Looming Large or Seeming Small? Attitudes Towards Losses in a Representative Sample*

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Abstract

We measure individual-level loss aversion using three incentivized, representative surveys of the U.S. population (combined $N = 3{,}000$). We find that around 50% of the U.S. population is *loss tolerant*—they are willing to accept negative-expected-value gambles that contain a loss. This is counter to expert predictions and earlier findings—which mostly come from lab/student samples—that 70–90% of participants are loss averse. Consistent with the different findings in our study versus the prior literature, loss aversion is more prevalent in people with high cognitive ability. Further, our measure of gain-loss attitudes exhibits similar temporal stability and better predictive power outside our survey than measures of risk aversion. Loss-tolerant individuals are more likely to report recent gambling, investing a higher percentage of their assets in stocks, and experiencing financial shocks. These results support the general hypothesis that individuals value gains and losses differently, and that gain-loss attitudes are an important economic preference. However, the tendency in a large proportion of the population to emphasize gains over losses is an overlooked behavioral phenomenon.

JEL Classifications: C81, C9, D03, D81, D9

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1 Introduction

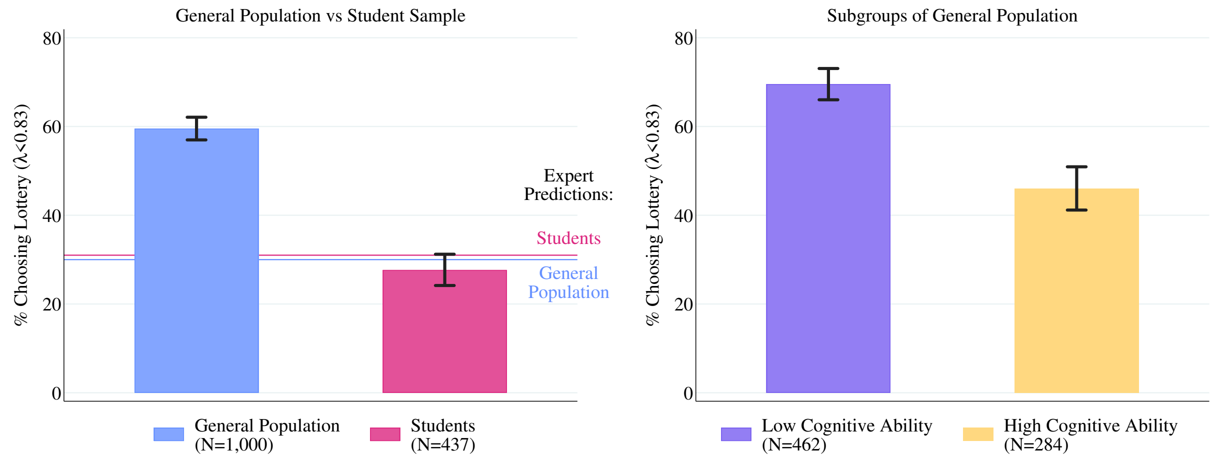
A central hypothesis in behavioral economics is that people treat losses and gains differently, resulting in most being *loss averse*: even if they are risk neutral, they tend to shy away from positive expected value gambles with negative payoffs (losses). Loss aversion is used as an explanation for a number of important economic phenomena, and is an essential ingredient in models of reference-dependent preferences (Kahneman and Tversky, 1979; Kőszegi and Rabin, 2006; O'Donoghue and Sprenger, 2018).[1] Yet, most evidence of loss aversion comes from economics and psychology labs, usually with university student participants. These participants often have different preferences than the general population (Walasek et al., 2018; Snowberg and Yariv, 2021).

We find that around 50% of people in the U.S. are *loss tolerant*—even if they are risk neutral, they embrace gambles with negative expected values—and around 50% are loss averse. We elicit individual estimates of gain-loss attitudes in three representative, incentivized surveys of the U.S. population (combined N = 3,000), using Dynamically Optimized Sequential Experimentation (DOSE; Chapman et al., 2010, 2018). We implement the same procedure in two samples of undergraduate students, and find similar levels of loss tolerance as in previous laboratory experiments. Consistent with this finding, loss aversion is more common in people with high cognitive ability within our representative samples. Loss aversion is also correlated with behavior outside of the survey environment: loss-tolerant individuals have more of their assets invested in stocks, are more likely to have recently gambled, are more likely to have experienced a recent financial shock, and have fewer financial assets. However, our elicitations of risk aversion are generally not correlated with these real-world behaviors. Together, this suggests that loss aversion captures an independent, and substantively important, part of risk attitudes.

Although surprising, the prevalence of loss tolerance is further evidence for Kahneman and Tversky's (1979) hypothesis that people treat gains and losses differently. In particular, it is evidence of substantial heterogeneity in the asymmetry, with potentially important consequences for consumer welfare and reference-dependent theories (Goette et al., 2019; Barberis et al., 2021). Loss aversion can, in theory, reduce the propensity to use financial products that exploit common characteristics like overoptimism and skew-love (Kahneman and Lovallo,

[1] Examples of phenomena that have been explained through loss aversion include the equity premium puzzle (Mehra and Prescott, 1985; Benartzi and Thaler, 1995), asymmetric consumer price elasticities (Hardie et al., 1993), reference-dependent labor supply (Dunn, 1996; Camerer et al., 1997; Goette et al., 2004; Fehr and Goette, 2007), tax avoidance (Rees-Jones, 2017), opposition to free trade (Tovar, 2009), performance in athletic contests (Pope and Simonsohn, 2011; Allen et al., 2016), and more.

Figure 1: Contrary to expert predictions, more than half of respondents accept a simple lottery with negative expected value.



Notes: The left-hand panel displays the proportion of participants in the general population sample and in the undergraduate student sample choosing a lottery with a 50% probability of gaining \$10 and a 50% probability of losing \$12, over a sure amount of \$0. The right-hand panel shows results for those in the bottom and top terciles of cognitive ability within the general population sample. Error bars represent 90% confidence intervals. See Section 2.3 for further details.

1993; Åstebro et al., 2015). Loss tolerance, on the other hand, makes it easier to exploit such characteristics. Moreover, our evidence suggests that loss tolerance is particularly prevalent in those who tend to gamble, and among groups that might benefit from more resistance to using problematic financial products: those with low income, education, and cognitive ability (Kornotis and Kumar, 2010; Chang, 2016).

1.1 Widespread Loss Tolerance

Our main result can be observed in choices over a simple 50:50 lottery with a negative expected value, as shown in Figure 1. All participants face a choice between a sure amount of \$0 and a lottery over a gain of \$10 and a loss of \$12, each with 50% probability.[2] As shown in the left-hand panel, 60% of those in the representative sample ($N = 1{,}000$) choose the lottery, demonstrating a significant degree of loss tolerance (under the common assumption of local risk neutrality)—and countering Kahneman and Tversky's (1979) assertion that "most people find symmetric bets of the form $(x, .50; -x, .50)$ distinctly unattractive" (p. 279). The proportion choosing the lottery is, however, much lower among a sample of University of Pittsburgh undergraduates ($N = 437$) completing a very similar incentivized online survey—only 28% of students choose the lottery. Consistent with this finding, in the right-hand panel of Figure 1, we see that those

[2] We thank Matthew Rabin for suggesting this simple test of loss tolerance.

in the representative sample with low cognitive ability were more likely to choose the lottery.

The proportion of loss-tolerant participants in our data is much higher than anticipated by economists completing a prediction survey (DellaVigna et al., 2019). The expert respondents ($N = 87$) accurately predicted the proportion of students that would accept the lottery (an average prediction of 31% versus the actual 28%), but severely underestimated the proportion in the representative sample (30% vs 60%).[3] Notably, it appears that respondents overestimated the similarity between undergraduates and the general population, making very similar guesses for the two samples. Further, only 10% of the expert respondents reported that they would accept the same lottery themselves, consistent with academics being unrepresentative of the extent of loss tolerance across the population.

The patterns in Figure 1 do not reflect a high willingness to gamble in general, due to, for instance, "house money effects" (Thaler and Johnson, 1990). Most participants demonstrated significant risk aversion when no potential loss was involved—for instance, only 39% of the representative sample preferred a lottery with a 50% chance of \$15 and 50% chance of \$0 to a sure amount of \$5.90. This proportion is lower than predicted in the expert survey (average prediction = 56%) and—in contrast to Figure 1—lower than the proportion of students (49%) accepting the same lottery. Thus, our data suggest that the general population is more loss tolerant but—consistent with previous studies (see, for example, Snowberg and Yariv, 2021)—more risk averse than undergraduate students.[4]

1.2 Further Investigation of Heterogeneity in Gain-Loss Attitudes

We confirm and extend the above findings using DOSE to elicit accurate individual-level estimates of loss aversion. A single choice, such as the one used in Figure 1, cannot distinguish between loss aversion—a change in behavior near the reference point (of \$0)—from utility curvature (risk aversion). Disentangling these preferences generally requires a parametric model and multiple questions—causing standard elicitation methodologies to yield, at best, imprecise estimates due to measurement error and/or inconsistent choice. Moreover, standard designs offer a fixed set of questions to all participants, thus likely underestimating heterogeneity in gain-loss attitudes. DOSE designs around these challenges using a parametric model and Bayesian updating to dynamically select a personalized sequence of simple binary choices. Our Bayesian

[3] The survey was completed November 17–30, 2020. Recruitment was carried out via social media, research networks, and https://socialscienceprediction.org/predict/.

[4] Within the subsample of our representative sample that is most like students—those under 35 with a college education ($N = 138$)—the proportion loss tolerant (31%) is similar to within our student samples.

prior assumes considerable loss aversion, and the adaptive design robustly identifies loss tolerance by offering participants several negative-expected-value gambles. We thus use DOSE to verify the findings in Figure 1, and then to investigate the usefulness of gain-loss attitudes—as captured by predictive power outside of our survey—and their stability over time.

Our DOSE-elicited measure of loss aversion also indicates a much higher level of loss tolerance in representative samples of the U.S. population than among students. We compare our main sample (N = 1,000)—with two DOSE elicitations—and a supplementary sample (N = 2,000)—studied twice, six months apart—to two student samples (N = 437 and 369) recruited from the University of Pittsburgh Experimental Laboratory that participated in extremely similar online studies. In our three representative samples, the proportion of loss-tolerant participants is 57%, 47%, and 55%; in the corresponding student samples and elicitations, the proportions are 32%, 22%, and 16%. As a further comparison, across eleven studies that report individual-level heterogeneity in gain-loss attitudes, the average proportion loss tolerant is 33%.[5] The similarity between our student samples and these previous studies—largely carried out in the laboratory using a number of different methodologies—offers further evidence that the degree of loss tolerance we observe is not an artefact of our approach.

Our study suggests that individual gain-loss attitudes are an important economic preference, with high predictive power for self-reported economic behaviors and financial outcomes. The individual loss aversion parameters elicited by DOSE are as stable over time as DOSE-elicited measures of risk aversion and discounting, and more stable than traditional measures of risk aversion (Chapman et al., 2023b, 2024). Moreover, our experimental measure of loss aversion demonstrates "predictive validity" (Mata et al., 2018): loss-tolerant participants report a higher percentage of assets in the stock market, more recent exposure to financial shocks, and lower total financial assets. Loss tolerance is also associated with a propensity to engage in both casual (lottos and scratch cards) and serious (casinos or online) gambling. These correlations are striking given that behavioral measures of risk aversion generally have little predictive power for real-world outcomes, either in our survey or in the general literature (see Friedman et al. 2014 and Charness et al. 2020 for reviews).

Our results are robust to a number of factors, including possible misspecification and removing participants least likely to be paying attention. Eliciting loss aversion using traditional (multiple price list) methods produces similar estimates of loss tolerance, and identifies similar differences between the representative and student samples. Allowing for different specifications

[5] Delavande et al. (2023), in a study of uncertainty attitudes released after our initial working paper, report that 43% of participants in a representative sample are loss tolerant.

of the utility function, or alternative reference point models, still results in much lower estimates of loss aversion and much higher estimates of loss tolerance than prior studies on student/lab populations. A model accounting for participants' limited liability within the study—a potential cause of house money effects—fits the choice data very poorly. Moreover, we show our findings are not driven by inattention, nor by our parametric specification; they simply reflect a consistent pattern of many participants accepting negative-expected-value lotteries.

The paper concludes with a discussion of how our findings affect the broader endeavor to understand gain-loss attitudes. Importantly, our results do not represent a challenge to the key insights of prospect theory. Our findings instead raise the question of why loss tolerance has received little attention in the previous literature. The most straightforward explanation, given our results, is the focus in prior studies on lab/student samples. However, methodological limitations or publication bias may also provide part of the answer (Walasek et al., 2018; Yechiam, 2019). Whatever the reason, our findings suggest that loss tolerance, in addition to loss aversion, is an important behavioral regularity warranting deeper investigation. Indeed, the correlations we find between loss tolerance and problematic behaviors suggest that loss tolerance may be particularly harmful.

1.3 Related Literature

This paper expands on and supersedes an earlier working paper that found similar population-wide estimates of loss tolerance (Chapman et al., 2018). The current study elicits a wider range of loss aversion measures from two new samples, and adds a number of new robustness tests to address concerns raised by various readers and seminar participants.

Our findings differ from the majority of prior studies, which tend to find significant loss aversion. The loss aversion parameter in Prospect Theory, λ, indicates loss aversion when $\lambda > 1$, and loss tolerance when $\lambda < 1$ (Kahneman and Tversky, 1979). A recent meta-analysis reports mean $\lambda = 1.96$ across more than 150 studies in both the lab and the field (Brown et al., forthcoming)—including an earlier general population study which reported median $\lambda = 2.38$ (von Gaudecker et al., 2011).[6] The high estimates of loss aversion in these earlier studies may, at least in part, be explained by their elicitation methods. A series of studies in social psychology have shown that loss aversion can be inflated by elicitations that offer participants choices which are asymmetric in the range of possible gains and losses, or that conflate loss aversion

[6]von Gaudecker et al. (2011) estimate a distribution of loss aversion for the population, rather than at the individual level, and report a median λ that ranges from 0.12 to 4.47 depending on parametric assumptions. Similarly, in a study released after our initial working paper, Blake et al. (2021) estimate a population-level loss aversion parameter in the U.K., and report a preferred estimate of 1.21–2.41.

with the endowment effect or status quo bias (see Ert and Erev, 2013; Zeif and Yechiam, 2022). von Gaudecker et al. (2011) for instance, offered participants 56 lotteries, but none involved a negative-expected-value gamble—which is necessary to identify significant loss tolerance when assuming a reference point of zero.[7]

Our investigation of the correlates of loss aversion extends the recent literature studying the relationship between cognitive ability and economic decision-making. Previous studies have generally concluded that higher cognitive ability is associated with greater normative rationality, based primarily on investigating either patience or risk aversion (for example, Frederick, 2005; Dohmen et al., 2010; Benjamin et al., 2013).[8] Consistent with most earlier work, we find that higher cognitive ability individuals are less risk averse over lotteries involving only potential gains (see Dohmen et al., 2018, for a detailed review of the literature). However, when confronted with potential losses, both low- and high-cognitive-ability people tend to depart from normative rationality, but in different ways—with low-cognitive-ability people being more loss tolerant, and high-cognitive-ability people being more loss averse.

We also contribute to three broader literatures. In finance, there is a large literature that applies prospect theory to financial market decisions. Similar to us, Dimmock and Kouwenberg (2010) find that loss-averse households invest less in the stock market, consistent with several theoretical studies suggesting that loss aversion may reduce household investment in equities (see Barberis et al., 2021, and citations therein). Our findings also contribute to the study of gambling by showing that loss tolerance may contribute to individuals' willingness to gamble, adding an additional explanation to a literature that has focused on probability misperceptions (Snowberg and Wolfers, 2010), skewness of the utility function (Golec and Tamarkin, 1998), or non-expected utility models (Chark et al., 2020). Finally, our paper contributes to the literature examining the (generally poor) external validity of lab-based measures of economic preferences.

2 Measuring Loss Aversion

This section introduces the data and methods we use to measure loss aversion and other behaviors. Our primary measures use DOSE, and we also implement two traditional multiple price

[7]Another example is the commonly-used elicitation introduced by Fehr and Goette (2007), in which participants are offered the choice between a safe status quo option and a series of hypothetical lotteries—in which the only option demonstrating loss tolerance is the worst in the available set of options.

[8]Few studies have investigated the relationship between measures of cognitive skill and loss aversion: Stango and Zinman (2023) report a positive relationship in a large sample in the U.S., while Andersson et al. (2016) find no evidence of any relationship in a large sample in Denmark. Consistent with our results, van Dolder and Vandenbroucke (2022) find a positive correlation between education and an individual-level measure of loss aversion in a sample of financial professionals and investors.

list elicitations, as described in Section 2.2. Section 2.3 introduces our data, which are drawn from two representative samples and two student samples.

2.1 Theoretical Definition

In line with most empirical studies of loss aversion, we estimate the parameters of a prospect theory utility function (Tversky and Kahneman, 1992) with power utility. In this specification, participants value payments relative to a reference point, which we assume is zero, in line with the previous experimental literature (Brown et al., forthcoming, Table 3). Loss aversion is conceptualized as distinct from utility curvature, reflecting a kink in the utility function at zero. The standard S-shaped utility function in prospect theory implies that, for common parameter values, participants are risk averse over positive payments (gains), and risk loving over negative payments (losses). Formally:

$$v(x, \rho_i, \lambda_i) = \begin{cases} x^{\rho_i} & \text{for } x \geq 0 \\ -\lambda_i(-x)^{\rho_i} & \text{for } x < 0, \end{cases} \tag{1}$$

in which λ_i parameterizes loss aversion, ρ_i risk aversion, and $x \in \mathbb{R}$ is a monetary outcome relative to the reference point. If $\lambda_i > 1$, which is generally assumed, then the participant is loss averse. If $\lambda_i < 1$, then the participant is loss tolerant. Our main estimates impose the same utility curvature in both the gain and loss domain, so that λ captures all differences in valuation of gains and losses. To make tables and figures easier to interpret, we use the *coefficient of relative risk aversion*, $1 - \rho_i$, so that higher numbers indicate greater risk aversion.

To estimate individual-level risk and loss aversion we use DOSE, which is designed to tackle the issues associated with estimating multiple preference parameters simultaneously. In the case of loss aversion, multiple question types are needed: choices over lotteries over gains and losses separately (risk aversion) and *mixed lotteries*—those including both gains and losses. Inconsistent choice across different question types may even prevent the estimation of parameters, if, for example, some responses violate first-order stochastic dominance.[9] Such issues have led many previous studies, including those in representative samples, to estimate population-level statistics rather than elicit individual-level loss aversion parameters. DOSE overcomes these issues by adapting the question sequences individuals receive to rapidly home in on their

[9]For example, two studies in the Netherlands (Booij and Van de Kuilen, 2009; Booij et al., 2010) attempted to estimate loss aversion in a representative sample, but were only able to obtain estimates for less than 30% of their participants due to dominated choices.

preferences, while accounting for inconsistent choices. As a result, in simulations, the method measures parameters more accurately than more established elicitation methods, particularly for participants that are likely to make mistakes (Chapman et al., 2018). Moreover, DOSE produces a large quantity of choice data that we use to investigate loss aversion without parametric assumptions or with alternative parametric forms (see Section 5.2 and Appendix C.1).

2.2 Measurement

Our implementations of DOSE ask participants a personalized sequence of simple questions, such as those displayed in Figure 2. The participant is given a simple explanation of the upcoming choices, as in Figure 2a. He or she is then given a series of binary choices between a lottery and a sure amount, similar to those in Figure 2b. The sure amounts, and the prizes in the lotteries, are selected to maximize the informativeness of the choice for the parameters of interest, λ and ρ, given a flat prior over those parameters and the participant's previous choices. The support of the prior distribution covers individual estimates obtained in lab data: $\lambda \in [0.1, 4.5]$ and $\rho \in [0.2, 1.7]$. Thus, the mean of the prior is both loss averse ($\lambda = 2.3$) and risk averse ($\rho = 0.95$).[10]

Our main measure of loss aversion was obtained from a 20-question DOSE sequence, containing three types of binary choices. To help pin down individual risk aversion (ρ), some questions contained lotteries with only gains, while others contained lotteries with only losses. The third type of question then included both gains and losses, helping to pin down λ. To make the choices as simple as possible, all lotteries have 50% probabilities of payoff, and the set of payoffs always contains one value that is zero.[11] When a lottery contains a gain and a loss, then the sure amount is always zero. When the choices contain only non-negative or non-positive payoffs, one of the payoffs of the lottery is always zero.

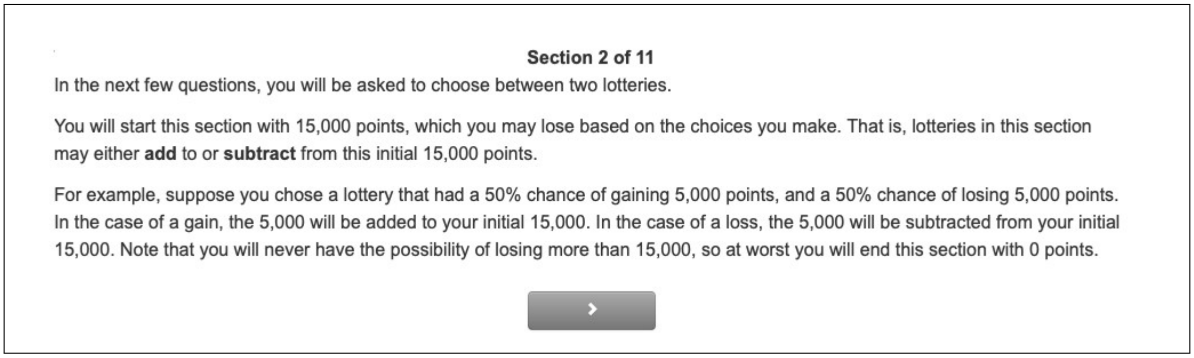
Participants were also asked a 10-question DOSE sequence, for comparison with an earlier survey completed in 2015, as well as two multiple price list (MPL) modules eliciting preferences over mixed lotteries—that is, lotteries with prizes in both the gain and loss domain.[12] The shorter DOSE sequence did not contain choices with only non-positive payoffs. In the 10-

[10] Questions are chosen to maximize the Kullback-Leibler divergence, see Appendix A for a technical treatment, and Chapman et al. (2018) for an exhaustive discussion of the method and its properties.

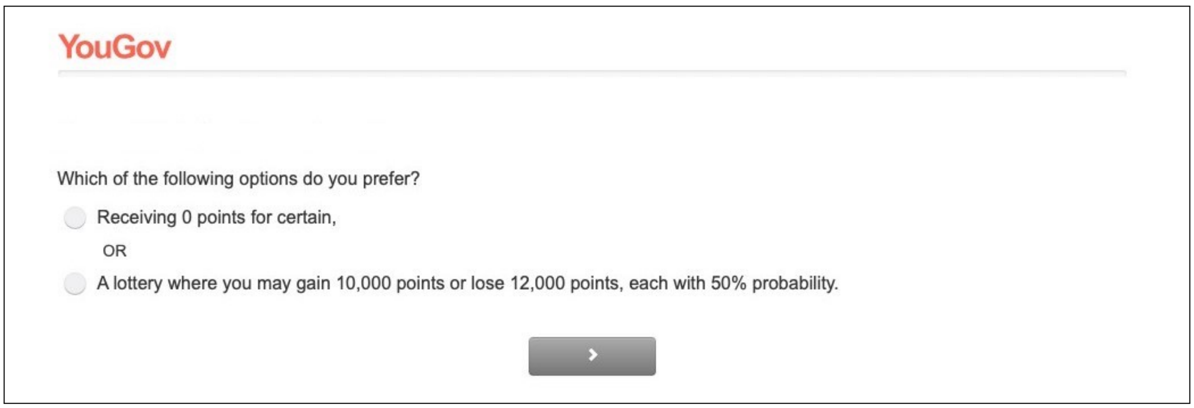
[11] Our focus is on loss aversion, so we use 50/50 probabilities of two outcomes in lotteries to minimize probability distortions. Experimental evidence suggests that participants make more consistent choices when lotteries have this structure (Olschewski and Rieskamp, 2021).

[12] The order of the modules was randomized. Specifically, the two DOSE modules were randomized to appear either at the beginning or end of the survey. The MPL modules appeared in a random order between the DOSE modules. We discuss possible order effects in Section 5.4.

Figure 2: DOSE Instructions and Example Question



(a) DOSE Instructions



(b) Example DOSE Choice (analyzed in Figure 1)

question sequence, the sure amount appeared first, reversing the order from the longer 20-question sequence. We find a similar level of loss tolerance across both the DOSE modules (see Section 3) and the MPL modules (see Section 5.1).

To implement losses in the survey, participants were endowed with a stock of points at the start of each section containing a potential loss, in line with standard experimental procedure (see, for example, Figure 2a). This could, in principle, lead to participants not considering any payoffs as losses, because they are playing with "house money" (Thaler and Johnson, 1990). Such effects do not appear to be a concern in our data, see Section 5.3.[13]

2.3 Data

Main Sample: We measured loss aversion in a large, representative, incentivized survey of the U.S. population which contained both a 20- and a 10-question DOSE sequence, as well as the two

[13]Etchart-Vincent and l'Haridon (2011) investigate different methods for implementing experimental losses, and observe similar behavior when paying losses out of an endowment or out of a participant's own pocket.

MPL modules described above. The survey collected a number of behavioral and demographic measures from 1,000 U.S. adults, and was conducted online by YouGov between February 21 and March 24, 2020.[14] Participants in the survey were drawn from a large panel maintained by YouGov. Most importantly for our results, this approach allowed us to capture the preferences of lower-education individuals that are often overlooked in both laboratory experiments and online crowdsourcing platforms such as Prolific.[15] All participants had previous experience with YouGov's online survey platform, and had to pass a test showing that they understood the instructions before starting the survey.

All measures of economic preferences in the survey, such as risk and loss aversion, were incentivized, with one module randomly selected for payment at the end of the survey.[16] All outcomes were expressed in YouGov points, an internal YouGov currency used to pay panel members, which can be converted to U.S. dollars using the approximate rate of $0.001 per point. For ease of interpretation, we generally convert points to dollars. To enhance the credibility of these incentives, we took advantage of YouGov's relationship with its panel, and restricted the sample to those who had already been paid (in cash or prizes) for their participation in surveys. The average payment to participants (including the show-up fee) was $10 (10,000 points), which is approximately four times the average for YouGov surveys of a similar length. The median completion time was 42 minutes.

The conversion from points to awards can only be done at specific point values, which leads to a slightly convex payment schedule.[17] In principle, participants' choices could be influenced by the opportunity to cross one of these thresholds. We subject this possibility to extensive checks in Appendix C.6, and do not observe differences in the extent of loss tolerance based on the number of points participants began the survey with, or the difference between their initial point balance and the next threshold. In particular, we find extremely similar results when we consider only participants who began the survey with 55,000–100,000 points, who are especially

[14]For screenshots of experimental instructions and the questions used in this paper, see Appendix E. Full design documents for all our samples can be found at eriksnowberg.com/wep.html.

[15]YouGov builds representative samples using targeted quota sampling from a large panel and by constructing sample weights to account for differential non-response. This produces better representative samples than other non-probability sampling procedures, and performs better than traditional probability sampling in eliciting attitudes (Pew Research Center, 2016, YouGov is Sample I).

[16]Participants did not receive any feedback about their choices until the payment screen. Adaptive methods such as DOSE are not generally incentive compatible, as in principle participants can make choices strategically to affect the questions received in future. However, such strategic behavior does not appear to be a concern in practice: even very sophisticated participants do not seem to respond strategically after being explicitly informed that a question sequence is manipulable (Ray, 2015).

[17]Major exchange thresholds exist at 25,000 points (the minimum exchange amount; for a $15 gift card), 30,000 points ($25 gift card), 55,000 points ($50 gift card), and 100,000 points ($100 as a gift card or in cash).

likely to treat points as equivalent to cash. Moreover, the payment schedule does not appear to affect other behavioral regularities, for which we observe behavior in line with prior literature (see Table 2 of Chapman et al., 2023a).[18] These findings are perhaps unsurprising given that panelists tend to accrue points over several years, and that neither participants' points totals nor the exchange thresholds are made salient during recruitment or when taking the survey.

Supplementary Sample: The 10-question DOSE module was also included in an earlier incentivized, representative survey ($N = 2{,}000$) conducted in March–April 2015, and a follow-up conducted around seven months later. This sample was the subject of our initial working paper (Chapman et al., 2018), which also serves as documentation for the modeling choices and analysis in this paper.

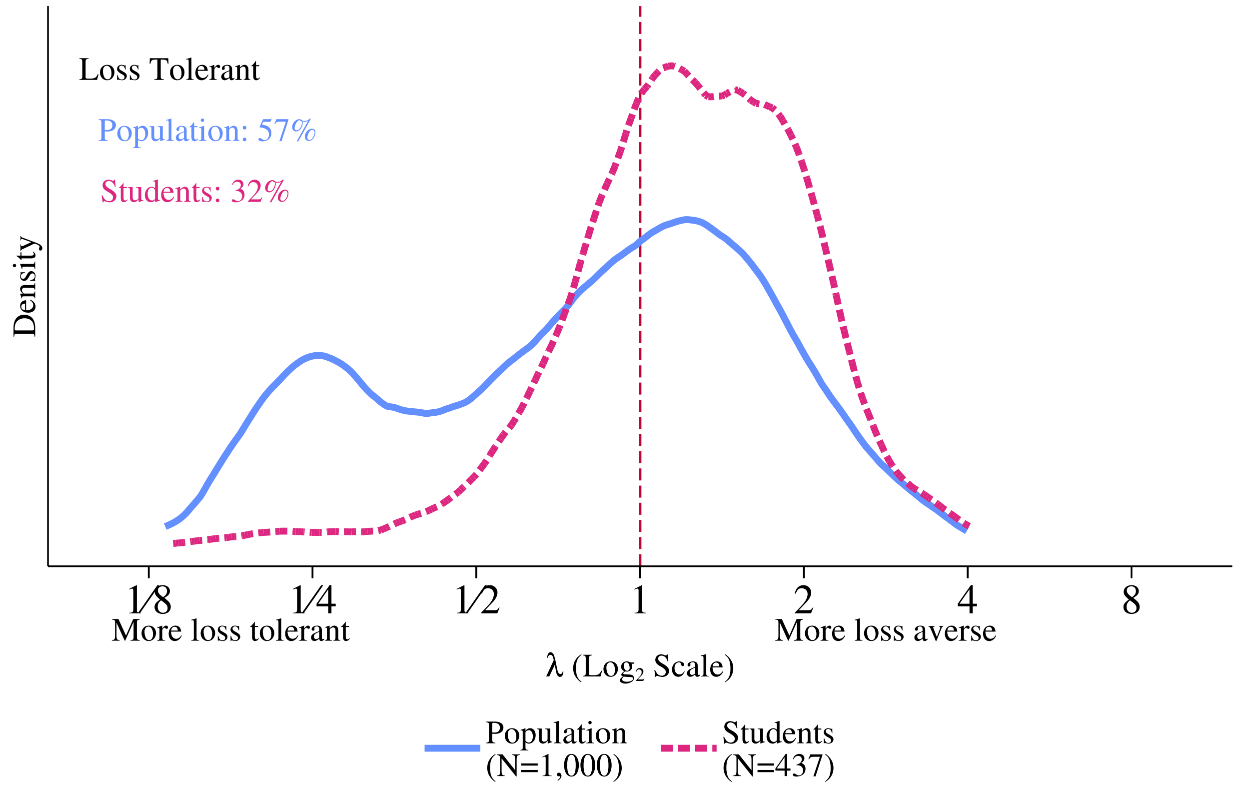
Student Samples: To provide a comparison to our results in the general population we elicited loss aversion from a sample of students ($N = 437$) recruited from the University of Pittsburgh Experimental Laboratory mailing list in November 2021. The implementation of the study was extremely similar to the one used with YouGov's panel: the students completed the survey online, and questions were presented with the same point values as in our representative sample. The only significant difference was that students received the value of their points converted into cash within two weeks, via a Visa gift card, rather than deposited into a YouGov account. The average payment was $\approx$ \$10.70, compared to \$10 in the representative sample. The planned comparison between the student and general population sample in Figures 1 and 3 was pre-registered with the Open Science Framework (Chapman et al., 2021). We also elicited loss aversion using only a 10-question DOSE module in a Pittsburgh student sample ($N = 369$) in January 2019, in a study comparable to our supplementary sample.

3 Loss Aversion in a Representative Sample

The U.S. population is substantially more loss tolerant than participants in student samples. Consistent with this finding, higher-cognitive-ability participants are more loss averse. Both loss aversion and loss tolerance are about as stable over six months as risk aversion and discounting.

[18]For example, we find that most participants in both of our general population samples, and in the sample in Chapman et al. (2023a), exhibit an endowment effect. However, the endowment effect is uncorrelated with any of our elicitations of loss aversion, see Chapman et al. (2023b).

Figure 3: The U.S. population is substantially more loss tolerant than student populations.



Notes: Figure displays the kernel density of each parameter, plotted using Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator.

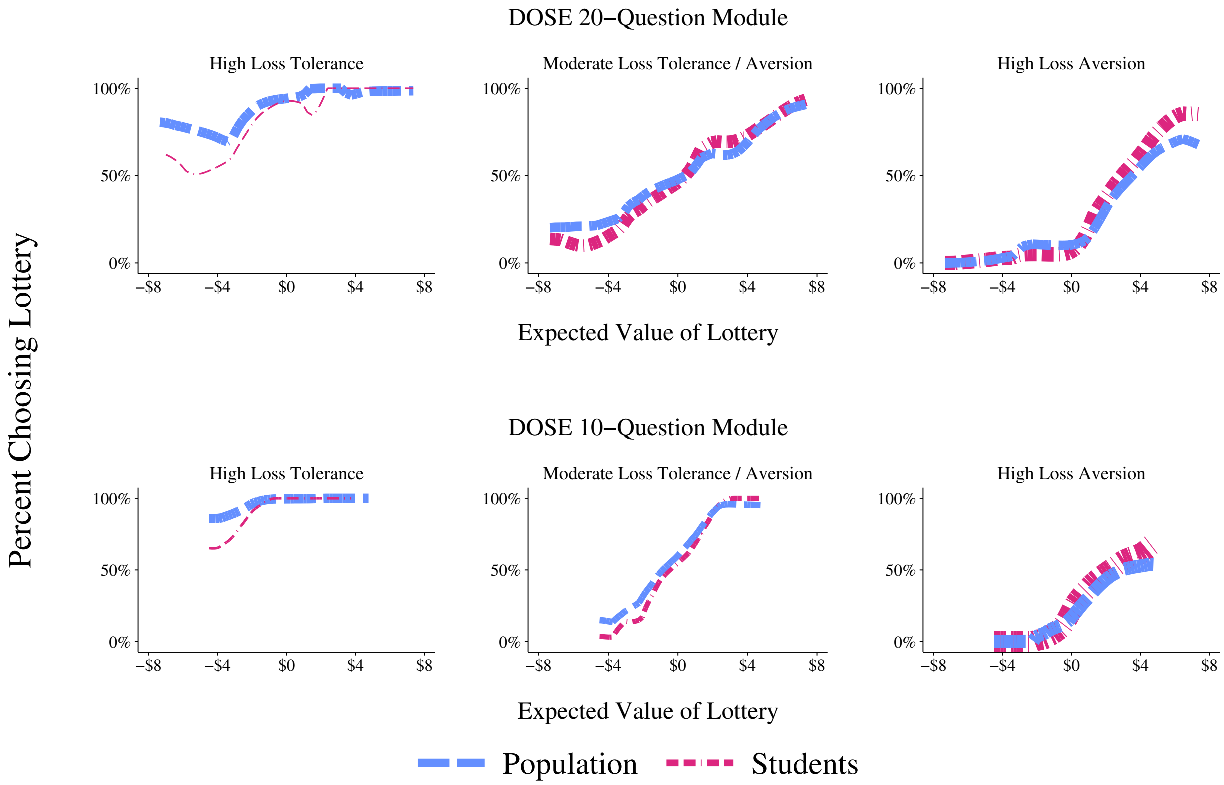
3.1 Widespread Loss Tolerance in the U.S. Population

Our main finding—that the general population contains a far higher proportion of loss-tolerant individuals than student samples—is displayed in Figure 3. Estimating λ using the 20-question DOSE sequence, 57% of participants in the representative sample are loss tolerant, similar to the proportion observed in Figure 1. The parametric estimates, however, allow us to investigate the heterogeneity in gain-loss attitudes in more detail, as they identify the degree of individuals' loss tolerance or loss aversion.

The distribution of estimates is markedly different in our student sample, where 68% of individuals are classified as loss averse. Across our two student samples and the two DOSE sequences, we find that approximately 22% of students are loss tolerant. This proportion is lower than across eleven previous studies that have investigated individual loss aversion in student/lab experiments, which classify, on average, 33% of participants as loss tolerant (combined $N = 1{,}882$).[19] Note that this difference does not simply reflect a greater willingness

[19] These studies are Schmidt and Traub (2002); Brooks and Zank (2005); Abdellaoui et al. (2007, 2008); Sokol-

Figure 4: DOSE parametric estimates reflect a clear pattern of choices.



Notes: Each panel displays the kernel density of the percentage of participants choosing a lottery with different expected values rather than a sure amount of \$0, plotted using Epanechnikov kernel with a bandwidth of 1. “High loss tolerance” ($\lambda < 0.57$), “moderate loss tolerance / loss aversion” ($0.57 < \lambda < 1.23$), and “high loss aversion” ($\lambda > 1.23$) are defined according to the terciles of the λ elicited from the representative sample for the 20-question DOSE module. The top row uses estimates from the 20-question module and our main samples (1,000 in the general population and 437 students), and the bottom uses estimates from the 10-question module (3,000 in the general population and 806 students). Line widths are scaled based on the relative proportion of participants in a sample within each of these categories.

to accept lotteries in the general population: 90% of the general population sample—and 89% of those classified as loss tolerant—were classified as risk averse, compared to 76% of students. This is in line with prior research showing students are less risk averse than the general population (see Snowberg and Yariv, 2021, and references therein).

Choices during our survey clearly demonstrate that losses do not “loom larger than gains” (Kahneman and Tversky, 1979, p.279) for a large proportion of the U.S. population. Close to two-thirds of participants in our main sample preferred at least one 50/50 lottery with negative expected value—that is, with a potential loss greater than the potential gain—to a sure amount of zero within the 20-question DOSE module. In many cases, losses appear to

Hessner et al. (2009); Abdellaoui et al. (2011); Brooks et al. (2014); Goette et al. (2019); Koch and Nafziger (2019); L’Haridon et al. (2021); Bocquého et al. (2022).

have been discounted substantially, with just short of 40% of participants accepting a lottery with a potential loss of more than double a possible gain (see Appendix Figures B.2 and B.3). We see similar results in the MPL elicitations discussed in Section 5.1, demonstrating that such choices are not limited to the DOSE modules. Our data thus provide direct evidence of loss tolerance, even in the absence of parametric assumptions.

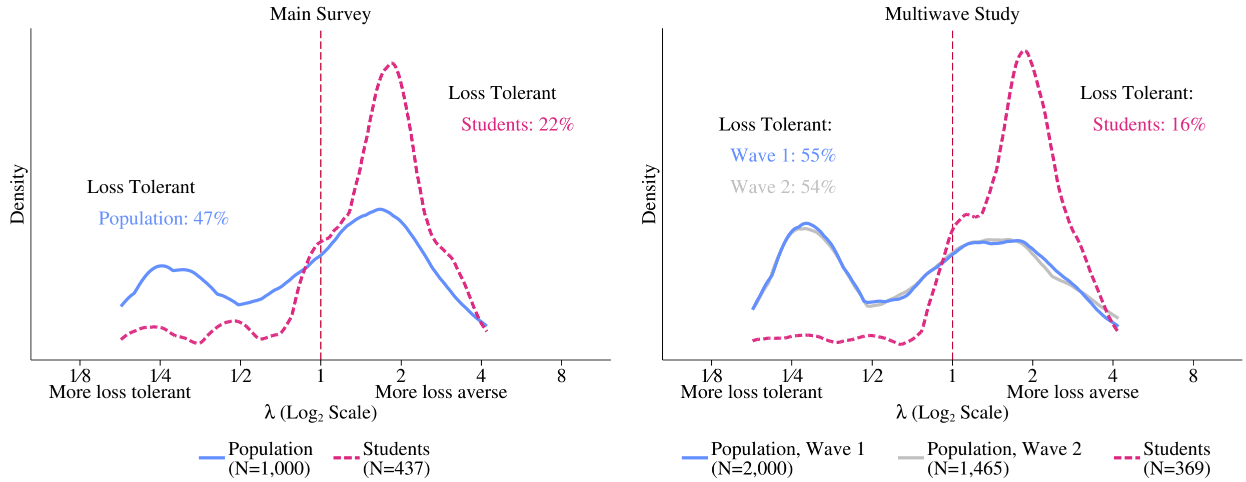
We present a summary of participants' choices in the DOSE sequences in Figure 4, drawing on more than 35,000 individual choices over mixed lotteries.[20] Each panel in this figure displays the percentage of participants choosing a mixed lottery as a function of the difference between the lottery's expected value and a sure amount of \$0. The top row of the figure presents the choice data from the 20-question DOSE sequence, which were used to produce the parameter estimates in Figure 3. Each panel presents participants from a different tercile of estimated λ. The bottom panel presents choices from the 10-question DOSE sequence, combining the choices of participants in both our main and supplementary samples. The width of each line in the figure captures the proportion of participants within each range of λ. For example, there are very few students classified as highly loss tolerant, so the lines representing student choices in the two left-hand panels are very thin.

The DOSE parametric estimates are underpinned by a robust pattern of choices, easily observable by examining the panels of Figure 4. Participants categorized as having high loss tolerance accept a large proportion of lotteries with negative expected value (87%)—a much larger share than those categorized as having high loss aversion (6%). As expected, most lines are generally upward sloping, reflecting the fact that participants become more likely to accept mixed lotteries as the expected value increases.[21] Importantly, the lines for students and the general population broadly mirror each other, indicating that the major difference between the samples is the proportion of people falling within each category, rather than different patterns of choices within categories. Finally, comparing the top and bottom panels demonstrates how the longer, 20-question sequence allows more refined parameter estimates by offering participants a broader range of possible choices—and consequently leading to parameter estimates that are further away from the initial prior. This difference is also reflected in the parametric estimates from the 10-question sequence that we present in the following subsection.

[20] Appendix B.1 presents additional analysis of the choice data, including showing choices in questions offering lotteries in only the gain or loss domain, and analyzing differences in choices according to cognitive ability tercile.

[21] However, the DOSE question selection algorithm means that this is not always the case, particularly when choices discriminate between possible parameter values far from the mean of the Bayesian prior. In particular, the flatter parts of lines in the left-hand panels reflect that DOSE only offers lotteries with large negative expected values to participants that have already revealed loss tolerance through their prior choices.

Figure 5: DOSE estimates of loss aversion are similar using a 10-question DOSE module, and are stable over time



Notes: Figure displays the kernel density of each parameter, plotted using Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator.

3.2 Stability of Loss Aversion

The loss aversion estimates from our 10-question DOSE sequence show similar levels of loss tolerance as our main estimates, and also demonstrate that the DOSE-elicited estimates of loss aversion are stable over time. As described in Section 2.2, we used this shorter DOSE sequence to elicit loss aversion in our main sample, and also in two waves of the supplementary sample. Consistent with the estimates in Figure 3, we find that approximately half the U.S. population is loss tolerant. Further, loss aversion is nearly as stable over time as risk aversion and discounting, suggesting that all three are similarly useful in describing individual preferences.

The percentage of participants who are loss tolerant—ranging from 47% to 55%—in the 10-question DOSE sequence is similar to our main results, as shown in Figure 5. This figure displays the distribution of loss aversion (λ) elicited using the 10-question DOSE sequence in our main sample (left-hand panel) and the multi-wave supplementary sample (right-hand panel). The slightly smaller proportion of loss-tolerant participants in the 10-question module is consistent with the fact that the mean of the prior on λ (2.3) assumes everyone is loss averse. Loss-tolerant participants with a true λ slightly lower than 1 will require more questions to pull our estimates away from the prior and below 1. However, the fact that the final estimates of the proportion loss tolerant are relatively similar across the 10- and 20-question DOSE modules suggests a relatively small effect of the prior. Moreover, we once again observe a much smaller proportion of students categorized as loss tolerant; 22% amongst those completing a version of our main survey, and 16% of those completing a version of the supplementary survey.

The estimates from the 10-question DOSE module are very stable over time, as shown in the right-hand panel of Figure 5. The correlation of DOSE estimates of loss aversion across the two survey waves, collected six months apart, was 0.38 (s.e. = .04). This over-time correlation was similar to that for DOSE elicitations of risk aversion (ρ)—0.41 (.04)—and for time discounting (δ)—0.45 (.05).[22] The within-person stability was lower when using other risk elicitation techniques—between 0.26–0.33 (all with s.e. = .04) across two MPLs and a risky project question (Gneezy and Potters, 1997)—consistent with lower measurement error in the DOSE estimates. Moreover, loss tolerance is as stable as loss aversion: of those classified as loss tolerant by DOSE on the first survey, 71% were also classified as loss tolerant on the second, whereas for loss aversion the figure is 67%. The stability of the DOSE-elicited parameters both provides reassurance about the robustness of our results, and suggests that gain-loss attitudes are a useful descriptor of economic preferences.

3.3 Economic Preferences and Cognitive Ability

Cognitive ability is the strongest correlate of both loss and risk aversion we examine, even after controlling for important socio-demographic characteristics. High-cognitive-ability participants are less risk averse—consistent with most previous studies—but more loss averse. These patterns are robust to controlling for individual characteristics such as income and education, and reflect both low- and high-cognitive-ability participants consistently making choices that do not maximize expected value.

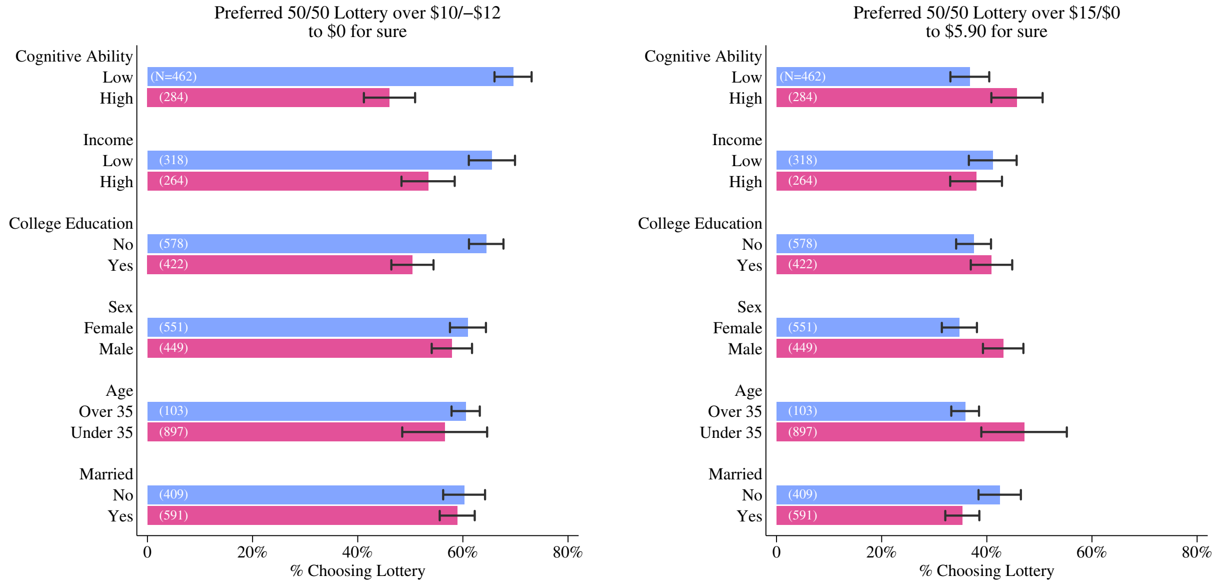
We measure cognitive ability using a set of nine questions. Six questions from the International Cognitive Ability Resource (ICAR; Condon and Revelle, 2014) capture IQ: three are similar to Raven's Matrices, and the other three involve rotating a shape in space. We also administer the Cognitive Reflection Test (CRT; Frederick, 2005): three arithmetically straightforward questions with an instinctive, but incorrect, answer. Our cognitive ability score is the sum of correct answers to these nine questions.[23]

Participants' choices in two fixed lottery questions, displayed in Figure 6, are consistent with the finding that the general population is less loss averse and more risk averse than lab/student populations. In particular, subgroups of the population that are more similar to college students are generally less likely to accept the negative-expected-value gamble discussed

[22]See Chapman et al. (2024) to compare these figures with the stability of a broad range of preference measures, including social preferences, overconfidence, and risk and time preferences.

[23]We combine the IQ and CRT measures because they are highly correlated (0.43, s.e. = .03). The pattern of correlations with each of these two components is similar to the combined measure—see Appendix Table C.1. This appendix table also presents correlations with additional socio-demographic measures.

Figure 6: A high proportion of participants in every population subgroup accept a negative-expected-value gamble.



Notes: The figure reports choices made by participants in different demographic groups. The left-hand panel displays the proportion of each group preferring a lottery with a 50% chance of winning $10 and a 50% chance of losing $12 to a sure amount of $0. The right-hand panel displays the proportion of each group preferring a lottery with a 50% chance of winning $15 and a 50% chance of winning $0 to a sure amount of $5.90. "Low" and "High" cognitive ability and income refer to the bottom and top terciles within the sample. Error bars represent 90% confidence intervals.

in the introduction—and are therefore more likely to be loss averse—but are more likely to accept a similar lottery where only gains are involved—suggesting they are less risk averse. The left-hand-panel of Figure 6 investigates the willingness to accept a negative-expected-value lottery—between gaining $10 and losing $12—across subgroups of our general population sample. As we have seen in Figure 1, 60% of the representative sample preferred this lottery to a sure amount of $0, whereas only 28% of our student sample did. Here we can see that the proportion choosing the lottery is above 40% in each demographic group within the representative sample, suggesting that loss tolerance is prevalent across different population categories—and that undergraduate students are an unusually loss averse demographic. Further, individuals with high cognitive ability—a characteristic that is typical of undergraduates (Snowberg and Yariv, 2021)—or a college education, are less likely to accept the lottery. However, as shown in the right-hand panel, these groups are more willing to accept a $0/$15 lottery over a sure amount of $5.90—suggesting that they are also less risk averse.

Correlations between the DOSE-elicited estimates of loss aversion and other individual char-

Table 1: Loss aversion is positively correlated with cognitive ability ($N = 1{,}000$).

	DV = Loss Aversion (λ)		DV = Risk Aversion (1-ρ)	
	Univariate Correlations	Multivariate Regression	Univariate Correlations	Multivariate Regression
Cognitive Ability	0.20***	0.17***	−0.30***	−0.29***
	(0.044)	(0.049)	(0.044)	(0.045)
Income (Log)	0.10**	0.06	−0.03	0.02
	(0.050)	(0.053)	(0.066)	(0.068)
Education	0.16***	0.10*	−0.12**	−0.06
	(0.045)	(0.051)	(0.051)	(0.048)
Male	−0.06	−0.09*	−0.05	−0.01
	(0.049)	(0.049)	(0.048)	(0.044)
Age	−0.05	−0.04	0.14***	0.10**
	(0.054)	(0.052)	(0.053)	(0.046)
Married	0.01	−0.03	0.07	0.09**
	(0.050)	(0.049)	(0.049)	(0.045)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Robust standard errors, in parentheses, come from a standardized regression. The first and third columns report univariate correlations, and the second and fourth columns report the coefficient from a multivariate regression. See Appendix C.2 for additional specifications with alternative definitions of loss aversion, control variables, and cognitive ability.

acteristics, reported in Table 1, confirm the most important visual patterns of Figure 6. The first column in the table reports univariate correlations between loss aversion and each characteristic, while the second column reports the results of a multivariate regression. The correlations we observe are very similar to the patterns of choices displayed in Figure 6. In particular, more educated and more cognitively-able individuals tend to be more loss averse and also less risk averse. In line with previous studies, younger individuals also tend to be less risk averse, and perhaps also more loss averse—although the latter finding is not robust across samples and specifications.[24]

Both high- and low-cognitive-ability participants consistently deviate from expected-value maximization in our data—but in very different ways. Less than than 2% of participants made an EV-maximizing choice in more than 18 out of 20 questions. Consistent with some previous studies (for example, Burks et al., 2009; Benjamin et al., 2013), participants in the highest

[24] We find a statistically-significant negative correlation between age and loss aversion elicited with the 10-question DOSE sequence. Age is also associated with being less risk averse over losses when allowing for differential utility curvature across the gain and loss domains. See Appendix C.2 for more details.

tercile of cognitive ability were slightly more likely to make an expected-value maximizing choice (doing so in 66% of questions versus 56% for those in the lowest tercile of cognitive ability). Low-cognitive-ability participants were more likely than high-cognitive-ability participants to choose mixed lotteries, whether or not those lotteries had a positive (74% vs. 65%) or negative (60% vs. 35%) expected value. The correlation between loss aversion and cognitive ability is thus underpinned by a clear pattern of individual choices.

One notable feature of Table 1 is that the groups that tend to be more loss tolerant—the less educated, lower income, and less cognitively able—are also those we might expect to have encountered more losses in life. This raises the intriguing possibility that loss tolerance either shapes or is shaped by everyday experiences. While our survey cannot test this hypothesis directly, in the next section, we investigate the relationship between loss aversion and individuals' exposure to losses outside of the survey environment.

4 Loss Aversion and Exposure to Real World Losses

Our measure of loss attitudes is correlated with important real-world behaviors and outcomes. Loss-tolerant participants in our survey are more likely to risk potential losses through gambling or investing in stocks. Loss-tolerant individuals also appear to experience more losses: they are more likely to report a recent financial shock and also hold fewer financial assets. Our data do not allow us to distinguish the direction of causality in these relationships: individuals may be more likely to spend and invest in a way that leads to real-world losses because they are loss tolerant, or they may become loss tolerant due to experiencing losses. However, these results demonstrate that our measure of loss aversion reflects individuals' exposure to real-world losses.

4.1 Measures of Behavior Outside of the Survey

To understand the relationship between loss aversion and behavior outside of the study, we asked participants about their equity investments, recent gambling, and household shocks. Participants were asked to specify their total investable financial assets (excluding the value of their home), and the percentage of those assets invested in the stock market (directly or through mutual funds).[25] There is likely some noise in these measures, which will tend to bias the correlations with estimated preference parameters towards zero (Gillen et al., 2019).

[25] Specifically, participants were asked to include, "the value of your bank accounts, brokerage accounts, retirement savings accounts, investment properties, etc., but NOT the value of the home(s) you live in or any private business you own."

Table 2: Principal Components Analysis

Gambling (Last Time Gambled)	Components: Serious	Casual	Household Shocks (Experienced in Last 12 Months)	Components: Financial	Personal
Sports Bets	0.45	-0.05	Unemployment	0.37	0.08
Online	0.40	0.00	Injury	0.38	0.33
Slots	0.26	0.26	Auto Accident	0.51	-0.37
Casino	0.43	0.04	Housing Related	0.44	0.03
Friends / Family	0.43	-0.03	Divorce	-0.01	0.86
Lotteries/ Lottos	-0.03	0.68	Other	0.51	0.04
Scratch Cards	-0.00	0.67			
Other	0.45	-0.06			
% of Variation	41%	21%	% of Variation	29%	18%

Notes: Only first two principal components are shown, rotated using varimax rotation.

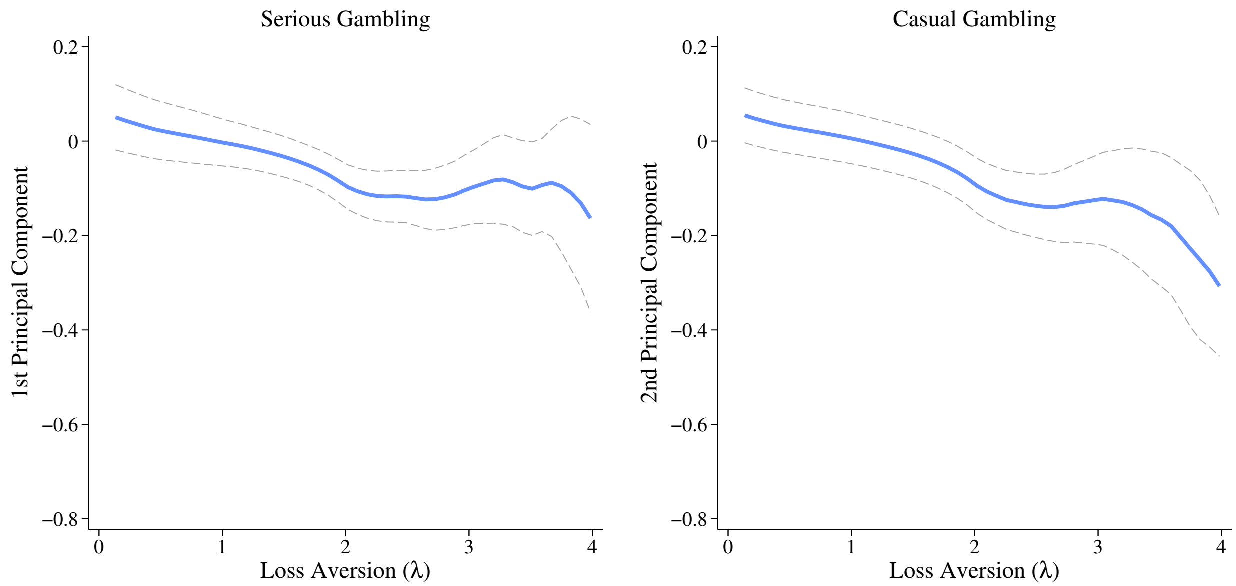
Gambling behavior and the experience of household shocks were each measured using a battery of questions that we summarize using principal components analyses. Table 2 provides a brief description of each question, and shows that two principal components emerge for each module.[26] Most types of gambling behavior load on the first component, which we term *Serious* gambling. The second component captures *Casual* gambling—lottos and scratch cards—which involve smaller stakes, and can often be done at supermarkets and convenience stores. The two components of household shocks correspond to shocks that are primarily *Financial*, and to shocks which are more *Personal* in nature, including divorce and (to a lesser extent) injury.

4.2 Gambling and Equity Investing

Loss-tolerant individuals are more willing to expose themselves to losses through gambling activity and financial markets. Gambling is the most natural real world analog to the simple lotteries offered by DOSE, and so provides a test of whether our findings are an artefact of the stylized survey environment. Moreover, a large literature in finance has suggested that loss aversion may inhibit equity investments (see van Bilsen et al., 2020, for a survey). Consistent with that literature, we find that loss-averse individuals are less willing to invest in stocks,

[26] Questions on household shocks were taken from Pew Research Center (2015, p4); questions on gambling were adapted from Gonnerman and Lutz (2011). Appendix D details the principal components analyses.

Figure 7: Loss tolerance is associated with more recent gambling.



Notes: Each panel refers to a principal component of our gambling measures—see Section 4.1 for details. The figure displays local mean regressions, plotted using Epanechnikov kernel with bandwidth of 0.8. Grey dotted lines represent 90% confidence intervals.

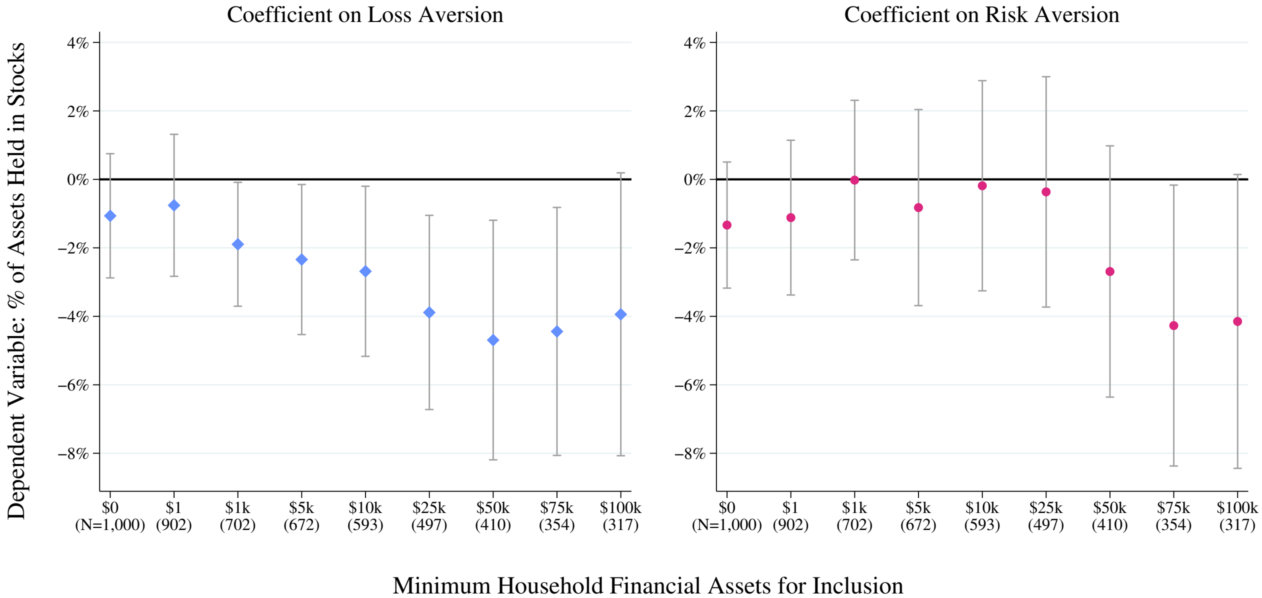
conditional on their asset holdings.

Loss aversion is negatively correlated with both of the principal components of gambling activity, as shown in Figure 7. Moreover, Table 3 shows that these relationships are robust to controlling for other individual characteristics, including risk aversion and cognitive ability. Loss-tolerant individuals not only accept negative-expected-value bets in our study; they participate in such gambles in their day-to-day lives.

Loss-tolerant individuals also hold a greater proportion of their investable assets in the stock market, as shown in Figure 8. That figure plots the results from regressing the percentage of all financial assets held in the stock market against our measures of risk aversion and loss aversion, controlling for demographic characteristics, cognitive ability, and total asset ownership. The left-most point includes the whole sample. Each point further to the right progressively limits the sample to those with greater assets. The coefficient is consistently negative, and becomes statistically significant at conventional levels once the sample is restricted to those with at least $1,000 of financial assets.[27] Combined with the results regarding gambling behavior, these findings suggest that loss-tolerant individuals might be more likely to spend and invest in a

[27]These results do not conflict with previous studies finding that low IQ inhibits stock market participation (see, for instance Grinblatt et al., 2012): our data also show a negative correlation between cognitive ability and whether an individual has any stock market investment.

Figure 8: Loss aversion is negatively correlated with stock market investments, conditional on total financial assets.



Notes: Figures display coefficients from regressing the percentage of an individual's assets invested in the stock market on loss aversion and risk aversion, controlling for log household financial assets, cognitive ability, home ownership, and the socio-demographic variables in Table 1. Loss and risk aversion are standardized, and so the coefficients represent a one standard deviation change in the relevant variable. Error bars represent 90% confidence intervals. See Appendix Table C.12 for full regression results, and Appendix Figure C.8 for results with alternative sets of control variables.

way that leads to real-world losses.

Loss aversion is a much stronger predictor of both gambling and investment behavior than small-stakes risk aversion. The regressions in Table 3 show little evidence that risk aversion predicts either component of gambling behavior: the results are similar even when loss aversion is excluded (see Appendix Tables C.9 and C.13). We do find some evidence that risk aversion is associated with smaller investments in the stock market—see the right-hand panel of Figure 8—but only amongst those with very high financial assets.

4.3 Shocks and Total Assets

A plausible explanation for the existence of loss tolerance is that individuals become habituated to repeated losses. The correlations in Table 1 are consistent with this explanation: loss tolerance is more common among groups that we would expect to experience more losses—those with lower cognitive ability, education, and income. This subsection shows that loss tolerance is associated with both being more likely to have experienced a recent financial shock, and

Table 3: Correlations between loss aversion and gambling are robust to controlling for risk aversion and other individual characteristics (N = 1,000).

	Serious Gambling			Casual Gambling		
Loss Aversion (λ)	-0.12**	-0.11**	-0.10**	-0.13***	-0.12***	-0.09**
	(0.052)	(0.051)	(0.049)	(0.045)	(0.046)	(0.043)
Risk Aversion (1 - ρ)		0.03	0.04		0.05	-0.03
		(0.051)	(0.051)		(0.052)	(0.046)
Cognitive Ability			-0.13***			-0.14***
			(0.050)			(0.045)
Education			0.03			-0.06
			(0.050)			(0.048)
Income (Log)			0.11*			0.03
			(0.061)			(0.051)
Age			-0.20***			0.22***
			(0.065)			(0.049)
Male			0.45***			0.18**
			(0.097)			(0.086)
Married			-0.18*			0.01
			(0.107)			(0.088)
Owns Home			0.22*			0.24**
			(0.118)			(0.093)

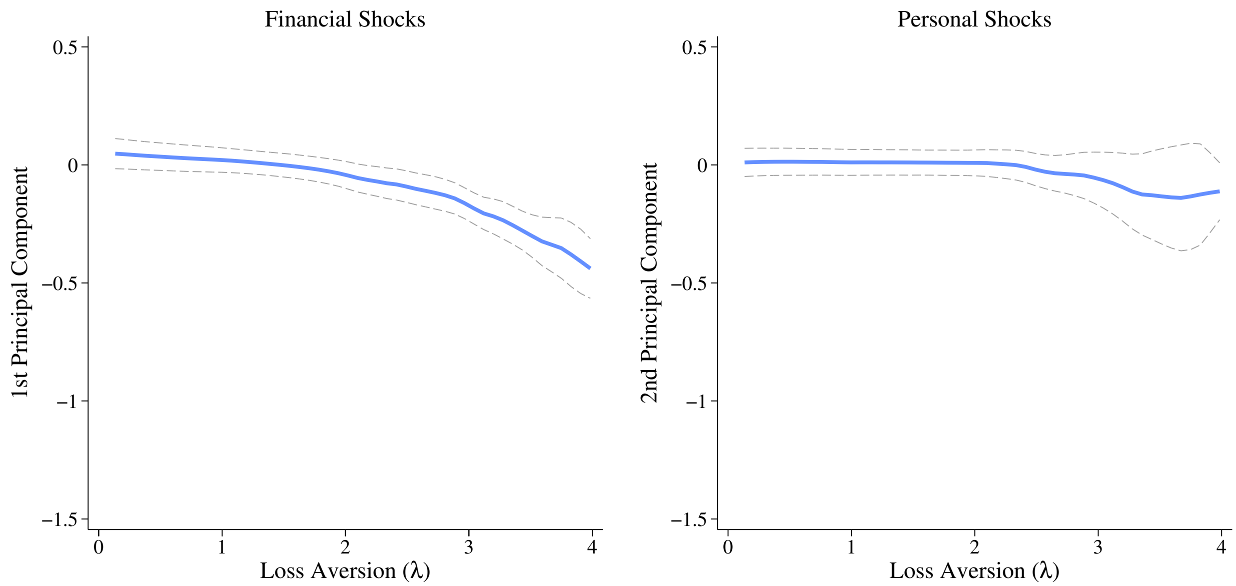
Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses. The magnitude and statistical significance of the coefficients for loss and risk aversion are similar when including controls as categorical variables—see Appendix Table C.8. There is no statistically significant relationship between risk aversion and any of the dependent variables when loss aversion is excluded—see Appendix Table C.9.

holding fewer financial assets, even after controlling for other characteristics.

Loss aversion is negatively correlated with having experienced a recent financial shock, but not a personal shock, as shown in Figure 9 and in Table 4. There is a clear negative relationship between loss aversion and financial shocks—unemployment, housing, automotive, and other losses—the first principal component of household shocks (see Table 2). However, there is no relationship with personal shocks (the second principal component), which loads heavily on divorce and personal injury. As might be expected, given that we measure loss aversion in the domain of monetary gambles, our measure of loss aversion is associated with losses which are likely of a financial, rather than personal, nature.

Loss-tolerant individuals also hold fewer total financial assets, as shown in Table 4. There is a strong positive relationship between loss aversion and the amount of financial assets owned, even after controlling for income, cognitive ability, and other demographics. The final column of the table shows that the relationship is also robust to controlling for home ownership, which

Figure 9: Loss aversion is associated with less exposure to financial shocks.



Notes: Each panel refers to a principal component of our household shocks measures—see Section 4.1 for details. The figure displays local mean regressions, plotted using Epanechnikov kernel with bandwidth of 0.8. Grey dotted lines represent 90% confidence intervals.

could capture either familial wealth or other major asset holdings. Moreover, the rate of home ownership is, if anything, slightly lower among participants classified as loss tolerant (55% versus 59%), suggesting that the results are not due to loss-tolerant individuals investing more into alternative assets.

The findings in this section provide suggestive evidence that loss tolerance is a harmful behavioral bias. Loss-tolerant individuals are more likely to gamble, and they also experience more financial shocks—consistent with making life choices that carry a more substantial risk of potential losses. The fact that loss tolerance is associated with greater stock market investment could, in principle, help overcome the general tendency of individuals to have too little of their portfolio in equities (Benartzi and Thaler, 1995) and hence lead to positive financial outcomes. In practice, however, loss-tolerant individuals end up with fewer financial assets, even conditional on other individual characteristics. Pinning down whether loss tolerance causes these outcomes is beyond the scope of this study, but the results point to a need for further research into the causes and consequences of loss aversion.

Table 4: Loss-tolerant individuals experience more financial shocks and have fewer financial assets (N = 1,000).

	Financial Shocks		Personal Shocks		Financial Assets (Log)	
Loss Aversion (λ)	-0.12***	-0.13***	-0.01	-0.00	0.14***	0.07*
	(0.044)	(0.043)	(0.051)	(0.047)	(0.048)	(0.038)
Risk Aversion (1-ρ)	-0.09*	-0.04	0.03	0.05	0.05	0.06
	(0.051)	(0.048)	(0.056)	(0.050)	(0.070)	(0.041)
Cognitive Ability		0.08*		0.01		0.06
		(0.045)		(0.046)		(0.041)
Education		0.07		-0.09*		0.08**
		(0.049)		(0.052)		(0.038)
Income (Log)		-0.14**		0.13*		0.40***
		(0.062)		(0.067)		(0.053)
Age		-0.17***		-0.01		0.09*
		(0.052)		(0.058)		(0.045)
Male		0.11		0.06		-0.05
		(0.090)		(0.102)		(0.074)
Married		0.23**		-0.16		-0.00
		(0.097)		(0.112)		(0.090)
Owns Home		-0.15		-0.35**		0.35***
		(0.102)		(0.138)		(0.091)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses. The magnitude and statistical significance of the coefficients for loss and risk aversion are similar when including controls as categorical variables—see Appendix Tables C.10. There is no statistically significant relationship between risk aversion and any of the dependent variables when loss aversion is excluded—see Appendix Table C.11.

5 Robustness

The widespread willingness to accept negative-expected-value gambles, displayed in Figures 1, 4, and 6, demonstrates that our central finding—that a large proportion of the U.S. population is loss tolerant—is not driven by the DOSE elicitation method or by our parametric assumptions. However, our data present the opportunity to further reduce concerns about the robustness of our results, while learning more about participants' behavior. First, we find a similar level of loss tolerance when preferences are elicited using the more traditional multiple price list procedure. Second, we analyze alternative parametric specifications, allowing for differences in risk aversion across the gain and loss domain (second subsection), and then for heterogeneity in participants' reference points (third subsection). Finally, the fourth subsection shows that inattention and fatigue seem to be relatively unimportant in our study, and do not confound our results. Across all these robustness tests, the estimated proportion of the population that is loss tolerant is consistently around 50%.

5.1 Traditional Elicitations of Loss Aversion

Our results are similar when using multiple price lists (MPLs; Holt and Laury, 2002), rather than DOSE, to elicit loss aversion. An MPL offers participants a table with two columns of outcomes. In each row, the participant is asked to make a choice between the outcomes in the columns. One column contains the same outcome in all rows, while outcomes in the other column vary, becoming more attractive as one moves down the table.[28] Each MPL then provides a set of binary choices which we use to estimate risk and loss aversion using the same parametric form, priors, and Bayesian procedure as the DOSE method.

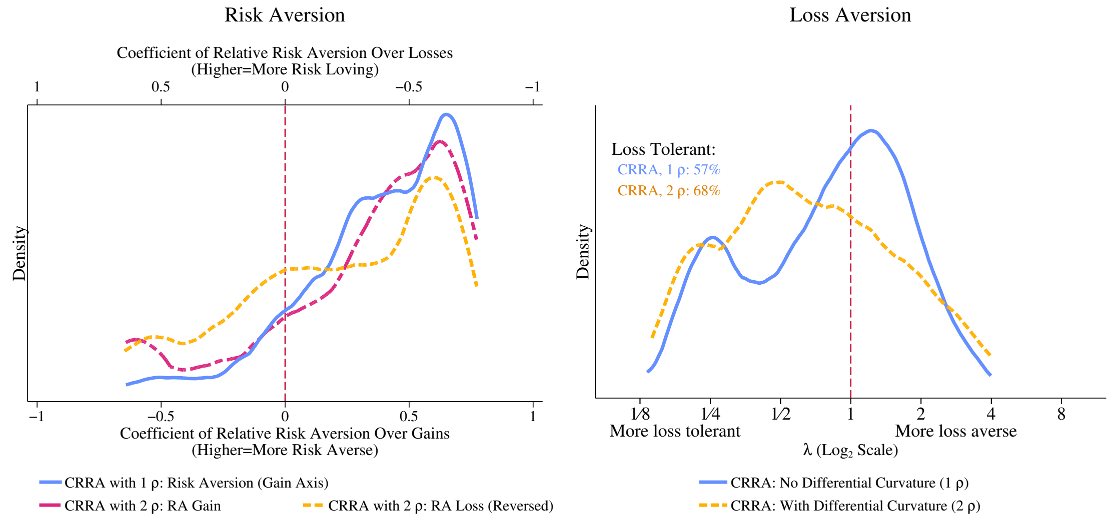
The survey elicited loss attitudes using two different MPL elicitation methods. First, participants answered two MPLs eliciting *Lottery Equivalents* for a fixed amount of \$0. Specifically, the lottery consisted of a fixed positive amount y and a varying negative amount c with equal probabilities. The MPL therefore elicited the amount c, such that the participant was indifferent between gaining y and losing c with equal probability, and getting zero for sure. The second set of MPLs then elicited *Certainty Equivalents* for two mixed lotteries. Participants were asked two questions eliciting their certainty equivalent for a 50/50 lottery between a loss and a gain—for example a lottery with a 50% chance of winning \$5 and a 50% chance of losing \$5. To estimate risk and loss aversion, the answers to these MPLs were combined with the responses to two additional MPLs which elicited participants' certainty equivalents for two lotteries involving only positive prizes.

Consistent with the DOSE estimates, the estimated proportion of loss-tolerant participants is much higher in the general population than amongst the student sample. Using the *Lottery Equivalent* elicitation technique, 54% of participants in the general population are classified as loss tolerant (compared to 57% using DOSE), whereas only 35% of students are (compared to 32% using DOSE). The *Certainty Equivalent* method also finds a higher degree of loss tolerance in the representative sample than the student sample (42% versus 23%).

The Bayesian estimates account for individual heterogeneity in risk aversion, and so provide a direct comparison to DOSE, but we can observe widespread loss tolerance simply by examining choices in the MPLs—as we discuss in detail in Appendix B.2. Specifically, we can simply assume equal utility curvature in both the gain and loss domains, and classify choices in the four mixed-risk MPLs as demonstrating loss aversion or loss tolerance. Doing so, we find

[28] Participants who understand the question should choose the former option for early rows, and at some point switch to choosing the latter (varying) option for all remaining rows. In our survey participants were not allowed to proceed if there were multiple switches in their choices. Participants had to complete an MPL training module at the start of the survey, and were able to return to the instructions if they made an error. See Appendix Figures E.26–E.31 for screenshots of the MPL elicitations.

Figure 10: The finding of widespread loss tolerance is robust to allowing for utility curvature to differ between losses and gains.



Notes: The figure displays the results from estimating alternative utility specifications using choice data from the 20-question DOSE sequence presented to our representative sample ($N = 1{,}000$). "CRRA with 1ρ"—our preferred specification—imposes the same utility curvature over gains and losses. "CRRA with 2ρ" allows for differential curvature across gains and losses. Distributions are plotted using an Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator.

the range of loss-tolerant responses is 41%–63% across the four mixed-risk MPLs. Further, a significant proportion of participants demonstrated strong loss tolerance; for example, 22% of participants preferred a lottery between -\$10 and \$4 to a sure amount of \$0. Choices in the MPLs thus provide further reassurance that loss tolerance is not an artifact of our parametric assumptions, or of the DOSE question format.

5.2 Allowing for Differential Utility Curvature Over Losses

The choice data elicited by DOSE allows us to investigate the robustness of our results to alternative utility specifications. In this subsection, we use the choice data from the 20-question DOSE module to show that our results about the prevalence of loss tolerance are robust to re-estimating individual preference parameters allowing for the curvature of the utility function to differ between gains and losses. That is, we re-estimate our main specification (1), but allow for separate risk parameters for gains ($\rho+$) and for losses ($\rho-$) (Tversky and Kahneman, 1992).

Allowing for differential curvature does not affect our conclusion of widespread loss tolerance. Most participants (60%) are risk averse over gains and risk loving over losses, in line with prior experiments and prospect theory (Kahneman and Tversky, 1979)—see the left-hand panel of

Figure 10. The average difference between the $\rho+$ and $\rho-$ parameters is small (mean = 0.11, s.e. = 0.02), offering support for our main specification. The distribution of risk aversion for gains is similar to that of our main risk aversion estimates; however, it appears that imposing the same curvature on both domains may slightly exaggerate the degree of risk-loving over losses. If so, our main specification would underestimate the extent of loss tolerance at the reference point. This is confirmed by the right-hand panel of Figure 10—more individuals have $\lambda < 1$ when allowing for differential curvature than in our main model (68% versus 57%).[29] However, λ should be interpreted differently across the two specifications. In our main specification, λ captures all differences in attitudes towards gains versus losses; once we allow for differential curvature, λ reflects only a kink around the reference point. The difference between the $\rho+$ and $\rho-$ parameters captures other differences in preferences between the gain and loss domains, which may vary with the payoff x.

5.3 Reference Points

Our preferred model, with a reference point of \$0, fits participants' choices better than other common reference-dependent models listed in Table 5. The model correctly predicts 74% of choices in the DOSE 20-question module (20Q), and 91% in the DOSE 10-question (10Q) module. Models with alternative reference points correctly predict fewer choices, particularly in the 10Q module. Further, our basic finding that the majority of participants are loss tolerant is unchanged when incorporating these alternative reference points.[30]

The first row of Table 5 features the most obvious alternative model: participants evaluating each option relative to the amount they began the survey with. In this case, the endowment of \$15 given at the start of the 20Q module (or \$10 in the case of the 10Q module) would be incorporated into the values of the various options, and every payoff—even those presented as a loss—would be evaluated as a gain. This alternative model fits the data much worse, correctly predicting only 59% of choices in the 20Q module and 54% in the 10Q module—little better than random guessing. Further, the model performs better than our preferred \$0 reference

[29]Similar results are obtained when employing the constant absolute risk aversion (CARA) utility function suggested by Köbberling and Wakker (2005) to provide a scale-independent measure of loss aversion, see Appendix C.1. Appendix Table C.7 shows the correlations between the parameters of different models and cognitive ability.

[30]Appendix C.4 shows that our preferred model performs even better in the 20Q module if we allow for differential curvature over gains and losses—the model correctly predicts 82% of choices, and alternative models provide a better fit for only around 10% of participants. These results suggest that the higher proportion of choices fit by our preferred model in the 10Q module is because the absence of questions with only losses allows ρ and λ to be pinned down more precisely. Consistent with this, if we re-estimate the 20Q module excluding question with losses, the results are close to the 10Q module.

Table 5: Our preferred model fits better than other standard reference-dependent models.

Model of Reference Point	% Participants with Improved Fit 20Q	% Participants with Improved Fit 10Q	% Loss Tolerant 20Q	% Loss Tolerant 10Q
Endowment	20%	0%	–	–
EV of Lottery	22%	8%	73%	58%
Sure Option	39%	13%	47%	41%
Stochastic	32%	6%	49%	49%
Choice	25%	7%	46%	49%
Best Model for Each Person	47%	13%	43%–65%	38%–49%

Notes: The table displays the results from fitting participants' choices using alternative reference points, using choice data from the 20-question DOSE sequence presented to our representative sample (N = 1,000). % Participants with Improved Fit is the percent of participants for whom the model in each row correctly predicts more choices than our preferred model—a reference point of \$0. % Loss Tolerant is the percent of participants with $\lambda < 1$ according to the model in the row. The row "Best Model for Each Person" refers to the reference point model(s) which best fits each participant's choices.

point for only 20% of participants in the 20Q module and none at all in the 10Q module.

The next two rows feature models with fixed reference points: either the expected value (EV) of the lottery or the sure amount in each question.[31] Either of these reference points could capture the "first focus" concept of Kőszegi and Rabin (2006).[32] These models fare slightly better than incorporating the endowment; however, this is partly because the reference point is often similar to \$0—our preferred model.

The final two rows show similar results using stochastic reference point models, as in Kőszegi and Rabin (2006, 2007). First, we model a stochastic reference point—that is, allowing the lottery reference point to vary probabilistically according to the distribution of prizes in the lottery. Next, we implement Kőszegi and Rabin's (2007) "Choice-Acclimating Personal Equilibrium," in which the decision determines both the reference point and the outcome. That is, before a participant chooses, he or she evaluates the lottery with the stochastic reference point, and

[31]Using EV as the reference point is similar to the models of Loomes and Sugden (1986) and Bell (1985). The sure amount is a possible reference point as it is both the maxmin and minmax payoff, and also the highest probability outcome.

[32]For instance, the reference point could be shaped by the first option participants see. In that case, the ordering of the options could matter; however, we do not see evidence of this—the performance of the two models is similar across the 10Q and 20Q modules, despite the lottery appearing first throughout the 20Q module and second throughout the 10Q module.

evaluates the sure amount relative to that reference point.

Finally, our core finding of widespread loss tolerance is unchanged if we allow for heterogeneity in the reference points participants use.[33] The proportion of loss-tolerant participants is greater than 41% regardless of the reference point used, and our preferred estimate (57%) is near the midpoint of all the models we examine here. If we classify each participant according to the model that fits their choices best, as in the final row of Table 5, the proportion of loss-tolerant individuals ranges from 45% to 65%.[34]

5.4 Inattention and Fatigue

While there is little reason for concern about confusion and fatigue—the main results are similar across different elicitation methods and correlate with real-world behavior—we also check that our results are robust to excluding participants most likely to have been inattentive to the survey. Nearly all participants successfully passed three attention screeners placed throughout the survey, and our results are robust to removing very fast or slow responses. We see widespread loss tolerance even in questions appearing early in the survey.

The results change little when restricting the sample to those participants most likely to be paying close attention. The left-hand panel of Figure 11 shows that a large majority (90%) passed three attention checks in our survey, and the degree of loss tolerance is very similar—53% of participants—even when excluding individuals who failed one of these checks.[35] The proportion of participants that is classified as loss tolerant is also similar (58%) when excluding those who completed the survey relatively quickly—in less than the median response time—which could reflect lower attention.[36]

The right-hand panel of Figure 11 shows that the finding of widespread loss tolerance is not driven by survey fatigue. The order of the 10-question and 20-question DOSE modules was

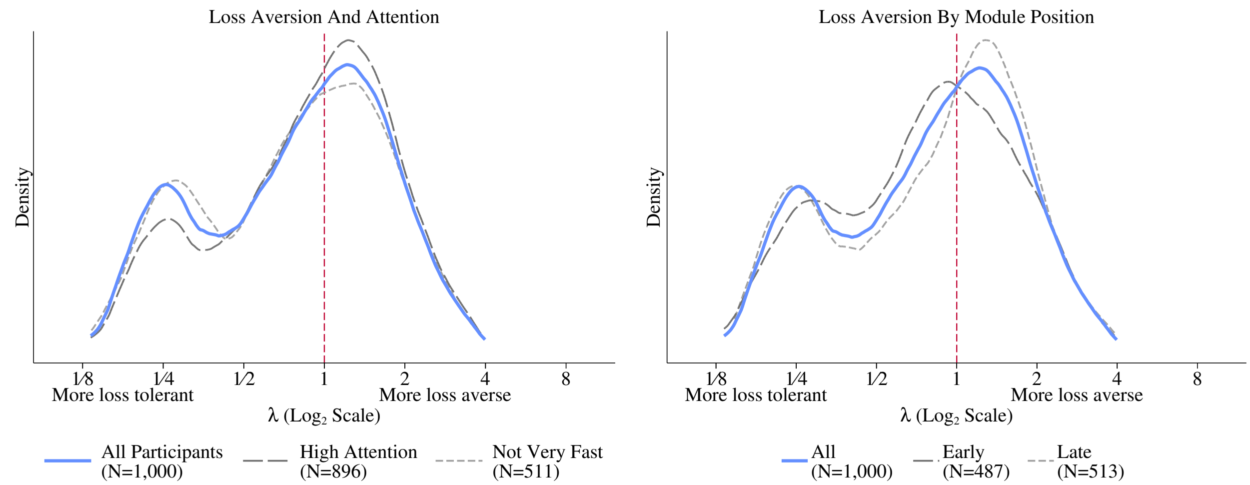
[33] Baillon et al. (2020) provide one of few empirical studies of heterogeneity in reference points. To the extent that their design is comparable to ours, their results are consistent: one of the two best performing reference points in their exercise is the "status quo," similar to our preferred model.

[34] The range reflects the fact that there may be ties between the best models for each individual. The reference point of $0 also provides the best fit for the majority of participants classified as loss tolerant in our main estimates—see Appendix Tables C.14–Tables C.15.

[35] See Figures E.34–E.37 for question wording. One of the three attention checks involved reading comprehension; failing this test could capture misunderstanding rather than a lack of attention. Ninety-four percent of participants passed the other two attention screeners, which involved presenting participants with misleading information they should ignore. The rate of passing the attention checks was similar in the sample of students in the online survey (94% passed all three checks) and higher than in a controlled laboratory environment: 18% of UBC students failed at least one of the three checks, and 11% failed one of the two simpler checks (Snowberg and Yariv, 2021).

[36] One way of moving quickly through the DOSE sequence could be to choose the same option (the lottery or the sure amount) in every question—very few (2%) participants did so.

Figure 11: Widespread loss tolerance is not due to fatigue or inattention.



<u>Notes:</u> The figure displays the distribution of estimated loss aversion (λ) from the 20-question DOSE sequence for different subgroups of our representative sample ($N = 1{,}000$). "High attention" excludes any participant that failed any attention check. "Not Very Fast" excludes participants completing the survey in less than the median response time. Distributions are plotted using an Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator.

randomized across participants, with each module appearing as either the second or seventh module in the survey. Loss aversion is, if anything, higher later in the survey—62% of participants were classified as loss tolerant when the 20Q module appeared early, and 53% when it appeared late.

Appendix C.5 presents evidence that inattention—either during the DOSE modules or across the survey as a whole—does not explain our results. First, we show that the distribution of loss aversion is similar when we remove participants according to the amount of time they take to complete either the survey or just the DOSE module. Second, we carry out an experimental test of whether the sequential nature of the DOSE procedure affects participants' behavior through, for example, inadvertently creating a reference point. We find no evidence that interrupting the DOSE sequence, using a randomly-placed "page break," affected behavior either in the sample as a whole or within particular subgroups. Third, we show that the correlation we document between cognitive ability and loss aversion is not an artifact of some participants making "mistakes," which would be revealed by these participants making inconsistent choices in the DOSE module.

6 Discussion

We find considerable heterogeneity in gain-loss attitudes across the U.S. population, with around 50% of people being loss tolerant over small stakes. Those with greater cognitive ability, education, and income are more likely to be loss averse, and those with lower cognitive ability are more likely to be loss tolerant. Further, loss-tolerant individuals gamble more frequently, commit a greater portion of their assets to equities, experience more frequent financial shocks, and hold fewer financial assets, suggesting that loss tolerance is a harmful behavioral bias requiring deeper investigation.

We model gain-loss attitudes using a standard prospect theory utility function, but more substantial departures from the literature may be appropriate. While we rule out many theoretical concerns regarding parametric form or participants' reference points in Section 5, other possible rationalizations for widespread acceptance of negative-expected-value lotteries exist. Loss tolerance could, for example, reflect an extremely low probability weight on losses relative to gains, or low salience of losses. Reference points could, in principle, vary according to whether a lottery is over only gains or includes both potential gains and potential losses.

The paper has three major implications for applied theorists investigating gain-loss attitudes. First, the degree of loss tolerance we observe poses a challenges for the theoretical assumption of universal loss aversion—as found, for instance, in responses to the Rabin (2000) critique that attribute all small-scale risk attitudes to gain-loss attitudes (see, for example, Kőszegi and Rabin, 2006). Second, appropriate theoretical assumptions are likely to vary by context. An assumption of $\lambda > 1$ may be appropriate for groups with higher education and income—such as those manipulating tax liabilities (Rees-Jones, 2017) or participating in financial markets (Barberis et al., 2021; Wolff, 2021)—who we find to be more loss averse on average. In other markets, however, loss tolerance may play an important role—near-universal loss aversion is hard to square with the high frequency of gambling in the U.S. population—approximately 85% of U.S. adults have gambled at least once in their lives (NCPG, 2023). Moreover, we find significant heterogeneity in gain-loss attitudes within all the demographic groups we study, indicating that loss-tolerant behavior may be present even if the average person in a given environment is loss averse. In financial markets, for example, Payzan-LeNestour and Doran (2024) observe that traders frequently invest in negative-expected-value trades, while Abdellaoui et al. (2013) find that a substantial minority of a sample of financial professionals are loss tolerant. Third, failing to account for variation in gain-loss attitudes may confound empirical tests of models of reference-dependence and, in general, further theorizing about the consequences of heterogeneous preferences may be a fruitful avenue for future research (Goette et al., 2019).

Our findings suggest that there are likely to be high proportions of loss-tolerant participants in all participant pools. Thus, experimental findings of low levels of loss aversion need not be treated with skepticism or stigmatized. In reviewing the loss aversion literature we found that studies sometimes present findings of loss tolerance cautiously, with, for instance, high proportions being reported without comment or in footnotes (for example, Delavande et al., 2023; Koch and Nafziger, 2019). This caution may reflect the fact that, "Since the publication of Tversky and Kahneman (1992), any estimates of loss aversion that deviate significantly from the value of two have been eyed with great suspicion, notwithstanding the fact that the original estimate was based on 25 subjects, hypothetical decisions over relatively large stakes, and that no standard errors were reported." (Fehr-Duda and Epper, 2012, p. 576). Reviewing the loss aversion literature, Yechiam (2019, p. 1) asserts that, "[T]he findings of some of these studies have been systematically misrepresented to reflect loss aversion, though they did not find it." This claim finds some support in two recent meta-analyses of empirical estimates of λ, both of which report evidence consistent with some publication bias (Walasek et al., 2018; Brown et al., forthcoming). We document that loss tolerance is an important behavioral regularity, and point to the importance of further study of heterogeneity in gain-loss attitudes.

The paper also demonstrates that researchers should take care in calibrating experimental designs based on their own intuition, or results in laboratory samples. Only 10% of the economists in our expert panel stated that they would accept the simple lottery displayed in Figure 1—introspection may thus lead us to consider loss aversion a more "plausible" bias. Respondents to our expert survey, as well as the authors of this study, failed to anticipate the significant differences between the behavior of the general population and that of undergraduate students. It was only because the DOSE method implements personalized question sequences drawn using a diffuse prior that we initially identified substantial loss tolerance in our representative sample.

We provide suggestive evidence as to possible causes and/or consequences of loss tolerance, but our data do not allow us to pin down the direction of causality. A natural explanation is that loss tolerance is an inherent, stable trait, leading to individuals to make choices where a loss is possible—particularly gambling and investments in stocks. Alternatively, loss attitudes could be shaped by the patterns of losses and gains that individuals experience. Experiencing a series of negative shocks could reduce the fear of further losses—individuals could, for instance, recognize that their reference point adapts to reduced income—or may lead individuals to “chase” their losses. While distinguishing between these explanations is beyond the scope of this study, our results point to a need for deeper research into the causes and consequences of heterogeneity in gain-loss preferences.

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Online Appendix—Not Intended for Publication

Table of Contents

A DOSE Procedure and Survey Implementation

A.1 DOSE Procedure

This subsection presents further details of the design choices for each of the two DOSE sequences in our online survey. We start by detailing the information criterion and error specification that we implement in both the DOSE sequences. We then explain the implementation of the question selection in our online survey, and specify the particular design choices made for each of the 10-question and 20-question sequences. For full details of the DOSE elicitation method, see Chapman et al. (2018).

Overview of DOSE procedure The DOSE procedure selects a personalized sequence of questions for each participant. Questions are selected sequentially, using a participant's previous answers to identify the most informative question at that point in time. In our implementation, DOSE selects each question to maximize the expected Kullback-Leibler (KL) divergence between the prior and possible posteriors associated with each answer. That is, the question that is picked at each point is the one with the highest expected information gain given the initial prior and previous answers.

Formally, consider a finite set of possible parameter vectors θ_k for $k = 1, ..., K$, where each $\theta_k = (\rho_k, \lambda_k, \mu_k)$ is a combination of possible values of the parameters of interest. Each θ_k has an associated probability p_k of being the correct parameters. In the first question, these probabilities are the priors chosen by the experimenter; they are then updated in each round according to the participant's answers. The expected Kullback-Leibler divergence between the prior and the posterior when asking question Q_j is:

$$KL(Q_j) = \sum_{k \leq K} \sum_{a \in A} \log \left(\frac{l_k(a; Q_j)}{\sum_{j \in \mathcal{K}} p_j l_j(a; Q_j)} \right) p_k l_k(a; Q_j) \tag{2}$$

where $a \in A$ are the possible answers to the question, and $l_k(a; Q_j)$ is the likelihood of answer a given θ_k—in our implementation this is determined by the logit function in (3). DOSE selects the question that maximizes $KL(Q)$, the participant answers it, model posteriors are updated, the question Q_j that now maximizes $KL(Q)$ (and has not already been asked) is selected.

Mistakes and Choice Consistency An important feature of DOSE is that it accounts for the possibility that the participant may make mistakes in their previous choices. In this paper, we model the mapping between utility and choices using a logit function—Chapman et al. (2018) show that the procedure is robust to misspecifying the error specification. Specifically, for any choice between options o_1 and o_2 with $V(o_1) > V(o_2)$:

$$\text{Prob}[o_1] = \frac{1}{1 + e^{-\mu_i (V(o_1) - V(o_2))}}. \tag{3}$$

In Specification (3), the probability of making a mistake is $1 - \text{Prob}[o_1]$, and so μ_i represents greater consistency in choices.

Survey Implementation: The design of YouGov's online platform precluded using DOSE to choose questions in real time and so, instead, simulated responses were used to map out all possible sets of binary choices in advance. That tree was then used to route participants through the survey. Mapping such a tree with a refined prior was infeasible given both computational constraints and the limitations of YouGov's interface (mapping such a tree over 20 questions would involve over 500,000 routes through the survey). As such, questions were selected using a coarser prior and then final individual-level estimates were obtained by performing the Bayesian updating procedure with a joint 100-point discretized uniform prior.[1]

10-question Sequence: The 10-question sequence was selected using the utility function in Specification 1. Two types of lottery were used. The first had a 50% chance of 0 points, and a 50% chance of winning a (varying) positive amount of points (of up to 10,000). The second had a 50% chance of winning an amount up to 10,000 points, and a 50% chance of a loss of up to 10,000 points. In the latter case, the sure amount was always 0 points.[2] The lottery always appeared first in both types of question

To account for the survey environment we restricted the question selection procedure in two ways. First, to focus the procedure on obtaining a precise estimate of ρ before moving onto estimates of λ, the first four questions in the module were restricted to be lotteries over gains. Second, to make it harder for participants to identify the adaptive nature (and hence attempt to manipulate) the procedure, the maximum prize was restricted to be no more than 7,000 points in each even numbered round.

See Figures E.23–E.25 for module instructions and example questions.

20-question Sequence: The 20-question sequence was selected using a power utility function allowing for differential curvature over gains and losses—see Specification (4) below. Three types of lottery were used. The first two types were the same as those in the 10-question sequence listed above—except that potential prizes ranged from a loss of 15,000 to a gain of 15,000. The third type of question, included to identify curvature over losses, offered a choice between losing a (varying) fixed amount points, or a lottery with a 50% chance of 0 points, and a 50% chance of losing up to 15,000 points. The sure amount always appeared first in all questions, reversing the order from the 10-question module.

In order to facilitate comparisons across the sample, the question selection procedure was restricted so that three questions were fixed for all participants. The first question of the sequence offered a choice between a gain of 5,900 points, or a lottery with a 50% chance of 0 points and a 50% chance of 15,000 points. The fourth question—reported in Figure 1—offered participants a fixed prize of 0 points or a lottery with a 50% chance of gaining 10,000 points, and a 50% chance of losing 12,000 points. No questions with possible losses were allowed before

[1] Specifically, the prior for question selection was constructed using the estimates for laboratory participants obtained by Sokol-Hessner et al. (2009) and Frydman et al. (2011): 0.2–1.7 for ρ (12 mass points), and 0–4.6 for λ (20 mass points).

[2] The set of potential questions allowed for gains ranging between 1,000 and 10,000 points in 500 point increments, and sure amounts and losses varying ranging from 500 points to 10,000 points in 100 point increments. Questions were excluded if one choice was first-order stochastically dominated for all values of the prior distribution. Questions were also selected as if the prize amounts were 3 times the actual amounts offered in the lottery to improve discrimination of the risk and loss aversion parameters.

this question. The twentieth question of the sequence offered a similar choice: a 50% chance of gaining 11,000 points, and a 50% chance of losing 13,000 points.[3]

See Figure 2 for the 20-question sequence instructions, and an example of a question involving a gain and a loss. Figure E.20 presents an example of a question involving only a gain, and Figure E.21 an example of a question involving only a loss.

A.2 Other Survey Measures

This subsection summarizes the definition of the other measures used in the paper.

MPLs Eliciting Certainty Equivalents The survey included four MPLs eliciting participants' certainty equivalent for a fixed lottery—see Figures E.28–Figures E.31. Two MPLs elicited the certainty equivalent for a 50/50 lottery between a loss and a gain, while two elicited the certainty equivalent for a 50/50 lottery including only gains. The specific lotteries offered were:

1. 50% chance of winning \$5 and a 50% chance of losing \$5
2. 50% chance of winning \$4 and a 50% chance of losing \$4
3. 50% chance of winning \$0 and a 50% chance of winning \$5
4. 50% chance of winning \$1 and a 50% chance of winning \$4

MPLs Eliciting Lottery Equivalents Two MPL offered participants a choice between a fixed prize of \$0, and a 50/50 lottery with a variable prize—see Figures E.26–Figures E.27. Specifically, the lottery consisted of a fixed positive amount y (\$5 or \$4) and a varying negative amount c with equal probabilities. The MPL therefore elicited the participant's lottery equivalent for c such that the participant was indifferent between gaining y and losing c with equal probability, and getting zero for sure.

Cognitive Ability: We measure cognitive ability using a set of nine questions. Six questions from the International Cognitive Ability Resource (ICAR; Condon and Revelle, 2014) capture IQ: three are similar to Raven's Matrices, and the other three involved rotating a shape in space. The other three are taken from the Cognitive Reflection Test (CRT; Frederick, 2005): three arithmetically straightforward questions with an instinctive, but incorrect, answer.

[3]The set of potential questions was as follows. For questions with only gains, possible prizes varied between 700 and 14,700 points, in increments of 700. For questions with only losses: possible prizes varied between 100 and 14,800 points, in increments of 700 points. For questions with gains and losses the gain prizes varied between 300 and 15,000 points, in increments of 700 points; loss prizes varied between 300 and 15,000 points, in increments of 700 points. Questions were excluded if the highest maximum absolute value of the prize was less than 8,000 points, or if the lottery was not the optimal choice under any value of the parameters in the prior. This question set was chosen to provide sufficient flexibility for DOSE to elicit precise estimates, to ensure some variation in the questions respondents received, and computational constraints due to the need to simulate the question tree in advance.

Education: Education is measured on a six point scale, with categories including: No high school, graduated high school, some college, two-years of college, four-year college degree, and a postgraduate degree.

Income: Participants reported their income in sixteen categories, ranging from "Less than \$10,000" to "\$500,000 or more". 11% of participants chose not to state their income. We linearize this variable by taking the mid-points of each category (or use \$500,000 for the top category), and use random imputation to impute missing values of log income based on age, sex, education, and employment status. In robustness tests below we include the variable in quartiles and add a dummy variable capturing missing responses.

Sex: Sex was measured as a binary choice of "Male" or "Female".

Age: Participants were asked to state their birth year, which we convert into age. In robustness tests below we include the variable split into quartiles.

Marital Status: Participants reported their marital status in six categories: "Married", "Separated", "Divorced", "Widowed", "Never married", or "Domestic / civil partnership". We create a binary variable based on these responses.

Gambling Behavior: Gambling behavior was measured using a battery of questions adapted from Gonnerman and Lutz (2011) (see Figure E.32). Two principal components were extracted from this battery of measures—see Appendix D for scree plots.

Household Assets and Stock Investments: Participants were first asked to specify their financial assets, by answering: "the value of your bank accounts, brokerage accounts, retirement savings accounts, investment properties, etc., but NOT the value of the home(s) you live in or any private business you own." The following question then asked "What percentage of your investable financial assets is currently invested in stocks, either directly or through mutual funds?" These questions were taken from Choi and Robertson (2020).

For the analysis in Table 4, the value of household assets was linearized by taking the midpoint of each category (or \$1 in the bottom category, \$100,000 for the top category).

Household Shocks: Household shocks were measured using a battery of six binary questions adapted from Pew Research Center (2015, p4)—see Figure E.33 for an example. Specifically, participants were asked whether in the past 12 months,

1. In the past 12 months, has anyone in your household brought in less income than expected due to unemployment, a pay cut, or reduced hours?
2. In the past 12 months, has someone in your household suffered an illness or injury requiring a trip to the hospital?
3. In the past 12 months, has anyone in your household divorced, separated, or was widowed from a spouse or partner?

4. In the past 12 months, has anyone in your household needed a major repair or replacement to their car, truck, or SUV?
5. In the past 12 months, has the place you live in or any appliances needed major repair or replacement?
6. Has your household had some other large, unexpected expense in the past year? [If yes, add a text box with the question: Can you tell us a bit more about this expense?]

Two principal components were extracted from this battery of measures—see Appendix D for scree plots.

Attention Screeners: The survey included three questions designed to check a participant was paying attention. See Figures E.34–E.37 for question wording.

B Choice Data

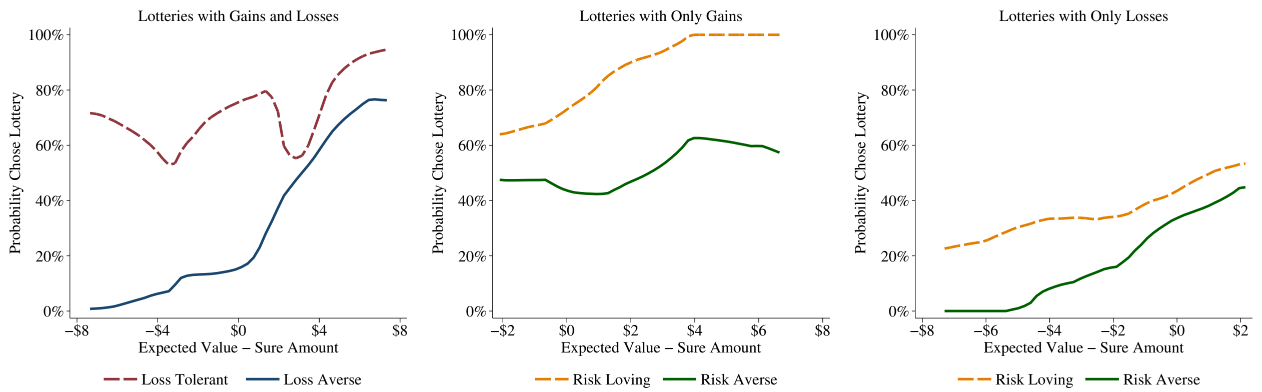
The analysis in the main text has primarily estimated loss aversion using parametric specifications. The parametric approach allows us to disentangle loss aversion from the curvature of the utility function, but could lead to concerns that the results are driven by our choice of utility function. In this Appendix we use the survey data to show that there is a clear pattern of choices underpinning our parametric estimates. First we demonstrate that the classification of loss tolerant by DOSE reflects participants accepting a number of negative-expected-value lotteries. The second subsection shows a similar pattern in the MPL choice data.

B.1 Choice Data From DOSE

The DOSE parameter estimates reflect clear patterns in choice, as shown in Figure B.1. In each panel we split participants according to their classification in the 20-question DOSE module. The x-axis is the difference between the expected value of a lottery and the sure amount in a given choice. The left-hand panel shows that loss-tolerant participants ($\lambda < 1$) are clearly more likely to choose lotteries with losses than those who are loss averse ($\lambda > 1$). Similar patterns exist for risk aversion over gains (middle panel) and losses (right hand panel): individuals classified as risk loving are more likely to choose gambles in the relevant domain at every expected value difference. For all six groups of participants, the probability of choosing the lottery generally increases with the difference between the expected value of the lottery and the sure amount. However, portions of the lines in each panel are flat, reflecting the fact that the questions participants receive are determined by their previous answers. For instance, in the left-hand panel, DOSE will only offer a question with expected value far below the sure amount to participants that have already revealed loss tolerance through prior choices of lotteries with large negative expected values. Selection into receiving questions with large expected value differences is thus not random.

Figure B.2 shows that our finding of widespread loss tolerance in the representative sample reflects a common tendency to accept negative-expected-value gambles. In both panels, we order participants according to the smallest expected value of a mixed lottery (offering both gains and losses) that they accepted in the 20-question (left-hand panel) and 10-question (right-hand

Figure B.1: A clear pattern of choices underpins the DOSE-elicited parameters.



Notes: The figure displays choices from the 20-question DOSE sequence using local mean regressions with Epanechnikov kernel and bandwidth 1. Loss Tolerant (Averse) refers to participants for who $\lambda < 1$ ($\lambda > 1$) according to the DOSE 20-question estimates. Similarly, Risk Averse (Loving) refers to participants for who $\rho < 1$ ($\rho > 1$) according to the DOSE 20-question estimates for lotteries with only gains, and $\rho > 1$ ($\rho < 1$) for lotteries with only losses.

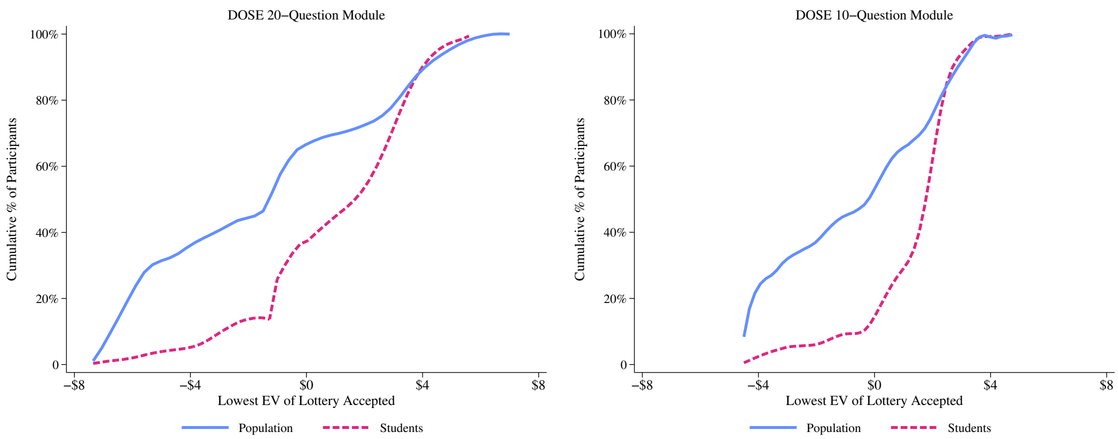
panel) DOSE modules. More than 64% of participants in the representative sample accepted at least one lottery with negative expected value in the 20-question module (left-hand panel) and 48% did so in the 10-question module (right-hand panel). These proportions are much higher than among students, of whom 35% and 12% accepted a negative-expected-value lottery in the respective modules.

Figure B.3 shows that the classification of participants as loss tolerant by DOSE reflects participants' willingness to accept lotteries with negative expected value, and is not an artefact of our parametric assumptions. Here, we investigate choices by examining the ratio between the possible gain (g) and the possible loss (l) for a mixed lottery accepted by participants (over a sure amount of \$0). This ratio offers a simple measure of the loss aversion coefficient: with linear utility, a participant should accept a mixed lottery if $\frac{g}{l} \geq \lambda$.[4] The figure shows that the DOSE-elicited parameters capture such choices: more than three-quarters of participants with estimated $\lambda > 2$ (bottom-right panel) accepted only lotteries with $\frac{g}{l} > 2$, while almost all participants with estimated $\lambda \leq 0.5$ (top-left panel) accepted a lottery with $\frac{g}{l} \leq 0.5$. These results offer further evidence that the DOSE parameter estimates reflect a widespread willingness to accept negative-expected-value lotteries.

There are clear differences in choices according to cognitive ability, as shown in Figure B.4. Similarly to Figure B.1, each panel displays the likelihood of accepting a lottery for each category of question. Now we compare the choices of participants according to their level of cognitive ability. Low-cognitive-ability participants consistently accept lotteries with negative expected value (left-hand-panel). High-cognitive-ability participants, in contrast, choose such lotteries less frequently. When lotteries contain only gains (middle panel) low-cognitive-ability participants are less likely to accept lotteries where the expected value exceeds the sure amount than participants with high cognitive ability—consistent with the negative correlation between risk aversion and cognitive ability reported in Table 1.

[4]We can also construct individual-level loss-aversion measures based on the range of $\frac{g}{l}$ values accepted by participants—doing so leads to an estimate of 53% of participants as loss tolerant.

Figure B.2: There is greater willingness to accept negative-expected-value gambles among the general population than among students.



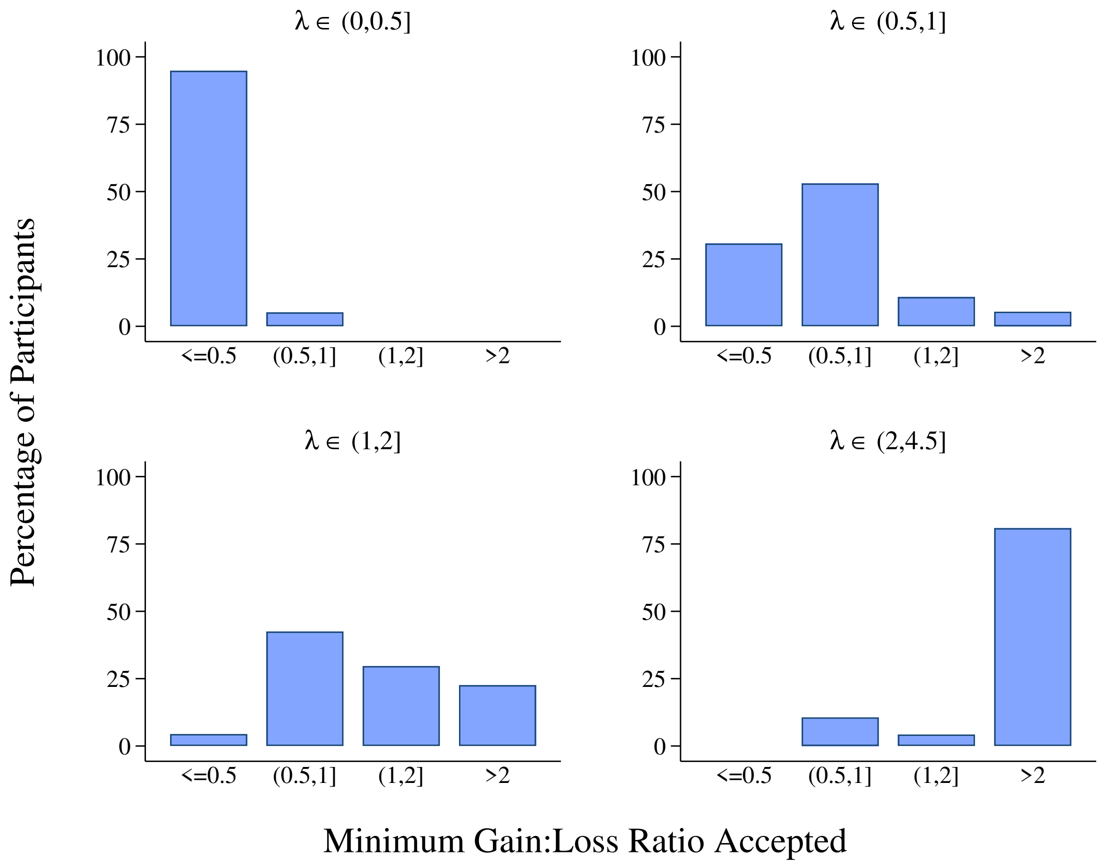
Notes: Each panel presents the cumulative density of participants, ranked according to the smallest expected value of a mixed lottery (i.e., offering both gains and losses) that they chose to accept. Densities are plotted using a local cubic polynomial, with a bandwidth of 0.5. The left-hand panel includes participants in the main survey sample, the right-hand panel includes participants in both the main and supplementary samples. Participants that never accepted a mixed lottery are excluded from the figure.

B.2 Choice Data from MPL Elicitations

Figure B.5 displays the choices made in the six MPL elicitations discussed in Section 5.1. The first two rows relate to the MPLs used to identify loss aversion, through eliciting lottery equivalents or certainty equivalents. The final row displays the two MPLs over only gains, which identify the curvature of the utility function. Choices in all six MPLs clump around salient rows, including at end-points of the distribution, and some choices are first-order stochastically dominated.

In the main text we use the MPL choice data to estimate Bayesian parameters. Alternatively, we can estimate loss aversion parameters using a double MPL method (Andersen et al., 2008; Andreoni and Sprenger, 2012), in which risk aversion is estimated separately by eliciting the certainty equivalent for a lottery over gains. This method is problematic because many participants select the (highly salient) top or bottom rows of the MPL leading to extreme parameter estimates (for example, $\lambda > 100$) or choices that are first-order stochastically dominated. Consequently, the method is unable to estimate λ for a significant proportion of the population: ranging from 10% to 42% of the sample across the four MPLs. However, we observe a high degree of loss tolerance among the subsample for which we obtain parameter estimates: between 39% and 62% of these participants are classified as loss tolerant.

Figure B.3: DOSE estimates of λ reflect participants' willingness to accept mixed lotteries.



Notes: Each panel of the figure represents different groups of participants, grouped according to the estimated λ elicited by the 20-question DOSE sequence. The bars in each panel represent the smallest gain-loss ratio in a mixed lottery accepted by the participant. Eight participants never accepted a mixed lottery and are excluded from the figure.

C Additional Results and Robustness

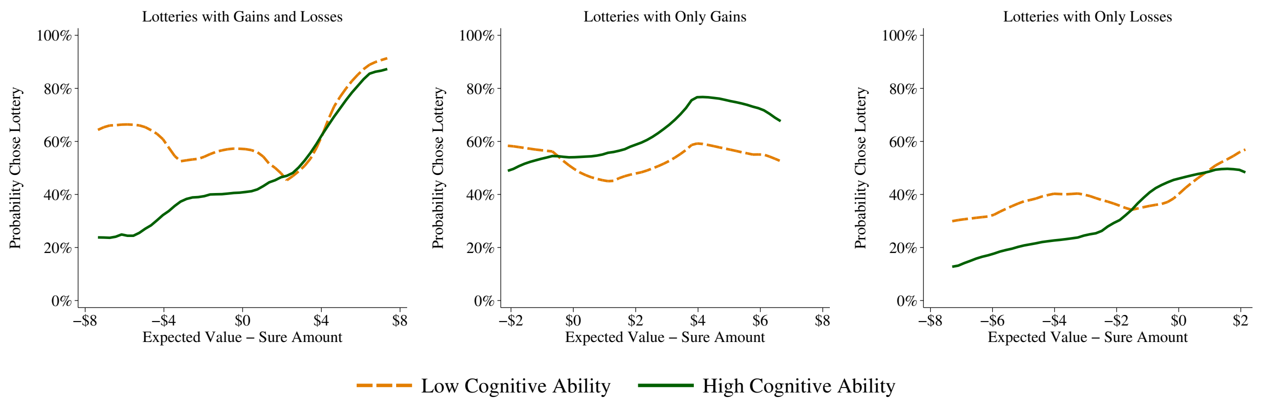
C.1 Alternative Utility Specifications

This Appendix presents the estimates, discussed in Section 5.2, obtained when allowing for the curvature of the utility function to differ between gains and losses, as suggested by Prospect Theory (Kahneman and Tversky, 1979). Specifically, we estimate the following unrestricted power utility function:

$$u(x, \rho_i^+, \rho_i^-, \lambda_i) = \begin{cases} u(x) = x^{\rho_i^+} & \text{for } x \geq 0 \\ u(x) = -\lambda_i(-x)^{\rho_i^-} & \text{for } x < 0 \end{cases} \tag{4}$$

We also re-estimate the loss aversion parameter using the exponential utility function suggested by Köbberling and Wakker (2005):

Figure B.4: Low-cognitive-ability participants make different choices to participants with high cognitive ability, supporting the correlations reported in Table 1.



Notes: The figure displays choices from the 20-question DOSE sequence using local mean regressions with Epanechnikov kernel and bandwidth 1. "Low" and "High" cognitive ability refer to the bottom and top terciles within the sample.

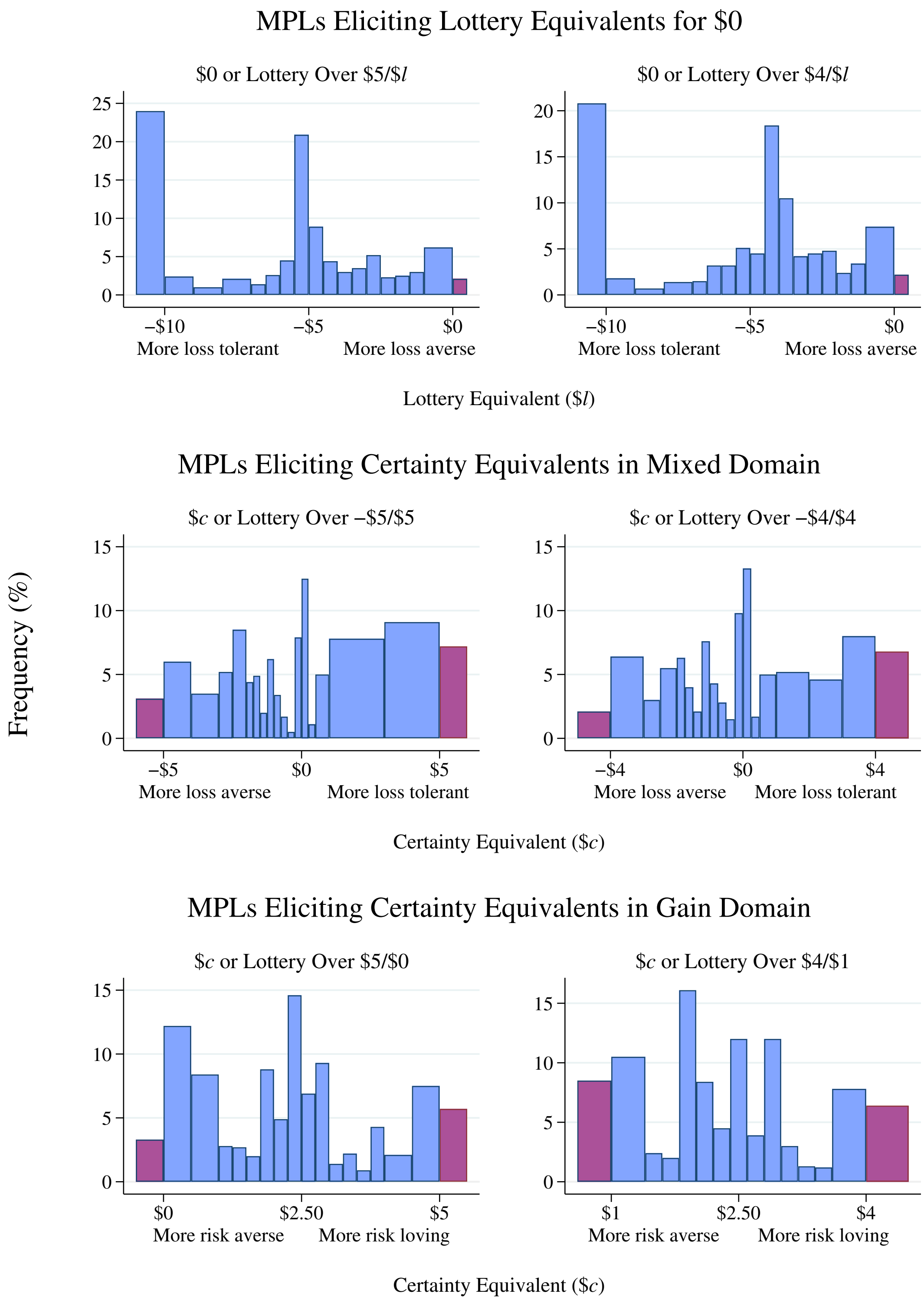
$$u(x, \gamma_i, \lambda_i) = \begin{cases} \frac{1-e^{-\gamma_i x}}{\gamma_i} & \text{for } x \geq 0 \\ \lambda_i \left(\frac{e^{\gamma_i x}-1}{\gamma_i} \right) & \text{for } x < 0 \end{cases} \tag{5}$$

where λ_i represents loss aversion (as in our main estimates) and γ_i captures risk aversion. This utility specification exhibits Constant Average Risk Aversion, and so we refer to the associated estimates as "CARA" in the following.

Our finding of widespread loss tolerance is robust to these alternative specifications as shown in Figure C.6. The left-hand panel presents results from re-estimating the data from the 20-question DOSE sequence using unrestricted CRRA utility curvature (specification (4) and CARA utility (specification 5). The right-hand panel presents the results from the 10-question DOSE sequence—the unrestricted CRRA model is not presented here, since the sequence did not include any questions involving only losses, and so we cannot identify utility curvature over losses. We can see that the CARA estimates are extremely similar to our main estimates. We observe more difference from our preferred estimates when allowing for differential curvature over gains and losses—more than two-thirds of the U.S. population are classified as loss tolerant by this specification.

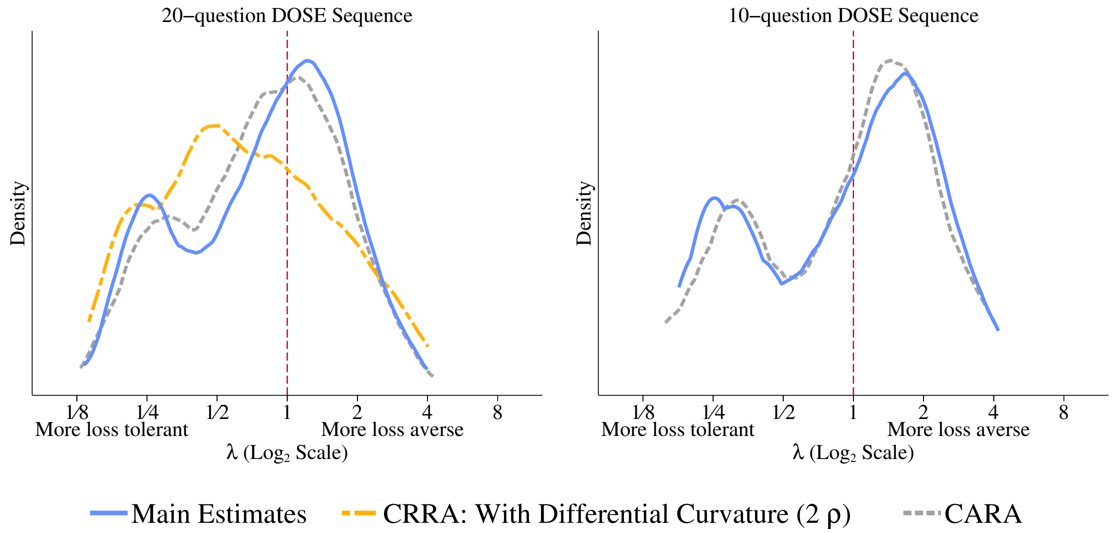
In Figure C.7 we investigate the estimates of risk aversion over gains and losses, obtained by estimating Specification 4. The left-hand panel shows that our risk aversion parameter in the main specification is closely correlated to the risk aversion over gains when allowing for differential curvature (r=0.59; s.e.=0.04). The restricted parameter is more weakly correlated with risk aversion over losses (r=-0.41; s.e.=0.04). The right-hand panel of the figure shows that the average risk aversion parameter is similar across the two domains, providing some support for our assumption that utility curvature is the same over gains and over losses. The mean difference in the two parameters is small, although statistically distinguishable from zero (-0.11; s.e.=0.03). These results are consistent with previous findings that utility over losses is closer to linearity (Booij et al., 2010). However, it is clear from the figure that there is considerable individual heterogeneity that is not captured by the average estimate.

Figure B.5: Choices in MPLs also show widespread loss tolerance.



Notes: All lotteries involved 50% probabilities of each outcome. Red bars at extremes of the MPL reflect choices that are first-order stochastically dominated.

Figure C.6: The finding of widespread loss tolerance is robust to alternative utility specifications ($N = 1,000$).



Notes: The figures display the kernel density of loss aversion (λ) parameters estimated from our main sample using various utility specifications, and plotted using an Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator. The "Main Estimates" refer to the specification in Equation (1), and classify 57% of participants as loss tolerant in the 20-question sequence, and 47% as loss tolerant in the 10-question sequence. "CRRA: With Differential Curvature" refers to the specification in Equation (4), and classifies 68% of participants as loss tolerant in the 20-question sequence (the 10-question sequence does not contain questions with only losses, and so we do not estimate this specification). "CARA" refers to the specification in Equation (5), and classifies 60% of participants as loss tolerant in the 20-question sequence, and 47% in the 10-question sequence.

C.2 Additional Correlations with Individual Characteristics

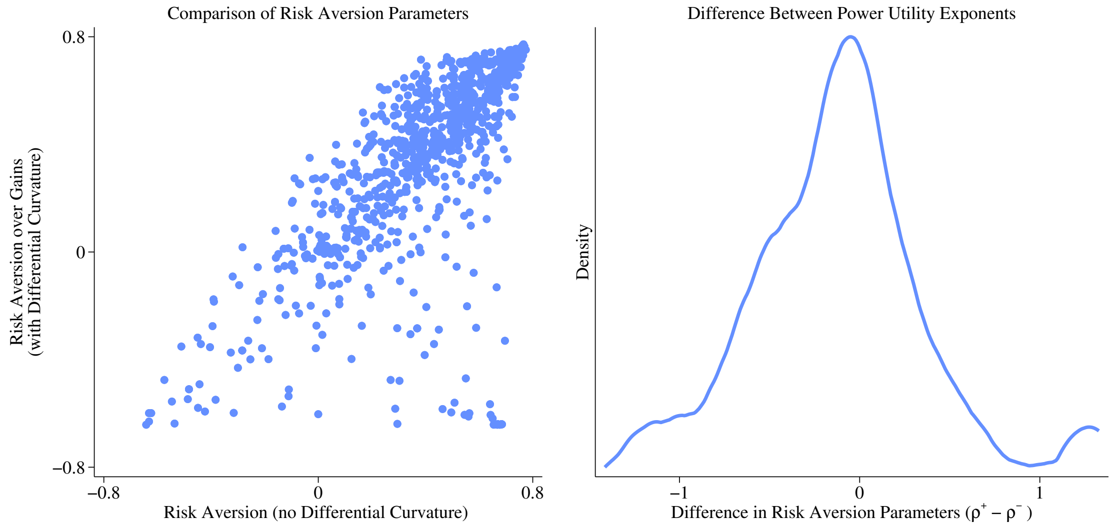
This appendix presents robustness tests relating to the correlations presented in Table 1. In addition, we present correlations relating to the choice consistency parameters and individual characteristics.

Table C.1 presents a fuller version of the univariate correlations contained in Table 1. The table separates the two components of our cognitive ability measure, and also includes variables relating to race and employment status. The final two columns include correlations with the choice consistency measure estimated by the two DOSE sequences. Perhaps surprisingly, higher-cognitive-ability participants make less consistent choices in DOSE, although the correlation is relatively small, and not as robust, the correlations with the loss and risk aversion parameters.

Table C.2 repeats the analysis, but using unweighted Spearman rank correlations. The pattern of correlations is similar to our main results—if anything, the relationship between individual characteristics and both loss and risk aversion is slightly stronger.

Table C.3 demonstrates that the multivariate regression results reported in Table 1 are robust to alternative variable definitions. The first and fourth column in this table replicate the results in the main text, but include the control variables as categorical, rather than continuous, variables. The remaining specifications include cognitive ability split into terciles, rather than as a continuous variable—first with continuous controls (second and fifth specifications) and

Figure C.7: Comparison of Risk Aversion over Gains and Losses



<u>Notes:</u> The left-hand panel compares the estimates of risk aversion over gains (y-axis) to the risk aversion parameter when imposing the same curvature over gains and losses (our main specification, x-axis). The right-hand panel displays the density of the difference in the risk aversion parameters over gains and losses when estimating Specification (4).

then the categorical controls (third and sixth specifications). There is strong evidence that higher cognitive ability is associated with being more loss averse, and less risk averse, in all specifications.

There is evidence of a strong correlation between cognitive ability and loss aversion even in the absence of parametric assumptions, as we can see in Table C.5. Here we use choices in our survey to estimate correlations with individual characteristics without any assumptions about the form of the utility function. The first two specifications use the lottery equivalents and certainty equivalents from the MPLs discussed in Section 5.1, without seeking to distinguish loss aversion from utility curvature. Similarly, the fourth specification uses the certainty equivalents from the two MPLs over gains to estimate risk aversion. The third and fifth specifications estimate risk preferences using the four fixed binary choices received by all survey participants. The two choices in specification 3 offer a sure amount of \$0, or a lottery between a gain and similarly sized loss: i) \$0 for sure, or a lottery between \$10 and -\$12, each with 50% probability, and ii) \$0 for sure, or a lottery between \$10 and -\$12, each with 50% probability. The fifth specification uses two lotteries over only gains: i) a fixed amount of \$5.90, or a lottery between \$0 and \$15, each with 50% probability, and ii) a fixed amount of \$5.20, or a lottery between \$0 and \$10, each with 50% probability.

The pattern of correlations with these non-parametric measures is similar—but noisier—to those in Table 1. Cognitive ability is again strongly positively correlated with all three measures of loss aversion. We also observe a negative correlation between our risk aversion measure and cognitive ability, although in this case it is not statistically significant. The patterns for education, sex, and age, are also similar to those in previous tables but, again, not always statistically significant). The differences may be explained by the level of noise in the MPL measures given that—in contrast to the Bayesian estimates in Table C.4—here we are not accounting for choice inconsistency (see Chapman et al., 2018).

Table C.1: Additional correlations between DOSE-elicited parameters and individual characteristics.

	Loss Aversion (λ)		Risk Aversion (1-ρ)		Choice Consistency (μ)	
DOSE Sequence	20Q	10Q	20Q	10Q	20Q	10Q
Cognitive Ability	0.20***	0.21***	-0.30***	-0.11***	-0.13***	-0.06**
	(0.044)	(0.024)	(0.044)	(0.024)	(0.040)	(0.024)
IQ	0.16***	0.17***	-0.26***	-0.11***	-0.14***	-0.05**
	(0.045)	(0.027)	(0.047)	(0.025)	(0.039)	(0.025)
CRT	0.19***	0.19***	-0.26***	-0.09***	-0.05	-0.04
	(0.044)	(0.024)	(0.039)	(0.025)	(0.042)	(0.026)
Income (Log)	0.10**	0.09***	-0.03	-0.07**	-0.07	-0.00
	(0.050)	(0.027)	(0.066)	(0.032)	(0.064)	(0.035)
Income (Categories)	0.07	0.12***	-0.03	-0.10***	-0.05	-0.05
	(0.053)	(0.028)	(0.060)	(0.029)	(0.058)	(0.030)
Education	0.16***	0.12***	-0.12**	-0.04	-0.07	-0.03
	(0.045)	(0.026)	(0.051)	(0.028)	(0.051)	(0.027)
Male	-0.06	0.05*	-0.05	-0.11***	-0.01	-0.03
	(0.049)	(0.028)	(0.048)	(0.028)	(0.047)	(0.028)
Age	-0.05	-0.09***	0.14***	0.08***	0.09*	0.07**
	(0.054)	(0.028)	(0.053)	(0.030)	(0.053)	(0.030)
Married	0.01	0.03	0.07	0.02	0.07	0.04
	(0.050)	(0.028)	(0.049)	(0.028)	(0.048)	(0.028)
Employed	0.00	0.06	0.02	-0.02	0.00	0.02
	(0.074)	(0.047)	(0.080)	(0.046)	(0.083)	(0.050)
Not White	-0.14***	-0.14***	0.01	0.01	-0.03	0.03
	(0.048)	(0.027)	(0.054)	(0.030)	(0.054)	(0.031)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Standard errors, in parenthesis, come from a standardized regression. Each cell corresponds to a single regression. $N = 1,000$ for the 20-question (20Q) DOSE sequence, and $N = 3,000$ for the 10-question (10Q) sequence. Due to non-response, when using "Income (Categories)" the number of observations is 889 for the 20-question sequence, and 2,629 for the 10-question sequence. When using "Employed" the number of observations is 511 for the 20-question sequence, and 1,634 for the 10-question sequence, as participants outside the labor force (for example, if they are retired) are excluded.

We observe a similar pattern of correlations between loss aversion and other individual characteristics regardless of the utility specification used, as we can see in Table C.7. Higher cognitive ability is consistently associated with being more loss averse. When we allow for differential curvature in the loss domain, we observe that high cognitive ability is also associated with more risk aversion over losses, in addition to being associated with a higher value of λ (representing a kink at the reference point). However, higher cognitive ability is associated with being less risk averse over gains with each of the utility specifications.

Table C.2: Spearman Rank unweighted correlations between DOSE-elicited parameters and individual characteristics.

	Loss Aversion (λ)		Risk Aversion (1-ρ)		Choice Consistency (μ)	
DOSE Sequence	20Q	10Q	20Q	10Q	20Q	10Q
Cognitive Ability	0.22***	0.26***	-0.32***	-0.19***	-0.04	-0.04***
	(0.031)	(0.018)	(0.030)	(0.018)	(0.032)	(0.018)
IQ	0.17***	0.21***	-0.26***	-0.16***	-0.07**	-0.04**
	(0.031)	(0.018)	(0.031)	(0.018)	(0.032)	(0.018)
CRT	0.20***	0.25***	-0.29***	-0.17***	0.02	-0.03
	(0.031)	(0.018)	(0.030)	(0.018)	(0.032)	(0.018)
Income (Log)	0.09***	0.12***	-0.14***	-0.12***	-0.01	-0.00
	(0.032)	(0.018)	(0.031)	(0.018)	(0.032)	(0.018)
Income (Categories)	0.08***	0.14***	-0.13***	-0.13***	0.02	-0.00
	(0.033)	(0.019)	(0.033)	(0.019)	(0.034)	(0.020)
Education	0.19***	0.15***	-0.18***	-0.08***	0.01	-0.02
	(0.031)	(0.018)	(0.031)	(0.018)	(0.032)	(0.018)
Male	-0.00	0.05***	-0.11***	-0.14***	0.04	-0.04**
	(0.032)	(0.018)	(0.031)	(0.018)	(0.032)	(0.018)
Age	-0.02	-0.05***	0.07**	0.05***	0.05	0.03
	(0.032)	(0.018)	(0.032)	(0.018)	(0.032)	(0.018)
Married	0.04	0.04**	-0.01	-0.01	0.04	0.02
	(0.032)	(0.018)	(0.032)	(0.018)	(0.032)	(0.018)
Employed	0.01	0.07***	-0.04	-0.06***	0.03	0.01
	(0.044)	(0.025)	(0.044)	(0.025)	(0.044)	(0.025)
Not White	-0.06*	-0.09***	0.03	0.04*	-0.10***	0.01
	(0.032)	(0.018)	(0.032)	(0.018)	(0.032)	(0.018)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Each cell corresponds to the unweighted Spearman Rank correlation between the column and row variables. $N = 1,000$ for the 20-question (20Q) DOSE sequence, and $N = 3,000$ for the 10-question (10Q) sequence. Due to non-response, when using "Income (Categories)" the number of observations is 889 for the 20-question sequence, and 2,629 for the 10-question sequence. When using "Employed" the number of observations is 511 for the 20-question sequence, and 1,634 for the 10-question sequence, as participants outside the labor force (for example, if they are retired) are excluded.

Table C.3: Correlations between economic preferences and cognitive ability are robust to alternative definition of control variables ($N = 1,000$).

	Loss Aversion (λ)			Risk Aversion (1-ρ)		
Cognitive Ability Measure:						
Continuous	0.18***			-0.29***		
	(0.049)			(0.045)		
Categorical:						
Medium		0.33***	0.36***		-0.22**	-0.22**
		(0.117)	(0.119)		(0.110)	(0.110)
High		0.40***	0.42***		-0.64***	-0.64***
		(0.131)	(0.130)		(0.113)	(0.113)
Continuous Controls	N	Y	N	N	Y	N
Categorical Controls	Y	N	Y	Y	N	Y

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. Loss aversion and risk aversion are standardized. "Medium" and "High" cognitive ability refer to the second and third terciles. "Continuous Controls" include the set of variables reported in Table 1. "Categorical Controls" include the same variables but in categorical form—including quartiles of income (and an indicator variable for missing values) and age, and six levels of education. Robust standard errors are displayed in parentheses.

Table C.4: Correlations between MPL-elicited parameters and individual characteristics ($N = 1,000$).

	Loss Aversion (λ)		Risk Aversion (1-ρ)		Choice Consistency (μ)	
Elicitation	LEs	CEs	LEs	CEs	LEs	CEs
Cognitive Ability	0.14***	0.15***	-0.12***	-0.16***	0.07	0.06
	(0.040)	(0.042)	(0.043)	(0.041)	(0.048)	(0.045)
IQ	0.13***	0.11***	-0.12***	-0.15***	0.02	0.04
	(0.042)	(0.044)	(0.046)	(0.045)	(0.052)	(0.045)
CRT	0.10**	0.15***	-0.07*	-0.11***	0.13***	0.07
	(0.045)	(0.042)	(0.041)	(0.041)	(0.041)	(0.046)
Income (Log)	0.10**	0.06	-0.12**	-0.16***	-0.00	0.02
	(0.049)	(0.048)	(0.053)	(0.056)	(0.051)	(0.056)
Income (Categories)	0.07	0.06	-0.12**	-0.16***	0.00	0.02
	(0.056)	(0.052)	(0.052)	(0.053)	(0.052)	(0.055)
Education	0.12***	0.08*	-0.04	-0.09*	0.10**	0.08
	(0.044)	(0.043)	(0.049)	(0.051)	(0.048)	(0.052)
Male	0.04	-0.05	-0.14***	-0.07	-0.11**	0.01
	(0.048)	(0.046)	(0.047)	(0.049)	(0.047)	(0.049)
Age	0.04	-0.14***	0.11**	0.04	0.05	-0.05
	(0.043)	(0.050)	(0.054)	(0.056)	(0.054)	(0.053)
Married	0.03	-0.01	0.07	0.03	0.08*	-0.02
	(0.047)	(0.047)	(0.048)	(0.050)	(0.047)	(0.049)
Employed	0.10*	-0.03	-0.06	-0.12	0.11	0.09
	(0.055)	(0.069)	(0.080)	(0.072)	(0.074)	(0.066)
Not White	-0.08	-0.13***	0.03	0.11**	-0.10**	0.00
	(0.050)	(0.047)	(0.051)	(0.053)	(0.050)	(0.053)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. The table displays correlations between individual characteristics and the MPL-elicited parameters discussed in Section 5.1. "LEs" refers to the two MPLs eliciting lottery equivalents, and "CEs" to the two MPLs eliciting certainty quivalents. Robust standard errors, in parentheses, come from a standardized regression. Each cell corresponds to a single regression. Due to non-response, when using "Income (Categories)" the number of observations is 889. When using "Employed" the number of observations is 511 for the 20-question sequence, and 1,634 for the 10-question sequence, as participants outside the labor force (for example, if they are retired) are excluded.

Table C.5: Correlations between non-parametric preference measures and individual characteristics ($N = 1,000$).

	Loss Aversion (λ)			Risk Aversion (1-ρ)	
Elicitation	MPL LEs	MPL CEs	Binary Choices	MPLs CEs	Binary Choices
Cognitive Ability	0.22***	0.14***	0.23***	-0.02	-0.04
	(0.044)	(0.042)	(0.046)	(0.047)	(0.048)
IQ	0.21***	0.11***	0.18***	-0.02	-0.04
	(0.041)	(0.047)	(0.050)	(0.049)	(0.048)
CRT	0.15***	0.13***	0.23***	0.01	-0.02
	(0.048)	(0.038)	(0.044)	(0.040)	(0.050)
Income (Log)	0.15***	0.04	0.15***	-0.10*	0.01
	(0.052)	(0.050)	(0.049)	(0.056)	(0.058)
Income (Categories)	0.13***	0.04	0.13***	-0.07	0.01
	(0.052)	(0.054)	(0.051)	(0.053)	(0.054)
Education	0.15***	0.09**	0.20***	0.04	0.00
	(0.047)	(0.044)	(0.046)	(0.052)	(0.050)
Male	0.04	-0.01	-0.00	-0.15***	-0.10**
	(0.047)	(0.047)	(0.049)	(0.048)	(0.049)
Age	-0.04	-0.08*	-0.03	0.08	0.13**
	(0.048)	(0.048)	(0.055)	(0.054)	(0.058)
Married	0.06	0.02	0.03	0.09*	0.05
	(0.047)	(0.047)	(0.049)	(0.049)	(0.049)
Employed	0.12*	-0.07	0.08	-0.01	0.08
	(0.071)	(0.068)	(0.078)	(0.082)	(0.073)
Not White	-0.11**	-0.11**	-0.08	-0.05	-0.08
	(0.051)	(0.051)	(0.052)	(0.056)	(0.052)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. The table displays correlations between individual characteristics and non-parametric measures of each preference. "MPL LEs" is the average of two lottery equivalents for a sure amount of $0. "MPL CEs" is the average of two certainty equivalents for a lottery between a possible loss and possible gain. "Binary choices" involved choices between a lottery and a sure amount. See text for further details. Robust standard errors, in parentheses, come from a standardized regression. Each cell corresponds to a single regression. Due to non-response, when using "Income (Categories)" the number of observations is 889. When using "Employed" the number of observations is 511 for the 20-question sequence, and 1,634 for the 10-question sequence, as participants outside the labor force (for example, if they are retired) are excluded.

Table C.6: Correlations between individual characteristics and economic preferences are robust to checks for fatigue and inattention.

	Loss Aversion (λ):					Risk Aversion (1-ρ):				
Subgroup	Below Median Resp Time.	Above Median Resp. Time	Passed Attention Checks	DOSE Early in Survey	DOSE Late in Survey	Below Median Resp Time.	Above Median Resp. Time	Passed Attention Checks	DOSE Early in Survey	DOSE Late in Survey
Cognitive Ability	0.18***	0.22***	0.16***	0.20***	0.19***	-0.32***	-0.28***	-0.29***	-0.27***	-0.33***
	(0.068)	(0.056)	(0.045)	(0.063)	(0.062)	(0.060)	(0.064)	(0.046)	(0.064)	(0.062)
Income (Log)	0.15***	0.05	0.10*	-0.04	0.25***	-0.03	-0.03	-0.08	0.03	-0.09
	(0.060)	(0.075)	(0.056)	(0.076)	(0.054)	(0.091)	(0.095)	(0.070)	(0.090)	(0.095)
Education	0.12*	0.19***	0.12***	0.07	0.23***	-0.11*	-0.14*	-0.12**	-0.13*	-0.11
	(0.066)	(0.060)	(0.048)	(0.062)	(0.062)	(0.064)	(0.075)	(0.054)	(0.073)	(0.072)
Male	-0.11	-0.01	-0.07	0.03	-0.13**	-0.03	-0.08	-0.07	-0.02	-0.08
	(0.066)	(0.071)	(0.052)	(0.073)	(0.065)	(0.066)	(0.069)	(0.049)	(0.069)	(0.066)
Age	-0.16**	0.05	-0.12**	-0.02	-0.09	0.10	0.20**	0.22***	0.12	0.17***
	(0.070)	(0.077)	(0.058)	(0.076)	(0.075)	(0.063)	(0.089)	(0.052)	(0.082)	(0.069)
Married	-0.03	0.06	0.01	-0.01	0.03	0.12*	0.03	0.07	0.05	0.09
	(0.067)	(0.075)	(0.054)	(0.073)	(0.068)	(0.065)	(0.073)	(0.051)	(0.070)	(0.069)
N	489	511	896	487	513	489	511	896	487	513

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. The table displays univariate correlations between each economic preference (in columns) and other individual characteristics (in rows)—as in columns (1) and (3) of Table 1 for various subgroups. "Below" and "Above" Median Response Time refer to response time on the entire survey. "Passed attention checks" includes participants passing all three attention checks on the survey. "DOSE Early" and "DOSE Late" refer to the position of the 20-question DOSE sequence in the survey. Robust standard errors, in parentheses, come from a standardized regression.

Table C.7: Correlations between individual characteristics and economic preferences are robust to alternative utility specifications.

	DOSE-Elicited Preference Parameter										
	Loss Aversion:						Risk Aversion:				
Utility Specification	CRRA (1ρ)	CARA	CRRA (2ρ)	CRRA (1ρ)	CARA	CRRA (2ρ)	CRRA (1ρ)	CARA	CRRA (2ρ)	CRRA (1ρ)	CARA
Parameter	λ	λ	λ	λ	λ	$1-\rho^{-}$	$1-\rho$	γ	$1-\rho^{+}$	$1-\rho$	γ
DOSE Sequence	20Q	20Q	20Q	10Q	10Q	20Q	20Q	20Q	20Q	10Q	10Q
Cognitive Ability	0.20***	0.19***	0.20***	0.21***	0.20***	0.26***	-0.30***	-0.30***	-0.12**	-0.11***	-0.15***
	(0.044)	(0.044)	(0.038)	(0.024)	(0.024)	(0.040)	(0.044)	(0.043)	(0.051)	(0.024)	(0.025)
Income (Log)	0.10**	0.09*	0.09*	0.09***	0.08***	0.04	-0.03	-0.07	0.03	-0.07**	-0.10***
	(0.050)	(0.049)	(0.047)	(0.027)	(0.027)	(0.054)	(0.066)	(0.059)	(0.061)	(0.032)	(0.031)
Education	0.16***	0.15***	0.13***	0.12***	0.12***	0.11***	-0.12**	-0.15***	-0.03	-0.04	-0.06**
	(0.045)	(0.043)	(0.044)	(0.026)	(0.026)	(0.047)	(0.051)	(0.049)	(0.056)	(0.028)	(0.028)
Male	-0.06	-0.05	0.06	0.05*	0.04	-0.09*	-0.05	-0.06	-0.13***	-0.11***	-0.11***
	(0.049)	(0.048)	(0.045)	(0.028)	(0.027)	(0.047)	(0.048)	(0.048)	(0.051)	(0.028)	(0.027)
Age	-0.05	-0.04	0.05	-0.09***	-0.08***	-0.12**	0.14***	0.12**	0.11*	0.08***	0.07***
	(0.054)	(0.052)	(0.048)	(0.028)	(0.028)	(0.052)	(0.053)	(0.052)	(0.058)	(0.030)	(0.029)
Married	0.01	0.02	0.06	0.03	0.03	-0.05	0.07	0.03	0.07	0.02	0.01
	(0.050)	(0.049)	(0.045)	(0.028)	(0.027)	(0.049)	(0.049)	(0.049)	(0.051)	(0.028)	(0.027)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. The table displays univariate correlations between each economic preference (in columns) and other individual characteristics (in rows)—as in columns (1) and (3) of Table 1. $N = 1,000$ for the 20-question (20Q) DOSE sequence, and $N = 3,000$ for the 10-question (10Q) sequence. Robust standard errors, in parentheses, come from a standardized regression.

Table C.8: The relationship between loss aversion and gambling is robust to using alternative definition of control variables ($N = 1{,}000$).

	Non-Casual Gambling			Casual Gambling		
Loss Aversion (λ)	-0.11**	-0.12**	-0.11**	-0.10**	-0.11***	-0.09**
	(0.050)	(0.049)	(0.047)	(0.048)	(0.041)	(0.042)
Risk Aversion (1 - ρ)	0.02	0.07	0.04	0.01	0.02	-0.01
	(0.050)	(0.050)	(0.047)	(0.053)	(0.048)	(0.048)
Cognitive Ability:						
Medium	0.08		-0.03	-0.12		-0.13
	(0.131)		(0.114)	(0.113)		(0.100)
High	-0.13		-0.31***	-0.33***		-0.37***
	(0.098)		(0.115)	(0.117)		(0.105)
Control Variables	N	Y	Y	N	Y	Y

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. The dependent variables, loss aversion, and risk aversion are standardized. "Medium" and "High" cognitive ability refer to the second and third terciles. "Control Variables" include the set of variables reported in Table 3, but in categorical form—including quartiles of income (and an indicator variable for missing values) and age, and six levels of education. Robust standard errors are displayed in parentheses.

Table C.9: No evidence of a relationship between risk aversion and gambling when excluding loss aversion ($N = 1{,}000$).

	Non-Casual Gambling			Casual Gambling		
Risk Aversion (1 - ρ)	0.05	0.03	0.05	0.07	0.02	-0.02
	(0.052)	(0.051)	(0.051)	(0.050)	(0.051)	(0.044)
Cognitive Ability		-0.07	-0.15***		-0.15***	-0.16***
		(0.045)	(0.052)		(0.046)	(0.044)
Education			0.02			-0.06
			(0.050)			(0.048)
Income (Log)			0.11*			0.02
			(0.062)			(0.051)
Age			-0.20***			0.22***
			(0.066)			(0.050)
Male			0.47***			0.19**
			(0.101)			(0.088)
Married			-0.17			0.01
			(0.108)			(0.089)
Owns Home			0.21*			0.23**
			(0.119)			(0.094)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses.

C.3 Additional Regressions with Real World Behaviors

Table C.10: The relationships between loss aversion and financial outcomes are similar when using alternative definition of control variables ($N = 1{,}000$).

	Financial Shocks		Personal Shocks		Financial Assets (Log)	
Loss Aversion (λ)	-0.13***	-0.13***	-0.02	-0.01	0.11**	0.08**
	(0.045)	(0.042)	(0.052)	(0.046)	(0.048)	(0.038)
Risk Aversion (1-ρ)	-0.07	-0.04	0.04	0.06	0.10	0.05
	(0.050)	(0.048)	(0.052)	(0.053)	(0.067)	(0.046)
Cognitive Ability:						
Medium	0.08	0.02	0.09	0.12	0.30***	0.15*
	(0.117)	(0.103)	(0.127)	(0.124)	(0.105)	(0.084)
High	0.15	0.10	0.01	0.08	0.41***	0.13
	(0.112)	(0.104)	(0.108)	(0.125)	(0.120)	(0.095)
Control Variables	N	Y	N	Y	N	Y

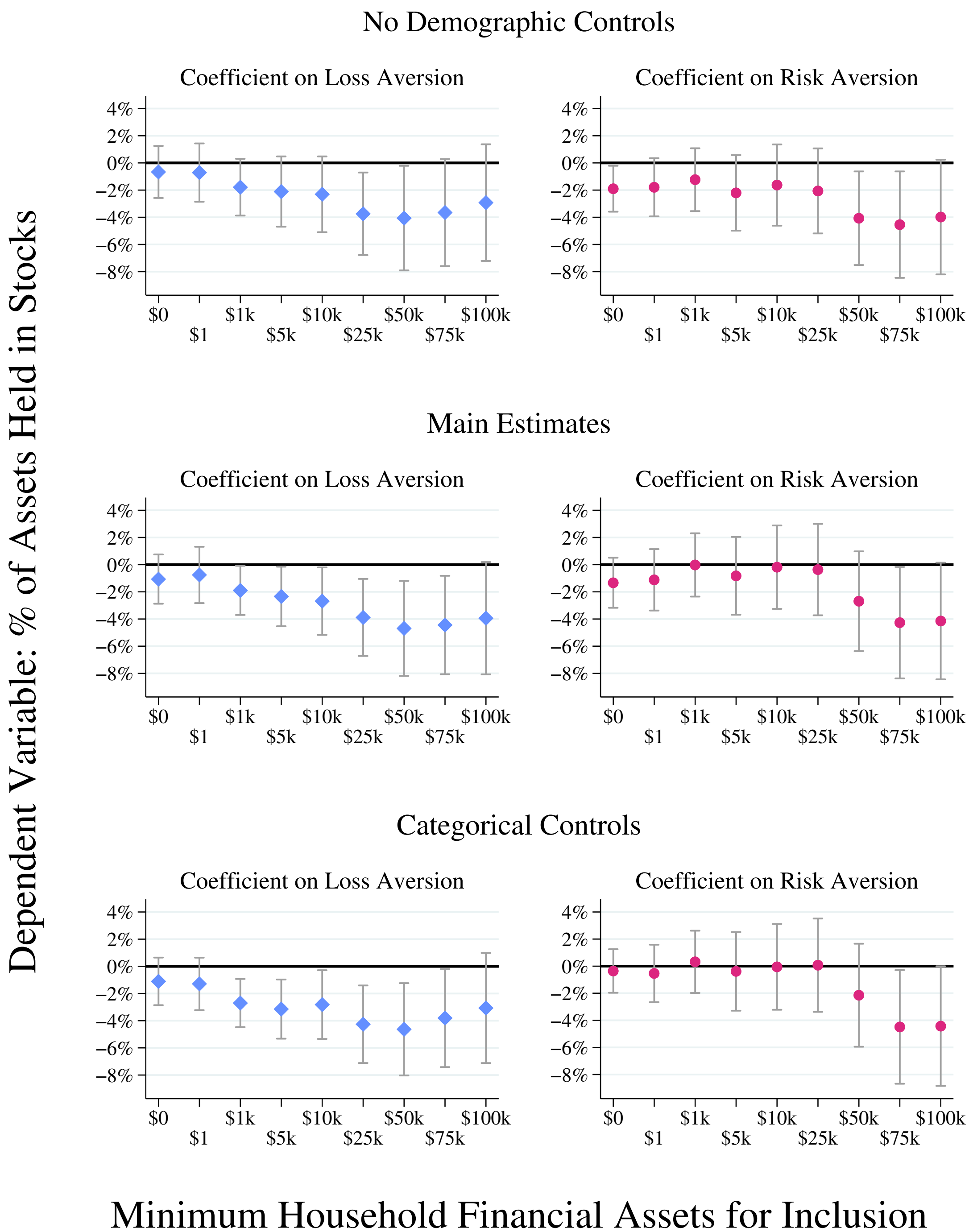
Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. The dependent variables, loss aversion, and risk aversion are standardized. "Medium" and "High" cognitive ability refer to the second and third terciles. "Control Variables" include the set of variables reported in Table 4, but in categorical form—including quartiles of income (and an indicator variable for missing values) and age, and six levels of education. Robust standard errors are displayed in parentheses.

Table C.11: No evidence of a relationship between risk aversion and either household shocks or financial assets when excluding loss aversion ($N = 1{,}000$).

	Financial Shocks		Personal Shocks		Financial Assets (Log)	
Risk Aversion (1-ρ)	-0.07	-0.02	0.04	0.05	0.03	0.05
	(0.053)	(0.050)	(0.056)	(0.051)	(0.072)	(0.042)
Cognitive Ability		0.06		0.01		0.07*
		(0.045)		(0.046)		(0.040)
Education		0.05		-0.09*		0.09**
		(0.050)		(0.052)		(0.039)
Income (Log)		-0.14**		0.13*		0.41***
		(0.064)		(0.068)		(0.055)
Age		-0.16***		-0.01		0.08*
		(0.053)		(0.058)		(0.046)
Male		0.14		0.06		-0.06
		(0.092)		(0.103)		(0.075)
Married		0.23**		-0.16		-0.01
		(0.098)		(0.113)		(0.091)
Owns Home		-0.16		-0.35**		0.35***
		(0.103)		(0.138)		(0.092)

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses.

Figure C.8: Relationship between stock investments and economic preferences is robust to alternative definition of control variables ($N = 1,000$).



Notes: The figure displays the results from estimating the regressions reported in Figure 8 and Table C.12, with alternative sets of control variables. Error bars represent 90% confidence intervals. "No demographic controls" indicates that the only control is log financial assets. "Main estimates" includes the control variables listed in Table C.12. "Categorical controls" includes the same set of variables, but in categorical form—including tercile of cognitive ability, quartiles of income (and an indicator variable for missing values) and age, and six levels of education.

Table C.12: Full Results of Regressions Reported in Figure 8

	DV=% Household Financial Assets in Stock Market								
Household Assets:	$\geq$ \$0	$\geq$ \$1	$\geq$ \$1k	$\geq$ \$5k	$\geq$ \$10k	$\geq$ \$25k	$\geq$ \$50k	$\geq$ \$75k	$\geq$ \$100k
Loss Aversion (λ)	-1.06	-0.76	-1.90*	-2.34*	-2.68*	-3.89**	-4.69**	-4.44**	-3.94
	(1.103)	(1.260)	(1.100)	(1.332)	(1.510)	(1.723)	(2.127)	(2.202)	(2.511)
Risk Aversion ($1-\rho$)	-1.33	-1.12	-0.02	-0.82	-0.19	-0.36	-2.69	-4.27*	-4.15
	(1.120)	(1.374)	(1.416)	(1.741)	(1.866)	(2.045)	(2.230)	(2.494)	(2.609)
Financial Assets (Log)	8.92***	23.32***	32.29***	40.39***	57.18***	78.54***	33.37	269.53	
	(0.881)	(2.369)	(3.623)	(5.352)	(8.283)	(17.706)	(35.508)	(164.259)	
Cognitive Ability	1.03	0.23	1.11	1.39	1.30	1.45	0.96	1.04	0.54
	(1.181)	(1.293)	(1.249)	(1.440)	(1.576)	(1.746)	(1.908)	(2.063)	(2.259)
Education	5.20***	5.06***	5.59***	6.34***	5.89***	5.20**	6.92***	6.24**	6.76**
	(1.233)	(1.314)	(1.425)	(1.618)	(1.788)	(2.167)	(2.487)	(2.777)	(3.015)
Income (Log)	3.74***	3.06**	3.66**	3.77*	4.28*	4.20*	2.43	0.32	1.01
	(1.307)	(1.455)	(1.714)	(2.166)	(2.297)	(2.509)	(2.491)	(3.485)	(3.564)
Male	4.53**	4.56**	3.92*	4.56*	3.19	2.01	1.63	-1.36	-1.54
	(2.044)	(2.281)	(2.340)	(2.698)	(2.978)	(3.317)	(3.729)	(4.142)	(4.361)
Age	3.17***	2.82**	2.18	2.22	3.03**	3.72**	4.82**	5.36**	6.48**
	(1.085)	(1.235)	(1.345)	(1.497)	(1.529)	(1.744)	(2.231)	(2.710)	(2.832)
Married	0.50	-1.17	-0.68	-1.86	-2.97	-3.19	0.14	4.50	3.04
	(2.180)	(2.390)	(2.596)	(3.001)	(3.424)	(3.971)	(4.431)	(5.649)	(6.261)
Owns Home	5.97**	3.92	3.83	4.61	0.43	-3.08	-0.86	-3.89	-5.83
	(2.364)	(2.581)	(2.902)	(3.462)	(3.921)	(4.936)	(5.898)	(6.785)	(7.379)
Observations	1,000	902	792	672	593	497	410	354	317

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses. As total financial assets is categorical, this variable contains only one value in the right-most column, hence there is no regression coefficient on that variable in that column.

Table C.13: Relationship between risk aversion and stock ownership is similar when excluding loss aversion.

	DV=% Household Financial Assets in Stock Market								
Household Assets:	$\geq$ \$0	$\geq$ \$1	$\geq$ \$1k	$\geq$ \$5k	$\geq$ \$10k	$\geq$ \$25k	$\geq$ \$50k	$\geq$ \$75k	$\geq$ \$100k
Risk Aversion (1-ρ)	-1.22	-1.00	0.27	-0.59	-0.01	-0.25	-2.71	-4.64*	-4.35
	(1.128)	(1.379)	(1.373)	(1.727)	(1.878)	(2.098)	(2.345)	(2.618)	(2.727)
Financial Assets (Log)	8.81***	23.25***	31.98***	39.57***	55.44***	75.95***	23.51	257.01	
	(0.891)	(2.364)	(3.689)	(5.526)	(8.366)	(17.957)	(36.656)	(175.535)	
Cognitive Ability	0.88	0.11	0.78	0.99	0.89	1.04	0.45	0.44	0.03
	(1.147)	(1.244)	(1.269)	(1.478)	(1.629)	(1.830)	(2.014)	(2.145)	(2.350)
Education	5.11***	5.01***	5.48***	6.19***	5.64***	4.84**	6.39**	5.66**	6.15**
	(1.238)	(1.315)	(1.440)	(1.643)	(1.813)	(2.232)	(2.581)	(2.849)	(3.058)
Income (Log)	3.73***	3.10**	3.78**	3.97*	4.48*	4.71*	3.19	0.65	1.31
	(1.315)	(1.458)	(1.719)	(2.169)	(2.309)	(2.504)	(2.543)	(3.514)	(3.585)
Male	4.73**	4.68**	4.25*	4.90*	3.62	2.55	1.86	-1.60	-2.00
	(2.037)	(2.270)	(2.367)	(2.729)	(3.022)	(3.418)	(3.832)	(4.187)	(4.335)
Age	3.22***	2.89**	2.30*	2.34	3.27**	3.95**	4.71**	5.45**	6.57**
	(1.105)	(1.253)	(1.370)	(1.536)	(1.570)	(1.809)	(2.289)	(2.744)	(2.874)
Married	0.55	-1.11	-0.48	-1.52	-2.68	-3.08	-0.29	4.76	2.75
	(2.197)	(2.404)	(2.607)	(3.018)	(3.455)	(4.080)	(4.651)	(5.731)	(6.209)
Owns Home	5.94**	3.84	3.77	4.56	0.67	-2.95	0.22	-3.55	-5.13
	(2.385)	(2.594)	(2.939)	(3.512)	(3.977)	(5.088)	(6.232)	(7.048)	(7.742)
Observations	1,000	902	792	672	593	497	410	354	317

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses. As total financial assets is categorical, this variable contains only one value in the right-most column, hence there is no regression coefficient on that variable in that column.

Table C.14: Performance of reference-dependent models in 10-question DOSE sequence.

	All Participants		Loss-Tolerant Subgroup		
Reference Point	% Improve. over Chance	% with Improved Fit	% Improve. over Chance	% with Improved Fit	% Loss Tolerant
Preferred—$0	83%	–	83%	–	47%
Endowment	7%	0%	0%	0%	–
EV of Lottery	28%	8%	26%	11%	58%
Sure Option	44%	13%	39%	15%	41%
Stochastic	29%	6%	29%	10%	49%
Choice	30%	7%	34%	10%	49%

Notes: Loss-Tolerant Subgroup is the group of participants our preferred model classifies as loss tolerant. % Improvement over chance is equal to 2∗(the percent of choices fit − 50%). % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

C.4 Additional Results from Alternative Reference Point Models

This Appendix presents additional results from the tests of models with alternative reference points reported in Section 5.3. First, in we present more detailed results for the 10-question (Table C.14) and 20-question sequences (Table C.15). Each table reports the percentage improvement on chance from each model, and also separates results for those individuals classified as loss tolerant in our main model. As we can see, the results for this sub-group are very similar, providing further evidence that loss tolerance is not explained by individuals using a reference point other than the $0 assumed in Equation 1.

The following two tables report additional results for the 20-question module. Table C.16 presents the results when allowing for differential curvature over losses and gains for each reference point model. Comparing to Table 5 we can see that the model with the $0 reference point model fits the data better than when restricting curvature. The performance of the other models, in contrast, is quite similar—meaning that they represent an improved fit for a much smaller percentage of participants.

Finally, Table C.17 presents the results for the 20Q DOSE module excluding any lotteries that just include losses. That is, we re-estimate each of the models—and examine model performance—removing these questions entirely. We can see that the estimates are now quite similar to those in Table 5. The difference in performance between the two DOSE sequences thus appears to be driven by the fact we impose the same utility curvature over gains and losses, rather than any difference in participant behavior.

C.5 Additional Tests of Survey Fatigue and Inconsistency

This Appendix presents results from additional tests that our results are not driven by survey fatigue. First, we show that the distribution of loss aversion changes very little when removing

Table C.15: Performance of reference-dependent models in 20-question DOSE sequence.

Reference Point	All Participants: % Improve. over Chance	All Participants: % with Improved Fit	Loss-Tolerant Subgroup: % Improve. over Chance	Loss-Tolerant Subgroup: % with Improved Fit	% Loss Tolerant
Preferred—$0	48%	–	46%	–	57%
Endowment	18%	20%	5%	17%	–
EV of Lottery	26%	22%	19%	21%	73%
Sure Option	48%	39%	47%	37%	47%
Stochastic	40%	32%	35%	28%	49%
Choice	30%	25%	33%	30%	46%

Notes: Loss-Tolerant Subgroup is the group of participants our preferred model classifies as loss tolerant. % Improvement over chance is equal to 2∗(the percent of choices fit − 50%). % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

Table C.16: Performance of reference-dependent models when allowing for differential curvature.

Reference Point	All Participants: % Improve. over Chance	All Participants: % with Improved Fit	Loss-Tolerant Subgroup: % Improve. over Chance	Loss-Tolerant Subgroup: % with Improved Fit	% Loss Tolerant
Preferred—$0	64%	–	63%	–	68%
Endowment	18%	6%	16%	7%	–
EV of Lottery	32%	10%	28%	10%	88%
Sure Option	45%	11%	45%	12%	49%
Stochastic	36%	8%	35%	8%	50%
Choice	24%	11%	29%	14%	20%

Notes: Loss-Tolerant Subgroup is the group of participants our preferred model classifies as loss tolerant. % Improvement over chance is equal to 2∗(the percent of choices fit − 50%). % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

those completing the survey particularly fast. Second, we carry out an experimental test of inattention within the DOSE module, both in the sample as a whole and within particular subgroups. We find little evidence that choices are due to fatigue or inattention within the survey or within the DOSE modules. Third, we show that individual choice inconsistency does

Table C.17: Performance of reference-dependent models in 20Q DOSE module without loss-only questions.

Reference Point	All Participants: % Improve. over Chance	All Participants: % with Improved Fit	Loss-Tolerant Subgroup: % Improve. over Chance	Loss-Tolerant Subgroup: % with Improved Fit	% Loss Tolerant
Preferred—$0	63%	–	59%	–	51%
Endowment	16%	5%	1%	4%	–
EV of Lottery	29%	9%	20%	10%	69%
Sure Option	54%	23%	50%	27%	46%
Stochastic	41%	12%	34%	14%	50%
Choice	31%	14%	36%	20%	55%

Notes: Loss-Tolerant Subgroup is the group of participants our preferred model classifies as loss tolerant. % Improvement over chance is equal to 2∗(the percent of choices fit − 50%). % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

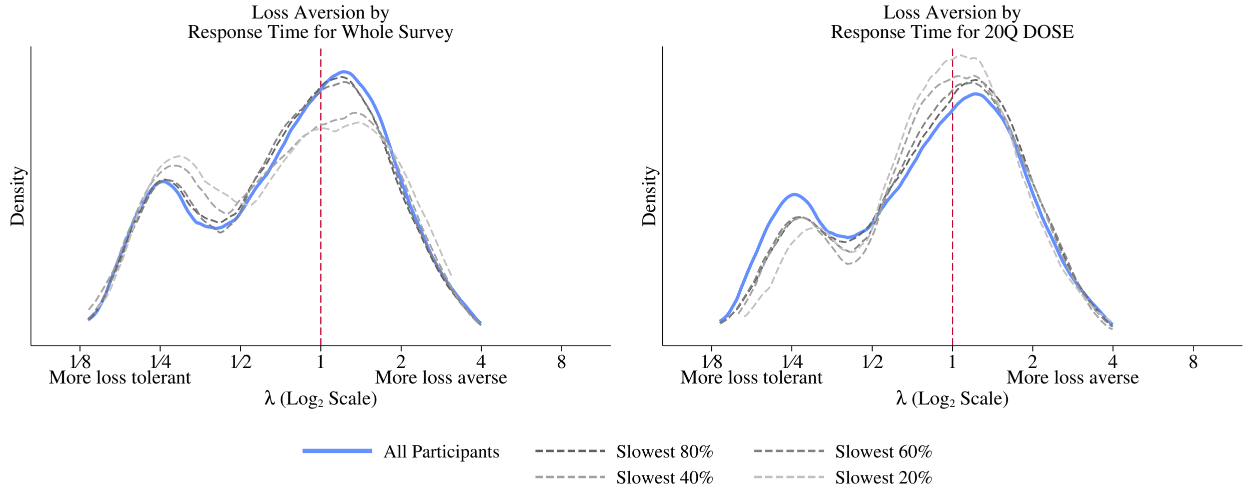
not explain the relationship we observe between cognitive ability and loss aversion.

Figure C.9 shows that the distribution of loss aversion is largely unchanged when removing the fastest responses. Speed on the survey could reflect a participant becoming bored and clicking through screens quickly. In this figure, we first look at the slowest 80% of participants, then the slowest 60%, and so on, across the whole survey (left-hand panel) and within the 20-question DOSE module (right-hand panel). The distributions overlap almost entirely, and the percentage classified as loss tolerant ranges between 54% and 59%. Combined with the results reported in Figure 11 and Table C.6, we find no evidence that fast response or inattention explain our results.

As a check of inattention within the 20-question DOSE sequence, we carried out an experimental test using a measure of *surprise*—the extent to which a person makes choices the Bayesian prior does not expect. In principle, we could be concerned that people stop paying attention as they face a sequence of similar choices and begin "clicking through" the survey at random. We investigate whether this is the case using the fact that, for each question, the DOSE prior identifies the probability an individual will make each choice. If participants are choosing randomly then we would expect them to make choices with a lower prior probability, that is, with a high degree of surprise. Using this metric, we can test whether participants begin to act more randomly later in the DOSE module or when DOSE appears later in the survey. We also check whether the question sequencing affects behavior in some way through, for instance, inadvertently creating a reference point.

We see no evidence that survey fatigue or inattention affects choices in DOSE, as shown in Figure C.10. Here we plot the percentage of "unexpected choices"—those with prior probability less than 0.5—in each round. The left-hand side shows that the proportion is similar regardless of the position of the DOSE module in the survey, and that unexpected choices

Figure C.9: Distribution of loss aversion is similar when removing participants with fast response times.



Notes: The figure displays the distribution of loss aversion estimated in the 20-question DOSE module, plotted using Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator.

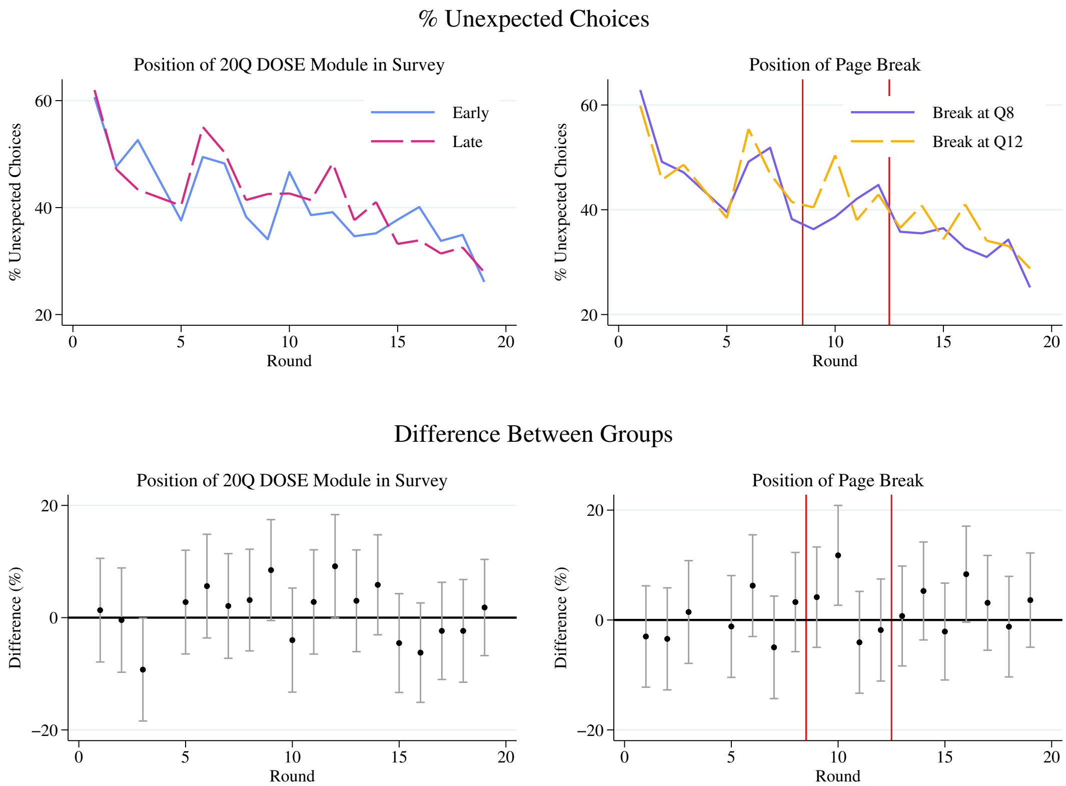
decrease as participants progress further in the module, suggesting fatigue does not lead to random decision-making. On the right-hand side, we use a randomly-located page break to test whether interrupting the question sequence affects choices.[5] As we can see, participant behavior did not change after the sequence was broken, suggesting that choices are not driven by presenting questions sequentially. Thus, as far as we can observe, participants consider each binary choice separately, and pay attention throughout our DOSE modules.

Figure C.11 addresses the concern that fatigue could affect some subgroup within the population, even if it is not evident across the whole sample. Here we repeat the analysis in Figure C.10—analyzing the percentage of choices that are "unexpected" by DOSE—in four subgroups that are particularly important in our analysis. The top row splits the sample according to whether participants are classified as loss tolerant or loss averse by the 20-question DOSE sequence. The bottom row focuses on participants with low or high cognitive ability (the bottom or top terciles). There is little evidence that the randomly-inserted page break affects the level of unexpected choices in any of the groups. The percentage of unexpected choices is not increasing towards the end of the sequence, as would be expected if participants start choosing randomly due to fatigue. Thus our results do not appear to be explained by fatigue amongst either participants classified as loss-tolerant or those with low cognitive ability.

The figure also provides a useful demonstration of how the DOSE updates beliefs about those participants less represented in laboratory experiments. At the first few questions of the sequence, there are more unexpected choices amongst participants classified as either low cognitive ability or loss tolerant. This difference represents the fact that these groups make choices that are further away from our initial prior—which was developed based on participants in earlier laboratory experiments, who tend to tend to be more cognitively able and more loss averse (as discussed in the main text, participants in the laboratory). However, by the end of

[5] The page break consisted of a separate screen (see Appendix Figure E.22) stating "You are almost halfway done with this section. You will now be asked some more questions with a choice between a lottery and an amount of points for certain."

Figure C.10: No evidence of fatigue or inattention within the 20-question DOSE sequence.



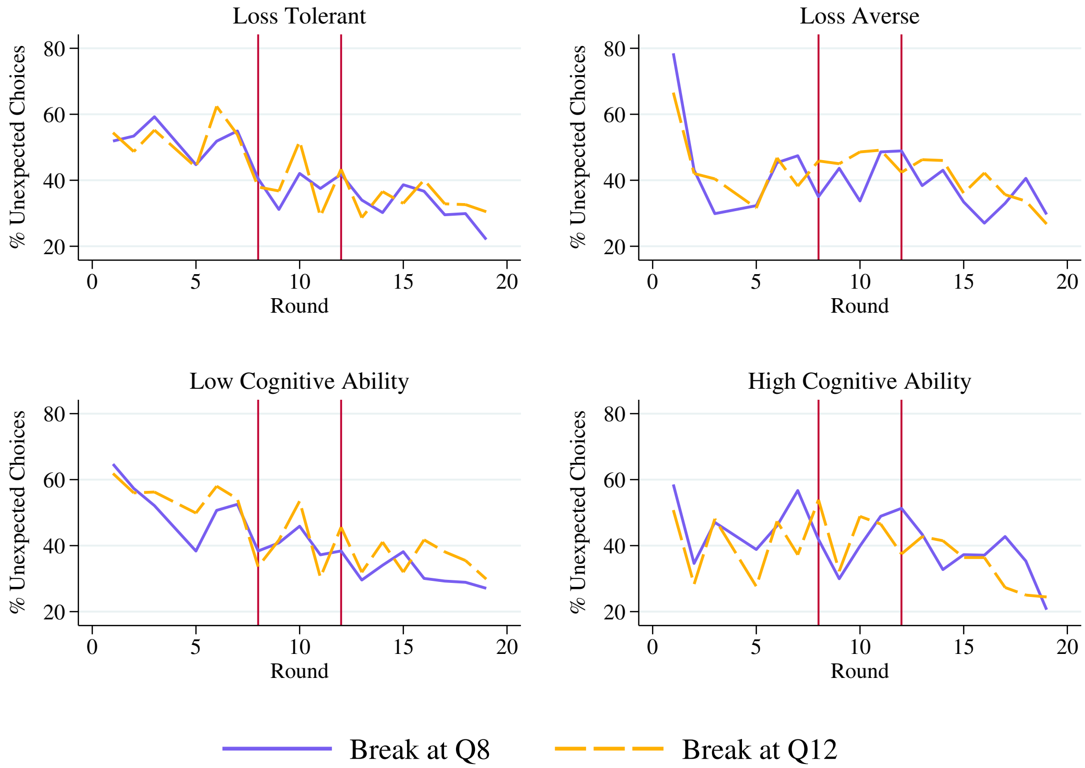
Notes: The figures plot the percentage of participants making choices with a prior probability of less than 0.5. Questions 4 and 20, which were not chosen by DOSE, are excluded.

the sequence, the level of unexpected choice is similar across all four panels, suggesting that the information elicited by DOSE allows posterior estimates that are equally informative across the four groups.

Finally, we investigate whether inconsistent choice could explain the correlations we document between cognitive ability and loss aversion in Table 1. Cognitive ability is negatively correlated with the DOSE choice consistency parameter (μ; $r = -0.13$, s.e. $= .04$), consistent with previous studies that examine the level of "noise" in preference elicitation (Andersson et al., 2016; Mechera-Ostrovsky et al., 2022). However, it is not the case that low cognitive ability participants are simply acting randomly—the temporal stability of our estimates is relatively high for participants with each level of cognitive ability. Specifically, the over-time correlation of loss aversion for those in the lowest tercile of cognitive ability is 0.34 (s.e. $=$ .07), for the middle tercile it is 0.30 (.06), and for the top tercile it is 0.42 (.06).

Further, the correlation between cognitive ability and loss aversion is similar when accounting for inconsistent choice, inattention, or fatigue. Appendix Table C.6 shows that the correlations are similar when splitting the sample according to a number of inattention indicators. Further, the correlation with cognitive ability is even higher when constraining the sample to those with μ above the sample median ($r = 0.34$, s.e. $= .06$). This higher correlation is in line with simulation estimates, reported in Chapman et al. (2018), that inconsistent choice leads to greater measurement error in DOSE estimates of loss aversion. However, by directly accounting

Figure C.11: No evidence of fatigue for specific subgroups.



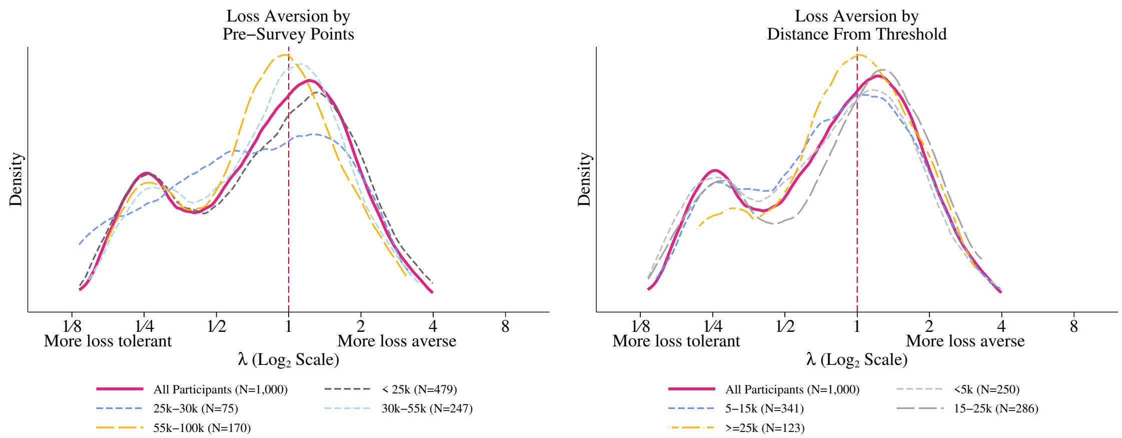
Notes: The figure plots the proportion of participants making choices with a prior probability of less than 0.5. Questions 4 and 20, which were not chosen by DOSE, are excluded. Loss Tolerant (Averse) refers to participants for who $\lambda < 1$ ($\lambda > 1$) according to the DOSE 20-question estimates. Similarly, Risk Averse (Loving) refers to participants for who $\rho < 1$ ($\rho > 1$) according to the DOSE 20-question estimates. "Low" and "High" Cognitive Ability refer to the bottom and top terciles.

for inconsistent choices, DOSE estimates are quite accurate even for participants making many mistakes. Lower-cognitive-ability participants do make less consistent choices in our survey, but the correlations we observe are not explained by a high propensity to make mistakes.

C.6 Tests of Payment Schedule Effects

In this appendix we address the possible concern that our results are an artefact of the YouGov payment system. Throughout the paper we assume that participants translate YouGov's internal currency—points—into monetary amounts at a flat exchange rate of \$0.001 per point. This exchange rate is based on the fact that participants can exchange 100,000 points for \$100 in cash. However, participants can also exchange their points at lower points thresholds at a lower exchange rate, leading to some convexity in the payment schedule. The most significant change in this schedule occurs between the 25,000 and 30,000 point thresholds: 25,000 points can be traded in for a \$15 gift card (\$0.6 per 1,000 points), whereas 30,000 points can be traded in for a \$25 gift card (\$0.83 per 1,000 points). Further significant changes then occur at 55,000 points, which can be cashed in for a \$50 gift card (\$0.91 per 1,000 points), and the highest threshold of 100,000 points, which can be cashed out for \$100 cash or a \$100 gift card (\$1 per 1,000 points).

Figure C.12: Distribution of DOSE 20Q loss aversion estimates by pre-survey points.



<u>Notes:</u> The subgroup of participants with above 100,000 points ($N = 29$) is excluded from the left-hand panel due to small sample size.

There are three features of this payment schedule that could, in principle, affect our results:

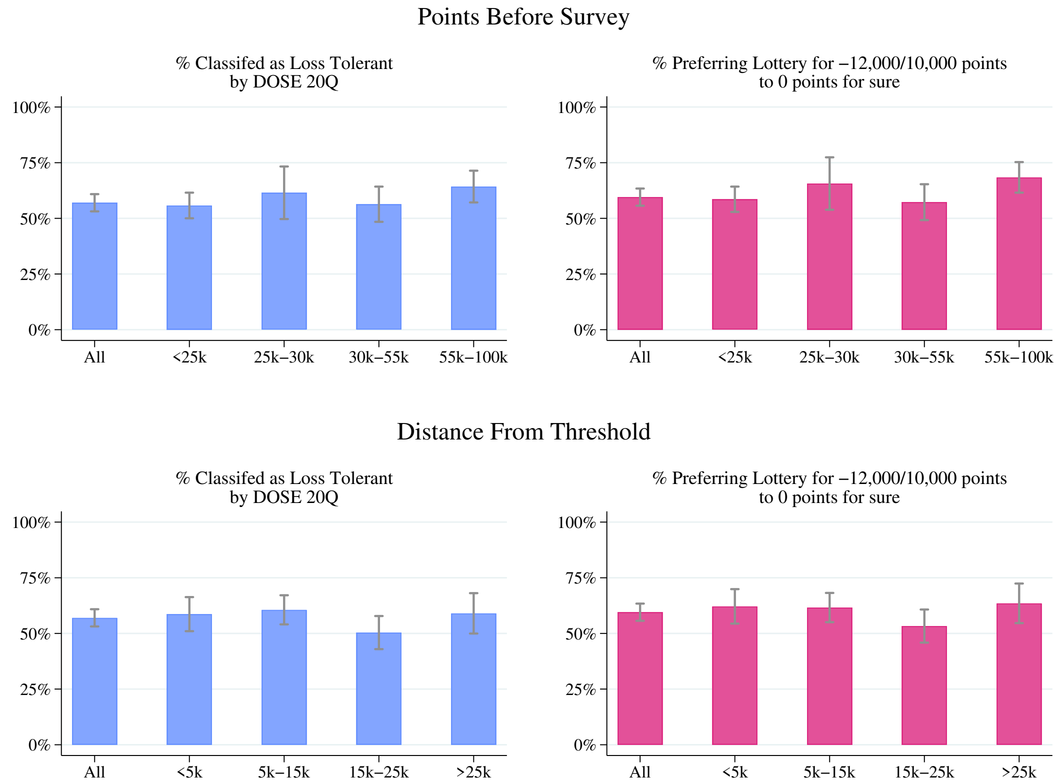
1. The use of points rather than monetary amounts, which could cause respondents to be insensitive to the reference point (or have the wrong reference point) in a way that does not generate loss aversion,
2. The convexity of the payment schedule, and
3. The fact that participants can only "cash out" their points at specific thresholds.

The first item is directly addressed by the results in Section 3.1: undergraduate students, also facing decisions using points, exhibit levels of loss aversion that accord with prior studies. Moreover, even within our representative sample, a sizeable minority of participants exhibit loss aversion. The robustness tests presented in Section 5.3 and Appendix C.4 provide further evidence that participants responded to our assumed $0 reference point.

To test whether items 2 and 3 could explain our results, we first investigate whether the level of loss tolerance varies according to the number of points participants held before the survey. We then test specific hypotheses regarding behavior around thresholds that could generate observed loss tolerance. Throughout this analysis we refer to all survey rewards in terms of points (rather than converting to monetary amounts, as in the main text), allowing direct comparison to the thresholds in the payment system. We find no evidence that the payment schedule significantly affects behavior either within the sample as a whole, or for two particular subgroups: participants with low cognitive ability, and participants possessing some latent factor that drives both the real world behaviors (gambling, financial shocks) we measure, and their response to the payment schedule.

Pre-survey points—binned by either level or distance from a threshold, do not seem to affect measured loss aversion, as shown in Figure C.12. The left-hand panel shows the distribution of λ estimated for different groupings of pre-survey points, with each group corresponding to a different level of reward per point. Three items are worth mentioning. First, the distribution

Figure C.13: Loss Tolerance by Pre-survey Points: All Participants



Notes: Sample sizes in top panel: "All" $N = 1{,}000$, <25k $N = 479$; 25–30k $N = 75$; 30–55k $N = 247$; 55–100k $N = 170$. Sample sizes in bottom panel:"All" $N = 1{,}000$, < 5k $N = 250$; 5–15k $N = 341$; $\geq$15–25k $N = 286$; ≥ 25k $N = 123$. Error bars represent 90% confidence intervals.

of the loss aversion parameter (λ) for those who enter the survey with < 25k points (48% of our sample), and hence potentially affected by the most significant point of convexity in the payment schedule, closely resembles that of the overall sample. Second, the main mode of the distribution seems, if anything, to shift towards increasing loss tolerance as the convexity of the payment schedule declines—the opposite of what one would expect if convexity were the source of loss tolerance—although we will see below that these differences are not statistically significant. Finally, the distribution of λ for the 75 participants who started the survey with between 25–30k points is much flatter than other distributions. While this is likely driven by small sample size, our results are robust to omitting these participants.

The right-hand panel of Figure C.12 groups participants by the number of points they require at the start of the survey to cross a major cash-out threshold. While the width of these bins is arbitrary, the figure shows a clear pattern: the distribution of our estimates of λ does not change much as one gets further from a major threshold. Of particular note are those who are more than 25k points away from a major threshold, as this entirely excludes the group potentially affected by the most significant point of convexity in the payment schedule.

Figure C.13 uses our choice data, as well as the DOSE estimates of λ, to investigate the possible role of pre-survey points in determining observed loss tolerance. In this figure we compute, within various bins, both the percent of participants we classify as loss tolerant using DOSE, and the percent choosing the −12,000/10,000 lottery over 0 points (the lottery that we describe in the introduction and analyze throughout the paper). The result of this analysis is very clear: there is no statistical or substantial difference between any of the bins for either of these variables. Moreover, there is no clear pattern in the point estimates.

C.6.1 A Theory of Threshold Response

We can conduct more powerful tests of whether thresholds seem to be changing responses by developing a specific theory of how threshold response could, in principle, generate loss tolerance. If participants are focused on the opportunity to cash in their points after crossing a threshold, we would expect them to be averse to potential losses that may take them below such a threshold—which would not threaten our main finding. However, they may also be unconcerned about any losses that do not drop them below a threshold—leading to an appearance of loss tolerance.

Specifically, consider a participant with pre-survey points P, who receives a survey completion fee ($S = 3,000$) and an endowment E at the start of a survey module (for instance, 15,000 in the case of the DOSE 20Q module). Suppose the participant is aiming to cash-in their points at a threshold T, and that $P + S + E > T$—that is, they will reach their goal unless they lose points during the survey module. The participant should then reject any loss $L > 0$ such that $P + S + E - L < T$. That is, the closer one is to a threshold when entering the survey, the more willing they will be to take losses, making them appear loss tolerant.

We test this hypothesis using data from three different elicitations in our survey, and find no evidence to support it. First, we consider choices regarding the binary lottery displayed in Figure 1, offering participants a choice between receiving 0 points for sure, or either -12,000 points or 10,000 points, each with 50% probability. Of the 434 participants at risk of falling below a threshold by choosing this lottery, 59% do so—compared to 60% amongst 566 not at risk (p-val = 0.74). Thus, it does not appear the likelihood of falling below such a threshold affects the willingness to accept this lottery.

Second, we consider the choices of participants in a multiple price list (MPL) eliciting the lottery equivalent X from a choice between 0 points for sure or a 50/50 lottery between 5,000 points and -X points. We observe that 65% of the 169 participants who may fall below a threshold by choosing the lottery make a loss tolerant choice (accepting $X \geq 5,000$). This level is slightly higher than amongst the 831 participants not at threat of falling below a threshold (57%, p-val=0.16). Again, it does not appear that the threat of falling below a threshold inhibits acceptance of losses.

Finally, we consider choices in an MPL eliciting certainty equivalents for a lottery between a loss of 5,000 points and 0 points, each with 50% probability. If participants were motivated to stay above a threshold, we would predict they would never accept a certain loss that took them beneath that threshold. Specifically, we consider participants for whom $T \leq P+S+E < T + 5000$. These participants should accept a certain loss $5,000 > L > 0$ if and only if $L \leq P + S + E - T$. They should accept the lottery if and only if $L > P + S + E - T$. Only 5/189 (2.6%) of participants in this group acted this way. Again, we see little evidence that participants' decisions are motivated by the presence of a threshold.

C.6.2 Subgroups

The results above substantially reduce the concern that the payment schedule explains the level of loss tolerance in the sample as a whole. However, an alternative concern could be that the payment schedule affects the responses of different groups differently, and hence can explain both a high level of loss tolerance and the correlations we find between loss aversion and individual characteristics. We thus provide further results to address this additional concern.

We consider two groups of participants that may be disproportionately affected by the payment schedule, making them (incorrectly) appear loss tolerant. First, those with low cognitive ability, using the measure obtained during the survey. Second, we consider the possibility that some other latent factor (such as "impulsivity") could, when interacted with the payment schedule, produce the correlations we observe between loss aversion and real world behaviors (as reported in Tables 3 and 4). We include separate analyses for each group.

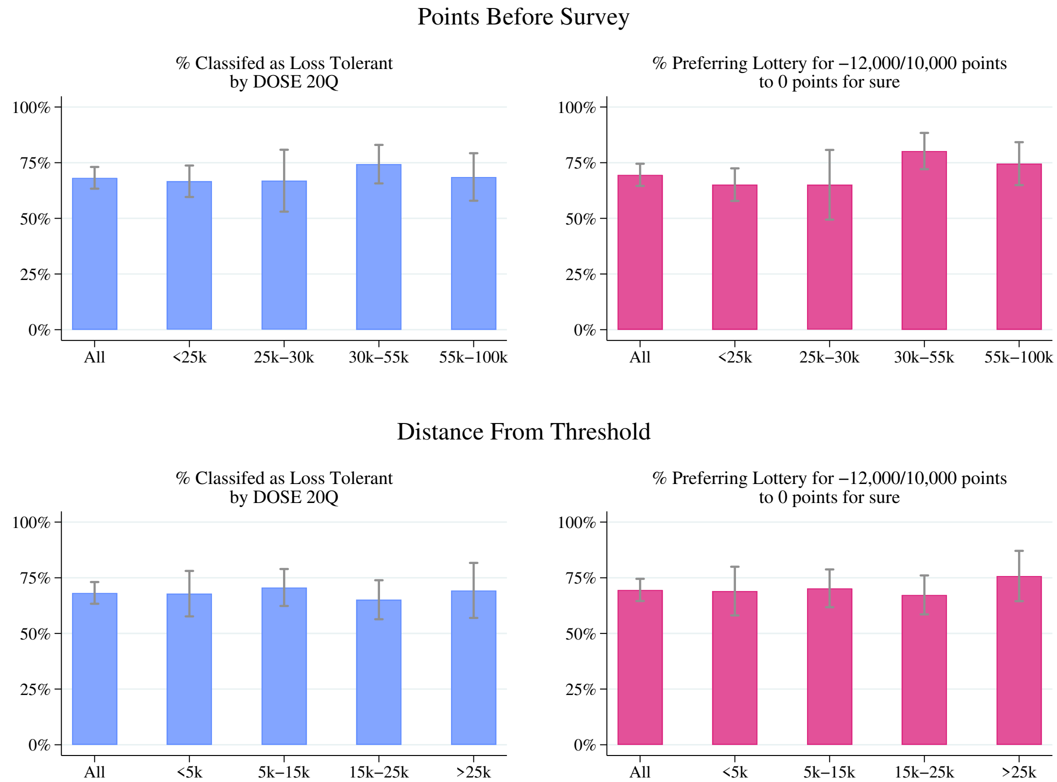
Participants with low cognitive ability (low CA): We first consider the hypothesis that low CA participants are particularly responsive to the payment schedule, making them appear more loss tolerant than those with higher cognitive ability (this differential responsiveness is necessary to explain the correlations in Table 1).

We address this concern by following the same arguments as with the full population, using our direct measure of cognitive ability. While addressing item 1 (the use of points rather than money) is no longer possible by pointing to the student sample, the fact that a substantial minority (32%) of low CA participants appears loss averse again suggests that reference points are "working" when rewards are expressed in points. We can also compare the level of loss tolerance after dividing the low CA participants into the same groups as above, based on which thresholds they are between, or how far away they are from crossing a threshold. Figure C.14 shows that the level of loss tolerance is similar across these groups, measured as either the percentage classified as loss tolerant, or the percentage that choose the -12,000/10,000 lottery.

Finally, we perform the three more specific tests based on our theory of threshold response. First, for participants that are low CA and at risk of falling below a threshold by choosing the -12,000/10,000 lottery, 67% choose the lottery versus 71% of those who are not at risk (p-val=0.51). Second, for those who are low CA and who have pre-survey points such that accepting a lottery (in a lottery equivalent MPL) with a possible loss of at least 5,000 points puts them at risk of falling below a threshold, 68% choose the lottery versus 67% of those not at risk (p-val=0.92). Third, only 2/92 low CA participants with $T \leq P + S + E < T + 5,000$ have a pattern of response consistent with the third direct test.

Participants with some latent factor (LF): We now turn to the concern that people who are more likely to gamble and also to experience financial shocks will respond to the payment schedule by making choices that appear loss tolerant. For example, participants who are more impulsive may both gamble more and be more likely to trade in their points at a lower points-to-cash value—meaning they face greater convexity in their payment schedule. The same argument would apply to people who have any latent factor (LF) that leads to these behaviors. This could explain the results in Tables 3 and 4 if LF is also orthogonal to our controls for cognitive ability and demographic characteristics (inclusion of which minimally changes the relationship between loss aversion and our measures of real world behaviors).

Figure C.14: Loss Tolerance by Pre-survey Points: Low Cognitive Ability Participants



Notes: The figure includes only participants in the bottom tercile of cognitive ability. Sample sizes in top panel: "All" $N = 462$; <25k $N = 246$; 25–30k $N = 37$; 30–55k $N = 100$; 55–100k $N = 69$. Sample sizes in bottom panel: "All" $N = 462$, < 5k $N = 121$; 5–15k $N = 151$; $\geq$15–25k $N = 142$; $\geq$25k $N = 48$. Error bars represent 90% confidence intervals.

As we do not have a direct measure of LF, we address this concern by constructing a proxy. To do so, we begin by noting that a theory where the payment schedule can explain all of our results would conjecture that:

$$\textit{Apparent Loss Tolerance} = (CA + LF) \times \textit{Payment Schedule} + \varepsilon$$

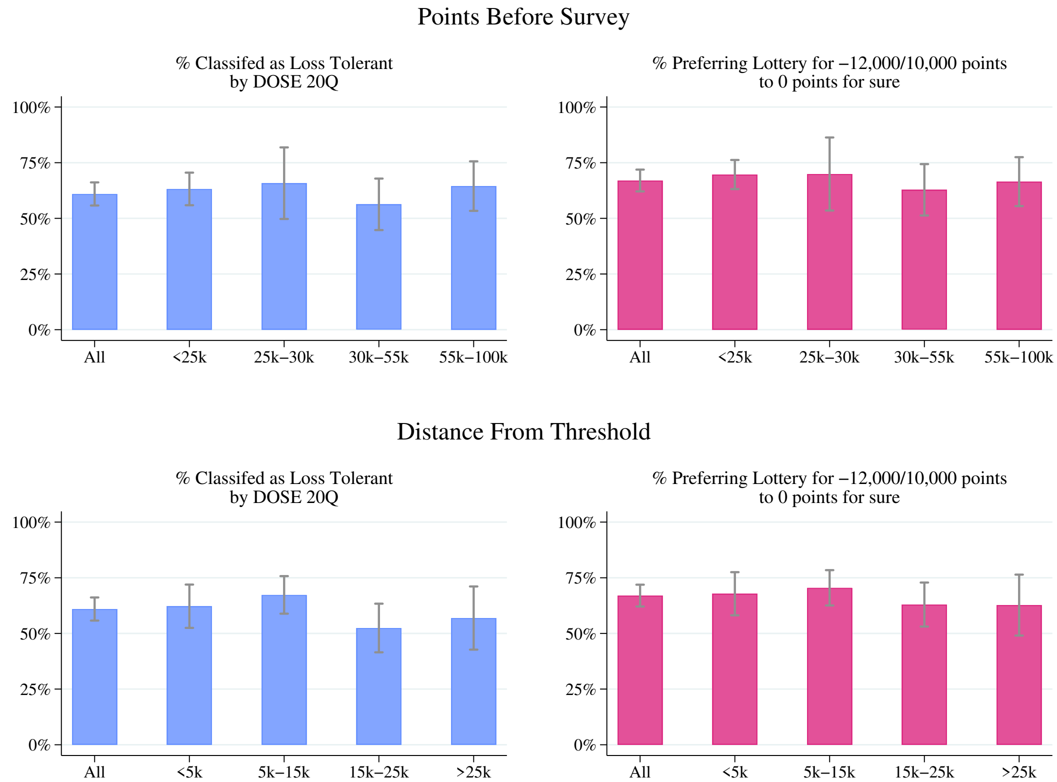
Further, under this theory, the positive correlation between measured loss tolerance and casual and serious gambling, and between loss tolerance and financial shocks is driven by the latent relationship between LF and gambling/financial shocks. Thus, LF is given by:

$$LF = (\textit{serious} + \textit{casual gambling} + \textit{financial shocks})|(CA,\ \textit{demographics})\ +\ \eta$$

We thus create a proxy by adding together our measures of gambling and experiencing financial shocks, regressing that on cognitive ability and demographics, and taking the residual. Higher levels of this residual are a proxy for greater values of LF.

We can then examine the pool of participants who have a high level of this LF proxy, and, in particular, investigate whether their behavior varies according to the number of points they held

Figure C.15: Loss Tolerance by Pre-survey Points: High LF Participants



Notes: The figure includes only participants above the median of the LF measure, defined in the text. Sample sizes in top panel: "All" $N = 490$, <25k $N = 247$; 25–30k $N = 40$; 30–55k $N = 117$; 55–100k $N = 41$. Sample sizes in bottom panel: "All" $N = 490$, < 5k $N = 136$; 5–15k $N = 172$; $\geq$15–25k $N = 127$; $\geq$ 25k $N = 55$. Error bars represent 90% confidence intervals.

pre-survey. Once again, a substantial minority (39%) appears loss averse, providing evidence that the reference point is "working." Also, similar to before, the degree of loss tolerance appears similar across all the groupings within this high LF group, as shown in Figure C.15.

Finally, we can perform the three more specific tests that come from our theory of response to thresholds. First, both participants that are and are not at risk of falling below a threshold by choosing the -12,000/10,000 and have high LF choose the lottery 67% of the time. Second, of those who have high LF and who have pre-survey points such that accepting a lottery (in a lottery equivalent MPL) with a possible loss of at least 5,000 points puts them at risk of falling below a threshold, 70% choose the lottery versus 59% of those not at risk (p-val=0.14). Third, only 2/97 high LF participants with $T \leq P + S + E < T + 5,000$ have a pattern of response consistent with the third direct test.

Together, these results provide strong evidence against the hypothesis that our results are driven by the reaction of these specific subgroups—participants with low cognitive ability or high LF—to the YouGov payment schedule. Loss tolerance is not concentrated in these subgroups, nor do these participants appear to react to the presence of thresholds.

D Principal Components Analysis

Figures D.16 and D.17 display scree plots for the Principal Components Analysis reported in Section 4.1.

Figure D.16: Scree Plot for PCA of Gambling Measures

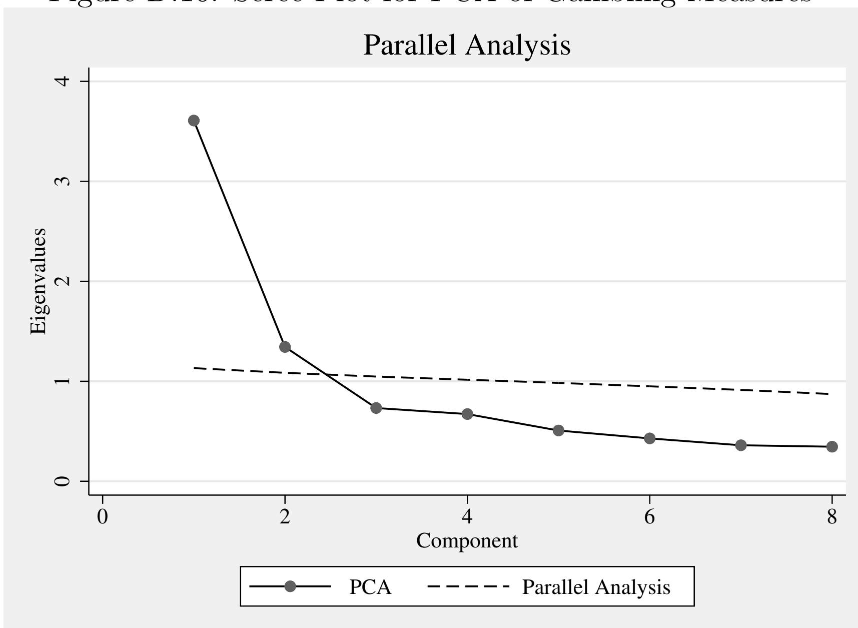
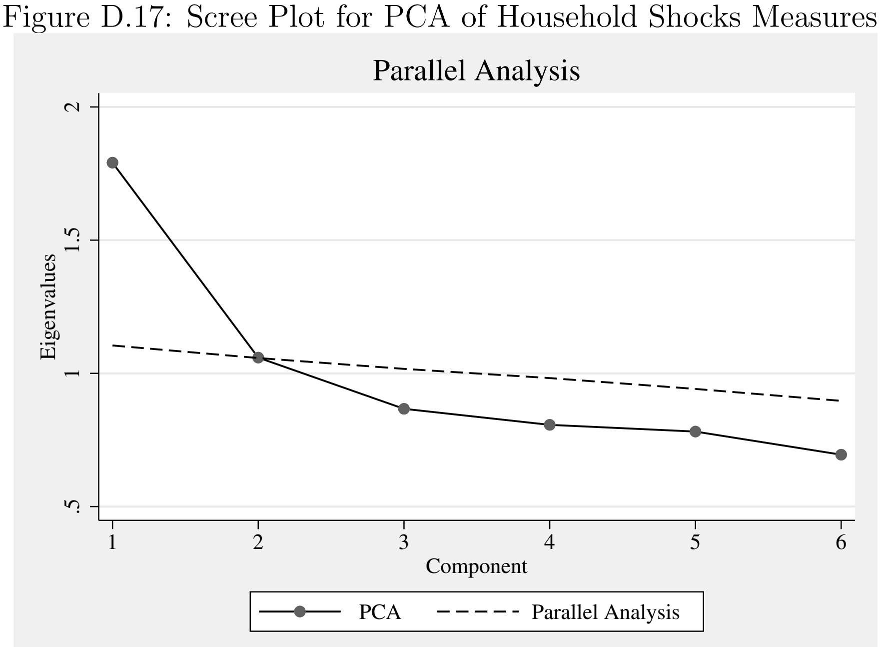


Figure D.17: Scree Plot for PCA of Household Shocks Measures



E Screenshots

This subsection contains screenshots of the experimental instructions, and examples of each type of questions analyzed in this paper. Full design documents and screenshots can be found at eriksnowberg.com/wep.html.

Figure E.18: Survey Instructions I

YouGov

YouGov is inviting you to take a **different** kind of survey.

If you read these instructions carefully and make good decisions **you may earn up to 33,000 points** by the end of the survey. **Please pay close attention**, as you will need to correctly answer a few questions about these instructions.

During the survey, you will be asked a number of questions that ask you to **choose between different types of lotteries and payments**. At the end of the survey, one of these questions will be selected randomly, and your answer to that question will determine how many points you earn.

For example, suppose your earnings were determined, in part, by a question that asked you to decide between

- a lottery that gave a 50% chance of 10,000 points and a 50% chance of 0 points, and
- a fixed amount of 1,000 points.

If you chose the lottery, then it would be run, and you would get **either** 0 or 10,000 points, each with 50% probability. **If you chose 1,000 points**, then 1,000 points would be directly credited to your account.

Thus, the points you earn will depend on both your choices and luck.

Some sections will **start you with a fixed number of points,** say 5,000, and choices in that section will have the possibility of a loss from that total.

For example, suppose your earnings were determined, in part, by a question that asked you to decide between

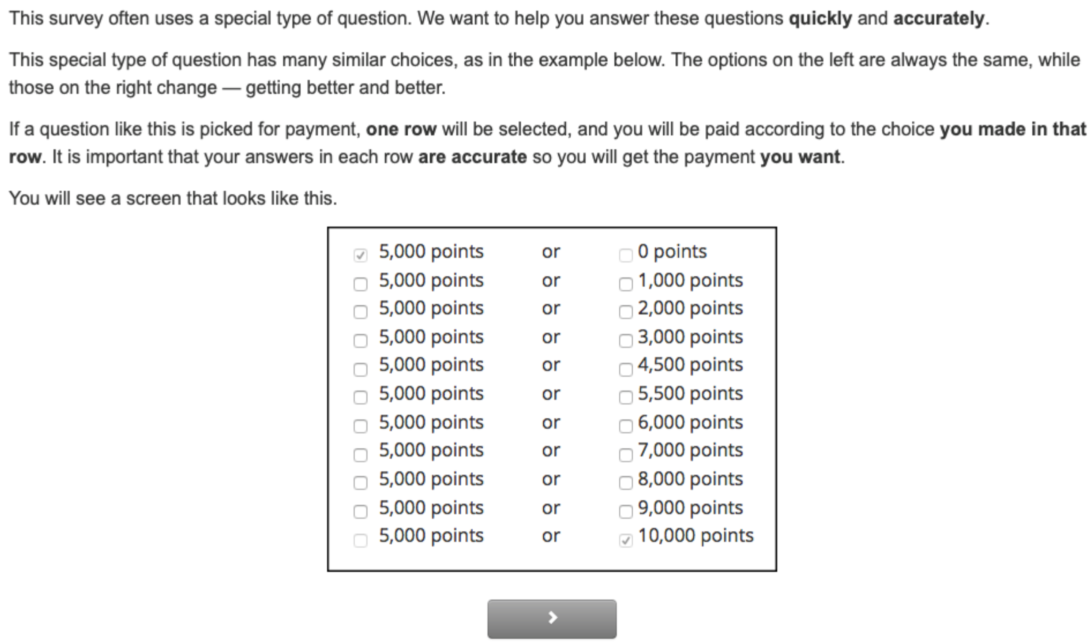
- a lottery that gave a 50% chance of losing 3,000 points and a 50% chance of gaining 5,000 points, and,
- a loss of 1,000 points.

If you chose the first option, and the lottery selected the loss of 3,000 points, then you would receive 5,000 − 3,000 = 2,000 points if this question were chosen for payment. **If the lottery selected the gain,** you would receive 5,000 + 5,000 = 10,000 points. **If you chose the second option,** then you would receive 5,000 − 1,000 = 4,000 points if this question were chosen for payment.

In addition to the points earned for your choices, you will earn **3,000** points for completing the survey. Thus, the **minimum** number of points you will earn for taking this survey is **3,000**. The **maximum is 33,000**. The **average is 15,000**. You will not earn points unless you complete the survey.

The survey pays so much more than usual because the survey will take about **45 minutes**, and we want you to pay close attention for that entire time.

Figure E.19: Survey Instructions II



This survey often uses a special type of question. We want to help you answer these questions **quickly** and **accurately**.

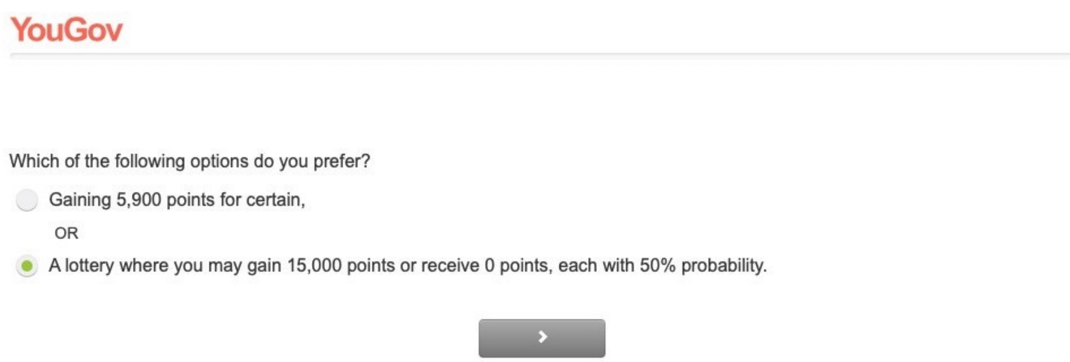
This special type of question has many similar choices, as in the example below. The options on the left are always the same, while those on the right change — getting better and better.

If a question like this is picked for payment, **one row** will be selected, and you will be paid according to the choice **you made in that row**. It is important that your answers in each row **are accurate** so you will get the payment **you want**.

You will see a screen that looks like this.

☑ 5,000 points	or	☐ 0 points
☐ 5,000 points	or	☐ 1,000 points
☐ 5,000 points	or	☐ 2,000 points
☐ 5,000 points	or	☐ 3,000 points
☐ 5,000 points	or	☐ 4,500 points
☐ 5,000 points	or	☐ 5,500 points
☐ 5,000 points	or	☐ 6,000 points
☐ 5,000 points	or	☐ 7,000 points
☐ 5,000 points	or	☐ 8,000 points
☐ 5,000 points	or	☐ 9,000 points
☐ 5,000 points	or	☑ 10,000 points

Figure E.20: DOSE 20-question Sequence Example Question: Gains Only



YouGov

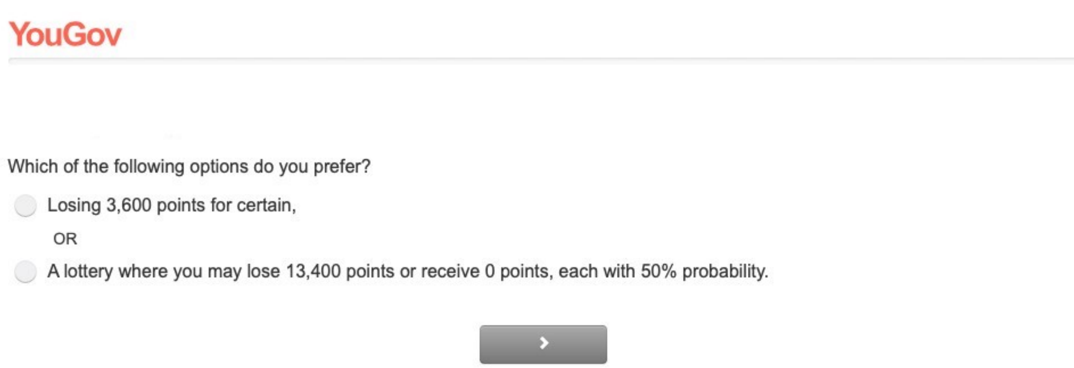
Which of the following options do you prefer?

Gaining 5,900 points for certain,

OR

A lottery where you may gain 15,000 points or receive 0 points, each with 50% probability.

Figure E.21: DOSE 20-question Sequence Example Question: Losses Only



YouGov

Which of the following options do you prefer?

Losing 3,600 points for certain,

OR

A lottery where you may lose 13,400 points or receive 0 points, each with 50% probability.

Figure E.22: DOSE 20-question Sequence Page Break

You are almost halfway done with this section. You will now be asked some more questions with a choice between a lottery and an amount of points for certain.

Figure E.23: DOSE 10-question Sequence Instruction Screen

Section 7 of 11

In the next few questions, you will be asked to choose between two lotteries.

You will start this section with 10,000 points, which you may lose based on the lotteries you choose in this section. That is, some of the lotteries in this section may both **add** to or **subtract** from this initial 10,000 points.

For example, suppose you chose a lottery that had a 50% chance of adding 5,000 points, and a 50% chance of subtracting 5,000 points. In the case of winning, the 5,000 will be added to your additional 10,000. In the case of a loss, the 5,000 will be subtracted from your initial 10,000. Note that you will never have the possibility of losing more than 10,000, so at worst you will end this section with 0 points.

Figure E.24: DOSE 10-question Sequence Example Question: Both Gains and Losses

YouGov

Which of the following options do you prefer?

- A lottery where you can either receive 7,000 points or lose 6,300 points, each with probability 50%;

OR

- Receiving 0 points for certain.

Figure E.25: DOSE 10-question Sequence Example Question: Gains Only

YouGov

Which of the following options do you prefer?

- A lottery where you can either receive 10,000 points or receive 0 points, each with probability 50%;

OR

- Receiving 5,200 points for certain.

Figure E.26: First MPL Eliciting Lottery Equivalent for a Fixed Amount of Points

For each row in the table below, which option would you prefer?

☐ 0 points	or	☐ A 50% chance of losing 10,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 9,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 8,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 7,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 6,500 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 6,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 5,500 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 5,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 4,500 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 4,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 3,500 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 3,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 2,500 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 2,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 1,500 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of losing 1,000 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☐ A 50% chance of 0 points, and a 50% chance of gaining 5,000 points
☐ 0 points	or	☑ A 50% chance of gaining 1,000 points, and a 50% chance of gaining 5,000 points

Reset

Autofill

Review the instructions

Figure E.27: Second MPL Eliciting Lottery Equivalent for a Fixed Amount of Points

For each row in the table below, which option would you prefer?

☐ 0 points	or	☐ A 50% chance of losing 10,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 9,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 8,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 7,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 6,500 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 6,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 5,500 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 5,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 4,500 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 4,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 3,500 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 3,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 2,500 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 2,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 1,500 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of losing 1,000 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☐ A 50% chance of 0 points, and a 50% chance of gaining 4,000 points
☐ 0 points	or	☑ A 50% chance of gaining 1,000 points, and a 50% chance of gaining 4,000 points

Reset

Autofill

Review the instructions

Figure E.28: First MPL Eliciting Certainty Equivalent for a Mixed Lottery

For each row in the table below, which option would you prefer?

☑ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 6,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 5,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 4,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 3,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 2,500 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 2,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 1,750 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 1,500 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 1,250 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 1,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 750 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 500 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Losing 250 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ 0 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Gaining 250 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Gaining 500 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Gaining 1,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Gaining 3,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☐ Gaining 5,000 points
☐ A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points	or	☑ Gaining 7,000 points

Figure E.29: Second MPL Eliciting Certainty Equivalent for a Mixed Lottery

For each row in the table below, which option would you prefer?

☑ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 5,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 4,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 3,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 2,500 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 2,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 1,750 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 1,500 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 1,250 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 1,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 750 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 500 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Losing 250 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ 0 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Gaining 250
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Gaining 500 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Gaining 1,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Gaining 2,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Gaining 3,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☐ Gaining 4,000 points
☐ A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points	or	☑ Gaining 5,000 points

Figure E.30: First MPL Eliciting Certainty Equivalent for a Lottery over Gains

For each row in the table below, which option would you prefer?

☑	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ -500 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 0 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 500 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 1,000 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 1,250 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 1,500 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 1,750 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 2,000 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 2,250 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 2,500 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 2,750 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 3,000 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 3,250 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 3,500 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 3,750 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 4,000 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 4,500 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☐ 5,000 points
☐	A 50% chance of 5,000 points, and a 50% chance of 0 points	or	☑ 5,500 points

Figure E.31: Second MPL Eliciting Certainty Equivalent for a Lottery over Gains

For each row in the table below, which option would you prefer?

☑	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	600 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	1,000 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	1,400 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	1,600 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	1,800 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	2,000 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	2,200 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	2,400 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	2,600 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	2,800 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	3,000 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	3,200 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	3,400 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	3,600 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☐	4,000 points
☐	A 50% chance of 4,000 points, and a 50% chance of 1,000 points	or	☑	4,600 points

Reset

Autofill

Review the instructions

Figure E.32: Questions on Gambling Activity

When was the last time, if at all, you bet or gambled for money on each of the following?

	Within the past 30 days	Between 30 days and 12 months ago	More than 12 months ago	Never
Lotteries or lottos such as Powerball or Mega Millions.	○	○	○	○
Lottery scratch tickets.	○	○	○	○
Betting on sports whether online or with a sports book.	○	○	○	○
Online card games, online slot machines, or other types of online gambling.	○	○	○	○
Slot machines, bingo, keno, or video gambling, at a casino or elsewhere.	○	○	○	○
Card games, roulette, or other games of chance or skill at a casino.	○	○	○	○
Bet or wagered with friends, family, or others outside a casino (e.g., on card games, or basketball).	○	○	○	○
Betting or gambling using some other game, activity, or event we have not listed.	○	○	○	○

Figure E.33: Example of Questions on Household Shock

In the past 12 months, has someone in your household suffered an illness or injury requiring a trip to the hospital?

- ○ Yes
- ○ No

Figure E.34: Attention Screener I

People spend their time doing different things. Over the last year, how frequently have you done each of these activities?

	Never	Less than once a month	About once a month	Once a week	More than once a week
Ridden a bus or subway					
Flown on an airplane					
Been to the gym					
Traveled to the moon					
Gone to the grocery store					
Read a book					
Cooked dinner					
Given birth					
Gone to a religious service					
Gotten a haircut					

Figure E.35: Attention Screener II

People like many different colors. What about you? To demonstrate that you are reading this question, please select purple and yellow from the list below. That's right, just select these two options, no matter what your favorite color is.

- Blue
- Red
- Green
- Purple
- Black
- Orange
- Yellow
- Gold

Figure E.36: Attention Screener III Part 1

We'd like to know how you feel about local news coverage. Please read this short article. On the next page, we will ask you a few questions about your reactions to this article.

MAN ARRESTED FOR STRING OF BANK THEFTS

Columbus Police have arrested a man they say gave his driver's license to a teller at a bank he was robbing.

According to court documents, Bryan Simon is accused of robbing four Central Ohio banks between October 3 and November 5, 2018.

During a robbery on November 5 at the Huntington Bank, the sheriff's office says Simon was tricked into giving the teller his drivers' license.

According to court documents, Simon approached the counter and presented a demand note for money that said "I have a gun." The teller gave Simon about $500, which he took.

Documents say Simon then told the teller he wanted more money. The teller told him a driver's license was required to use the machine to get out more cash. Simon reportedly then gave the teller his license to swipe through the machine and then left the bank with about $1,000 in additional cash, but without his ID.

Detectives arrested him later that day at the address listed on his ID.

Figure E.37: Attention Screener III Part 2

Do you think this article is typical of local news coverage?

- Yes
- Maybe
- No

Do you think there is too much coverage of crime in local newspapers?

- Yes
- Maybe
- No

How was Simon identified by police for the crime he allegedly committed?

- A police officer recognized him
- From video surveillance
- Because he left his ID
- He turned himself in
- None of the above

How much money did Simon allegedly steal?

- About $500
- About $1,500
- About $25,000
- About $1 million dollars
- None of the above

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