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Working Paper

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

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

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, with many participants accepting negative-expected-value gambles. This is counter to earlier findings—which mostly come from lab/student samples—and expert predictions that 70-90% of participants are loss averse. Consistent with the difference between our study and the prior literature, loss aversion is more prevalent in people with high cognitive ability. Loss-tolerant individuals are more likely to report recent gambling and to have experienced financial shocks. These results support the general hypothesis that individuals value gains and losses differently, although the tendency in a large proportion of the population to emphasize gains over losses is an overlooked behavioral phenomenon.

JEL-Codes: C810, C900, D030, D810, D900.

Keywords: loss aversion, DOSE, risk preferences, cognitive ability, negative shocks, gambling.

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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.² 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., 2018). We implement the same procedure in two samples of undergraduate students, and find similar levels of loss tolerance (average: 22%) as in previous laboratory experiments. Consistent with this finding, in our representative samples, loss aversion is more common in people with high cognitive ability. 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 lower overall assets. Moreover, 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

¹Examples 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.

²The loss aversion parameter in Prospect Theory, λ , indicates loss aversion when $\lambda > 1$, and loss tolerance when $\lambda < 1$.

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.³ 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., 2018; 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, 1993; Åstebro et al., 2015). Loss tolerance, on the other hand, makes people more susceptible to exploitation of these 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).

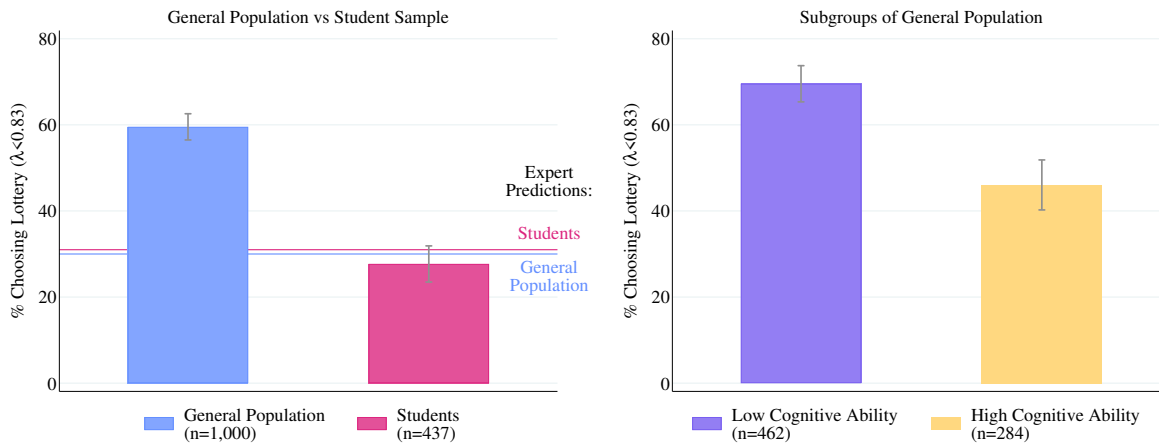
Our main result can be observed in choices over a simple 50:50 lottery with a negative expected value, as shown in Figure 1. All participants face a choice between a sure amount of \$0 and a lottery between a gain of \$10 and a loss of \$12, each with 50% probability.⁴ As shown in the left-hand panel, 60% of those in the representative sample ($N = 1,000$) choose the lottery, demonstrating a significant degree of loss tolerance (assuming local risk neutrality, see, Rabin, 2000; Kőszegi and Rabin, 2006). This proportion is much higher than among a sample of University of Pittsburgh undergraduates ($N = 437$) completing a very similar incentivized online survey—only 28% of students chose the lottery. Consistent with this finding, in the right-hand panel of Figure 1, we see that those in the representative sample with low cognitive ability were more likely to choose the lottery; our results thus likely differ from the literature, in part, due to our use of a representative sample.

The proportion of loss-tolerant participants in our data is much higher than anticipated by expert economists completing a prediction survey (DellaVigna et al., 2019). The expert

³Our data also show that a large proportion of the population exhibits an endowment effect for lottery tickets. However, this is uncorrelated with all our elicitations of loss aversion, see Chapman et al. (2021b).

⁴We thank Matthew Rabin for suggesting this simple test of loss tolerance.

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. See Section 2.3 for further details.

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%).⁵ 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, which is consistent with academic audiences being unrepresentative of the extent of loss tolerance across the population.

The paper documents these findings in detail using DOSE (Chapman et al., 2018) to elicit accurate individual-level estimates of loss aversion, as detailed in Section 2. 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).

⁵These results do not reflect a general willingness to gamble in the survey due to, for instance, a “house money effect” (Thaler and Johnson, 1990). Only 39% of the representative sample chose a lottery with a 50% chance of \$15 and 50% chance of \$0. over a sure amount of \$5.90. Expert respondents predicted that 56% of participants would choose the lottery. The survey was completed November 17–30, 2020. Recruitment was carried out via social media, research networks, and <https://socialscienceprediction.org/predict/>.

Disentangling these preferences generally requires a parametric model and asking 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, meaning that they may underestimate 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 prior assumes considerable loss aversion, and the adaptive design robustly identifies loss tolerance by offering participants several negative-expected-value gambles. However, our results are not driven by this relatively new method: in Section 5 we find similar levels of loss tolerance using two more traditional multiple price list elicitation procedures.

There is a much higher level of loss tolerance in representative samples of the U.S. population than among students recruited at the University of Pittsburgh Experimental Laboratory (PEEL), as shown in Section 3.1. We can compare our main sample ($N = 1,000$) and a supplementary sample ($N = 2,000$)—the former with two DOSE elicitations, and the second sample studied twice, six months apart—to two student samples ($N = 437$ and 369) that participated in similar incentivized surveys. In our three representative samples, the proportion of loss-tolerant participants is 57%, 47% and 55%; in the corresponding student samples and elicitation, the proportions are 32%, 22%, and 16%.⁶ Further, our estimates of loss aversion have similar levels of within-person, over-time stability as risk aversion and discounting, indicating they are an important descriptor of preferences.

Our experimental measure of loss aversion is correlated with the tendency to gamble, a greater percentage of assets in the stock market, recent exposure to financial shocks, and lower total assets. More loss tolerance was associated with a propensity to engage in both casual (lotteries and scratch cards) and serious (for example, casinos or online) gambling.

⁶Moreover, those in our representative sample with greater education and cognitive ability, and lower age, are more likely to be loss averse. These attributes describe the student samples usually used in studies of loss aversion. Indeed, in our representative sample, 31% of those under 35 with a college education ($N = 138$) were loss tolerant.

That is, the willingness to accept negative-expected-value bets in our study reflects a similar propensity outside of the study. Loss tolerance is also associated with a greater proportion of assets invested in the stock market, and recent financial shocks. Finally, loss tolerance is also associated with lower total assets. Notably, there is little evidence that risk aversion is correlated with any of our measures of real world experience and behavior—evidence that loss aversion is an independent, and important, economic preference.

Our results are robust to a number of factors, including possible misspecification and removing participants least likely to be paying attention, as shown in Section 5. 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 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. We find little evidence of house money effects: a model accounting for participants’ limited liability within the study fits the choice data very poorly. Removing participants that may be “rushing through” the survey, or just the DOSE module(s), has minimal effects on the distribution of DOSE-estimated parameters. Additional robustness checks are conducted in Appendix C.

The paper concludes with a discussion, in Section 6, of how our results affect the broader endeavor to understand gain-loss attitudes, including potential reasons why prior studies have found different patterns of loss attitudes. An obvious possibility, based on our own results, is a focus in prior studies on lab/student samples. In the nine studies we are aware of that investigate heterogeneity in loss aversion in the laboratory, the percent loss tolerant ranges from 13–30% (weighted average 22%, $N = 1,109$).⁷ Moreover, there is some evidence that the (very few) studies that do try to ascertain loss aversion in general populations rely on elicitation methods that are calibrated based on lab results, and hence do not allow

⁷These studies are Schmidt and Traub (2002); Brooks and Zank (2005); Abdellaoui et al. (2007, 2008); Sokol-Hessner et al. (2009); Abdellaoui et al. (2011); Sprenger (2015); Goette et al. (2018); L’Haridon et al. (2021). The figure for Sprenger (2015) is reported in Footnote 8 of Goette et al. (2018).

participants to fully express their degree of loss tolerance. For example, von Gaudecker et al. (2011) offered participants fifty-six lotteries, but none involved a negative-expected-value gamble, which is necessary to identify significant loss tolerance with a reference point of zero.⁸ Other common measurement approaches potentially conflate loss aversion with either the endowment effect (for example, Gächter et al., 2021) or status quo bias (for example, Fehr and Goette, 2007). Finally, publication bias may be 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 bias warranting deeper investigation. Indeed, our correlations between loss tolerance and problematic behaviors such as accepting negative-expected-value gambling in the real world, suggest that while loss aversion impairs individual choice, loss tolerance may be even more costly.

1.1 Related Literature

This paper significantly expands a prior study of ours 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 (one drawn from the general population, and one from a student population), and adds a number of new robustness tests to address concerns raised by various readers and seminar participants. Specifically, the earlier paper elicited loss aversion using a 10-question DOSE sequence. Here, we supplement that sequence with the simple lottery choice summarized above in Figure 1, two Multiple Price List measures of loss aversion, and a new, 20-question DOSE sequence. The latter extends our initial DOSE implementation by adding choices that only involve losses, presenting choices with the options in the opposite order from the 10-question sequence, and including a randomly-inserted “break” to check participant attentiveness. Finally, we added questions about gambling, financial shocks, and total assets and asset allocation, which are all analyzed

⁸In general, offering participants questions with asymmetry in the range of gains and losses may generate a finding of loss aversion (Walasek and Stewart, 2015). See Ert and Erev (2013) for a broader discussion of issues associated with common elicitation of loss aversion.

in Section 4. Our central finding of widespread loss tolerance is robust to these changes and additions.

The paper contributes to a vast literature investigating loss aversion in both economics and psychology. A large majority of studies finds significant loss aversion—a recent meta-analysis reports a mean loss aversion coefficient (λ) of 1.96 (Brown et al., 2021) across more than 150 studies in both the lab and the field.⁹ This seeming uniformity belies a dizzying array of elicitation techniques, estimation techniques, contexts, and target populations. Thus, we focus here on the few studies that have investigated loss aversion in general population samples.

Our study is the first to elicit individual-level estimates of loss aversion in a general population sample, allowing us to investigate gain-loss attitudes in greater depth than previous work. A small number of other papers have investigated loss aversion in representative samples, but have only reported population-level statistics. Closest to our work is von Gaudecker et al. (2011), who estimate the population distribution of λ in the Netherlands, without eliciting individual-level estimates of loss aversion. They report a median λ that ranges from 0.12 to 4.47, depending on their estimation choices—our results, in contrast, are robust to different utility specifications and alternative reference points (see Sections 5.2, 5.3, and Appendix C.1).¹⁰ Three other papers, published after our initial working paper, report only first moments of the loss aversion distribution: their findings are consistent with our finding of widespread loss tolerance.¹¹ By eliciting individual-level preference parameters, we are able to document the heterogeneity of loss attitudes across the population, investigate within-person stability of loss aversion over time, and tie our estimates of loss aversion to

⁹A growing literature in psychology suggests that loss aversion may not extend across contexts (see the review in Gal and Rucker, 2018). For example, decisions made with feedback may reduce or eliminate loss aversion (Erev et al., 2008).

¹⁰von Gaudecker et al. (2011)’s main results, which produce a median λ of 2.38, do not allow them to use the S-shaped utility function suggested by Prospect Theory (Kahneman and Tversky, 1979). The full range of parameter estimates is reported in their appendix.

¹¹Specifically, Blake et al. (2021) elicit loss aversion using hypothetical questions, and find $\lambda \approx 1$ for the U.K. population. Delavande et al. (2020) report a median λ of 1.26 in a U.K. sample skewed towards college-educated individuals—a group we find to be relatively loss averse. Lampe and Weber (2021) report a median $\lambda \approx 1$ for intertemporal choices in a small sample drawn from the Dutch population. Two earlier studies in the Netherlands (Booij and Van de Kuilen, 2009; Booij et al., 2010) also attempted to estimate loss aversion in a representative sample, but were able to obtain estimates for less than 30% of their participants.

individual characteristics and behaviors.

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). Consistent with most earlier work, we find that higher cognitive ability individuals are less risk averse over lotteries involving only potential gains.¹² 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.

This paper also contributes 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 literature on gambling in economics and finance 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 external validity of lab-based measures of economic preferences. In general, our results suggest that loss aversion has more predictive power than risk aversion for behavior outside of our survey environment, in line with previous mixed results regarding the external validity of laboratory

¹²Consistent with our findings, Stango and Zinman (forthcoming) find a positive correlation between cognitive skill and a measure of loss aversion. The limited experimental evidence also suggests cognitive ability is negatively associated with risk aversion over lotteries involving losses (see Dohmen et al., 2018, for a detailed review of the literature examining the relationship between cognitive ability and risk preferences). In contrast to our results, Andersson et al. (2016a) find no evidence of a relationship between loss aversion—or risk aversion—and cognitive ability in a large, non-representative, sample of the Danish population.

measures of risk attitudes (see Charness et al., 2020, for a review).

2 Measuring Loss Aversion

This section introduces the data and methods we use to measure loss aversion and other behaviors. Our primary measure of loss and risk aversion uses DOSE, a method designed to tackle the challenges of estimating loss aversion—the need for multiple choices and a parametric model—and that is well-suited to an online survey environment (Chapman et al., 2018). We supplement this primary measure with traditional multiple price list elicitations, described in Section 5, as well as specific questions from within the DOSE procedure, as in Figure 1.

2.1 Theoretical Definition

We measure loss aversion by estimating the parameters of a Prospect Theory utility function (Tversky and Kahneman, 1992). Many definitions of loss aversion exist in the literature; our approach considers loss aversion as a “kink” in the utility function at a reference point. This parametric approach provides an easily interpretable measure of loss aversion, but requires disentangling gain-loss attitudes from utility curvature—which is particularly difficult if participants make inconsistent choices. Our main estimates use DOSE, which is designed to tackle these challenges.

In line with most empirical studies of loss aversion, we model risk and loss aversion using a Prospect Theory utility function 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., 2021, Table 3).¹³ Loss aversion is conceptualized as distinct from utility curvature, reflecting a kink in the utility function at zero. The standard

¹³In Section 5.3, we examine the possibility that individuals use alternative reference points, and find that our preferred model performs better than alternatives suggested in the theoretical literature. Alternative models also classify a large proportion of the population as loss tolerant.

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:

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

in which λ_i parameterizes loss aversion, ρ_i parameterizes 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. That is, an individual with $\rho_i < 1$ demonstrates risk aversion over gains and risk love over losses.¹⁴ 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.

Without parametric assumptions it is difficult—if not impossible—to measure individual-level loss aversion. This is due to a combination of extreme data requirements and inconsistent choice. Many theoretical definitions characterize loss aversion as a function of the *entire* utility function—someone is said to be loss averse if $-U(-x) > U(x)$ for all $x > 0$ (Kahneman and Tversky, 1979)—making it unmeasurable without assuming a functional form.¹⁵ Specifically, individuals often make choices whereby $-U(-x) > U(x)$ but $-U(-y) < U(y)$ (for $x, y > 0$): in this case it is unclear whether the individual is loss averse or not, or is

¹⁴Assuming the same curvature across gains and losses also avoids an issue with power utility: different curvatures mean that estimates of loss aversion depend on scaling. Our results are similar using the exponential (CARA) utility function Köbberling and Wakker (2005) suggest to avoid these issues (see Appendix C.1). Our focus is on loss aversion, and so we do not allow for probability weighting—accordingly all the lotteries in our questions have 50/50 probabilities of two outcomes to minimize probability distortions.

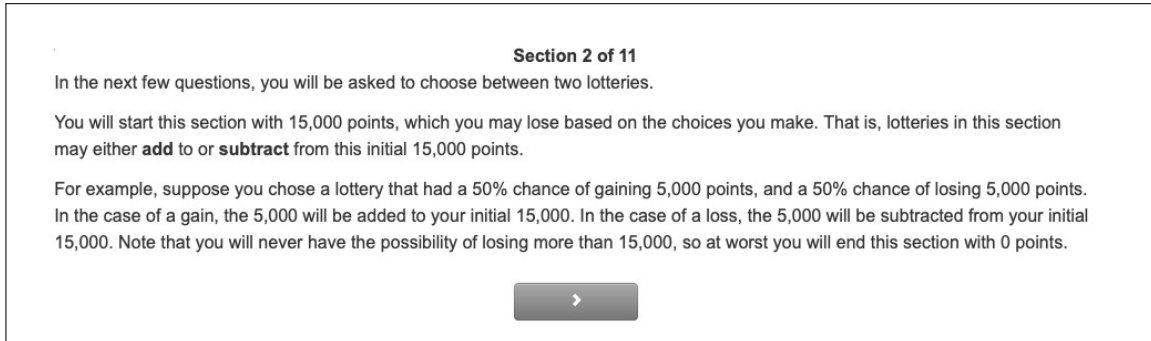
¹⁵Alternative definitions, such as Wakker and Tversky (1993), have focused on loss aversion as meaning greater sensitivity to losses, and so compare the slope of the utility function over losses to that over gains (see also Bowman et al., 1999). Later approaches have focused on loss aversion as reflecting the kink in the utility function near a reference point (Köbberling and Wakker, 2005), which is also unmeasurable without data on choices with x infinitesimally close to the reference point.

simply making a mistake. As a result, non-parametric elicitation techniques usually cannot classify loss attitudes for a large proportion of people. The parametric approach avoids this issue, but risks misspecifying individual preferences. As such, we check that our results are robust to several alternative utility specifications, including allowing curvature to differ between the gain and loss domains (see Section 5.2 and Appendix C.1.)

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. Estimating multiple parameters is complicated, because it necessitates asking participants a number of questions—in this case, to capture preferences for lotteries over gains (risk aversion) and *mixed lotteries*—those including both gains and losses. Inconsistent choice across different questions can lead to noisy estimates and, at worst, preclude parameters being estimated at all, if, for example, some responses violate First Order Stochastic Dominance. 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.¹⁶ Some laboratory studies overcome such issues by asking a very large number of questions—around 120 (Sokol-Hessner et al., 2009; Frydman et al., 2011)—which is infeasible in a survey environment—and use MLE to model choice inconsistencies. DOSE overcomes these issues by adapting the question sequences individuals receive to rapidly home in on their preferences, while accounting for inconsistent choices. As a result, in simulations, the procedure measures parameters more accurately than more established elicitation methods, particularly for participants that are likely to make mistakes. The following subsection describes the DOSE method in more detail. For an exhaustive discussion, including simulation results, see Chapman et al. (2018).

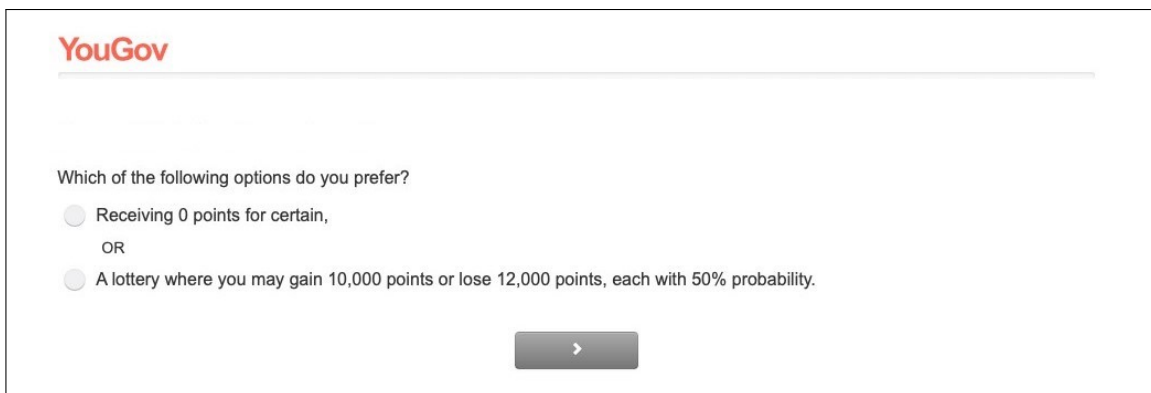
¹⁶For example, Blake et al. (2021) report that 16% of participants made choices such as valuing a 50/50 lottery with prizes £0 and £10 more than a similar lottery with prizes of £0 and £100. See Section 1.1 for further discussion.

Figure 2: Example of DOSE Question



The screenshot shows a screen titled "Section 2 of 11". The text reads: "In the next few questions, you will be asked to choose between two lotteries. You will start this section with 15,000 points, which you may lose based on the choices you make. That is, lotteries in this section may either **add** to or **subtract** from this initial 15,000 points. For example, suppose you chose a lottery that had a 50% chance of gaining 5,000 points, and a 50% chance of losing 5,000 points. In the case of a gain, the 5,000 will be added to your initial 15,000. In the case of a loss, the 5,000 will be subtracted from your initial 15,000. Note that you will never have the possibility of losing more than 15,000, so at worst you will end this section with 0 points." At the bottom center, there is a grey button with a white right-pointing arrow.

(a) DOSE Instructions



The screenshot shows a YouGov logo at the top left. Below it, the text asks: "Which of the following options do you prefer?". There are two radio button options: "Receiving 0 points for certain," and "A lottery where you may gain 10,000 points or lose 12,000 points, each with 50% probability." The word "OR" is centered between the two options. At the bottom center, there is a grey button with a white right-pointing arrow.

(b) Sample DOSE Choice

2.2 Measurement

We elicit loss aversion using Dynamically Optimized Sequential Experimentation (DOSE; Chapman et al., 2018). DOSE asks 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 (which was analyzed in Figure 1). The sure amounts and the prizes in the lotteries are chosen 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.¹⁷

¹⁷The support of the prior distribution covers individual estimates obtained in lab data: $\lambda \in [0.1, 4.5]$, $\rho \in [0.2, 1.7]$ and $\mu \in [1, 8]$. Questions are chosen to maximize the Kullback-Leibler divergence, see Appendix A for a technical treatment.

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.¹⁸ 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. To provide an experimental test of whether participant inattention affected the results, the sequence was interrupted by a page break, which appeared randomly after either the eighth or twelfth question—see Section 5.4.

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 modules eliciting preferences over mixed lotteries—that is, lotteries with prizes in both the gain and loss domain.¹⁹ The shorter DOSE sequence did not contain choices with only non-positive payoffs. In these questions, the sure amount appears first, reversing the order from the longer 20-question sequence. The level of loss tolerance is similar in both DOSE modules, as shown in Section 3, suggesting that the results are not due to a reference point created by the ordering of the options. We also observe similar levels of loss aversion in the MPL elicitations—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 lead to participants not considering any payoffs as losses, because they are playing with “house money” (Thaler and Johnson, 1990). However, as we show in Section 5.3, such behavior does not appear to be a concern in our

¹⁸Experimental evidence suggests that participants make more consistent choices when questions include a sure amount, and when lotteries include 50% probabilities (Olschewski and Rieskamp, 2021; Olschewski et al., 2022).

¹⁹The 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.

data.²⁰ Specifically, we can attempt to fit observed choices after shifting all prizes into the gain domain (for example, adding 15,000 points—\$15—to all prizes). Doing so yields a model that predicts at best 59% of choices correctly—barely better than random guessing—across the two DOSE modules. Our preferred model, in contrast, correctly predicts 91% of choices in the 10-question module, and 74% in the 20-question module.

2.3 Data

Main Sample: We measured loss aversion in a large, representative, incentivized survey of the U.S. population. 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, 2020.²¹ Participants in the survey were drawn from a panel maintained by YouGov.²²

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.²³ 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.²⁴ 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,

²⁰Etchart-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.

²¹For screenshots of experimental instructions and the questions used in this paper, see Appendix E. Full design documents for both our main survey and the supplementary sample can be found at eriksnowberg.com/~snowberg/wep.html.

²²YouGov continually recruits new people to the panel, especially from hard-to-reach and low-socioeconomic-status groups. To generate a representative sample, it randomly draws people from various Census Bureau products, and matches them on observables to members of their panel. Differential response rates lead to the over- and under-representation of certain populations, so YouGov provides sample weights to recover estimates that would be obtained from a fully representative sample. We use these weights throughout the paper. According to Pew Research, YouGov’s sampling and weighting procedure yields better representative samples than traditional probability sampling methods with non-uniform response rates, including Pew’s own probability sample (Pew Research Center, 2016, YouGov is Sample I).

²³Participants 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 (Ray, 2015; Chapman et al., 2018).

²⁴The conversion from points to awards can only be done at specific point values, which leads to a slightly convex payoff schedule. This is of little concern here as these cash-out amounts are further apart than the maximum payoff from the survey.

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. The median completion time was 42 minutes.

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 an earlier working paper that serves as documentation for the modeling choices and analysis in this paper (Chapman et al., 2018).

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 (PEEL) 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 average payment was \approx \$10.70, compared to \$10 in the representative sample. The only significant difference was that students received the value of their points in cash within two weeks, via a Visa gift card, rather than YouGov points. The planned comparison between the student and population sample (see Figures 1 and 3) was pre-registered with the Open Science Framework (Chapman et al., 2021a). We also elicited loss aversion using only a 10-question DOSE module in an earlier sample of students ($N = 369$) from PEEL in January 2019. This previous study was designed to be comparable with our supplementary sample.

3 Loss Aversion in a Representative Sample

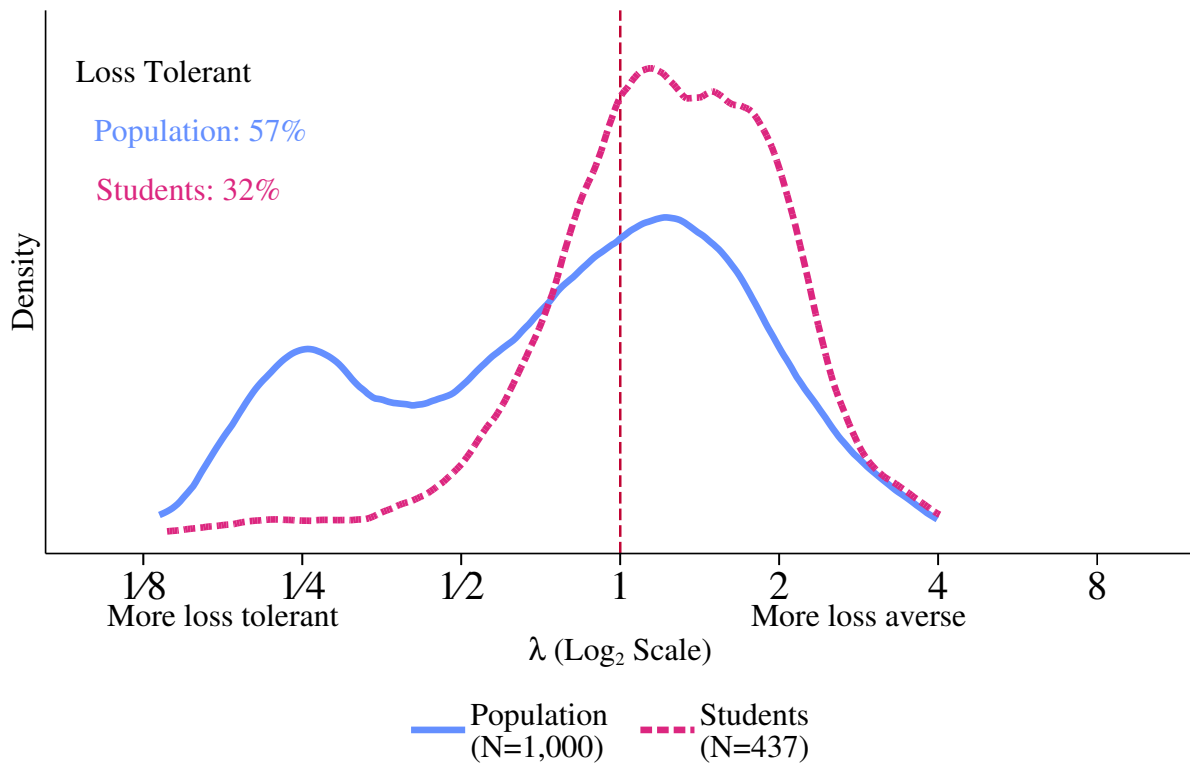
The U.S. population is substantially more loss tolerant than participants in student samples. Consistent with this finding, higher-cognitive-ability participants are more loss averse. This contrasts with the prior literature that suggests that behavioral biases are concentrated in those of lower cognitive ability (see, for example, Frederick, 2005; Dohmen et al., 2010; Benjamin et al., 2013). Moreover, as we document in Section 4, loss aversion captures aspects of behavior outside of the survey environment even once we control for risk aversion, cognitive ability, and other demographic characteristics.

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. This is a slightly smaller proportion than might be expected from the single lottery question displayed in Figure 1, reflecting the fact that the DOSE procedure also estimates individuals’ risk aversion (utility curvature).

Loss tolerant individuals do not simply prefer lotteries in general: nearly all (89%) those classified as loss tolerant were also classified as risk averse. These classifications by DOSE reflect a clear pattern of choices, in which loss-tolerant participants tended to accept mixed lotteries (such as those in Figure 1), but turned down lotteries involving only positive prizes. Given that the initial DOSE prior implied considerable loss aversion ($\lambda = 2.3$), participants had to accept multiple negative-expected-value mixed lotteries to be classified as loss tolerant. Thus, the finding of widespread loss tolerance is underpinned by a clear pattern of choices both in the DOSE modules—see Appendix B.1—and also in two Multiple Price List modules—see 5.1 and Appendix B.2. Consequently, our results are not driven by the particular utility function we estimate and are robust to alternative parametric specifications and

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.

assumptions regarding individual reference points, as shown in Sections 5.2 and 5.3.

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 similar to the nine previous studies that have investigated individual loss aversion in laboratory experiments. Those studies, cited in the introduction, classify between 13% and 30% of participants as loss tolerant (weighted average: 22%, $N = 1,109$). In line with prior research (see Snowberg and Yariv, 2021, and references therein), we find that the student sample is also less risk averse than the general population: 90% of the general population sample were classified as risk averse, compared to 76% of students.

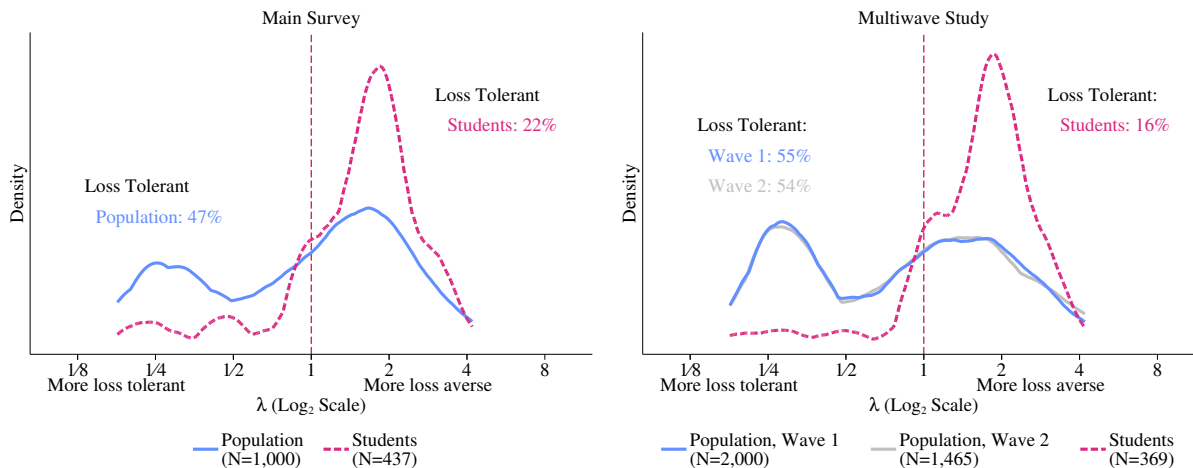
3.2 Stability of Loss Aversion

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 4. This figure displays the distribution of loss aversion from the 10-question DOSE sequence in our main sample (left-hand panel) and our 2015 multiwave survey (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 prior on λ assumes everyone is fairly loss averse, with a mean $\lambda = 2.3$, based on previous laboratory studies. 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 suggests a relatively small effect of the prior on final estimates. Moreover, we 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 2015 survey.

The estimates from the 10-question DOSE module are very stable over time, as shown in the right-hand panel of Figure 4. The correlation of DOSE estimates of loss aversion across the two survey waves, collected six months apart, was 0.40 (s.e. = .04). This over-time correlation was similar to that for DOSE elicitations of risk aversion (ρ)—0.44 (0.04)—and for time discounting (δ)—0.47 (.04). The within-person stability was lower when using other

Figure 4: 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.

elicitation techniques, both within our survey and in previous studies, consistent with lower measurement error in the DOSE estimates.²⁵ Moreover, loss tolerance is as stable as loss aversion: of those who DOSE classified as loss tolerant on the first survey, 68% were also classified as loss tolerant on the second, whereas for loss aversion the figure is 71%.

The stability of the DOSE-elicited parameters both provides reassurance about the robustness of our results, and suggests that loss attitudes are a useful descriptor of economic preferences. Our finding of widespread loss tolerance is not an artefact of the 20-question DOSE sequence, or specific design choices in our main survey sample—for instance, the fact we ask participants many questions involving possible losses. Section 5 reports the results of additional robustness tests.

²⁵Within the survey, the over-time correlations ranged from 0.26–0.33 (all with s.e. = .04) across two MPLs and a risky project question (Gneezy and Potters, 1997). For discounting, the over-time correlations from two MPLs were 0.20 and 0.28 (both .06). Previous studies using similar elicitation methods have provided stability estimates of a similar magnitude—see Chapman et al. (2018) for a detailed discussion.

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 involved 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 was the sum of correct answers to these nine questions.²⁶

The correlations between loss aversion and other individual characteristics, reported in Table 1, are consistent with the finding that the general population is less loss averse than lab/student populations. 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. We can see that more educated and more cognitively-able individuals—both characteristics of student samples (Snowberg and Yariv, 2018)—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 maybe also more loss averse—although the latter finding is not robust across samples and specifications.²⁷

Inconsistent choice does not drive our results—the correlation between cognitive ability

²⁶We combine the IQ and CRT measures because they are highly correlated (0.43, s.e. = .029). 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.

²⁷We find a statistically-significant negative correlation between age and loss aversion elicited with the 10-question DOSE sequence, and age is also associated with being less risk averse over losses, when allowing for differential curvature across the gain and loss domains. See Appendix C.2 for more details.

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

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

and loss aversion is even higher when constraining the sample to those with μ above the sample median ($r = 0.34$, s.e. = .06).²⁸ The temporal stability of our estimates, documented in the previous subsection, is similar regardless of cognitive ability: even participants classified as less cognitively able display consistent patterns of behavior.²⁹ In general, as we detail in Section 5.4, we see little evidence of participants being inattentive to the survey, and our results are robust to removing subsets of participants failing attention checks or completing the survey quickly.

Both high- and low-cognitive-ability participants consistently deviate from expected-value

²⁸The 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 for inconsistent choices, DOSE estimates are quite accurate even for participants making many mistakes.

²⁹The over-time correlation of loss aversion for those in the lowest tercile of cognitive ability is 0.37 (s.e. = .07), and for risk aversion 0.39 (.08). For the middle tercile, the respective figures are 0.32 (.06) and 0.45 (.09); and for the top tercile 0.43 (.06), and 0.40 (.06).

maximisation in our data—but in very different ways. Consistent with some previous studies (for example, Burks et al., 2009; Benjamin et al., 2013), participants in the highest tercile of cognitive ability were slightly more likely to make an expected maximizing choice (doing so in 66% of questions versus 57% 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 or negative expected value.³⁰ 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 that we might expect to have encountered more losses in life. This raises the intriguing possibility that loss tolerance 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 expose themselves to potential losses through gambling or investing in stocks. Loss-tolerant individuals also appear to actually experience more losses—they are more likely to report a recent financial shock—and accumulate fewer financial assets. The behaviors and outcomes are, at best, weakly correlated with risk aversion. Our data does not allow us to distinguish the direction of causality in these relationships: individuals may expose themselves to losses because they are loss tolerant, or they may become loss tolerant after experiencing losses. However, our

³⁰Low-cognitive-ability participants chose the lottery in 60% of questions with a negative expected value, versus 35% for those of high cognitive ability. For lotteries with positive expected value, the rates were 74% and 65%. Less than 1% of participants in the whole sample made an EV-maximizing choice in more than 18 out of 20 questions.

measure of loss aversion clearly captures 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).³¹ There is likely some noise in these measures, which will tend to bias the correlation between these measures and estimated preference parameters towards zero (Gillen et al., 2019).

Gambling behavior and household shocks were each measured using a battery of questions. Table 2 provides a brief description of each question, and shows the results from running a principal components analysis to summarize the information from each module.³²

For both gambling behavior and the experience of household shocks two components with intuitive interpretations emerge. 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—for the latter, divorce and (to a lesser extent) injury.

³¹Specifically, 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.”

³²Questions on household shocks were taken from Pew Research Center (2015, p4); questions on gambling were adapted from Gonnerman and Lutz (2011). See Appendix D for further details of our principal components analyses.

Table 2: Principal Components Analysis

	Gambling (Last Time Gambled)		Household Shocks (Experienced in Last 12 Months)		
	Components		Components		
	Serious	Casual	Financial	Personal	
Sports Bets	0.45	-0.05	Unemployment	0.38	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	0.10	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%

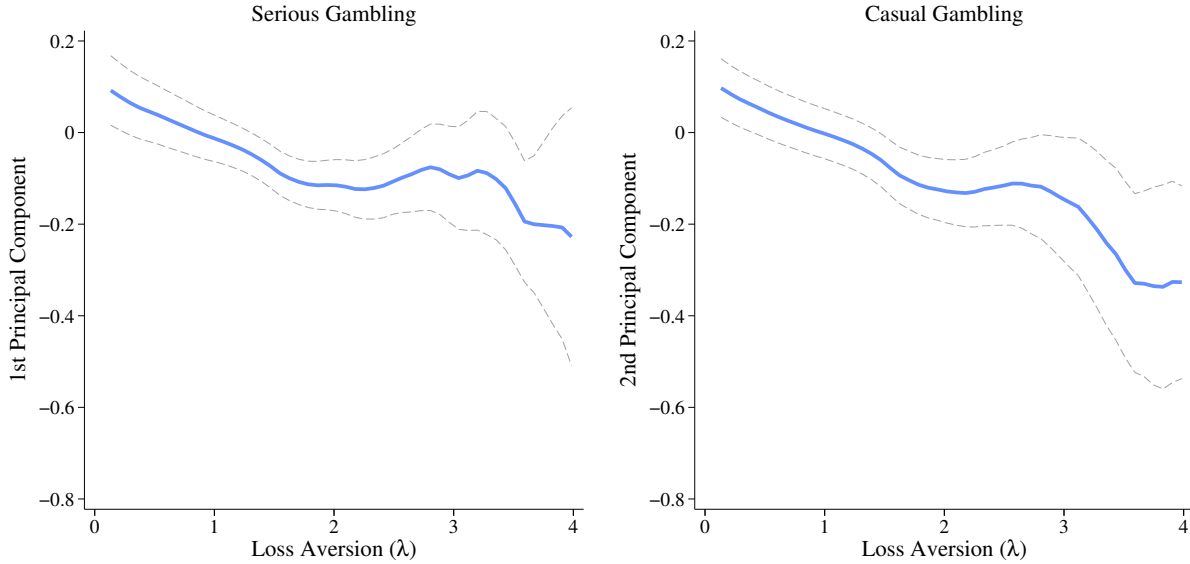
Notes: Only first two principal components are shown, rotated using varimax rotation.

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, conditional on their asset holdings.

Loss aversion is negatively correlated with both of the principal components of gambling activity (see Table 2), as shown in Figure 5. There is a clear negative relationship in both panels. Moreover, these relationships are robust to controlling for other individual characteristics, including risk aversion and cognitive ability (see Table 3). Loss-tolerant individuals not only accept negative-expected-value bets in our study; they seek out and participate in

Figure 5: Loss aversion is associated with gambling less recently.



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 0.6. Grey dotted lines represent 90% confidence intervals.

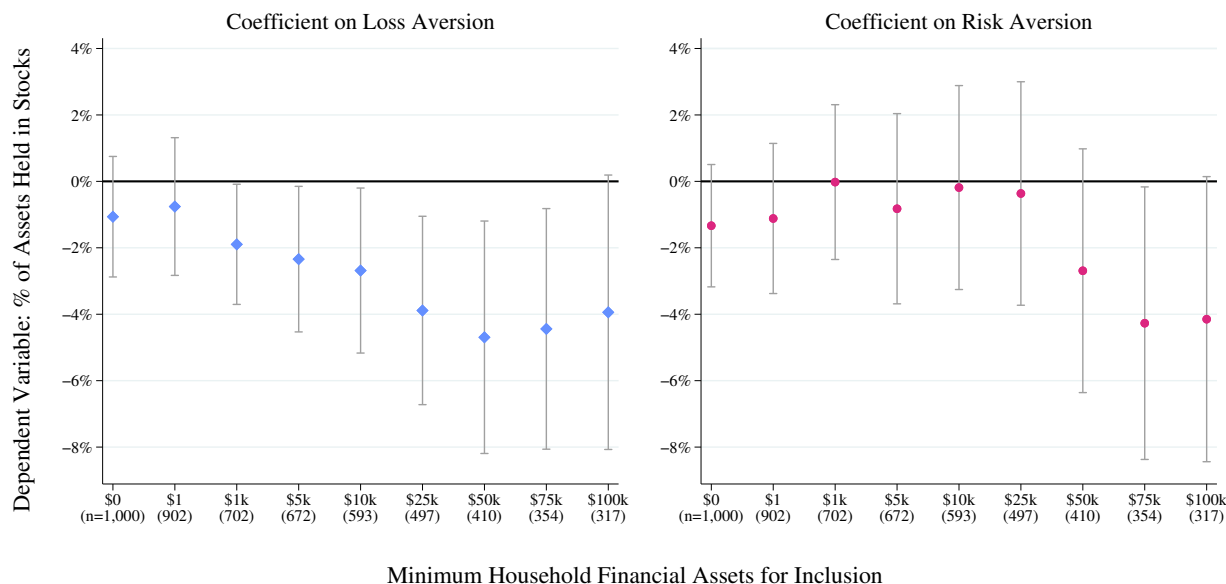
such gambles in their day-to-day lives.

Loss-tolerant individuals also hold a greater proportion of their investable assets in the stock market, as shown in Figure 6. 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.³³ Combined with the results regarding gambling behavior, these findings add further evidence that loss-tolerant individuals are more willing to spend and invest in a way that exposes them to real-world losses.

Loss aversion is a much stronger predictor of both gambling and investment behavior

³³These 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 6: 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. Bars represent 90% confidence intervals. See Appendix Table C.12 for full regression results, and Appendix Figure C.6 for results with alternative sets of control variables.

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 6—but only amongst those with very high financial assets. These results are consistent with previous studies that find limited evidence that experimental measures of risk aversion predict behavior outside of the laboratory (Charness et al., 2020). Loss aversion appears an important component of risk attitudes, warranting further study in its own right.

While we document strong correlations between loss aversion and behavior, we must be cautious in considering the direction of causality. Loss aversion may be a fairly stable attitude that drives individual choices. Alternatively, loss tolerance may be shaped by past

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

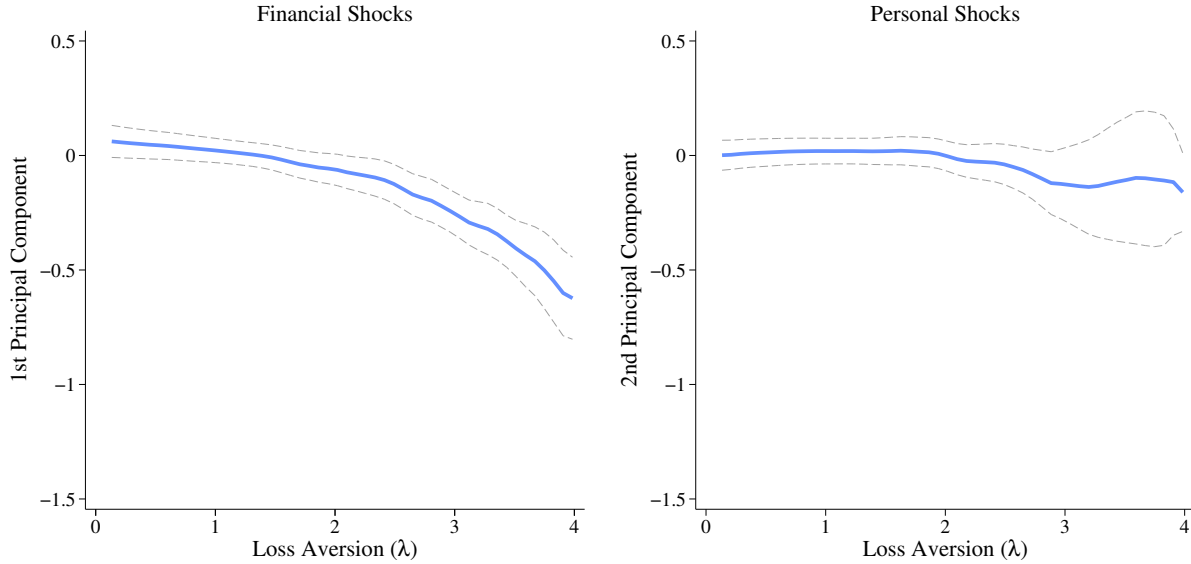
Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses. The magnitude and statistical significance of the coefficients for loss and risk aversion are similar when including controls as categorical variables—see Appendix Tables 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.

experience of negative outcomes: repeatedly experiencing losses could remove the fear of losses in the future. The following subsection examines whether loss-tolerant individuals are more likely to have experienced recent shocks.

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 likely among groups—those with less cognitive skill, education, and income—that we would expect to experience more losses. This subsection shows that loss tolerance is associated with being more likely to have experienced a recent financial shock,

Figure 7: 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 0.6. Grey dotted lines represent 90% confidence intervals.

even after controlling for other characteristics. Further, loss-tolerant participants own fewer financial assets, even controlling for income, offering suggestive evidence that loss tolerance leads to worse financial outcomes.

Loss aversion is negatively correlated with having experienced a recent financial shock, but not a personal shock, as shown in Figure 7 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, as we have measured 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, education, cognitive ability, and other demograph-

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

ics. The relationship is also robust to controlling for home ownership, which could capture either familial wealth or other major asset holdings. Moreover, there is no correlation between loss aversion and home ownership (correlation 0.05, p-value = 0.51), 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.

5 Robustness

Examining Figure 1 in the Introduction demonstrates that our finding of widespread loss tolerance in the U.S. population is not driven by the DOSE elicitation method, or by our parametric assumptions. A loss-averse participant should never accept a lottery with negative expected value rather than a certain amount of \$0. Yet, more than half the survey participants do. Moreover, the results in our student samples are similar to those in prior laboratory studies using a range of different elicitation methods.

Our data provide the opportunity to further reduce concerns about the robustness of the results, while learning more about behavior in the general population. In this section, we present four such analyses. The first subsection shows that more traditional elicitations—in particular MPLs—measure similar levels of loss tolerance in our representative sample, and similar differences between representative and student samples. The subsequent two subsections estimate different utility specifications using choice data. The first of these focuses on differences in risk aversion across the gain and loss domain, and the second on reference points. The proportion of the population that is loss tolerant is consistently around 50% across various measurement techniques, parametric forms for utility, and a number of reference-dependent models. The fourth and final subsection utilizes direct and indirect evidence from our survey to examine whether fatigue or inattention affect our results. We find little evidence that either play an important role.

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.³⁴ 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.³⁵

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 partici-

³⁴Participants 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.19–E.24 for screenshots of the MPL elicitations.

³⁵Alternatively, 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.

pants 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%), although the rate of loss tolerance is lower than in our other elicitation methods for both groups. The range of estimates across these different elicitations may reflect the influence of MPL structure on participant choices (see, for example, Andersson et al., 2016b); the simple binary choices in the DOSE procedure are likely less vulnerable to such issues.

The Bayesian estimates provide a direct comparison to DOSE, but we can observe widespread loss tolerance simply by examining the choice data from the mixed-risk MPLs, as we discuss in Appendix B.2. Specifically, we can simply assume equal utility curvature in both domains, and classify choices in the mixed-risk MPLs as demonstrating loss aversion or loss tolerance. Doing so, we find 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 the results in Figures 1, 3, and 4 are not an artefact of our parametric assumptions, or of the DOSE question format.

5.2 Allowing for Differential Utility Curvature Over Losses

In this subsection, we use the choice data from the 20-question DOSE module to re-estimate individual preference parameters when 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). This exercise provides a more refined examination of loss attitudes than the sparser model we have used so far, as well as acting as a robustness test for our main results.

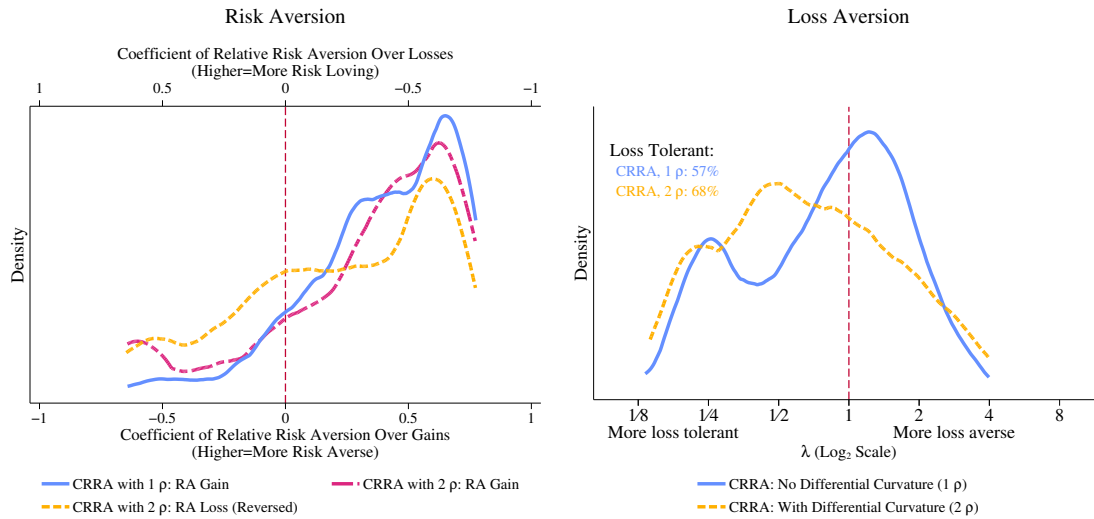
We estimate that most participants (64%) are risk averse over gains and risk loving over losses, inline with prior experiments and Prospect Theory (Kahneman and Tversky, 1979)—see the left-hand panel of Figure 8. The average difference in the curvature between the domains is small (mean = 0.11, s.e. = 0.02), offering support for our main specification, although there is considerable individual heterogeneity (see Appendix C.1). The distribution of risk aversion for gains is similar to that of our main risk aversion estimates, demonstrating that our questions over only gains pin down this parameter quite well. On the other hand, our main estimates may slightly exaggerate the degree of risk-loving over losses. This implies we are underestimating the extent of loss tolerance at the reference point, and that the distribution of λ in Figure 3 may be biased upwards.

Indeed, the right-hand panel of Figure 8 shows that more individuals have $\lambda < 1$ when allowing for differential curvature than in our main model (68% versus 57%). However, in line with the discussion in Section 2.1, the interpretation of this parameter is now slightly different. 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 the other differences between the two domains. If loss aversion is defined by behavior at the reference point, our main estimates may underestimate loss tolerance.

The correlations between loss aversion and cognitive ability are also largely robust to allowing for differential curvature, as shown in Appendix Table C.7. We find a strong positive correlation between λ and cognitive ability, and also that higher-cognitive-ability participants are more risk averse over losses—meaning that their utility is closer to linearity.

Our results regarding loss aversion are also robust to re-estimating with alternative utility functions and error specifications. In Appendix C.1, we use the DOSE choice data to estimate the parameters of an exponential (Constant Absolute Risk Aversion) utility function as suggested by Köbberling and Wakker (2005) to provide a scale-independent measure of loss aversion: under this specification, 60% of the population is loss tolerant. Further,

Figure 8: Distributions of loss and risk aversion are similar when allowing for utility curvature to differ between losses and gains.



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

in Chapman et al. (2018) we show that DOSE is robust to misspecifying the way in which individuals make mistakes. Our main estimates model the error process using a logit function, but the distribution of loss aversion is similar when either assuming a probit specification, or implementing a random parameter model as per Apesteguia and Ballester (2018).

An alternative possible source of misspecification is the reference point. We have assumed throughout that individuals evaluate losses and gains relative to a reference point of \$0, but many alternatives have been suggested in previous studies. The next subsection investigates whether our results could be explained by participants using alternative reference points.

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,

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

Model of Reference Point	% Participants with Improved Fit		% Loss Tolerant	
	20Q	10Q	20Q	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%	45%–65%	39%–49%

Notes: % Participants with Improved Fit is the percent of participants for whom the model 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. “Best Alternative” classifies each participant according to the reference point model(s) which best fits their 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.

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.³⁶ This alternative model fits the data much worse, correctly predicting only 59% choices in the 20Q module and 54% in the 10Q module—only slightly better than random guessing. As the table shows, this alternative model performs better than the \$0 reference 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.³⁷ Either of these reference points

³⁶See Figure 2a for text relating to the endowment.

³⁷Using expected value as the reference point is similar to the models of Loomes and Sugden (1986) and

could capture the “first focus” concept of Kőszegi and Rabin (2006).³⁸ These models fare slightly better than incorporating the endowment. However, this is partly because the reference point is often similar to our preferred model: in the 20Q module the sure option is \$0 in all lotteries containing gains and losses (48% of choices), while the EV is between -\$1 and \$1 in 15% of choices.

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 evaluates the sure amount with that amount as the reference point.

The specification with a reference point of \$0 performs even better if we allow for differential curvature over gains and losses. As shown in Appendix C.4, once we allow for differential curvature, our preferred model correctly predicts 82% of choices in the 20Q module. The other models now provide a better fit for only around 10% of participants. These results also offer an explanation for the higher proportion of choices fit in the 10Q module by our preferred model: there are no questions with only losses, allowing ρ and λ to be pinned down more precisely.³⁹

Finally, our core finding of widespread loss tolerance is unchanged if we allow for alternative reference points. The proportion of loss-tolerant participants is greater than 41%

Bell (1985). With our question structure, the sure amount represents the “MaxMin”, “MinMax”, and “X at Max P” (the outcome with the highest probability) reference points analyzed in Baillon et al. (2020).

³⁸For 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 DOSE module and second throughout the 10Q DOSE module. Further, we have already seen in Section 3 that the degree of loss tolerance is similar across the two DOSE modules.

³⁹Similarly, if we re-estimate the 20Q module excluding question with losses, the results are close to the 10Q module—see Appendix Table C.17.

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%.⁴⁰ While we cannot rule out some amount of heterogeneity in reference points, this does not alter the conclusion that a large proportion of the population is loss tolerant.⁴¹

These results demonstrate that our DOSE estimates reflect participants’ choices, and are not due to misspecification of either the utility function or the reference point individuals use. However, these estimates cannot speak to the extent to which those choices accurately reflect individual preferences or, specifically, whether participants paid attention to our elicitation methods—a question we address in the next subsection.

5.4 Inattention and Fatigue

We see little evidence of either fatigue or inattention. 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. Participants do not appear to choose more randomly as they progress through the survey, or through each DOSE module.

There is little reason to think that either confusion or fatigue would play a major role in our results. The DOSE questions were designed to be as simple as possible, involving binary choices that do not require complex calculations. All survey participants had previous experience with YouGov’s online survey platform, and had to pass a test that they understood the instructions before starting the survey. The main results are similar across different

⁴⁰The 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.

⁴¹There is limited empirical evidence regarding heterogeneity in reference points. One exception is Baillon et al. (2020) who explore the possibility of person-specific reference points. To the extent that results are comparable, ours agree with theirs: one of the two best models in their exercise is a “status quo” reference point, which would be \$0 in our implementation—as in our preferred model.

elicitation mechanisms. Further, the correlations with real-world experiences in Section 4 suggest our experimental measure of loss aversion captures behavior beyond our survey.

Despite the fact that there is little reason for concern about confusion and fatigue, we can examine the data directly. The left-hand panel of Figure 9 provides the first evidence that our results are not driven by lack of attention. A large majority (90%) passed three attention checks in our survey, and the degree of loss tolerance is very similar even when excluding participants who failed one of these checks.⁴² Further, the distribution of loss aversion is similar when we exclude participants who may have sped through the survey—those in the fastest tercile of response times—which could also reflect a lack of attention.⁴³

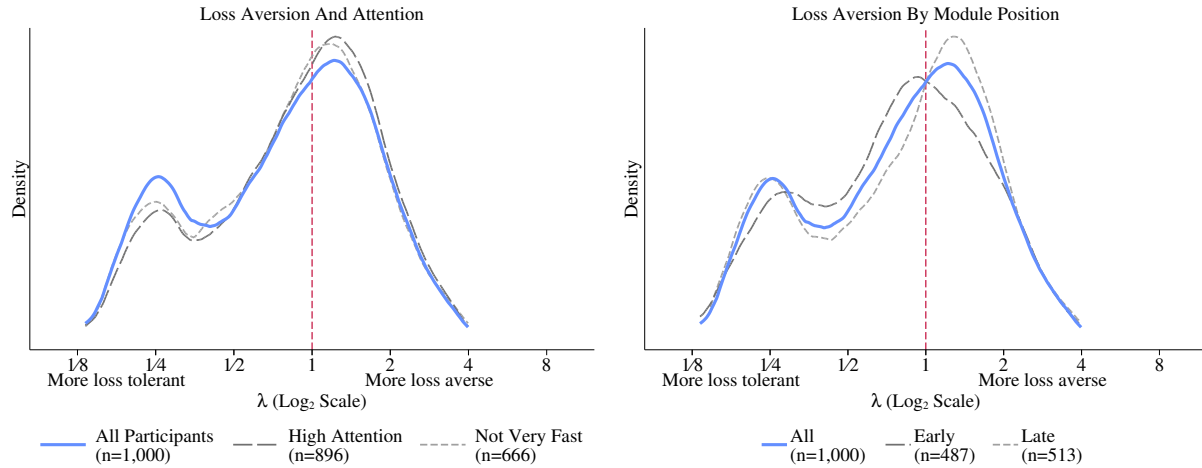
The finding of widespread loss tolerance is not driven by fatigue as participants progress further in our survey, as shown in the right-hand panel of Figure 9. The order of the 10-question and 20-question DOSE modules was randomized across participants, with each module appearing as either the second or seventh module in the survey. Loss aversion is, if anything, higher later in the survey—the median value of λ is 0.84 when the module appears early, but 0.98 when it appears late. Similarly, 67% of participants preferred the lottery of -\$12/\$10 to a sure amount of \$0 early in the survey (meaning it was the first time participants faced a potential loss); whereas 52% preferred the lottery when the question appeared later.

We carried out an experimental test of fatigue within the 20-question DOSE module using a measure of *surprise*—the extent to which a person makes choices the Bayesian prior does not expect. 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

⁴²See Figures E.27–E.30 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 that 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).

⁴³One 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. The distribution of loss aversion is also similar when we remove participants by quintile of response time either in the survey, or in just the DOSE module—see Appendix Figure C.7.

Figure 9: Widespread loss tolerance is not due to fatigue or inattention.



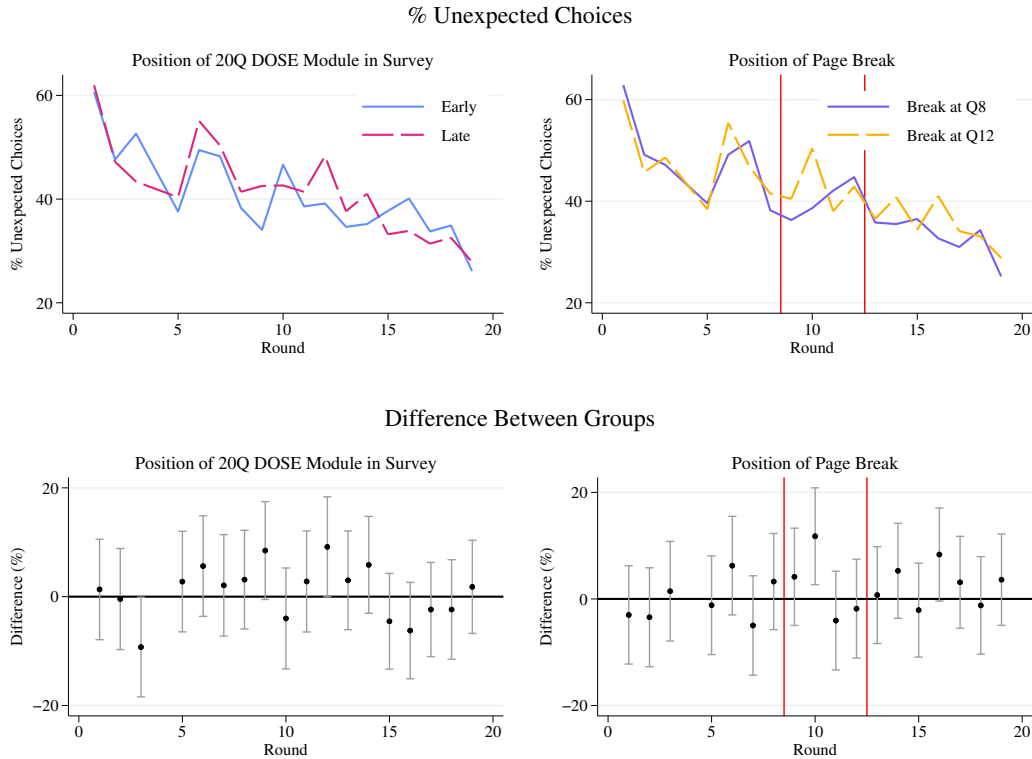
Notes: Figures display the distribution of loss aversion (λ) from the 20-question DOSE sequence. “High attention” excludes any participant that failed any attention check. “Not Very Fast” excludes participants in the fastest tercile of response times. The percentage of participants classified as loss tolerant in each group is as follows: whole sample, 57%; “High Attention”, 53%; “Not Very Fast”, 56%. When the sequence appeared early in the survey, 62% of participants were classified as loss tolerant, compared to 53% when the sequence appeared later.

make choices with a lower prior probability, that is, with a high degree of surprise. Using this metric, we can test whether participants act more randomly when DOSE appears later in the survey, or when the DOSE sequence is interrupted.

We see no evidence that survey fatigue affects choices in DOSE, as shown in Figure 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. On the right-hand side, we use a randomly-located page break to test whether interrupting the question sequence affects choices.⁴⁴ In principle, the question sequencing could inadvertently create a reference point or simply lead participants to pay less attention—however, as we can see, participant behavior did not change after the sequence was broken. Further, unexpected choices decrease as participants progress further in the module, suggesting fatigue does not lead to random decision-making.

⁴⁴The page break consisted of a separate screen (see Appendix Figure E.15) 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 10: No evidence of fatigue 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.

Thus, as far as we can observe, participants pay attention to our DOSE modules and throughout the survey.

6 Discussion

We find that around 50% of the U.S. population is loss tolerant over small stakes, differing from prior studies that have found a strong majority of loss-averse participants, usually in lab/student samples. 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. This, along with the fact that DOSE in a student sample produces similar results to prior studies, suggests that differences in samples are likely the source of the difference between our results and the previous literature. Further, loss-tolerant individuals

appear more likely to gamble, commit a greater portion of their assets to equities, experience financial shocks, and have lower overall wealth, suggesting that loss tolerance is a harmful behavioral bias requiring deeper investigation.

Our findings about loss aversion diverge significantly from conventional wisdom, raising the possibility that the prior literature may have been influenced by factors beyond the inadvertent sample selection mentioned above. Hints can be found in Fehr-Duda and Epper (2012, p. 576), who observe, “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.” Many studies may not be designed to identify loss tolerance. Andersson et al. (2016a), for example, offer participants 40 lotteries, but only one involving a negative-expected-value gamble, similar to von Gaudecker et al. (2011), mentioned in the introduction. Such a design is sensible given prior beliefs that most individuals are loss averse, and a reliance on questions that are fixed for all participants. In contrast, the DOSE method uses personalized question sequences and so is less susceptible to this potential bias.

Loss tolerance may also have been overlooked because researchers over-estimate the extent to which the general population is similar to themselves, or to participants’ laboratory experiments. Only 10% of the academic experts suggested that they would accept the simple lottery displayed in Figure 1—introspection may thus lead academic audiences to consider loss aversion a more “plausible” bias. Further, respondents to our prediction survey failed to anticipate the significant differences between the behavior of the general population and that of undergraduate students. It is clear that students are less likely to take part in many activities—such as gambling—than the general population, and so perhaps it is not surprising that they also display different behavioral biases. Our results demonstrate the importance of exploring heterogeneity in economic preferences in broader samples.

Finally, publication bias may have inflated the estimates of λ found in prior literature.

Yechiam (2019, p. 1) asserts in a review of the loss aversion literature 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 loss aversion, both of which report evidence consistent with some publication bias (Walasek et al., 2018; Brown et al., 2021).

Regardless of the reasons researchers have overlooked loss tolerance, our findings have two immediate implications for studies of economic behavior. First, gain-loss attitudes seem to be quite important. Second, our results can make sense of the wide prevalence of gambling and related behaviors without necessarily impacting prior results that, say, tie loss aversion to financial market anomalies or tax manipulation.

Gain-loss attitudes appear to be about as stable as risk aversion and discounting, and more important than risk aversion for explaining the real-world behaviors we examine. This is consistent with responses to the Rabin (2000) critique that attribute all small-scale risk attitudes to gain-loss attitudes (see, for example, Kőszegi and Rabin, 2006; Sprenger, 2015). In our study, gain-loss attitudes are associated with gambling, total assets and asset allocation, and financial shocks; while risk attitudes—although separately measurable—are not.

Our study can reconcile stylized facts about gain-loss differences with widespread gambling, while perhaps not disturbing findings that attribute certain market behaviors to loss aversion. Near-universal loss aversion is hard to square with the 89% of people who report gambling in our study—65% in the prior year, and nearly 40% in the prior month. Recent evidence suggests that investors are willing to invest in negative-expected-value trades (Payzan-LeNestour and Doran, 2022), which is difficult to reconcile with universal loss aversion. Yet, our finding of widespread loss tolerance is not incompatible with studies that attribute, say, insurance choice, to loss aversion because those most likely to manipulate their tax liability—people with higher education and income—are also the most likely in our study to be loss averse (Rees-Jones, 2017). Moreover, recent research shows financial market anomalies can be generated with a relatively low level of loss aversion (Barberis et al., 2021).

More generally, the fact that loss aversion is correlated with many individual characteristics means we would expect to observe loss aversion in many non-randomly selected subsamples of the population. This may explain the finding of loss aversion in convenience samples (see, for example, Gächter et al., 2021; Toubia et al., 2013).

Our findings provide suggestive evidence as to possible causes and/or consequences of loss tolerance, but our data does not allow us to pin down the direction of causality. Loss tolerance could be an inherent trait, leading to individuals making choices where a loss is possible—particularly gambling and investments in stocks—but also perhaps in other life choices, such as in careers and personal relationships, that increase the chance of a major shock. 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. Distinguishing between these explanations is beyond the scope of this study; the 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

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 $k = 1, \dots, K$, 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:

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

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 $V(o_1) > V(o_2)$:

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

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

¹Specifically, 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).

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.16–E.18 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

²The 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.

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 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.13 presents an example of a question involving only a gain, and Figure E.14 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.21–Figures E.24. 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.19–Figures E.20.

³The 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.

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.

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.25). 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.26 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.27–E.30 for question wording.

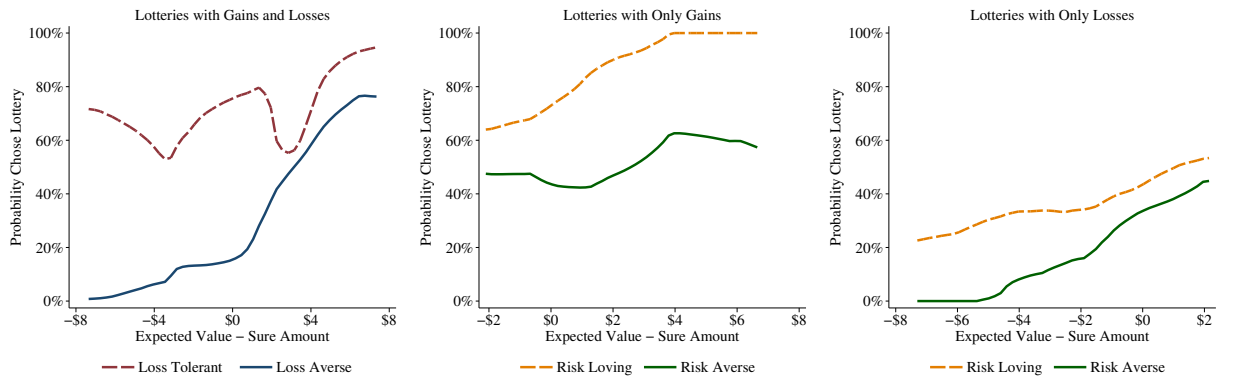
B Choice Data

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 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 increases with the difference between the expected value of the lottery and the sure amount.

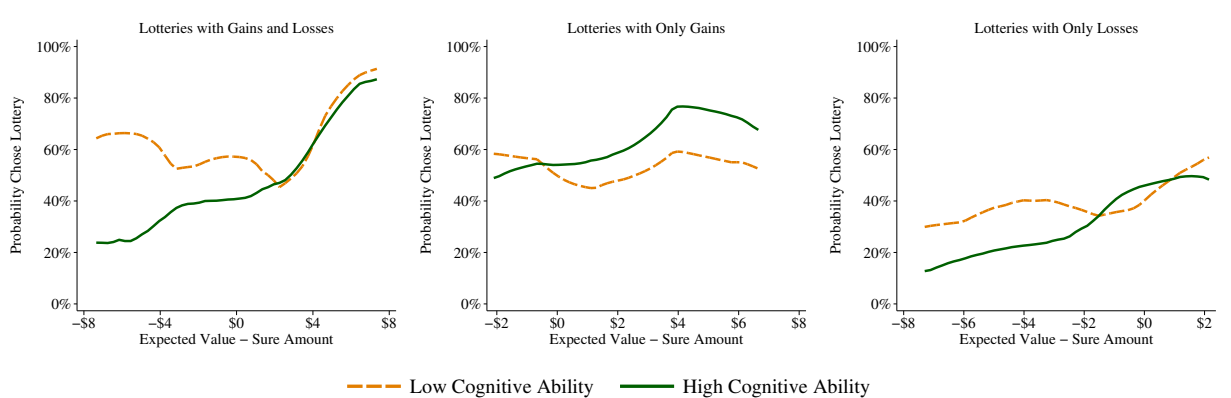
Figure B.1: A clear pattern of choices underpins the DOSE-elicited parameters.



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.

Figure B.2 shows that there are clear differences in choices according to cognitive ability. As in 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.

Figure B.2: Low-cognitive-ability participants make different choices to participants with high cognitive ability, supporting the correlations reported in Table 1.

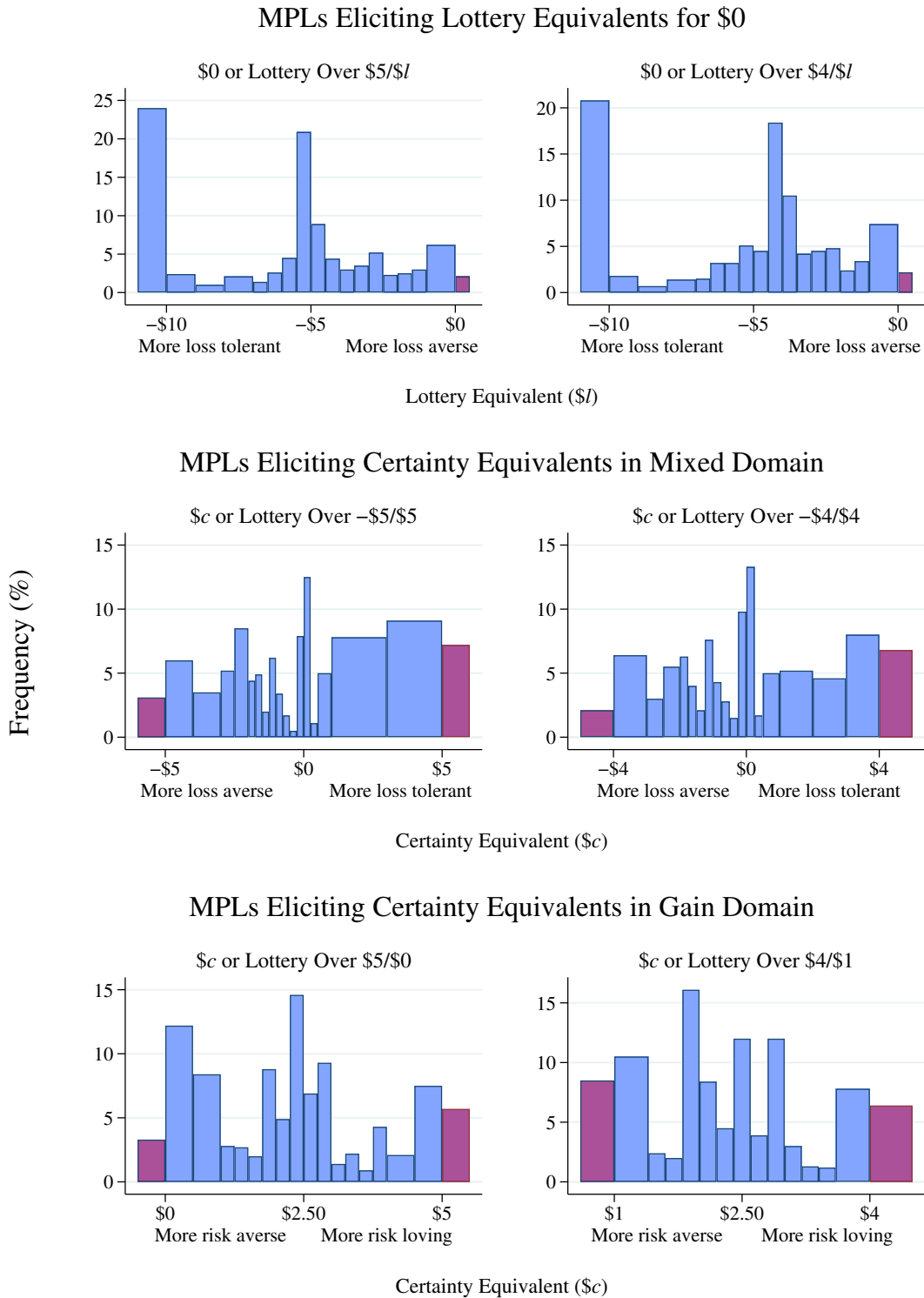


Notes: The figure displays choices from the 20-question DOSE sequence using local mean regressions with Epanechnikov kernel and bandwidth 1. “Low” and “High” cognitive ability refer to the bottom and top terciles within the sample.

B.2 Choice Data from MPL Elicitations

Figure B.3 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 identifies 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.

Figure B.3: 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.

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:

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

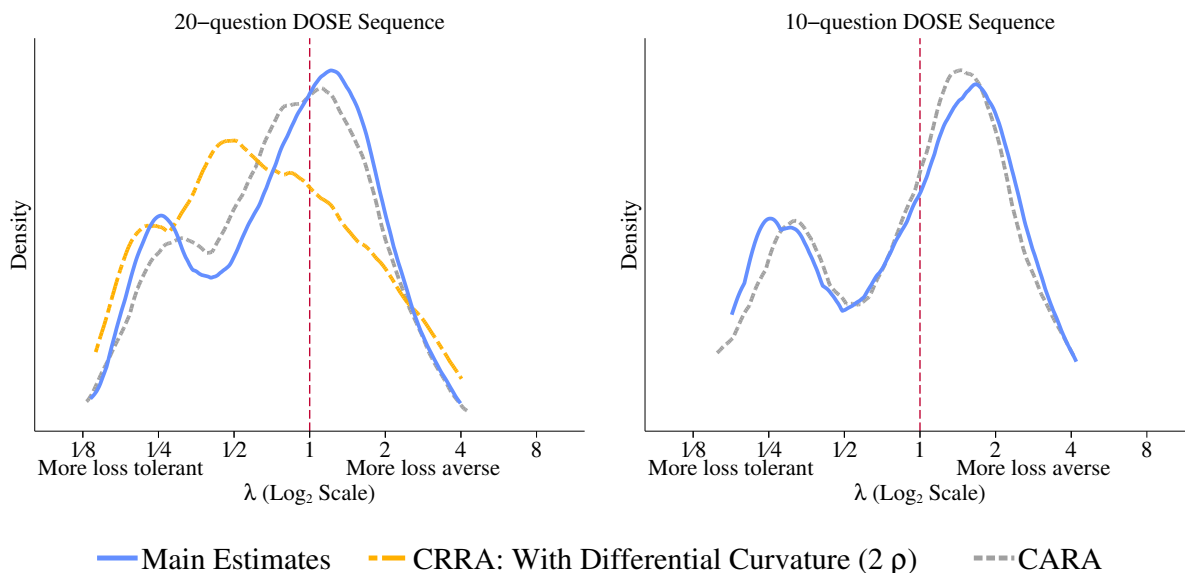
We also re-estimate the loss aversion parameter using the exponential utility function suggested by Köbberling and Wakker (2005):

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

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.4. 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

Figure C.4: Finding of widespread loss tolerance is robust to alternative utility specifications ($N = 1,000$).



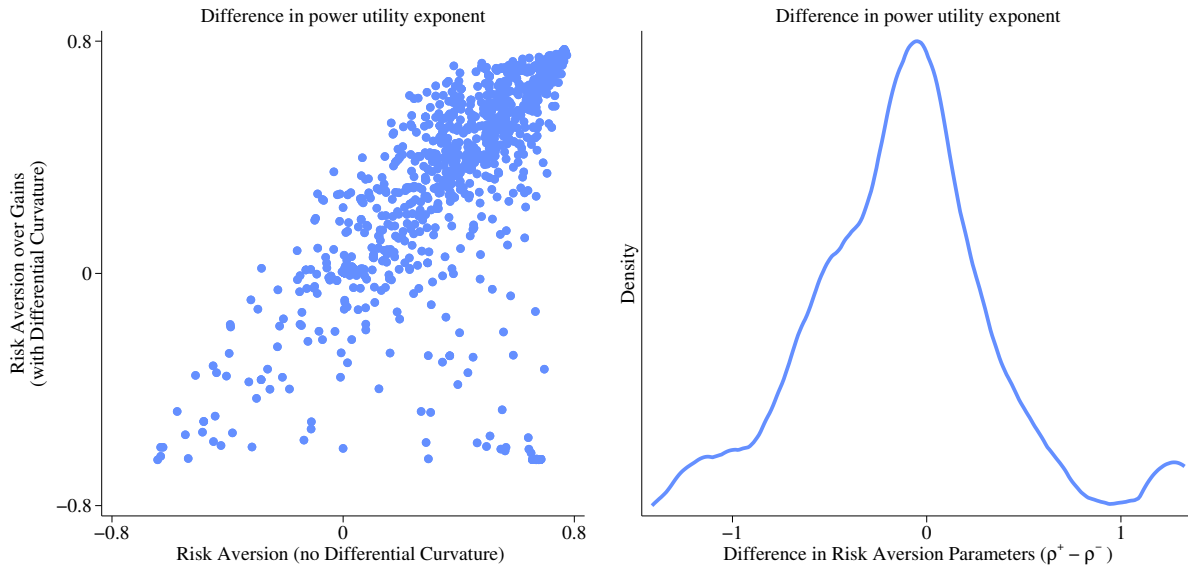
Notes: The figures display the kernel density of loss aversion (λ) parameters estimated from our main sample using various utility specifications, and plotted using an Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator. The “Main Estimates” refer to the specification in Equation (1), 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.

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.5 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 C.5: Comparison of Risk Aversion over Gains and Losses.



Notes: The left-hand panel compares the estimates of risk aversion over gains (y-axis) to the risk aversion parameter when imposing 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).

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

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

DOSE Sequence	Loss Aversion (λ)		Risk Aversion ($1-\rho$)		Choice Consistency (μ)	
	20Q	10Q	20Q	10Q	20Q	10Q
Cognitive Ability	0.20*** (0.044)	0.21*** (0.024)	-0.30*** (0.044)	-0.11*** (0.024)	-0.13*** (0.040)	-0.06** (0.024)
IQ	0.16*** (0.045)	0.17*** (0.027)	-0.26*** (0.047)	-0.11*** (0.025)	-0.14*** (0.039)	-0.05** (0.025)
CRT	0.19*** (0.044)	0.19*** (0.024)	-0.26*** (0.039)	-0.09*** (0.025)	-0.05 (0.042)	-0.04 (0.026)
Income (Log)	0.10** (0.050)	0.09* (0.050)	-0.03 (0.066)	-0.08 (0.060)	-0.07 (0.064)	-0.08 (0.071)
Income (Categories)	0.07 (0.053)	0.12*** (0.027)	-0.03 (0.060)	-0.10*** (0.031)	-0.05 (0.058)	-0.04 (0.031)
Education	0.16*** (0.045)	0.12*** (0.026)	-0.12** (0.051)	-0.04 (0.028)	-0.07 (0.051)	-0.03 (0.027)
Male	-0.06 (0.049)	0.05* (0.028)	-0.05 (0.048)	-0.11*** (0.028)	-0.01 (0.047)	-0.03 (0.028)
Age	-0.05 (0.054)	-0.09*** (0.028)	0.14*** (0.053)	0.08*** (0.030)	0.09* (0.053)	0.07** (0.030)
Married	0.01 (0.050)	0.03 (0.028)	0.07 (0.049)	0.02 (0.028)	0.07 (0.048)	0.04 (0.028)
Employed	0.02 (0.049)	0.06** (0.027)	-0.08* (0.047)	-0.04 (0.027)	-0.03 (0.047)	0.02 (0.027)
Not White	-0.14*** (0.048)	-0.14*** (0.027)	0.01 (0.054)	0.01 (0.030)	-0.03 (0.054)	0.03 (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.

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

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

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

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 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

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 ($1-\rho$)		
Cognitive Ability Measure:						
Continuous	0.18*** (0.049)			-0.29*** (0.045)		
Categorical:						
Medium	0.33*** (0.117)		0.36*** (0.119)		-0.22** (0.110)	
High	0.40*** (0.131)		0.42*** (0.130)		-0.64*** (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.

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—

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

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

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

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

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

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

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

Utility Specification	DOSE-Elicited Preference Parameter											
	Loss Aversion:						Risk Aversion:					
	CRRRA (1 ρ)	CARA λ	CRRRA (2 ρ)	CARA λ	CRRRA (1 ρ)	CARA λ	CRRRA (2 ρ)	CARA λ	CRRRA (1 ρ)	CARA γ	CRRRA (2 ρ)	CARA $1 - \rho^+$
DOSE Sequence	20Q	20Q	10Q	10Q	20Q	20Q	10Q	20Q	20Q	20Q	10Q	10Q
Cognitive Ability	0.20*** (0.044)	0.19*** (0.044)	0.20*** (0.038)	0.21*** (0.024)	0.20*** (0.024)	0.20*** (0.024)	0.26*** (0.040)	-0.30*** (0.044)	-0.30*** (0.043)	-0.12** (0.051)	-0.08* (0.043)	-0.15*** (0.025)
Income (Log)	0.10** (0.050)	0.09* (0.049)	0.09* (0.047)	0.09*** (0.027)	0.08*** (0.027)	0.04 (0.054)	-0.03 (0.066)	-0.07 (0.059)	0.03 (0.061)	0.03 (0.056)	-0.08 (0.060)	-0.10*** (0.031)
Education	0.16*** (0.045)	0.15*** (0.043)	0.13*** (0.044)	0.12*** (0.026)	0.12*** (0.026)	0.11*** (0.047)	-0.12** (0.051)	-0.15*** (0.049)	-0.03 (0.056)	-0.03 (0.051)	-0.04 (0.051)	-0.06** (0.028)
Male	-0.06 (0.049)	-0.05 (0.048)	0.06 (0.045)	0.05* (0.028)	0.05* (0.028)	-0.09* (0.047)	-0.05 (0.048)	-0.06 (0.048)	-0.13*** (0.051)	-0.15*** (0.051)	-0.15*** (0.051)	-0.11*** (0.027)
Age	-0.05 (0.054)	-0.04 (0.052)	0.05 (0.048)	-0.09*** (0.028)	-0.08*** (0.028)	-0.12** (0.052)	0.14*** (0.053)	0.12** (0.052)	0.11* (0.058)	0.11* (0.058)	0.16*** (0.060)	0.07*** (0.029)
Married	0.01 (0.050)	0.02 (0.049)	0.06 (0.045)	0.03 (0.028)	0.03 (0.027)	-0.05 (0.049)	0.07 (0.049)	0.03 (0.049)	0.07 (0.051)	0.07 (0.051)	0.02 (0.051)	0.01 (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** (0.050)	-0.12** (0.049)	-0.11** (0.047)	-0.10** (0.048)	-0.11*** (0.041)	-0.09** (0.042)
Risk Aversion ($1 - \rho$)	0.02 (0.050)	0.07 (0.050)	0.04 (0.047)	0.01 (0.053)	0.02 (0.048)	-0.01 (0.048)
Cognitive Ability:						
Medium	0.08 (0.131)		-0.03 (0.114)	-0.12 (0.113)		-0.13 (0.100)
High	-0.13 (0.098)		-0.31*** (0.115)	-0.33*** (0.117)		-0.37*** (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.

C.3 Additional Regressions with Real World Behaviors

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

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

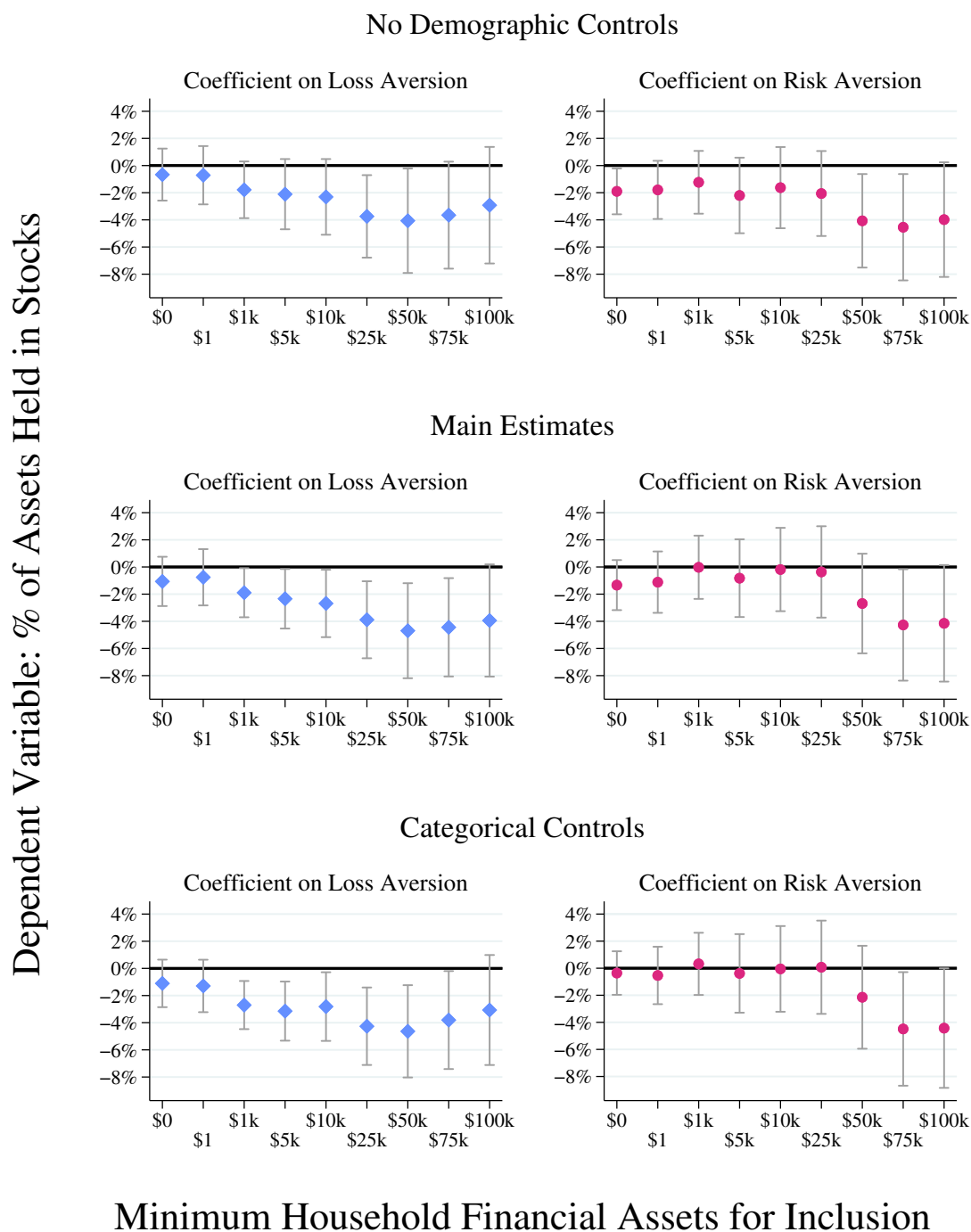
Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. The dependent variables, loss aversion, and risk aversion are standardized. “Medium” and “High” cognitive ability refer to the second and third terciles. “Control Variables” include the set of variables reported in Table 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 ($1-\rho$)	-0.07 (0.053)	-0.02 (0.050)	0.04 (0.056)	0.05 (0.051)	0.03 (0.072)	0.05 (0.042)
Cognitive Ability		0.06 (0.045)		0.01 (0.046)		0.07* (0.040)
Education		0.05 (0.050)		-0.09* (0.052)		0.09** (0.039)
Income (Log)		-0.14** (0.064)		0.13* (0.068)		0.41*** (0.055)
Age		-0.16*** (0.053)		-0.01 (0.058)		0.08* (0.046)
Male		0.14 (0.092)		0.06 (0.103)		-0.06 (0.075)
Married		0.23** (0.098)		-0.16 (0.113)		-0.01 (0.091)
Owns Home		-0.16 (0.103)		-0.35** (0.138)		0.35*** (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.6: 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 6 and Table C.12, with alternative sets of control variables. 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 6.

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

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

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

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 those completing the survey particularly fast. Second, we compare the degree of unexpected choice within the DOSE module across subgroups, finding little evidence of fatigue.

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

Reference Point	All Participants		Loss-Tolerant Subgroup		% Loss Tolerant
	% Improve. over Chance	% with Improved Fit	% Improve. over Chance	% with Improved Fit	
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 $2 \times (\text{the percent of choices fit} - 50\%)$. % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

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

Reference Point	All Participants		Loss-Tolerant Subgroup		% Loss Tolerant
	% Improve. over Chance	% with Improved Fit	% Improve. over Chance	% with Improved Fit	
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 $2 \times (\text{the percent of choices fit} - 50\%)$. % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

Figure C.7 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. However our results. In this figure, we first look at

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

Reference Point	All Participants		Loss-Tolerant Subgroup		% Loss Tolerant
	% Improve. over Chance	% with Improved Fit	% Improve. over Chance	% with Improved Fit	
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 $2 \times (\text{the percent of choices fit} - 50\%)$. % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

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

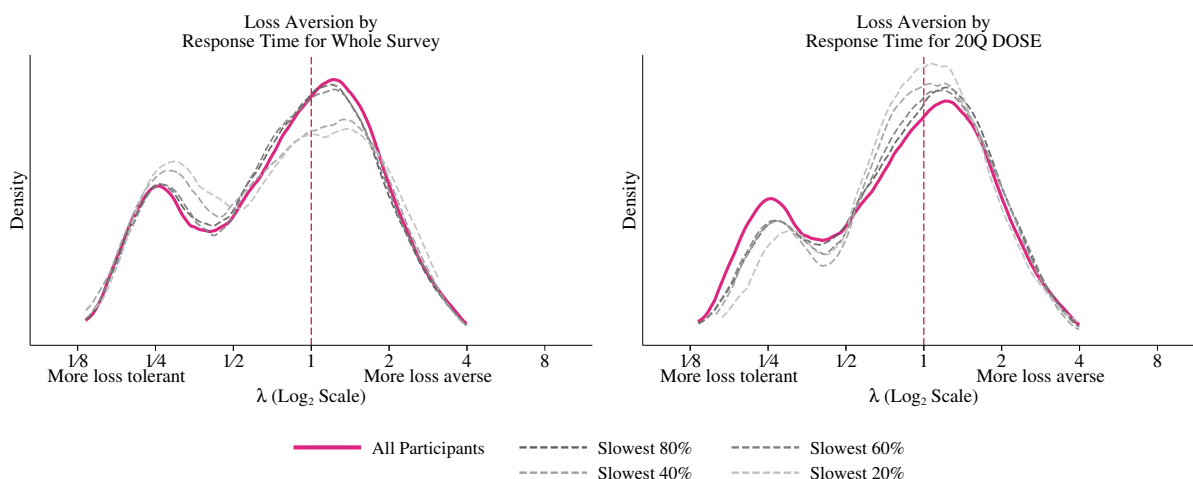
Reference Point	All Participants		Loss-Tolerant Subgroup		% Loss Tolerant
	% Improve. over Chance	% with Improved Fit	% Improve. over Chance	% with Improved Fit	
Preferred—\$0	63%	—	59%	—	51%
Endowment	16%	5%	1%	4%	—
EV of Lottery	29%	9%	20%	10%	69%
Sure Option	54%	23%	50%	27%	46%
Stochastic	41%	12%	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 $2 \times (\text{the percent of choices fit} - 50\%)$. % Participants Improved Fit is the percent of participants for whom the model in that row fits better than our preferred model.

the slowest 80% of participants, then the slowest 60%, and so on, across the whole survey (left-hand panel) and 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 9 and Table C.6, we find no evidence that fast response or inattention explain our results.

Figure C.7: Distribution of loss aversion is similar when removing participants with short response times.

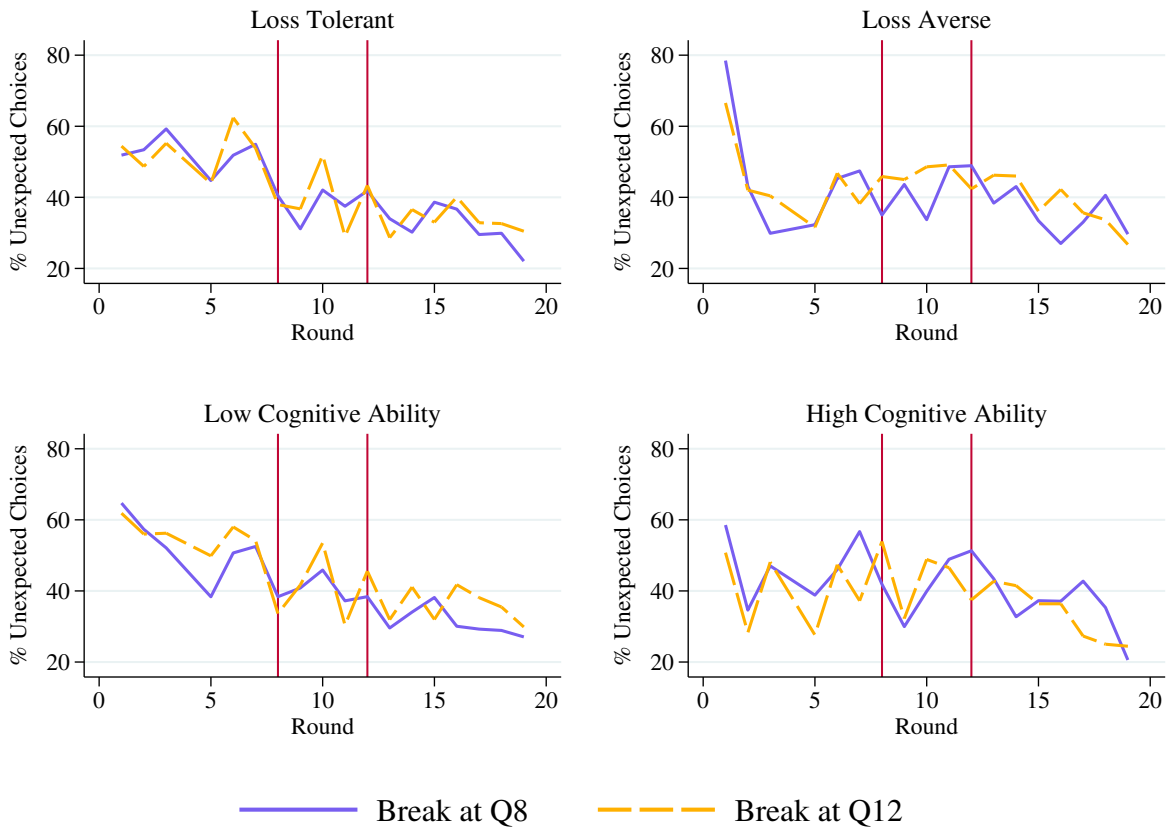


Notes: The figure displays the distribution of loss aversion estimated in the 20-question DOSE module, plotted using Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator.

Figure C.8 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 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 be more cognitively able and more loss averse (as discussed in the main text, participants in the laboratory). However, by the end of 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.

Figure C.8: 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.

D Principal Components Analysis

Figures D.9 and D.10 display scree plots for the Principal Components Analysis reported in Section 4.1.

Figure D.9: Scree Plot for PCA of Gambling Measures

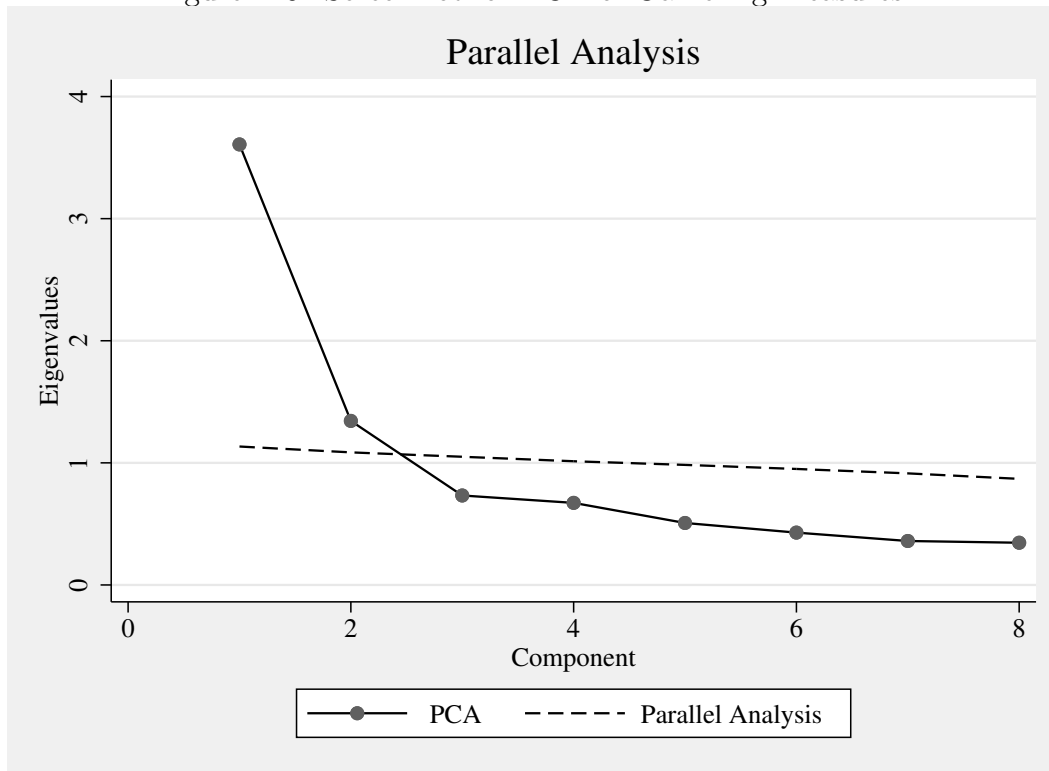
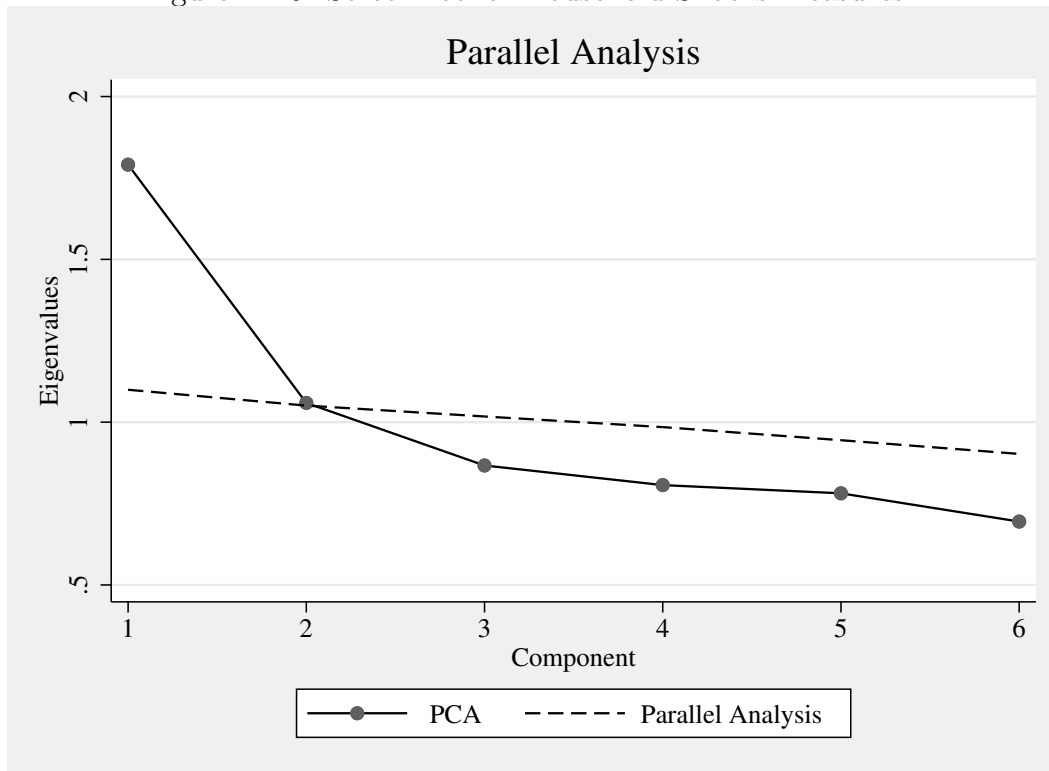


Figure D.10: Scree Plot for Household Shocks Measures.



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 hss.caltech.edu/~snowberg/wep.html.

Figure E.11: 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.12: 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.

<input checked="" type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 0 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 1,000 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 2,000 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 3,000 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 4,500 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 5,500 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 6,000 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 7,000 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 8,000 points
<input type="checkbox"/> 5,000 points	or	<input type="checkbox"/> 9,000 points
<input type="checkbox"/> 5,000 points	or	<input checked="" type="checkbox"/> 10,000 points



Figure E.13: 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.14: 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.15: 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.16: 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.17: 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.18: 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.19: First MPL Eliciting Lottery Equivalent for a Fixed Amount of Points

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

- | | | |
|-----------------------------------|----|--|
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 10,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 9,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 8,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 7,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 6,500 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 6,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 5,500 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 5,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 4,500 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 4,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 3,500 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 3,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 2,500 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 2,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 1,500 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 1,000 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of 0 points, and a 50% chance of gaining 5,000 points |
| <input type="checkbox"/> 0 points | or | <input checked="" type="checkbox"/> A 50% chance of gaining 1,000 points, and a 50% chance of gaining 5,000 points |

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Figure E.20: Second MPL Eliciting Lottery Equivalent for a Fixed Amount of Points

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

- | | | |
|-----------------------------------|----|--|
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 10,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 9,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 8,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 7,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 6,500 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 6,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 5,500 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 5,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 4,500 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 4,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 3,500 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 3,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 2,500 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 2,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 1,500 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of losing 1,000 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input type="checkbox"/> A 50% chance of 0 points, and a 50% chance of gaining 4,000 points |
| <input type="checkbox"/> 0 points | or | <input checked="" type="checkbox"/> A 50% chance of gaining 1,000 points, and a 50% chance of gaining 4,000 points |

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Figure E.21: First MPL Eliciting Certainty Equivalent for a Mixed Lottery

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

- | | | |
|---|----|--|
| <input checked="" type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 6,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 5,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 4,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 3,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 2,500 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 2,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 1,750 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 1,500 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 1,250 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 1,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 750 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 500 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Losing 250 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> 0 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Gaining 250 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Gaining 500 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Gaining 1,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Gaining 3,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input type="checkbox"/> Gaining 5,000 points |
| <input type="checkbox"/> A 50% chance of winning 5,000 points, and a 50% chance of losing 5,000 points | or | <input checked="" type="checkbox"/> Gaining 7,000 points |

Figure E.22: Second MPL Eliciting Certainty Equivalent for a Mixed Lottery

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

- | | | |
|---|----|--|
| <input checked="" type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 5,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 4,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 3,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 2,500 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 2,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 1,750 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 1,500 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 1,250 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 1,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 750 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 500 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Losing 250 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> 0 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Gaining 250 |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Gaining 500 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Gaining 1,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Gaining 2,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Gaining 3,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input type="checkbox"/> Gaining 4,000 points |
| <input type="checkbox"/> A 50% chance of winning 4,000 points, and a 50% chance of losing 4,000 points | or | <input checked="" type="checkbox"/> Gaining 5,000 points |

Figure E.23: First MPL Eliciting Certainty Equivalent for a Lottery over Gains

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

- | | | |
|--|----|--|
| <input checked="" type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> -500 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 0 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 500 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 1,000 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 1,250 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 1,500 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 1,750 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 2,000 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 2,250 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 2,500 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 2,750 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 3,000 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 3,250 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 3,500 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 3,750 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 4,000 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 4,500 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input type="checkbox"/> 5,000 points |
| <input type="checkbox"/> A 50% chance of 5,000 points, and a 50% chance of 0 points | or | <input checked="" type="checkbox"/> 5,500 points |

Figure E.24: Second MPL Eliciting Certainty Equivalent for a Lottery over Gains

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

- | | | |
|--|----|--|
| <input checked="" type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 600 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 1,000 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 1,400 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 1,600 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 1,800 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 2,000 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 2,200 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 2,400 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 2,600 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 2,800 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 3,000 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 3,200 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 3,400 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 3,600 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input type="checkbox"/> 4,000 points |
| <input type="checkbox"/> A 50% chance of 4,000 points, and a 50% chance of 1,000 points | or | <input checked="" type="checkbox"/> 4,600 points |

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Figure E.25: 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.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Lottery scratch tickets.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Betting on sports whether online or with a sports book.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Online card games, online slot machines, or other types of online gambling.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Slot machines, bingo, keno, or video gambling, at a casino or elsewhere.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Card games, roulette, or other games of chance or skill at a casino.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bet or wagered with friends, family, or others outside a casino (e.g., on card games, or basketball).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Betting or gambling using some other game, activity, or event we have not listed.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>



Figure E.26: 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.27: 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	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Flown on an airplane	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Been to the gym	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Traveled to the moon	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gone to the grocery store	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Read a book	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Cooked dinner	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Given birth	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gone to a religious service	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Gotten a haircut	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>



Figure E.28: 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.29: 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.30: 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

