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# 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
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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, 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.

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An online appendix is available at http://www.nber.org/data-appendix/w30241

# 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

[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, $\lambda$, 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).

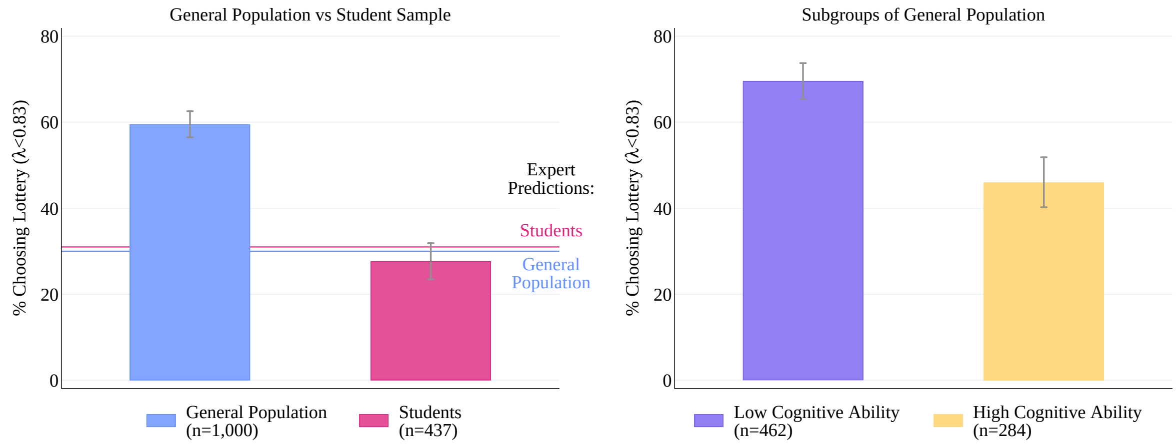
Our main result can be observed in choices over a simple 50:50 lottery with a negative expected value, as shown in Figure 1. All participants face a choice between a sure amount of \$0 and a lottery between a gain of \$10 and a loss of \$12, each with 50% probability.[4] As shown in the left-hand panel, 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

[3] Our 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).

[4] We 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).

[5]These 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.

[6]Moreover, 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

[7] 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); 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

[8]In 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 elicitations 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 ($\lambda$) 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 elicitations, 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 $\lambda$ in the Netherlands, without eliciting individual-level estimates of loss aversion. They report a median $\lambda$ 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

[9]A 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).

[10]von Gaudecker et al. (2011)'s main results, which produce a median $\lambda$ 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.

[11]Specifically, 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 $\lambda$ 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

[12] Consistent 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

[13]In 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:

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

in which $\lambda_i$ parameterizes loss aversion, $\rho_i$ 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 $\lambda$ 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

[14] Assuming 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.

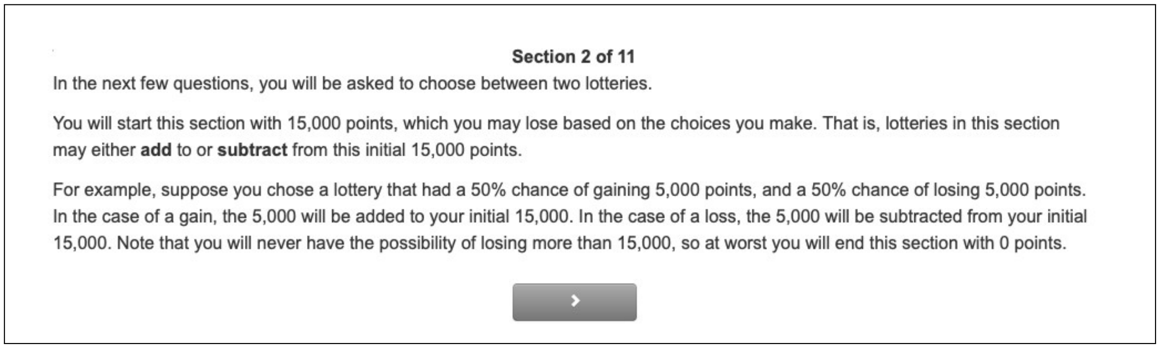
[15] Alternative definitions, such as Wakker and Tversky (1993), have focused on loss aversion as meaning greater sensitivity to losses, and so compare the slope of the utility function over losses to that over gains (see also Bowman et al., 1999). Later approaches have focused on loss aversion as reflecting 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.)

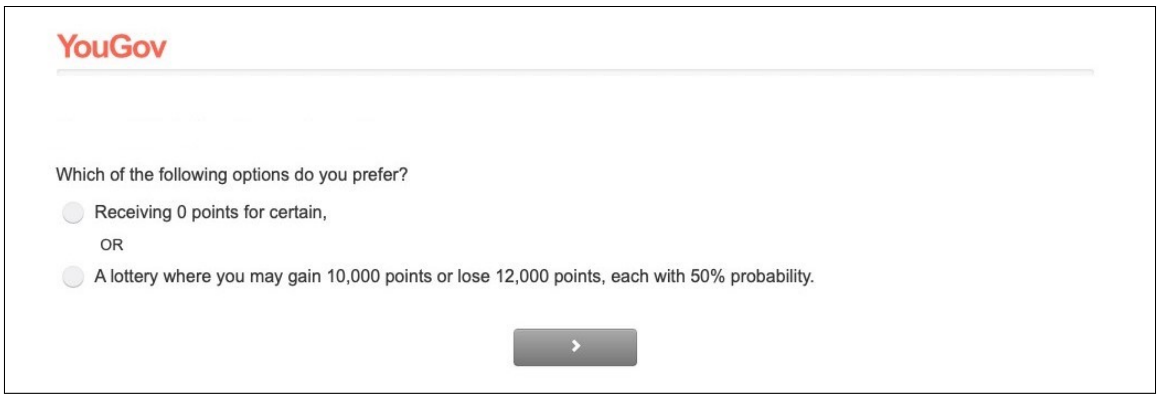
To estimate individual-level risk and loss aversion we use DOSE, which is designed to tackle the issues associated with estimating multiple preference parameters simultaneously. Estimating multiple parameters is complicated, because it is necessitates asking participants a number of questions—in this 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).

[16]For 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




(a) DOSE Instructions




(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, $\lambda$ and $\rho$, given a flat prior over those parameters and the participant's previous choices.[17]

[17] The 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 ($\rho$), 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 $\lambda$. 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

[18]Experimental 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).

[19]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.

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 Feburary 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,

[20]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.

[21]For 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.

[22]YouGov 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).

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

[24]The 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 ≈ \$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

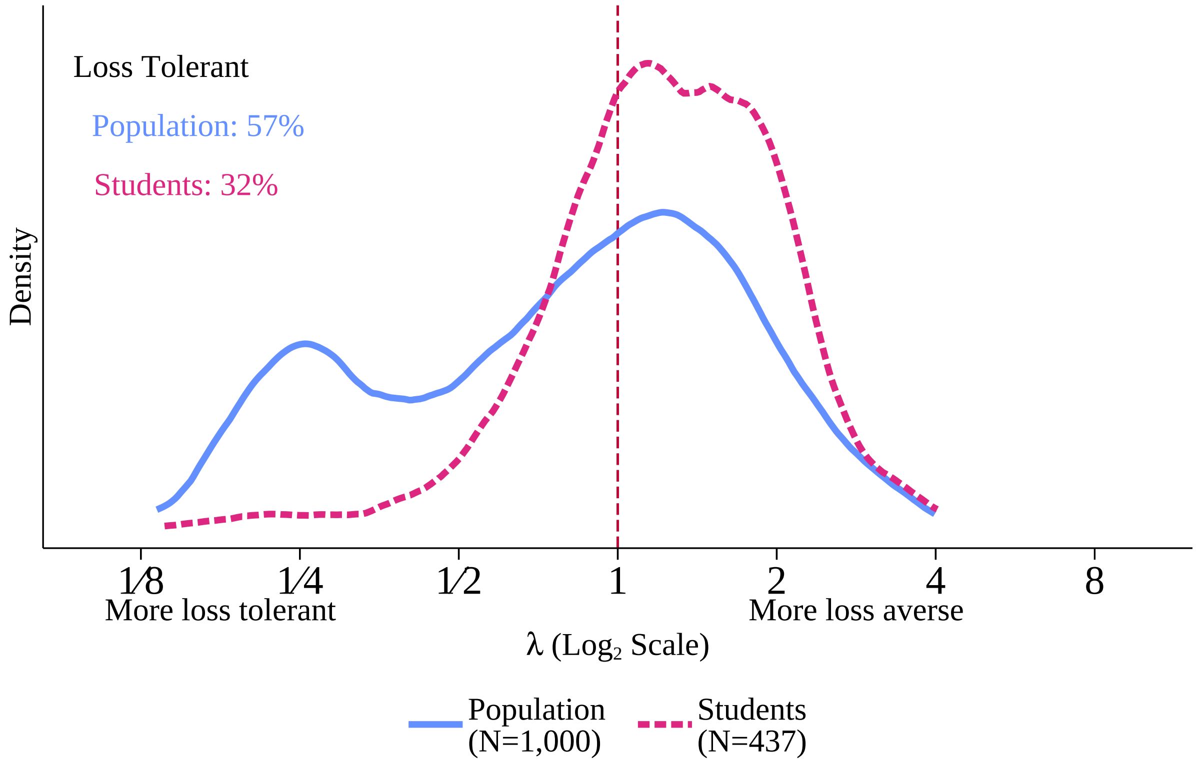
The U.S. population is substantially more loss tolerant than participants in student samples. Consistent with this finding, higher-cognitive-ability participants are more loss averse. This contrasts with the prior literature that suggests that behavioral biases are concentrated in those of lower cognitive 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 $\lambda$ 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.

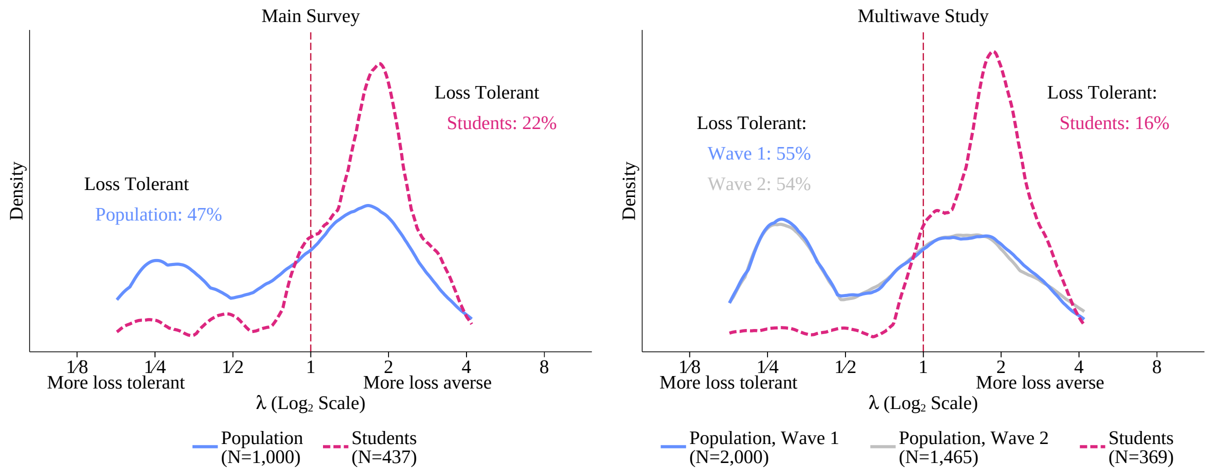
## 3.2 Stability of Loss Aversion

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 $\lambda$ assumes everyone is fairly loss averse, with a mean $\lambda = 2.3$, based on previous laboratory studies. Loss-tolerant participants with a true $\lambda$ 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 ($\rho$)—0.44 (0.04)—and for time discounting ($\delta$)—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.

[25]Within 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

[26]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.

[27]We 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 ($\lambda$) | | DV = Risk Aversion (1-$\rho$) | |
|---|---|---|---|---|
| | 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.

and loss aversion is even higher when constraining the sample to those with $\mu$ 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

[28]The 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.

[29]The 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

[30] Low-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 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.

[31] 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."

[32] Questions 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) | Components: Serious | Components: Casual | Household Shocks (Experienced in Last 12 Months) | Components: Financial | Components: 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% |

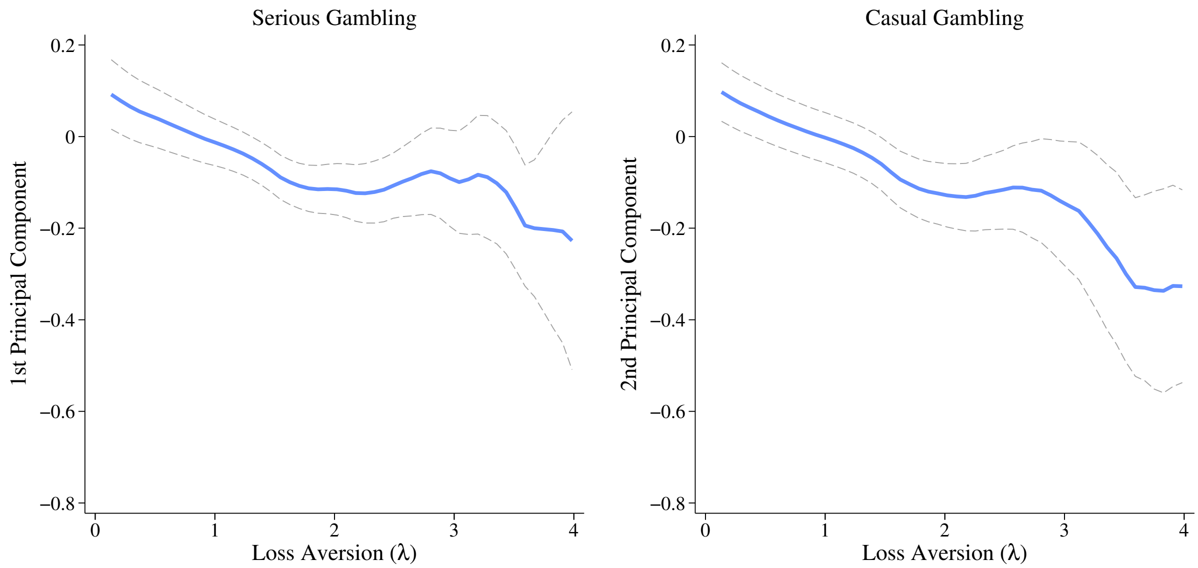
Notes: Only first two principal components are shown, rotated using varimax rotation.

## 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.

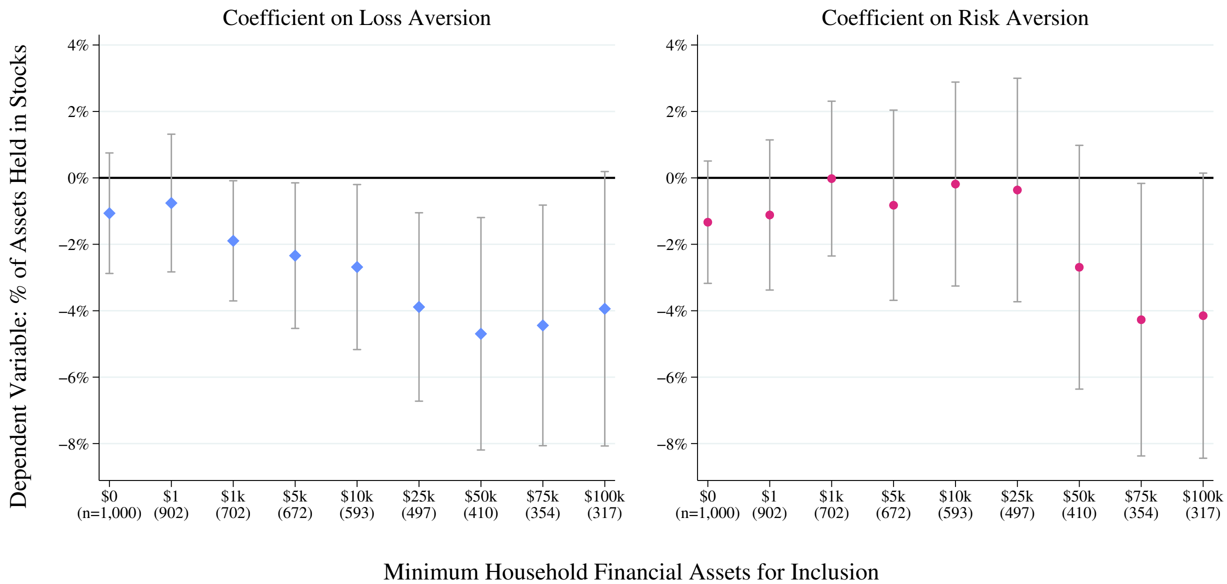
such gambles in their day-to-day lives.

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

[33] 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 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 ($\lambda$) | -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 - $\rho$) | | 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) |

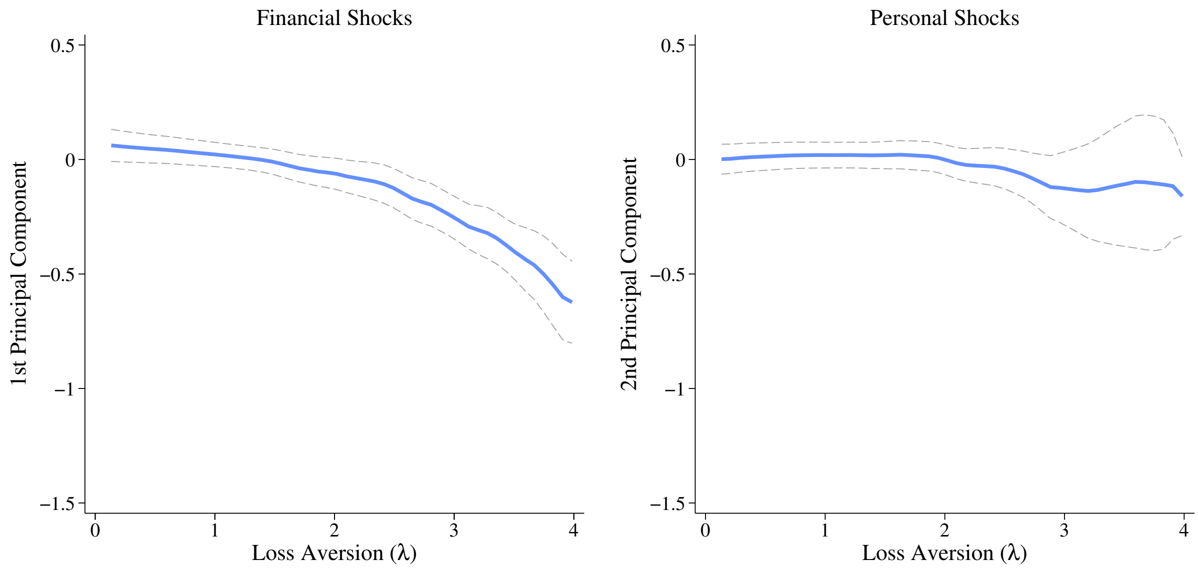
Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level. All continuous variables are standardized. Robust standard errors are displayed in parentheses. The magnitude and statistical significance of the coefficients for loss and risk aversion are similar when including controls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

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 ($\lambda$) | -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-$\rho$) | -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.

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-

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

[35] Alternatively, we can estimate loss aversion parameters using a double MPL method (Andersen et al., 2008; Andreoni and Sprenger, 2012), in which risk aversion is estimated separately by eliciting the certainty equivalent for a lottery over gains. This method is problematic because many participants select the (highly salient) top or bottom rows of the MPL leading to extreme parameter estimates (for example, $\lambda > 100$) or choices that are first-order stochastically dominated. Consequently, the method is unable to estimate $\lambda$ 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.

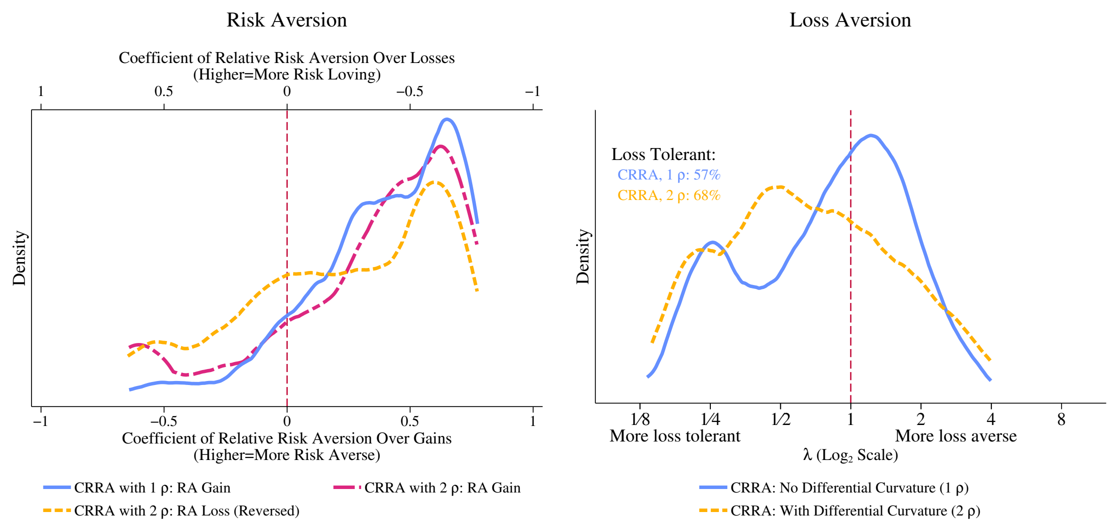
We estimate that most participants (64%) are risk averse over gains and risk loving over losses, inline with prior experiments and Prospect Theory (Kahneman and Tversky, 1979)—see the left-hand panel of Figure 8. The average difference in the curvature between the domains is small (mean = 0.11, s.e. = 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 $\lambda$ 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, $\lambda$ captures all differences in attitudes towards gains versus losses; once we allow for differential curvature, $\lambda$ 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 $\lambda$ 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.

| | % 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. "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

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

[37]Using 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 $\rho$ and $\lambda$ 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).

[38]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 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.

[39]Similarly, 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

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

[41] There 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]

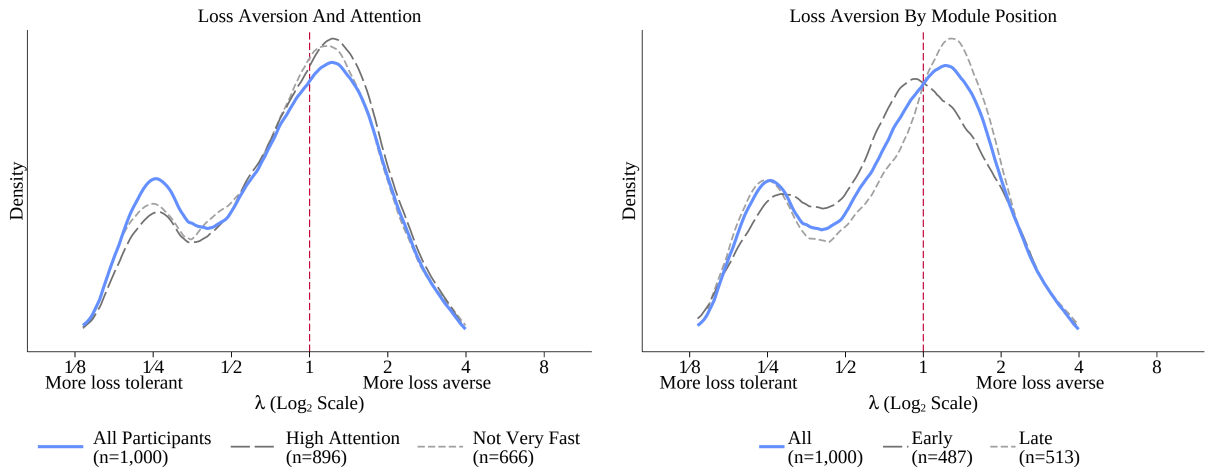
The finding of widespread loss tolerance is not driven by fatigue as participants progress further in our survey, as shown in the right-hand panel of Figure 9. The order of the 10-question and 20-question DOSE modules was randomized across participants, with each module appearing as either the second or seventh module in the survey. Loss aversion is, if anything, higher later in the survey—the median value of $\lambda$ 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

[42] See 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).

[43] 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. 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.



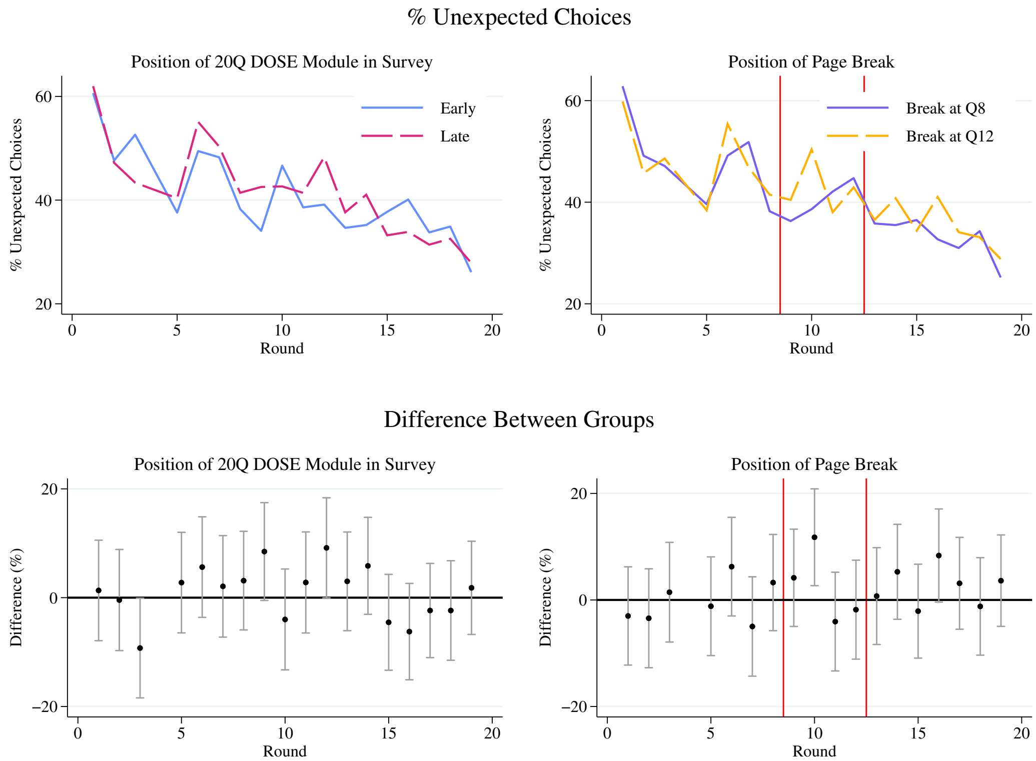

Notes: Figures display the distribution of loss aversion ($\lambda$) from the 20-question DOSE sequence. "High attention" excludes any participant that failed any attention check. "Not Very Fast" excludes participants in the fastest tercile of response times. The percentage of participants classified 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.

[44] The 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 $\lambda$ 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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