Self-Selection Attenuates the Realization Effect

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Abstract

The "realization effect," put forth by Imas (2016), predicts how individuals will change risk-taking behavior following a loss. The theory is defined for individuals choosing whether to accept a positively skewed lottery, and previous experiments have focused in this domain. We test the realization effect using a variation of the bomb risk elicitation task, which gives a much wider range of lottery options. We identify conditions under which the realization effect makes predictions in this environment, and test these predictions in the data. We find little support, but we also find that few individuals even select into those conditions where the realization effect applies.

KEYWORDS: loss chasing; prospect theory; probability weighting

I. Introduction

Many economically-relevant situations involve sequential decisions under uncertainty. As a result, it is important to understand how early gains or losses affect subsequent choices. Losses may induce more cautious behavior and reductions in risk taking. On the other hand, losses could lead to increased risk seeking with the hope of recovering the early loss. Empirical evidence is mixed—some papers have found risk to increase after a loss (Andrade and Iyer, 2009; Langer and Weber, 2008) while others found risk reduction (Shiv et al., 2006; Liu et al., 2010).

Imas (2016) proposes a theory in which prior losses decrease risk taking when those losses are actually realized, but increase risk taking when the losses are only on paper.[1] He refers to this as the *realization effect*. The realization effect operates through three primary channels: choice bracketing, loss aversion, and probability weighting. *Choice bracketing* determines the manner in which risky decisions are evaluated, and is the main addition of the theory to standard cumulative prospect theory (CPT) (Kahneman and Tversky, 1979). The realization effect theory assumes that mental accounts remain open after paper gains or losses, but accounts close after realized gains or losses. As a result, subsequent lotteries are bracketed and evaluated *together* with paper gains or losses, but are evaluated *separately* from realized gains or losses. In other words, a decision maker who suffers a paper loss and then considers accepting a second lottery evaluates the second

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[1] For example, a day of betting at the horse track constitutes a series of paper gains/losses until the individual settles his account at the end of the day and "realizes" his final earnings or losings.

lottery's prospects in conjunction with the previous loss. However, a decision maker who suffers a realized loss does not integrate this loss with the prospects of future lottery decisions.[2]

Second, *loss aversion* works to give extra attraction to lotteries that offer the opportunity to erase previous paper losses. A loss averse individual experiences a sharp decrease in utility when he "realizes" outcomes below his reference point. After experiencing a paper loss, the individual gains a heightened attraction to gambles that offer a large reward which could cancel out the paper loss. Since the paper loss has not yet been realized, this new gamble offers the opportunity to avoid realizing any loss altogether, which is particularly appealing to a loss averse decision maker. Lotteries following realized losses don't offer the possibility of erasing the negative payment since the loss has already been realized. As a result, loss aversion along with the assumed manner of choice bracketing provide differing risk-taking incentives following realized and paper losses, leading to differences in predicted choices.

Finally, *probability weighting* affects how individuals view "tail" events. Individuals tend to overweight low probability events, such as a long-shot chance to win a large sum. Probability weighting skews the individual's perception of winning the lottery, making the possibility appear more likely. As a result, probability weighting provides incentive for individuals to favor positively skewed lotteries, where the potential upside is larger than the potential downside and where the probability of a gain is less than the probability of a loss. Loss aversion provides an incentive to chase this long-shot lottery after a *paper loss*, since it offers the decision maker the possibility that he will never have to realize the loss. Realized losses, on the other hand, provide no such incentive. As a result, probability weighting combined with loss aversion induces individuals to become more willing to chase long-shot risks after paper, compared to realized, losses.

Imas demonstrates the realization effect through a series of experiments involving risky investment decisions with both realized and paper losses. The realization effect theory applies directly to loss averse individuals choosing whether to accept or reject a positively skewed gamble. In this paper, we study a richer and more natural risk environment. We use a variation of the bomb risk elicitation task (BRET) (Crosetto and Filippin, 2013) to analyze the difference in changes in risk behavior following realized and paper losses. In this task, subjects choose to open a number of boxes, one of which contains a "bomb." Opening more boxes gives a higher potential reward if the boxes don't contain the bomb, but increases the probability of selecting the bomb. We describe the BRET in detail in Section II. The BRET is an easy and intuitive way to measure risk behavior, and allows for identification of relatively loss seeking individuals.

In addition, the BRET offers lotteries of varying "skew," where the potential upside is higher/lower than

[2]For example, consider a lottery that offers a chance to win $500 at the risk of losing $100. Informally, a decision maker who loses in the first round but does not realize this loss considers the second lottery as offering him the chance to finish with earnings of $400 or -$200, integrating his first loss into the lottery outcomes. A decision maker who realizes the first loss does not perform this integration and brackets the second lottery separately.

the potential downside. Previous studies of loss chasing and realization look at positively skewed or 50-50 gambles (Andrade and Iyer, 2009; Langer and Weber, 2008; Shiv et al., 2006). Expanding the set of risks under consideration gives new evidence in these domains. We identify individuals for whom the realization effect makes unambiguous predictions, and we also study general behavior after realized and paper losses.

Overall, we find little evidence for any of the predicted changes in behavior. However, the relevant sample sizes are very small. Despite analyzing data from over 2,000 subjects, very few individuals find themselves in a situation where the realization effect makes clear predictions. This demonstrates a limitation in considering differences in realized versus paper losses in general environments. In most situations, there is no unambiguous prediction for how risk will change after a realized or paper loss, nor is there a clear prediction on the difference between these two. The theory makes strongest predictions for individuals who experience a loss after choosing negatively skewed lotteries in Round 3. However, negatively skewed lotteries are exactly those with a low probability of losing, so few individuals even find themselves in an environment where the predictions apply.

Our results indicate that we expect to see little difference between realized and paper losses in these more natural settings where individuals can choose their level of risk. Individuals self-select away from positively skewed lotteries, which are exactly the types of lotteries considered by the realization effect theory. This suggests caution in applying insights from Imas (2016) to general environments.

II. Experimental Design

We outline the experimental design and then derive specific predictions for this environment. We conduct the experiment online using a survey programmed in Qualtrics and subjects from the general population on Amazon's Mechanical Turk, an online labor platform. Subjects are required to be over 18 years of age, residents of the United States, and are screened for basic Mechanical Turk competency.[3] In total, we analyze data from 2,069 survey responses.[4] The survey takes about 8 minutes to complete and average total payments are just over $0.50 per subject including a $0.10 show-up fee, which is very typical for the Amazon Mechanical Turk workforce.

We adapt the BRET to test the effect of realized versus paper losses on subsequent risk taking. We endow subjects with $0.40 and present them with a 5x5 grid of boxes. Most of the 25 boxes are empty, but 1 randomly-selected box contains a "bomb." Subjects choose how many boxes to open with the implicit goal of not opening

[3]We excluded participates who had never completed a task on Mechanical Turk, and we restricted our sample to participants who had completed fewer than 1,000 tasks. We also excluded participants with low approval ratings from previous Mechanical Turk tasks.

[4]A drawback of online data collection is that we cannot perfectly verify survey responses. "Spam" accounts and user-written programs to automatically detect and submit surveys introduce fake data which can be detected through short recorded survey duration time. We dropped responses with duration below 100 seconds, which excluded 282 responses leaving us with a total sample of 2,069.

the box containing the bomb. If a subject opens the box that contains the bomb, he loses \$0.10 for that round. If he opens only empty boxes in a round, he gains \$$c$ per box opened. To mitigate any effects of confusion and learning, on every decision screen we inform subjects of the probability of selecting a bomb for every possible number of boxes opened, along with how much they would earn if they do not select the bomb and how much they would lose if they do select the bomb. Subjects are also required to answer correctly a number of comprehension questions before starting the experiment.

Subjects select all boxes they wish to open and then learn which box contains the bomb and whether they had selected it.[5] After revealing the bomb, we inform subjects of their earnings from that round and then they proceed to the next decision screen. After a "practice round" to gain familiarity with the interface, all subjects participate in a total of 4 rounds. As such, a participant can lose his entire endowment if he clicks the bomb in every round, and can gain a maximum of \$24c per round otherwise. This structure follows the experiments in Imas (2016), aside from the fact that we use the BRET while Imas uses a risky investment decision.

Our implementation of "realization" mirrors the Robustness Check of Study 2 in Imas (2016): Participants are randomly assigned to either the *Realization* or *Paper* treatment. In the instructions of the Realization treatment, we tell subjects that their earnings will be finalized after Round 3. That is, we will transfer their winnings to their account or subtract losses away from their starting balance. At the time of realization, subjects are notified of their current earnings or losses and are asked to type "Close Account" to make the transfer and finalize their balance. After this, they proceed to Round 4 to make choices in the final round in the same way described above. In the Paper treatment, we eliminate this account-closing stage but subjects are still notified of their current earnings before proceeding to Round 4. A full copy of instructions and screenshots can be found in the Appendix.

Parameterizations

In the "low stakes" condition ($n = 896$), subjects gain \$0.01 per box opened ($c = 0.01$). In the "high stakes" condition ($n = 1,173$), we double the reward to \$0.02 ($c = 0.02$). This small change allows us to study the effect of realization on lotteries of differing skew. In the low stakes condition, expected earnings under risk neutrality are maximized by opening 7 boxes.[6] This is a *negatively skewed* lottery, with potential gain of \$0.07 ($pr(gain) = 0.72$) and potential loss of \$0.10 ($pr(loss) = 0.28$), denoted by (\$0.07, 0.72; −\$0.10).[7] On

[5]Note, we do not use a sequential version of the BRET where boxes are "opened" upon selection, more akin to the "balloon task" (Lejuez et al., 2002). We did not want subjects updating their plans within a round, and we wanted to avoid the truncated observations that would result from selecting the bomb early on.

[6]Expected earnings are the same opening 7 or 8 boxes, and the following discussion holds similarly for opening 8 boxes.

[7]In a negatively skewed lottery, the downside is larger in magnitude than the upside, and the probability of a gain is larger than the probability of a loss. A positively skewed lottery is exactly opposite, where the upside is larger in magnitude than the downside and the probability of a loss is larger than the probability of a gain.

the other hand, expected earnings in the high stakes BRET are maximized by opening 10 boxes, or choosing the *unskewed* lottery ($\$0.20, 0.60; -\$0.10$). In both high and low stakes versions of the task, the lotteries become *positively skewed* after opening more than 12 boxes. See the Appendix for a full list of probabilities and potential earnings.[8] We run both conditions to see a larger range of lottery choices, spanning a range of "riskiness" and skew.

III. Realization Effect Theory

We briefly overview the realization effect theory and its main behavioral implications, and then derive predictions for our experiment. The model is formally presented in the Appendix of Imas (2016), and we direct the interested reader there for details. The model is based on Cumulative Prospect Theory (CPT) (Tversky and Kahneman, 1992).

Denote a lottery, L, which gives x^i with probability p^i by $L = (x^1, p^1; x^2, p^2; ...; x^n, p^n)$. For simplicity we assume $x^i > x^{i+1}\ \forall i$. We denote a lottery with only two alternatives by $(x^i, p; x^j)$. The decision maker evaluates a lottery as

$$\sum_{i=1}^{n} \pi^i V(x^i|r)$$

where r is the reference point and π^i are decision weights. Under CPT, decision weights are given by $\pi^i = w(p^i + ... + p^n) - w(p^{i+1} + ... + p^n)$ for $x^i \geq r$ and $\pi^i = w(p^1 + ... + p^i) - w(p^1 + ... + p^{i-1})$ for $x^i < r$. The utility function may exhibit loss aversion, parameterized by $\lambda > 1$. $V(x^i|r)$ is defined below, where $v(\cdot)$ is a concave function—

$$V(x^i|r) = \begin{cases} v(x^i - r) & \text{if } x^i \geq r, \\ -\lambda v(-(x^i - r)) & \text{if } x^i < r. \end{cases}$$

In the environment Imas (2016) considers, a decision maker is offered a positively skewed lottery, $L = (x^g, p; x^l)$, where $p < 0.5$, $x^g > 0 > x^l$, and $x^g > |x^l|$. Imas assumes the reference point to be the status quo, $r = 0$. The decision maker can accept or reject the lottery in period one. If he accepts the lottery, he observes the lottery outcome before proceeding to period two, where he makes the same decision to accept or reject L once again. If he rejects the lottery in period one, he is not offered a lottery in period two. The primary question, both theoretical and empirical, is whether the decision maker will become more or less likely to accept the lottery in period two after accepting and losing the lottery in period one. The predictions of the realization

[8] Mechanical Turk poses a challenge for studying losses under positively skewed risk in a task like the BRET. Calibrating parameters so that the expected earnings are maximized in opening many boxes requires c to be very large. This is atypical for payments on Mechanical Turk, so subjects tend to open very few boxes to secure a large payment, a type of "satisficing." As a result, very few subjects experience losses. In a small pilot session with $c = 50$, subjects opened 2 boxes per round on average, even though expected earnings under risk neutrality are maximized by opening 12 boxes. These forces lead us to have relatively few observations for positively skewed lotteries despite our large sample.

effect theory depend on whether the loss from L in period one is "realized" or not. The theory predicts that the decision maker will become more likely to accept L if the loss in period one is not realized, and will become less likely to accept L if the period one loss is realized.

We apply this model directly to our experimental design to predict whether risk taking will increase or decrease from Round 3 to Round 4, following Imas (2016). Because we consider change in risk from Round 3 to 4, decisions will also depend on accumulated earnings from Rounds 1 and 2.

To generate predictions, we assume the Kahneman and Tversky (1979) value function, $v(x) = x^{\alpha}$, and the Prelec (1998) probability weighting function, $w(p) = e^{-(-lnp)^{\beta}}$. We fix $\beta = 0.60$ and allow for $\alpha \in [0,2]$ and $\lambda \in [0,4]$.[9] Let x denote the number of boxes an individual chooses to open. Under the setup of the BRET, the probability of winning the lottery reduces to $p = 1 - 0.04x$, the reward is given by cx, and the loss is fixed at -0.10. We assume a reference point of 0. Based on choices and outcomes in Rounds 1 and 2, an individual can enter Round 3 with a wide range of possible current earnings which will affect his optimal choices in Rounds 3 and 4. In the Paper treatment, an individual with a balance, b, at the start of Round 3 chooses x to maximize

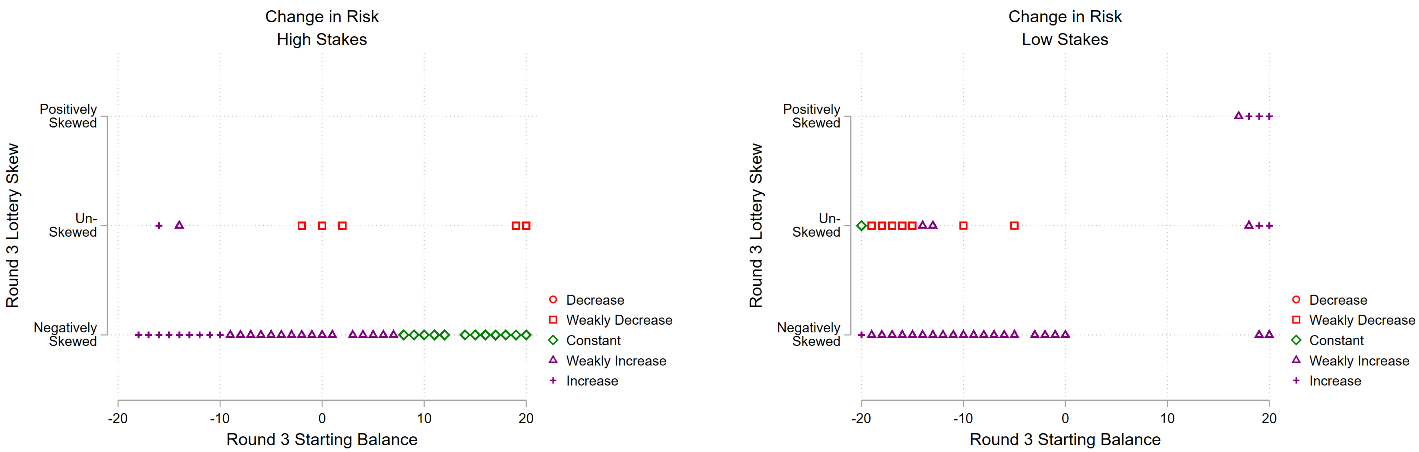
$$\sum_{i=1}^{n} \pi^i V(\cdot) = \begin{cases} -\lambda w(p)v(cx+b) - \lambda w(1-p)v(-b+0.10) & \text{if } b < 0 < cx < |b|, \\ w(p)v(cx+b) - \lambda w(1-p)v(-b+0.10) & \text{if } b < 0 < |b| \leq cx \\ w(p)v(cx+b) - \lambda w(1-p)v(0.10-b) & \text{if } 0 < b < 0.10 \\ w(p)v(cx+b) + w(1-p)v(b-0.10) & \text{if } 0.10 \leq b \end{cases} \tag{1}$$

The first case in Equation 1 is the situation where the individual has a negative balance at the start of Round 3, and winning the lottery is not enough to make up this loss. The second case again describes a negative starting balance in Round 3, but where winning the lottery in Round 3 would give the individual a (weakly) positive balance to start Round 4. In the third case, an individual has a positive Round 3 balance, but a loss would bring him negative. Finally, the last case is where the Round 3 starting balance is large enough to cover a loss in Round 3 while staying above the reference point.

At the start of Round 3, an individual can have a minimum balance of -0.20 if he lost in both previous rounds and can have a maximum balance of $0.48c$ from opening 24 empty boxes in each previous round. Since our primary interest is in risk change following a loss, we consider Round 3 starting balances $b \in [-20,20]$, which equates to $b' \in [-30,10]$ after a Round 3 loss. For each possible starting balance $b \in [-20,20]$, level of risk aversion $\alpha \in [0,2]$, and loss aversion $\lambda \in [0,4]$, we solve Equation 1 to find the utility-maximizing number of boxes, x, an individual will open in Round 3. Since outcomes in Rounds 1 and 2 have yet to be realized, the choice in Round 3 is the same in both treatments.

We assume the individual loses the lottery in Round 3 and again goes on to make the same choice of utility

[9] Tversky and Kahneman (1992) find estimates of $\alpha = 0.88$ and $\beta = 0.61$, Camerer and Ho (1994) find $\alpha = 0.32$ an $\beta = 0.56$, and Wu and Gonzalez (1996) find $\alpha = 0.52$ and $\beta = 0.74$. von Gaudecker et al. (2012) estimate loss aversion for multiple populations. They estimate $\lambda = 1.5$ for student populations, though it varies with the stakes of the decision. Only 8% of the population has $\lambda > 5$.



(1) High Stakes

(2) Low Stakes

Figure I: Paper Treatment Predictions

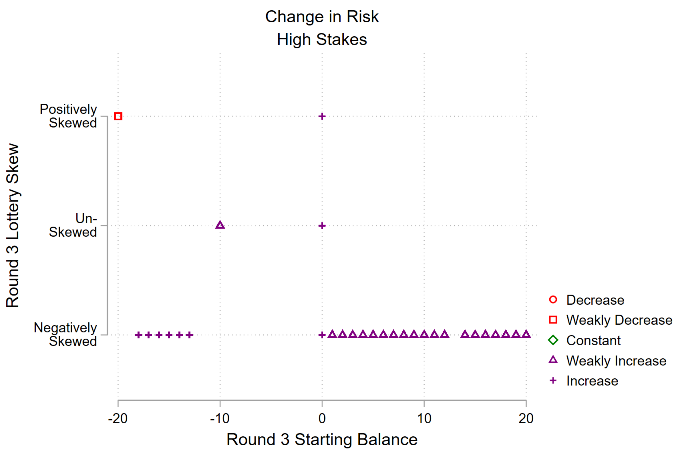
maximizing number of boxes, x', in Round 4. Given this assumption, an individual in the Paper treatment starts Round 4 with a balance $b' = b - 0.10$, and chooses x' to maximize Equation 1 given this balance. However, in the Realization treatment, the individual's balance is realized after Round 3, closing all choice brackets and mental accounts. This means that the balance at the start of Round 4, b', is reset at \$0.00 for all individuals in the Realization treatment. We measure the difference in risk as $x' - x$, where a positive difference indicates an individual took on more risk in Round 4 compared to Round 3.[10]

Analytical results generate the expected comparative statics—given a level of risk aversion, α, individuals who are more loss averse are likely to open fewer boxes. Similarly fixing λ, individuals who are more risk averse are likely to open fewer boxes.[11] In general, predictions can vary dramatically with α, λ, and b, and there are few predictions that hold universally. We look for regions where the theory does make general predictions which do not depend on α and λ.

Figure I shows the predicted changes that hold for all individuals in the Paper treatment choosing a negative-, positive-, or un-skewed lottery in Round 3, regardless of $\alpha \in [0,2]$ and $\lambda \in [0,4]$. Primarily, we see that individuals who have a negative balance and choose a negatively skewed lottery in Round 3 should (weakly) *increase* risk taking following a Round 3 loss, in both stakes conditions. In the high stakes condition, this prediction also holds for a small range of positive balances. Individuals with large positive balances

[10] This discussion focuses on a simple case where agents are myopic—they don't consider future outcomes and decisions when making current choices. Imas (2016) also considers non-myopic agents, both ones who are sophisticated and ones who are naive about any potential dynamic inconsistencies. The non-myopic case is very complicated, requiring that the decision maker form a strategy contingent on all risk realizations. Even in Imas (2016), who considers the simple case of accepting or rejecting a fixed lottery, the analysis requires simulations to characterize optimal strategies. Our environment is significantly more complicated, with individuals choosing over a menu of lotteries with many possible balances and decision paths, so solving the non-myopic case is beyond the scope of this paper.

[11] We find the expected discontinuities at $\lambda = 1$ and some balances, such as \$0.10, which interact with loss aversion.



(1) High Stakes

(2) Low Stakes

Figure II: Realization Treatment Predictions

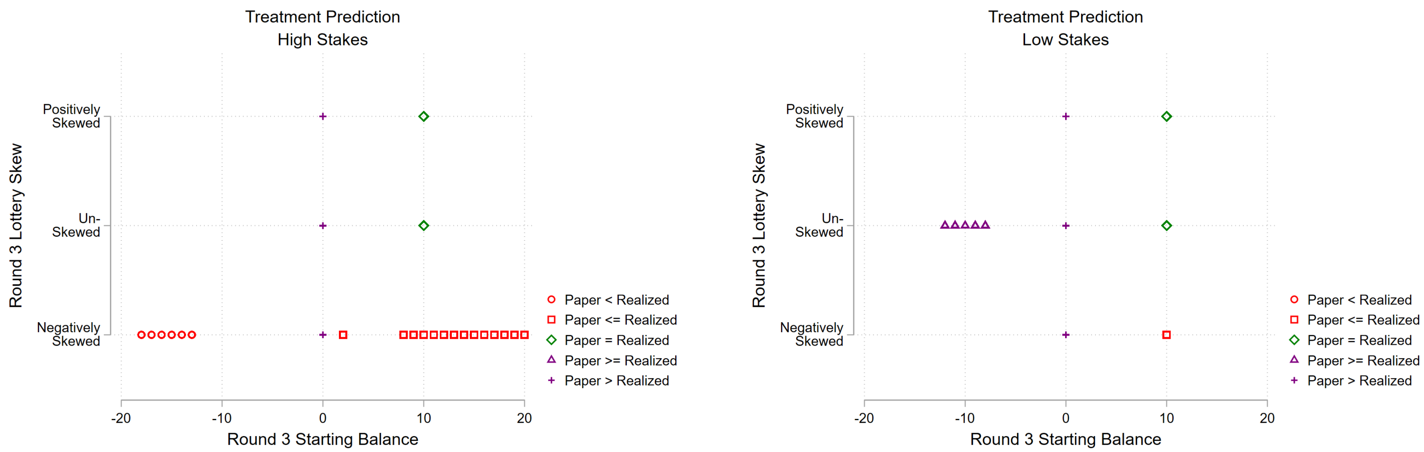
should not change risk taking at all in Round 4.

In contrast to the standard realization effect theory, we see few predictions for those choosing positively skewed lotteries. This is because individuals for whom a positively skewed lottery is utility-maximizing are those who are more loss-loving and/or risk-loving. In our environment, loss-averse and risk-averse individuals will not choose positively skewed lotteries, so the conditions of the theory are not satisfied.

Turning to the Realization treatment, Figure II shows the predicted changes that hold for all individuals choosing a negative-, positive-, or un-skewed lottery in Round 3 of the Realization treatment, regardless of $\alpha \in [0,2]$ and $\lambda \in [0,4]$. In the high stakes condition, we see that all individuals choosing a negatively skewed lottery with a positive balance should weakly increase risk taking after realizing a loss after Round 3. There is a range of negative balances for which individuals in the high stakes condition should increase risk taking, as well. In the low stakes condition, individuals with large negative balances should decrease risk taking following a choice of a positively skewed lottery and realized loss in Round 3.

Finally, we look to see ranges where there is a clear predicted treatment difference between realized and paper losses. Figure III plots the results. The clearest predictions come from individuals choosing negatively skewed lotteries in Round 3 of the high stakes condition. Those with very negative balances as well as those with very positive balances should increase risk taking *more* after realized losses compared to an equivalent paper loss.

We will test the unambiguous predictions within each treatment, as well as the between-treatment predictions. Outside these clear predictions, we look at descriptive statistics within- and between-treatments. This gives us a deeper understanding of how individuals behave in general risky environments with realized or



(1) High Stakes

(2) Low Stakes

Figure III: Between-Treatment Predictions

paper losses.

IV. Results

In each round, a subject chose his most preferred lottery from a set of 26 available lotteries, one for each number of boxes.[12] These included negatively skewed, positively skewed, and unskewed alternatives. Overall, we see no significant difference in the change in risk between the Paper and Realization treatments. Pooling over both high and low stake conditions, all balances, and all choices in Round 3, we find that individuals who lose the lottery in Round 3 open 0.802 more boxes in Round 4 of the Paper treatment and open 0.627 more boxes in Round 4 of the Realization treatment (Paper n=293, Realization n=284, Fisher-Pitman two-tailed $p = 0.552$)

However, as discussed in Section III, the realization effect does not necessarily make specific predictions for all individuals. We test the predictions derived above, and then turn to a general discussion of the data. We consider the predicted change as the alternative hypotheses in each test. We use Fisher-Pitman permutation tests for both one- and two-sample tests.

[12] For example, in the Low Stakes BRET, the available lotteries are $\{(\$0, 1), (\$0.01, 0.96; -\$0.10), (\$0.02, 0.92; -\$0.10), \ldots, (\$0.24, 0.04; -\$0.10), (-\$0.10, 1).\}$

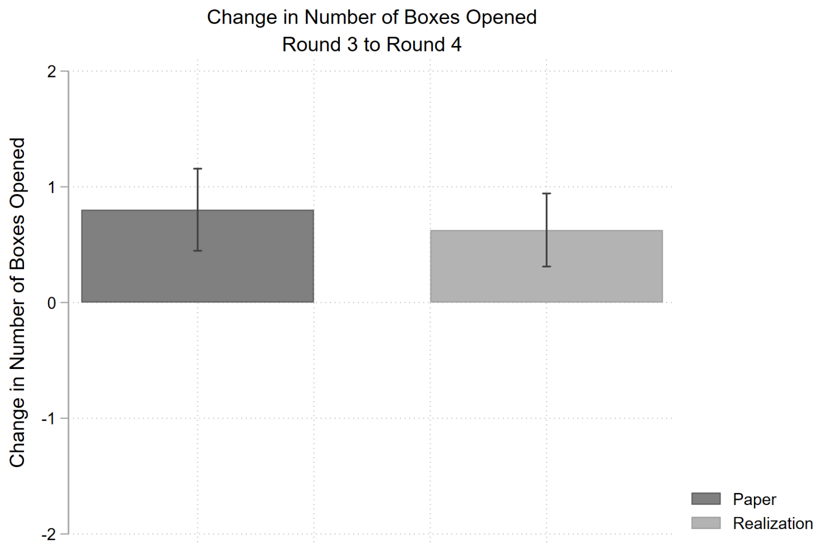


Figure IV: Overall change in number of boxes following paper and realized losses

Testing Unambiguous Predictions

As shown in Figure I, individuals with a balance less than \$0.07 (excluding a balance of \$0.02) choosing negatively skewed lotteries in Round 3 of the Paper treatment in the high stakes condition should weakly increase risk taking after a loss. We have only 5 individuals who satisfy the conditions of the prediction, and these individuals increase risk by opening 0.40 more boxes in Round 4, on average ($p = 0.31$). Individuals with a balance between \$0.08 and \$0.20 (excluding \$0.13) choosing negatively skewed lotteries in Round 3 of the Paper treatment in the high stakes condition should keep risk behavior constant after losing. There are 11 individuals satisfying these conditions, and they open -0.09 fewer boxes in Round 4, on average (H_0: change ≤ 0, $p = 0.61$). In the Realization treatment, individuals with a positive balance (excluding \$0.13) are predicted weakly to increase risk taking after choosing a negatively skewed lottery in Round 3 and losing. 12 individuals satisfy these conditions, and they open 0.75 more boxes in Round 4 ($p = 0.37$). There are no observations to test the prediction for balances between -\$0.18 and -\$0.13.

Between-treatment predictions indicate that the increase in risk should be larger in the Realization treatment for balances greater than 8 cents and balances between -\$0.18 and -\$0.13 cents, conditioning on individuals who choose negatively skewed lotteries and lose in Round 3. There are no observations to test the treatment difference prediction for balances between -\$0.18 and -\$0.13. For balances between \$0.08 and \$0.20, We find the change in risk after a loss in round 3 is -0.09 boxes for the Paper treatment and -0.20 boxes for the Realization treatment (n=11 Paper, n=10 realization, $p = 0.59$).

Turning to the low stakes condition, individuals with a negative balance (except for -\$0.04) choosing negatively skewed lotteries in Round 3 of the Paper treatment should increase risk taking after a loss in the low stakes condition. There are 13 individuals satisfying these conditions, and they increase risk by opening 0.38 more boxes in Round 4 ($p = 0.39$). Those with large negative balances choosing positively skewed lotteries in Round 3 of the Realization treatment should weakly decrease risk taking after a realized loss in Round 3. There are only 3 individuals satisfying these conditions, but they significantly decrease risk by opening 9.67 fewer boxes in Round 4 ($p = 0.13$). There are no substantial between-treatment predictions in the low stakes condition.

Overall, we are unable to reject the null hypothesis for any of the predicted changes in risk behavior. However, the sample sizes are very small. We view this as a takeaway from our experiment, rather than a miscalibration. Our small sample sizes make evident a limitation in considering differences in realized versus paper losses in general environments. Self-selection works to drive individuals away from positively skewed risk, which is where the realization effect has been studied to date. In most general situations, there is no clear direction for how risk will change after a realized or paper loss, nor is there a clear difference between these two. The theory makes strongest predictions for individuals who experience a loss after choosing negatively skewed lotteries in Round 3. However, negatively skewed lotteries are exactly those with a low probability of losing, so few individuals even find themselves in an environment where the realization effect will make unambiguous predictions. In these more general, and arguably more natural, risk environments, individuals will not demonstrate a difference between realized and paper losses.

Testing Average Predictions

Results above considered only cases where the realization effect theory makes unambiguous predictions on change in risk taking, regardless of individual risk and loss aversion parameters. This is a very strong requirement. In the Appendix, we consider the average predicted change in risk taking following a realized or paper loss. This assumes that individuals are uniformly distributed in (α, λ). Again we face small sample sizes, but we fail to reject the null hypotheses in most cases.

The one case where we do find strong evidence in favor of the realization effect predictions is for individuals choosing positively skewed lotteries. In both the high and low stakes conditions, and in both the Realization and Paper treatments, individuals choosing positively skewed lotteries are most often predicted to *decrease* risk taking following a loss. This prediction holds for a wide range of positive and negative balances. In general, we find support for this prediction—individuals take on significantly less risk in Round 4 after choosing a positively skewed lottery and losing in Round 3. In the next section, we show that this stems from a universal decrease in risk taking after a loss. Positively skewed lotteries are likely to bring about a loss, and individuals respond this by taking on less risk.

Explaining the Data

We document two phenomena in the data—the house money effect and decrease in risk taking after losses—which together explain the observed change in risk behavior. In this way, our results confirm most of the observations first put forth by Thaler and Johnson (1990). More recently in the literature, this has been named the "reinforcement effect," where individuals become more risk averse after a bad history than after a good history. The reinforcement effect has been documented in both lab (Thaler and Johnson, 1990; Ackert et al., 2006; Harrison, 2007; Peng et al., 2013) and field (Massa and Simono, 2005; Kaustia and Knüpfer, 2008; Liu et al., 2010; Malmendier and Nagel, 2011; Guiso et al., 2013; Knüpfer et al., 2017) experiments. Tserenjigmid (2017) demonstrates a theoretical basis for the effect—he shows that the reinforcement effect results from history-dependent risk preferences which satisfy monotonicity with respect to first-order stochastic dominance. Our results complement this literature, showing increased risk taking after a gain and decreased risk taking after a loss.

HOUSE MONEY EFFECT. — We find that subjects increase risk taking in the face of prior gains, which Thaler and Johnson (1990) term the "house money effect." As Thaler and Johnson describe, the house money effect captures the intuition behind gambling while ahead: "The essence of the idea is that until the winnings are completely depleted, losses are coded as reductions in a gain, as if losing some of 'their money' doesn't hurt as much as losing one's own cash" (Thaler and Johnson, 1990). As shown in Table I, subjects consistently open *more* boxes after experiencing a gain in the previous round, regardless of whether they have a positive or negative balance overall.[13] In each round, subjects who did not click the bomb in the previous round open significantly more boxes than they had opened previously. Presumably, the previous round's gain increases risk taking since a "loss" in this new lottery would be coded as a reduction from the previous round's windfall rather than as a true loss below the reference point of the starting balance.

[13] We group Realization and Paper treatments together for this analysis, but results hold on both subsets of the data independently.

	Positive Balance			Negative Balance		
	Round 2	**Round 3**	**Round 4**	**Round 2**	**Round 3**	**Round 4**
Previous Round Gain	0.314***	0.358***	0.212**	—	1.025***	0.685***
	(n=1,479)	(n=1,22)	(n=1,153)		(n=81)	(n=92)
Previous Round Loss	—	0.157	-0.540**	-0.898***	-0.668***	-0.987***
		(n=210)	(n=311)	(n=394)	(n=283)	(n=230)

Table I: Change in number of boxes opened following previous round gain or loss

RISK-AVERSION FOLLOWING LOSSES. — As a counterpart to the house money effect, we find that subjects significantly decrease risk taking after a loss in the previous round. Table I shows that subjects consistently open *fewer* boxes after experiencing a loss in the previous round. We run a regression, reported in Table II, to disentangle the effects of loss chasing and the reinforcement effect. The regression predicts the change in number of boxes opened from one round to the next. Independent variables include a dummy for losing the lottery in the previous round, a dummy for having a negative balance, an interaction between the two, and a round variable to control for pure time trends. We look at choices in rounds 2-4, and cluster errors at the subject level.[14]

	Change in Number of Boxes Opened
Loss (t-1)	-0.532***
	(0.166)
Negative Balance	1.047***
	(0.245)
Loss (t-1) * Negative Balance	-1.719***
	(0.354)
Round	-0.0709
	(0.0517)
Constant	0.555***
	(0.151)
Observations	6,207
R-squared	0.023

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table II: Regression predicting change in number of boxes opened from one round to the next

The negative coefficient on lagged loss confirms that individuals reduce risk taking after experiencing a loss in the previous round. The coefficient on the negative balance dummy is positive and significant, confirming evidence of loss chasing. Individuals are likely to take on more risk in the face of losses, on average. However, the interaction between the two dummies is significantly negative and large in magnitude. Thus, individuals

[14] Since we are looking at the effect of outcomes and choices in the *previous* round, we look only at rounds 2-4.

with a negative balance who lose in the previous round are even more likely to reduce risk taking compared to those with a positive balance who lose.

To conclude, we do see loss chasing outside the typical environment of positively skewed risk, but the phenomenon stems partially from a different source. Loss chasing in environments of negatively skewed risk arises in part because losses are relatively *uncommon* in these environments. We see a pure loss chasing effect, where individuals take on more risk in the face of a negative balance overall, but we also see a reinforcement effect, where individuals follow gains with increased risk and follow losses with decreased risk, regardless of current balance. Neither of these interacts with realization.

V. Discussion

Imas (2016) demonstrates the realization effect for loss averse individuals choosing over positively skewed risks. We derive predictions and provide evidence on the realization effect in a more general risk environment. We find that, in environments where individuals can choose their level of risk, most individuals select into an environment where the realization effect does not apply. As a result, we find no observed differences between realized and paper losses. In general, our subjects increase risk after winning the lottery and decrease risk after losing the lottery.

The realization effect relies heavily on positively skewed risk. In many environments, like in our experiment, positively skewed choices are those that are relatively riskier. This is especially true of financial risks, like choosing over a menu of potential stocks or investment projects which vary in their risk/reward tradeoff. Previous papers on loss chasing and the realization effect use lotteries with fixed probabilities of gains and losses, essentially "forcing" individuals into an environment of positively skewed risk. In environments where the risk is more akin to the BRET, where risk determines the probability of a gain or a loss, individuals can choose the skewness of their preferred risk. In these environments, loss averse individuals are the least likely to choose positively skewed risks. Thus, since the realization effect requires both positive skew and loss aversion, we are unlikely to see these choices in many risk environments.

More generally, we find support for the reinforcement effect, where individuals take on more risk after winning and take on less risk after losing (Thaler and Johnson, 1990; Massa and Simono, 2005; Ackert et al., 2006; Harrison, 2007; Kaustia and Knüpfer, 2008; Liu et al., 2010; Malmendier and Nagel, 2011; Peng et al., 2013; Guiso et al., 2013; Knüpfer et al., 2017). We hypothesize this effect will be more generalizable across domains, as it is robust to skewness and to loss preference parameters.

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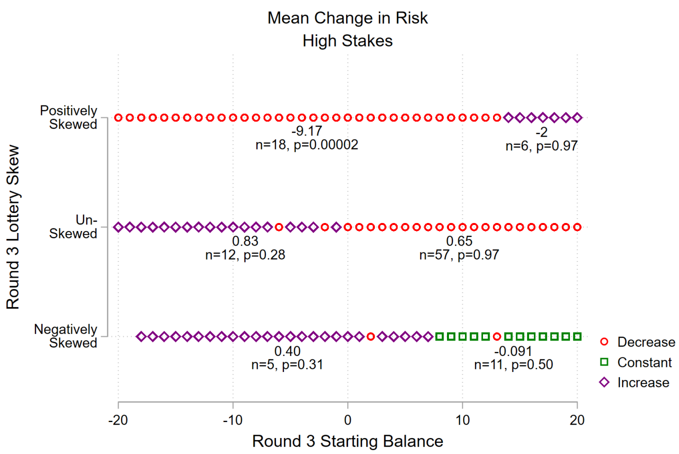
A. Probabilities

Number Boxes Opened	Probability of Bomb	Probability No Bomb	Low Stakes Gain	Low Stakes Loss	High Stakes Gain	High Stakes Loss
1	0.04	0.96	$0.01	-$0.10	$0.02	-$0.10
2	0.08	0.92	$0.02	-$0.10	$0.04	-$0.10
3	0.12	0.88	$0.03	-$0.10	$0.06	-$0.10
4	0.16	0.84	$0.04	-$0.10	$0.08	-$0.10
5	0.2	0.8	$0.05	-$0.10	$0.10	-$0.10
6	0.24	0.76	$0.06	-$0.10	$0.12	-$0.10
7	0.28	0.72	$0.07	-$0.10	$0.14	-$0.10
8	0.32	0.68	$0.08	-$0.10	$0.16	-$0.10
9	0.36	0.64	$0.09	-$0.10	$0.18	-$0.10
10	0.4	0.6	$0.10	-$0.10	$0.20	-$0.10
11	0.44	0.56	$0.11	-$0.10	$0.22	-$0.10
12	0.48	0.52	$0.12	-$0.10	$0.24	-$0.10
13	0.52	0.48	$0.13	-$0.10	$0.26	-$0.10
14	0.56	0.44	$0.14	-$0.10	$0.28	-$0.10
15	0.6	0.4	$0.15	-$0.10	$0.30	-$0.10
16	0.64	0.36	$0.16	-$0.10	$0.32	-$0.10
17	0.68	0.32	$0.17	-$0.10	$0.34	-$0.10
18	0.72	0.28	$0.18	-$0.10	$0.36	-$0.10
19	0.76	0.24	$0.19	-$0.10	$0.38	-$0.10
20	0.8	0.2	$0.20	-$0.10	$0.40	-$0.10
21	0.84	0.16	$0.21	-$0.10	$0.42	-$0.10
22	0.88	0.12	$0.22	-$0.10	$0.44	-$0.10
23	0.92	0.08	$0.23	-$0.10	$0.46	-$0.10
24	0.96	0.04	$0.24	-$0.10	$0.48	-$0.10
25	1	0	$0.25	-$0.10	$0.50	-$0.10

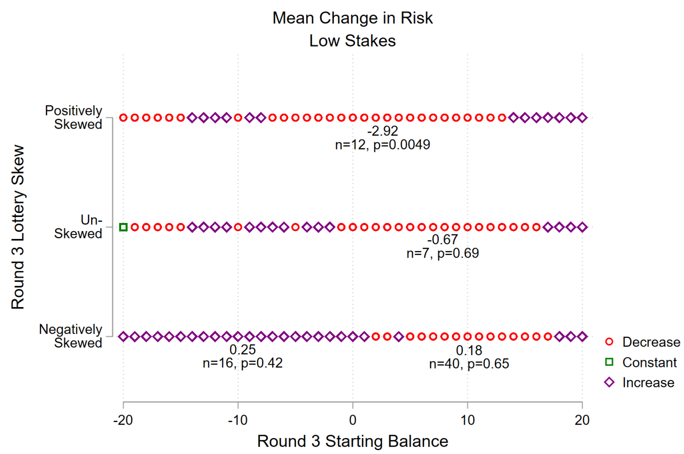
Table III: Gain and loss probabilities and payoffs

B. Average Predictions

We include results on the average predicted change in both treatments, as well as the average predicted between-treatment difference. We compare experimental data to these predictions according to subjects' balance at the start of Round 3. To increase power of our tests, we test the widest range of possible values, within reason. If there are a few values for which the same prediction does not apply within a large stretch of balances, we simply exclude subjects with balances of these values.

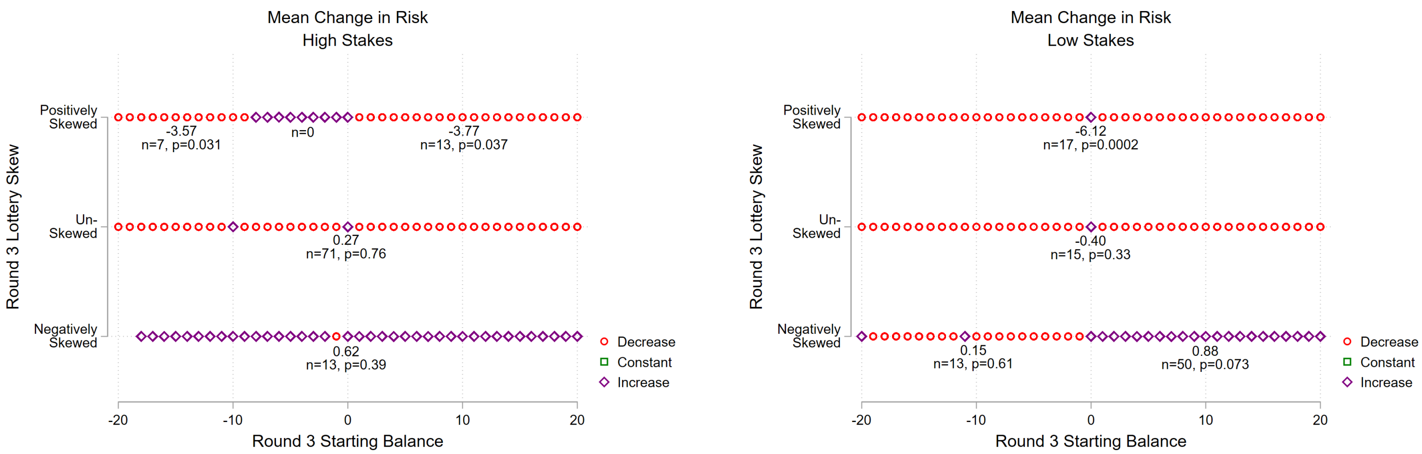


(1) High Stakes



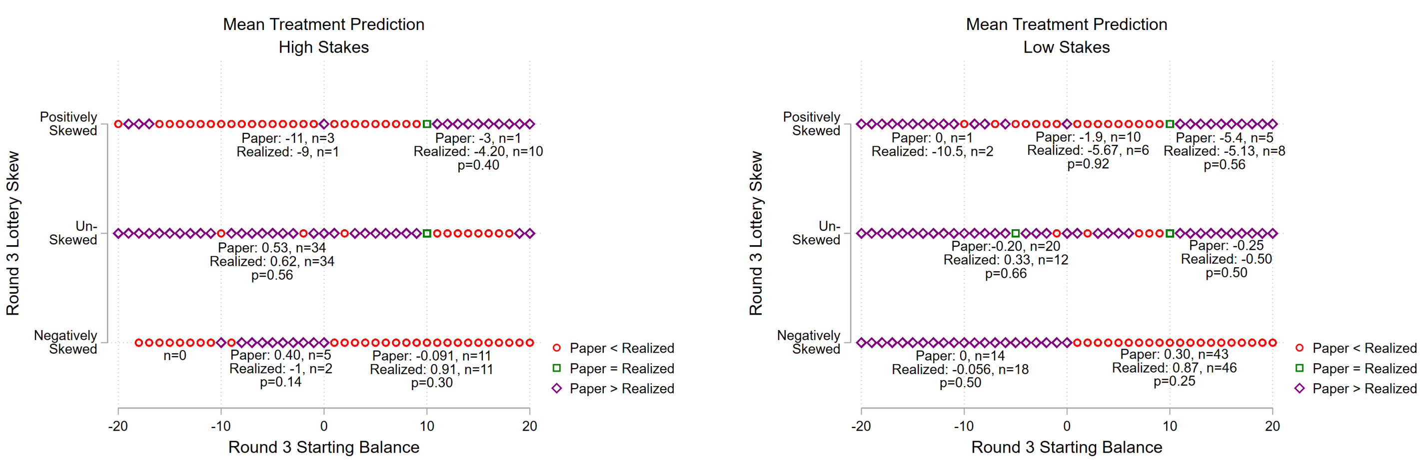
(2) Low Stakes

Figure V: Paper Treatment Predictions



(1) High Stakes **(2)** Low Stakes

Figure VI: Realization Treatment Predictions



(1) High Stakes **(2)** Low Stakes

Figure VII: Between-Treatment Predictions

Instructions

Welcome! Thank you for participating in this HIT.

In addition to your $0.10 for participating, you have now been given a starting balance of $0.40. Any additional money you gain will be added to this starting balance, and losses will be subtracted from this balance.

In this HIT, you will make decisions over 4 rounds. For each round, you will see a 5x5 grid containing 25 boxes, an example of which is shown below.

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

Most of these boxes are empty, but 1 of them contains a "bomb." The placement of the bomb is completely random – each of the 25 boxes is equally likely to contain the bomb.

You can choose to open as many boxes as you like, from 0-25 (Note: This means you are not required to open any boxes if you do not wish to do so). If you open the box that contains the bomb, you will lose $0.10. However, if you only open empty boxes, you will gain $0.02 per box opened.

You will click on all the boxes you wish to open, and then progress to the next page to reveal which box contained the bomb. You will NOT see whether a box contains the bomb until you've made ALL your choices on which boxes to open and have progressed to the next page. That is, if you've clicked on the bomb, you will not learn that immediately. You will see the bomb placement after you've opened all of the boxes you want to open and you progress to the next page.

You will make these decisions over 4 separate rounds. [*However, after the 3rd round, we will finalize your earnings up until that point by adding your earnings to your account balance or withdrawing your losses from your account balance. So if you have positive earnings, we will add those to your $0.40 starting balance, and we will finalize this account balance before Round 4. If you have negative earnings, we will subtract these from your $0.40 starting balance, and then finalize your account balance before Round 4.*

We will tell you your balance before you start Round 4. Then, we will transfer your earnings to your account (in the case of positive earnings) or away from your account (in the event of losses), and then you will participate in one final round. Your earnings from the last round will be transferred separately at the end of the task. Note: You can still earn money by opening empty boxes in Round 4, and you will still lose $0.10 from your balance if you open a bomb in Round 4. But in Round 4, we will have already taken money out of your balance (if you've clicked on a bomb) and we will have added money to your balance (if you've opened empty boxes).]

The placement of the bomb is completely random across these 4 rounds, so the bomb is equally likely to be behind any of the boxes in any of the rounds.

Please remember that, if you click on a bomb, you won't be notified of that in "real-time." You'll find out after you have made all your choices and progressed to the next round.

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

>>

You chose 1, 4, 5, 8, 10, 12, 13, 18, 23, 25.

The bomb was behind box 4. You will lose $0.10.

1	2	3		5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

You chose 1, 5, 7, 9, 13.

The bomb was behind box 12. You did not select the bomb! You will gain 10 cents.

1	2	3	4	5
6	7	8	9	10
11		13	14	15
16	17	18	19	20
21	22	23	24	25

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You are about to begin Round 4. To establish your earnings before you make your final decisions, the amount you've lost will be subtracted from your $0.40 starting balance.

Your current earnings: -10 cents

This amount will now be withdrawn from your account and transferred back to the experimenter.
To transfer your losses and finalize your account balance, you must enter "Close Account" below.

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