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

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Abstract

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

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

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1 Introduction

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

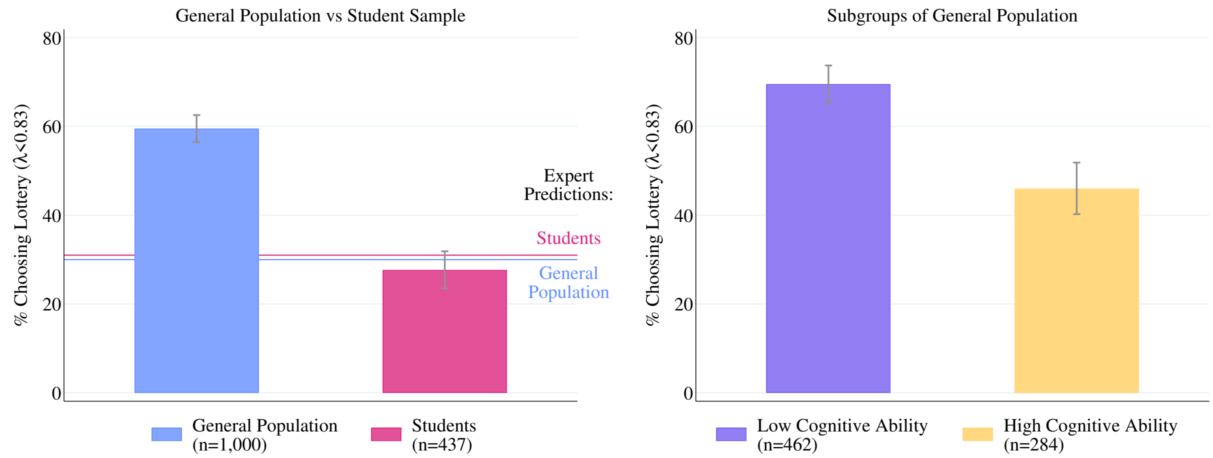
We find that around 50% of people in the U.S. are *loss tolerant*—even if they are risk neutral, they embrace gambles with negative expected values—and around 50% are loss averse.[2] We elicit individual estimates of gain-loss attitudes in three representative, incentivized surveys of the U.S. population (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 as in previous laboratory experiments. Consistent with this finding, loss aversion is more common in people with high cognitive ability within our representative samples. Loss aversion is also correlated with behavior outside of the survey environment: loss-tolerant individuals have more of their assets invested in stocks, are more likely to have recently gambled, are more likely to have experienced a recent financial shock, and have fewer financial assets. However, our elicitations of risk aversion are generally not correlated with these real-world behaviors. Together, this suggests that loss aversion captures an independent, and substantively important, part of risk attitudes.

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

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

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

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.

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

1.1 Widespread Loss Tolerance

Our main result can be observed in choices over a simple 50:50 lottery with a negative expected value, as shown in Figure 1. All participants face a choice between a sure amount of \$0 and a lottery over a gain of \$10 and a loss of \$12, each with 50% probability.[3] As shown in the left-hand panel, 60% of those in the representative sample ($N = 1{,}000$) choose the lottery, demonstrating a significant degree of loss tolerance (under the common assumption of local risk neutrality)—and countering Kahneman and Tversky's (1979) assertion that "most people find symmetric bets of the form $(x, .50; -x, .50)$ distinctly unattractive" (p. 279). The proportion choosing the lottery is, however, much lower among a sample of University of Pittsburgh undergraduates ($N = 437$) completing a very similar incentivized online survey—only 28% of students choose the lottery. Consistent with this finding, in the right-hand panel of Figure 1, we see that those

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

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

The proportion of loss-tolerant participants in our data is much higher than anticipated by economists completing a prediction survey (DellaVigna et al., 2019). The expert respondents ($N = 87$) accurately predicted the proportion of students that would accept the lottery (an average prediction of 31% versus the actual 28%), but severely underestimated the proportion in the representative sample (30% vs 60%).[4] Notably, it appears that respondents overestimated the similarity between undergraduates and the general population, making very similar guesses for the two samples. Further, only 10% of the expert respondents reported that they would accept the same lottery themselves, consistent with academics being unrepresentative of the extent of loss tolerance across the population.

The patterns in Figure 1 do not reflect a high willingness to gamble in general, due to, for instance, "house money effects" (Thaler and Johnson, 1990). Most participants demonstrated significant risk aversion when no potential loss was involved—for instance, only 39% of the representative sample preferred a lottery with a 50% chance of \$15 and 50% chance of \$0 to a sure amount of \$5.90. This proportion is lower than predicted in the expert survey (average prediction = 56%) and—in contrast to Figure 1—lower than the proportion of students (49%) accepting the same lottery. Thus, our data suggest that the general population is more loss tolerant but—consistent with previous studies (see, for example, Snowberg and Yariv, 2021)—more risk averse than undergraduate students.[5]

1.2 Further Investigation of Heterogeneity in Gain-Loss Attitudes

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

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

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

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

Our DOSE-elicited measure of loss aversion also indicates a much higher level of loss tolerance in representative samples of the U.S. population than among students. We compare our main sample (N = 1,000)—with two DOSE elicitations—and a supplementary sample (N = 2,000)—studied twice, six months apart—to two student samples (N = 437 and 369) recruited from the University of Pittsburgh Experimental Laboratory that participated in extremely similar online studies. In our three representative samples, the proportion of loss-tolerant participants is 57%, 47%, and 55%; in the corresponding student samples and elicitations, the proportions are 32%, 22%, and 16%. As a further comparison, across eleven studies that report individual-level heterogeneity in gain-loss attitudes, the average proportion loss tolerant is 33%.[6] The similarity between our student samples and these previous studies—largely carried out in the laboratory using a number of different methodologies—offers further evidence that the degree of loss tolerance we observe is not an artefact of our approach.

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

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

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

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

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

1.3 Related Literature

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

Our findings differ from the majority of prior studies, which tend to find significant loss aversion—a recent meta-analysis reports mean $\lambda = 1.96$ across more than 150 studies in both the lab and the field (Brown et al., forthcoming)—including an earlier general population study which reported median $\lambda = 2.38$ (von Gaudecker et al., 2011).[7] The high estimates of loss aversion in these earlier studies may, at least in part, be explained by their elicitation methods. A series of studies in social psychology have shown that loss aversion can be inflated by elicitations that offer participants choices which are asymmetric in the range of possible gains and losses, or that conflate loss aversion with the endowment effect or status quo bias (see Ert and Erev, 2013; Zeif and Yechiam, 2022). von Gaudecker et al. (2011) for instance, offered participants 56

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

lotteries, but none involved a negative-expected-value gamble—which is necessary to identify significant loss tolerance when assuming a reference point of zero.[8]

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).[9] Consistent with most earlier work, we find that higher cognitive ability individuals are less risk averse over lotteries involving only potential gains (see Dohmen et al., 2018, for a detailed review of the literature). However, when confronted with potential losses, both low- and high-cognitive-ability people tend to depart from normative rationality, but in different ways—with low-cognitive-ability people being more loss tolerant, and high-cognitive-ability people being more loss averse.

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

2 Measuring Loss Aversion

This section introduces the data and methods we use to measure loss aversion and other behaviors. Our primary measures use DOSE, and we also implement two traditional multiple price list elicitations, as described in Section 2.2. Section 2.3 introduces our data, which are drawn from two representative samples and two student samples.

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

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

2.1 Theoretical Definition

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

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

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

To estimate individual-level risk and loss aversion we use DOSE, which is designed to tackle the issues associated with estimating multiple preference parameters simultaneously. In the case of loss aversion, multiple question types are needed: choices over lotteries over gains and losses separately (risk aversion) and *mixed lotteries*—those including both gains and losses. Inconsistent choice across different question types may even prevent the estimation of parameters, if, for example, some responses violate first-order stochastic dominance.[10] Such issues have led many previous studies, including those in representative samples, to estimate population-level statistics rather than elicit individual-level loss aversion parameters. DOSE overcomes these issues by adapting the question sequences individuals receive to rapidly home in on their preferences, while accounting for inconsistent choices. As a result, in simulations, the method measures parameters more accurately than more established elicitation methods, particularly for participants that are likely to make mistakes (Chapman et al., 2018). Moreover, DOSE pro-

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

duces a large quantity of choice data that we use to investigate loss aversion without parametric assumptions or with alternative parametric forms (see Section 5.2 and Appendix C.1).

2.2 Measurement

Our implementations of DOSE ask participants a personalized sequence of simple questions, such as those displayed in Figure 2. The participant is given a simple explanation of the upcoming choices, as in Figure 2a. He or she is then given a series of binary choices between a lottery and a sure amount, similar to those in Figure 2b. The sure amounts, and the prizes in the lotteries, are selected to maximize the informativeness of the choice for the parameters of interest, λ and ρ, given a flat prior over those parameters and the participant's previous choices. The support of the prior distribution covers individual estimates obtained in lab data: $\lambda \in [0.1, 4.5]$ and $\rho \in [0.2, 1.7]$. Thus, the mean of the prior is both loss averse ($\lambda = 2.3$) and risk averse ($\rho = 0.95$).[11]

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.[12] When a lottery contains a gain and a loss, then the sure amount is always zero. When the choices contain only non-negative or non-positive payoffs, one of the payoffs of the lottery is always zero.

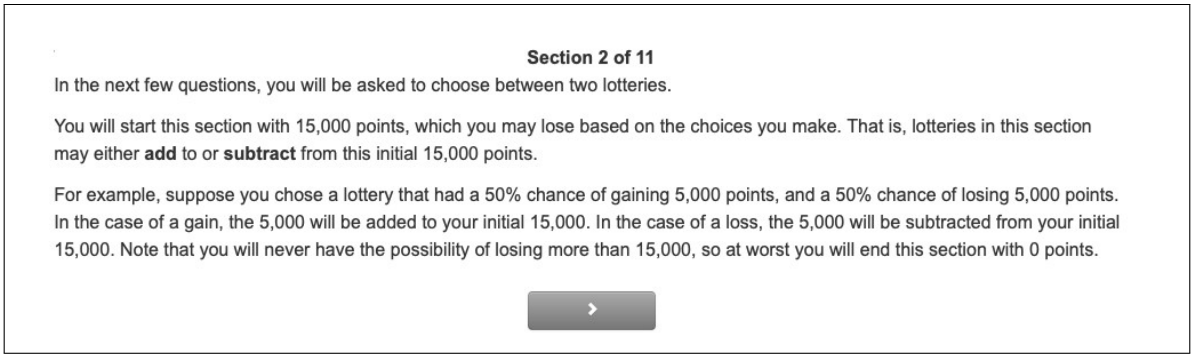
Participants were also asked a 10-question DOSE sequence, for comparison with an earlier survey completed in 2015, as well as two multiple price list (MPL) modules eliciting preferences over mixed lotteries—that is, lotteries with prizes in both the gain and loss domain.[13] The shorter DOSE sequence did not contain choices with only non-positive payoffs. In the 10-question sequence, the sure amount appeared first, reversing the order from the longer 20-question sequence. We find a similar level of loss tolerance across both the DOSE modules (see Section 3) and the MPL modules (see Section 5.1).

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

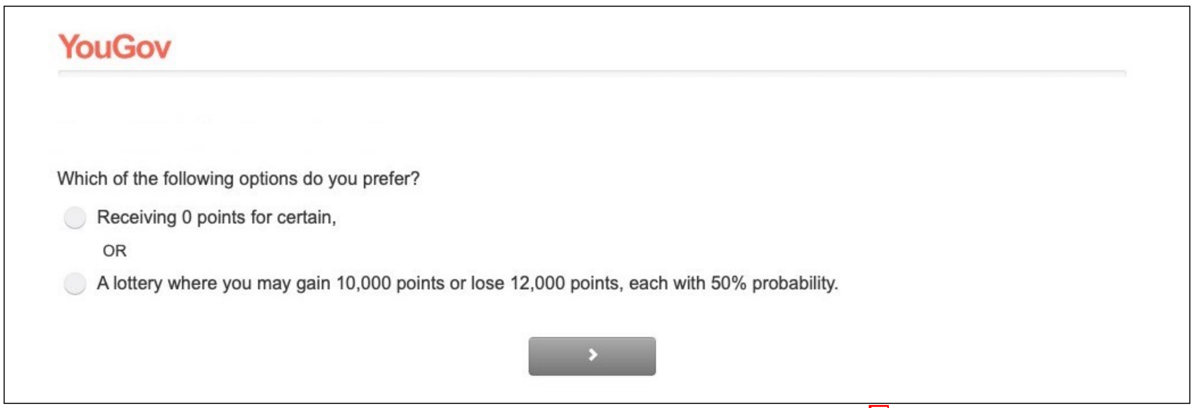
[12] Our focus is on loss aversion, so we use 50/50 probabilities of two outcomes in lotteries to minimize probability distortions. Experimental evidence suggests that participants make more consistent choices when lotteries have this structure (Olschewski and Rieskamp, 2021).

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

Figure 2: DOSE Instructions and Example Question



(a) DOSE Instructions



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

To implement losses in the survey, participants were endowed with a stock of points at the start of each section containing a potential loss, in line with standard experimental procedure (see, for example, Figure 2a). This could, in principle, lead to participants not considering any payoffs as losses, because they are playing with "house money" (Thaler and Johnson, 1990). Such effects do not appear to be a concern in our data, see Section 5.3.[14]

2.3 Data

Main Sample: We measured loss aversion in a large, representative, incentivized survey of the U.S. population which contained both a 20- and a 10-question DOSE sequence, as well as the two MPL modules described above. The survey collected a number of behavioral and demographic measures from 1,000 U.S. adults, and was conducted online by YouGov between February 21

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

and March 24, 2020.[15] Participants in the survey were drawn from a large panel maintained by YouGov. Most importantly for our results, this approach allowed us to capture the preferences of lower-education individuals that are often overlooked in both laboratory experiments and online crowdsourcing platforms such as Prolific.[16] All participants had previous experience with YouGov's online survey platform, and had to pass a test showing that they understood the instructions before starting the survey.

All measures of economic preferences in the survey, such as risk and loss aversion, were incentivized, with one module randomly selected for payment at the end of the survey.[17] All outcomes were expressed in YouGov points, an internal YouGov currency used to pay panel members, which can be converted to U.S. dollars using the approximate rate of $0.001 per point. For ease of interpretation, we generally convert points to dollars. To enhance the credibility of these incentives, we took advantage of YouGov's relationship with its panel, and restricted the sample to those who had already been paid (in cash or prizes) for their participation in surveys. The average payment to participants (including the show-up fee) was $10 (10,000 points), which is approximately four times the average for YouGov surveys of a similar length. The median completion time was 42 minutes.

The conversion from points to awards can only be done at specific point values, which leads to a slightly convex payment schedule.[18] In principle, participants' choices could be influenced by the opportunity to cross one of these thresholds. We subject this possibility to extensive checks in Appendix C.6, and do not observe differences in the extent of loss tolerance based on the number of points participants began the survey with, or the difference between their initial point balance and the next threshold. Moreover, the payment schedule does not appear to affect other behavioral regularities, for which we observe behavior in line with prior literature (see Table 2 of Chapman et al., 2023a).[19] These findings are perhaps unsurprising given that

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

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

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

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

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

panelists tend to accrue points over several years, and that neither participants' points totals nor the exchange thresholds are made salient during recruitment or when taking the survey.

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

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

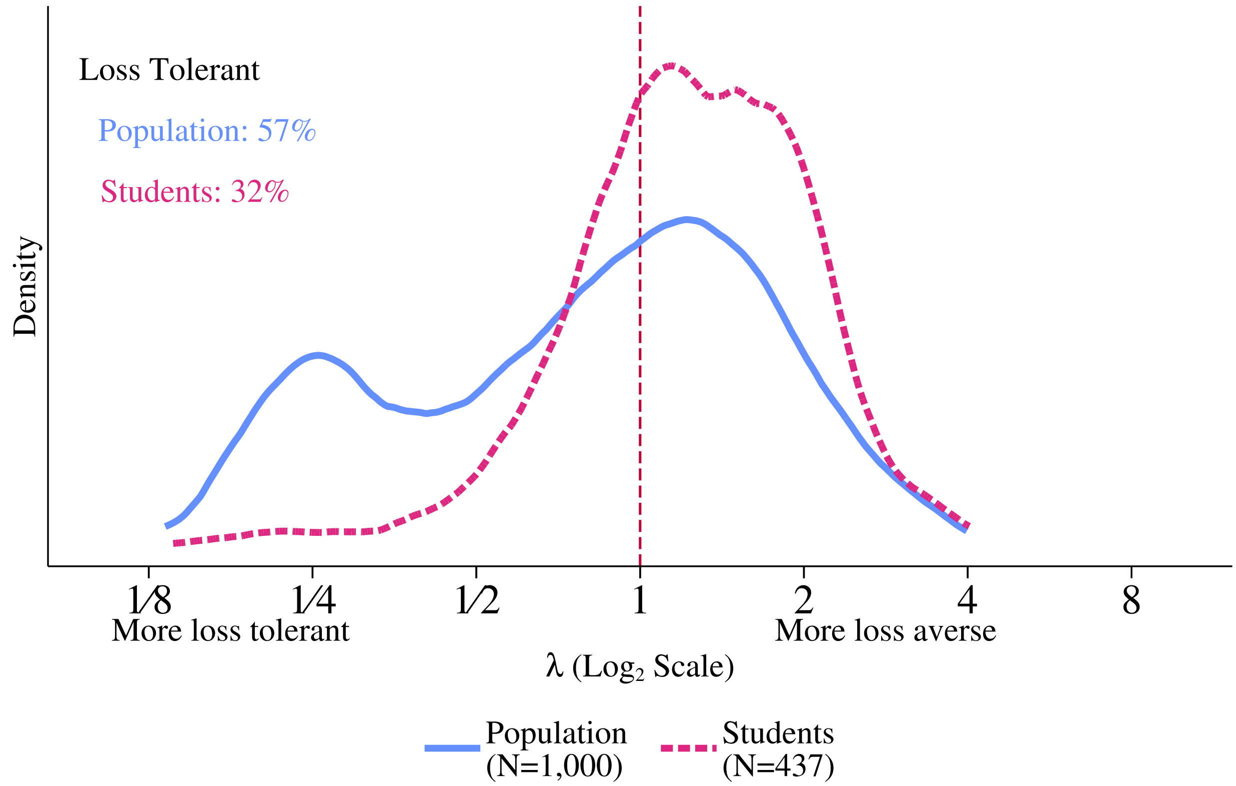
3 Loss Aversion in a Representative Sample

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

3.1 Widespread Loss Tolerance in the U.S. Population

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

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



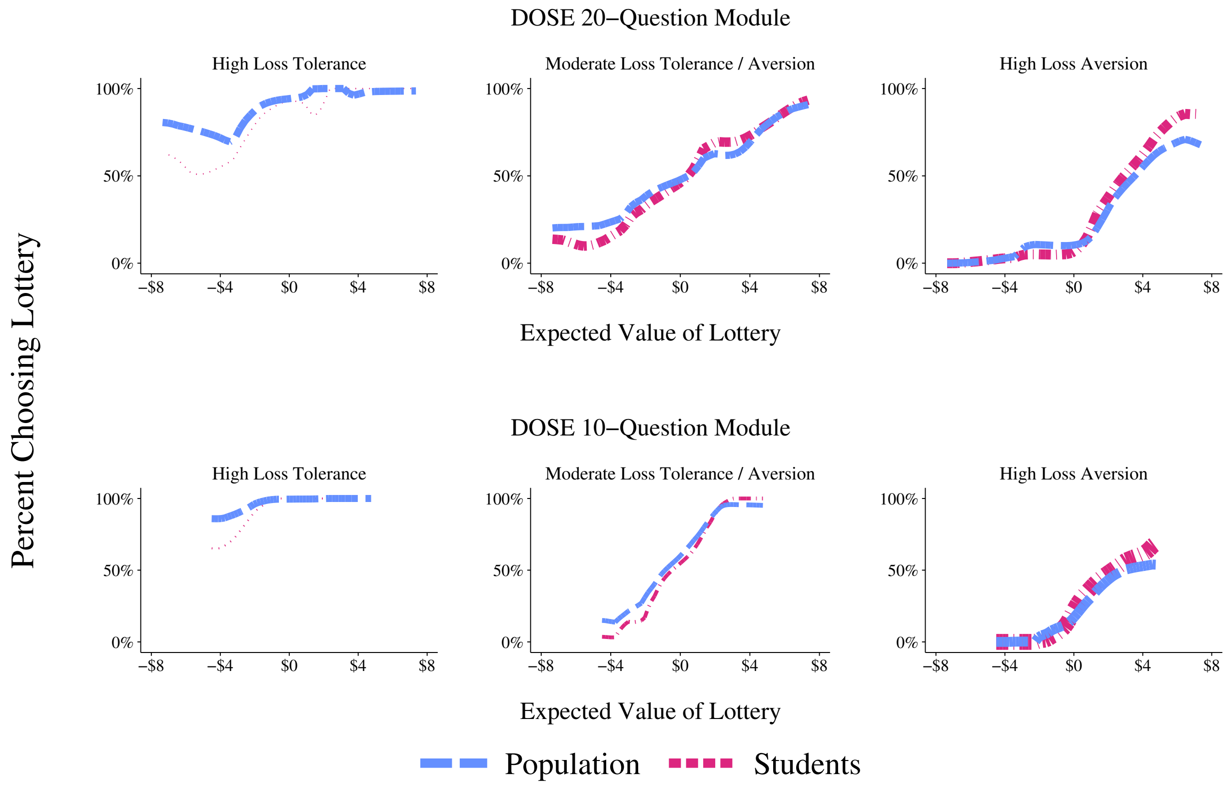
<u>Notes:</u> Figure displays the kernel density of each parameter, plotted using Epanechnikov kernel with bandwidth chosen by rule-of-thumb estimator.

the heterogeneity in gain-loss attitudes in more detail, as they identify the degree of individuals' loss tolerance or loss aversion.

The distribution of estimates is markedly different in our student sample, where 68% of individuals are classified as loss averse. Across our two student samples and the two DOSE sequences, we find that approximately 22% of students are loss tolerant. This proportion is lower than across eleven previous studies that have investigated individual loss aversion in student/lab experiments, which classify, on average, 33% of participants as loss tolerant (combined $N = 1{,}882$).[20] Note that this difference does not simply reflect a greater willingness to accept lotteries in the general population: 90% of the general population sample—and 89% of those classified as loss tolerant—were classified as risk averse, compared to 76% of students. This is in line with prior research showing students are less risk averse than the general population (see Snowberg and Yariv, 2021, and references therein).

[20] These studies are Schmidt and Traub (2002); Brooks and Zank (2005); Abdellaoui et al. (2007, 2008); Sokol-Hessner et al. (2009); Abdellaoui et al. (2011); Brooks et al. (2014); Goette et al. (2019); Koch and Nafziger (2019); L'Haridon et al. (2021); Bocquého et al. (2022).

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



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

Choices during our survey clearly demonstrate that losses do not "loom larger than gains" (Kahneman and Tversky, 1979, p.279) for a large proportion of the U.S. population. Close to two-thirds of participants in our main sample preferred at least one 50/50 lottery with negative expected value—that is, with a potential loss greater than the potential gain—to a sure amount of zero within the 20-question DOSE module. In many cases, losses appear to have been discounted substantially, with just short of 40% of participants accepting a lottery with a potential loss of more than double a possible gain (see Appendix Figures B.2 and B.3). We see similar results in the MPL elicitations discussed in Section 5.1, demonstrating that such choices are not limited to the DOSE modules. Our data thus provide direct evidence of loss tolerance, even in the absence of parametric assumptions.

We present a summary of participants' choices in the DOSE sequences in Figure 4, drawing on more than 35,000 individual choices over mixed lotteries.[21] Each panel in this figure displays the percentage of participants choosing a mixed lottery as a function of the difference between the lottery's expected value and a sure amount of $0. The top row of the figure presents the choice data from the 20-question DOSE sequence, which were used to produce the parameter estimates in Figure 3. Each panel presents participants from a different tercile of estimated λ. The bottom panel presents choices from the 10-question DOSE sequence, combining the choices of participants in both our main and supplementary samples. The width of each line in the figure captures the proportion of participants within each range of λ. For example, there are very few students classified as highly loss tolerant, so the lines representing student choices in the two left-hand panels are very thin.

The DOSE parametric estimates are underpinned by a robust pattern of choices, easily observable by examining the panels of Figure 4. Participants categorized as having high loss tolerance accept a large proportion of lotteries with negative expected value (87%)—a much larger share than those categorized as having high loss aversion (6%). As expected, most lines are generally upward sloping, reflecting the fact that participants become more likely to accept mixed lotteries as the expected value increases.[22] Importantly, the lines for students and the general population broadly mirror each other, indicating that the major difference between the samples is the proportion of people falling within each category, rather than different patterns of choices within categories. Finally, comparing the top and bottom panels demonstrates how the longer, 20-question sequence allows more refined parameter estimates by offering participants a broader range of possible choices—and consequently leading to parameter estimates that are further away from the initial prior. This difference is also reflected in the parametric estimates from the 10-question sequence that we present in the following subsection.

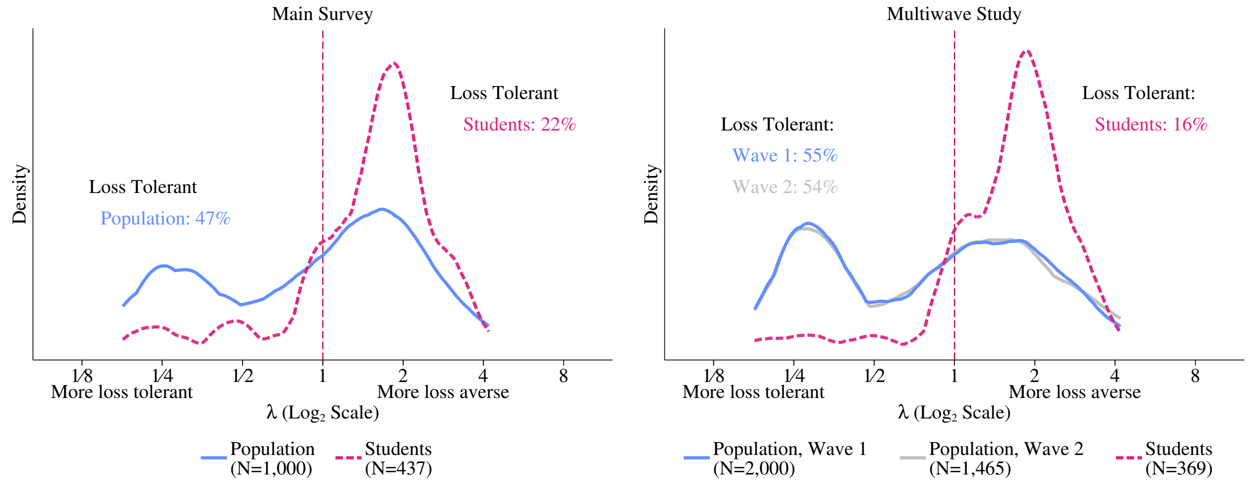
3.2 Stability of Loss Aversion

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

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

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

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



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

to elicit loss aversion in our main sample, and also in two waves of the supplementary sample. Consistent with the estimates in Figure 3, we find that approximately half the U.S. population is loss tolerant. Further, loss aversion is nearly as stable over time as risk aversion and discounting, suggesting that all three are similarly useful in describing individual preferences.

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

The estimates from the 10-question DOSE module are very stable over time, as shown in the right-hand panel of Figure 5. The correlation of DOSE estimates of loss aversion across the two survey waves, collected six months apart, was 0.38 (s.e. = .04). This over-time correlation was similar to that for DOSE elicitations of risk aversion (ρ)—0.44 (.04)—and for time discounting (δ)—0.41 (.04).[23] The within-person stability was lower when using other risk elicitation techniques—between 0.26–0.33 (all with s.e. = .04) across two MPLs and a risky project question (Gneezy and Potters, 1997)—consistent with lower measurement error in the DOSE estimates. Moreover, loss tolerance is as stable as loss aversion: of those classified as loss tolerant by DOSE on the first survey, 71% were also classified as loss tolerant on the second, whereas for loss aversion the figure is 67%. The stability of the DOSE-elicited parameters both provides reassurance about the robustness of our results, and suggests that gain-loss attitudes are a useful descriptor of economic preferences.

3.3 Economic Preferences and Cognitive Ability

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

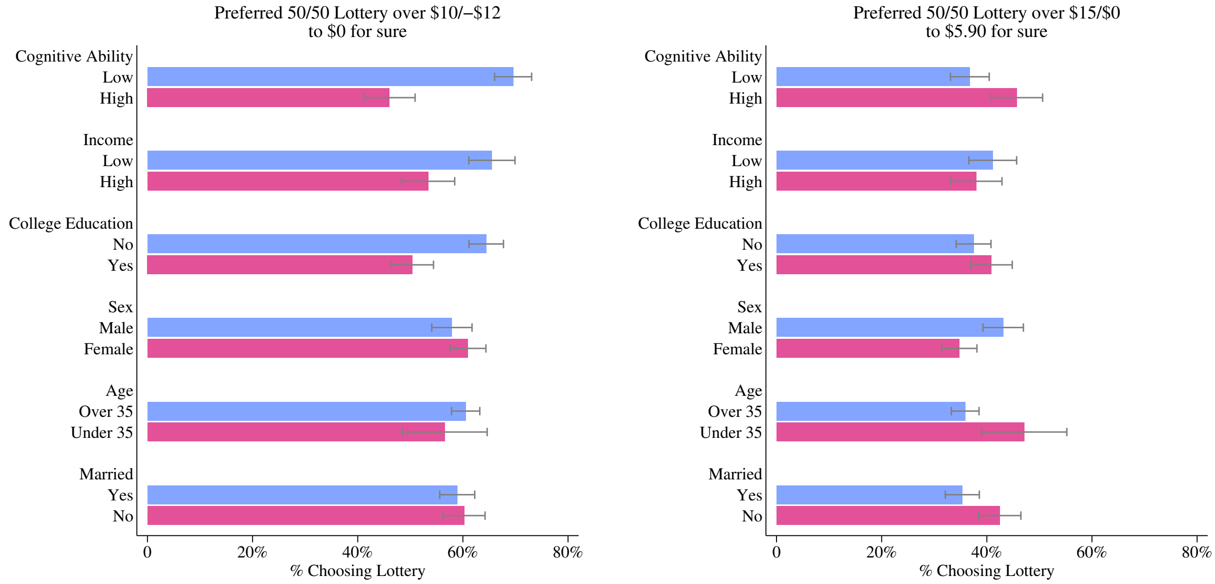
We measure cognitive ability using a set of nine questions. Six questions from the International Cognitive Ability Resource (ICAR; Condon and Revelle, 2014) capture IQ: three are similar to Raven's Matrices, and the other three involve rotating a shape in space. We also administer the Cognitive Reflection Test (CRT; Frederick, 2005): three arithmetically straightforward questions with an instinctive, but incorrect, answer. Our cognitive ability score is the sum of correct answers to these nine questions.[24]

Participants' choices in two fixed lottery questions, displayed in Figure 6, are consistent with the finding that the general population is less loss averse and more risk averse than lab/student populations. In particular, subgroups of the population that are more similar to college students are generally less likely to accept the negative-expected-value gamble discussed in the introduction—and are therefore more likely to be loss averse—but are more likely to accept a similar lottery where only gains are involved—suggesting they are less risk averse. The left-hand-panel of Figure 6 investigates the willingness to accept a negative-expected-value lottery—between gaining \$10 and losing \$12—across subgroups of our general population sam-

[23] See Chapman et al. (2023c) to compare these figures with the stability of a broad range of preference measures, including social preferences, overconfidence, and risk and time preferences.

[24] We 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.

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



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

ple. As we have seen in Figure 1, 60% of the representative sample preferred this lottery to a sure amount of $0, whereas only 28% of our student sample did. Here we can see that the proportion choosing the lottery is above 40% in each demographic group within the representative sample, suggesting that loss tolerance is prevalent across different population categories—and that undergraduate students are an unusually loss averse demographic. Further, individuals with high cognitive ability or family income—characteristics that are typical of undergraduates (Snowberg and Yariv, 2021)—or a college education, are less likely to accept the lottery. However, as shown in the right-hand panel, these groups are more willing to accept a $0/$15 lottery over a sure amount of $5.90—suggesting that they are also less risk averse.

Correlations between the DOSE-elicited estimates of loss aversion and other individual characteristics, reported in Table 1, confirm the most important visual patterns of Figure 6. The first column in the table reports univariate correlations between loss aversion and each characteristic, while the second column reports the results of a multivariate regression. The correlations we observe are very similar to the patterns of choices displayed in Figure 6. In particular, more

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

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

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

educated and more cognitively-able individuals tend to be more loss averse and also less risk averse. In line with previous studies, younger individuals also tend to be less risk averse, and perhaps also more loss averse—although the latter finding is not robust across samples and specifications.[25]

Both high- and low-cognitive-ability participants consistently deviate from expected-value maximization in our data—but in very different ways. Less than than 1% of participants made an EV-maximizing choice in more than 18 out of 20 questions. Consistent with some previous studies (for example, Burks et al., 2009; Benjamin et al., 2013), participants in the highest tercile of cognitive ability were slightly more likely to make an expected-value maximizing choice (doing so in 66% of questions versus 56% for those in the lowest tercile of cognitive ability). Low-cognitive-ability participants were more likely than high-cognitive-ability participants to choose mixed lotteries, whether or not those lotteries had a positive (74% vs. 65%) or negative

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

(60% vs. 35%) expected value. The correlation between loss aversion and cognitive ability is thus underpinned by a clear pattern of individual choices.

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

4 Loss Aversion and Exposure to Real World Losses

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

4.1 Measures of Behavior Outside of the Survey

To understand the relationship between loss aversion and behavior outside of the study, we asked participants about their equity investments, recent gambling, and household shocks. Participants were asked to specify their total investable financial assets (excluding the value of their home), and the percentage of those assets invested in the stock market (directly or through mutual funds).[26] There is likely some noise in these measures, which will tend to bias the correlations with estimated preference parameters towards zero (Gillen et al., 2019).

Gambling behavior and the experience of household shocks were each measured using a battery of questions that we summarize using principal components analyses. Table 2 provides a brief description of each question, and shows that two principal components emerge for each

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

Table 2: Principal Components Analysis

Gambling (Last Time Gambled)	Components		Household Shocks (Experienced in Last 12 Months)	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.

module.[27] Most types of gambling behavior load on the first component, which we term *Serious* gambling. The second component captures *Casual* gambling—lottos and scratch cards—which involve smaller stakes, and can often be done at supermarkets and convenience stores. The two components of household shocks correspond to shocks that are primarily *Financial*, and to shocks which are more *Personal* in nature, including divorce and (to a lesser extent) injury.

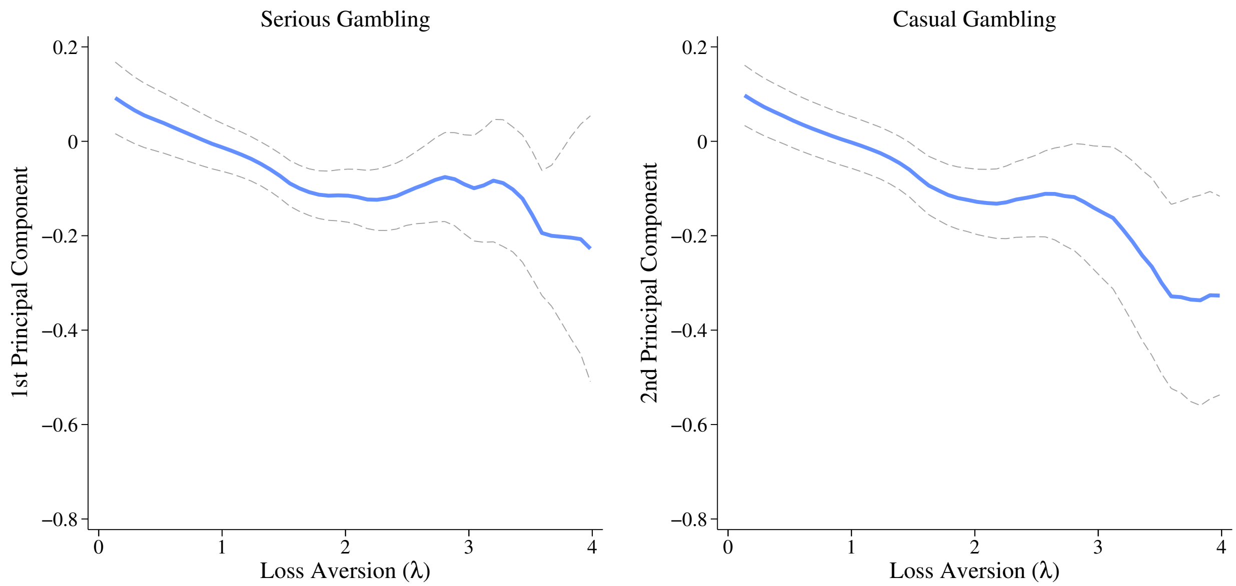
4.2 Gambling and Equity Investing

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

Loss aversion is negatively correlated with both of the principal components of gambling activity, as shown in Figure 7. Moreover, Table 3 shows that these relationships are robust

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

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



Notes: Each panel refers to a principal component of our gambling measures—see Section 4.1 for details. The figure displays local mean regressions, plotted using Epanechnikov kernel with bandwidth of 0.6. Grey dotted lines represent 90% confidence intervals.

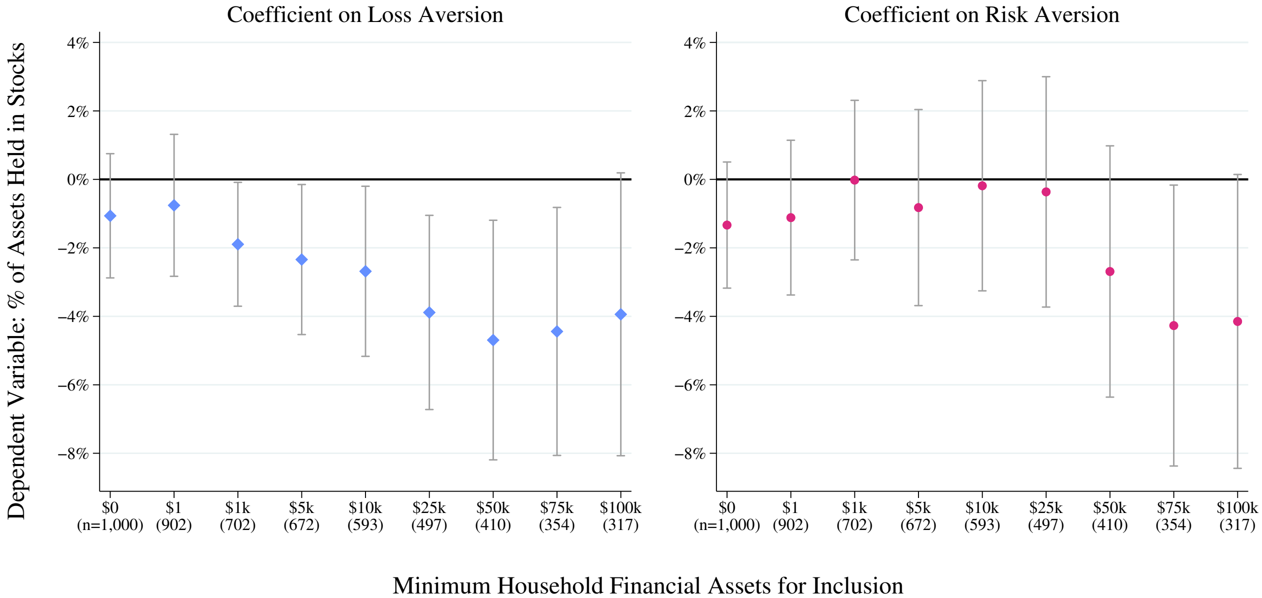
to controlling for other individual characteristics, including risk aversion and cognitive ability. Loss-tolerant individuals not only accept negative-expected-value bets in our study; they participate in such gambles in their day-to-day lives.

Loss-tolerant individuals also hold a greater proportion of their investable assets in the stock market, as shown in Figure 8. That figure plots the results from regressing the percentage of all financial assets held in the stock market against our measures of risk aversion and loss aversion, controlling for demographic characteristics, cognitive ability, and total asset ownership. The left-most point includes the whole sample. Each point further to the right progressively limits the sample to those with greater assets. The coefficient is consistently negative, and becomes statistically significant at conventional levels once the sample is restricted to those with at least $1,000 of financial assets.[28] Combined with the results regarding gambling behavior, these findings suggest that loss-tolerant individuals might be more likely to spend and invest in a way that leads to real-world losses.

Loss aversion is a much stronger predictor of both gambling and investment behavior than small-stakes risk aversion. The regressions in Table 3 show little evidence that risk aversion

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

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



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

predicts either component of gambling behavior: the results are similar even when loss aversion is excluded (see Appendix Tables C.9 and C.13). We do find some evidence that risk aversion is associated with smaller investments in the stock market—see the right-hand panel of Figure 8—but only amongst those with very high financial assets.

4.3 Shocks and Total Assets

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

Loss aversion is negatively correlated with having experienced a recent financial shock, but not a personal shock, as shown in Figure 9 and in Table 4. There is a clear negative relationship

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

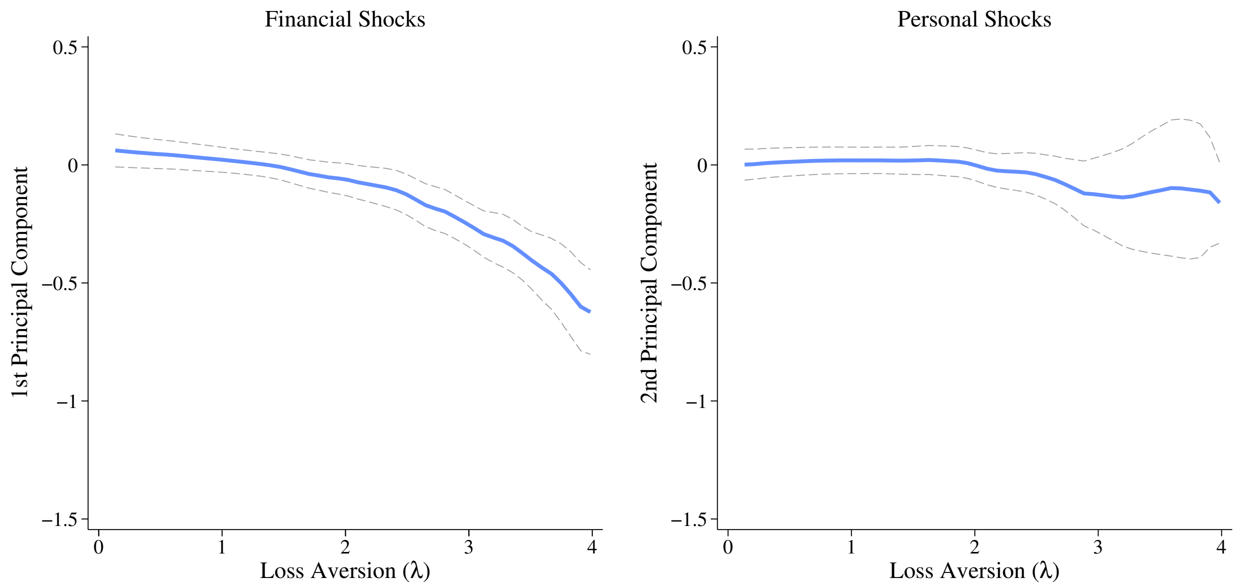
	Serious Gambling			Casual Gambling		
Loss Aversion (λ)	-0.12**	-0.11**	-0.10**	-0.13***	-0.12***	-0.09**
	(0.052)	(0.051)	(0.049)	(0.045)	(0.046)	(0.043)
Risk Aversion (1 - ρ)		0.03	0.04		0.05	-0.03
		(0.051)	(0.051)		(0.052)	(0.046)
Cognitive Ability			-0.13***			-0.14***
			(0.050)			(0.045)
Education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

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

between loss aversion and financial shocks—unemployment, housing, automotive, and other losses—the first principal component of household shocks (see Table 2). However, there is no relationship with personal shocks (the second principal component), which loads heavily on divorce and personal injury. As might be expected, given that we measure loss aversion in the domain of monetary gambles, our measure of loss aversion is associated with losses which are likely of a financial, rather than personal, nature.

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

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



Notes: Each panel refers to a principal component of our household shocks measures—see Section 4.1 for details. The figure displays local mean regressions, plotted using Epanechnikov kernel with bandwidth of 0.6. Grey dotted lines represent 90% confidence intervals.

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

The widespread willingness to accept negative-expected-value gambles, displayed in Figures 1, 4, and 6, demonstrates that our central finding—that a large proportion of the U.S. population is loss tolerant—is not driven by the DOSE elicitation method or by our parametric assumptions. However, our data present the opportunity to further reduce concerns about the robustness of our results, while learning more about participants' behavior. First, we find a similar level

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

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

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

of loss tolerance when preferences are elicited using the more traditional multiple price list procedure. Second, we analyze alternative parametric specifications, allowing for differences in risk aversion across the gain and loss domain (second subsection), and then for heterogeneity in participants' reference points (third subsection). Finally, the fourth subsection shows that inattention and fatigue seem to be relatively unimportant in our study, and do not confound our results. Across all these robustness tests, the estimated proportion of the population that is loss tolerant is consistently around 50%.

5.1 Traditional Elicitations of Loss Aversion

Our results are similar when using multiple price lists (MPLs; Holt and Laury, 2002), rather than DOSE, to elicit loss aversion. An MPL offers participants a table with two columns of outcomes. In each row, the participant is asked to make a choice between the outcomes in the columns. One column contains the same outcome in all rows, while outcomes in the other column vary, becoming more attractive as one moves down the table.[29] Each MPL then provides a set of binary choices which we use to estimate risk and loss aversion using the same parametric form, priors, and Bayesian procedure as the DOSE method.

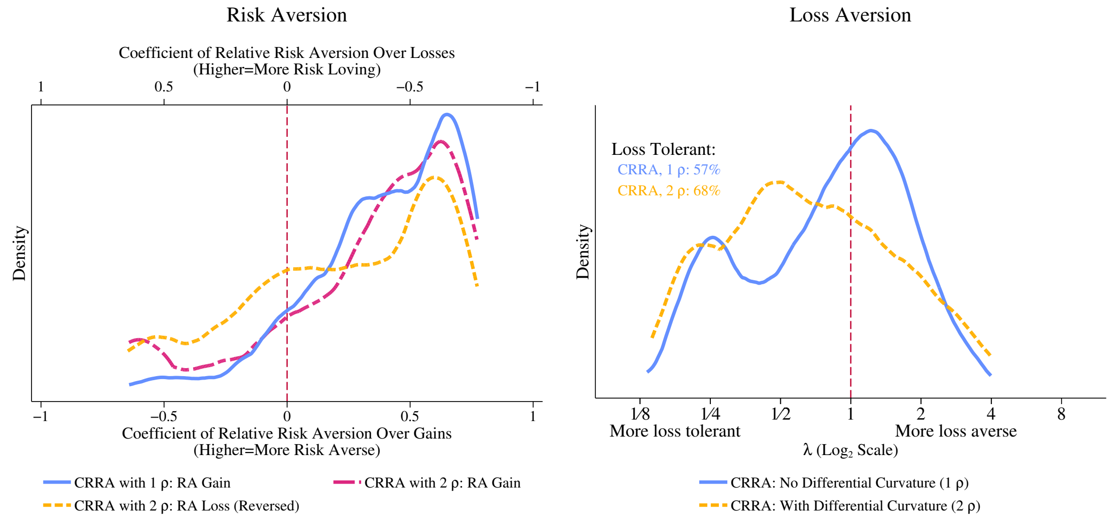
The survey elicited loss attitudes using two different MPL elicitation methods. First, participants answered two MPLs eliciting *Lottery Equivalents* for a fixed amount of \$0. Specifically, the lottery consisted of a fixed positive amount y and a varying negative amount c with equal probabilities. The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

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

The Bayesian estimates account for individual heterogeneity in risk aversion, and so provide a direct comparison to DOSE, but we can observe widespread loss tolerance simply by examining choices in the MPLs—as we discuss in detail in Appendix B.2. Specifically, we can simply assume equal utility curvature in both the gain and loss domains, and classify choices in the four mixed-risk MPLs as demonstrating loss aversion or loss tolerance. Doing so, we find the range of loss-tolerant responses is 41%–63% across the four mixed-risk MPLs. Further, a significant proportion of participants demonstrated strong loss tolerance; for example, 22% of participants preferred a lottery between -\$10 and \$4 to a sure amount of \$0. Choices in the MPLs thus provide further reassurance that loss tolerance is not an artifact of our parametric assumptions, or of the DOSE question format.

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

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



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

5.2 Allowing for Differential Utility Curvature Over Losses

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

Allowing for differential curvature does not affect our conclusion of widespread loss tolerance. Most participants (64%) are risk averse over gains and risk loving over losses, in line with prior experiments and prospect theory (Kahneman and Tversky, 1979)—see the left-hand panel of Figure 10. The average difference between the $\rho+$ and $\rho-$ parameters is small (mean = 0.11, s.e. = 0.02), offering support for our main specification. The distribution of risk aversion for gains is similar to that of our main risk aversion estimates; however, it appears that imposing the same curvature on both domains may slightly exaggerate the degree of risk-loving over losses. If so, our main specification would underestimate the extent of loss tolerance at the reference point. This is confirmed by the right-hand panel of Figure 10—more individuals have $\lambda < 1$ when allowing for differential curvature than in our main model (68% versus 57%).[30] However,

[30]Similar results are obtained when employing the constant absolute risk aversion (CARA) utility function

λ should be interpreted differently across the two specifications. In our main specification, λ captures all differences in attitudes towards gains versus losses; once we allow for differential curvature, λ reflects only a kink around the reference point. The difference between the $\rho+$ and $\rho-$ parameters captures other differences in preferences between the gain and loss domains, which may vary with the payoff x.

5.3 Reference Points

Our preferred model, with a reference point of \$0, fits participants' choices better than other common reference-dependent models listed in Table 5. The model correctly predicts 74% of choices in the DOSE 20-question module (20Q), and 91% in the DOSE 10-question (10Q) module. Models with alternative reference points correctly predict fewer choices, particularly in the 10Q module. Further, our basic finding that the majority of participants are loss tolerant is unchanged when incorporating these alternative reference points.[31]

The first row of Table 5 features the most obvious alternative model: participants evaluating each option relative to the amount they began the survey with. In this case, the endowment of \$15 given at the start of the 20Q module (or \$10 in the case of the 10Q module) would be incorporated into the values of the various options, and every payoff—even those presented as a loss—would be evaluated as a gain. This alternative model fits the data much worse, correctly predicting only 59% of choices in the 20Q module and 54% in the 10Q module—little better than random guessing. Further, the model performs better than our preferred \$0 reference 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.[32] Either of these reference points could capture the "first focus" concept of Kőszegi and Rabin (2006).[33] These models fare

suggested by Köbberling and Wakker (2005) to provide a scale-independent measure of loss aversion, see Appendix C.1. Appendix Table C.7 shows the correlations between the parameters of different models and cognitive ability.

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

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

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

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

	% Participants with Improved Fit		% Loss Tolerant	
Model of Reference Point	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. The row "Best Model for Each Person" refers to the reference point model(s) which best fits each participant's choices.

slightly better than incorporating the endowment; however, this is partly because the reference point is often similar to \$0—our preferred model.

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

Finally, our core finding of widespread loss tolerance is unchanged if we allow for heterogeneity in the reference points participants use.[34] The proportion of loss-tolerant participants is greater than 41% regardless of the reference point used, and our preferred estimate (57%) is near the midpoint of all the models we examine here. If we classify each participant according to the model that fits their choices best, as in the final row of Table 5, the proportion of loss-tolerant individuals ranges from 45% to 65%.[35]

module and second throughout the 10Q module.

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

[35] The range reflects the fact that there may be ties between the best models for each individual. The

5.4 Inattention and Fatigue

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

The results change little when restricting the sample to those participants most likely to be paying close attention. The left-hand panel of Figure 11 shows that a large majority (90%) passed three attention checks in our survey, and the degree of loss tolerance is very similar—57% of participants—even when excluding individuals who failed one of these checks.[36] The proportion of participants that is classified as loss tolerant is also similar (53%) when excluding those who completed the survey relatively quickly—those in the fastest tercile of response times—which may reflect a lack of attention.[37]

The right-hand panel of Figure 11 shows that the finding of widespread loss tolerance is not driven by survey fatigue. The order of the 10-question and 20-question DOSE modules was randomized across participants, with each module appearing as either the second or seventh module in the survey. Loss aversion is, if anything, higher later in the survey—62% of participants were classified as loss tolerant when the 20Q module appeared early, and 53% when it appeared late.

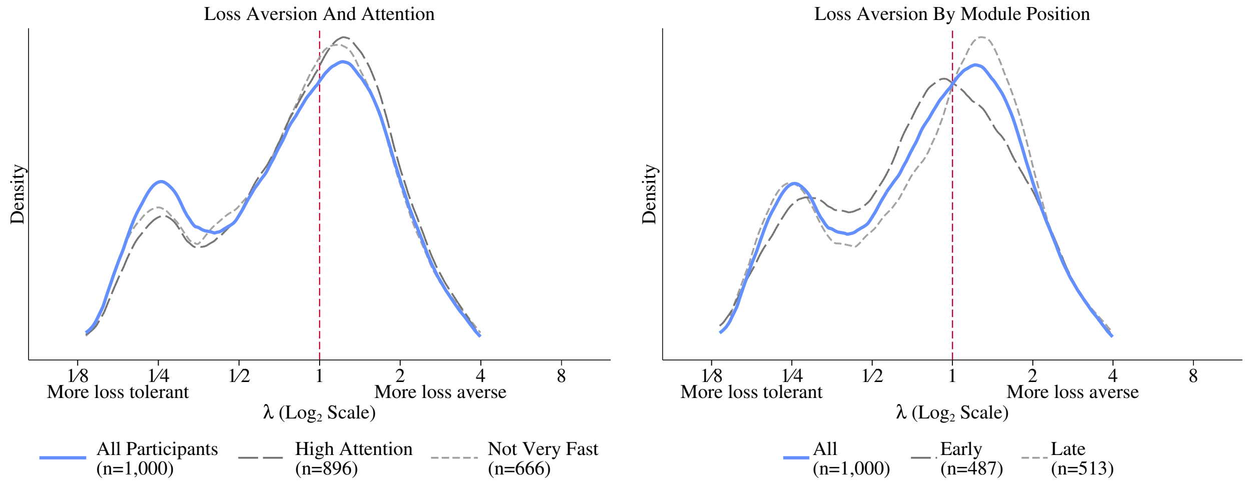
Appendix C.5 presents evidence that inattention—either during the DOSE modules or across the survey as a whole—does not explain our results. First, we show that the distribution of loss aversion is similar when we remove participants according to the amount of time they take to complete either the survey or just the DOSE module. Second, we carry out an experimental test of whether the sequential nature of the DOSE procedure affects participants' behavior through, for example, inadvertently creating a reference point. We find no evidence that interrupting

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.

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

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

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



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 DOSE sequence, using a randomly-placed "page break," affected behavior either in the sample as a whole or within particular subgroups. Third, we show that the correlation we document between cognitive ability and loss aversion is not an artifact of some participants making "mistakes," which would be revealed by these participants making inconsistent choices in the DOSE module.

6 Discussion

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

We model gain-loss attitudes using a standard prospect theory utility function, but more substantial departures from the literature may be appropriate. While we rule out many theoretical concerns regarding parametric form or participants' reference points in Section 5, other possible rationalizations for widespread acceptance of negative-expected-value lotteries exist.

Loss tolerance could, for example, reflect an extremely low probability weight on losses relative to gains, or low salience of losses. Reference points could, in principle, vary according to whether a lottery is over only gains or includes both potential gains and potential losses.

The paper has three major implications for applied theorists investigating gain-loss attitudes. First, the degree of loss tolerance we observe poses a challenges for the theoretical assumption of universal loss aversion—as found, for instance, in responses to the Rabin (2000) critique that attribute all small-scale risk attitudes to gain-loss attitudes (see, for example, Kőszegi and Rabin, 2006). Second, appropriate theoretical assumptions are likely to vary by context. An assumption of $\lambda > 1$ may be appropriate for groups with higher education and income—such as those manipulating tax liabilities (Rees-Jones, 2017) or participating in equity markets (Barberis et al., 2021)—who we find to be more loss averse on average. In other markets, however, loss tolerance may play an important role—near-universal loss aversion is hard to square with the high frequency of gambling in the U.S. population—approximately 85% of U.S. adults have gambled at least once in their lives (NCPG, 2023). Moreover, we find significant heterogeneity in gain-loss attitudes within all the demographic groups we study, indicating that loss-tolerant behavior may be present even if the average person in a given environment is loss averse. In financial markets, for example, Payzan-LeNestour and Doran (2022) observe that traders frequently invest in negative-expected-value trades, while Abdellaoui et al. (2013) find that a substantial minority of a sample of financial professionals are loss tolerant. Third, failing to account for variation in gain-loss attitudes may confound empirical tests of models of reference-dependence and, in general, further theorizing about the consequences of heterogeneous preferences may be a fruitful avenue for future research (Goette et al., 2019).

Our findings suggest that there are likely to be high proportions of loss-tolerant participants in all subject pools. Thus, experimental findings of low levels of loss aversion need not be treated with skepticism or stigmatized. In reviewing the loss aversion literature we found that studies sometimes present findings of loss tolerance cautiously, with, for instance, high proportions being reported without comment or in footnotes (for example, Delavande et al., 2023; Koch and Nafziger, 2019). This caution may reflect the fact that, "Since the publication of Tversky and Kahneman (1992), any estimates of loss aversion that deviate significantly from the value of two have been eyed with great suspicion, notwithstanding the fact that the original estimate was based on 25 subjects, hypothetical decisions over relatively large stakes, and that no standard errors were reported." (Fehr-Duda and Epper, 2012, p. 576). Reviewing the loss aversion literature, Yechiam (2019, p. 1) asserts that, "[T]he findings of some of these studies have been systematically misrepresented to reflect loss aversion, though they did not find it."

This claim finds some support in two recent meta-analyses of empirical estimates of λ, both of which report evidence consistent with some publication bias (Walasek et al., 2018; Brown et al., forthcoming). We document that loss tolerance is an important behavioral regularity, and point to the importance of further study of heterogeneity in gain-loss attitudes.

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

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

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