Supplemental Appendix

Decisions Under Risk are Decisions Under Complexity

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A Additional Results

A.1 Between-Subjects Comparison

A natural concern about our results is that they may be a consequence of contagion between mirrors and lotteries resulting from our use of a within-subjects design. Perhaps subjects re-use heuristics they first employ in lotteries in their later mirror decisions or vice versa, causing behavior in the two treatments to be similar on average for reasons artificial to our design?

We can evaluate this alternative interpretation simply by restricting attention to *subjects facing the first of the two treatments they are assigned*, transforming our within-subjects design (with potential contamination) into a between-subjects design (without scope for contamination). This transformation is credible because subjects facing their first treatment (Mirror or Lottery) were not aware that they would later be facing the other treatment (Lottery or Mirror), removing scope for even prospective contamination. Figure 5 reconstructs Figure 1 using only this subset of the data and produces nearly identical qualitative results, suggesting that these results are not an artifact of cross-treatment contamination. Subjects continue to display very similar evidence of the pattern in mirrors and lotteries even when they have not yet experienced (or even learned of the existence of) the other treatment. Valuations continue to deviate significantly (at at least the 5% level via Wilcoxon tests) from expected value in the direction of the pattern in both lotteries and mirrors for all valuations.

A related concern is that the correlations between lotteries and mirrors visualized in Figure 4 are driven by subjects carrying over their behavior from the first treatment into the second, rather than by a deep connection in behavioral mechanism between the two treatments. A reason to doubt this interpretation is that (as just discussed) we find nearly identical initial behavior across the two treatments before subjects know the other treatment exists. What's more, the correlations between the two treatments in Figure 4 are also nearly identical regardless of the order of treatments.[10] Since contagion doesn't seem to be a first order driver of behavior and the correlations between treatments are not affected by order, the correlations are instead likely to be driven by subjects using similar valuation strategies in the two different treatments in the first place.

Thus our evidence suggests that our results are not an artifact of order effects or cross-treatment contagion.

Result 6 *The classical pattern continues to arise in both mirrors and lotteries in between-subjects comparisons. There is little evidence of contagion or order effects in the data.*

A subtler version of the same concern is that, for reasons that have little do with contagion, subjects might be drawn to heuristics usually reserved for interpreting (or valuing) probabilities

[10] For absolute deviations (the left panel of Figure 4) the correlation is 0.71 when mirrors come first and 0.65 when lotteries come first; for normalized deviations (the right panel) it is 0.61 when mirrors come first and 0.64 when lotteries come first.

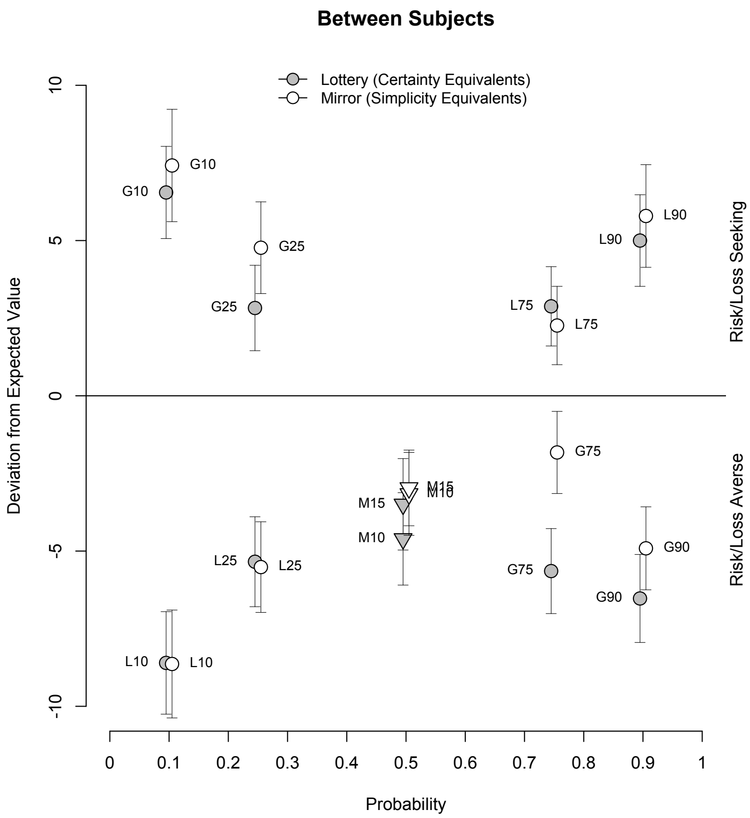


Figure 5: Between-subjects mean deviations from expected value in lotteries (gray dots) and mirrors (hollow dots) from the main (MPL) treatment. *Notes: For fourfold lotteries, the y-axis measures the difference between subjects' certainty/simplicity equivalent and expected value, as stated in the axis label. The x-axis is the probability of the non-zero payoff. For loss aversion tasks, the y-axis measures instead the difference between the certain/simple payoff and the expected value of the mixed lottery/mirror. Two-standard-error bars are included for every task.*

when valuing riskless mirrors. For instance, it may be that subjects apply risk preferences or distort probabilities in mirrors simply because they contain probabilities and subjects are acccustomed to responding to probabilities in a distorted way whenever they see them. However, it is important to emphasize that we deliberately attempted to rule this out in our design by framing the entire exercise in frequentist terms. Mirrors were described entirely as a "box opening" exercise in order to allow us to completely avoid mention of probabilities, likelihoods or randomness in our framing and instructions of this treatment. Consequently, subjects who were initially assigned mirrors (and who, recall, were not told that they would later be assigned lotteries) had no basis for importing lottery-like responses to the deterministic weights we assigned in these valuation tasks. The fact that (as Figure 5 shows) these subjects continue to display the pattern strongly suggests that such "mis-importation" of loettry behavior is unlikely to account for our results. If subjects apply probabilistic reasoning to these frequentist problems, arguably we should equally expect them to do so in virtually any other deterministic valuation task as well.

A.2 Student Sample

An important question is whether our results are a consequence of implementation choices such as (i) our use of an online subject pool rather than a conventional student pool, (ii) limitations in training of subjects due to our online implementation, or (iii) the scale of incentives we used in our design (recall we only pay subjects based on their choices with 20% chance). Perhaps our results are artifacts of unsophisticated subjects, insufficient trading or weak incentives – any of which could plausibly exaggerate noisy and biased behavior.

We ran a nearly identical version of our main design using 113 undergraduate students at UC Santa Barbara in a manner that removes (or at least reduces) these concerns by using more intensive training and stronger incentives. First, this experiment used undergraduate students at a selective university rather than an online subject pool. Experiments were run on Zoom in conventional, fixed experimental sessions monitored by the experimenter, allowing subjects to ask the experimenter clarifying questions in real time before and during the experiment. Second, this experiment featured more intensive training than in our main design. Specifically, we quadrupled the number of comprehension questions subjects were asked immediately before each of the treatments (Mirror and Lottery). These questions were designed to highlight for subjects the differences between the incentives of lotteries vs. mirrors in order to remove the possibility that subjects mistook one payoff rule for the other. Finally, this experiment quintupled the incentives in the main experiment by paying subjects based on a random lottery with certainty (rather than with 20% chance).

The UCSB sessions were conducted in February and March 2021 using 113 subjects from the subject pool of the Laboratory for the Integration of Theory and Experiments (LITE) at UC Santa Barbara. Because of the Covid-19 pandemic, the physical laboratory was closed at this time so the five sessions of data collection were held remotely on Zoom. In each session no more than 25 subjects from the undergraduate population at UC Santa Barbara were invited by email to log into our Zoom account at a pre-specified time. They were then given a link to the experimental software and were allowed to ask the experimenter questions throughout the session.

Relative to the main sessions run on Prolific, the UC Santa Barbara sessions differed in three major respects:

- The main sessions conducted on Prolific were more demographically diverse, drawing subjects from throughout the United States and included largely non-student subjects. By contrast, the UCSB sessions included only students from the University of California, Santa Barbara, a selective public university.
- As the instructions in Supplemental Appendix B discuss, we gave subjects four identical quiz questions concerning the nature of payments immediately prior to the Lottery treatment and again prior to the Mirror treatments in the Prolific sessions. Because the answers to these questions differed across the two treatments, these questions allowed us to make payoff differences across treatments salient to subjects. In the UCSB sessions we quadrupled the number of questions, adding additional questions in both the gains and loss domain. Thus these sessions intensified subjects' training.
- In the Prolific sessions we gave subjects a $6 fixed payment for participation and paid 20% of subjects (randomly selected, ex post) a bonus based on their decision in a random price list and row. By contrast, in the UCSB sessions we paid subjects a $5 fixed payment and, in addition, paid *all* subjects a bonus based on their decision in a random price list and row. Incentives were therefore substantially larger in the UCSB sessions.

Additionally, the sessions differed in two respects that are less likely to have influenced the results reported in the paper:

- In the Prolific sessions, we asked subjects a number of unincentivized questions at the end of the experiment about their decision-making (reviewed in Supplemental Appendix A.5). In the UCSB sessions, we included only the cognitive reflection test and a single cognitive uncertainty measure.
- The UCSB sessions included four additional price lists not included in the Prolific sessions. These were rather more complex lotteries designed to gather non-parametric measures of prospect-theoretic value function curvature using methods suggested by Wakker & Deneffe (1996). These lists, intriguingly, produced evidence of similar degree of value function curvature in Mirrors and Lotteries, but the results were extremely noisy and sensitive to specification. For this reason (and because these results are only of secondary importance to our main motivating questions), we did not use these lists in our main Prolific sessions.

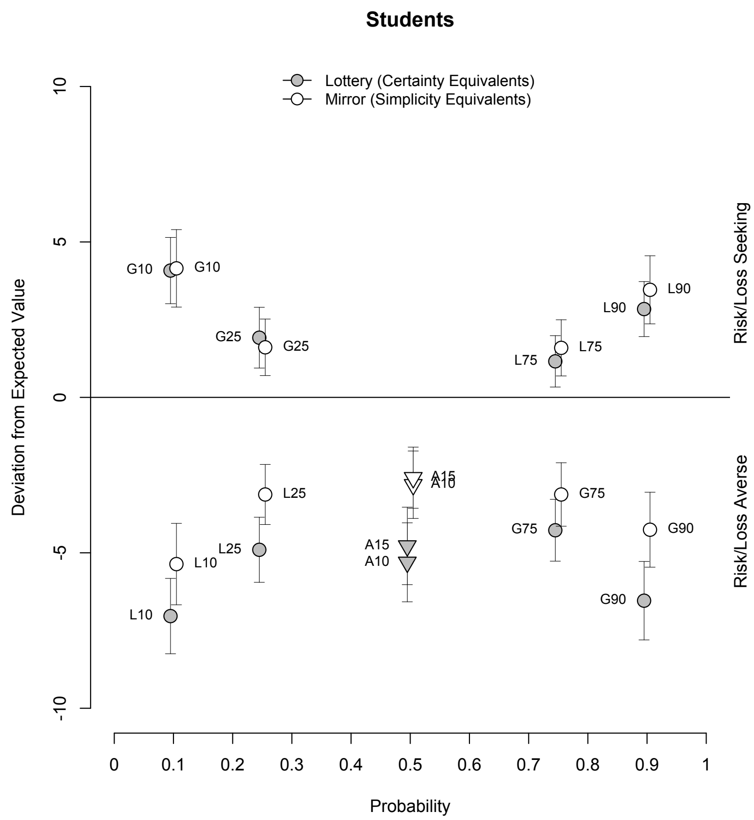


Figure 6: Student sample deviations from expected value in lotteries (gray dots) and mirrors (hollow dots). *Notes: For fourfold lotteries, the y-axis measures the difference between subjects' certainty/simplicity equivalent and expected value, as stated in the axis label. The x-axis is the probability of the non-zero payoff. For loss aversion tasks, the y-axis measures instead the difference between the certain/simple payoff and the expected value of the mixed lottery/mirror. Two-standard-error bars are included for every task.*

In all other respects, including instructions, software and decision tasks the UCSB sessions were identical to the main sessions.

Figure 6 plots the results from these sessions and they strongly suggest that these features of the implementation are not driving our results. The plot shows continued evidence that the full classical pattern appears in mirrors and to a similar degree as in lotteries; we can reject the hypothesis that subjects choose expected value in every list for both lotteries and mirrors (at the 1% level by Wilcoxon tests). We also continue to find a similarly strong correlation between the pattern in the two cases ($\rho = 0.64$ for absolute deviations and $\rho = 0.5$ for deviations normalized in the direction of the pattern). The main difference in this sample is that by some metrics there is a somewhat larger "gap" between the strength of the pattern in mirrors and lotteries: summed errors in the direction of the fourfold pattern are overall 82% as large and loss aversion 54% as large in Mirrors as Lotteries.

Result 7 *A robustness sample of university students with increased training and quintupled incen-*

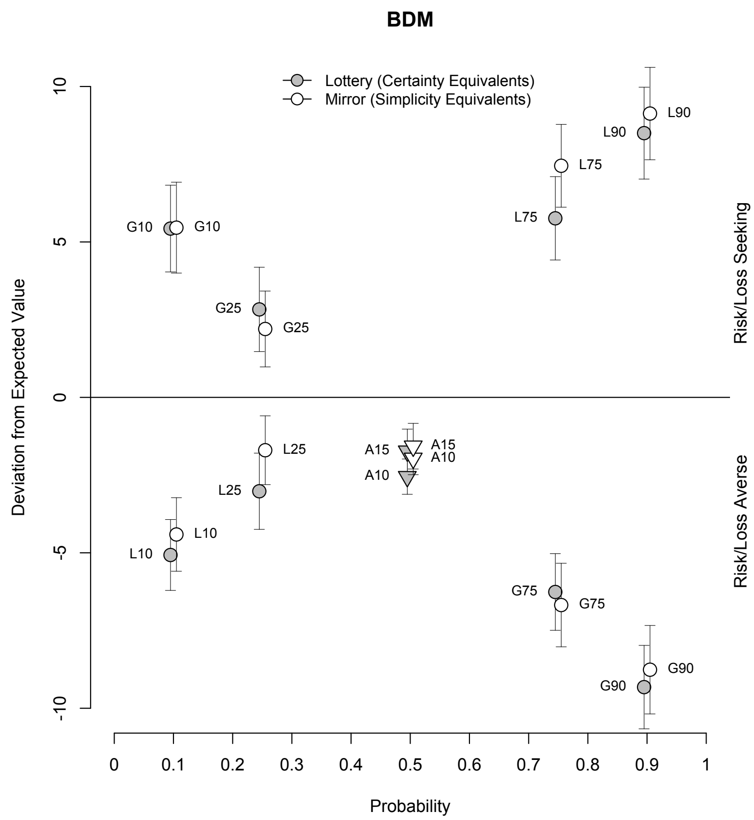


Figure 7: Mean deviations from expected value in BDM lotteries (gray dots) and mirrors (hollow dots). *Notes: For fourfold lotteries, the y-axis measures the difference between subjects' certainty/simplicity equivalent and expected value, as stated in the axis label. The x-axis is the probability of the non-zero payoff. For loss aversion tasks, the y-axis measures instead the difference between the certain/simple payoff and the expected value of the mixed lottery/mirror. Two-standard-error bars are included for every task.*

tives produces results similar to those in the main dataset.

A second interesting difference is, as is clear from Figure 6, we find a somewhat weaker fourfold pattern in this data than in the main sample: valuations are closer to expected value. But this is true in both lotteries and mirrors, meaning whatever mechanism drives these sample effects is linked to complexity (shared by lotteries and mirrors) rather than risk or risk preferences. Conversely, we find an intensification of loss aversion in lotteries in our student sample, but no such intensification in mirrors, driving the increased gap in loss aversion. This increase in loss aversion in student samples has been reported in recent work (Chapman et al. 2022) and may suggest that the "gap" in loss aversion between lotteries and mirrors is driven by true loss averse preferences operating as a secondary driver of loss averse valuation.

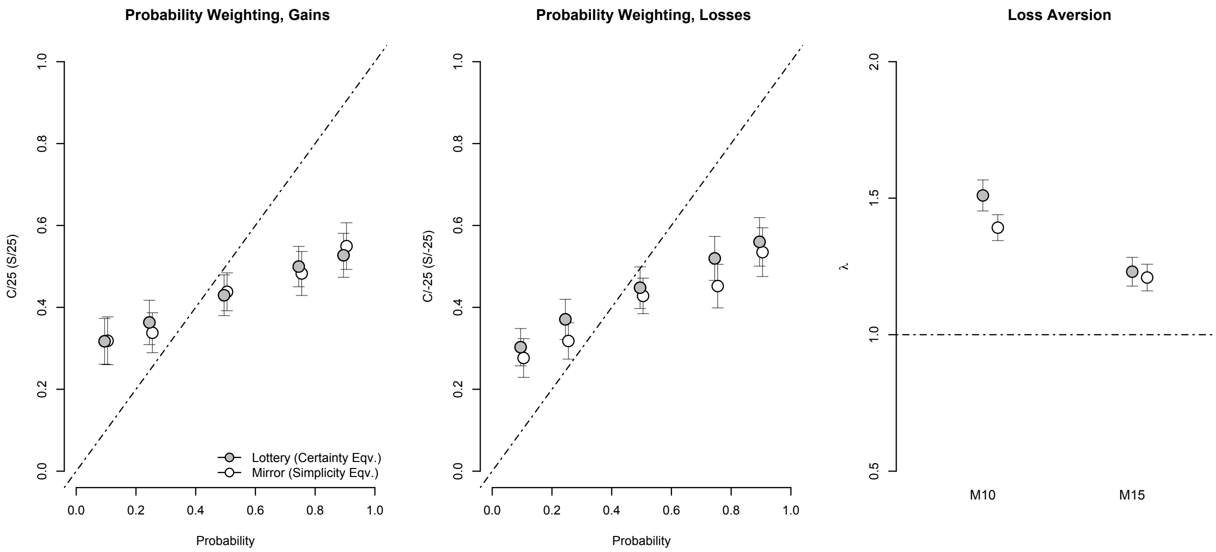


Figure 8: Naive visualization of the probability weighting functions (left two panels) and the loss aversion parameter, λ in the BDM treatment. *Notes: The first two panels plot a naive estimate of the probability weighting function (following Tversky & Kahneman (1992)) by plotting the ratio of the certainty/simplicity equivalent to the non-zero payment amount as a function of the probability of the non-zero payoff amount. The final panel plots a naive estimate of λ, the standard linear parameter of loss aversion, under the assumption of a reference point of zero.*

A.3 BDM Treatment

Another natural question about our results is whether they are a special outgrowth of our use of mulitiple price lists (MPLs), or if they are a more general phenomenon of valuation. To answer this question we ran the the BDM treatment ($N = 100$, collected on Prolific in April 2023) in which we replicated our main MPL design but elicited certainty/simplicity equivalents using the Becker-Degroot-Marschak or "BDM" mechanism (Becker et al. 1964). In our BDM tasks, subjects are shown the lottery being evaluated (e.g., G10) and asked to express their willingness to pay either to acquire (WTP-to-acquire) or to avoid (WTP-to-avoid) this lottery. Specifically, subjects were asked to enter a certainty/simplicity equivalent C in the lottery's support in a text box (see Figure 18 for a screen shot from a WTP-to-acquire task and Figure 19 for a screen shot from a WTP-to-avoid task). The subject was informed that the computer would later draw a random price P in the support. For WTP-to-acquire tasks, if C<P the subject is not assigned a payment based on the lottery in question; if C≥P, the subject acquires the lottery and pays price P. For WTP-to-avoid tasks, if C<P the subject is assigned the lottery; if C≥P, the subject is not assigned the lottery and pays price P.

The fourfold lotteries used in this design are identical to those used in the main MPL treatment. However, because it is difficult to measure quantities other than certainty/simplicity equivalents using the BDM we are unable to use lottery equivalents (i.e. tasks A10 and A15) to measure loss aversion. We instead measure loss aversion by eliciting certainty/simplicity equivalents for

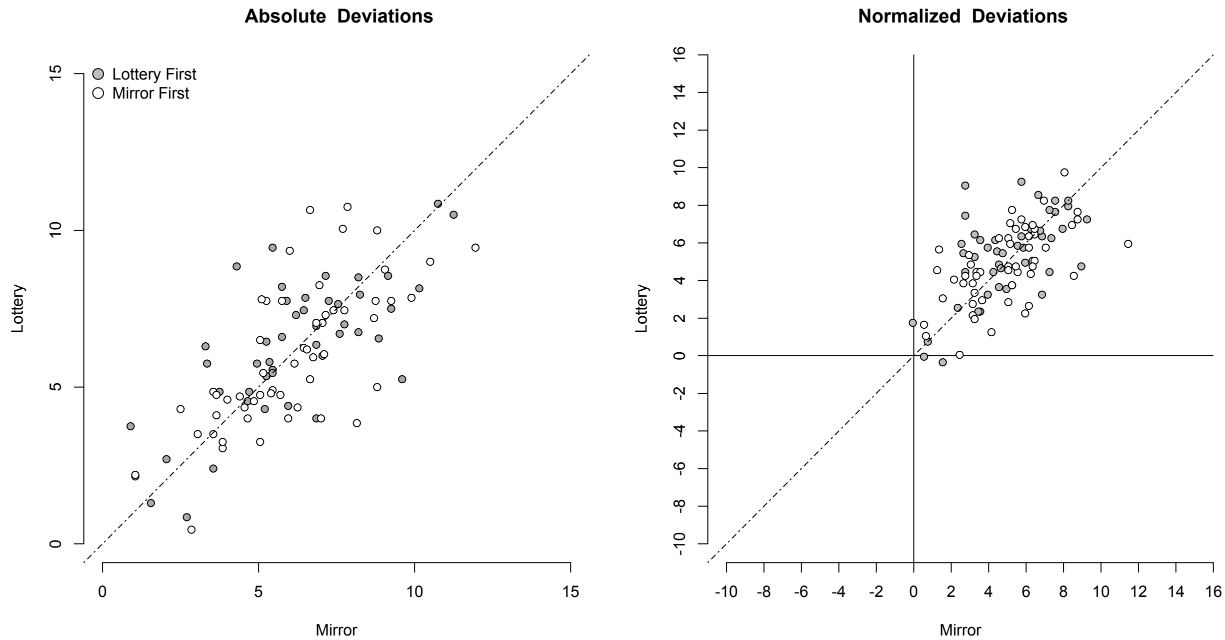


Figure 9: Deviations from expected value maximizing choices in mirrors (x-axis) versus lotteries (y-axis) in the BDM treatment, by subject. *Notes: Each dot represents a separate subject. On the x-axes we plot the subject's data from the Mirror treatment and on the y-axes the same subject's data from the Lottery treatment. The left panel plots the mean absolute deviation from expected value. The right panel plots the mean deviation, normalized to be positive if it runs in the direction of the classical pattern. Gray dots are subjects who were assigned the Lottery treatment first, hollow dots subjects who were assigned the Mirror treatment first.*

(i.e. willingness to pay to avoid) the mixed lotteries/mirrors $M10 = (0.5; 5, -10)$ and $M15 = (0.5; 5, -15)$. We chose these negative expected value lotteries to create scope for subjects to reveal not only loss averse but also loss seeking valuations in simple elicitations of subjects' willingness-to-pay-to-avoid. We thus subjects' WTP-to-acquire lotteries G10, G25, G50, G75 and G90 and their WTP-to-avoid lotteries L10, L25, L50, L75, L90, M10 and M15 in these experiments. Subjects were paid at the end based on their choice in one randomly selected task and one randomly selected price, P.

We present our findings in Figures 7, 8 and 9, designed to mirrors Figures 1, 2 and 4, respectively, from the body of the paper. As Figure 7 shows, from the perspective of our main motivating questions, the BDM results are very similar to those for the main MPL treatment. As with MPL, we find evidence of the fourfold pattern in both lotteries and mirrors. Summing up pattern-consistent choices, we find that the fourfold pattern is 99% as strong in mirrors as in lotteries. We also find evidence of loss aversion in both lotteries and mirrors, with loss aversion 83% as strong in the latter as in the former. In each of our 12 tasks we find (as in MPL) that for the median subject the difference in valuations between lotteries and mirrors is 0. As Figure 9 shows, mirror and lottery deviations are strongly correlated: we find a correlation of 0.72 for absolute deviations and 0.6 for normalized deviations, closely matching results from the MPL treatment.

We conclude that our main results are not driven by our use of multiple price lists, but instead reflect a more general phenomenon of valuation.

Result 8 *Results from the BDM treatment are similar to those from our main MPL treatment.*

Visual comparison of Figures 7 and 1 (from the body of the paper) reveals significant effects of the method of elicitation (MPL vs. BDM) on estimates of the severity of the fourfold pattern in lotteries. In particular, deviations from expected value are somewhat smaller at low probabilities and much larger at high probabilities in BDM than in MPL. As we discuss in Section 5 these kinds of "elicitation effects" are standard in the literature – measured risk preferences (including prospect theoretic parameters) tend to vary (often within-subject) across choice contexts. What is new here is that we find virtually identical elicitation effects in mirrors, with the shape of the fourfold pattern changing in identical ways in the two contexts. As a result, mirror behavior tracks lottery behavior across elicitation methods, suggesting that elicitation effects themselves have little to do with risk or risk preferences.

This is important for the interpretation of our results, because it strongly reinforces our finding that lottery valuations fail to reveal risk preferences. As we show in the paper, changing the objective function itself – the preferences these elicitations are generally deployed to measure – by inducing risk neutral preferences using mirrors has surprisingly small effects on lottery valuations. By contrast, changing seemingly superficial details of the elicitation method has large, first-order effects *that are identical across objective functions* (i.e. across lotteries and mirrors). Comparing the change in valuations due (i) to changes in the objective function (mirrors vs. lotteries) and (ii) to changes in the method of elicitation (MPL vs. BDM), we find that the latter effect is at least twice as large for every one of our tasks and typically much larger. Pooling across all of our tasks we find that changes in the method of elicitation are, on average, four times larger in absolute value than changes in the underlying objective function (2.96 vs. 0.737). This differential strongly suggests that valuation is dominated by heuristic behaviors that respond to details of the choice environment but that have little connection to underlying preferences.

It is also apparent when comparing Figures 7 and 1 that loss aversion estimates differ between MPL and BDM, a finding that may be notable for a different reason. A very conventional explanation for the large differences in loss aversion in these two cases is that while A10/A15 (studied in MPL) likely firmly establishes a reference point of zero, M10/M15 (studied in BDM) plausibly establishes a reference point of less than zero. As a result λ, as we've calculated it, plausibly underestimates loss aversion in M10/M15 relative to A10/A15 due to a change in the reference point across the two cases. Perhaps surprisingly, we find an identical "reference point effect" in mirrors, with an almost identical weakening of loss averse behavior in M10/M15 relative to A10/A15. Of course, this effect (like the effects observed in the fourfold pattern) might be due, in both lotteries and mirrors, to the change in the elicitation mechanism. However, to the degree we interpret this weaking of measured loss aversion as a reference point effect, the results suggest that not only does loss aversion and probability weighting survive the removal of risk, so does reference dependence

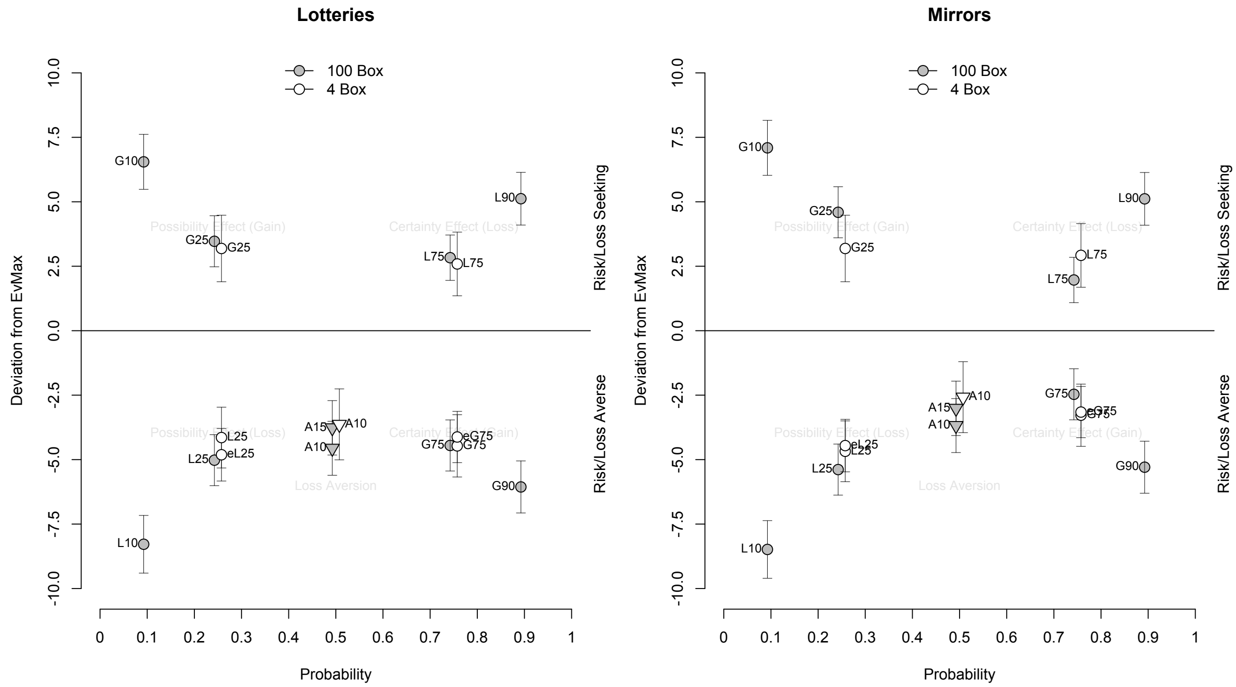


Figure 10: Results from the Easier treatment (4 box), overlaid on on results from the main sample (100 box). *Notes: Panels are included for Lotteries (left) and Mirrors (right). For fourfold lotteries, the y-axis measures the difference between subjects' certainty/simplicity equivalent and expected value (as stated in the axis label). The x-axis is the probability of the non-zero payoff. For loss aversion tasks, the y-axis measures instead the difference between the certain payoff and the expected value of the mixed lottery. Two-standard-error bars are included for every lottery. .*

and its sensitivity to manipulations of the reference point.

Result 9 *Variation in the method of elicitation influences the anomalies of the classical pattern in identical ways in lotteries and mirrors. Variation in the method of elicitation has a substantially larger effect on these anomalies than does variation in the objective function itself.*

A.4 4-Box Treatment

A further question about our main results is whether they are a consequence of arithmetic difficulties that arise due to the numbers used in the main design. For instance, we describe lotteries/mirrors using 100 outcomes (i.e., 100 boxes) and perhaps it is difficult to perform calculations involving this many outcomes. Likewise, the non-zero payment in our fourfold lotteries was $25 which does not produce whole-number expected values in any of our lotteries – perhaps this makes it unnecessarily difficult to calculate true value in mirrors and the expected value in lotteries. Perhaps subjects are constrained in their ability to perform arithmetic, causing them to make errors that show up as the classical pattern.

A strong ex ante reason to doubt this interpretation is that all of our treatments were run online, meaning all of our subjects had ready access to powerful calculators that make the arithmetic trivial. This means that subjects were not constrained in their ability to (with some minor effort) precisely calculate expected value. To reinforce this point, we report a robustness treatment we call "4-Box" in which we reduce the difficulty of the arithmetic required to calculate expected value. First, in our main dataset, likelihoods are described using 100 boxes, each of which contains a dollar amount, and non-zero payments are described as appearing in 10, 25, 50, 75 or 90 of the boxes. In the 4-Box treatment we shrink the outcome space from 100 boxes to 4 boxes *without changing the underlying probabilities*. Doing this allows us to express payoffs occurring with 0.25, 0.5 and 0.75 probabilities as dollar amounts contained in 1,2 or 3 of the boxes instead of 25, 50 or 75 of the boxes, plausibly making the problem easier to reason about and mathematical calculations easier to conduct. Thus, in the 4-Box treatment we repeat the G25, G50, G75, L25, L50, L75 and A10 lotteries but describe them using 4 boxes instead of 100.[11]

The 4-Box treatment was conducted in May of 2022 using 90 subjects on Prolific and MPL elicitation. The treatment repeated Lotteries G25, G50, G75, L25, L50, L75 and A10. The reason we did not include G10, G90, L10 and L90 is because the main idea of the treatment is to describe probabilities in frequentist terms using four outcomes (four "boxes") instead of 100. While 25%, 50% and 75% odds can be described using this coarse of a state space, clearly 10% and 90% cannot. The treatment also included (i) a repetition of L50 and G50 and (ii) treatments sG75 and sL25 which replaced the non-zero payment of $25 in G75 and L25 with $20. The instructions, implementation and payoff rules from the 4-Box treatment were identical to those in the main treatment except for the descriptions of frequencies. Instead of describing 25%, 50%, 75% and 100% as payouts contained in 25 out of 100, 50 out of 100, 75 out of 100 and 100 out of 100 boxes (as in the rest of the dataset), we described them as being contained in 1 out of 4, 2 out of 4, 3 out of 4 and 4 out of 4 boxes.

Figure 10 plots the results. It includes one panel for lotteries and another for mirrors and in these panels repeats the data pictured in Figure 1 using solid dots (100 box data), for reference. On each of these panels we overlay, using hollow dots, data from 4-box versions G25, G50, G75, L25, L50, L75 and A10 lotteries from the 4-Box treatment. We make two observations. First, the pattern continues to arise (for both lotteries and mirrors) under this simplified framing – Wilcoxon tests continue to allow us to reject the hypothesis of valuation at expected value for both Lotteries and Mirrors ($p < 0.01$ throughout). Second, valuations change little in either lotteries or mirrors when we move from 100-box to 4-box frames – Wilcoxon tests allow us to reject the hypothesis of identical valuation in 100-box and 4-box lotteries for only one of the ten comparisons (G25 mirrors). We conclude that the number of outcomes has at most a secondary effect on the appearance and

[11] It is important to highlight that this treatment does not make lotteries/mirrors any less disaggregated (the lottery's support continues to contain two elements) and therefore it does not make it any less *complex* in the sense of Bernheim & Sprenger (2020), Puri (2023) and Fudenberg & Puri (2022). This treatment holds the amount of information that has to be processed (the number of elements that must be aggregated) constant but attempts to reduce the mathematical difficulty of that processing.

severity of the pattern.

A second potential source of arithmetic difficulties in the main dataset is the use of a non-zero payoff of \$25 in the fourfold lotteries, which may be more difficult to reason about than a rounder number that is more easily multiplied by the relevant probabilities/weights in the task. To examine this we added to the 4-Box treatment a repetition of lotteries L25 and G75 but with a payoff of \$20 instead of \$25. We ran this also with the 4-box (rather than 100-box) design, making intuitive calculations of expected value particularly easy (\$20 in 2 or 3 boxes is easily seen to imply expected values of \$10 or \$15 through simple whole-number division). We call these lotteries sL25 and sG75 and plot valuations from these lotteries in Figure 10. We find no overall reduction in the severity of the pattern. Again, this suggests that mere arithmetic difficulty has little power to explain our results.

Together, these treatment interventions (combined with our already maximally simple 2-outcome setting, featuring a zero-outcome in one of the two outcomes) produce perhaps the arithmetically simplest possible lotteries in which the pattern can be measured. Our \$20 lists ask subjects to value lotteries that have the minimal possible number of outcomes (for a true lottery), one of these outcomes pays nothing and can be ignored in computation, the numbers describing the likelihoods are small and the non-zero payoff is calibrated to allow for whole-number computations of expected value by simple division. Nonetheless, we continue to find strong evidence of the pattern both in lotteries and their mirrors even in these maximally arithmetically simple valuation tasks.

Result 10 *Making valuation tasks arithmetically easier has only minor effects on the severity of the classical pattern in mirrors or lotteries.*

A.5 Correlates of the Pattern

Strong correlations between behavior in lotteries and mirrors suggest they are driven by a common mechanism and, because there is no risk in mirrors, suggest that this mechanism is rooted in the complexity the two types of tasks share. In order to gather some clues as to the common mechanisms that drive the pattern in both lotteries and mirrors, we collected a number of auxiliary measures and here we study to what degree these measures predict the severity of classical anomalies in both cases. We gathered three types of measures and we conduct a primarily exploratory analysis of how they relate to the incidence and severity of anomalous behavior in our main treatment. For this analysis, we restrict attention to our main MPL treatment where we have the most data and therefore the most reliable estimates.

First, we gathered several behavioral measures. Most importantly, we *repeated* two random valuation tasks in both lotteries and mirrors, allowing us to measure re-test consistency of choices in identical problems. The mean absolute difference in valuation between identical problems gives us a direct measure of **noise** in subjects' decision making. Next, we measured the average response **time** for each subject's choices – a commonly used measure of effort. Finally, after the main experiment

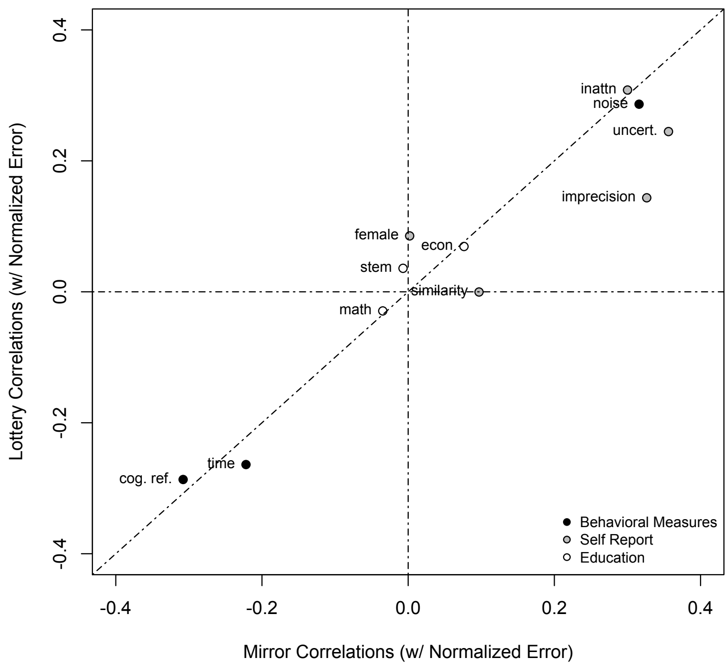


Figure 11: Correlates predictors (labeled dots) with pattern-consistent bias in mirrors (x-axis) and lotteries (y-axis). *Notes: Each dot is a different predictor and the x- and y-axes show the correlation of each predictor with pattern-consistent bias in mirrors and lotteries, respectively.*

we administered a three-question **cognitive reflection** test (Frederick (2005)), commonly used to measure how strongly subjects lean on intuitive vs. careful decision making.

Second, we administered several post-experiment questions that asked subjects to reflect on their choices. For instance, we we asked subjects how confident they were (in percentage terms) that they made the optimal choice in both lotteries and mirrors. Measures of **cognitive uncertainty** like this have proved predictive of the fourfold pattern and other anomalies in recent work (e.g., Enke & Graeber (2023), Enke et al. (2023)). We also asked subjects (separately for lotteries and mirrors) to report on a 100-point Likert scale how much attention they paid (0 for little attention, 100 for a lot of attention) to the number of boxes (i.e., to the probabilities) and to the dollar amounts (i.e., payoffs) when evaluating lotteries/mirrors. This gives us measures of **inattention** for each subject for both lotteries and mirrors. Likewise we asked subjects to use a 100-point Likert scale to estimate the degree to which they "guessed" (0) versus "made a precise (exact) decision" (100) in their valuations, again for both lotteries and mirrors. This gives us a self-reported measure of **imprecision** of decisions.

Third, we gathered several demographic measures, focused on measures that proxy for mathematical ability. We asked subjects to report their highest level of **math** education, coding subjects as 1 (relatively advanced mathematical training) if they had taken any college-level math and 0 otherwise. We asked a similar question about whether subjects had any college-level economics training. We also asked subjects their college major, coding them as **STEM** if they reported majoring in Science, Mathematics or Business. Finally, we asked for the subject's gender which is of interest because of debates in the literature about whether risk preferences are related to gender.

In Figure 11, we estimate the Pearson correlation between each measure and the mean error (normalized to be positive if in the direction of the classical pattern) in mirrors and lotteries, plotting the correlation coefficient ρ for (i) mirrors on the x-axis and (ii) lotteries on the y-axis.[12] We make several observations.

First and perhaps most importantly, there is a strikingly strong relationship between the correlates of the pattern in mirrors and lotteries. Correlation coefficients hover around the 45 degree line and there is a ρ =0.94 correlation between correlation estimates across the two valuation problems This relationship strongly reinforces our conclusion that the two types of behavior are driven by the same underlying behavioral mechanisms and that the driver of the pattern in lotteries is therefore likely rooted in the way people respond to disaggregation.

Result 11 *There is a strong similarity in the predictors of the classical pattern in lotteries and mirrors.*

Second, the strongest correlations are for variables that relate to the types of simpler-than-optimal decision procedures the literature has proposed as potential proximal mechanisms for the classical pattern. We find that (i) self-reported inattention is strongly positively correlated and (ii) correct responses in cognitive reflection test questions are strongly negatively correlated with pattern-consistent errors. This is potentially evidence in favor of the hypothesis that the classical pattern occurs because subjects use inattentive procedures, like those described by Bordalo et al. (2012). We also find that (i) noise in decision making and (ii) self-reported cognitive uncertainty are both strongly positively correlated with pattern-consistent errors. This is highly consistent with the hypothesis that the classical pattern occurs because subjects use imprecise strategies that produce cognitive noise (e.g., Blavatskyy 2007, Woodford 2012*a*, Steiner & Stewart 2016, Woodford 2020, Enke & Graeber 2023, Woodford 2012*b*, Khaw et al. 2022, Vieider 2023, Frydman & Jin 2023). Both types of accounts seem consistent with our finding that decision time is strongly negatively correlated with the classical pattern – potential evidence that such behavior is especially strong for subjects who expend less effort on the valuation task.

Third, by contrast, we find much weaker evidence that our other variables are very predictive of the classical pattern. Perhaps most importantly, we find little evidence linking the classical pattern to mathematical preparation. Prior mathematical or economic training and reporting majoring in a STEM training have, at best, weak predictive power in either lotteries or mirrors. This seems consistent with our finding that varying the arithmetic difficulty of calculating expected value has

[12] To reduce risks of attenuation, we pooled several of these measures. In particular, we averaged our post-experiment cognitive uncertainty, inattention and imprecision measures at the subject level and used a single pooled noise measure.

little effect on the classical pattern in our sample. This does not mean that there isn't a strong cognitive dimension to these findings, but rather that prior training in arithmetic calculation doesn't seem to be a major modulator of the effect.

We summarize the results of this correlational analysis as a further result:

Result 12 *The classical pattern is especially pronounced in subjects who (i) invest less time in valuation, (ii) report paying less attention to valuation, (iii) make mistakes on cognitive reflection test, (iv) make noisy or inconsistent decisions and (v) report cognitive uncertainty about the quality of their valuations.*

Together, these results seem to suggestthat subjects consciously (and perhaps deliberately) use hasty, casual, inattentive and imprecise strategies to value disaggregated objects like lotteries and mirrors and that this choice is an important driver of pattern-consistent errors.

A.6 Additional MPL data

We originally ran our main MPL treatment on Prolific in May of 2022 with 186 subjects. During the reviewing process, a helpful referee discovered a typo in one of the examples used to explain price lists in this treatment. In particular, the "Choosing a Set of Boxes" page of the instructions (reproduced in Section B.2.1 of this Appendix), in the second sentence of the second bullet point read "Set B has 50 boxes containint $10 and 50 boxes containing $0" instead of "Set B has 40 boxes containing $10 and 60 boxes containing $0" as it should have (and as the current instructions does). The referee raised legitimate concerns that this might have confused subjects and caused or intensified some of our findings.

For this reason, we re-ran the main MPL treatment (as described in the body of the paper) with this typo fixed, and report the results from the original run of the experiment in this Appendix. The original run of the experiment was nearly identical to the experiment that has taken its place in the main body of the paper. The only difference is that in the original version of the experiment we repeated tasks G50 and L50 for each subject, while in the revised the experiments we randomly selected two tasks to be repeated.

We present data from the original run of the experiment in Figures 12, 13 and 14, which mirror Figures 1, 2 and 4 for MPL in the main text. The results are virtually identical. As with the main dataset, we find in Figure We present data from the original run of the experiment in Figures 12 evidence of the fourfold pattern in both lotteries and mirrors. Summing up pattern-consistent choices, we find that the fourfold pattern is 97% as strong in mirrors as in lotteries. We also find evidence of loss aversion in both lotteries and mirrors, with loss aversion 64% as strong in the latter as in the former. This is somewhat smaller than in our main MPL sample and in our BDM treatment. Nonetheless, in each of our 12 tasks we find (as in the main dataset) that for the median subject the difference in valuations between lotteries and mirrors is 0. As Figure 14 shows, mirror

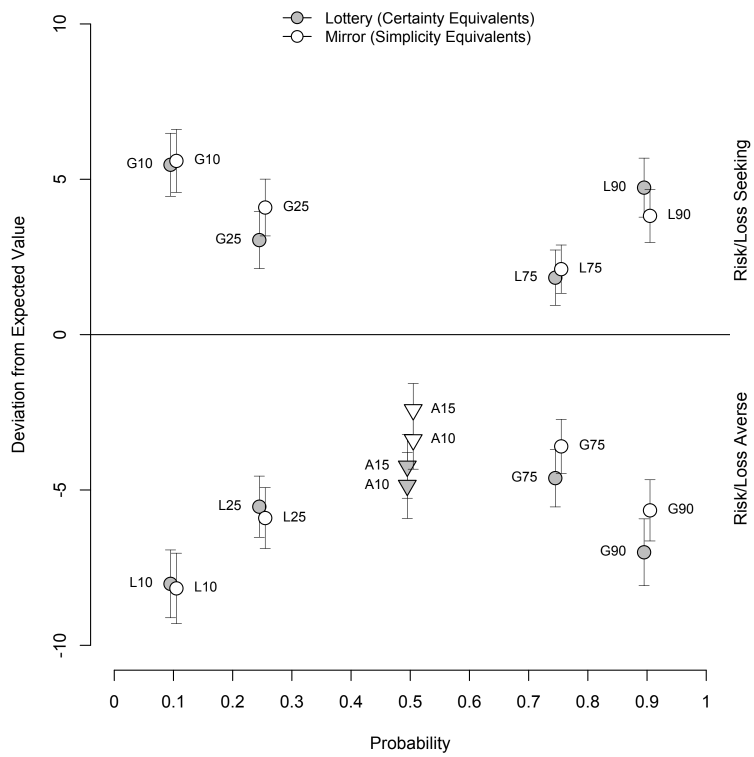


Figure 12: Mean deviations from expected value in lotteries (gray dots) and mirrors (hollow dots) in the original run of the main MPL treatment. *Notes: For fourfold lotteries, the y-axis measures the difference between subjects' certainty/simplicity equivalent and expected value, as stated in the axis label. The x-axis is the probability of the non-zero payoff. For loss aversion tasks, the y-axis measures instead the difference between the certain/simple payoff and the expected value of the mixed lottery/mirror. Two-standard-error bars are included for every task.*

and lottery deviations are strongly correlated. We find a correlation of 0.65 for absolute deviations and 0.59 for normalized deviations, closely matching results from the main MPL sample.

A.7 Analysis of G50 and L50

In Figure 15 we plot deviations from expected value for the 50/50 lotteries (G50 and L50) we included in all of our treatments, mirroring Figure 1 (recall, for space reasons we omitted these lotteries from the main Figure). These lotteries are potentially interesting because they seem particularly arithmetically easy to evaluation – they require math no more difficult than simple averaging (i.e. to calculate expected value). Evaluating behavior in these tasks provides another opportunity (alongside the analysis in Supplemental Appendix A.4) to examine to what degree our main results are rooted in the arithmetic difficulty of lottery/mirror valuation. Under the hypothesis that it is arithmetic difficulty that drives the pattern, we might expect errors to diminish in mirrors relative to lotteries in these easier problems, allowing lotteries to reveal true risk preferences.

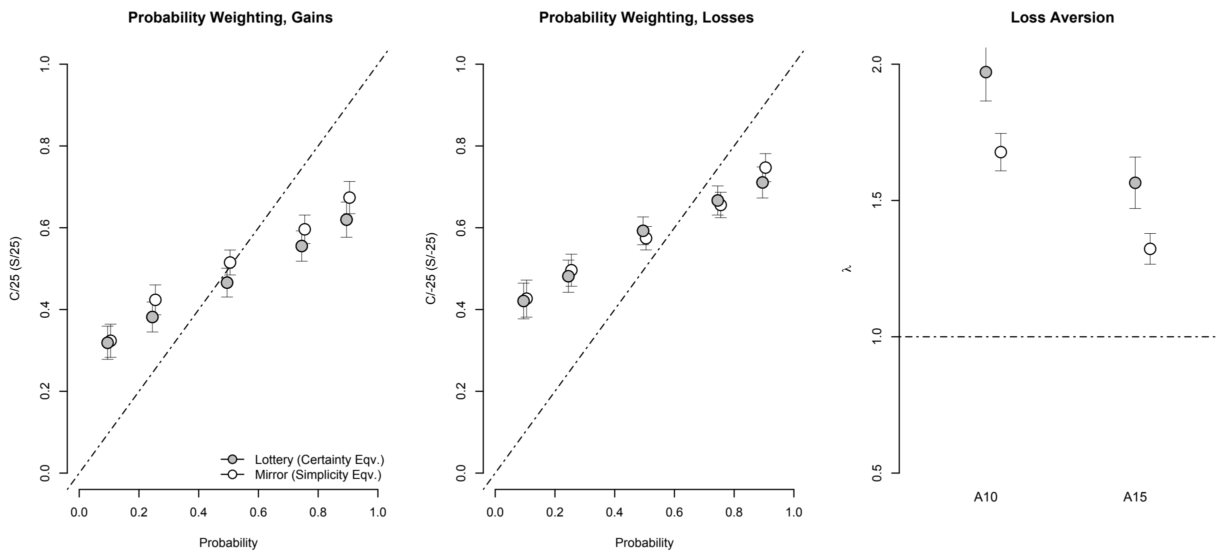


Figure 13: Naive visualization of the probability weighting functions (left two panels) and the loss aversion parameter, λ in the original run of the main MPL treatment. *Notes: The first two panels plot a naive estimate of the probability weighting function (following Tversky & Kahneman (1992)) by plotting the ratio of the certainty/simplicity equivalent to the non-zero payment amount as a function of the probability of the non-zero payoff amount. The final panel plots a naive estimate of λ, the standard linear parameter of loss aversion, under the assumption of a reference point of zero.*

However, we find little evidence of this. In most cases, lottery and mirror valuations are identical, and deviations are never systematically closer to expected value in mirrors than lotteries in any cases.[13]

A.8 Additional Tables and Figures

A.8.1 Correlations By Anomaly

Figure 16 repeats the analysis reported in the right-hand panels of Figure 4 separately for the fourfold pattern and loss aversion. In particular, the left hand panels plots mean bias measured in "fourfold lotteries" (G10, G25, G75, G90, L10, L25, L75, L90) for mirrors and lotteries (each dot, again, is an individual subject). In the right hand panel we do the same for biases from "loss aversion lists" (A10 and A15 or M10 and M15). In MPL, for fourfold lists (left hand panel) we measure a lottery-mirror correlation of $\rho = 0.63$ ($p < 0.001$) and for loss aversion (right hand panel) we measure $\rho = 0.50$ ($p < 0.001$). In BDM, for fourfold lists (left hand panel) we measure a lottery-mirror correlation of $\rho = 0.58$ ($p < 0.001$) and for loss aversion (right hand panel) we

[13] The lotteries G50 and L50 produce deviations in opposite directions in lotteries and mirrors in our main sample and student sample, which is the biggest difference we find. Clearly this isn't a very robust pattern as it doesn't show up in losses, BDM or 4-Box framings of the problem. What's more, in our main sample the deviations are more severe in mirrors than lotteries.

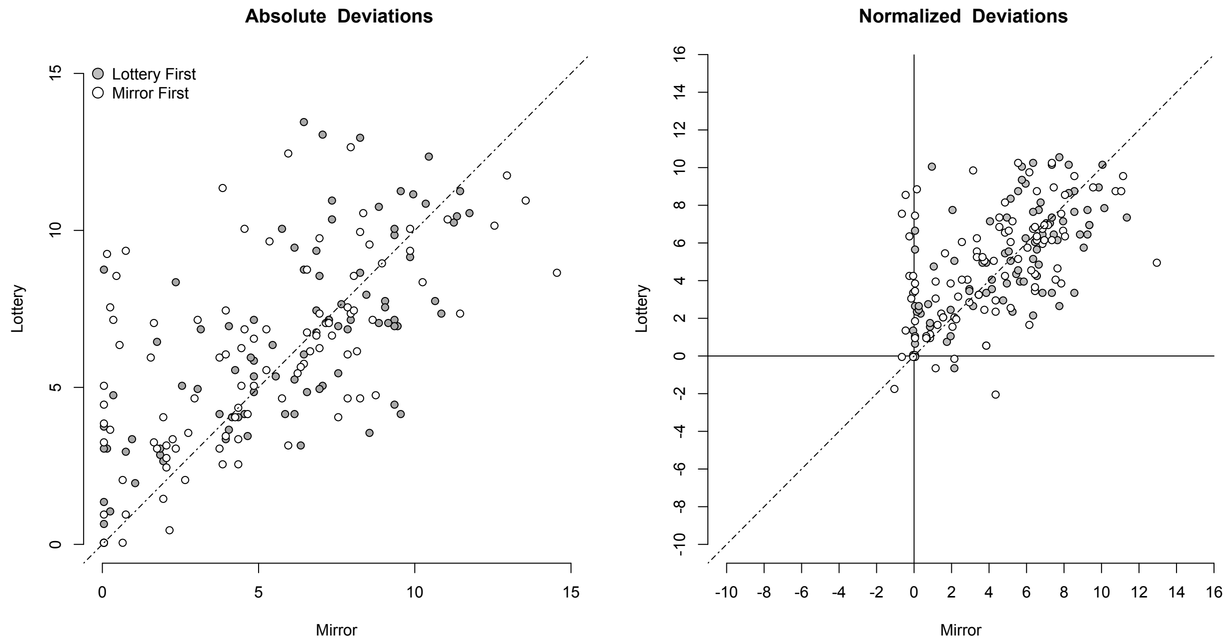


Figure 14: Deviations from expected value maximizing choices in mirrors (x-axis) versus lotteries (y-axis) in the original run of the main MPL treatment, by subject. *Notes: Each dot represents a separate subject. On the x-axes we plot the subject's data from the Mirror treatment and on the y-axes the same subject's data from the Lottery treatment. The left panel plots the mean absolute deviation from expected value. The right panel plots the mean deviation, normalized to be positive if it runs in the direction of the classical pattern. Gray dots are subjects who were assigned the Lottery treatment first, hollow dots subjects who were assigned the Mirror treatment first.*

measure $\rho = 0.616$ ($p < 0.001$).

A.8.2 Screenshots

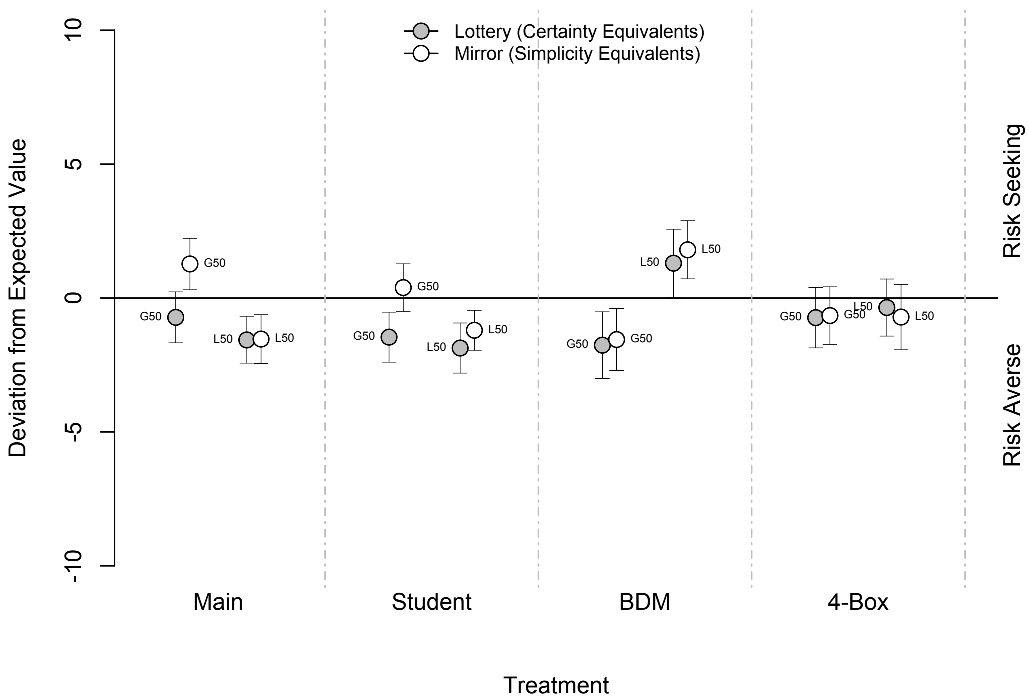


Figure 15: Mean deviations from expected value in 50/50 unmixed lotteries (gray dots) and mirrors (hollow dots). *Notes: The y-axis measures the difference between subjects' certainty/simplicity equivalent and expected value (as stated in the axis label). On the x-axis is experimental treatment.*

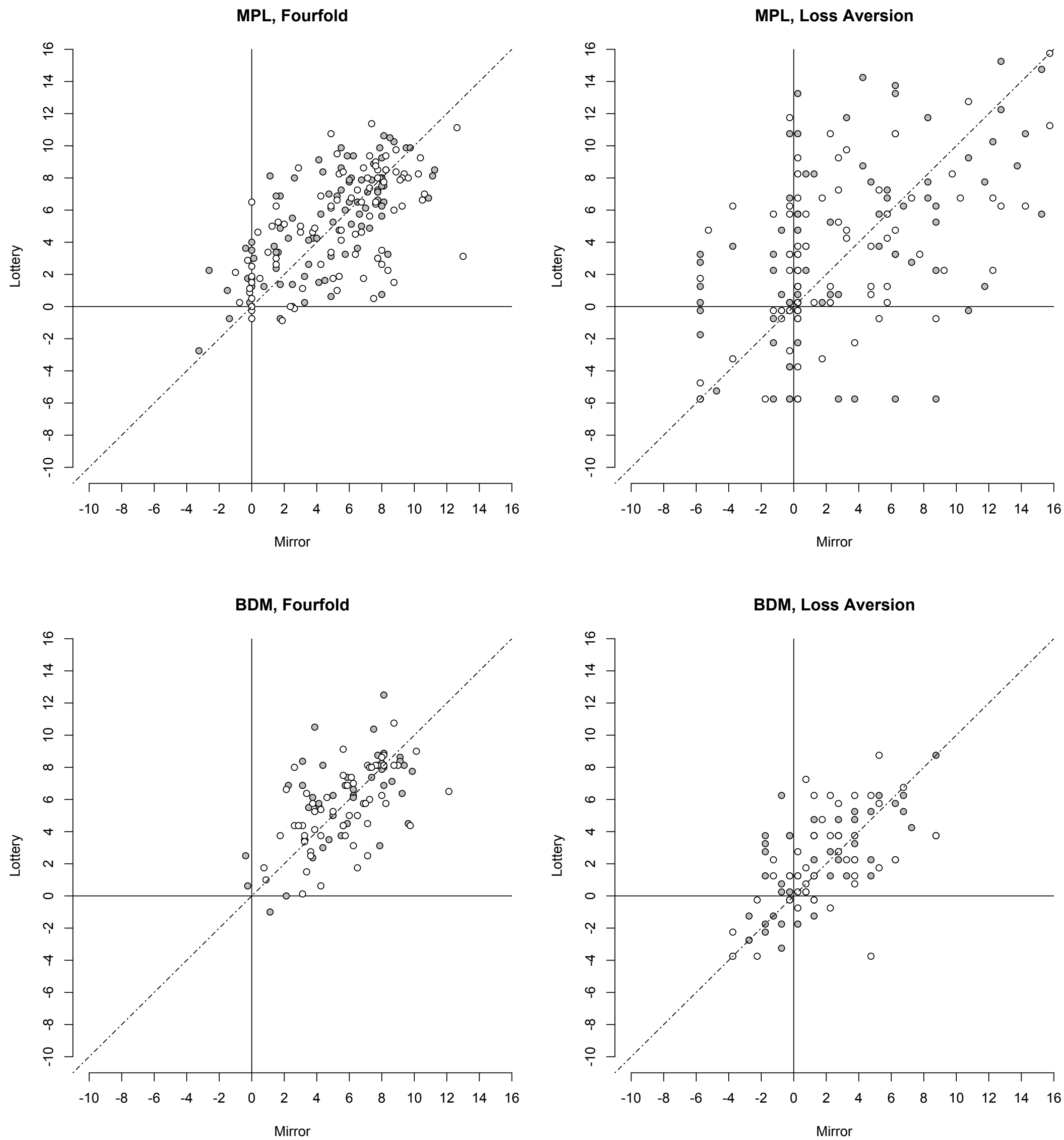


Figure 16: Deviations from expected value maximizing choices in mirrors (x-axis) versus lotteries (y-axis), by subject and pattern: the fourfold pattern (left panel) and loss aversion (right panel). *Notes: Each dot represents a subject. "Lottery First" designates subjects who were initially assigned lotteries (Mirror First is the reverse). The left panel plots mean "bias" (mean deviations normalized to be positive if they are in the direction of the classical pattern) for "fourfold lists" (G10, G25, G75, G90, L10, L25, L75, L90) while the right hand panel plots the same for "loss aversion lists" (A10 and A15 or M10 and M15).*

Initial Money: $5.00

- Please select which Set (A or B) you'd prefer for each row of the table (each **version** of the problem) and click the Submit button.
- If this task is selected for payment, the computer will **randomly** select one row (one version) and use your choice in this row to determine your earnings.
- You will be paid $5 **plus** the value of **all** of the boxes from the Set you selected, **added up** and divided by 100.

	Set A	Set B	
Version	100 Boxes	10 Boxes	90 Boxes
1	$25.00	$25.00	$0.00
2	$24.00	$25.00	$0.00
3	$23.00	$25.00	$0.00
4	$22.00	$25.00	$0.00
5	$21.00	$25.00	$0.00
6	$20.00	$25.00	$0.00
7	$19.00	$25.00	$0.00
8	$18.00	$25.00	$0.00
9	$17.00	$25.00	$0.00
10	$16.00	$25.00	$0.00
11	$15.00	$25.00	$0.00
12	$14.00	$25.00	$0.00
13	$13.00	$25.00	$0.00
14	$12.00	$25.00	$0.00
15	$11.00	$25.00	$0.00
16	$10.00	$25.00	$0.00
17	$9.00	$25.00	$0.00
18	$8.00	$25.00	$0.00
19	$7.00	$25.00	$0.00
20	$6.00	$25.00	$0.00

Figure 17: Screenshot from a mirror task (list G10) under MPL. *Notes: In lottery tasks, the screen is identical except for the text in green which instead reads "...plus the value of one of the boxes from the Set you selected, randomly chosen by the computer."*

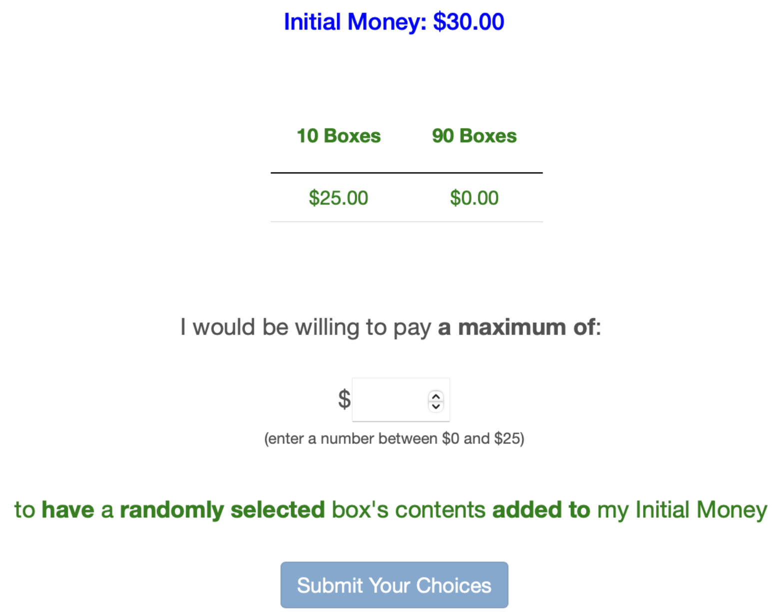


Figure 18: Screenshot from a lottery task (task G10) under BDM. *Notes: In mirror tasks, the screen is identical except for the text at the bottom which instead reads "...to have the average of these boxes' contents added to my Initial money.'*

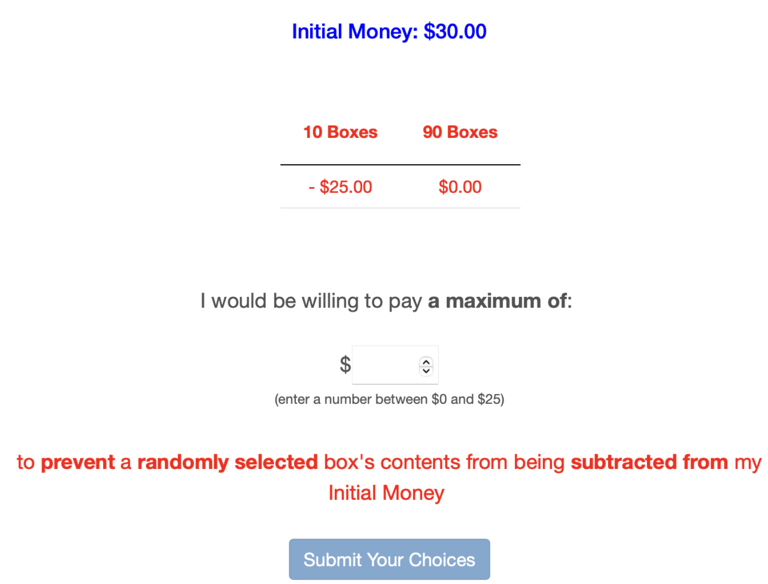


Figure 19: Screenshot from a lottery task (task L10) under BDM. *Notes: In mirror tasks, the screen is identical except for the text in green which instead reads "...to prevent the average of these boxes' contents from being subtracted from my Initial Money."*

B Instructions to Subjects

B.1 MPL Treatment

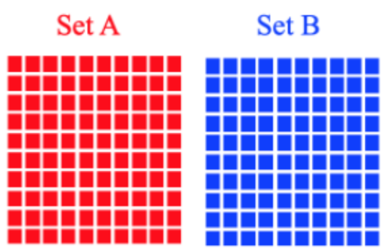
B.1.1 Beginning of Instructions

The first part of the instructions are given at the beginning of the session, regardless of whether subjects are assigned ,mirrors or lotteries first.

Boxes With Money

- In each of several tasks, we will give you an **INITIAL** sum of money.

- You will then choose which **set of BOXES** -- Set A (consisting of 100 boxes) or Set B (also consisting of 100 boxes) -- you would like the computer to open.



- Each box contains either a **POSITIVE** or **NEGATIVE** amount of money (or nothing). When the computer opens one or more boxes from your chosen set, the amount of money in the opened boxes will be added to (or subtracted from) your **INITIAL** money to determine your **FINAL EARNINGS**.

The Decision Table

- The two sets of boxes will be described in a **TABLE** like the one below. For each set, one or more counts of boxes (for instance 75, 25 or 100 boxes) are listed at the top, and the positive or negative amount of money in that number of boxes (for instance $20, $0, $7) is shown in the row of the Table.

Set A		Set B
75 Boxes	25 Boxes	100 Boxes
$20.00	$0.00	$7.00

- In the example above, Set A consists of **75** boxes each containing $20 and **25** boxes each containing $0. Set B consists of **100** boxes ALL of which contain $7.

- In the example below, Set A consists of **25** boxes with -$12 (negative $12) in each box and **75** boxes with $0 in each box. Set B consists of **100** boxes ALL of which contain -$3 (negative $3).

Set A		Set B
25 Boxes	75 Boxes	100 Boxes
- $12.00	$0.00	- $3.00

- Your job will be to click on the Table to decide which set of boxes (A or B) you would like the computer to pay you based on. Clicking on the Table will turn one of the sets yellow. Whichever set is highlighted in yellow will be selected by the computer to determine your **FINAL EARNINGS**.

Set A		Set B
75 Boxes	25 Boxes	100 Boxes
$20.00	$0.00	$7.00

- In the example above you have highlighted Set B and so will be paid based on that set.

B.1.2 Treatment Instructions

Next, one of the following two pages of instructions is given, depending on whether subjects are assigned mirrors or lotteries first. After subjects have completed making choices in the first treatment (Mirror or Lottery), they are given the *other* page from the Treatment Instructions, below.

A Random Box

- In the upcoming set of Tasks, the computer will **RANDOMLY** select one of the 100 boxes from whichever Set you've chosen (each box in the Set you chose is **EQUALLY** likely to be selected by the computer). If the amount in the box is positive, it will be **ADDED** to your initial money. If the amount is negative, it will be **SUBTRACTED** from your initial money.

- Example: In the example below, there are **100** boxes in each Set. For Set A, **50** boxes contain $16.00 and **50** of them contain $0.00. If you choose Set 1, there is therefore **50% chance** $16 will be added to your initial amount of money and a **50% chance** $0 will be added. For Set B all **100** boxes contain $4.00 so if you choose this Set, you have a **100% chance** of having $4 added to your initial money.

Set A		Set B
50 Boxes	50 Boxes	100 Boxes
$16.00	$0.00	$4.00

- Example: In the example below, there are also **100** boxes in each Set. For Set A, **50** boxes contain -$8.00 and **50** of them contain $0.00. If you choose Set 1, there is therefore a **50% chance** you will have $8 subtracted from your initial amount of money (you lose $8) and a **50% chance** you have $0 subtracted. For Set B all **100** boxes contain -$6.00 so if you choose this Set, you have a **100% chance** you will have $6 substracted from your initial money.

Set A		Set B
50 Boxes	50 Boxes	100 Boxes
- $8.00	$0.00	- $6.00

The Average Box

- In the upcoming tasks, the computer will pay you by calculating the **AVERAGE** amount of money across all 100 boxes for **whichever set you've chosen**. That is, it will add up the amount of money from each of the 100 boxes and divide that sum by 100. If the amount is positive, that amount will be **ADDED** to your initial money. If the amount is negative, it will be **SUBTRACTED** from your initial money.

- Example: In the example below, there are **100** boxes in each set. For Set A, **50** boxes contain $16.00 and **50** of them contain $0.00. If you choose Set A, the computer will therefore add (50×$16 + 50×$0)/100 = $8 to your initial amount of money. For Set B, all **100** boxes contain $4.00 so if you choose this set, you will add (100×$4)/100 = $4 to your initial money.

Set A		Set B
50 Boxes	**50 Boxes**	**100 Boxes**
$16.00	$0.00	$4.00

- Example: In the example below, there are also **100** boxes in each Set. For Set A, **50** boxes contain -$8.00 and **50** of them contain $0.00. If you choose Set A, the computer will pay you (-$8×50 + $0×50)/100 = -$4 for your choice; it will therefore subtract $4 from your initial amount of money (that is, you will lose $4). For Set B all **100** boxes contain -$6.00 so if you choose this set, the computer will pay you (-$6×100)/100 = -$6 for your choice. That is, you will have $6 subtracted from your initial money.

Set A		Set B
50 Boxes	**50 Boxes**	**100 Boxes**
- $8.00	$0.00	- $6.00

B.2 Comprehension Questions

Regardless of treatment, subjects are given 4 comprehension questions like the following which they must answer correctly before moving on. Crucially, although the questions are identical regardless of treatment, the correct answers to these questions depend on whether subjects are about to enter the Mirror or Lottery treatment. After subjects have completed the first treatment (Mirror or Lottery) and have read instructions for the next treatment, they are given the *same* 4 comprehension questions, now with different correct answers. This makes the difference between the payment schemes especially salient to subjects and is designed to prevent subjects from confusing payoffs in the two treatments.

Comprehension Questions

Set A		Set B
50 Boxes	50 Boxes	100 Boxes
$16.00	$0.00	$4.00

Suppose that the choice in the example above determines your payment, and you chose Set A.

- *What is the chance that $16 is added to your earnings?*

  ○ 0 in 100 (0%)
  ○ 50 in 100 (50%)
  ○ 100 in 100 (100%)

  Submit Quiz

- *What is the chance that $8 is added to your earnings?*

  ○ 0 in 100 (0%)
  ○ 50 in 100 (50%)
  ○ 100 in 100 (100%)

  Submit Quiz

- *What is the chance that $4 is added to your earnings?*

  ○ 0 in 100 (0%)
  ○ 50 in 100 (50%)
  ○ 100 in 100 (100%)

  Submit Quiz

B.2.1 Final Part of Instructions

Choosing A Set of Boxes

- In the actual experiment, we will have you choose between between **MULTIPLE VERSIONS** of Set A and Set B. Each version will be shown as a **DIFFERENT ROW** of of the Table.

- Example: In the first row (**Version 1**) in the example below, Set A has **100** boxes containing $10 while Set B has **40** boxes containing $10 and 60 boxes containing $0. However in the second row (**Version 2**) is a different version in which Set A has **100** boxes containing $9, while Set B has **40** boxes containing $10 and **60** boxes containing $0. The other rows have other versions of Set A / Set B.

	Set A	Set B	
Version	100 Boxes	40 Boxes	60 Boxes
1	$10.00	$10.00	$0.00
2	$9.00	$10.00	$0.00
3	$8.00	$10.00	$0.00
4	$7.00	$10.00	$0.00
5	$6.00	$10.00	$0.00
6	$5.00	$10.00	$0.00
7	$4.00	$10.00	$0.00
8	$3.00	$10.00	$0.00
9	$2.00	$10.00	$0.00
10	$1.00	$10.00	$0.00

- You will make a choice for **EACH VERSION** of Set A / Set B by clicking on the Table and highlighting either Set A or Set B in each row of the Table.

	Set A	Set B	
Version	100 Boxes	40 Boxes	60 Boxes
1	$10.00	$10.00	$0.00
2	$9.00	$10.00	$0.00
3	$8.00	$10.00	$0.00
4	$7.00	$10.00	$0.00
5	$6.00	$10.00	$0.00
6	$5.00	$10.00	$0.00
7	$4.00	$10.00	$0.00
8	$3.00	$10.00	$0.00
9	$2.00	$10.00	$0.00
10	$1.00	$10.00	$0.00

- Example: In the example above, you selected Set A in Version 1, 2, 3, 4, 5, 6 and 7, and selected Set B in Version 8, 9 and 10.
- At the end of the experiment, the computer will randomly pick **ONE ROW** of the Table (one Version, with each row/version equally likely) and pay you based on your choice in that row. This means you should carefully consider your choice in **EACH ROW (EACH VERSION)** as any row/version could determine your payment.
- When you make your choices in the Table, the computer will put some limits on your choices. Specifically, you can only switch from choosing Set A to Set B at one point on the Table (though you are also welcome to choose Set A or only Set B in every row). You may click on the Table as many times as you like until you are happy with your choices. Then press the green button to finalize your choices.

Several Tables

- Over the course of the experiment, we will show you several Tables. Each Table has a different **initial amount of money** and **different Versions** displayed in rows. You must make a choice for each Version in every Table. At the end of the experiment the computer will **RANDOMLY** select **ONE** Table and then **RANDOMLY** select **ONE** Version (row) from that Table and determine your payment based on your choice in that Version.

  Since you do not know which choice will be selected, you should make each choice as if it alone determines your payment.

B.3 BDM Treatment

B.3.1 Beginning of Instructions

The first part of the instructions are given at the beginning of the session, regardless of whether subjects are assigned mirrors or lotteries first.

Boxes With Money

- In each of several tasks, we will give you an **INITIAL** sum of money.
- You will then evaluate a **set of 100 BOXES** which the computer may open to either increase or decrease this initial sum.

- Each box contains either a **POSITIVE** or **NEGATIVE** amount of money (or nothing). When the computer opens one or more boxes from a set, the amount of money in the opened boxes will be added to (or subtracted from) your **INITIAL** money to determine your **BONUS** (if you are randomly selected to be paid a bonus).

The Decision Table

- Each set of boxes will be described in a **TABLE** like the one below. For each set, one or more counts of boxes (for instance 75, 25 or 100 boxes) are listed at the top, and the positive or negative amount of money in that number of boxes (for instance $20, $0, $7) is shown in the row of the Table.

75 Boxes	25 Boxes
$20.00	$0.00

- In the example above, the set consists of **75** boxes each containing $20 and **25** boxes each containing $0.

- In the example below, the set consists of **25** boxes with -$12 (negative $12) in each box and **75** boxes with $0 in each box.

25 Boxes	75 Boxes
- $12.00	$0.00

- Depending on the task, your job will be to decide how much you'd be willing to pay to either **cause** the computer to open boxes from the set to modify your **BONUS** or **prevent** the computer from opening the boxes to modify your bonus.

B.3.2 Treatment Instructions

Next, one of the following two pages of instructions is given, depending on whether subjects are assigned mirrors or lotteries first. After subjects have completed making choices the first treatment (Mirror or Lottery), they are given the *other* page from the Treatment Instructions, below.

A Random Box

- In the upcoming tasks, if the computer opens boxes, it will pay you by **RANDOMLY** selecting one of the 100 boxes (each box in the set is **EQUALLY** likely to be selected by the computer). If the amount in the box is positive, it will be **ADDED** to your initial money. If the amount is negative, it will be **SUBTRACTED** from your initial money.

- Example: In the example below, there are **100** boxes in the set. For this set, **50** boxes contain $16.00 and **50** of them contain $0.00. If the computer opens the boxes, there is therefore **50% chance** $16 will be added to your initial amount of money and a **50% chance** $0 will be added.

50 Boxes	50 Boxes
$16.00	$0.00

- Example: In the example below, there are also **100** boxes in the set. For this set, **50** boxes contain -$8.00 and **50** of them contain $0.00. If the computer opens the boxes, there is therefore a **50% chance** you will have $8 subtracted from your initial amount of money (you lose $8) and a **50% chance** you have $0 subtracted.

50 Boxes	50 Boxes
- $8.00	$0.00

The Average Box

- In the upcoming tasks, if the computer opens boxes, it will pay you by calculating the **AVERAGE** amount of money across all 100 boxes. That is, it will add up the amount of money from each of the 100 boxes and divide that sum by 100. If the amount is positive, that amount will be **ADDED** to your initial money. If the amount is negative, it will be **SUBTRACTED** from your initial money.

- Example: In the example below, there are **100** boxes in the set. For this set, **50** boxes contain $16.00 and **50** of them contain $0.00. If the computer opens these boxes, it will therefore add (50×$16 + 50×$0)/100 = $8 to your initial amount of money.

50 Boxes	50 Boxes
$16.00	$0.00

- Example: In the example below, there are also **100** boxes in the set. In this set, **50** boxes contain -$8.00 and **50** of them contain $0.00. If the computer opens these boxes, the computer will pay you (-$8×50 + $0×50)/100 = -$4 for your choice; it will therefore subtract $4 from your initial amount of money (that is, you will lose $4).

50 Boxes	50 Boxes
- $8.00	$0.00

B.4 Comprehension Questions

We next gave subjects the same comprehension questions used in the MPL treatment.

B.4.1 BDM Mechanism

Paying <u>for</u> a Set of Boxes

- In the experiment, we will ask you **the maximum amount you would be willing to pay** either to **cause** or **prevent** the computer from opening the set of boxes on your screen to modify your Initial earnings.

- In some tasks (colored in green) we will show you a set that contains positive amounts of money, and ask you to tell us how many dollars you would (**at the very maximum**) be willing to pay to **cause** the computer to open boxes from the set to increase your earnings. Or, in other words, we will ask you how much do you think it is worth to you to have these boxes influence your earnings?

- <u>Example</u>: On your screen, we will show you a text box like the one below. Just enter the amount of money you think the set is worth to you (the maximum amount you'd be willing to pay for the set to be opened - the screen will give you the range you can enter):

I would be willing to pay **a maximum of**:

$

(enter a number between $0 and $25)

- To **reward you** for giving an **honest answer**, we are going to use a special set of rules to determine your payments in these tasks. We will randomly pick a **price** (equally likely between 0 and the maximum value you are allowed to enter) for the set of boxes (you won't know the price when you make your choice). If the amount you entered is **greater than or equal to** that random price, the computer will open the set of boxes on the screen to modify your Initial earnings as described **and** you will pay the amount of the random price (**not** the amount you entered) from your total earnings. If your maximum amount is less than the random price, the computer will not open the boxes on your screen and you will simply earn your initial amount (and you will not pay the random price).

- <u>Important</u>: If the computer uses boxes from the set to modify your earnings, you will not have to pay the maximum amount you enter, but instead will pay the random price. The maximum amount you enter just lets you tell us the range of random prices you are willing to pay for the set of boxes.

- If this sounds confusing, it is **actually very simple**. We've designed the payments so it is in your best interest to **tell us honestly** the most you would be willing to pay to have the set of boxes opened to influence your bonus. So just think about how much at a maximum you'd be willing to give up to have the computer modify your bonus based on the set of boxes on your screen, and enter this amount truthfully.

Paying to <u>Avoid</u> a Set of Boxes

- In other tasks (colored in red) we will show you a set that contains negative amounts of money, and ask you to tell us how many dollars you would (**at the very maximum**) be willing to pay to **prevent** the computer from opening boxes from the set to decrease your earnings. Or, in other words, we will ask you how much do you think it is worth to you to prevent these boxes from influencing your earnings?

- <u>Example</u>: On your screen, we will, again, show you a text box like the one below. Just enter the amount of money you think it is worth to <u>prevent</u> the computer from using that set to modify your bonus (the maximum amount you'd be willing to pay to prevent it - the screen will give you the range you can enter):

I would be willing to pay **a maximum of**:

$

(enter a number between $0 and $25)

- To **reward you** for giving an **honest answer**, we are, again, going to use a special set of rules to determine your payments in these tasks. We will randomly pick a **price** (equally likely between 0 and the maximum value you are allowed to enter) required to **prevent** the set of boxes from influencing your earnings (you won't know the price when you make your choice). If the amount you entered is **greater than or equal to** that random price, the computer will **not open** the set of boxes on the screen to modify your Initial earnings as described **and** you will pay the amount of the random price (**not** the amount you entered) from your total earnings. If your maximum amount is less than the random price, the computer **will** open the set of boxes on your screen to modify your initial earnings (but you will not pay the random price).

- <u>Important</u>: If you prevent the computer from opening boxes from the set, you will not have to pay the maximum amount you enter, but instead will pay the random price. The maximum amount you enter just lets you tell us the range of random prices you are willing to pay to avoid the set of boxes.

- If this sounds confusing, it is **actually very simple**. We've designed the payments so it is in your best interest to **tell us honestly** the most you would be willing to pay to prevent the set of boxes from being opened to influence your bonus. So just think about how much at a maximum you'd be willing to give up to prevent the computer from modifying your bonus based on the set of boxes on your screen, and enter this amount truthfully.

B.4.2 Final Part of Instructions

Several Sets of Boxes

- Over the course of the experiment, we will show you several sets of boxes. Each may have a different **initial amount of money** and **different** amounts of money distributed across the boxes.

- Important:. Make sure you pay attention to the type of question we are asking in each task. In some tasks colored in green we are asking you to tell us how much you'd be willing to pay to **cause** the boxes to influence your earnings. In other tasks negative we are asking you to tell us how much you'd be willing to pay to **prevent** the boxes from influencing your earnings.

- **One out of five (1/5 of)** participants will be randomly selected by the computer to be paid a **BONUS** based on their choices. If you are one of these participants, at the end of the experiment the computer will **RANDOMLY** select **ONE** Task and then **RANDOMLY** select a **PRICE** to determine your payment based on how much you said you're willing to pay.

  Since you do not know which choice will be selected, you should make each choice as if it alone determines your payment.