price they received until after the purchase. Note that $3.50 is the better price for buyers, and hence the certain price dominates the uncertain price. After participants learned the price of their previous purchase, they decided whether or not to purchase another gift card. They repeated this purchase procedure until they did not want to purchase any more cards.

After making all purchases, the participants were asked to recall and report on their decision-making process. They first indicated whether they experienced resolving any uncertainty about price, and if so, they answered the question, "Focus on the resolution of uncertainty—the experience that you find out something you did not know, not the outcome you discover. How did the uncertainty resolution itself make you feel?" Participants rated their resolution experience on a 9-point scale that ranged from "very bad" (coded as -4) to "very good" (coded as +4) with "neutral/not applicable" coded as 0. If a participant indicated that they did not experience uncertainty resolution, their rating was automatically coded as 0. All participants also answered the question, "Focus on the exact prices you got. How did you feel about the prices you received?" by rating price attractiveness on the same 9-point scale.

Results and Discussion

Behavioral results: purchase repetition. To test hypothesis 1, we examined purchase repetition—the total number of gift cards purchased by those who made purchases—and found that the participants in the uncertain-price condition (M = 11.12, SD = 13.53) made more purchases than those in the certain-price condition (M = 8.76, SD = 8.66; $t(432) = 2.19$, $p = .029 < .05$).

Noticeably, our finding on cost uncertainty is different from the prediction based on prospect theory that people are risk-seeking when it comes to losses (Kahneman and Tversky 1979). People do not perceive prices as losses (Thaler 1985; Novemsky and Kahneman 2005), and thus, prospect theory does not predict that people will favor uncertainty in prices, especially when the uncertain price is financially worse.

Process evidence: resolution experience. According to our theory, the key to the reinforcing-uncertainty effect is uncertainty resolution utility. In support of the theory, we found that the majority (90%) of participants in the uncertain-price condition reported having experienced uncertainty resolution, whereas very few participants (only 2%) in the certain-price condition did so ($\chi^2 = 340.48$, $p < .001$). We further found that those who did experience uncertainty resolution rated their experience as positive rather than negative (M = 1.21, SD = 1.80; one-sample $t(185) = 9.17$, $p < .001$), indicating that uncertainty resolution has positive utility.

Next, we examined the extent to which uncertainty resolution utility explains the reinforcing-uncertainty effect. A set of simple regression models revealed that price uncertainty predicts purchase repetition via resolution experience, independent of price attractiveness. Specifically, controlling for price attractiveness, price uncertainty alone predicts purchase repetition ($B = 3.13$, SE = 1.10, $p = .005$). Also, price uncertainty influences resolution experience ($B = 1.07$, SE = .12, $p < .001$), and in turn, resolution experience predicts purchase repetition ($B = 1.67$, SE = .39, $p < .001$), again controlling for price attractiveness (Table 1). Moreover, controlling for price attractiveness, resolution experience fully mediates the effect of price uncertainty on purchase repetition (based on 10,000 bootstrap samples: 95% bootstrap C.I. = [.65, 3.48]; Preacher, Rucker, and Hayes 2007). A multiple regression on purchase repetition, using both price uncertainty and resolution experience, and controlling for price attractiveness, yielded a significant effect of resolution experience ($B = 1.46$, SE = .44, $p = .001$) and a reduced, non-significant effect of price uncertainty ($B = 1.32$, SE = 1.21, $p > .2$, *n.s.*; all these findings held even when we did not control for price attractiveness in the statistical models, though according to the theoretical model, price attractiveness should serve as a covariant.)

Table 1: Mediation Analysis Procedure Examining the Role of Resolution Experience in the Effect of Price Uncertainty on Purchase Repetition, Controlling for Price Attractiveness (Among Participants Who Made At Least One Purchase)

DV	(1) Number of Purchases	(2) Uncertainty Resolution	(3) Number of Purchases	(4) Number of Purchases
Price Uncertainty	3.1253*** (1.0954)	1.0717*** (0.1208)		1.3232 (1.2087)
Price Attractiveness	1.0012*** (0.3297)		0.5744* (0.3210)	0.6927** (0.3386)
Resolution Experience			1.6739*** (0.3906)	1.4616*** (0.4360)
Constant	6.2159*** (1.1093)	0.0129 (0.0822)	7.7461*** (0.8761)	6.9822*** (1.1199)
N	434	434	434	434

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: All models used a standard OLS approach. In model (1), price uncertainty alone significantly predicts purchase repetition, controlling for price attractiveness. In model (2), price uncertainty significantly predicts resolution experience. In model (3), resolution experience significantly predicts purchase repetition, controlling for price attractiveness. In model (4), resolution experience significantly reduces and hence fully mediates the effect of price uncertainty on purchase repetition, controlling for price attractiveness.

Lastly, we investigated how uncertainty resolution utility (measured as resolution experience) operates under different incentive conditions while controlling for outcome acquisition utility (measured as price attractiveness). Regression models, by condition, of the effect of price uncertainty on purchase repetition while controlling for price attractiveness revealed that resolution experience positively correlates with purchase repetition when the price is uncertain (B = 1.89, SE = .56, p = .001), but not when the price is certain (B = -1.28, SE = 1.92, p > .5, *n.s.;* Table 2). Both results lend support to our resolution-as-reward account: resolution reinforces repetition under uncertainty.

Table 2: OLS Regression Models for Purchase Repetition by Condition (Among Participants Who Made At Least One Purchase)

DV	(1) Uncertain Price: Number of Purchases	(2) Certain Price: Number of Purchases
Resolution Experience	1.8944***	-1.2839
	(0.5567)	(1.9222)
Price Attractiveness	-0.2716	1.4981***
	(0.5965)	(0.3563)
Constant	9.5535***	4.9678***
	(1.3632)	(1.0606)
N	201	233

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: In model (1), in the uncertain-price condition, resolution experience significantly predicts purchase repetition, but price attractiveness does not. In model (2), in the certain-price condition, price attractiveness significantly predicts purchase repetition, but resolution experience does not.

Summary. This study demonstrated the reinforcing-uncertainty effect in the context of purchase decisions and supported the resolution-as-reward account. Uncertain prices beget uncertainty resolution, and therefore exert a positive effect on purchase repetition. Meanwhile, this study also showed that uncertainty resolution utility is a mental reward that is unique to uncertain incentives and drives behavioral repetitions under incentive uncertainty.

Supplementary Material 3

Additional Experimental Details and the Statement for Disclosure of Sample, Conditions, Measures, and Exclusions

- Study 1 in the paper
- Study 2 in the paper
- Study 3 in the paper
- Study 4 in the paper
- Additional Study 1
- Additional Study 2

Study 1

1. Sample size for each cell: not determined by the researchers. It was the total number of running club members who showed up for this event, divided by the number of conditions.

2. Conditions: two (uncertain-points vs. certain-points) between-subjects conditions

3. Data exclusions: By the end of the recruitment deadline, 111 local residents, the majority of whom were associated with the university, became new members of the club and signed up for the Spring Running event via WhatsApp messages, the club's QR scan code, or the event's online Google Sheet. Of those who signed up, 29 were not able to show up for various reasons such as physical injuries, schedule conflicts, and miscommunication. That left a total number of 82 members (49 women, average age = 20.03 years old) who took part in the event. We included them all in the study.

4. Measures

a. Behavioral measurement: number of laps each participant completed on each day of the event (DV)

b. Questionnaire question: gender

c. Questionnaire question: age

d. Questionnaire question: first language

Table 3: Ordinary Least Squares (OLS) Regression Models Exploring Different Effects of Point Uncertainty

DV	(1) Total Number of Days Exercised	(2) Number of Laps Completed	(3) Number of Laps Completed
Point Uncertainty	0.0976 (0.1910)	6.4786** (3.0790)	5.5628** (2.5237)
Total Number of Days Exercised			9.3812*** (1.4747)
Constant	2.9500 (0.1367)	7.4500*** (2.2036)	-20.2247*** (4.7094)
N	82	82	82

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Point uncertainty takes a value of 1 for the uncertain-point condition and 0 for the certain-point condition. In model (1), the regression model regresses the total number of days a person exercised on the independent variable (point uncertainty). Point uncertainty does not predict the total number of days a person came to exercise. Then, two regression models regress the dependent variable (number of laps completed) on different sets of independent variables. In model (2), point uncertainty significantly predicts the number of laps a person completed during the entire 15-day period. The average participant completed 6.48 more laps if incentivized by uncertain points than by certain points. In model (3), controlling for the number of days a person showed up, point uncertainty still significantly predicts the number of laps completed during the entire 15-day period. Even if controlling for the number of days a person showed up, participants incentivized by uncertain points still completed 5.56 more laps than those incentivized by certain points.

Study 2

1. Sample size: determined in advance of the experiment. The experimenter followed the stopping rule that data collection closed at the end of the week in which there were at least 20 participants in each cell of the experiment.

2. Conditions: three (uncertain-prize/with-resolution vs. uncertain-prize/without-resolution vs. certain-prize) between-subjects conditions

3. Data exclusion: none (all participants took some practice rounds)

4. Measures

a. Behavioral measurement: number of practice rounds each participant took during the study program (DV)

Note: We are aware that the effect size for the difference between the uncertain-prize/with-resolution and uncertain-prize/without-resolution conditions is considerably larger than other differences, such as the effect size of the difference between the uncertain-prize/with-resolution condition and the certain-prize condition. Our interpretation is that both of the former conditions were treatment conditions and the certain-prize condition was the control; the uncertain-prize/with-resolution condition incentivized participants to work more while the uncertain-prize/without-resolution condition incentivized participants to work less.

b. Behavioral measurement: test score = number of questions participants completed in the final test

Result: Our theory does not hold predictions regarding test score, that is, the number of calculation questions the participants completed in the final test. But for the sake of curiosity, we explored the effects on test score and found that participants in both the uncertain-prize/with-resolution condition ($M = 7.06$, $SD = 2.42$) and the certain-prize condition ($M = 6.94$, $SD = 2.98$) performed similarly well ($t < .2$, $p > .85$) and did marginally better than those in the uncertain-prize/without-resolution condition ($M = 5.91$, $SD = 2.23$; uncertain-prize/without-resolution vs. uncertain-prize/with-resolution: $t(66) = 2.04$, $p =.045$; uncertain-prize/without-resolution vs. certain-prize: $t(67) = 1.62$, $p = .109$).

c. Questionnaire question: gender

d. Questionnaire question: age

e. Questionnaire question: first language

Study 3

1. Sample size: determined in advance of the experiment. The experimenter followed the stopping rule that data collection closed at the end of the week in which there were at least 20 participants in each cell of the experiment.

2. Conditions: three (uncertain-discount vs. certain-discount vs. yoked, certain-varied-discount) between-subjects conditions

3. Data exclusion: Six participants who did not make any extra purchases, that is, did not participate in repeated purchases at all, were excluded from data analyses on repetition. In particular, 0% of participants in the uncertain-discount condition, 14% of participants in the certain-discount condition, and 7% of participants in the yoked condition were excluded from the hypothesis testing analyses. We could not use a chi-square test because one of the values is 0%. Hence, we instead had to regress the probability of continuing to make extra purchases (equivalent to percentage when multiplying probability by 100) on a 3-level categorical variable for condition (uncertain-discount vs. certain-discount vs. yoked, certain-varied-discount) and found no significant difference across discount conditions (B = .0357, $p > .3$). This result either replicates Goldsmith and Amir (2010) or suggests a ceiling effect as the explanation for the null effect on entry. Note that uncertainty resolution may kick in after the practice rounds.

Table 4: Linear Probability Model for Probability of Making Extra Purchases

	(1) Probability of Making Extra Purchases
Discount: Uncertain vs Certain vs Certain-Varied (Yoked)	0.0357
	(0.0346)
Constant	0.8571***
	(0.0748)
N	84

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4. Measures

a. Behavioral measurement: number of purchases each participant made among those who made extra (non-mandatory) purchases (DV)

b. Questionnaire question: gender

c. Questionnaire question: age

d. Questionnaire question: first language

Table 5: Descriptive Statistics for Behavioral Measurements

	Total Number of Purchases			Percentage of Those Making Extra Purchases	Total Number of Purchases Among Those Making Extra Purchases	
	Mean	*Median*	*SD*	*Percentage*	*Mean*	*SD*
Uncertain Discount	13.64	12.50	5.44	100%	13.64	5.44
Certain Discount	8.50	6.50	5.45	86%	9.42	5.36
Certain-Varied Discount (Yoked)	8.25	7.50	3.31	93%	8.65	3.07

Notes: Because not all participants made extra purchases beyond the mandatory purchases, we analyzed participants' purchase decisions in two ways.

We first examined the total number of purchases (i.e., including the three required purchases) made by all the participants, regardless of whether or not they made extra purchases. Our manipulation produced a significant effect on the total number of purchases across conditions ($F(2, 83) = 11.08$, $p < .001$). Specifically, the participants in the uncertain-discount condition ($M = 13.64$, $SD = 5.44$) made more purchases than both those in the certain-discount condition ($M = 8.50$, $SD = 5.45$; $t(54) = 3.53$, $p = .001$) and those in the yoked, certain-varied-discount condition ($M = 8.25$, $SD = 3.31$; $t(54) = 4.48$, $p < .001$). Also, participants made a similar number of purchases in the certain-discount and yoked, certain-varied-discount conditions ($t < .5$, $p > .80$).

We further investigated the purchase data with a focus on those who chose to make extra purchases beyond the initial mandatory ones. First, we examined the percentage of participants who chose to make extra purchases, and we encountered a ceiling effect across all conditions (uncertain: 100%; certain: 86%; yoked: 93%), indicating the general popularity of the sales promotion program. Second and more importantly, we focused on those who made extra purchases and examined the total number of purchases they made, which varied significantly across conditions ($F(2, 77) = 8.64$, $p < .001$). In support of our prediction, the participants in the uncertain-discount condition ($M = 13.64$, $SD = 5.44$) made more purchases than those in the certain-discount condition ($M = 9.42$, $SD = 5.36$; $t(50) = 2.81$, $p < .01$). Those in the uncertain-discount condition also made more purchases than those in the yoked condition ($M = 8.65$, $SD = 3.07$; $t(50) = 4.10$, $p < .001$). The participants in the certain-discount and yoked conditions made a similar number of purchases ($t < 1$, $p > .50$). These results indicate that outcome uncertainty, not outcome variety, was the driver behind purchase repetition.

Study 4

1. Sample size: determined based on responses to recruitment, after which we randomly assigned 480 participants to each condition

2. Conditions: two (uncertain pay vs. certain pay) between-subjects conditions. The experiment setting yielded a mixed design, 2 (mode: entry vs. repetition) x 2 (pay uncertainty: uncertain vs. certain), of which mode is a within-subjects factor and pay uncertainty is a between-subjects factor. This design incorporated self-selection issues in the within-subjects factor (mode), which we addressed in the statistical models. We designed various incentive schemes for multiple different research projects but tested them at the same Summer Survey Season event. Other incentive schemes are irrelevant to this research and hence not included in this paper.

3. Data exclusion: none

4. Measures

a. Behavioral measurement: whether a worker completed a specific survey (i.e., the survey available at a specific time point) and how much the worker received for the completed survey (DV)

Table 6: Linear Probability Models Clustered by Participant, Exploring Different Factors that Influence Probability of Taking a Survey at Time *t*

	(1) Probability of Taking a Survey at Time *t*	(2) Probability of Taking a Survey at Time *t*	(3) Probability of Taking a Survey at Time *t*	(4) Probability of Taking a Survey at Time *t*
Pay Uncertainty	0.1346*** (0.0348)	0.1401*** (0.0394)	0.2234*** (0.0328)	0.09113*** (0.0221)
Past Outcome		0.0164 (0.0363)		0.0149 (0.0156)
Good Pay Streak			0.0349*** (0.0023)	0.0081*** (0.0010)
Earnings				0.0001 (0.0001)
Surveys Completed				0.0289*** (0.0043)
t				-0.0241*** (0.0008)
Constant	0.4836*** (0.0240)	0.4992*** (0.0439)	0.3867*** (0.0222)	0.6362*** (0.0278)
N	15582	14065	15256	14065

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All analyses in Table 6 include all participants who completed at least one survey. The columns follow the chronological order in which results are reported in the paper, under the repetition section. All models are clustered at the participant level.

The first variable, pay uncertainty, is coded as 1 for participants in the uncertain-pay condition and 0 for those in the certain-pay condition. The second variable, past outcome, is coded as 1 if the participant received the better outcome (payment of HK$40) for the most recent completed survey, and 0 if the participant received the worse outcome (payment of HK$20). This variable is not restricted to the survey offered in the preceding 12 hours, but rather records the outcome from the most recent period in which the participant took a survey. Good-pay streak tracks the number of consecutive times the participant has received the better outcome; it resets when a streak is broken. For example, suppose that for the past 5 consecutive rounds, Participant X has received HK$40 (the better outcome). The good-pay streak takes on the value of 5. If the participant now receives HK$20 (the worse outcome), the good-pay streak variable will take on 0 again. Earnings denotes the participant's total earnings up until the current period. Lastly, surveys completed is an index of the number of periods in which a participant has taken a survey up until now, and the variable *t* indicates the time period the participant is in.

Specifically, in model (1), we demonstrate that participants in the uncertain-pay condition were, on average, more likely to take a specific survey than those in the certain-pay condition. In model (2), where we switch the DV from the average number of surveys to the probability of taking the survey in a given period, we again find that participants in the uncertain-pay condition are significantly more likely to take the survey compared to participants in the certain-pay condition. In model (3), we add past outcome as a control and find that this factor cannot explain the difference between the certain- and uncertain-pay conditions. In model (4), we take multiple considerations into account at the same time.

We find that the addition of the good-pay streak factor has a significant, positive coefficient, indicating that the probability of taking the survey in a given period increases as the length of the good-pay streak increases. Nevertheless, the coefficient and effect on the indicator for certain vs. uncertain pay is still significant and cannot be explained completely. Lastly, we add further controls and show that our result is robust to all controls combined, indicating that uncertainty resolution is an effect above and beyond any of these controls. It is worth noting that the *N* is smaller for linear probability models, including past outcome, because the observation for which each participant has no past outcome is automatically dropped from the analysis.

Table 7: Linear Probability Model Clustered by Participant, Exploring Difference in Time Trends Between Conditions

	(1) Probability of Taking a Survey at Time *t*
Pay Uncertainty	-0.0526
	(0.0398)
t	-0.0042***
	(0.0006)
Pay Uncertainty * *t*	0.0021***
	(0.0008)
Constant	0.5132***
	(0.0279)
N	20160

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Here we examine the time series *t* and the interaction of *t* with uncertain pay. Pay uncertainty and *t* are defined as above, and thus their interaction becomes self-explanatory. Furthermore, we include all participants in the analysis, unlike in Table 6 where we include only the participants who took at least one survey. We thus examine the likelihood of a participant choosing to take a survey at all (rather than taking a survey and then repeating), given the incentive. The model is clustered at the participant level.

In model (1), the probability of taking a survey at time *t* is regressed on pay uncertainty and *t*, as well as their interaction. The significant positive coefficient of the interaction indicates that over time, participants were more likely to choose to take a survey in the uncertain-pay condition than in the certain-pay condition.

Additional Study 1

1. Sample size: determined in advance of the experiment. The experimenter followed the stopping rule that data collection closed at the end of the week in which there were at least 20 participants in each cell of the experiment.

2. Conditions: 2 (mode: performance vs. prediction) × 3 (payment: uncertain vs. certain high value vs. certain expected value) between-subjects design

3. Data exclusion: none. We recruited participants of only one sex to avoid large sex-based variations in performance on intense physical tasks, and we did not permit anyone with heart or breathing problems to participate in this study.

4. Measures

a. Behavioral measurement: predicted or actual number of round trips each participant made (DV)

b. Questionnaire question: age

Additional Study 2

1. Sample size for each cell: we set a predetermined recruitment size of 275 per cell.

2. Conditions: two (uncertain price vs. certain price) between-subjects conditions

3. Data exclusions: We preset a total recruitment number of 550 on MTurk with 275 participants in each condition. We received data from a total of 506 participants in Qualtrics and then excluded participants who did not make any purchases, that is, did not participate in repeated purchases at all. In particular, 14% of participants in the uncertain-price condition and 14% in the certain-price conditions were excluded from the hypothesis testing analyses. There was no difference across the two ($\chi^2 = 0.00$, $p > .9$). This result either replicates Goldsmith and Amir (2010) or suggests a ceiling effect as the explanation for the null effect on entry.

4. Measures:

a. Behavioral measurement: number of gift card purchases among the participants who made repeated purchases (DV)

b. Questionnaire question: “Every time after you bought a card, was the uncertainty about the price resolved?” with multiple choice answers yes (coded as 1) and no (coded as 0)

c. Questionnaire question: “Focus on the resolution of uncertainty—the experience that you find out something you did not know, not the outcome you discover. How did the uncertainty resolution itself make you feel?” on a 9-point scale from “very bad” (coded as -4) to “very good” (coded as +4) with “neutral/not applicable” as 0 (used in mediation). Results: see Table 9.

d. Questionnaire question: “Focus on the exact prices you got. How did you feel about the prices you received?” on a 9-point scale from “very bad” (coded as -4) to “very good” (coded as +4) with “neutral/not applicable” as 0 (used in mediation).

e. Questionnaire question: gender

f. Questionnaire question: age

g. Questionnaire question: first language

Table 8: Descriptive Statistics for Behavioral Measurements

	Total Number of Purchases			Percentage of Those Making Extra Purchases	Total Number of Purchases Among Those Making Extra Purchases	
	Mean	*Median*	*SD*	*Percentage*	*Mean*	*SD*
Uncertain Price	9.51	6	13.12	86%	11.12	13.53
Certain Price	7.54	5	8.58	86%	8.76	8.66

Table 9: Descriptive Statistics for Decision-Making Process Measurements (Among Participants Who Made at Least One Purchase)

	Resolution Experience		Price Attractiveness	
	Mean	*SD*	*Mean*	*SD*
Uncertain Price	1.08***	1.82	1.78***	1.70
Certain Price	.01	.29	2.55***	1.54
Difference	$t(433) = 8.87$, $p < .001$		$t(433) = -4.91$, $p < .001$	

One-sample T-test against 0: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Mediation Analysis Procedure Examining the Role of Resolution Experience in the Effect of Price Uncertainty on Purchase Repetition, Without Controlling for Price Attractiveness (Among Participants Who Made at Least One Purchase)

DV	(1) Number of Purchases	(2) Uncertainty Resolution	(3) Number of Purchases	(4) Number of Purchases
Price Uncertainty	2.3604**	1.0717***		0.5343
	(1.0761)	(0.1208)		(1.1498)
Resolution Experience			1.7808***	1.7040***
			(0.3870)	(0.4211)
Constant	8.7639***	0.0129	8.9503***	8.7420***
	(0.7324)	(0.0822)	(0.5625)	(0.7197)
N	434	434	434	434

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: We replicated the mediator role of resolution experience in the effect of price uncertainty on purchase repetition even without controlling for price attractiveness (based on 10,000 bootstrap samples: 95% bootstrap C.I. = [.83, 3.44]; Preacher, Rucker, and Hayes 2007). All models used a standard OLS approach. In model (1), price uncertainty alone significantly predicts purchase repetition. In model (2), price uncertainty significantly predicts resolution experience. In model (3), resolution experience significantly predicts purchase repetition. In model (4), resolution experience significantly reduces and hence fully mediates the effect of price uncertainty on purchase repetition.

Supplementary Material 4

Meta-Analysis for Key Findings Across All Studies

Results in all studies are summarized in Table 11.

For the meta-analysis (the last two rows), we include the standard comparison in each study for a test of the reinforcing-uncertainty effect: the certainty condition and the uncertainty condition. The analysis focuses on repetition, and hence we include only the participants who completed at least one round of the task. The complete list of studies and conditions included are as follows:

- Study 1: certain and uncertain
- Study 2: certain and uncertain/with-resolution
- Study 3: certain-fixed and uncertain
- Study 4: certain and uncertain
- Additional Study 1: performance/certain-expected value, performance/certain-high value, and performance/uncertain
- Additional Study 2: certain and uncertain

Table 11: A Summary of All Results

Study	**Condition**		**Repetition**		**Overall Effect**
			# of rounds completed per participant who completed at least one round		# of rounds completed per participant (all)
			Mean	*Median*	*Mean*
Study 1 (*N* = 82)	Certain		7.45 [a]	5	7.45 [a]
	Uncertain		13.93 [b]	6	13.93 [b]
Study 2 (*N* = 103)	Certain		4.85 [a]	4.5	4.85 [a]
	Uncertain: With Resolution		8.62 [b]	8.5	8.62 [b]
	Uncertain: Without Resolution		3.74 [c]	4	3.74 [c]
Study 3 (*N* = 84)	Certain: Fixed		8.65 [a]	8	8.25 [a]
	Certain: Varied		9.42 [a]	8	8.50 [a]
	Uncertain		13.64 [b]	12	13.64 [b]
Study 4 (*N* = 480)	Certain		20.31 [a]	23.5	17.77 [a]
	Uncertain		25.96 [b]	31	17.42 [a]
Additional Study 1 (*N* = 134)	Prediction	Certain: Expected Value	7.00 [a]	8	7.00 [a]
		Certain: High Value	11.48 [b]	6	11.48 [b]
		Uncertain	7.65 [a]	5.5	7.65 [a]
	Performance	Certain: Expected Value	7.25 [a]	7	7.25 [a]
		Certain: High Value	7.13 [a]	7	7.13 [a]
		Uncertain	8.38 [b]	8	8.38 [b]
Additional Study 2 (*N* = 506)	Certain		8.76 [a]	6	7.54 [a]
	Uncertain		11.12 [b]	7	9.51 [b]
Meta-Analysis (*N* = 1,264)	**Certain**		**8.81 [a]**		**10.02 [a]**
	Uncertain		**12.64 [b]**		**11.48 [b]**

Notes: Only the “Repetition (mean)” column is hypothesis testing.

1. Within each column of each study, values with different superscripts are significantly different from each other, while values with the same superscript are not.

2. All pairwise differences were tested using *t*-tests.

3. The meta-analysis tested the reinforcing-uncertainty effect by focusing on the standard comparison between a certainty condition and a dominated-uncertainty condition in each study. It did not include the additional conditions (e.g., the uncertain-prize/without-resolution condition of study 2) that were designed for other purposes. All studies were dummy-coded; see Table 12 for results.

Table 12: OLS Regression Using All Six Studies, Regressing the Total Number of Rounds Completed on Uncertain Condition Dummy with Dummy Fixed Effects for Each Study

	(1) Repetition: Only Participants Who Completed at Least One Round	(2) Overall: All Participants
Outcome Uncertainty	3.8256***	1.4566**
	(0.7154)	(0.7120)
Study 2	-3.9863**	-4.0152*
	(1.9156)	(2.0671)
Study 3	0.3497	0.3209
	(2.0247)	(2.1848)
Study 4	12.2938***	6.8432***
	(1.4263)	(1.5060)
Additional Study 1	-3.7759**	-3.4100*
	(1.8895)	(2.0384)
Additional Study 2	-0.7235	-2.2442
	(1.4068)	(1.5007)
Constant	8.8088***	10.0222***
	(1.3408)	(1.4388)
N	1083	1264

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Outcome uncertainty takes a value of 1 if the participant is in an uncertainty condition and a value of 0 if the participant is in a certainty condition. Similarly, Additional Studies 1 and 2 and Studies 2-4 take a value of 1 if the data point is from that specific study, and 0 otherwise. In model (1), using only participants who completed at least one round, we regress the total number of times a participant completed a round on outcome uncertainty and 5 study dummies. After controlling for each study, we find that participants in the uncertainty conditions, on average, completed 3.83 more repetitions than participants in the certainty conditions. In model (2), using all participants, we regress the total number of times a participant completed a round on outcome uncertainty and 5 study dummies. Similarly, we find that on average, participants completed more rounds in the uncertainty conditions than in the certainty conditions. Nevertheless, the effect size decreases to a difference of 1.46.

Supplementary Material 5

Stats Check: *p*-checker Input and Results (http://shinyapps.org/apps/p-checker/)

The hypothesis test stats in each study

Study 1, H1: t(80) = 2.10, *p* = .039, cohen's *d* = 0.47, 95% C.I. = [0.3511, 12.6060], power = 0.56
Study 2, H1: t(66) = 5.28, *p* < .001, cohen's *d* = 1.28, 95% C.I. = [2.3413, 5.1881], power = 1.00
Study 2, H2: t(67) = 8.43, *p* < .001, cohen's *d* = 2.02, 95% C.I. = [3.7201, 6.0295], power = 1.00
Study 3, H1: t(50) = 4.10, *p* < .001, cohen's *d* = 1.12, 95% C.I. = [2.5493, 7.4288], power = 0.98
Study 3, H1: t(50) = 2.81, *p* < .01, cohen's *d* = 0.78, 95% C.I. = [1.2067, 7.2457], power = 0.79
Study 4, entry: χ^2 (1) = 28.50, *p* < .001, ϕ = 0.24, 95% C.I. = [13.1206, 27.7127], power = 1.00
Study 4, H1: t(371) = 3.82, *p* < .01, cohen's *d* = 0.40, 95% C.I. = [2.7397, 8.5667], power = 0.97
Add Study 1, H1: t(46) = 3.03, *p* < .01, cohen's *d* = 0.87, 95% C.I. = [0.4183 , 2.0817], power = 0.84
Add Study 1, H1: t(46) = 2.78, *p* < .01, cohen's *d* = 0.80, 95% C.I. = [0.3117, 1.9383], power = 0.78
Add Study 1, H3: t(39) = 2.07, *p* = .045, cohen's *d* = 0.65, 95% C.I. = [0.0809, 7.5715], power = 0.53
Add Study 2, H1: t(432) = 2.19, *p* = .029, cohen's *d* = 0.21, 95% C.I. = [0.2453, 4.4755], power = 1.00

Results

1. *R*-Index analysis

Success rate = 1, Median observed power = 0.8674, Inflation rate = 0.1326, R-Index = 0.7349

Table 13: Detailed Results for Each Hypothesis Test Statistic

study_id	type	df1	df2	statistic	p.value	p.crit	Z	obs.pow	sig.	median.obs.pow
Study 1, H1	t	80	NA	2.100	0.039	0.050	2.065	0.542	TRUE	0.542
Study 2, H1	t	66	NA	5.280	0.000	0.050	4.805	0.998	TRUE	0.998
Study 2, H2	t	67	NA	8.430	0.000	0.050	6.936	1.000	TRUE	1.000
Study 3, H1	t	50	NA	4.100	0.000	0.050	3.788	0.966	TRUE	0.867
Study 3, H1	t	50	NA	2.810	0.007	0.050	2.694	0.769	TRUE	0.867
Study 4, entry	chi2	1	NA	22.870	0.000	0.050	4.782	0.998	TRUE	1.00
Study 4, H1	t	371	NA	3.860	0.000	0.050	3.819	0.969	TRUE	0.969
Add Study 1, H1	t	46	NA	3.030	0.004	0.050	2.878	0.821	TRUE	0.789
Add Study 1, H1	t	46	NA	2.780	0.008	0.050	2.658	0.758	TRUE	0.789
Add Study 1, H3	t	39	NA	2.070	0.045	0.050	2.004	0.517	TRUE	0.517
Add Study 2, H1	t	432	NA	2.190	0.029	0.050	2.183	0.588	TRUE	0.588

2. Test of Insufficient Variance (TIVA)

Variance = 2.4808

Chi2(10) = 24.808; p = .994

Variance < 1 suggests bias. The chi2 tests the H0 that variance >= 1; a significant result indicates that the empirical variance is significantly smaller than 1.

3. Statistical Inference on *p*-curve

a) Studies contain evidential value: Z = - 5.815; p < .001

A significant *p*-value indicates that the *p*-curve is right-skewed, which indicates evidential value.

b) Studies' evidential value, if any, is inadequate: Z = 3.754; p = 1.000

A significant *p*-value indicates that the *p*-curve is flatter than one would expect if studies were powered at 33%, which indicates that the results have no evidential value.

c) Studies lack evidential value and were intensely *p*-hacked: Z = 5.815; p = 1.000

A significant *p*-value indicates that the *p*-curve is left-skewed, which indicates *p*-hacking/selective reporting.

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